

# TOWARDS URBAN MOBILITY-BASED ACTIVITY KNOWLEDGE DISCOVERY:

Interpreting motion trajectories



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*Towards Urban Mobility-based Activity Knowledge Discovery:*  
Interpreting motion trajectories

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*dedicated to my dear parents*

*Ohana* means family.  
Family means nobody gets left behind, or forgotten.  
— Lilo & Stitch



## ABSTRACT

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Understanding travel behaviour is important for an effective urban planning and to enable different context-aware mobility service provisions. To this end, it is essential to model different mobility-based activities in available trajectory data. However, the semantics of activity varies from context to context, which poses a challenge for developing a connected knowledge flow for different services.

Currently, such mobility-based information is typically collected through manual paper-based surveys. These surveys preserve context, but come with their own inherent quality issues, and are expensive in comparison to data analytics methods. To address this issue this research leverages the emerging concept of smartphone-based travel surveys that collect people's movement behaviour in terms of raw trajectories.

This research proposes an ontological framework that can model activities in a hierarchical manner adapting to different contexts and thereby addressing the challenges of trajectory data analytics mentioned above. This research also explores how raw trajectories collected by a smartphone can be interpreted to generate mobility information (e.g., transport modes, trips). While interpreting the trajectories this thesis models uncertainties that may exist during people's travel behaviour and interpretation process.

In this research, a particular focus is given to knowledge representation, that is understanding urban movement behaviour from detecting transport modes in trajectories. One presented form of knowledge representation is a fuzzy logic based approach to mode detection. The knowledge representation is essential to extract semantics related to a given activity. This research also introduces the concept of *near-real time* mode detection and investigates the performance of a purely knowledge-driven model works effectively in a near-real time scenario. Since a knowledge-driven model at different temporal granularities while detecting a given transport mode. The knowledge-driven model that works in offline, typically requires kinematic features computed over sufficiently long segments. But in near-real time these segments must be shorter and requires the model to be adaptive. To address this issue a machine learning based model has been deployed, which can learn from the historical data, and work in varied conditions. But machine learning models work as a black box and cannot explain their reasoning scheme owing to a semantic gap in the activity knowledge base. On the other hand, a fuzzy logic based model can explain its reasoning scheme but cannot adapt to varying conditions. To bridge the trade-off between these approaches this research proposes a hybrid knowledge-driven framework that is capable of self-adaptation and explaining its reasoning scheme. The results show the hybrid model performs better than a purely knowledge-driven model and works at par with the machine learning models for transport mode detection. This research also justifies a

hybrid approach can model the activity in a consistent and adaptive manner while explaining the semantics related to different mobility-based activities.

In this research different uncertainties related to a motion trajectory interpretation process have been addressed. A particular focus is given on modelling the temporal uncertainties that exist between predicted, scheduled and reported trips. Such a temporal uncertainty quantification measures the reliability (or uncertainty) in an inference process in the interest of information retrieval at different contexts. Considering the lack of semantics in GPS trajectories an investigation is also made whether incorporating low sampled IMU information in addition to a GPS trajectory can improve the accuracy. This research also identifies existing trajectory segmentation approaches (e.g., clustering-based or walking-based approaches) are subjective and thus lacks adaptivity. In order to address these issues a novel state-based bottom-up trajectory interpretation model is developed, which can generate mobility information at different temporal granularities. The model also demonstrates its efficacy, flexibility, and adaptivity over the existing top-down approaches. This research also demonstrates that using a GPS trajectory, it is possible to generate modal state information comparatively at a coarser granularity but shorter than the time required to generate information from a historical GPS trajectory. The response time is subject to a particular application domain.

The research presented in this thesis has a potential to improve the background intelligence in smartphone-based travel surveys and smartphone-based travel applications facilitating mobility-based context-aware service provisions where the notion of *activity* is prevalent at different granularities. However, this research cannot distinguish composite activities, which require future work. With the emergence of Web 2.0 and ubiquitous location sensing technologies, the location information can come from various sources with the different level of inaccuracies and space-time granularities. The models developed in this research currently work best on GPS trajectories sampled at 1 Hz to 2 Hz frequency, which may be enriched with IMU information. However, the models need some adjustments and incorporations of additional features and rules when the location information comes not only from GPS but also from GSM, Wi-Fi, smart-card. The models developed in this research are flexible, transparent and offer provisions for further enrichment of raw trajectories and extract finer activity information. This research has a potential to understand mobility patterns at an aggregate and a disaggregate level, and thereby serve different application domains e.g., personalized activity recommendations during a travel, emergency service provisions, real-time traffic management and long term urban policy making.

## DECLARATION

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This is to certify that:

- this thesis comprises only my original work towards the degree of Doctor of Philosophy,
- due acknowledgement has been made in the text to all other material used,
- the thesis is fewer than 100,000 words in length exclusive of tables, maps, bibliographies and appendices.

Rahul Deb Das

*Parkville, Melbourne, Australia,  
September 2017*





## PUBLICATIONS

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The thesis is based on research published in the following places. Each chapter cites individually where its material has appeared first. I am the first author of all these publications, as I have been the responsible researcher. My co-authors have been research supervisors, providing guidance and feedback. Accordingly, my co-authors agreed on the following extent of the first author's contribution to the cited work.

### JOURNAL ARTICLES (PEER REVIEWED)

- **Das, RD.**, Winter, S. (2016): A Context-Sensitive Conceptual Framework for Activity Modelling, *Journal of Spatial Information Science*, 12 [contribution of 80%]
- **Das, RD.**, Winter, S. (2016): A Hybrid Knowledge driven Framework for Urban Transport Mode Detection from GPS Trajectory, *ISPRS International Journal of Geo-information*, 5(11) [contribution of 80%]
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### CONFERENCE PROCEEDINGS AND WORKSHOP (PEER REVIEWED)

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- **Das, RD.**, Ronald, N., Winter, S. (2015): A Simulation Study on Automated Transport Mode Detection in Near-Real Time using a Neural Network, *Research at Locate*, Brisbane, Australia [contribution of 80%]
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## ACRONYMS

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API	Application Programming Interface
DL	Description Logic
FIS	Fuzzy Inference System
GDA <sub>94</sub>	Geocentric Datum of Australia 1994
GIS	Geographical Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GTFS	General Transit Feed Specification
HDOP	Horizontal Dilution of Precision
HCI	Human Computer Interaction
HTS	Household Travel Survey
ICT	Information and Communication Technology
MaaS	Mobility-as-a-Service
MFIS	Mamdani Fuzzy Inference System
ML	Machine Learning
MLP	Multi-Layered Perceptron
OWL	Web Ontology Language
POI	Point of Interest
SPARQL	SPARQL Protocol and RDF Query Language
TSK	Takagi-Sugeno-Kang
UML	Unified Modeling Language
WGS84	World Geodetic System 1984



## INTRODUCTION

---

*Mobility* is central to any activity that involves a bodily movement from one location to another location over a constrained or unconstrained space-time domain at different granularities. For example, to perform an activity *cooking* requires a bodily movement from the current location in the house to the kitchen. While at a coarser granularity to participate in an activity *working in the office* requires a movement from home to office. Such movement may occur through a number of transport modes starting with the most basic type *walking* to more sophisticated modes (*taking a train* or (*taking an aeroplane* or even (*taking an autonomous car*). The interest of this research particularly lies in how such movement occurs in terms of a particular transport mode from one location to another location. In this research, the words ‘movement’, ‘mobility’ and ‘travel’ – all refer to a change in space at different granularities. These words will be used interchangeably with very subtle differences throughout this thesis. This research will address *granularity* from two different perspectives.

- Granularity (extent) from the perspective of space-time.
- Granularity (level of details) from the perspective of information retrieval.

The information of a given transport mode can be treated as a contextual cue used by a context-aware device to provide more personalized and contextualized services. For example, it is possible to retrieve the nearest restaurants within a given search radius based on the user’s transport mode with the least for walking and comparatively longer distance for the motorized mode (Fig 1). Another example could be activating an auto-answer on the phone while the user is driving in order to avoid the distraction.

Understanding transport mode information at an aggregate level can help in urban planning and transport management by estimating the travel demands in terms of mode specific patronage, people’s mode choice and travel behaviour. In the same line, a transport planner often looks for various mobility-based information from people’s movement behaviour. For example, a transport planner wants to know travel demand in terms of people’s origins and destinations, when do they make their trips (trip start and end time), how do they travel (mode of travel), what did they do on their way (activity), why do they travel (trip purpose) and whom do they travel with (accompaniment). These information will help in providing more adaptive transport services to meet travel demand at different space-time granularities.

By combining these two aspects – mobility and context-awareness, it is then possible to develop seamless context-aware service provisions that can assist a user at different contexts using the same computing platform throughout all modes and activities. The



Figure 1: Retrieved location information of restaurants within walkable distance (in contrast to distances accepted for other travel modes) from the Engineering Workshop depending on the *walking* mode.

service can recommend the best possible itinerary to a given user in order to travel from location  $A$  to location  $B$  based on the user's preference or the user's current transport modal state. The service can also incorporate an intermediate wayfinding assistance system while navigating in an unfamiliar environment based on the user's context (Tenbrink and Winter, 2009; Timpf, 2005), e.g., providing route guidance during transfer between two aeroplanes in an airport.

In all the above-mentioned cases (enabling context-aware mobility service provisions to support mobility-based activities, and managing public transport infrastructure) the authorities, service providers, and the computing devices (smartphones) need to know people's activity states, movement behaviour, and their current context at different temporal granularities. Today, with the advent of advanced ICT and ubiquitous computing people tend to leave their digital trails or footprints during their mobility-based activities. More recently, these footprints are being traced, sampled, and recorded for understanding movement behaviour and travel demand. This has been greatly supported by a number of positioning systems e.g., Global Positioning System (GPS), Global System for Mobile Communications (GSM), Wi-Fi, Bluetooth and a number of inertial navigation sensors including accelerometer, proximity sensor, gyroscope, magnetic sensor, mobile camera – all onboard of smartphones or other navigation devices.

In order to understand human travel behaviour and travel demand, currently manual travel surveys are conducted over a region for a certain time period through face-to-

face, telephone, paper-based, or computer assisted interview (Wolf, 2000; Stopher et al., 2003). With growing urban complexity and population, it is an increasingly difficult effort to manage travel surveys with these approaches. Besides, the efficacy of such travel survey methods is highly dependent on respondent's memory and their ability to describe their travel experience with finer details. Since this process involves time gap between the actual travel takes place, and describing the travel experience at some later time from memory, eventually this reconstruction process results in under-reporting or missing trips with inaccurate travel start and end time, mode taken, intermediate transfers, trip purpose, and other finer activity details (McGowen and McNally, 2007). With the advent of GPS based tracking, travel surveys have taken a new form where the movement traces are captured automatically with reduced respondent's burden (Wolf, 2000).

Nowadays smartphones come with varieties of indoor and outdoor positioning sensors and are carried by their users almost everywhere and whenever they go. Thus, smartphones can be used to track and capture people's movement with low survey investment and higher accuracy and flexibility. According to a market research, the total number of smartphone users globally was 2.16 billion in 2016, which is expected to reach 2.56 billion by the end of 2018 (Table 1)<sup>1</sup>

Table 1: Worldwide smartphone users and penetration rate (2012-2017 projected)

	2013	2014	2015	2016	2017	2018
<b>Users (billions)</b>	1.13	1.64	1.91	2.16	2.38	2.56
<b>% change</b>	32.4	25.0	16.8	12.6	10.4	7.6
<b>% mobile user</b>	34.3	38.4	42.9	46.4	49.5	51.7

That said, there is an enormous amount of movement data (collected by smartphones) being generated at various granularities in terms of sampling frequency, extent of the tracking area. The vast amount of data is not bound to the small sample rate of current paper-based or telephone-based surveys. In this regard if a smartphone-based travel survey is implemented at different granularities, it can generate trajectories of whole population segments with different travel behaviour at different granularities. The smartphone-based travel survey has been realized in some of the recent ongoing smartphone-based travel surveys including *Future Mobility Sensing* (FMS) in Singapore (Cottrill et al., 2013) and alike surveys elsewhere (Safi et al., 2013). These trajectories require background intelligence process to extract mobility information related to people's movement behaviour. However, the results inferred from the back-

<sup>1</sup> To be found online at (last accessed: November, 2016)

<https://www.emarketer.com/Article/2-Billion-Consumers-Worldwide-Smartphones-by-2016/1011694>.

Percentage figures are based on total world's population.

ground intelligence still requires user’s validation in the form of prompted recall surveys, which is time consuming and resource intensive. Automation is required in the background intelligence process to interpret the smartphone trajectories more effectively with the least user intervention.

Although movement takes place in a continuous manner, due to system architecture and hardware limitations, it is captured in a discrete way, which approximates the path taken by the user (Long, 2016). Thus, a movement trace of a moving person or a vehicle is generally recorded in terms of a sequence of discrete location information at given time stamps. The sequence of time-ordered spatio-temporal points is termed as trajectory in this research. A trajectory collected in its raw form cannot provide much meaningful information related to a user’s travel behaviour except the approximated location information and geometrical properties of his movement history. Consider, Figure 2a shows Joe’s home-to-office travel. Figure 2b shows a schematic representation of how Joe performed different activities at different time periods on his way. Joe spent some time at home from 5 am to 8 am and then he walked down to the nearest train station at 8:05 am, where he was waiting for the next connecting train for 5 mins. Then he reached the city and got off from the train at 8:30 am. Following that, Joe started walking out of the station and took a tram at 8:33 am and got off at 8:40 am. Then he walked to a coffee shop where he had his morning coffee while reading the newspaper. At 9 am he left the coffee shop and reached his office at 9:05 am and worked until 3 pm.

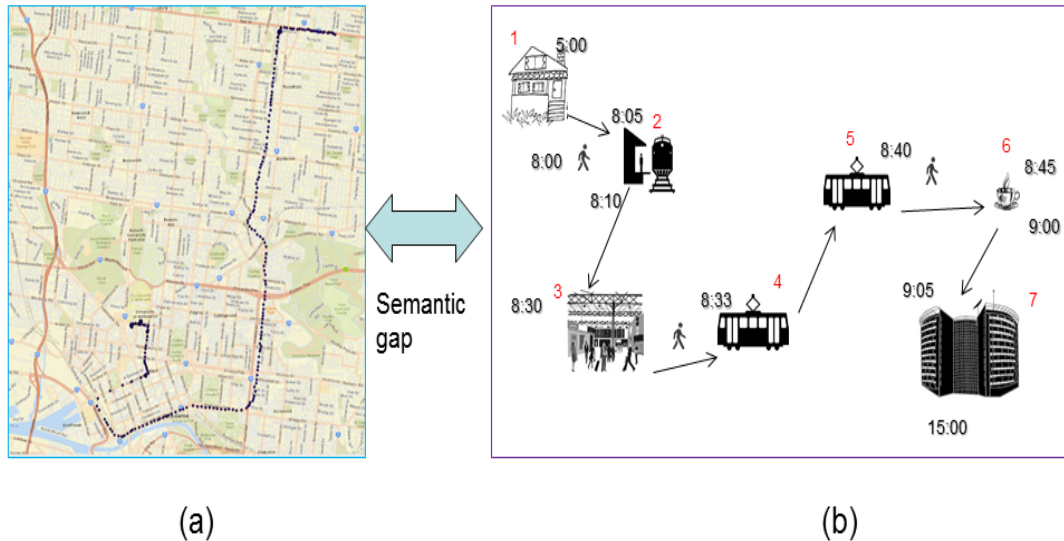


Figure 2: Raw trajectory captured by a smartphone (a). Joe’s reported travel history (b).

When Joe's travel history was captured by a smartphone the raw trajectory (Fig 2a) cannot provide information what transport mode(s) Joe used during his home-to-office travel. Thus there exists a semantic gap between the raw trajectory and the description of the user's travel behaviour.

In order to gain insight and explore various mobility-based activities, the raw trajectories are enriched with relevant contextual information. This enrichment process is known as semantic enrichment and the enriched trajectory is termed as semantic trajectory. These semantic trajectories are then analysed to understand movement behaviour and mobility pattern(s). Some researchers tried to enrich the trajectories and analyse them through manual map-matching (Van-Langelaar and Spek, 2010). But this manual approach fails when there is a massive amount of data with varied granularities and complexities. In the context of conventional travel surveys, participants do not always note down the particular transport modes and other mobility-based activity information. They may also miss finer details. That is why a background intelligence is required to interpret raw trajectories for further analysis at different temporal granularities.

From the perspective of a context-aware service provision it is essential to understand a user's activity states to provide relevant services in different situations. The notion of activity, however, is context-dependent. For example, considering Joe's home-to-office travel (Fig 2) Joe has performed different activities at different contexts. In the first context, while looking from the perspective of an urban planner the notion of an activity is primarily bound to the time spent at a given location. Thus, in the first context, Joe's activities are *resting at home* and *working at office*. In the second context, suppose Joe seeks recommendations from his mobile device (smartphone) to follow the quickest path to reach his office from home. In this context, travelling from home to office is an activity in itself. Now imagine, there is a construction work going on at the train station. Due to the construction work some of the subways and escalators are blocked. Once reached at the train station at 8.30 am (Fig 2b), Joe requires a wayfinding support from his mobile device to find the exit. In this third context, *finding the way during transfer* becomes an activity.

## 1.1 PROBLEM DEFINITION

Thus while extracting mobility based activity information this research has identified the following problems that will be addressed within the scope of this research.

- Trajectories collected in their raw forms cannot explain the user's travel behaviour at different granularities (Fig 2). The raw trajectories thus require an adaptive interpretation process.
- The notion of activity varies across different contexts. This poses difficulties for a context-aware service provision to perceive a user's activity state in a consistent

manner at different contexts. In order to maintain a consistent definition of activity across different domains it requires an overarching ontological framework, which is currently missing in the state-of-the-art.

- Current approaches in spatial computing are looking at interpreting smartphone sensor information to analyse people's activities mainly from machine learning point of view. However, machine learning approaches act as a black box and require substantial training data. Machine learning based trajectory interpretation approaches also fall short in explaining the semantics of different mobility-based activities since they are limited in explaining their own knowledge base.
- Besides, detecting activities at different granularities from people's movement trajectories is challenging due to various uncertainties present during the movement. In order to distinguish different activity states during a travel, a segmentation is performed on a given trajectory where each segment bears a specific activity state at a given context. Current trajectory segmentation approaches are top-down and assume predefined thresholds e.g., minimum walking distance, or maximum speed. Such assumptions are contextual and subjective. Thus, existing segmentation approaches are not adaptive enough. In order to address these issues, an adaptive and automated framework is required which can detect the mobility-based activity states at different temporal granularities; and this framework should allow for real-time, near-real time, and offline semantic interpretations.

## 1.2 RESEARCH OBJECTIVE

Based on the problem definition this thesis aims at closing the two semantic gaps by the following ways.

- Closing the first gap: There exists a semantic gap in a raw trajectory captured during a travel and activities performed along that travel. This gap has been closed by providing hybrid knowledge-driven methods that can interpret raw trajectories to detect a number of mobility-based activity information (transport modes, trips, transfers) from GPS and inertial measurement units e.g., accelerometer and gyroscope (see Section 3.2).
- Closing the second gap: While addressing the trajectory interpretation process, it is identified that there is another knowledge gap in activity definition. This research aims to bridge this second knowledge gap by modelling an activity from an ontological perspective.



### 1.3 RESEARCH QUESTIONS AND HYPOTHESES

Since a context-aware mobility-based application requires activity information at different contexts, there is a need to understand the semantics of different activity information consistently from smartphone sensor information. However, existing interpretation processes are either machine learning based or purely knowledge-based with the trade-off between the expressiveness and adaptivity. A hybrid model can only bridge the trade-off and can generate more relevant information at a given context.

**OVERARCHING RESEARCH QUESTION:** The overarching research question for the thesis is formulated as follows:

How the knowledge gap in activity definition can be bridged while interpreting a trajectory at different granularities?

**HYPOTHESIS 1:** Based on the above facts explained earlier in this chapter, the primary hypothesis of this research states that *hybrid models allow a consistent and adaptive interpretation of activities from smartphone trajectories*.

In order to justify the primary hypothesis a number of sub-hypotheses have been formulated with the corresponding research questions, which are structured and addressed into two parts.

- **Part I:**

The research starts out with a fundamental research agenda on the definition and modelling of an *activity* from a motion trajectory in [Chapter 4](#). Since the term *activity* is understood differently by different application domains, there is a basic research question as follows.

**RESEARCH QUESTION 1:** What is an activity and how can an activity be modelled to maintain the underlying semantics at different contexts on a motion trajectory?

**HYPOTHESIS 1.1:** In order to address the above research question [Chapter 4](#) hypothesizes that *the semantics of activity depends on the spatial and temporal granularity suggested by context. Shifts in granularity will enable processing motion trajectories, and activity knowledge can be represented in various contexts facilitating flexible, appropriate and relevant information representation or provision, and thereby develops a connected knowledge flow*.

- **Part II:**

Following the overarching framework developed in [Chapter 4](#), the next three

chapters ([Chapter 5](#), [Chapter 6](#), [Chapter 7](#)) develop three different models to detect transport mode information at different temporal granularities ([Fig 4](#)). These three chapters address the following research question.

**RESEARCH QUESTION 2:** How can a raw trajectory be analysed to extract transport mode information automatically at different granularities?

In order to address the research question 2 [Chapter 5](#) investigates how different transport modes can be detected over historical trajectories in offline. Whereas [Chapter 6](#) explores transport mode information generated in near-real time, comparatively at a finer temporal granularity than that of an offline strategy. On the other hand, [Chapter 7](#) has developed a more adaptive and flexible framework that can be applied in different scenarios and at different temporal granularities. Assuming there exist several uncertainties in a trajectory the following research questions have been posed.

**RESEARCH QUESTION 3:** What are the different uncertainties that exist in a trajectory interpretation process especially in transport mode detection? How can such uncertainties be modelled?

While addressing the uncertainties [Chapter 5](#) has primarily investigated the kinematic uncertainties whereas [Chapter 7](#) has addressed the issue of temporal uncertainties in a trajectory interpretation process.

**HYPOTHESIS 1.2:** The model developed in [Chapter 5](#) hypothesizes that *A multiple-input multiple-output fuzzy logic based knowledge-driven approach is able to detect different transport modes effectively based on the expert knowledge from historical trajectories. The knowledge-driven approach will also model the uncertainties present in the movement behaviour in a transparent way.*

As extracting semantics related to a given activity is essential to perceive a given context, this thesis primarily focuses on knowledge-driven aspects in comparison to the existing machine learning aspects used in transport mode detection. While interpreting motion trajectories this thesis has posed the following research question in order to investigate the performance and expressiveness of different mode detection models.

**RESEARCH QUESTION 4:** What are the advantages and disadvantages of a machine learning approach and a knowledge-driven approach while detecting transport modes from the raw trajectories? How can the trade-off between a machine learning model and knowledge-driven model be bridged so that it is

possible to represent the reasoning scheme of a predictive model that works on motion trajectories and at the same time the model is able to self-adaptation?

**HYPOTHESIS 1.3:** The model proposed in [Chapter 6](#) states that *in near-real time scenario a neuro-fuzzy based hybrid knowledge-driven framework will perform better than a purely knowledge-driven model. This will also bridge the trade-off between a purely knowledge-driven model and machine learning model in terms of expressiveness and learning ability.*

In an offline trajectory interpretation process, a segmentation strategy is used once the entire travel is complete. Such segmentation involves temporal uncertainties at different granularities especially during a trip start or trip end, which has been addressed in [Chapter 7](#). Such temporal uncertainties are essential to understand travel behaviour at a finer granularity and to measure the reliability (or uncertainty) in an inference process to enable a given context-specific application.

**HYPOTHESIS 1.4:** With this view, the research presented in [Chapter 7](#) hypothesizes that *a state-based bottom-up approach is more adaptive than any top-down approach, and in addition, it will be flexible enough to detect activity states in a progressive manner at different temporal granularity.*

This translates into the fact that the temporal uncertainty of trip transition depends on the length of chosen space-time kernel. The shorter the kernel the less is the uncertainty, but at a cost of overall detection accuracy.

#### 1.4 CONTRIBUTIONS

This research has made contributions both at a conceptual level and also at a methodological level. The contributions are divided into two parts. Part I presents a conceptual framework that models activity at different contexts. Part II consists of a set of chapters each having a number of contributions that interprets raw trajectories ([Fig 3](#)).

**PART I: TOWARDS MODELLING THE ACTIVITY:** In this research, an ontological framework has been proposed that can develop a connected knowledge flow for modelling an activity at different contexts ([Chapter 4](#)), and thereby bridge the gap while defining the activity by different application domains.

A particular focus has been given on the mobility-based activities from motion trajectories, e.g., *travel by a given transport mode, transfer, and making a trip* – which are some of the basic aspects of urban mobility.

**PART II: DETECTING THE MOBILITY-BASED ACTIVITY:** Second part of this research explores the uncertainties exist in movement behaviour and develops a fuzzy logic based knowledge-driven model (Fig 4) to detect the mobility-based activities (in particular *travelling on a given transport mode(s)*) from motion trajectories in offline (Chapter 5).

To bridge the trade-off between the expressiveness and adaptivity of a trajectory interpretation process a hybrid knowledge-driven framework (Fig 4) has been developed that can detect transport modes in near-real time to generate just-in-time information (Chapter 6).

The length of response time required to fetch different (mobility) information varies from one service domain to another. To address this issue a more sophisticated and adaptive framework is proposed (Fig 4) that can handle different uncertainties and data qualities that are inherent in people's movement behaviour (Chapter 7). Such an adaptive framework consists of a predictive model that can serve as the background intelligence for interpreting the motion trajectories in real time, near-real time and offline mode to generate relevant information to support smartphone-based travel surveys.

The signal gap in GPS trajectories has been a critical problem while interpreting motion trajectories. Thus, a final contribution of this research is to investigate how signal gaps present in trajectories can be bridged at different temporal granularities using knowledge-driven and hybrid techniques by using GPS and other inertial sensors.

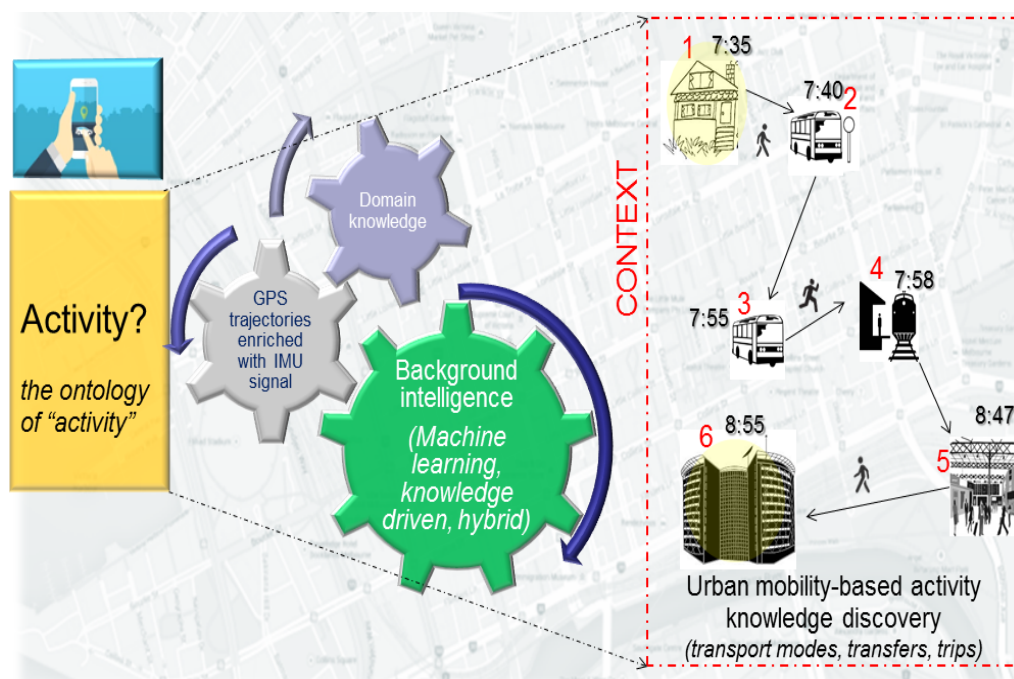


Figure 3: The contribution of the thesis: from a conceptual framework for *activity* modelling to mobility-based activity discovery.

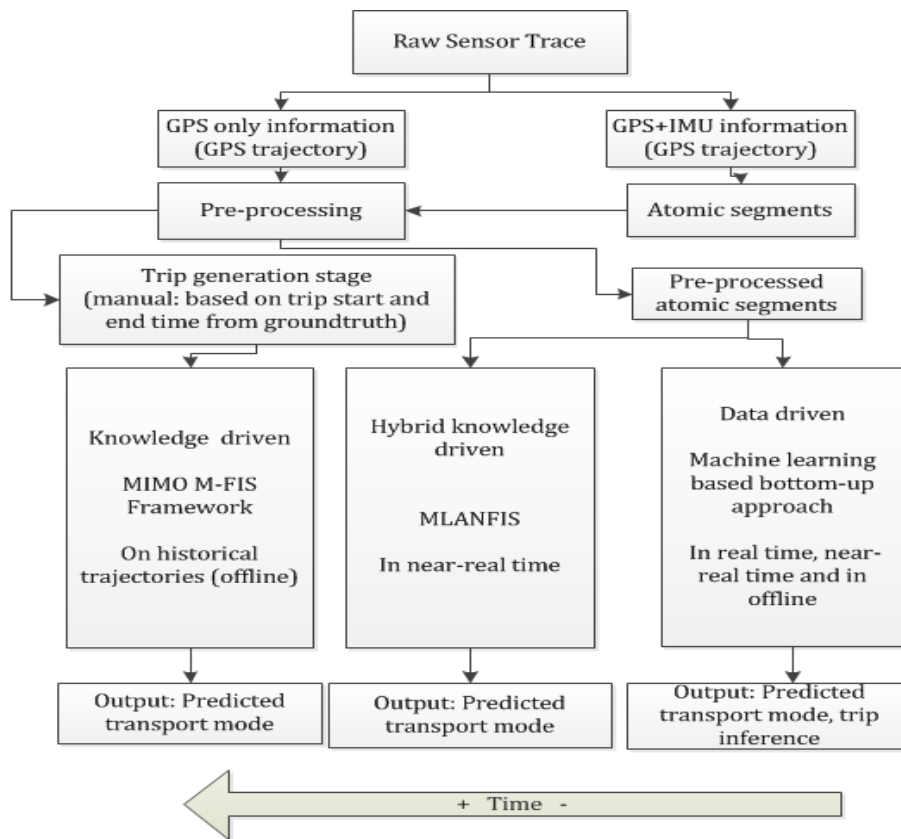


Figure 4: Contribution of part II: Three different frameworks: MIMO MFIS - a knowledge driven fuzzy mode detection model; MLANFIS - a hybrid knowledge-driven model; State based bottom-up approach - an adaptive and robust framework that can work in different granularity and in different contexts. The time line shows the length of response time to fetch mobility information by different models, shortest for the state based bottom-up model and the longest for the MIMO MFIS.

The models developed in this research work effectively on GPS trajectories. However, the models may need further information and (pre)processing phases when the location information comes from other sources e.g., GSM, Wi-Fi, a smart-card or a Bluetooth.

## 1.5 ORGANIZATION OF THE THESIS

The thesis is organized as follows. [Chapter 1](#) introduces the background of the research. [Chapter 2](#) presents a literature review that covers different aspects of mobility surveys and an overview of activity modelling and trajectory interpretation methods. [Chapter 3](#) describes some basic concepts and data sets used in this research. [Chapter 4](#) presents a conceptual framework that models activity at different contexts. [Chapter 5](#)

develops a knowledge-driven model for detecting urban transport modes. [Appendix A](#) contains the fuzzy rule base used to construct the knowledge-driven model in [Chapter 5](#). [Chapter 6](#) proposes a hybrid knowledge-driven framework to detect transport modes in near-real time. [Chapter 7](#) presents an adaptive state-based bottom-up approach to interpret trajectories with different response time to serve different service provisions. [Chapter 8](#) discusses the critical aspects of the research followed by the future research directions and concluding remarks in [Chapter 9](#).

## LITERATURE REVIEW

---

This chapter presents background of the research and current state-of-the-art. The literature review touches on different aspects of urban mobility starting with the data collection strategies and practices through traditional mobility surveys to GPS-based travel surveys and the recently emerging concept of smartphone-based travel surveys. Since this research is motivated by context-aware mobility service provisions, a section is presented with different facets of mobility-based services. The literature review also gives an overview of how motion trajectories are modelled and interpreted to infer different mobility-based activities along with a conceptual modelling of activity from different perspectives.

### 2.1 MOBILITY SURVEYS

A mobility survey is the process of collecting movement data to understand people's movement behaviour and travel patterns over a given space-time region. In an urban context, a mobility survey generally involves collecting people's movement data with additional information over a certain period of time. This can help transport planners and policy makers to understand current travel behaviour and travel demand, future trend and response to the change in household demographics, socio-economic facets, environment and transport infrastructure in a short-term as well as in a long-term basis. Mobility surveys are also known as travel surveys or travel demand surveys or travel behaviour surveys in the literature with similar underlying concepts. Ortuzar and colleagues gave an overview of traditional mobility surveys at different scales and intervals (Ortuzar et al., 2010).

Urban mobility survey can be broadly classified into two categories: a one-off survey that takes place once over a certain region within a large scale temporal window and a regular survey that continues for a longer period (generally year after year) and is repeated over a certain region. A regular survey is always better and promising than a one-off survey since it is conducted for a long time (literally for an indefinite time). A regular survey reflects a general movement pattern and travel demand at different situations and various spatio-temporal granularities, whereas a one-off survey sometimes reflects biased travel behaviour affected by circumstantial influence at a given time period. For example, in 1973-74 the National Travel Survey, a one-off large scale mobility survey in France took place during the first oil crisis. In 1993-94 the survey was again conducted during an extreme financial crunch. In both cases, due to adverse socio-economic situations numbers of trips were reduced compared to non-surveyed

times and thus the overall travel data was biased (Ampt and Ortuzar, 2004; Ampt et al., 2009). On the other hand, a regular survey e.g., National Mobility Survey in the Netherlands, which is repeated every year, can capture travel behaviour at different conditions across the country. In this context a concept of large-scale ongoing urban mobility surveys have come up. This type of survey takes place continuously in a city under the administration of a local planning authority. This type of survey takes place every day over a time frame set by the survey requirement. In the case of one-off surveys there is a gap in consistency and loss of expertise and resources during inter-survey periods, whereas regular surveys retain the resources, smooth flow of funding and overall consistency. Geographical scale wise both the surveys can be further categorized as nationwide mobility survey and regional or metropolitan mobility survey. A nationwide mobility survey takes place across the country whereas a regional or metropolitan survey takes place at a regional level or metropolitan level. Ampt and Richardson discussed advantages and disadvantages of regular large scale and one-off surveys (Ampt and Ortuzar, 2004; Richardson and Battellino, 1997). The following section gives an overview of past and current regular large scale mobility surveys in different parts of the world at national and regional level.

#### 2.1.1 *Nationwide regular mobility survey*

The Netherlands' *National Mobility Survey* was started as the longest and perhaps the oldest nationwide regular mobility survey in 1978. Over the course of time the survey methodology was redesigned at different epochs at 1985, 1998, 2004 and 2009 in order to have more participation and less attrition rates. This survey has involved about 1.8 million participants from more than 800,000 households up to 2008 (Ampt et al., 2009; Ortuzar et al., 2010).

The former Federal Republic of Germany carried out regular mobility surveys in 1976, 1982 and 1989 named as *Continuous Survey of Travel Behaviour* (KONTIV) under the administration of the Ministry of Transport. In 2001-2002 a new travel survey named as *Mobility in Germany* (MiD) was conducted. In 2008, the survey was modified and again restarted. The survey is being conducted through telephone interview and a paper based approach. There are around 25,000 households selected for the survey. Main objective of this survey is to understand people's travel behaviour including origin and destination, trip purpose, mode taken, accompaniment and their socio-demographic and household characteristics.<sup>1</sup>

After five one-off surveys, in 1998 another nationwide mobility survey was started in England named as *National Travel Survey* which also expanded into Scotland, Wales and in the northern part of Ireland by 1999. The survey was started with only 5040 households in 1998 which was subsequently increased up to 15000 by 2002. The sur-

<sup>1</sup> To be found online at (last accessed: November, 2016)  
<http://daten.clearingstelle-verkehr.de/223/>



vey was performed with a 7 day self-completion travel diary filled by the respective household member (Ampt et al., 2009). In 1992 Denmark started the Danish National Travel Survey with around 16,000 computer assisted telephone interviews with the help of Statistics Denmark. In 1998, the travel survey showed an unexpected drop in travel behaviour. The most recent travel survey started in 2006 based on internet and telephone interviews. However, the new trend has been shifted from activity based to trip based approach (Ampt et al., 2009).

Since 2001 Italy is conducting their national mobility survey named as *Audimob* with the help of the *Istituto Superiore di Formazione e Ricerca er i Trasporti* (ISFORT). This is based on telephone-based interview where every year 15,000 phone calls are made to randomly selected respondents to record their travel behaviour (Ampt et al., 2009).

New Zealand has started a nationwide *New Zealand Travel Survey* in 2002 with 2200 households per year until 2007. In 2008, the sample size has been increased to 4600, a major contribution coming from the cities. The survey required the participants to record their travel behaviour on specific two days.

In the USA first national travel survey – *Nationwide Personal Travel Survey* (NPTS) was conducted in 1969, 1977, 1983, 1990 and 1995. Later in 2001 the survey got a new form and was performed as *National Household Travel Survey* (NHTS). The most recent national large scale travel survey was conducted in 2009 (FHWA, 2014).<sup>2</sup>

Apart from these surveys there are several other countries including Sweden and South Africa who have conducted their nationwide large scale regular mobility surveys in the past, and some of them are still continuing with different sample sizes and gradual modifications.

### 2.1.2 Regional level mobility survey

This section briefly describes some of the well known regional level mobility surveys in Australia and South America. The first long standing mobility survey started in Australia in 1993 under the flagship of the Victorian Activities and Travel Survey (VATS) (Richardson et al., 1995). The survey involved a paper-based self-completion travel diary fill up. VATS was a significant regional travel survey initiative in Victoria. Following this survey, various short-range similar regional surveys were undertaken in various parts of Australia and New Zealand by the *Urban Transport Institute* (TUTI) in Perth (2002-2005), Brisbane (2003, 2006), Melbourne (2004, 2005), Sunshine Coast (2004, 2007), Gold Coast (2004, 2008), Auckland (2006) (Richardson et al., 1995).

In 2006-2007, VATS was transformed as *Victorian Integrated Survey of Travel and Activity* (VISTA), which follows a paper-based self-completion travel survey approach.

<sup>2</sup> To be found online at (last accessed: November, 2016)  
<http://www.fhwa.dot.gov/policyinformation/nhts.cfm>

VISTA survey was conducted from 2007 to 2008 and again from 2009 to 2010 in Greater Melbourne, Geelong and some selected parts of Victoria.<sup>3</sup>

In 1997 Sydney started its first ongoing regional travel survey as *Sydney Household Travel Survey* (HTS) with 5,000 households per year sample size. However, in practice the survey reached around 3,500 households due to sample losses. HTS is still running in Sydney Greater Metropolitan Area (GMA). This survey has been benchmarked as the best regional survey in Australia.<sup>4</sup> Unlike VATS and VISTA, Sydney HTS is a face-to-face travel survey where the field staff interviews the household respondents about their travel over 24 hours periods. Sydney HTS employs a cross-sectional strategy to select its samples every year. However, in order to provide more consistent and high quality data 3 years of survey data are pooled over regions in Sydney GMA. The questionnaire mainly focuses on household characteristics, number of persons in the household, vehicle ownership and travel history.

In 2001 the *The Santiago de Chile Mobility Survey* started a mobility survey in Chile with 15,537 households. After 2002 the survey was stopped by the government due to unsatisfactory results. In 2004 the survey was again started and ran until 2007. This survey was based on self-completion paper based travel diaries as well as face-to-face interviews similar to the Sydney HTS, with respective advantages and disadvantages (Ampt et al., 2009). A paper based self-completion approach is more flexible and could be completed by the participants at any time at their discretion, whereas a face-to-face interview is temporally constrained. At the same time a self-completion travel diary is more suitable for participants who do not have time to attend a face-to-face interview. On the other hand, self-completion travel diaries are not effective for those who cannot follow the instructions or cannot complete the questionnaire due to language problems. In such situations face-to-face interviews are found to be a better option (Ampt et al., 2009).

### 2.1.3 Technological revolution in travel survey

With technological advancement, mobility surveys have also passed through several improvements over last few years. Earlier mobility survey or travel surveys were based on face-to-face and paper-based questionnaires. This was followed by telephone assisted and computer assisted surveys. But there was a significant burden on the surveyor's side in order to design and execute the survey. Since these surveys also required respondents' mental effort to recall their past travel activities, most of the time this resulted in under reporting or missing trips. This problem was highly mitigated by GPS based surveys where the trip activities were captured automatically with fewer burdens on respondents and surveyors. But GPS based surveys turned out to be sub-

<sup>3</sup> To be found online at (last accessed: November, 2016)

<http://www.transport.vic.gov.au/research/statistics/victorian-integrate-survey-of-travel-and-activity>

<sup>4</sup> <http://www.bts.nsw.gov.au/Statistics/Household-Travel-Survey>

ject to several limitations such as uncertainty in origin destination of the trip, data loss, battery depletion and thus sometimes respondents could not perform their real travel behaviour. With growing use of smartphones, more recently researchers started looking into smartphone based mobility survey which can overcome the previous issues with face-to-face, paper-based, computer-based or GPS based mobility survey as the smartphone can be used to record a person's travel behaviour continuously at a finer granularity using the sensors onboard. Based on the technological revolution, this report has categorised the mobility survey into three classes as follow.

#### 2.1.3.1 *Face-to-face, paper, telephone based travel diary and Computer assisted survey*

The earlier mobility surveys are done manually through either face-to-face interviews or paper based questionnaires – starting from selecting the sample, distributing the survey brochure, executing the survey process and collecting the response. In both the cases, field staffs were subject to manual labour. Both of these surveys use cross-sectional or longitudinal sampling strategies. VATS was one of the significant self-completion paper-based travel diaries. A standard workflow of VATS is discussed below (Ampt et al., 2009).

- Sample households are selected from Census Collection Districts (CCD) GIS database.
- Existence and validity of household addresses are checked followed by dispatching pre-contact letters with survey brochure to each household. This generally took place on Tuesday of the respective survey week.
- Based on the validation sample addresses are corrected and GIS database is updated. The correction procedure is performed on Wednesday of the survey week.
- Once all the sample household addresses are fixed, paper-based questionnaires are delivered to the respective household on Saturday or Sunday. The duration of travel days generally ranged from next Monday to Sunday.
- A motivational phone call is made to remind the participants about their travel day and clarify any doubts they may have.
- Over the next 7 days, the participants record their trip records on the travel diary by filling out the questionnaire. On seventh day, field staffs use to collect the questionnaires in person.
- Once the travel data are collected the data are cleaned and processed. VATS used special software named Speedit for this purpose. This process involves geocoding of addresses where the participants travel. There are six geocoding options such as geocoding of home address, full street, partial street address, landmark, cross-street and centroid of the town or suburb mentioned by the participants.

- Once the data are geocoded there are further checked against range error and logical error.
- This process is followed by correcting any error in the processed data and integrates them together in a separate file made for each household.
- If still problem persists, a phone call is made to the respective participants for further information in order to resolve the issues.
- After 1 week a reminder call and letter are used to make to those households who have not submitted their questionnaire.

The success of face-to-face and self-completion travel diaries is highly dependent on the ability of the field staff to motivate the respondents. In order to keep the field staff focused and motivated, regular team meetings and training are held. However, it has been found that wage is one of the motivational factors for field staffs.

Apart from a paper-based strategy, another popular approach is using telephone or computer or internet to conduct mobility survey. A computer-based approach is particularly suitable at intercept survey where travellers at a certain transit, toll, corridor or a given region are interviewed ad-hoc. Computer-based intercept surveys have also been conducted in certain locations e.g., rest area and shopping mall where people generally have more free time to participate. A computer-based travel survey consists of GUI, icons and visual cues. In contrast to paper-based and face-to-face interview, telephone assisted travel surveys have also been conducted where a phone call is made to the predefined participants to record their trip-activity pattern. Although these survey types are highly manual labour intensive both from surveyor's side as well as respondent's side, which is quite burdensome and tedious.

#### 2.1.3.2 *GPS assisted survey*

Since 1994 GPS gained a significant attention in travel survey or mobility survey in order to collect high quality travel data with more detailed information. GPS based travel survey was found to be quite flexible and effective in terms of quality and quantity of travel data and reducing respondent's burden. Table 2 presents a comparative study between different survey strategies.

Initially, GPS based travel surveys were performed as proof-of-concept to prove the efficacy and flexibility offered by GPS over traditional paper-based travel surveys. The first of this kind of study took place in Lexington, Kentucky MPO as a part of its large household travel survey (Auld et al., 2009; Battelle, 1997; Murakami and Wagner, 1999). This study was performed on 100 households sample selected from the total pool and asked to record their movement using in-vehicle GPS receiver and on-board computer for additional trip information. Some of the earlier works were intended to assess the applicability and acceptability of GPS based approach in traditional paper based travel

Table 2: Comparison between different survey strategies (Zhang, 2012)

Survey type	Advantage	Disadvantage
Roadside interview	High response rate	Low sampling rate
	Accurate information provided	Expensive and time consuming
Mail-back/Paper based survey	Less expensive	Sampling rate can be large
	Low response rate	Inaccurate information exists
Online survey	Less expensive	Comprehension issue
	Low response rate	Inaccurate information exists
Telephone survey	High response rate	Moderate sampling rate
	Inaccurate information exists	Expensive and time consuming

survey (Draijer et al., 2000; Guensler and Wolf, 1999; Murakami and Wagner, 1999; Zito et al., 1995).

Early GPS assisted travel surveys were based on in-vehicle tracking due to heavy weight and battery issues (Stopher et al., 2003; Wolf et al., 2004). These studies showed a promising result with more accurate travel data. However, in-vehicle GPS based travel surveys have lots of shortcomings. First of all, the exact origin and destination of the person was not clearly understood since the tracking took place only when the vehicle was moving. Besides, in-vehicle GPS studies used to provide biased sample data mostly on private vehicles movement behaviour and thus it excludes other modalities such as walking, biking and public transits. These modalities involve with more mode sharing and route sharing by the daily commuters which play an important role in travel demand modelling. Although GPS was proved to be a critical travel data collector but it involved a lot of efforts made in post-processing stage in order to extract semantic information relevant to travel behaviour from the raw GPS traces or movement trajectories. From 2005 onwards, there was a significant improvement in GPS receivers in terms of weight, accuracy, data storage, affordability and portability, and this advancement made a drastic shift from in-vehicle GPS based travel survey to

handheld GPS based travel survey. Handheld GPS based travel survey was able to generate activity-trip data with finer details including trip origin and destination, route taken, travel on public transit etc which were difficult to infer or capture using earlier in-vehicle GPS based studies.

The efficacy of handheld GPS survey has been proved in various research works (Auld et al., 2009; Bohte and Maat, 2009; Chen et al., 2010; Chung and Shalaby, 2005; Elango and Guensler, 2010; Gong et al., 2012; Roorda et al., 2011; Schuessler and Axhausen, 2009; Shen and Stopher, 2011; Tsui and Shalaby, 2006). A handheld GPS travel survey is more flexible and can record activity-trip behaviour continuously with accuracy up to 10-15 m. The participant has to carry the GPS logger along his or her travel and the device can record automatically. When the participant finishes his or her travel, he or she can directly upload the data to a central server or download the data from the device and then can upload the data to the server. The duration of survey can span from one day to several weeks depending on the survey requirement. However, handheld GPS are subject to theft or lost and thus it may lead to data loss. The accuracy of the recorded data also depends on where the GPS logger is kept and if it can view at least four satellites. Thus, the positional data use to vary depending on the position of the logger. If it is kept in the pocket then the result would be different than when it is kept in hand. Handheld GPS loggers are also subject to quick battery depletion. The participants have to always remember to carry the logger with them, which creates extra mental burden on the survey participants. Due to this stringent survey practice participants can not follow their real travel behaviour (Safi et al., 2013), and the collected data lacks the actual travel behaviour. This problem is further mitigated by using smartphones for activity-trip data collection.

#### 2.1.3.3 *Mobile phone and smartphone assisted survey*

In 1999 a mobile phone based mobility survey was carried out on 100 participants in Japan (Asakura and Hato, 2004). The study proved the usefulness of mobile phone based travel survey. The trip legs were identified as move and stay by an episodic trajectory segmentation algorithm.

Following this study in 2004 Ohmori and colleagues developed a mobile phone based travel survey application where respondents were supposed to enter trip information manually (Ohmori et al., 2005). The application contained a questionnaire that required input from respondents about their trip start/end time, activity location and type, transport mode(s) along the trip, accompaniment etc. Once the memory was full respondents can send the information to the surveyor through email. This research was conducted in two stages on total 50 respondents. The authors also compared the delay time and frequency of recording an activity on mobile phone as well on paper based questionnaire and in both the cases, a mobile phone based travel survey outperformed the traditional paper based survey. It was found that mobile phone based travel survey takes less time to pre-process and analyse the data. However, since the

respondents were to input their trip information manually into their travel diaries, it was a burden on them. The application also faced negative financial issues with expensive data transfer rate which was 900 JPY (roughly 10.9 AUD at that time). Besides the application was not able to run in background and thus the respondents were not able to make calls or send messages while running the application (Ohmori et al., 2005). Besides, in order to save the battery power the application was set to sample at 10 minute intervals and due to such low sampling frequency the information was not reliable and accurate enough.

In the same year 2004, Itsubo and Hato also conducted a mobile phone based travel survey on 31 respondents over 5 days with 30 seconds sampling interval and compared the result with paper-based survey on the same respondents (Itsubo and Hato, 2006). It was found mobile phone based survey produce better accuracy and response rate. A web based validation survey was also performed followed by the mobile phone travel survey in order to enhance the accuracy check. However, like the earlier applications (Asakura and Hato, 2004; Ohmori et al., 2005), battery depletion, inflexibility in using other mobile functionalities and expensive data transfer rate were some of the key issues in their research. These limitations caused respondents to alter their real behaviour which made the travel data biased.

With recent emergence of smartphones, researchers started coming up with more user friendly survey applications. Gonzalez and colleagues developed a smartphone-based travel survey application named as TRACT-IT on Java ME platform in 2008. The main objective of their research was to detect various transportation modes using neural network approach. The research involved 14 respondents. The application recorded positional information at 4 seconds interval and transmitted to a data server immediately (Gonzalez et al., 2010). However, TRACT-IT was also subject to battery depletion problem and expensive data transfer rate.

Charlton and colleagues developed a smartphone-based travel survey named as CycleTracks mainly focused on cyclists. This was implemented in 2009 in San Francisco to understand cyclist's movement behaviour. This application required the respondents to click finish or save button after finishing their trip. Once clicked, the logged data was sent to web server. The application also included a bike bell and vibration alert which started alerting the respondents after 15 minutes of data logging and after every 5 minutes thereof. This was respondents could track the battery resource. Although the application was quite useful but it suffered from various issues such as cold start, lack of user-friendliness, data transfer and GPS positioning issues mostly in urban canyon (Charlton et al., 2010).

In order to save battery power Jariyasunant and colleagues came up with another smartphone-based movement tracking application named as Quantifiable Traveller. This application was based on Wi-Fi and GPS with 2 minutes sampling interval. Due to low sampling frequency and Wi-Fi the data quality was not so promising and led inaccuracies in detecting transport modes and routes taken by the respondents. How-

ever, the application was developed to give various statistics to the users on their travel behaviour. The information included carbon foot print, burned calories (Jariyasunant et al., 2011).

Recently Singapore-MIT Alliance for Research and Technology (SMART) has developed a smartphone-based travel survey as a part of *Singapore Household Travel Survey* named as *Future Mobility Survey* (FMS). FMS consists of four phases (Fig 5) such as registration, pre-survey, activity diary and feedback or exit survey (Cottrill et al., 2013; Pereira et al., 2013).

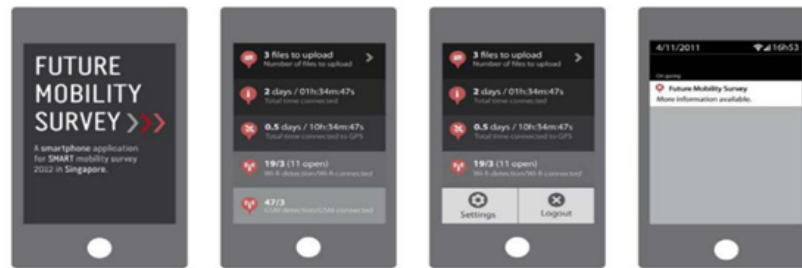


Figure 5: Future mobility survey (FMS) app installed on smartphone; reproduced from (Cottrill et al., 2013).

In registration phase the household responsible (HR) registers on the FMS portal on getting an invitation from FMS team and provides basic household information including age range, genders at home, family education status, relationship between members and contact email ids of members. In pre-survey phase more information is provided by the HR reflecting socio-economic, demographic, vehicle ownership information. Next phase is activity diary phase where participants download and install the application on their mobile devices and start recording their trips. After finishing, the recorded data is transferred to the server and a trajectory map is generated with activity trip information on the respective web page (Fig 6).<sup>5</sup> This follows by a prompt recall survey where respondents can validate the imputed results by editing, adding, deleting on the web page. Once done the validation, respondents give their feedback and experience in feedback phase (Fig 7). The application was developed on iOS and Android platform. The initial project was conducted on 30 respondents with SG\$ 30 incentive in Singapore mostly young generation. In order to manage the battery resources, Cottrill and colleagues implemented phased sampling concept where the application collects data using GPS and accelerometer alternatively (Cottrill et al., 2013). Respondents were also given autonomy to upload the data either continuously based on mobile data plan or opportunistically based on presence of Wi-Fi hotspot. FMS was first performed on February, 2012 and showed a promising result. Unlike

<sup>5</sup> To be found online at (last accessed: December, 2015)  
<http://its.mit.edu/fms>.



the previous applications FMS application can be minimized while other using other mobile functionalities which helps respondents to maintain their regular behaviour. However, battery depletion, user comprehension and improvement in background intelligence were still a major challenge.

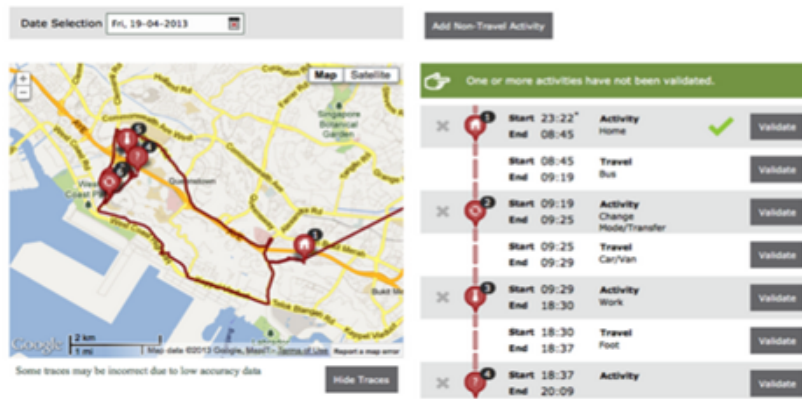


Figure 6: FMS activity diary.

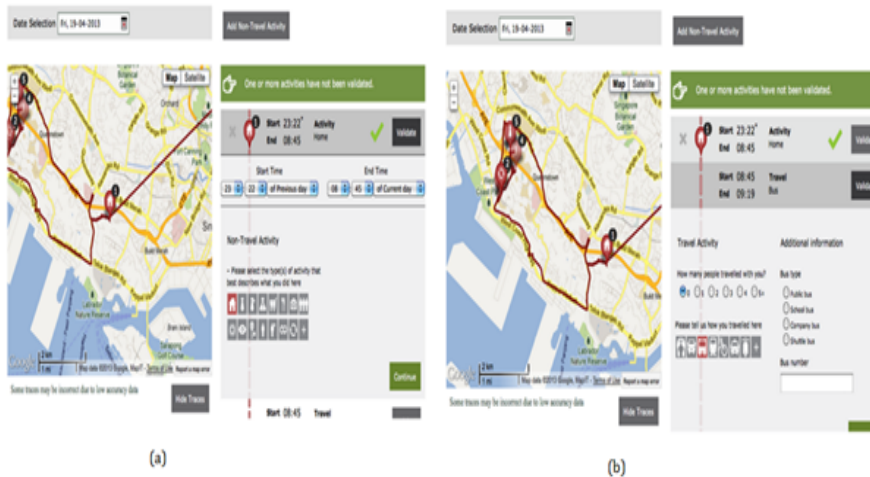


Figure 7: FMS validation- validating stop (a); validating segment between two stops (b).

Following the FMS survey, Safi and colleagues developed an iOS based mobile application – *Advanced Travel Logging Application for Smart-phone* (ATLAS). The application employs an active travel survey approach where the respondents have to provide information on trip start, trip mode, and trip purpose before starting a new trip. A questionnaire is also attached in the application which collects critical information on socio-economic and demographic status of the respondents including age range, gender, income, vehicle ownership and mode choice of the respondent on weekdays and

weekends. So far the project is done in two stages. First stage focuses on data collection strategy while the second stage is more in to resource management and increasing participation through prompted recall survey from respondents (Safi et al., 2013).

#### 2.1.3.4 Prompted recall (PR) survey

With growing positioning technologies, capturing positioning data has become easier. But the semantic enrichment and knowledge discovery from trajectories is still in their infancy. Following several technological waves in travel diary survey starting with the face-to-face, paper-based, GPS assisted surveys respondents are still required to provide additional trip and household information in order to supplement background intelligence. Active travel surveys such as face-to-face or telephonic interview survey requires respondent's complete attention in order to answer survey questions which are quite memory intensive, time consuming and expensive. Passive travel surveys such as GPS based surveys can collect respondent's movement data automatically but it poses problem in post-processing of trajectories and understanding respondent's activity-trip behaviour without further information. Thus to overcome these issues recently travel surveys are designed in hybrid manner where the data is collected passively without bothering the respondents and after data collection or before the survey starts the respondents are asked to recall their travel behaviour and supplement with additional information (Auld et al., 2009). This hybrid surveys are more commonly known as promoted recall (PR) survey.

Doherty and colleagues discussed different types of PR surveys such as sequential, temporal or tabular and spatial PR surveys (Doherty et al., 2006). In sequential PR survey respondents are asked for more information after or during the survey. This is generally accomplished by telephonic interview post travel diary phase. However, some surveys used computer logger to input trip information including trip purpose, trip start end, and route taken etc during the survey process (Murakami and Wagner, 1999). Temporal or tabular PR survey involves arranging the imputed activity-trip history in chronological order and presented in tabular format with corresponding time stamp and other information. This includes trip start, trip end, activity performed, mode used etc. This is very useful way of validation for those who are not familiar with the map but maintain their calendar or personal activity schedule. Another sophisticated method discussed by Doherty and colleagues is spatial PR survey. This method includes post-processing based on GIS and displays the imputed result in map format with spatial cues, icons and text boxes for validation. In this method, respondents can visualize their movement history; they can see the imputed routes, activities and locations they passed through. They can easily add, delete or modify this information wherever necessary from their memory. Thus the burden on respondents is greatly reduced. Currently a hybrid form of spatial and tabular PR surveys have been performed with promising result where GIS generated maps are produced for further validation followed by eight page questionnaire to collect more recalled information

(Stopher and Collins, 2005). Current smartphone based surveys also need validation and input after data collection and analysis. FMS also involves post-analysis validation phase where the respondents can validate their activity and trip on the webpage (Cottrill et al., 2013). Respondents can add or delete or modify a stop, segment or other trip history (Fig 7).

Safi and colleagues in their ATLAS project made a provision to collect post-survey input from respondents in order to obtain additional information such as trip purpose and transport mode. They have also attached a questionnaire in the end of the survey to collect socio-economic and demographic characteristics of the respondents (Safi et al., 2013).

In summary, mobility survey is important to understand people's travel behaviour and their activity patterns in an urban environment. Current survey practices are manual – paper based or telephonic which involves quality issues in terms of accuracy and the information details. In order to cope with this issue currently smartphone based approaches are being explored. Smartphones come with different location and inertial sensors which can be used to capture its user's travel behaviour and activity pattern in the form of a trajectory or a sensor trace at finer granularity. However, such raw sensor information needs to be interpreted to extract various mobility based information. This thesis proposes a number of frameworks to improve such a background intelligence to interpret such sensor information collected by smartphones.

Based on the existing survey practice a composite summary of different kinds of survey strategy and their categorization is presented in tabular form (Table 3).

Table 3: Travel survey types based on different classification criteria

<b>Technological revolution</b>	<b>User interaction</b>	<b>Travel duration</b>	<b>Survey coverage</b>	<b>Sampling strategy</b>	<b>Motivational and behavioural response</b>
Face-to-face, telephonic, computer based	Active (paper based, face-to-face, telephonic)	One-off survey	Regional survey	Intercept survey (randomly selected on the fly)	Preference and adaptation survey
GPS	Passive	Continuous survey	Nationwide survey	Panel survey (same sample year after year)	Activity scheduling process survey
Mobile phones and smartphones	Hybrid (prompted recall survey using smartphones)	Continuous survey	Adaptive	Cross-sectional survey (different samples)	Gaming and simulation based survey and think aloud protocol

## 2.2 MOBILITY-BASED SERVICES

Mobility surveys capture people's travel behaviour, which can be used for different transport planning purposes as well as in order to enable various mobility-based services to improve people's travel experience. The most common type of mobility-based service provisions are recommendation systems. A recommendation system assists a user to perform a given activity. In order to support mobility-based activities the most common type of recommendation systems are travel recommendation systems (also known as advanced traveler information system), and activity or place recommendation systems during a travel.

A travel recommendation system suggests routing sequences using a single mode or multiple mode with a predefined origin and destination given by a user. The information can be shown on a web application on computer or on a mobile device (Lathia et al., 2012). Such systems use the underlying route network and scheduled arrival and departure temporal information of different transport services and then suggest all possible travel plans or the shortest route depending on the user's interest and system design. Chen and colleagues developed a computer-based multimodal daily travel planner (Chen et al., 1999). Liu and colleagues used a switch point based algorithm to develop a multimodal trip planning application (Liu and Meng, 2009). Zhang and colleagues developed a trip planning application in the USA (Zhang et al., 2011b). Su and Chang developed a similar application in Taiwan (Su and Chang, 2010). Houda and others proposed a conceptual framework for modelling public transportation service (Houda et al., 2010).

Earlier travel recommendation systems used to generate static information and could not cope with the real time delays in the network or changes occurred in real time. In order to address the real time changes in the transport network Li and colleagues developed a more sophisticated trip planning application that could support *Park-n-Ride* activity states (Li et al., 2010a). They used the locations of parking lots near different stop locations and intersections in their model. The algorithm is based on K-shortest path method to suggest the most optimal routes given an origin and destination. Borole and colleagues developed a real time intra-city travel recommendation system in India (Borole et al., 2013). Borole and colleagues considered the delay times in arterial roads and the GPS signal shortage. Like Li and colleagues, Borole's model is also based on K-shortest path algorithm to generate the shortest routes from a given origin to a destination in real time. Unlike the other researchers who mainly focused on multimodal public trip planning applications, Su and others developed a futuristic multimodal trip planning system in Taiwan that can establish a coordination between different types of transport services for a seamless and effective transportation (Su and Chang, 2010). Such a coordinated trip planning application is gaining interest in the context of mobility-as-a-service (MaaS) where public and private partners are aiming to provide an integrated mobility solution through a unified gateway (Hietanen, 2014).

Although there is no generalized definition of MaaS yet, but MaaS can be described as a business model and a technological platform that can integrate different transport service types, ICT, and financial institutions to better manage transport resources, and improve travel experiences. Current transport services lack the coordination among different service types especially private and public players. A given MaaS application can generate more personalized travel plans with different offerings and subscriptions. Thus an MaaS application provides more flexibility and mobility options. In Sweden a pilot project named as *Ubigo*<sup>6</sup> was tested in 2014 followed by another proposed project known as *MaaS.fi*<sup>7</sup> in Finland. The main driving forces behind such an integrated and flexible mobility services are emerging concept of shared economy, shared resources, urbanization and climate change (Holmberg et al., 2016). In 2015 another MaaS-alliance framework was developed by European network for ITS deployment<sup>8</sup>. Holmberg and colleagues mentioned in their report the current status of MaaS still lies at a conceptual level with few test cases mostly in European countries. They have also mentioned different conceptual MaaS models in their study (Holmberg et al., 2016). The main component in MaaS is the way a person mediates between two locations on a given transport mode. Hence understanding a person's travel behaviour and usage of different transport modes is very important to provide more personalized offerings and recommendations.

Bertou and Shahid developed a more personalized public transportation planning application based on a user's preferences (Bertou and Shahid, 2013). The model developed by Bertou and Shahid provides travel suggestions at different granularity. Lathia and colleagues proposed a multi-layered personalized mobility service application (Lathia et al., 2012). Lathia and colleagues considered four aspects while developing their prototype e.g., a) personal preference information, b) personal route planning and execution, c) natural language processing, and d) personalized mobile interface for relevant information representation.

With the advancement of ubiquitous computing the concept of context-awareness has become prevalent (Schilit et al., 1994). Although there is no commonly agreed definition of *context*, however, from an operational perspective, the word *context* can be defined as *any information that characterizes a situation of an entity where the entity could be a person or a physical object at a different spatial scale (including a location) which are relevant to the interaction between a human user and the application. The entities also include the user and the application as well* (Dey and Abowd, 2000). As described in Chapter 1 the notion of context depends on a particular application domain and the situation of a given entity, Dey and Abowd (2000) categorized a *context* in terms of *location, time, identity, and activity* from a generic operational perspective. On the other hand,

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6 To be found online at (last accessed: February, 2017)

<http://www.ubigo.se/>

7 <https://maas.global/>

8 <http://www.ertico.com>

from web engineering point of view Kaltz and colleagues categorized a *context* in terms of *user and role, process and task, location, time, and device*. In both the typology four elements are common and they are required to develop the context-awareness in a system that relies on a person's activity state at a given location and time. These elements are an *actor* which is termed as *user* by (Kaltz et al., 2005), the *identity* of an user by (Dey and Abowd, 2000), *location, time, and activity* which is analogous to *process* by (Kaltz et al., 2005).

Understanding a user's context can enable a given service provision to assist the user to perform the activity more efficiently and effectively. However, current context-aware computing service provisions are mainly dependent on user's location and proximity to a given point of interest (POI). For example, Google place recommendation system uses current location of the user and preferences selected from a predefined list and nearby POIs<sup>9</sup>. Claus and Raubal developed an application to find the suitable hotels by a given user based on her current location, spatio-temporal constraints, and preferences (Claus and Martin, 2004). Marmasse and Schmandt developed a model that can recommend a user to perform an activity from her to-do list depending on the vicinity of the corresponding activity centre or the POI (Marmasse and Schmandt, 2000). Although much of the research in context-aware services done based on user's location but there is a need to explore other contextual cues e.g., user's activity state. In this line Mokbel and Levandoski proposed a recommendation framework known as *careDB* that can suggest nearby restaurants depending on the user's current location, user's dietary requirements, and reachability based on road traffic condition (Mokbel and Levandoski, 2009).

In summary, understanding a user's current or historical modal state can also help in augmenting more personalized mobility offerings as a part of MaaS. This thesis presents frameworks to detect a transport modal state at different temporal granularity (see Chapter 6, Chapter 7) that can be used to increase the context-awareness of a given user while recommending a given location or service.

### 2.3 SEMANTIC TRAJECTORY MODELLING AND KNOWLEDGE DISCOVERY

Over last few years with the growing use of portable location sensing devices including the smartphones, it has been possible to obtain enormous amount of movement tracks and trajectories. These raw movement tracks and trajectories, however, cannot say much about the movement behaviour except the location information and geometric patterns such as convergence, encounter, flock, leadership, chasing and avoidance (Alvares et al., 2011; Laube et al., 2005). Whereas, a planner wants to get more out these trajectories for their planning and analysis such as for urban mobility study, one needs to know trip purpose, activity undertaken, mode taken, route taken, travel experience. This is partly mitigated by spatio-temporal aspects related to movement

<sup>9</sup> <https://developers.google.com/places/web-service/search>

behaviour (Alvares et al., 2007; Nanni and Pedreschi, 2006; Pelekis et al., 2007). Space and temporal information, however, is not sufficient to understand detailed movement behaviour and related facts. In order to interpret raw trajectories, a number of different algorithms have been proposed as follows.

### 2.3.1 *Episodic trajectory segmentation*

In order to analyse raw trajectories in offline, the most popular approach is performing trajectory segmentation once the entire travel is complete. Then the analysis takes place over each segment. Spaccapietra and colleagues developed an episodic algorithm known as stop-and-move-on-trajectories (SMoT) from a top-down perspective: first the trajectory is segmented into a number of segments and then an activity state is detected over a particular segment using a machine learning approach or expert system-based model (Spaccapietra et al., 2008). This algorithm assumes a person will stop at a certain location for minimal amount of time in order to perform a certain activity and then start moving until reaching the next destination. Thus a raw trajectory is segmented into two different episodes and each episode is semantically enriched. A move episode reflects a person's travel behaviour, whereas a stop episode reveals a person's activity behaviour within a constrained space

The SMoT algorithm was implemented in different forms (Fig 8). Alvares and colleagues developed an intersection-based approach (IB-SMoT) to model the stop and move episodes. IB-SMoT evaluates which spatio-temporal points of the trajectory intersect a given candidate region for a minimal time duration (Alvares et al., 2007). If the respective points satisfy the spatio-temporal condition those points will be considered as stop points, and the points that do not fall within a candidate region will be considered as move points. Palma and colleagues developed clustering-based stops and moves (CB-SMoT) where a clustering kernel is run over a trajectory, and the clusters containing low speed points with respect to a predefined threshold are called potential stop clusters (Palma et al., 2008). Then each potential stop cluster is investigated if the cluster intersects any given region of interest and labeled as stop episode.

Rocha and colleagues developed a direction-based algorithm (DB-SMoT) based on change of directions of GPS points in a trajectory (Rocha et al., 2010). Application of IB-SMoT and CB-SMoT is context dependent. For example, in tourist movement study IB-SMoT can be used where the main goal is to understand where the tourist went and what did he or she visit within a ROI. Whereas, in traffic analysis CM-SMoT is very useful which can indicate slow movement of vehicles by clustering alike spatio-temporal points and the corresponding POI or ROI (Bogorny et al., 2011). Moreno and colleagues have used rule based model to detect stops and substops using semantic information (Moreno et al., 2010). The work leaves open questions in order to detect ambiguous activities at some stop location. For example it may be inferred that a person may is at a shopping mall (stop) but it is difficult to detect if he or she is



watching a movie (substop) or shopping (substop). Some others used the notion of POI and region of interest (ROI) in order to enrich semantic information base.

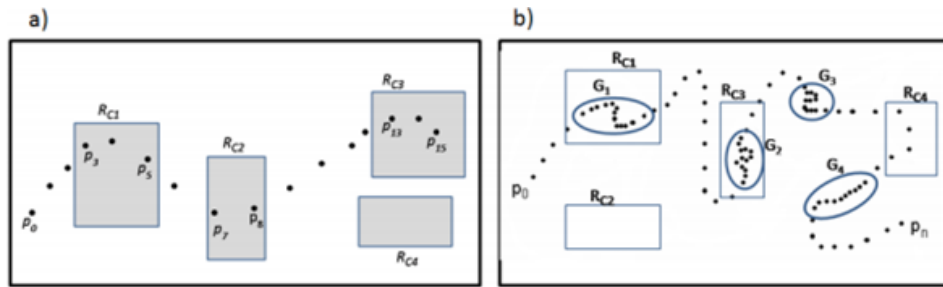


Figure 8: IB-SMoT (a); CB-SMoT (b); reproduced from (Bogorny et al., 2011)

Ashbrook and Starner developed a predefined clustering method to detect the stops from GPS trajectories (Ashbrook and Starner, 2003). On the other hand, Zimmermann and colleagues developed a spatio-temporal clustering method to detect the stops and moves (Zimmermann et al., 2009). In the same line, Andrienko and colleagues developed a stop detection framework by considering temporal duration and a user defined distance threshold (Andrienko et al., 2013). Gong and colleagues extended the traditional clustering based stop detection approach by incorporating a machine learning module. They have developed a two stage model for detecting stops and stop types. Gong and colleagues used an improved clustering algorithm (C-DBSCAN) to detect the stops based on the spatial proximity of the GPS points. Then they have used a SVM-based supervised machine learning technique to infer the stop type in terms of activity or non-activity (Gong et al., 2015). Clustering-based approaches, however, work well on the dense GPS trajectories with good to moderate positional accuracy. During signal gap or in urban canyon clustering-based approach does not work well. Assuming walking is necessary between two non-walking episodes, Zheng and colleagues proposed a walking-based segmentation approach in their transport mode detection research (Zheng et al., 2008).

Yan and colleagues in their first piece of contribution developed a semantic enrichment process using three sets of spatial object such as point, line and region (Yan et al., 2011). They used various topological relationships, movement attributes and spatial join operation between each points of the trajectory and the spatial object in order to discern specific episodes. In this context definition of POI and ROI is application dependent. Some researchers used frequency of visit or pass through a certain location in order to define it as a POI or ROI (Giannotti et al., 2007; Uddin et al., 2011). This further helps to understand what possible activities could be conducted at those stop locations or along the move episode. From travel demand perspective, some specific activities along a move episode include modality, route taken etc. Detailed discussion on modality is given in activity-travel section. Yan and colleagues developed a hier-

archical approach for semantic trajectory construction with three logical layers. The first layer involves cleaning and compressing the raw trajectories. Second layer detects portions of movement and stop in the trajectory based on velocity, change in direction and density of points. Third layer adds contextual information to different segments of the trajectory and construct a semantic rich trajectory (Yan et al., 2011).

Mao and others developed a trajectory similarity measure based on trajectory segmentation approach (Mao et al., 2017). Mao and colleagues presented a segment-based dynamic time warping method by integrating three different distance measures e.g., point-segment, prediction distance and segment-segment. The method presented by Mao and colleagues achieves better accuracy compared to the existing methods e.g., longest common subsequence, edit distance method and traditional dynamic time warping (Mao et al., 2017).

In order to annotate raw trajectories various smartphone based semantic enrichment applications have been developed which require user's interaction more or less. Some of the online or real time annotation tools are EasyTracker (Doulamis et al., 2012) which allows on-the-fly annotation for trajectory segmentation in the first phase and then manual transport mode labelling in the next phase. Another application is TripZoom (Broll et al., 2012) which allows observing an individual's movement behaviour and social networking activities. Some of the annotation work also used open source movement tracking application on smartphones for collecting crowdsourced movement data (Zilske and Nagel, 2012). However, annotating in real time sometimes poses difficulties while the person is driving or in hurry or he or she is too casual to annotate the small movements but significant activities such as going to an ATM for cash out. In order to address these issues offline semantic annotation process is quite useful. Recently several offline desktop level annotation tools have been developed such as DayTag (Rinzivillo et al., 2013) which allows the user to visualize and annotate trajectories. Similar concepts are used in background intelligence of smartphone based travel survey to analyse activity-trip behaviour (Cottrill et al., 2013).

Existing trajectory segmentation approaches are subjective and creates spatial and temporal ambiguity (Cich et al., 2016). A vast majority of literature on transport mode detection and trip generation does not address this ambiguity during the trajectory inference process. Recently, from the transport mode detection perspective Prelipcean and colleagues developed a new error measure based on the quality of alignment of inferred segment to their groundtruth counterpart to address such uncertainty during segmentation based on Allen's temporal calculi (Prelipcean et al., 2016). Prelipcean and colleagues modelled three types of error measures using a cardinality of the measurement and spatial and temporal discrepancy e.g., implicit, explicit-holistic, and explicit-consensus-based segmentation (Prelipcean et al., 2016). Their framework, however, is limited and cannot model all the possible temporal relations in the context of trips.

In this thesis a density-based clustering algorithm based on the CB-SMoT approach has been explored in Chapter 7 to detect the transfers. The assumption behind the

research presented in [Chapter 7](#) is, a transfer breaks a trajectory into a number of distinct trips. However, in this thesis it is argued that a density-based clusters can be of arbitrary shape and size, which poses ambiguity in inferring a trip start and end. In order to address such temporal and spatial ambiguity [Chapter 7](#) develops a novel state-based bottom-up approach that can address the limitations of existing trajectory segmentation approaches e.g., a clustering based approach. This thesis also addresses the temporal ambiguity that may exist during an inference process using nine Allen's temporal relationships in [Chapter 7](#) that supports prior research on temporal ambiguity.

Discovering mobility-based knowledge from motion trajectories is a challenging task. Earlier researches were focused into non-semantic trajectory knowledge discovery and understanding movement pattern mostly based on movement attributes. With recent conceptualization of semantic trajectory, most of the trajectory knowledge discovery process employs geographic and contextual information in order to understand trajectory behaviour and extract more meaningful application specific knowledge. There are three well known techniques in order to understand trajectory behaviour and pattern mining as follows.

- Clustering
- Classification
- Frequent behaviour mining

Clustering is an unsupervised technique which is commonly performed in order to group trajectories or some segments of trajectories which share some similar characteristics. Clustering has also been applied to an individual trajectory as well as group of trajectories to discover certain interesting behaviour at certain segment in space and time of the trip. Pelekis and others used distance measure on a set of trajectories' movement attributes to group them. They used the whole trajectory ([Pelekis et al., 2012](#)) whereas, Lee and colleagues used segment of trajectories to evaluate their similarity and group them. Investigating a trajectory as a whole or segment-wise is application dependent. On the other hand, clustering a trajectory once the entire travel is complete, can help to understand origin-destination of a group of people or from one traffic analysis zone to another traffic analysis zone along with the intermediate stop episodes. This can also help understand similar behaviour of a set of trajectories. For example this can reflect if the trajectories represent home to office trip or tourist trip, whereas, segment wise clustering helps in finer information extraction and behaviour mining at various granularities. Lee and colleagues used segment wise clustering algorithm on tourist trajectories in Paris to understand how they moved together, where they diverged ([Lee et al., 2007](#)).

This idea can be extended to understand how people share route, modality, perform similar activities upto a certain distance etc which are quite relevant information in or-

der to understand travel demand. Laube and others developed *relative motion* (REMO) framework based on movement attributes such as speed, acceleration, azimuth in 8 cardinal directions (Jeung et al., 2011; Laube et al., 2005). Classification is a supervised technique which is also used to group trajectories to predefine classes as whole or part there-of. Lee and colleagues used segment wise trajectory analysis to classify them if they belong to container ship, tanker ship or fishing ship from seeing their detouring pattern (Lee et al., 2007). Others used segment wise trajectory classification in urban mobility studies- for transport mode detection (Zheng et al., 2008), route taken and so on.

### 2.3.2 Trip characterization from motion trajectories

Trip characterization from a motion trajectory involves deriving various movement attributes from the trajectory such as trip start and end location, trip travel time, trip distance, transport mode and trip purpose.

Before GPS based travel survey came in to existence, trip origin and destination were used to retrieve from respondent's memory which sometimes resulted in under reporting of trips or inaccurate trip origin and destination. GPS based survey no doubt a significant improvement and can produce more accurate trip information including trip origin and destination. Earlier car mounted GPS studies only track the car trajectory and thus the actual origin and destination of the person before getting on the car or after getting off the car is not known (Wolf, 2000). This problem was largely overcome by using wearable or smartphone based GPS sensors to some extent. However, these low quality sensors take time (15 seconds to 4 minutes or more) to get fix on the satellites (cold start) even after the trip started and thus recorded trip starting point and actual origin do not coincide which leads to inaccurate trip origin. GPS trajectories also subject to discontinuity due to GPS signal loss in urban canyon and heavy foliage and thus create semantic gap and sometimes false origin and destination. Besides in case of multi day travel survey due to randomness of GPS signal or different parking positions, although the destination is same but the trip ends do not coincide with the destination and thus gives false trip destination. This problem can be mitigated by simple clustering approach where neighbourhood of each trip end is queried and if there is sufficient number of trip ends within the close proximity then all the trip ends in the cluster are assigned as the same destination and the process iterates until all the trip end points are visited. Unknown trip ends are assigned to the nearest destination (Schonfelder and Samaga, 2003). Trip start and end are also detected using land use information with satisfactory accuracy (Axhausen et al., 2003; Stopher et al., 2008; Wolf, 2000). A multi sensor approach is expected to increase the accuracy and reduce Type I and II error.

Traditional travel surveys fail to report the exact trip timing. This problem was solved by using GPS and other sensors. Car based GPS cannot give the actual trip start

and end time since in-vehicle GPS only records during car movement. However, nowadays using smartphone this problem has been greatly reduced as the smartphones are carried by the users almost everywhere they travel unlike an in-vehicle GPS receiver that can only sense the location of the car. Thus if the user parks her car in a parking lot and starts walking, then the last known position shown by the in-vehicle GPS would be the parking lot whereas the smartphone can sense the user's next whereabouts. In-vehicle GPS receivers have limited capacity and does not work when the car engine stops.

Trip length can be calculated using point-to-point (PP) approach or link-to-link (LL) approach. In PP approach the distance between two successive points is calculated using Pythagorean formula in Euclidean space or by multiplying instantaneous speed by the time interval between two successive points. In PP approach no additional information (including GIS network) is required and the approach is simple and could be used in real time. In urban canyons or indoor environment, however, the distance is overestimated or underestimated due to the error in GPS position. This problem could be solved by considering distance travelled after certain time interval (typically 10 seconds) instead of considering immediate time interval. LL approach requires GIS network information. This involves matching the trajectory points with the underlying road network. Then calculating the length of corresponding road segments which is covered by the trajectory and add them up which is actual trip length or trip distance. This way this can solve the signal loss. Since this relies on map-matching, the accuracy depends on quality and quantity of GPS points (Murakami and Wagner, 1999).

Trip purpose identification is important to understand people's intention to travel (why people travel) and that in turn help in travel demand modelling when applied in large scale at different granularities. As mentioned in previous section, some researchers used map matching (point-in-polygon) to understand trip purpose (Forrest and Pearson, 2005; Wolf, 2000). The issue with this approach is it requires comprehensive and accurate GIS network information. Sometimes, a trip end cannot be correlated with the exact land use type or polygon due to inherent GPS randomness or parking or stopping at different locations close to different point of interest(s). In order to address this problem, Wolf and colleagues came up with a clustering algorithm (Wolf et al., 2004). This algorithm creates a cluster of potential trip end points. Then the cluster centre is estimated and all the POIs are spatially queried within a given search radius (300 m considered by Wolf). Then each POI is given some weightage based on its proximity to the cluster centre (POIs within 50 m of buffer zone are given 1.5, POIs within 50 m to 100 m are given a weightage of 1, POIs which fall within 100 m to 200 m are given a weightage of 0.7 and POIs falling within 200 m to 300 m are assigned a weightage of 0.4). A similar approach was introduced by others where they used 200 m tolerant radius from the trip end to identify if it is home and visiting frequency to identify as work. Some of the trip ends were not classified as home or work. Those were labelled as "most probable" trip purpose which were later labelled using rule

based map matching (Axhausen et al., 2003; Schonfelder et al., 2002; Schuessler and Axhausen, 2009). Some researchers used pre-defined trip purpose categories to classify the trip purpose based on the distance between the trip end and POI. Clifford and colleagues used eight categories such as home based work, home based education, home based shopping and home based others, non-home based work, non-home based education, non-home based shopping and non-home based others and the tolerant radius from the trip end to the POI was considered as 200 m (Clifford et al., 2008).

Detecting trips provides valuable information on travel demand estimation. Earlier travel demand models were mostly based on the 4-step aggregate approach. The main thrust in post-processing mode was to extract only trip information for creating origin-destination (OD) matrix to understand trip characteristics at regional levels. This includes, trip generation over a particular region, distribution of trips between regions, modal choices and route taken (Jovicic, 2001). With the advent of in-vehicle GPS travel survey, researchers were mainly interested in detecting car trip ends and trip purpose to understand movement behaviour and how it affects over all travel demand in the network. With progressive paradigm shift in travel demand modelling from 4-step aggregate perspective to activity based perspective, a great deal of thrust was put on activity recognition from movement traces and trip characterization to better understand individual travel demand. This is generally supplemented by additional information regarding household, socio-demographics and financial condition of the person.

Recent post-processing phase involves characterization of activities and trips at different granularities to model activity-trip pattern. The following section discusses various facets of activity and trip behaviour from movement data. More recently, travel has been recognized as a derived activity to achieve some goal in space-time domain. In this regard, a trip is essentially required to perform activities at different locations in spatial domain. Hence, a trip can be conceptualized as a connection between two subsequent disjoint activities in space-time domain.

### 2.3.3 *Detecting transport modes from motion trajectories*

The existing literature explores historical trajectories (i.e., solves the interpretation of the raw data once the trip is complete) in order to infer different transport modes that had been used during the travel, based on different features. Such detection frameworks are called offline mode detection models. An offline mode detection workflow generally involves a preprocessing stage that removes erroneous or uncertain GPS points based on positional inaccuracy, number of satellite visible (NSAT), trajectory smoothing through path interpolation, time conversion if required, data projection from one coordinate system (commonly WGS84) to another coordinate system for various spatial computation. (Wu et al., 2016).

In order to perform preprocessing operation, Stenneth and colleagues used speed-based measures and positional (in)accuracy (Stenneth et al., 2012). Lari and colleagues used maximum speed value to clean a trajectory (Lari and Golroo, 2015). Assuming the fact that for cheap GPS sensors installed on the smartphones the speed is generally calculated from geographical coordinates. Hence the speed measure is subject to positional inaccuracy. Zheng and colleagues also used a speed based filtration method to get rid of noisy GPS points (Zheng et al., 2010). Reddy and colleagues used speed, positional accuracy and temporal information in their preprocessing stage (Reddy et al., 2010). Biljecki and colleagues used positional information, signal gap in their work (Biljecki et al., 2012).

On the other hand, Xiao and colleagues developed a rule base to clean a raw trajectory (Xiao et al., 2015). In the first stage any incomplete record is discarded. In the second stage based on the number of satellites or HDOP value  $\geq 4$  are removed. In the third stage any GPS point which has altitude value greater than 200 m are removed. Following this Xiao and colleagues converted the temporal information from UTC to local time, and then create user specific data repository for further analysis. Based on a current literature survey (Wu et al., 2016) and existing research Table 4 summarizes some preprocessing operations performed by selected authors.

Since a travel can take place by more than one modality, there is a need to break the entire trajectory into trajectory segments travelled in the same mode. This process is known as segmentation or trip identification (TI) or segment identification (SI) (Wu et al., 2016). Thus in the second stage in offline mode detection the preprocessed trajectories are undergone a segmentation operation where each segment bears a homogeneous (single) modal state. Following this a mode is predicted over a given segment. Thus the accuracy of offline mode detection depends on the efficacy of the segmentation strategy. Current segmentation approaches are generally top-down which is based on either detecting a stop episode or extracting a low speed or walking segment.

Assuming walking is necessary between two motorized (or bicycle) mode Zheng and colleagues developed a change point based approach that segment a given trajectory into low speed and high speed segments (Zheng et al., 2010). Eventually the low speed segment indicates a higher chance of being a walking trip. Such approach uses speed information and a critical distance threshold. Zheng and colleagues used a low speed threshold to first separate different segments based on speed. Then they used a distance threshold to detect a sufficiently long low speed segment that is deemed to be a walking segment that connects two consecutive non-walk segments.

Zhang and colleagues used a low speed, direction change and distance measure for segmentation (Zhang et al., 2011a). They used five continuous points to measure the distance threshold (5 m), speed threshold ( $\leq 0.5$  m/s), and direction change threshold ( $\geq 100$  degrees).

Biljecki and colleagues have developed two different types of segmentation strategies in their work (Biljecki et al., 2012). In the first strategy the trajectories are seg-

mented into journeys. A journey is a segment of a trajectory that connects two meaningful locations (say home and office). In order to extract the journey a signal shortage information is used. The assumption was user will perform some activity for a prolonged period of time at these locations and during that time period they will turn off their device, or there may be signal gap as the user is in indoor. Once the journeys are extracted Biljecki and colleagues segmented a given journey into a number of segments based on stop episodes. Due to positional and kinematic uncertainties the number of segments may be more than or less than the actual number of trips that took place during a given travel. Having said that Biljecki and colleagues argued while segmenting a trajectory an over segmentation is always better than under segmentation. In case of an over segmentation if two consecutive segments are found to be same modal state then they can be merged in post-processing stage.

Mountain and Raper used a direction and speed change measure to segment a trajectory (Mountain and Raper, 2001). Such approaches may fail during signal loss or in urban canyon where the positional information is not very accurate.

Liao and colleagues used geodata for proximity analysis – mainly the stop information (e.g., bus stop) in order to detect the transfers (Liao et al., 2007). A transfer essentially separates a trajectory into two different modes. However, this approach is limited and does not work well in areas where the stops are densely distributed or fall in the GPS positional confidence ellipse. This approach also fails when there is a signal loss.

Motivated by other research agenda apart from mode detection there are several instances of work that aimed at extracting different episodes of travel from a trajectory using different approaches such as *stop-and-move*, clustering based, direction based, intersection based and other types (see Section 2.3.1). Such segmentation approaches are also relevant in this context and can be applied in mode detection.



Table 4: Summary of preprocessing operations by selected authors

<b>Authors</b>	<b>Device</b>	<b>Features used for preprocessing</b>	<b>Preprocessing method</b>
Xiao et al. (2015)	GPS onboard smartphone	NSAT, HDOP, altitude	Rule based 3 stage operation
Lari and Golroo (2015)	GPS, accelerometer onboard smartphone	Maximum speed value	Speed based filtering
Nitsche et al. (2014)	GPS onboard smartphone	Positional information	Kalman filter based position estimation; Tri-axial accelerometer signal transformation
Stenneth et al. (2011)	GPS onboard smartphone	Positional accuracy, speed	Heuristics based: Low speed – high speed containment
Reddy et al. (2010)	GPS, accelerometer onboard smartphone	Accuracy measure in horizontal, vertical reading, heading, speed value	–
Zheng et al. (2010)	Dedicated and mobile phone GPS	Speed, heading	Heuristics based: low speed – high speed containment
Biljecki et al. (2012)	Dedicated GPS	Positional information, signal loss	Rule based

In the third stage of offline mode detection process a particular transport mode is detected over a given segment based on a number of computed features. In order to develop a predictive model three different approaches can be used such as machine learning, knowledge driven and hybrid approaches.

Zheng and colleagues used mean velocity, expectation of velocity, heading rate change and top three acceleration measure as input variables. They tested four different machine learning models, decision tree (DT), Bayesian network (BN), conditional random Field (CRF) and support vector machines (SVM) with accuracy 74%, 70%, 47%, and 59% respectively (Zheng et al., 2008). They classified four modalities such as walk, car, bus and bike.

Since GPS comes with varying positional accuracy due to various environmental factors and signal shortages, recently, there is a trend to integrate different inertial navigation sensors, such as accelerometers, with GPS, which is explored in (Reddy et al., 2010). Reddy and colleagues distinguished five modalities such as still, walk, run, bike and motor.

Stenneth and colleagues used infrastructure information and speed information to distinguish five modalities such as car, bus, train, bike, stationary and walk. Stenneth and colleagues used several features such as average bus locations, candidate bus locations, proximity to rail network, bus stop closeness, average speed, average acceleration, heading rate change, positional accuracy. Stenneth and colleagues developed five predictive models based different machine learning algorithms with varied accuracy such as a Bayesian network (92.5%), decision tree (92.2%), random forest (93.7%), naive Bayes (91.6%) (Stenneth et al., 2011).

Ohashi and colleagues developed a vibration-based mode detection model using a Bayesian network with 80% accuracy with a focus on a fine distinction between a car and a motorbike, which is deemed to be a challenging problem, since both of them share the same route network and show almost a similar speed and acceleration profile. They have collected the vibration sensor signal on-board a smartphone to capture the vibration profile of different modalities without segmenting the trajectories. They also do not attempt to address the issue of composite modes (Ohashi et al., 2013).

Gonzalez and colleagues developed a neural network-based mode detection model using GPS sensors. They distinguish three modalities such as car, bus, walk using a number of features (Gonzalez et al., 2010). They used average acceleration, average speed, maximum speed, ratio of critical points over a trip distance and duration. Gonzalez and colleagues mainly focused on managing the data transmission rate and computational overhead in mode detection. Thus they have designed two experimental setup. In the first setup they used all the GPS points that are sampled and obtained 88.6% accuracy. In the second setup they used only the critical points with 91.23% accuracy. This shows while interpreting a trajectory not all points are relevant. The accuracy may be affected by irrelevant points.

Nitsche and colleagues used 5th, 50th, and 95th percentile of maximum speed, acceleration, deceleration, heading rate change, standard deviation of acceleration profile sampled at 50 Hz, power spectrum of acceleration signal and other features (77 in total). They detected eight modes such as walk, bicycle, motorcycle, car, bus, tram, metro and train. The accuracy varies from 65% to 95% with average accuracy 75% (Nitsche et al., 2014).

Hemminki and colleagues used accelerometer to detect modality with 1.2 s time window with 100 Hz sampling frequency. Since gravity component obscures accelerometer signals while interpreting movement behaviour, Hemminki and colleagues paid a special attention to model the gravity component while extracting the acceleration profile of different modes. They have used a discrete hidden Markov model (DHMM) and AdaBoost, with which they obtained 84.2% accuracy (Hemminki et al., 2013).

Xia and colleagues proposed a GPS and accelerometer-based model with 50 Hz sampling frequency without any walking-based or clustering-based segmentation approach. Xia and colleagues detected four activity states such as stationary, walking, bicycle, motorized modes using a SVM with 96.3% accuracy (Xia et al., 2014).

Dodge and colleagues used GPS trajectories and developed an SVM-based model with 82% accuracy for four modes using three kinematic features (Dodge et al., 2009). Dodge and colleagues have introduced the concept of global features and local features computed from a trajectory. They have primarily used variation in sinuosity and the deviation of different kinematic features, such as velocity and acceleration, from the median line (Dodge et al., 2009).

Xiao and colleagues developed a number of tree-based ensemble models for mode detection (Xiao et al., 2017). They developed global and local features to evaluate three different models based on a random forest (RF), gradient boosting decision tree (GBDT) and a XGBoost respectively. Xiao and colleagues evaluated their models on six transport modes e.g., walk, bus and taxi (combined in a single class), bike, car, subway, train. Their proposed models have been compared with the existing models based on a K-nearest neighbour, a decision tree and a support vector machine. Xiao and colleagues have shown that the proposed XGBoost model achieved 90.77% accuracy which outperformed existing mode detection models (Xiao et al., 2017).

Liao and colleagues also used GPS information to develop a CRF-based model to infer the modes along trajectories (Liao et al., 2005). Lari and colleagues used speed, bearing, accuracy and acceleration information to detect three modes such as car, bus, and walk. In order to develop a predictive model they used random forest. They split the data into 70%-30% in training and testing samples and obtained 96% accuracy.

Compared to the rich offline mode detection research, there have been only a few near-real time mode detection attempts made so far. In one of them, Byon and colleagues developed a neural network-based mode detection model using three kinematic features in near-real time on five modalities such as auto, bus, car, bike and walk. They claim the model works best on ten-minute query windows, for which they

obtained 82% accuracy. However, ten-minute time windows may be too long for certain applications, such as emergency services or context-sensitive location-based services (Byon and Abdulhai, 2007; Byon et al., 2009), and may lose out with more frequent change of modes.

In the same line, Reddy and colleagues' mode detection framework that works on a second-by-second basis with 74% accuracy (Reddy et al., 2010) is more relevant in real-time scenarios. Since GPS sensors on a commercial smartphone cannot sample at finer granularity due to hardware and software limitations, the literature shows that such small temporal query windows require additional sensors (at least an inertial navigation sensor) that can sample at higher frequencies. Reddy and colleagues utilized the accelerometer on-board a smartphone to calculate acceleration-based features. They also used the GPS sensors to get the speed value over one-second intervals.

Yang and colleagues developed a two-stage approach for detecting modes with a core focus on distinguishing bus and car modality on a set of trajectories collected by handheld GPS devices (Yang et al., 2016). In the first stage a machine learning algorithm was used to distinguish walk, bicycle and motorized trips. Then in the second stage a motorized mode is further identified as bus or car using a critical point method (Yang et al., 2016). Mountain and Raper used a change in speed and direction for segmenting a trajectory (Mountain and Raper, 2001). That said, a low speed (or walking) based segmentation approach creates ambiguity in certain cases especially when a vehicle moves slowly in heavy traffic or due to bad weather condition. Xia and colleagues proposed a GPS and accelerometer-based model with 50 Hz sampling frequency without any walking-based or clustering-based segmentation approach. Xia and colleagues detected four activity states such as stationary, walking, bicycle, motorized modes using a SVM with 96.3% accuracy (Xia et al., 2014).

Assuming the fact that location sensors consumes a considerable amount of energy resource which limits the smartphone usage for other purpose (talking, using internet for news update and communication), recently Fang and colleagues developed a low powered consumption model that uses low dimension feature space computed from inertial sensors only such as an accelerometer, a gyroscope and a magnetometer (Fang et al., 2016). They have also investigated memory usage and response time along with the accuracy improvement on a 1000 h smartphone inertial sensor data supplied by HTC. The model developed by Fang and colleagues is similar to Hemminki's two stage framework (Hemminki et al., 2013). In the first stage basic type of transportation modes are classified such as (still, walk, run, bike, vehicle) followed by a finer vehicular distinction in between motorcycle, car, bus, metro, train and high speed rail. Fang and colleagues used three machine learning models to develop their inference framework such as a DT, KNN and a SVM. They have designed two different experimental setups one with 7 features and another one with 14 features. When using 14 features, the accuracy is 79.59% using DT, 86.86% using KNN and 86.94% using SVM (Fang et al., 2016).

As machine learning-based mode detection models are data specific, the models require a substantial training data to train the models and also lack explanatory power. On the other hand, fuzzy logic-based mode detection models do not require any training. Here, the model is developed based on expert knowledge. Fuzzy logic-based models express the knowledge base in simple IF-THEN rules. The models can also handle uncertainty, vagueness and imprecision. Schussler and Axhausen developed a fuzzy logic-based mode detection model on five modalities using three speed-only features (Schuessler and Axhausen, 2009). Xu and colleagues developed a fuzzy logic based model that can distinguish four modalities with 93.7% accuracy (Xu et al., 2010), and Biljecki and colleagues developed a Sugeno-type fuzzy logic-based mode detection framework that can classify ten modalities with 91.6% accuracy (Biljecki et al., 2012). That said, in existing fuzzy logic based knowledge driven models the reasoning scheme is still not transparent and they do not explain the rules in linguistic forms to reflect different movement behaviour – and thus there exists still a research gap in knowledge driven aspect as how to represent the reasoning scheme that can capture different kinematic uncertainties and movement patterns.

The success of any fuzzy logic-based model depends on the expert knowledge brought in and the consistency between a particular observation and the universe of discourse for each fuzzy linguistic label. Since traditional Mamdani-type or Sugeno-type fuzzy logic-based models cannot tune their membership parameters, they suffer from low performance when there is a lack in expert knowledge, when they are applied on noisy observation data or when they are applied on observations from another spatial context. On the other hand, the neural network-based models developed by (Byon et al., 2009; Gonzalez et al., 2010) and others can adjust well in a varied condition.

Table 5 and Table 6 provide a brief summary of state-of-the-art mode detection work in terms of study area, sampling duration, sensors used, modes to be distinguished, use of spatial (GIS) information, models used, and the accuracy reported by the authors. The abbreviations used in Table 6 are as follows:

ANN: Artificial neural network; RF: Random forest; DT: Decision tree; KNN: K Nearest neighbour; ACO: Ant colony optimization; EPS: Ensembled probabilistic classifier; SVM: Support vector machines; DHMM: Discrete hidden Markov model; PSO-NN: Particle swarm optimization-neural network. 'Y' stands for Yes and 'N' stands for No.

Table 5: Summary of selected mode detection literature: Experimental design. A GPS sensor is installed on the smartphone unless otherwise stated as dedicated receiver. The duration reported in different papers are in different ways such as in terms of days, weeks, months or even at finer temporal precision such as hours and minutes. The data set also collected as a part of travel survey (with longer duration) as well as experimental survey (with shorter duration).

<b>Authors</b>	<b>Study area</b>	<b>Duration</b>
Bohte et al. (2008)	Netherlands	1 week
Byon et al. (2009)	Canada	–
Liao et al. (2007)	–	6 days
Gonzalez et al. (2010)	USA	114 trips
Tsui and Shalaby (2006)	Canada	–
Biljecki et al. (2012)	Netherlands	3.25 months
Stenneth et al. (2011)	USA	3 weeks
Ohashi et al. (2013)	–	–
Xu et al. (2010)	China	142 days
Hemminki et al. (2013)	Four different countries	150 hrs
Xiao et al. (2015)	China	4 months
Zheng et al. (2010)	China	6 months
Lari and Golroo (2015)	Iran	2 weeks
Yang et al. (2015)	China	–
Nitsche et al. (2014)	Austria	2 months
Wang et al. (2010)	China	12 hrs
Xia et al. (2014)	–	3.6 hrs
Bolbol et al. (2012)	UK	2 weeks
Gong et al. (2012)	USA	49 segments
Fang et al. (2016)	–	1000 h

Table 6: Summary of selected mode detection literature: Models used to detect transport modes, and maximum accuracy obtained (in round figures).

Authors	Modes	GIS	Criteria	Model	Segme- ntation	Avg accuracy (%)
Bohte et al. (2008)	4	Y	2	Rule based	N	70
Reddy et al. (2010)	4	N	3	HMM	N	74
Schuessler and Axhausen (2009)	5	N	3	Fuzzy logic	Y	–
Byon et al. (2009)	5	N	3	ANN	N	82
Liao et al. (2007)	3	Y	2	CRF	Y	90
Gonzalez et al. (2010)	3	N	8	ANN	N	88
Tsui and Shalaby (2006)	4	Y	3	Fuzzy logic	Y	91
Biljecki et al. (2012)	10	Y	2	Fuzzy logic	Y	91
Stenneth et al. (2011)	5	Y	5	DT	Y	93
Ohashi et al. (2013)	4	N	2	Bayesian	N	80
Xu et al. (2010)	5	N	4	Fuzzy logic	Y	93
Hemminki et al. (2013)	5	N	12	DHMM, Adaboost	N	84
Xiao et al. (2015)	4	N	6	PSO-NN	Y	94
Zheng et al. (2010)	4	N	5	DT, CRF, SVM, Bayesian	Y	74
Lari and Golroo (2015)	3	N	6	RF	N	95
Yang et al. (2015)	4	N	4	ANN	Y	85
Nitsche et al. (2014)	8	–	77	EPC- DHMM	Y	75
Wang et al. (2010)	6	N	23	DT, KNN, SVM	N	70
Xia et al. (2014)	4	N	134	ACO, SVM	N	98
Bolbol et al. (2012)	6	Y	3	SVM	–	88
Gong et al. (2012)	–	Y	3	Rule based	Y	82 <sup>45</sup>
Fang et al. (2016)	–	N	10	SVM, DT KNN	N	86
Xiao et al. (2017)	6	N	15	RF, GBDT XGBoost	Y	91

Thus the existing transport mode detection research can be broadly categorized into either a machine learning based or a knowledge-driven approach. A machine learning based approach is data specific and cannot explain the semantics of a given mobility based activity. A machine learning based approach also falls short in modelling the kinematic uncertainties which can be addressed by a fuzzy knowledge-driven approach. Existing fuzzy logic based models, however, cannot produce the multiple possibilities and lacks the transparency. In order to address that in this thesis a fuzzy logic based model has been proposed with more transparency ([Chapter 5](#)). On the other hand, a purely knowledge-driven model cannot adapt in varying conditions and thus when the duration of a feature vector is shorter which is a typical case in near-real time a purely knowledge-driven model does not perform well. In order to address this issue a novel hybrid knowledge-driven model has been proposed in [Chapter 6](#). This thesis also developed a more robust and adaptive framework based on machine learning approach in [Chapter 7](#) to detect transport modes at even a shorter temporal interval as well as in offline mode. Thus this thesis improves the existing knowledge-driven mode detection models and bridges the gap between machine learning based and purely knowledge-driven approaches.

#### 2.3.4 *Frequent behaviour mining and extracting significant places*

From travel demand perspective it is important to know significant places or activity centres in order to characterize travel and activity behaviour. In human geography, cell phone call data has been used to identify personal point of interest(s) such as home or office ([Ahas et al., 2010](#)). Another popular method is visual analytics which is in use for a long time ([Andrienko et al., 2007](#)). However, with the growing mobility data it is impossible to analyse each trajectory and identify the significant places or POIs. Some researchers used geographic information along with raw trajectories to extract POIs. Assuming that similar activities consume somewhat similar duration temporal signature has been added to enrich semantics of the trajectories. Andrienko and colleagues developed spatio-temporally constrained filtering process to extract significant POIs. They used three different datasets as follows ([Andrienko et al., 2013](#)).

- GSM trajectories of 67 persons in France for 49 days
- GPS trajectories of a single person in the USA for 351 days
- Georeferenced tweets from 2607 Twitter users for 60 days in the USA

Andrienko and colleagues used minimum bounding box to cluster the spatio-temporal points to group them in stop locations. Then they estimated temporal signature or dwell time at each stop locations and based on temporal signature stops are categorised in different predefined POIs and corresponding activities. The visualization



of their imputed result was presented in map, temporal and spatio-temporal cube formats. In their work they characterise temporal signature based on frequency of visiting the stop, time of visiting- day, week, and month and time series of visit.

Ying and colleagues worked on MIT Reality data set to predict a person's next location using two broad modules such as offline training module and online prediction module (Ying et al., 2011). The offline training module consists of three basic steps such as data pre-processing, semantic trajectory pattern mining and geographic mining. In data pre-processing step, individual trajectories are transformed in to sequence of stay locations using density based clustering approach and user defined temporal and crowd threshold. In the next step semantic trajectory patterns are created where each stay location is semantically annotated with closest landmark information and based on a set of movement behaviour each set of semantic locations is given a support value. For identifying individual frequent movement behaviour they used sequential pattern mining algorithm Prefix-Span which is detailed in Pei and colleagues work (Pei et al., 2001). They also figured out longer the trajectory pattern they mine, more subsequences are generated which becomes computationally inefficient while matching the person's current movement pattern with subsequences generated activity. They used clustering to group similar trajectories based on longest common subsequence algorithm. In the third step, they developed stay location pattern tree from geographic mining which was used in online prediction module. Online prediction module was used to develop candidate paths.

Yavas and colleagues developed association rules based on support and confidence to predict an individual's next location (Yavas et al., 2005). Morzy and colleagues also used similar approach and used a modified Apriori algorithm to detect frequent pattern of group movements. However, Morzy and colleagues did not use semantic location information (Morzy, 2006). Monreale and colleagues developed prefix tree based on order of locations, travel time and frequency of visit to predict next location (Monreale et al., 2009).

Using individual location history Ashbrook and colleagues also developed Markov models based on density based clustering approach and time spent at a certain location to identify significant location and future location of the person (Ashbrook and Starner, 2003). In this work, they considered GPS inaccuracies and thus the same place indicating different coordinates at different times. They used an iterative clustering approach to locate the same location from different GPS spatio-temporal points by shifting the mean. Once the locations are confirmed they used dwell time at each location to measure its potential. Then a Markov model is used to predict next location based on previous location history.

Liao and colleagues developed personal maps where they considered individual's significant locations, activities at those locations, routes taken and transport mode (Liao et al., 2006). They used 10 minutes temporal threshold for detecting stay locations followed by Relational Markov Network (RMN) for place classification. They also de-

tected anomaly in movement behaviour using dynamic Bayesian Network. Although main motivation for their work was to contribute in assisted cognition system (Kautz et al., 2003; Patterson et al., 2004) for cognitively impaired persons but this work has a potential to be used in context-aware smartphone based travel survey application.

Zheng and colleagues contributed to location prediction through generic and personalized travel recommendation system (Zheng and Xie, 2011; Zheng et al., 2009). They have modelled travel recommendation system in two ways. The first approach is generic one which is based on Tree Based Hierarchical Graph (TBHG) structure. The generic approach is developed using multiple users' GPS traces. First stay locations of the users are clustered in at different granularities. Each cluster can again be divided in to several clusters and form the children nodes and thus a tree based hierarchical model is built. Each level of this tree structure represents peer connected graphical structure which represents travel sequence from one cluster (stay point) to another cluster (stay point) in a chronological order. Then a Hypertext-Induced Topic Search (HITS) model is used to mine top 'm' locations and top 'k' travel sequences based on a geospatial query region using users travel experience and location interest in mutual reinforcement manner. The second approach was developing a personalized travel recommendation system where Zheng and colleagues estimated users travel experiences using hub score from TBHG and HITS model. Then they estimated correlation between locations and sequence of travel between them. Then based on the correlation between locations a Collaborative Filtering (CF) model is used to predict a single user's interest to visit next location.

### 2.3.5 *Privacy issues in motion trajectories*

Since daily trajectories indicate people's daily activities which involve their personal spheres including home, workplace, meeting place and hence these trajectory information are critical and need to be protected against privacy threats (Parent et al., 2013). With recent mobile applications and location based services privacy issues have become more prominent. Many countries have governed various privacy rules and policies to preserve and protect the personal information. However, these privacy policies are not sufficient to protect the personal information from malicious third parties who can deliberately access to the personal information through spatial trajectories and pose privacy threats. In order to ensure privacy from untrusted third parties various privacy enhancing technologies (PET) have been formulated. Parent and colleagues discussed contributions from various authors and researchers in the domain of privacy preserving research (Parent et al., 2013). They have also discussed two PET approaches in their survey. They have characterized PET from three perspectives as follows.

- Data model which involves preserving privacy at single positional level which is a typical case for streaming process for a potentially untrusted third party and

preserving privacy as a whole on all the trajectories in case of data publishing through a trusted third party.

- Privacy goal that defines the purpose of privacy of personal information. Personal information could be related to personal identity, location information and both.
- Application context- which includes whether the trajectories are treated in streaming process or data publishing.

Chow and colleagues discussed various privacy enhancing techniques in their location based service research (Chow and Mokbel, 2011). They have mentioned how different de-identified microdata can be linked to discern a person's personal information including identity and location. They have pointed out the weakness of k-anonymity due to lack of diversity in the equivalence class which leads to use of l-diversity approach. A thorough discussion of l-diversity has been governed by Machanavajhala and colleagues (Machanavajhala et al., 2007). Chow and colleagues categorized PET in to three broad categories such as false location, space transformation and spatial cloaking. They have also discussed in detail about various techniques such as group based and distortion based spatial trajectory preservation, mix-zones, vehicular mix-zones, path confusion and introduction of dummy trajectories.

Since a location reflects different degree of sensitivity depending on the context hence, a degree of sensitivity has been proposed by Damiani and colleagues (Damiani et al., 2010, 2011). This approach is particularly useful in travel demand analysis at aggregate and disaggregate level. A person can define a privacy degree for a certain location and based on that cloaking algorithms would generate coarse regions containing person's location. On querying, the algorithm would return the coarse region instead of person's actual precise location and in that way, the positional information can be saved.

There are instances when the untrusted party may have a person's background information or POI sequence information which helps to correlate a de-identified trajectory sequence with background information and can reveal personal information. Terrovitis and Mamoulis has proposed a suppression technique which can remove certain number of POIs from a person's trajectory and maintain k-anonymity and thus create ambiguity in identifying and extracting person specific information (Terrovitis and Nikos, 2008). Abul and colleagues developed an anonymization technique where the trajectories are clustered in a cylindrical volume and made them indistinguishable from each other (Abul et al., 2008).

Monreale and colleagues developed a hierarchical ontology of POIs in order to preserve the privacy (Monreale et al., 2009). Their privacy approach contributed at semantic level rather than just spatial level like spatial cloaking. They proposed to replace each POI by their generic types such as Eiffel Tower by *tourist place*. In that way, even if

the attacker has knowledge of POI sequence but the attacker cannot reveal person's actual POI since the actual POI is converted to a generic type. This approach can be used in travel demand analysis at disaggregate level in order to understand the sequence of travel of people in a generic way while preserving their personal information.

In summary, trajectory interpretation can provide travel behaviour at different resolutions. An offline trajectory interpretation requires an episodic segmentation prior to an actual activity detection takes place over a given segment. Existing segmentation approaches use a redefined threshold, hence the existing methods are subjective and lacks the adaptivity. The interest of this thesis is focused on extracting transport mode information from raw trajectories (see [Chapter 5](#), [Chapter 6](#)). This thesis presents an adaptive trajectory segmentation approach based on homogeneous activity state at different temporal granularities ([Chapter 7](#)).

## 2.4 TOWARDS THE NOTION OF ACTIVITY

Following the above discussion, it is evident that identifying activities and their pattern in space and time would result in understanding the movement of the person and how demand for travelling takes place at different granularities. However, there has been a semantic gap while defining the concept of activity by different application domains. For example in time geography and urban science activity a considerable time spent at a given location is considered as an activity whereas in pervasive and mobile computing body parts movements are considered as an activity. This raises consistency problem among different disciplines ranging from transportation science and time geography to cognitive science and pervasive computing.

The interest in activities of this thesis is driven by the challenges of motion analysis to model activity out of trajectories under different contexts, as studied by various disciplines. Hence there is a need to revisit all the conceptualizations of activities prominent in these different disciplines, and bring them together on a common ground. This section discusses the state of the research in the various disciplines.

### 2.4.1 *Activity in time-geography*

Many activities on an urban scale are bound by location and time (the where and the when), which determine opportunity, and shape of the located object, which determines affordance. Shopping is possible only where a shop is, when the shop is open, and whether there is a potential customer (to perceive and realize the affordance). In time geography ([Hägerstrand, 1970](#)) this located object would be a space-time station, and shopping would be characterized by the bundle of the space-time station and the trajectory of a person over a period of time. Constraints such as opening hours can be represented by interrupting the space-time station over periods. Other activities

are linked to change of location ('travel' on urban scale), which is similarly linked to opportunity and affordance.

In time-geography this is represented by non-stationary segments of a person's trajectory; a mediated travel, on board of a vehicle, would be represented by a non-stationary bundle of the person's and the vehicle's trajectory, although there exists some amount of space-time uncertainties in one's movement behaviour (Winter, 2009). Again other activities do not depend on location and time: interaction with systems, in terms of ubiquitous computing, can happen anywhere, anytime. With the emergence of advanced ICT the concept of time geography has been extended from a physical space to a virtual space, and this transformation led to change in activity pattern in urban environment (Shaw and Yu, 2009). For example, in order to buy an air ticket people no longer need to go to the airline's office (located in a physical space), rather people can purchase the ticket online (in a virtual space). Golledge and Stimson (Golledge and Stimson, 1997) explained collective activities in terms of two space-time paths and their relationships such as whether the space-time paths are meeting over a certain time window (co-location in time), whether the paths are meeting over a certain geographical space (co-location in space), or whether the two space-time paths meet over a given space and time window (co-existence). The idea can be extended for multiple individuals and their collective activity pattern through space-time bundle (Miller, 2004). Couclelis discussed how ICT influences a gradual transformation in activity pattern through fragmentation and reorganization of activity over a given space (Couclelis, 2004).

A physical interaction always happens with a tangible part of the world : be it a physical space or virtual space. An activity in physical space requires interaction with different objects and at the same time an activity in a virtual space requires at least an internet enabled smartphone or computing device to enter in that virtual space and perform different activities (such as e-banking, tele-conference) (Shaw and Yu, 2009). In all these cases especially, during the interaction with the smartphone, e.g., to start an app and to browse through the 'pages', and all this while the individual is somewhere at some time. Thus, activities are generally oriented towards certain objects in the world, and hence the properties of the given object are an important facet, especially its availability and its affordance. These properties can be expressed as spatio-temporal constraints by time-geography. But time geography lacks guidance on the level of granularity with which these space-time constraints should be formulated for a particular analysis, and it also lacks the notion of the cognitive constraints what objects in space facilitate to offer (Raubal et al., 2004).

#### 2.4.2 *The concept of activity in situated action modelling, activity theory, and distributed cognition*

The concept of activity has also been reflected in situated action modelling where the basic unit of analysis is “the activity of person-acting in setting” Nardi (1995). The focus of situated action modelling is the person and the setting. A setting is conceptualized as the relation between the person and the arena within which the person is acting (the concept of arena is equivalent to the concept of environment or world in activity theory and affordance theory). Lave (1988) mentioned arena as a stable institutional framework. If a person is shopping in a supermarket, then the particular supermarket is an arena of the institution supermarket.

According to activity theory (Nardi, 1995), an activity is not a monolithic concept; rather it is a hierarchical concept consisting of activity at the top layer, action in the middle layer, and operation in the bottom layer. In activity theory the unit of analysis is an activity, which consists of subject, object, actions and operations. Each of these layers can be broken down into finer layers with growing complexity of expressiveness. For example, an activity can be broken down into actions, which can be broken down into subactions, which can again be broken down into sub-subactions, and so on. A subject in activity theory can be a person or a group of persons or an organization having an objective that motivates them to perform an activity in relation to the environment (Lave, 1988; Leont’ev, 1978). Hence, actions are goal-directed; they contribute to performing an activity. A goal can be achieved by different actions. For example, a person can *eat* food at a restaurant or at home in order to achieve the activity “*having a meal*”. On the other hand operations are unconscious. An action becomes an operation over routine execution, and vice versa, an operation may be lifted to an action if there is a sudden change in the condition or the environment such that a routine is interrupted and conscious decisions have to be made. Thus the constituents of activity can change their semantics. In the HCI literature (Norman, 1991) as well as in wayfinding and navigation (Nardi, 1995; Hirtle et al., 2011; Timpf, 2005) actions are termed tasks, however, in this research the term action will be used consistently.

The concept of activity has also been explored in distributed cognition. In distributed cognition, the unit of analysis is a cognitive system which consists of individuals and artefacts with which the individuals interact (Nardi, 1995; Hutchins, 1995). Distributed cognition considers individuals, artefacts and the environment as a system, unlike traditional cognitive science that concentrates on an individual’s cognitive aspects (Newell and Simon, 1972). Distributed cognition analyses how individuals coordinate and share their actions to perform a goal.

All these theories are limited in terms of their *activity modelling* in the light of space, time and context. Thus, in this research an overarching framework has been developed to explore different activities based on location, time, needs and context – that can connect different facets of cognitive science, HCI, pervasive computing, and urban

transport geography. We further set our scope to an individual's interactions with systems in an urban sphere, i.e., activities that go beyond urban scale (e.g., travelling a country), or are confined to the private space (e.g., house cleaning) or to the own body (e.g., gesturing) are out of scope of this thesis. An elementary activity in the urban sphere is travelling from one location to another location to fulfill certain need(s). An earlier work by Hirtle and colleagues (Hirtle et al., 2011) discussed how granularity impacts on the conceptualization of an action or activity in the context of navigation. In this thesis a similar concept to explore travel activities in urban context at different granularities.

Activity theory does not specify or define human needs. Therefore in this research the typology of fundamental human needs defined by Max-Neef and colleagues (Max-Neef, 1991; Max-Neef et al., 1989) has been used that stretches across all spheres including urban environments. Unlike Maslow's *hierarchy of needs* Max-Neef's nine fundamental human needs are not hierarchical; rather they exhibit properties of simultaneousness and complementarity that involves four elements such as *being (qualities)*, *having (things)*, *doing (actions)*, and *interacting (settings)*.<sup>10</sup> The nine fundamental human needs are *subsistence, protection, affection, understanding, leisure, creation, identity, and freedom*.

In this research the reason why the categorization of Max-Neef's fundamental needs is chosen as this categorization is finite, classifiable, and constant throughout different human culture and historical time periods. What has changed over time is only the mediation of satisfying a given need through varying artefacts.

Thus activity can be viewed as is a hierarchical, qualitative and contextual concept. Activity can be reasoned and explained from different perspectives such as situational action modelling, distributed cognition and activity theory. However, activity is always oriented towards an objective to fulfil a need. The model presented in Chapter 4 will extend the concept of activity from activity theory and develop a conceptual framework to model activity out of a trajectory that explains an agent's movement behaviour and activity knowledge from a given trajectory.

#### 2.4.3 Concept of activity in travel demand modelling

In the field of transport engineering a long-standing challenge is predicting transport demand. Methodologically two approaches can be distinguished: the (still prevalent) Four-step Model of trip generation, trip distribution, mode choice and route choice, and the (substantially more complex) activity-based travel demand models (McNally and Rindt, 2007). Unlike four-step model the activity-based approach in transportation science estimates travel demand by assuming *activity* have to be performed, instead of

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<sup>10</sup> To be found online at (last accessed: January, 2017)  
<http://www.rainforestinfo.org.au/background/maxneef.htm>

locations have to be visited, in order to satisfy economical, physical and social needs. The needs can be of two types (Jones, 1979) as follows.

- Subsistence needs: basic needs such as clothing, food, income from work or school.
- Socio-cultural and user defined needs: various needs based on leisure and recreation.

Travel demand models consider activities throughout a day, determining their level of granularity. Some of the activities can be performed at home, or without travel. Some activities need to utilize some resources and opportunities (which is equivalent to affordance in affordance theory (Gibson, 1979) or motives in *activity theory* in HCI (Kaptelinin and Nardi, 2006). However, resources and opportunities are dispersed at different locations and for certain time duration. Hence in order to use a particular resource an individual should change their position, giving rise to travel from one location to another location in order to use certain resources and opportunities. Thus in activity-based travel demand models travel is viewed as a derived demand for activity participation in space and time.

Existing activity-based travel demand models consider activities are constrained by location (resources, opportunities) and needs. However, such models are not specific about the granularity of the location or time of an activity. The models mainly consider activities for longer duration at a given location such as home, office, school, or shops since they describe activities over the course of a day. The needs for travel depend on several factors such as activity type, individual role and responsibilities in the family, life style, space time and budget constraint, individual demographic profile (Jovicic, 2001). The activities themselves are modelled through activity patterns. But activity-based travel demand models cannot reason about the modelling of activity through actions. In contrast the model proposed in this thesis will explore and model activities at different granularities, which supplements activity-based travel demand models through more reasoning capability and more flexibility to extract activity knowledge at different level of detail.

#### 2.4.4 *Concept of activity in pervasive and mobile computing*

Existing research in pervasive or mobile computing or even public health research generally aims at recognizing activities at a micro level using low level sensor signals. Since these activities are ubiquitous hence in some literature these activities are also termed as activities of daily living (ADL). The concept of ADL is generally concerned with the physical activities involving body part movements. Understanding such activities and behaviour from users' perspective can allow computing systems



to help the users to perform given tasks (Abowd et al., 1998). Humans are always active in some sense to some extent and understanding their active state is important in a number of situations such as in public health research and medical science understanding patient's needs and their emergency situations based on their activities and modelling the rehabilitation task (Chen et al., 2005), understanding individual lifestyle such as brushing teeth (Choudhury et al., 2008), hand wash or taking food (Amft et al., 2007), medication intake (Oliveira et al., 2010). In urban analytics it is important to understand a person's mobility state (Byon et al., 2009). Understanding and recognizing activity is also important in many entertainment and sports scenarios to respond based on user's need. For example, in gesture based gaming models such as Nintendo Wii and Microsoft Kinect and Philips DirectLife or Nike's context-aware shoes can improve user interaction with its environment and improve physical fitness by providing feedback especially in sports activities (Bulling et al., 2014).

In earlier days activity recognition research used to be performed in a constrained research environment using still images and video cameras through image processing and analysis (Aggarwal and Ryoo, 2011; Mitra and Acharya, 2007). But in order to address more real issues there is a shift in research paradigm in recognizing ADL now different sensors on smartphones or sensors worn on body parts are being explored.

Nowadays, smartphones can be used to track people's indoor and outdoor movements for a variety of purposes such as health monitoring, extracting contextual information, or behavioural information. In mobile computing and biomedical domain activities are generally modelled around ambulatory movement, i.e., locomotion. Choudhury and colleagues showed how smartphone based accelerometer and microphone can be used to detect micro-activities such as walking, sitting, running, climbing stairs, jumping, or talking (Choudhury et al., 2008). Bao and colleagues used accelerometers at different parts of the body to understand different activities (Bao and Intille, 2004). However, these sensor data are subject to significant noise caused by their varying position and orientation in relation to the body. In addition, it is still a challenge to distinguish different concurrent activities (e.g., walking while talking over phone).

Based on the notion of location-based services and ADL in mobile computing, activities can be categorized into two types as follows.

- High level activity based on location and stay time such as work.
- Micro-level (or low level) activities based on body movements such as walking, running, or climbing stairs.

This distinction is relevant for interpreting trajectories at different levels of granularity. Even adaptive sampling can be implemented in order to better manage the battery resources (Cottrill et al., 2013; Pereira et al., 2013).

Until 1990 activity recognition research were mainly focused on gesture detection. A more recent classification of activities, based on the complexity of the activity, shows four different levels: gestures, actions, interactions and group activities (Aggarwal and

Ryoo, 2011). Aggarwal and Ryoo discussed the methodological framework to model and detect activities at different layers such as single layer and multiple layers. Aggarwal and Ryoo also highlighted different approach-based perspective to address activity at different levels such as from space-time perspective, sequential approach and hierarchical approach which can further be broken down into space-time volume, trajectories, different space-time feature based, exemplar-based, state-based, statistical, syntactic and descriptive (Aggarwal and Ryoo, 2011).

Single layer approaches are simple in the sense the active state is recognized based on sequence of images whereas multiple layer (hierarchical way) consists of simple actions for modelling complex activities. Aggarwal and Ryoo demonstrated different categorization schemes for taxonomic activity classification such as statistical approaches based on statistical model, syntactic approaches based on grammar syntax involved with sequential notion. Aggarwal and Ryoo aim at classifying activities at all the levels, starting from individual bodily movement (gesture), individual simple activities (action), engagement of an individual with another individual or an object (interaction) or coordinating among themselves (group activities) (Aggarwal and Ryoo, 2011). However, the model developed by Aggarwal and Ryoo is more focused on activity recognition, not activity modelling per se at different contexts. Hence the distinction between activity and action is blurred and not properly defined. They also do not address the conceptualization of need and goal. Their work is also specialized in computer vision research where analysis of an activity can be performed from images or videos.

In another work, Aggarwal and Park worked on articulated motion analysis and understanding high-level activities from video and still images (Aggarwal and Park, 2004). They have modelled a high-level activity based on low level simple actions which are dependent on movement of body parts. The authors, however, did not clearly define the semantics of activity and action in their model. It is only understood an activity is composed of actions but the model cannot explain the hierarchical structure of activity and action based on context. Aggarwal and Park developed their model on four basic components such as a) human body modelling in the image, b) level of details needed to address the human action, c) high-level recognition scheme coupled with domain knowledge (Aggarwal and Park, 2004). Aggarwal and Park demonstrate activity recognition can be based on “object-based” perspective (specific to a model) or “appearance-based” perspective (ad hoc basis). Thus Aggarwal and Park developed two activity recognition schemes e.g., recognition by reconstruction and direct recognition with varied level of granularity in activity knowledge. Nevertheless, their work cannot explain activity and action from need-based, goal-based and contextual perspectives.

Figo and colleagues explored different techniques used in activity recognition (Figo et al., 2010). Their focus was on low level bodily movement such as jumping, running and walking. Their main focus was to detect the activities in order to enable

different context-aware services based on user's active state. Figo and colleagues have compared the activity detection performance of different features either captured in time domain, frequency domain or symbolic representation. In order to correctly detect user's active state Figo and colleagues have discussed efficacy of using different features computed from accelerometer data such as root mean square metric, signal correlation coefficient, sample difference, zero-crossings, DC component, spectral energy, information entropy, Euclidean and non-Euclidean distance measure in signal value and dynamic time warping between a portion of signals (Figo et al., 2010). Their result demonstrates in three-activity situation frequency domain techniques are more robust than time domain techniques.

Bulling and colleagues gave an overview on activity recognition research with a focus on low level physical activities. They discussed specific challenges in activity recognition such as a proper definition of activity and diverse nature of activities. Bulling and colleagues pointed out taxonomic classification of activities based on different aspects such as metabolic activities which is vastly used in medical sector (Bulling et al., 2014) as well as time use pattern (Partridge and Golle, 2008). Bulling and others also discussed low level implementation of the models and class imbalance problems during training phase along with diverse nature of sensor signals, trade-off between sampling duration and accuracy (Bulling et al., 2014).

In order to detect the activities at different levels there has already been a significant thrust on integrating various sensors to generate a rich movement and activity data to understand travel behaviour. However, there is no clear definition of activity in the field of mobile computing or public health research so far. In this thesis, the ontological framework that will be designed can address the different levels of activity in activity recognition research (see Chapter 4).

#### 2.4.5 Activity recognition from GPS sensors

During in-vehicle GPS studies, trip end detection and trip purpose identification were the most important stages in post-processing phase. Most of the trip end or activity detection algorithms are rule based. An activity is identified if there is a longer period of non-movement or longer dwell time at a same point in space. An activity can be a trip end, going home or office, meeting friends at a restaurant, having coffee at a cafeteria and so on. Prior studies suggested that if the dwell time is greater than 120 seconds then that could be a probable trip end (Bohte and Maat, 2009; Clifford et al., 2008; Forrest and Pearson, 2005; Schonfelder et al., 2002; Stopher, 2004; Wolf et al., 2004). Earlier in-vehicle GPS travel survey assumed to have a trip end if there is no GPS points recorded in the logger for a long time due to turning-off the engine.

Over last few years, due to emergence of wearable GPS devices and smartphones, activity is no longer limited to stopping the engine or having a trip end (see 2.3.2). However, there might be cases of shorter stops than 120 s e.g., when a car stops for

passengers to get-on or drop-off of the vehicle while the engine is still running or may be a person quickly entering a shop to purchase a cigar or recharging his smart-card on his way.

To address such diverse activities, several hierarchical deterministic dwell time algorithms have been devised by many researchers. For example, GeoStats developed Trip Identification and Analysis System mainly to detect trip ends. This algorithm uses three temporal dwell time thresholds (Axhausen et al., 2003). If the dwell time is above 300 seconds then the trip end is defined as “confident” trip end. If the dwell time is in the range of 120 seconds to 300 seconds then the trip end is defined as “probable”. If it is in the range of 20 seconds to 120 seconds then the trip end is “suspicious delay”. A GIS road network is used for map-matching purpose to again filter the trip ends which are “probable” and “suspicious delay”.

In order to detect the trip end during signal loss rule based algorithms have been developed based on trip characteristics before and after signal loss with predefined dwell time without using any external GIS information (Stopher et al., 2002) and using GIS information for more accuracy (Stopher et al., 2008). Since travel is derived from activity participation, activity can also be identified by understanding trip purpose. Along this line, some of the seminal work was done by Wolf. In order to understand trip purpose land use information has been used in conjunction with the trip end identification algorithm backed by “point-in-polygon” approach (Wolf, 2000). Wolf used 25 pre-defined land use types and 11 trip-purpose classes. After identifying the trip ends those are matched with the land parcels and checked which land use type the trip end is matching to and a trip purpose is manually labelled based on the land use type, and other heuristics namely time of the day and dwell time or activity duration at that point. Trip purpose identification is discussed in more detail in subsequent sections.

Since rule based and deterministic activity recognition models are not able to address dynamic activities with various dwell time and spatial constraint, machine learning and probabilistic approaches have been explored to improve the recognition process. Liao and colleagues used conditional random field (CRF) and Relational Markov Network (RMN) to detect various activities and rank them (Liao et al., 2005, 2007). Li and colleagues used sequential mining to detect activity locations and activity pattern based on dwell time and location information (Li et al., 2010b). In order to explore travel demand at different granularity, activity at different levels (individual and collective) should be understood and hence a paradigm shift have occurred from understanding individual activity pattern to collaborative activity pattern by using reinforcement inference approach. This concept has been explored in Microsoft’s Geolife project where activity locations are mined using user’s comments and geotagged information (Zheng et al., 2008).

In summary, activity can be associated to travel or movement or navigation from one location to another location. The activity knowledge can be explored at different gran-

ularity that depends on the nature of analysis or the problem at hand. Based on the activity and its granularity relevant route directions and wayfinding information can be disseminated that would influence certain travel based actions at decision points or at planning, tracking or assessing phase during a travel. It turns out that the linguistic ambiguity between activity and action can be addressed in the hierarchies of activity theory in Section 2.4.2, can further be supported by the concept of granularity (Section 2.6).

#### 2.4.6 *Relating the concept of activity and action with the notion of event and process*

The recursive concept of activity and action presented in this research (Chapter 4) is comparable to the long standing preoccupation with *event* and *process* respectively in GIScience. The concepts of event and process have been studied for a while, however, the recent need to integrate two distinct GIS functionalities i.e. data modelling and process modelling, into a unified model (Galton, 2015). Galton has pronounced a need to formally describe these two concepts (Galton, 2006). An event could be viewed as a phenomenon with a clear start and end in time, whereas a process is a homogeneous phenomenon without any temporal bounds. For example, Galton (2015) explained the gradual erosion of a cliff along a coastline, the yearly growth of a tree, walking, eating – all these can be treated as processes. On the other hand, collapse of a cliff, fall of a tree, walking from home to office on a particular day, or having lunch on a particular day could be treated as events as in the latter case the phenomena are bounded in time or a *discrete chunk(s) of happening* (Galton, 2015). Prior research shows the concept of process and event is context-sensitive (Worboys, 2005; Galton, 2015). The formalization of process and event suggested by Galton (2006) partly aligns with the concept proposed by Yuan (2001) and Langran and Chrisman (1988).

While representing and modelling complex geographical phenomena using rainfall Yuan (2001) described *a process as being measured by its footprint in spatial and temporal domain* and an event is a *spatial and temporal aggregation of a number of connected processes*. To illustrate further, Yuan (2001) mentioned the occurrence of rainfall at a given location at a given period of time could be considered as an event whereas the way it rains could be viewed as an associated process. In a different work, Langran and Chrisman (1988) viewed an event as an instantaneous transition between two states, however, the time of transition between two states is context-sensitive and could be zoomed in or out at different temporal granularity. The idea of event and process proposed by Yuan (2001) aligns with Galton (2006) in terms of recursiveness. That means, based on the earlier work of Worboys (2005) an event can be broken down into a number of process and a process can be broken down a number of events. Although the model suggested by Langran and Chrisman (1988) does not provide an explicit hint of recursiveness between event and process, their idea also aligns with Galton (2015) in terms of changing the temporal granularity depending on the context. Thus based on the above discus-

sion it can be said that the concepts of process and event are context-sensitive. In this context, time plays an important role. Galton (2015) mentioned a process is an experiential phenomenon happening over a *fluid time* without no bounds whereas an event is a historical (or scheduled) phenomenon over a *frozen time* with a definite bound. These concepts are important while modelling the real world phenomena at different temporal granularity.

The concept of activity and action introduced in this thesis (Chapter 4) could be related to these concepts of event and process (Langran and Chrisman, 1988; Yuan, 2001; Worboys, 2005; Galton, 2006). Both concepts are recursive and context-sensitive in nature. In this regard, an activity could be viewed as an event with a known start and end time (in a given space). An activity consists of a number of actions, which is similar to an event subsumes a number of processes. With a change of the application context, an activity could be viewed as an action, in a similar way a process can be viewed as an event in another context.

In the context of mobility-based activities Abler et al. (1971) proposed a travel can be viewed as an activity whereas a trip (which is required to realize the travel) could be viewed as an action (Galton, 2015). From the perspective of process and event this thesis also conforms to the previous conceptualisation of Abler and others (Abler et al., 1971). Thus a trip can be viewed as an event as it has a reported or predicted or scheduled (crisp or fuzzy) start and end in time and space, whereas a travel is a phenomenon of changing location without a fixed origin, destination and start and end time. Thus the concept of travel is more general compared to a trip. However, relating to the recursiveness or mutual subsumption property of activity and action (also process and event) this thesis assumes the notion of travel is context-sensitive. A travel can be viewed both as an activity or action (see Chapter 4).

In a different work, Hornsby and Cole (2007) developed a foundational framework in order to analysing movement patterns in terms of their semantics from a sequence of events that are experienced by the moving object. Such a foundational work could be used to develop an automated event notification system (during a travel) or querying specific mobility-based events from a database. In order to model the movement patterns Hornsby and Cole (2007) used three primary attributes e.g., object identity, event location and event description.

Thus the literature provides a support and foundation of conceptualising the notion of mobility-based activity in the light of event and process. Although the connection between activity–action and process–event is not empirically established within the scope of this research, however, the state-of-the-art shows both the concepts (activity and action; event and process) could be comparable. As Galton (2015) highlighted the importance of the aspect of event and process in GIScience, particularly while developing agent-based models or a model that captures a real world spatio-temporal phenomenon as close as possible, where time is a critical factor. In this research the context-sensitive activity ontology also demonstrated that the notion of activity or ac-

tion depends on the temporal granularity suggested by the context (Section 4.1). Going back to Galton's idea of *fluid time* and *frozen time* (Galton, 2015), if an activity is currently being undertaken (as an experiential phenomenon) then that activity becomes a process. In order to perform the activity there are a number of actions performed with a definite start and end time sequential manner. Those actions could be viewed as events. However, in a different context when the focus lies on a past activity with a known start and end time then that activity will transform into an event. All the actions subsumed by that activity will also be events with a known start and end time. Thus the transformation between an activity–action and process–event is context dependent. As mentioned earlier, with the emergence of activity-based service provisions in mobile computing, the resemblance of activity and action with process and event is useful for conceptualising a user's experience and interaction with her surroundings over time (past, present, future). This will enable more detailed and personalized service solutions depending on a user's current activity state (over *fluid time*) or using the past activity behaviour with start time, end time and duration (over *frozen time*) to predict her future activity state(s) and trigger specific context-aware services.

## 2.5 CONCEPT OF AFFORDANCE

Objects in the environment offer different degrees of action potential which is contextual and often assessed by the agent or subject given the specific action that involves an object with a given affordance. These offerings for action potential are considered as affordance of given object in the environment. The concept of affordances is rooted in affordance theory (Gibson, 1977, 1979) which was motivated by the propositions of Gestalt psychology that governs perception as a whole rather than through its constituents (Koffka, 1935). Gibson linked the affordance of an object in the environment with the properties of both the object and the agent who needs to carry out a given action (Stoffregen, 2003). His initial concept of affordance was centred purely on visual spatial perception (Gibson, 1979). Some researchers put more emphasis on properties of the environment rather than agent's part (Turvey, 1992). Overall this concept is similar to the motive with the object in activity theory.

Affordance theory does not decompose or construct activity in a top-down or bottom-up approach, but it helps to model the suitability of an object in order to perform an action within the scope of an agent's capability. The concept of affordance has been used in many action-oriented scenarios starting from assessing the ability of a person on climbing stairs where the affordance depends on the ratio of the height of stair steps and the person's leg (Warren, 1984). It also has been used in wayfinding and navigation in an unfamiliar environment where the agents need to perceive the affordance of different objects in support of their decision making (Raubal, 2001). Affordance theory is not only limited to objects but also this has been used in modelling the suitability of places or locations for certain facilities. Considering the fact that different locations

provide different degree of affordance which is perceived differently by the agents, a suitability model for a restaurant has been studied depending on different actions it may offer such as eating, reading, socializing (Jordan et al., 1998). Affordance theory has also been used to evaluate the suitability measure for urban networks for pedestrians (Jonietz et al., 2013).

Inspired by Gibson's affordance theory of agent-environment mutuality, Zaff argued affordance can be characterized with respect to an agent and its context and its properties. This enables affordance to be viewed as a measurable aspect only in the context of an agent (Zaff, 1995). Norman explored affordance of everyday things such as telephones, radios, or doors (Norman, 1988). On the other hand Gaver viewed affordance from the perspective of agent's socio-cultural and intentional aspects (Gaver, 1991).

Raubal and Moratz developed a relational functional model for affordance-based agent framework by extending the traditional affordance theory through integration of cognitive aspects, situational aspects and social constraints (Raubal and Moratz, 2008). In this model they have categorized affordances into three classes such as physical affordance, social-institutional affordance and mental affordance. Their model is based on abstract functional representation of different affordance aspects and operational aspects of an agent. In this model, physical affordance is characterized by physical structure of the agent and the object, spatial cognitive capability of the agent, and a goal. Physical affordance is constrained by social-institutional affordance. However, in a spatio-temporal environmental setup an agent chooses certain affordances based on its requirements and decision strategy, which gives rise to third category of affordances called mental affordances, which are manipulated and processed mentally. Based on the action and environmental condition the agent perceives different affordances and performs an internal operation which depends on the agent's historical experience with the object. This results in an internal outcome. Following this stage, agent executes an external operation (equivalent to an action in this research) that results in an external outcome through some changes in the external environment (Raubal and Moratz, 2008).

In this regard transport modes being mobile objects offer an affordance to mediate people from one location to another location and thereby helps to perform an action (or activity) during a travel. This thesis explores four different mediation types e.g., mediated by a bus, train, tram or by walk.

## 2.6 GRANULARITY IN MOVEMENT BEHAVIOUR

Since travelling is an important facet in daily life as travel embeds various activities (or actions) this section will look into previous work on how travel has been modelled at different spatial and temporal granularity. Travel or movement is a continuous phenomenon. However, movement history is captured in a discretized way, whether recorded by sensors or by human reports post-travel. The recording is by waypoints.



The movement can be perceived at different level of details and thus can represent varying information. This level of detail at which the world is perceived at a given context is known as granularity: a certain grain size at which a phenomenon is perceived (Hobbs, 1990).

*“Our ability to conceptualize the world at different granularities and to switch among these granularities is fundamental to our intelligence and flexibility.”*

- J. R. Hobbs (1985)

The time-ordered set of waypoints of an agent and its interaction with its environment can be refined by additional waypoints, or coarsened by thinning out. Structurally equivalent to space-time paths in time geography (Miller, 1991), lifelines, or in their discrete form, lifeline threads, have been suggested in order to model movement behaviour in terms of precisely defined geometrical structures with varied granularity (Miller, 1991). A lifeline is a time-ordered set of waypoints an individual has passed through or occupied for a given time period (Hornsby and Egenhofer, 2002). Similarly, lifeline beads are equivalent to space-time prisms, and a lifeline necklace is equivalent to sequence of space-time prisms (Hornsby and Egenhofer, 2002; Miller, 1991). On a coarser granularity a lifeline bead can be transformed into a lifeline trace that contains only starting point and ending point or a necklace can be transformed into a convex hull that connects all the rim points and generalize the movement behaviour of an individual over a time period (Hornsby and Egenhofer, 2002).

Since activity is contextual and depends on the details of analysis and any occurrence is a function of time, temporal granularity plays an important role in defining an activity. Hornsby developed a set of temporal zoom operators to shift the temporal granularity over the identity states of an object and other objects that links during any transitional change (Hornsby and Egenhofer, 2002). There are also instances of work on spatial granularities for place descriptions (Richter et al., 2013). Hornsby and Egenhofer showed how a refinement operation can enhance the granularity and explores more information on temporal, spatial and speed aspects whereas an abstraction operation does the opposite and reduces the information content (Hornsby and Egenhofer, 2002). A fine grained lifeline model reveals more activity or action information as more relevant timestamps and locations that were otherwise unknown. At the same time a coarser grained representation can simplify the knowledge and give a general trend or high level activity knowledge.

The role of granularity has also been studied in wayfinding and navigation. Fonseca and colleagues proposed a model to explore spatial information at different granularity in order to disseminate varied level of details (Fonseca et al., 2002). Generally the choice of granularity in wayfinding depends on previous knowledge of the agent in the environment. Tenbrink and Winter proposed a framework for variable granularity in wayfinding and navigation. They have considered linear (1D) and areal (2D) granularities, and elaboration (Tenbrink and Winter, 2009). In the framework developed by Tenbrink and Winter, they have represented 1D granularity as a line with segments of

varying lengths. 2D granularity has been represented by polygons. Both 1D and 2D granularities are finite and discrete since network structure and zoom levels are finite and discrete, whereas elaboration is infinite as the route description can be enumerated at infinite level. They also discussed how route directions and descriptions can vary with varied details depending on person's knowledge of the environment, travel direction, location and more specifically pragmatic information needs. They have drawn a comparison on flexibility in providing direction information by humans and machines. The granularity of human-provided route descriptions is more adaptable to the information need than that of a machine. Machine generated route directions do not consider varied information needs based on travel direction and a-priori knowledge of the environment. Motivated by the works of Norman (Norman, 1988) and Kuipers (Kuipers, 1982), Timpf has studied the notion of granularity on spatial knowledge representation on a mobile device depends on the existing knowledge in the world (in terms of signage, landmarks, spatial cues), knowledge in the head (cognitive map of a place), and knowledge in the pocket (information contained in a mobile device in terms of maps and other spatial information) (Hirtle et al., 2011; Timpf, 2005). Timpf has developed a three-fold framework for any wayfinding activity such as wayfinding from place A to place B and this activity consists of three tasks (actions) such as planning, tracking and assessing. Each of these tasks can be implemented through different operations. Operations that implement the planning task include information gathering, finding routes, determining constraints, producing instructions. Operations that implement the tracking task include orientations, tracking locations, and comparisons to plan. Operations that implement the assessing task include assessing instructions and determining complexity of routes (Timpf, 2005).

With technological advancement there is a growing need of incorporating HCI in urban context for providing information to mobile information seekers for various location-based services (LBS). The information can be related to route recommendation (Klippel et al., 2005) or activity recommendation (Crease and Reichenbacher, 2013). In both cases spatio-temporal granularity and relevance play vital role in disseminating the information in the user's context (Hirtle et al., 2011; Hornsby, 2001; Raper, 2007). Hirtle and colleagues explored the influence of activities on relevance and granularity of route information by analysing different lexical indicators corresponding to certain activity types. They argued the concept of activity is a relative notion (Hirtle et al., 2011). Hirtle and others showed an example (Table 7) where taking a friend to an emergency room in a hospital is an activity that forms different actions (tasks) such as drive the car as fast as possible or call an ambulance, park the car next to the emergency room and take the friend to the emergency room. Whereas at a finer granularity if "driving the car to the hospital" is considered as an activity then this can be broken down into different tasks such as planning the fastest route, tracking the position and assessing the movement behaviour of oneself to reach the destination effectively and quickly.

Hirtle and colleagues also mentioned routine navigation (travelling) can be assumed as action to fulfill a purpose of an activity whereas in some cases navigation itself can be seen as an activity such as hiking, sailing or jogging (Hirtle et al., 2011).

Table 7: Activity and actions for different activity targeted to a same location. This table has been taken from (Hirtle et al., 2011).

Activity	Take a friend to emergency room at the hospital	Visit a friend at the hospital
Purpose	Get medical help fast	Socialize
Action 1	Drive your car to the hospital	Drive your car to the hospital
Goal	As fast as possible, fastest route	Take shortest path
Action 2	Park next to emergency room	Park where available
Goal	Nearest parking space	Least expensive
Action 3	Go to emergency room	Go to main entrance
Goal	As fast as possible	Find directory or information booth
Action 4	–	Go to friend’s room
Goal	–	Try not to get lost

## 2.7 TOWARDS AN APPROXIMATE REASONING ABOUT MOBILITY-BASED ACTIVITIES

Most of our cognitive processes and experiences revolve around the dynamics of the real world. Any dynamic phenomenon essentially involves a change in some way for example, in qualitative form, quantitative form or in visual form. In this regard, an activity could be viewed as a change (in state) over a given space and time depending on the context (see Chapter 4). Previous studies have demonstrated that any change requires integration of at least three basic concepts – space, time and movement (Galton, 1993). In real world the knowledge about any concept (a phenomena, an object, or a measurement) is often incomplete and imperfect. This also applies to the knowledge extracted by interpreting spatial trajectories. The inference is generally made through approximation based on the current state of the knowledge, which is either incomplete or partly unreliable, or presented in a subjective and (vague) linguistic form (Bhatnagar and Kanal, 1986). For example, although a movement takes place in a continuous

manner, however, due to system architecture and storage capacity the movement data is sampled (and stored) in a discrete way, which affects the completeness of the data that is being captured. Incompleteness may also take place due to signal gap or turning of the device abruptly. At the same time, the sources (e.g., GPS, GSM, Wi-Fi) used to record the movement data involve positional errors, which makes the measurements unreliable to some extent. The ground truth recorded or reported by the users may contain linguistic vagueness and sometimes associated with low reliability. All these issues affect the confidence in the measurement as well as in the inference. The lack in confidence introduces the aspect of uncertainty, both in measurement and inference.

According to Wordnet, uncertainty can be defined as *the state of being unsure of something*. In case of a mobility-based activity this notion can relate to sensor measurements and observations (positional accuracy), inference strategies (choosing the relevant features, developing the optimum propositions, setting up the optimal parameters) and activity states (detecting the mean of travelling).

Kosanovic (1995) and Palancioglu (2003) have pointed out that uncertainty can be addressed both through a stochastic approach or a fuzzy approach. However, a stochastic uncertainty is based on probability of an event occurrence with a given state of the knowledge. The limitation of a conventional stochastic process lies in its bivalent nature. On the other hand, a fuzzy approach measures the degree of truth of a fact or possibility of occurrence of an event with a given certainty factor. Stallings (1977), Cheeseman (1986), Lindley (1987) and others advocated in favour of probability theory by suggesting that any uncertainty can be modeled by probability theory. On the other hand, Zadeh (1986), Kosko (1990), and Mendel et al. (2006) argued that probability theory fails when the event or concepts are not well-defined. Probability theory also provides limited capacity while explaining the belonging of an element to different concepts. For example, based on the particular social setup the notion of "tall" varies from region to region. In a society where the average height is 150 cm, a person with a height of 165 cm could be considered as tall. On the other hand, in a different setup where the average height is 170 cm, a person with a height of 165 cm is not as tall as in the previous case. In this example, the belonging of the height to the concept of tall or not tall is a matter of degree of truth. This also applies to demarcating the bona fide boundary of a geographical object (Smith and Varzi, 2000; Vogt et al., 2012) e.g., delineating the boundary of a grassland from the adjacent forest area. The belonging of the elements around the margin often tends to be fuzzy. These vague situations cannot be addressed by a probability theory, rather an approximate reasoning mechanism e.g., a fuzzy logic is required to model these vague concepts. Probability theory also fails while modelling the vagueness in linguistics, e.g., *average speed*, and predicate quantifiers, e.g., *very, likely, slightly, extremely, almost*. Thus, probability theory offers limited capacity while dealing with subjective perceptions and uncertain qualitative state of affairs. In the context of mobility-based activity this can be further illustrated as follows.

Suppose, Joe was waiting for a bus at 7:00 AM. At 7:10 AM Joe saw the bus for the first time within his field of view. In a while, Joe boarded the bus and took a seat. Around 7:11 AM, he felt the vibration and realized the bus started moving. In this example, using a probability theory it is not possible to define the changes in Joe's activity states from waiting at the bus stop to boarding the bus. At what point in time we should say Joe has entered the bus? The epoch when Joe lifts his leg to make his first move inside the bus, or the moment when Joe puts one of his legs in the bus, or the moment when he puts both of his legs inside the bus? Thus, the transitions in the activity states are often fuzzy (and uncertain). Intuitively from the perspective of fuzzy logic, it can be said, when Joe lifts his leg with an intention to enter the bus can be considered as *about to* enter the bus, however, at the same time, since the bus has not started yet, it can also be said Joe's waiting activity is *almost* over. When Joe stepped into the bus, the activity state can be viewed as *almost* entering the bus, yet waiting for the bus to move<sup>11</sup>. Thus, Joe's activity state from 7:10 AM to 7:11 AM can be both *waiting* and *boarding the bus* with a gradual change in degree of truth as time elapses. On the other hand, a probability theory can tell given some apriori information, what the likelihood is that Joe is waiting for the bus at 7:00 AM.

Following the above example, it is worth noting that this thesis particularly looks at the activities performed while changing locations using a given transport mode. In this research a person who is moving from one location to another, or a vehicle in which the person is moving, are both considered as a moving object. Within the scope of this thesis, it is possible to interpret a trajectory using a probabilistic approach (Xu et al., 2011; Feng and Timmermans, 2016) as well as fuzzy approach (Biljecki et al., 2012; Sauerlander-Biebl et al., 2017), and infer a possible outcome (transport mode in this case) from an erroneous measurement (location or speed information from a GPS sensor). In this research, an uncertainty relates to the lack of confidence about a GPS-based measurement or in the ground truth collection (exact trip start, and end time), and also in inference process. Specifically, in order to model the confidence in the inference process, this thesis has contributed to the state-of-the-art in transport mode detection by introducing the concept of multiple transport mode possibilities with varied confidence (in terms of certainty factors). On the other hand, ambiguity relates to the linguistic values used to model each fuzzy set (e.g., high, moderate, low) of a given fuzzy variable (e.g., average speed). That said, the quantitative notion of "high average speed" may vary from person to person or from situation to situation. However, qualitatively the notion will generally remain same in all the situations. For example, it makes sense to say that a train moves at a high average speed of 80 km/h in cities, whereas a train moves at a high average speed of 150 km/h in the outskirts. It also makes sense to say that a train generally moves with higher average speed than a bus. Thus, the concept of "high speed" is ambiguous. In the same line, given a low speed profile during traffic congestion, the modal state could be either walking, riding

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<sup>11</sup> The predicate quantifiers *about to*, *almost* provide fuzzy connotations.

a bicycle, travelling in a bus or in a tram. Thus, in this case, the inference could be ambiguous given a limited number of fact(s). Fuzzy logic can encode such (linguistic) ambiguities and uncertainties (in measurements) in the antecedent (IF) and consequent (THEN) part while constructing a transparent rule base (Klir and Yuan, 1995).

The main motivation of using a fuzzy logic based approach in this research (Chapter 5) is its capability of inferring multiple possibilities of being different transport modes, given a set of spatial and kinematic facts. With a vast amount of unlabelled trajectory data being generated worldwide both from commercial vendors and user-generated sources with different granularities and accuracies, it is difficult to use data-driven approaches (e.g., machine learning based models) to interpret those (unlabelled) movement data due to lack of training samples. In this context, a multiple-input multiple-output fuzzy logic based approach can effectively interpret trajectories (with limited/no ground truth information) and can provide useful insights about people's movement behaviour or travel demand estimation at a given confidence level (see Chapter 5).

Past research has shown that in order to manage the moving object and to understand its behaviour, it is important to model the uncertainties associated with the movement during data collection, data indexing and inference stage (Sistla et al., 1997; Wolfson et al., 1999). Movement occurs in space and time. Thus, reasoning a moving object can be viewed as an extension of spatio-temporal reasoning with an added capacity of changing location through locomotion along a rectilinear or curvilinear path. Since current spatio-temporal systems are based on two-valued logic (Boolean logic), they provide limited inference ability (Dragicevic and Marceau, 1999). Conventional spatio-temporal reasoning schemes cannot address the vagueness in human perception and the varied confidence in an inference process. However, with the emergence of ubiquitous mobile devices and location-based context-aware service provisions, there is a growing need to incorporate human perceptions in the spatio-temporal systems. This requires both qualitative and quantitative reasoning (Peuquet, 1999). However, qualitative reasoning is more robust as it can handle the uncertainties more effectively, both from the measurements and linguistics. Qualitative reasoning can also provide better interpretation, which is required to extract the mobility signatures of a moving object (Palancioglu, 2003). In case of a trajectory, an interpretation could explain how a moving objects is related to another object during its discourse (Van de Weghe et al., 2005). An interpretation can also provide insight about a person's transport mode information.

Movement can be viewed as a function of time, which is realized over a given space. To date, there has been a significant contributions made in modelling and reasoning an object (or a set of objects) in space and time through a number of spatial (Egenhofer and Franzosa, 1991; Randell et al., 1992; Cohn et al., 1997) and temporal logics (Allen, 1983; Ligozat, 2013) separately. However, there is not much work done in reasoning movement behaviour of an object. While much of the qualitative spatio-temporal rea-

soning, particularly in the field of movement analysis, is based on symbolic representation and topological relationships (Van de Weghe et al., 2005; Bogaert et al., 2007; Ibrahim and Tawfik, 2007; Delafontaine et al., 2011), there is a growing interest to incorporate propositional rules that can provide the approximate reasoning about the movement behaviour of an object. In contrast to a probabilistic approach, a fuzzy propositional rule-based approach can handle uncertainties in a more effective way and can provide better transparency. Such transparency is important in order to extract movement knowledge and enrich the activity ontology at different contexts (see Chapter 4 and Chapter 5).

Although probability theory and fuzzy logic have fundamental difference in their modus operandi, the likelihood in probability theory and a membership value in a fuzzy logic both range from 0.0 to 1.0, where 0.0 and 1.0 indicate the minimum and maximum likelihood or degree of membership respectively. In 1995, Zadeh demonstrated that the two theories have their own applicability in different contexts, and thus they should not be treated in a competitive way (Zadeh, 1995). In this way Zadeh has bridged the gap in the initial argument in favour of fuzzy logic (Zadeh, 1986; Kosko, 1990) and the argument in favour of probability theory (Cheeseman, 1986; Lindley, 1987). Although an initial attempt was made by Loginov (1966) to bring a fuzzy logic and probability theory close to each other by transforming fuzzy membership functions into probability values based on the concept of consensus or voting. However, as Loginov's approach was based on bivalent notion of an event occurrence Zadeh (1995) argued that the complementarity between fuzzy logic and probability theory should not be bridged through consensus theory. Rather based on the previous studies (Goodman and Nguyen, 1985), Zadeh and others (Gudder, 2000; Beer, 2010) demonstrated a fuzzy set can be deduced from a random set and depending on the type of uncertainty a random variable can be converted to a fuzzy random variable, an event can be converted to fuzzy event which leads to a hybrid fuzzy probabilistic reasoning. Although a conventional fuzzy logic can not tune its membership function parameters, when integrating a machine-learning based approach (namely a neural network) through back propagation and least square optimization a hybrid neuro-fuzzy model can learn from historical data while modelling the uncertainty in an automated way (Jang, 1993).

As mentioned earlier fuzzy logic and a neuro-fuzzy approach have been previously used in trajectory interpretation mostly in map-matching (Syed and Cannon, 2004; Quddus et al., 2006), travel demand estimation (Seyedabrishami and Shafahi, 2011), and single-output based transport mode detection (Biljecki et al., 2012). In this thesis a fuzzy approach has been explored in order to develop a multiple-output based transport mode detection framework both in offline and in near-real time. The model presented in Chapter 5 can work in different kinematic situations with scarce or no ground truth information. The fuzzy approach can also be useful for modelling activity states (from waiting to boarding a bus) from an ontological perspective. Since the fuzzy rules can serve as an approximation of the movement signature of a moving ob-

ject, the fuzzy rule base can also be used as a qualitative trajectory reasoning scheme along with the existing topological and symbolic trajectory calculus (Van de Weghe et al., 2005; Delafontaine et al., 2011).

In summary, this chapter reviews different mobility surveys that took place across the world. Existing mobility surveys are subject to quality issues, which can be addressed by smartphones due to their capability to record people's travel behaviour continuously and at a finer details. Based on the existing literature it is evident that raw trajectories can be interpreted to reveal mobility based activity information at different resolutions. A particular focus is given on trip characterization and transport mode detection from raw trajectories. This research has presented a number of models that can interpret raw trajectories and extract transport mode information at different temporal granularities (Chapter 5, Chapter 6, Chapter 7). This research also reviews the notion of activity approached by different disciplines and a semantic gap in the definition of an activity. Chapter 4 presents a framework that aligns different disciplines together at different contexts. The framework extends the concepts of "activity theory" (Nardi, 1995) and supports existing work by (Raubal and Moratz, 2008) and (Hirtle et al., 2011). This chapter also presents reasoning mechanism of a moving object and the applicability of fuzzy logic based approach over a probabilistic approach while interpreting trajectories in the interest of transport mode detection.



## PRELIMINARIES

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This chapter provides definitions of basic concepts used in this research. This list is not exhaustive. Some concepts that are too specific to a given chapter, are defined in the particular chapter.

### 3.1 DEFINITIONS

#### 3.1.1 *Activity (AY)*

Activity is a phenomenon where an agent (e.g., human) interacts with an object situated in an environment to satisfy some need(s) at a given context. For detailed explanation on activity refer Section 4.3.2.2.

#### 3.1.2 *Context (C)*

Context is important while defining an activity. *Context* can be defined as any information that characterizes a situation that is relevant to the interaction of an actor with the objects in its environment in order to participate in a given activity (Abowd et al., 1997). For detailed explanation of context see Section 4.3.2.4.

#### 3.1.3 *Travel*

Travel is a phenomenon of moving from one location to another location over time. Travel can be viewed as an *activity*—a temporally extended process—or an *action*—a not further expanded event—depending on the context of the travel analysis. Furthermore, this notion of travel is open across a range of spatial scales. Inner-urban travel happens generally at environmental scale (Montello, 1993), but single parts, such as transfers between modes, can happen in vista scale. Inter-city travel is travel on geographic scale. This research is mainly interested in urban travel.

In this regard, the concept of vista scale used in this thesis is based on *vista space*. Vista space is a type of psychological space propounded by Montello (1993). The scale of a vista space is not absolute, rather it is based on the projective size relative to the user's body, which is often subjective and based on the user's physical structure and cognitive perception of her surroundings and based on the structure of the environment, i.e., what is in view. In this thesis, vista scale means any small scale indoor space such as a bus stop, train station, a portion of the airport terminal that is in view, where

a transfer may take place on user's feet (walking, climbing stairs or standing and waiting for the next connecting vehicle). However, bigger space such as the entire airport, office building are in Montello's terms, environmental space, because they cannot be seen from a single vantage point and require locomotion for exploration.

#### 3.1.4 Sensor Trace ( $\Gamma$ )

A sensor trace is a time ordered set of sensor observations that captures a user's activity states at a specific granularity defined by the sampling frequency. In this research the sensors are assumed to be installed on a smartphone, and may include a location sensor as well as an inertial measurement unit. A sensor trace  $\Gamma$  consists of signals of one or more sensors  $I_i$  (including sensors operating on different channels),  $i \in [1, n]$ , each expressed as a set of  $\{s(k)\}$  where  $k \in [1, m]$  and  $m$  is an integer. A sensor trace can be mathematically expressed as:

$$\Gamma = \{I_i\} : I_i = \{s(1)_i, \dots, s(m)_i, t_i\} | \forall i : t_{i-1} < t_i, i \in [1, n] \quad (1)$$

#### 3.1.5 Trajectory ( $\Pi$ )

A trajectory is a sequence of time ordered spatio-temporal points that represents a person's travel history with coordinates in a three-dimensional Euclidean space  $(x_i, y_i, z_i)$  at a given time  $(t_i)$ . In this research the 'z' value will be ignored as this value is not relevant to the models developed in this research. However, a 'z' value can be integrated where the altitude information is vital, for example, travels between levels of a complex built environment. From the definition of a sensor trace, all the trajectories that are captured using GPS sensors, Wi-Fi or 3G/4G localization onboard a smartphone are a type of sensor trace. A trajectory can be mathematically expressed as follows:

$$\Pi = \{P_i\} : P_i = (x_i, y_i, [z_i], t_i) | \forall i : t_{i-1} < t_i \quad (2)$$

Depending on the information content and level of processing a trajectory can be classified into three distinct types as follows.

- *Raw Trajectory* ( $\Pi_R$ ): A *raw trajectory* is an unprocessed set of time ordered spatio-temporal points with varying levels of inaccuracy due to the noise present in the sensor signals. A raw trajectory may also contain a number of signal gaps.
- *Preprocessed Trajectory* ( $\Pi_P$ ): A *preprocessed trajectory* is a set of time ordered spatio-temporal points which is pre-processed and filtered to some extent in order to discard inaccurate spatio-temporal points and other noise present in the data set. The level of processing depends on the application context.

- *Semantic Trajectory* ( $\Pi_S$ ): Both raw and preprocessed trajectories suffer from a semantic gap between the movement history of the traveller and their movement behaviour. Such a semantic gap can be bridged by enriching a raw or preprocessed trajectory by domain information including spatial, non-spatial and temporal information. A *semantic trajectory* is constructed from a raw trajectory through a semantic enrichment operation.

### 3.1.5.1 Segment (Seg)

A segment is a connected sequence of a sensor trace between a defined start and end point in time. A segment may include a portion of GPS trajectory, and/or other sensor observations at each time stamp.

### 3.1.5.2 Atomic Segment (ASeg)

An atomic segment is the smallest segment of a sensor trace, defined by a context-dependent kernel length.

### 3.1.5.3 Atomic Kernel ( $K_\eta$ )

An atomic kernel is an operator that extracts an atomic segment of a sensor trace, including a GPS trajectory. An atomic kernel has a defined, constant length ( $\eta$ ) within a specific context (Fig 9).

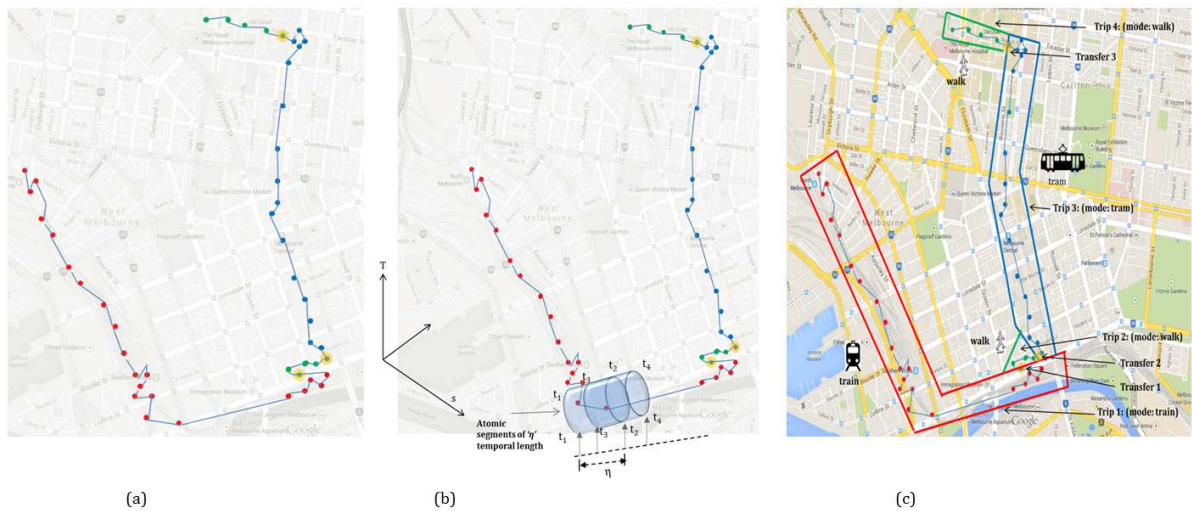


Figure 9: A raw trajectory is shown in Figure (a); Atomic segments are generated using an atomic kernel of time length  $\eta$  on the raw trajectory in Figure (b); Using a state-based bottom-up approach a given trajectory is then segmented into four segments that are detected as four distinct trips based on different transport modes with three transfers in Figure (c).

#### 3.1.5.4 *Trip (T)*

A trip is an action of changing location with a purpose. A travel can consist of more than one trip. A trip is characterized by a constant transport mode. Thus, the trips are attributed by their start location and time, end location and time, and a given transport mode. There may be different types of trips:

- *Actual Trip* ( $T_A$ ): An actual trip is what happens in reality while traveling from one location to another location.
- *Reported Trip* ( $T_R$ ): A reported trip is the trip that is annotated or reported by the traveler from memory, which often involves quality and granularity issues.
- *Scheduled Trip* ( $T_S$ ): A scheduled trip is a trip that is predefined by a given transport service with its trip origin, destination, trip start time, end time, route and the intermediate stops that are to be visited along during the travel.
- *Predicted Trip* ( $T_P$ ): A predicted trip is a trip that is inferred from a predictive framework based on the features computed from a given sensor trace that may include a GPS trajectory and IMU information.

In transportation engineering the concept of trip is based on travelling from one activity location to another activity location by one or more than one transport modes. Conventionally a trip may consist of multiple travel segments (trip legs) and a number of transfers. Each of these phenomena can be viewed as an action (see Chapter 4 for more detailed discussion on action and activity). As this thesis has demonstrated the notion of activity is context-sensitive, and thus the concept of a “trip leg” and a “trip” is also context-dependent. For example, conventionally a transfer connects two different trip legs. However, if the transfer becomes an activity in itself then the trip legs will be transformed to trips. Chapter 4 in this thesis has presented such contextual transformation of an action to an activity or vice-versa. It is assumed in this thesis that when a transfer becomes an activity, a travel segment with a constant transport modal state can be viewed as a trip (and when a transfer is an action, the preceding and succeeding segment is a trip leg). In order to avoid the confusion and to conform different disciplines (e.g., spatial information, transportation engineering, cognitive science, mobile computing), any movement using a constant (similar) transport mode between any two locations is termed a trip. And thus, walking to a tram, taking a tram and walking to the final destination is viewed as three different trips.

#### 3.1.5.5 *Transfer (Trans)*

A transfer is an action of changing from one transport mode to another transport mode.

### 3.1.5.6 Transport Mode (M)

A transport mode is a mediation of mobility, either by locomotion or by some vehicle. In the following experiment data was collected for four public transport modes: *bus*, *train*, *tram*, and *walk*. Other modes of urban mobility are *cycling*, *driving* a car, or *riding* in a car (being passenger in a car).

## 3.2 DATA SET

In this research two personalized data sets have been used for evaluating the hypotheses and addressing the research aim. The experiments performed in [Chapter 4](#), [Chapter 6](#), [Chapter 7](#) use a same trajectory data set. However [Chapter 7](#) uses an additional data set to further evaluate the model on fine grained sensor traces containing only inertial sensor information. Both the data sets were collected by an Android app installed on Samsung Galaxy smartphone. The application has been tested on different smartphones e.g., Samsung Galaxy, HTC, Asus, Motorola and LG Nexus. The application can adaptively sample different signals depending on the sensor available on the phone (Fig 10, 11, 12). The application supports all the modern inbuilt sensors e.g., GPS, accelerometer, gyroscope, light sensor, proximity sensor, barometer, magnetic sensor, sound sensor (Fig 10, Fig 11). It can be also understood how battery is draining over the sampling period which could be useful for adaptive sampling in future. There is also a user interface where the user can see her location in the application using the GPS sensor (Fig 12).

The data sets cover different travels in Greater Melbourne, Australia, over three months (Fig 19).

### 3.2.1 Data set 1

The data set contains 0.6 million GPS points over approximately 85 h sampled at 1 Hz-2 Hz. The data set reflects different trip behaviour in terms of kinematic profile and data quality mediated by four transport modes, e.g., *walk*, *bus*, *train* and *tram*, collected between 7 am to 11 pm along different routes. In order to capture the real world problems, the data set also covers cases of overlapping routes of different modes and single modes with different speed profiles (e.g., a bus moving *slowly* in the CBD and *fast* along an expressway, whereas maintaining a *moderate* speed in the suburb). Table 9 shows duration of different transport modes used.

Since different transport networks frequently overlap or located very close to each other along with the POIs (Fig 20,13), it is often difficult to distinguish between different modes from GPS-only data points. The problem becomes more challenging when there is frequent GPS signal loss or high positional uncertainty due to multipath effects. In order to estimate the overlapping area by the present transport networks (bus, train,

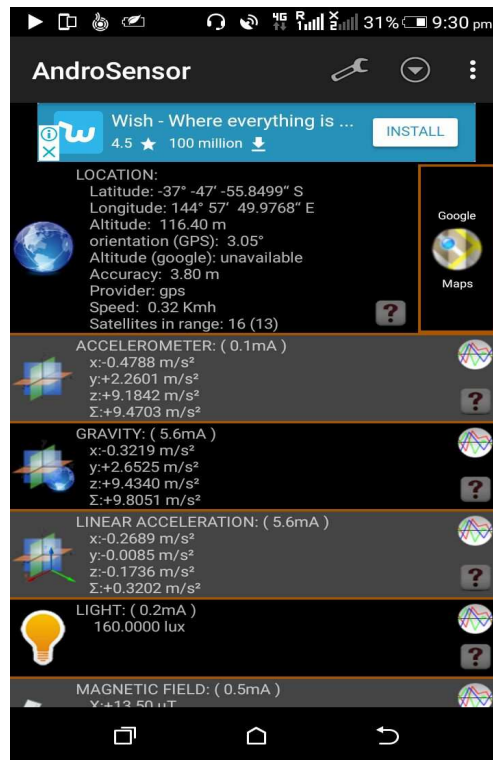


Figure 10: Sensor readings I: GPS, accelerometer, gravity, light sensor, magnetic sensor.

tram) a spatial analysis is performed where a set of minimum bounding rectangles (MBR) is developed that contains a given set of route networks. Then an intersection operation is performed to extract the common region that shows a significant overlap by all the public transport route networks. Such a region containing different route networks in close proximity is termed as zone of ambiguity (ZA), which is measured around 222 sq km (Fig 14a). Another spatial operation is performed on the trajectory data set to generate a convex hull to estimate an extent of the area covered by the trajectories for this experiment (Fig 14b). It is estimated that the data set collected for this research covers 139 sq km of the ZA, which is approximately 63% of the total ZA (Fig 14a) which poses significant challenge to distinguish between different transport modes particularly bus and tram.

Figure 15 shows a database schema for raw data collection with the selected sensors. The last column (state) is linked from the ground truth data. Figure 16 shows a transition from walking mode to tram mode. It is also observed that in CBD or under dense foliage or in indoor environment sometimes there was an interruption in GPS signal reception (Fig 17) which was later resolved by an interpolation technique (Fig 18).

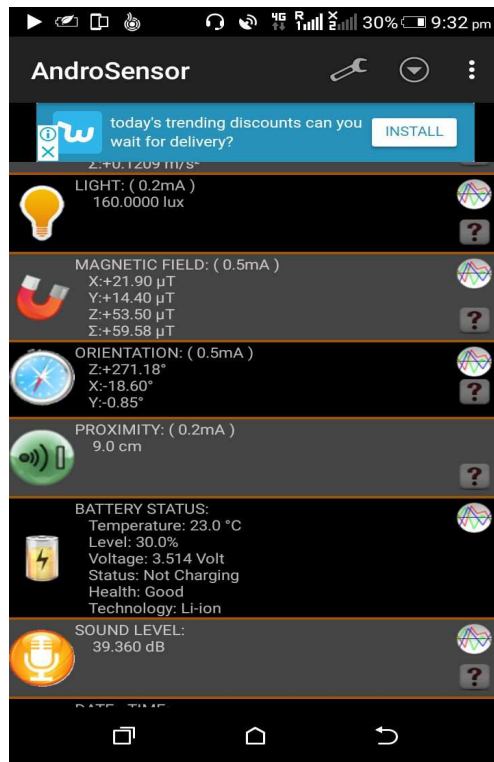


Figure 11: Sensor readings II: Magnetic sensor, gyroscope, proximity sensor, battery status, sound sensor, timestamp on the smartphone clock.

### 3.2.2 Data set 2

In order to evaluate the framework in absence of location information, a second set of data has been collected using high frequency IMU only (linear accelerometer and gyroscope) information across Greater Melbourne. The second data set has been recorded at a 50 Hz sampling frequency over approximately 8.5 h that covers bus, train, tram and walk trips.

Since a high frequency sensor data may contain noise mainly due to sudden hand movement, change in body inertia, or a jerk due to sudden brake, a low pass filter is applied to the signals collected along three axes of accelerometer and gyroscope. A low pass filter has been implemented on a  $x$ ,  $y$  and  $z$  axis of an accelerometer as follows, where  $a_f[k_t]$  is the filtered acceleration signal along  $k$  axis at  $t$  timestamp. Similarly,  $a[k_t]$  denotes the raw acceleration signal along  $k$  axis at  $t$  timestamp.  $\beta$  controls the smoothness of the filtered signal. A low pass filter allows the low frequency signal whereas blocks the high frequency signal. Thereby while recording the trajectories, if there is a sudden jerk or sudden change in activity state (e.g., from sitting to standing) while travelling the noise could be eliminated.

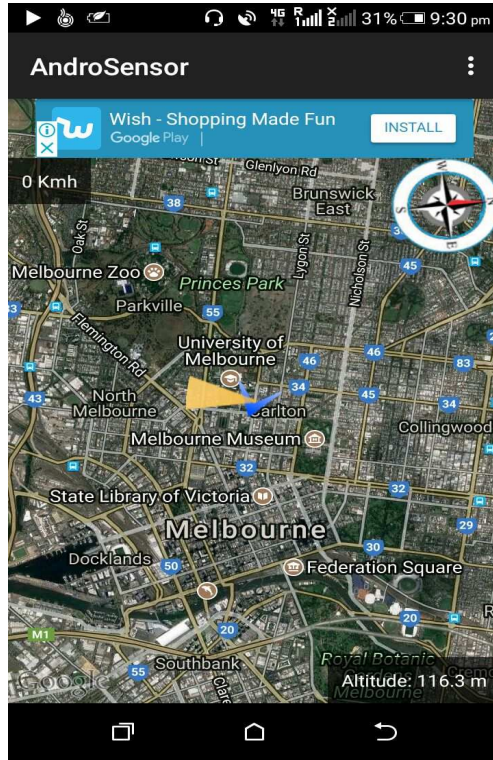


Figure 12: Location of the user at a given timestamp.

$$a_f[k_t] = \beta * a[k_{t-1}] + (1 - \beta) * a[k_t]; \quad (3)$$

Once the acceleration and gyroscope values are filtered a linear acceleration ( $L_a$ ) along a given axis is computed by subtracting the gravity component ( $g[k]$ ) from the accelerometer component along that axis at a given timestamp.

$$L_a[k_t] = a[k_t] - g[k_t]; \quad (4)$$

Table 10 shows which data set and sensor information are used in which model.

### 3.3 DATA MODELLING

Each raw observation  $I_i$  (data point) in a given sensor trace consists of following attributes (Table 8).

Figure 21 shows different axes of a smartphone in different positions (Saeedi and El-Sheimy, 2015). Conventionally the axes will remain constant irrespective of the phone's orientation.

A raw spatio-temporal point ( $O_i$ ) in a GPS trajectory consists of following attributes.





Figure 13: Bus stop located nearby to a tram stop.

- FID: Integer
- Date: String
- Time: String
- Latitude: Double
- Longitude: Double
- Accuracy: Double
- Speed: Double

In an urban environment a raw GPS trajectory is subject to signal gap and irregular pattern due to multipath in urban canyon which poses problem in near-real time mobility information retrieval from GPS only data set. Figure 22 shows a typical raw GPS trajectory with intermittent signal gaps especially in the city centre due to obstructions from the tall buildings.

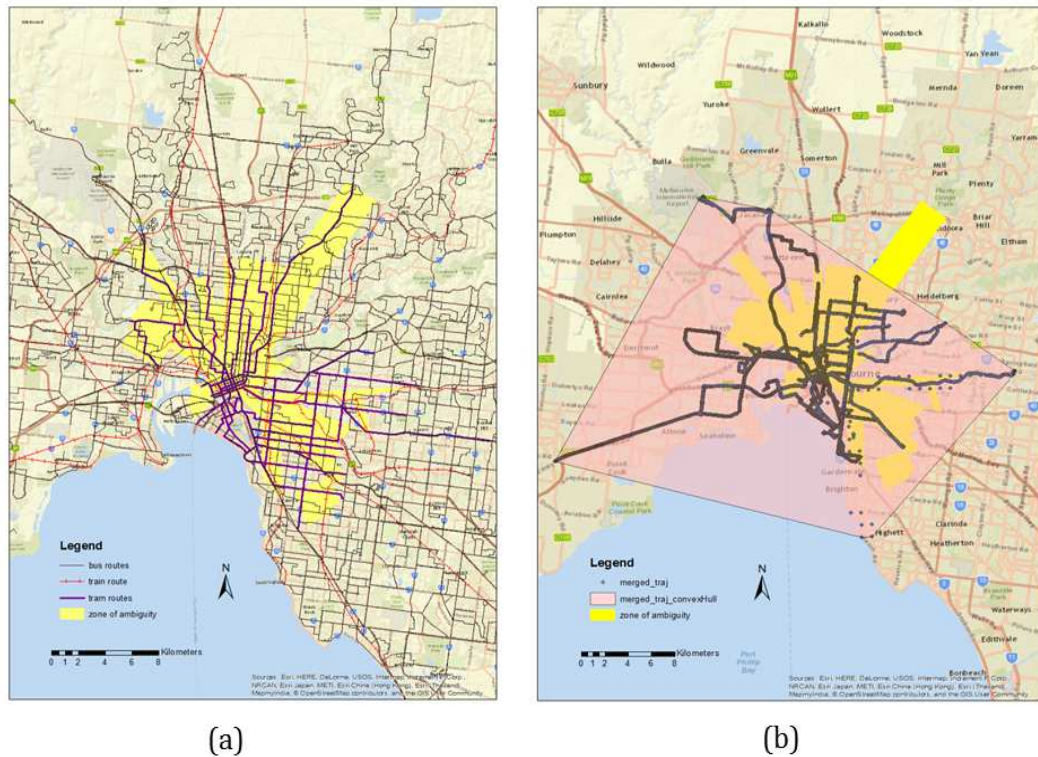


Figure 14: Map (a) shows the zone of ambiguity with a significant overlap between different public transport routes; Map (b) shows the overlap between the convex hull of the trajectory data set (Data set  $\tau$ ) and the zone of ambiguity.

Unlike GPS sensor, inertial sensors e.g., accelerometer and gyroscope do not depend on the external signal source. Hence while collecting the raw data sensor traces are recorded in such a way that when there is a signal loss the location information (Latitude, Longitude, Altitude) is logged as the last known position until there is a reacquisition of signal. However this ensures logging the inertial sensor information consistently at a given timestamp although the location information may not be correct at a given time period. Since this research mainly focuses on near-real time mobility knowledge discovery, in order to capture the real world situation adequately (during occasional signal gap) no interpolation is performed, rather an adaptive model is developed, which can bridge signal gaps by using the inertial sensor information (see [Chapter 6](#), [Chapter 7](#)).

id	Date_Time	timestamp	X	Y	accX	accY	accZ	linAccX	linAccY	linAccZ	gyroX	gyroY	gyroZ	Bearing	accuracy	satellite	Speed	busProx	trainProx	tramProx	streetProx	state
1	14-06-2015	4.51E+07	322521	5808711	0.4767	2.3155	9.7113	0.2288	0.2022	0.1383	-0.1093	-0.2755	0.2966	66	5	4	0.9	100	100	100	13.0202	walk
2	14-06-2015	4.51E+07	322521	5808711	1.0351	1.6072	9.7249	0.1128	0.0583	0.0854	-0.0641	-0.0666	0.2086	66	5	4	0.9	100	100	100	13.0202	walk
3	14-06-2015	4.51E+07	322521	5808711	0.3269	2.0431	9.4661	-0.0772	0.16	0.2108	0.2404	0.1304	0.2144	66	5	4	0.9	100	100	100	13.0202	walk
4	14-06-2015	4.51E+07	322521	5808711	0.3133	1.9613	9.9973	0.1075	0.1958	-0.0416	-0.0327	0.0195	0.0385	66	5	4	0.9	100	100	100	13.0202	walk
5	14-06-2015	4.51E+07	322521	5808711	-0.7355	1.975	10.3515	-0.5884	0.7275	0.7995	-0.1552	-0.0623	0.5534	66	5	4	0.9	100	100	100	13.0202	walk
6	14-06-2015	4.51E+07	322521	5808711	1.0624	1.6617	9.9156	1.3301	0.0238	0.0973	0.0031	0.1512	0.6035	66	5	4	0.9	100	100	100	13.0202	walk
7	14-06-2015	4.51E+07	322521	5808711	-2.2746	1.1713	10.0246	-0.5402	-0.0436	-0.1341	-0.4105	0.3977	0.9355	66	5	4	0.9	100	100	100	13.0202	walk
8	14-06-2015	4.51E+07	322521	5808711	-1.2395	1.0624	9.2346	0.5863	-0.1881	0.7884	-0.3122	-0.2343	0.1918	66	5	4	0.9	100	100	100	13.0202	walk
9	14-06-2015	4.51E+07	322521	5808711	-1.1713	0.6674	10.1063	0.3739	0.0046	0.4343	0.0504	-0.0079	-0.0461	66	5	4	0.9	100	100	100	13.0202	walk
10	14-06-2015	4.51E+07	322521	5808711	-1.5663	0.5857	10.1744	-0.0336	0.1716	0.1029	0.0289	0.0403	-0.5134	66	5	4	0.9	100	100	100	13.0202	walk
11	14-06-2015	4.51E+07	322521	5808711	-1.6344	0.1226	10.2834	0.1938	-0.0351	0.2983	-0.0999	-0.0791	0.0947	66	5	4	0.9	100	100	100	13.0202	walk
12	14-06-2015	4.52E+07	322521	5808711	-1.3484	-0.0953	10.0791	0.0622	0.0691	0.188	-0.0287	-0.0128	0.0501	66	5	4	0.9	100	100	100	13.0202	walk
13	14-06-2015	4.52E+07	322532	5808718	-1.5527	-0.0545	9.8339	-0.424	-0.0681	0.488	-0.048	-0.0092	0.0153	14	10	4	3.15	100	100	100	20.8663	walk
14	14-06-2015	4.52E+07	322532	5808718	-1.5527	0.0136	9.6568	-0.3774	-0.0838	0.3779	-0.0238	0.0293	0.0397	14	10	4	3.15	100	100	100	20.8663	walk
15	14-06-2015	4.52E+07	322530	5808725	-1.4438	-0.3541	9.793	-0.1381	-0.0752	0.5333	-0.0443	0.0281	0.0015	62	10	4	0.9	100	100	100	27.5903	walk
16	14-06-2015	4.52E+07	322530	5808725	-1.6753	-0.1498	10.0927	-0.1869	-0.0697	0.1992	0.0495	0.0278	0.0455	62	10	4	0.9	100	100	100	27.5903	walk
17	14-06-2015	4.52E+07	322530	5808728	-1.4029	-0.1362	10.0654	-0.2002	-0.1736	0.3416	0.0113	-0.1292	-0.0544	99	15	4	2.93	100	100	100	100	walk
18	14-06-2015	4.52E+07	322530	5808728	-1.2803	0.0409	9.8475	-0.1641	-0.1196	0.2629	0.1411	0.0156	0.0244	99	15	4	2.93	100	100	100	100	walk
19	14-06-2015	4.52E+07	322531	5808740	-1.3893	0.1226	10.0791	-0.2427	-0.1232	0.2994	0.0067	-0.033	-0.0067	125	15	4	2.93	100	100	100	100	walk
20	14-06-2015	4.52E+07	322531	5808740	-1.362	0.1498	10.1199	-0.2009	-0.136	0.3804	-0.004	-0.0476	-0.0122	125	15	4	2.93	100	100	100	100	walk
21	14-06-2015	4.52E+07	322530	5808730	-1.1577	-0.1226	10.0246	-0.1497	-0.1321	0.4519	0.0211	0.0021	-0.0177	88	20	4	1.35	100	100	100	100	walk
22	14-06-2015	4.52E+07	322530	5808730	-1.2939	-0.0136	10.0654	-0.1428	-0.0563	0.2177	0.0205	-0.036	-0.0247	88	20	4	1.35	100	100	100	100	walk
23	14-06-2015	4.52E+07	322530	5808733	-1.3757	0.2179	9.902	-0.5436	0.078	0.0737	0.0101	-0.0412	-0.0724	137	20	4	0.45	100	100	100	100	walk

Figure 15: A portion of database schema for the raw data for a given trajectory.

3064	14-06-2015	4.67E+07	321806	5807685	-3.228	9.0712	-0.2588	0.2594	-0.0852	0.1532	-0.037	-0.1432	0.1042	353	10	8	6.53	0.52285	100	0.24095	0.06861	walk
3065	14-06-2015	4.67E+07	321806	5807685	-3.2144	8.8532	-0.286	0.1627	-0.3376	0.256	0.0693	0.2318	0.0938	353	10	8	6.53	0.52285	100	0.24095	0.06861	walk
3066	14-06-2015	4.67E+07	321806	5807688	-3.0237	8.7034	-1.4982	0.0498	-0.585	-0.8282	-0.347	0.0302	0.1833	354	10	8	7.43	2.45691	100	2.22937	2.06624	walk
3067	14-06-2015	4.67E+07	321806	5807688	1.4438	8.1177	6.5514	0.7261	-0.249	1.4866	-0.9022	0.1732	0.5244	354	10	8	7.43	2.45691	100	2.22937	2.06624	walk
3068	14-06-2015	4.67E+07	321806	5807691	0.4495	6.8374	6.8647	0.0607	-0.5757	0.4565	-0.0507	0.1341	0.0281	353	10	8	7.88	3.93969	100	3.75382	3.59775	walk
3069	14-06-2015	4.67E+07	321806	5807691	0.6402	6.7829	7.0281	0.0715	-0.3472	0.3193	-0.0837	0.4087	0.0315	353	10	8	7.88	3.93969	100	3.75382	3.59775	walk
3070	14-06-2015	4.67E+07	321806	5807693	0.395	6.6331	7.1234	0.3152	-0.0286	-0.0728	-0.0067	-0.1042	-0.0308	341	10	8	5.18	5.16459	100	5.01315	4.86292	walk
3071	14-06-2015	4.67E+07	321806	5807693	-0.8308	6.7421	7.1915	-0.4876	0.2139	-0.1184	0.2373	-0.2291	0.1173	341	10	8	5.18	5.16459	100	5.01315	4.86292	walk
3072	14-06-2015	4.67E+07	321804	5807694	-0.3541	6.6059	7.7227	0.0232	0.1816	0.323	0.255	0.4893	0.0275	332	15	8	7.43	4.69899	100	4.59566	4.45368	tram
3073	14-06-2015	4.67E+07	321804	5807694	-0.4222	6.3743	7.5048	0.1273	0.0333	0.0443	-0.0721	-0.0681	-0.0528	332	15	8	7.43	4.69899	100	4.59566	4.45368	tram
3074	14-06-2015	4.67E+07	321801	5807697	-0.5312	6.1973	7.6002	-0.0303	0.0453	-0.0204	-0.0382	-0.0104	-0.0315	329	15	9	5.4	3.83941	100	3.80373	2.5215	tram
3075	14-06-2015	4.67E+07	321801	5807697	-0.6674	6.2926	7.5184	-0.2483	0.2842	-0.2207	-0.493	-0.3769	-0.0968	329	15	9	5.4	3.83941	100	3.80373	2.5215	tram
3076	14-06-2015	4.67E+07	321801	5807695	0.0272	5.5162	8.1586	0.1195	0.3899	-0.201	-0.0925	0.0241	0.0183	326	15	10	6.98	2.09159	100	2.03739	1.90392	tram
3077	14-06-2015	4.67E+07	321801	5807695	-0.0953	5.4618	8.2948	-0.0869	0.285	-0.0342	0.0027	0.0119	0.0556	326	15	10	6.98	2.09159	100	2.03739	1.90392	tram
3078	14-06-2015	4.67E+07	321798	5807693	-0.1498	5.6933	8.2267	-0.1856	0.0959	0.1745	-0.0385	0.0858	0.0168	327	10	10	5.63	0.95992	100	1.00769	1.14039	tram
3079	14-06-2015	4.67E+07	321798	5807693	-0.681	6.3198	7.7091	-0.0913	0.0604	0.183	0.1271	0.1878	0.0397	327	10	10	5.63	0.95992	100	1.00769	1.14039	tram
3080	14-06-2015	4.67E+07	321798	5807695	-0.5721	5.8431	7.8998	-0.2517	-0.0302	0.3272	-0.0559	-0.0339	0.0067	325	10	10	5.18	0.05736	100	0.07973	0.20817	tram
3081	14-06-2015	4.67E+07	321798	5807695	-0.4495	5.993	7.8317	-0.0356	-0.0303	-0.028	0.0034	0.0504	0.0171	325	10	10	5.18	0.05736	100	0.07973	0.20817	tram
3082	14-06-2015	4.67E+07	321796	5807695	-0.504	6.2517	7.3822	0.0434	-0.1359	0.0079	0.1136	0.0822	0.0351	324	10	10	5.18	1.10319	100	1.0937	1.2167	tram
3083	14-06-2015	4.67E+07	321796	5807695	-0.5857	6.3198	7.4095	-0.0438	-0.0252	-0.0608	0.0388	0.0425	0.0034	324	10	10	5.18	1.10319	100	1.0937	1.2167	tram
3084	14-06-2015	4.67E+07	321796	5807699	-0.7491	6.3198	7.4776	-0.0998	0.1202	0.101	-0.0125	-0.0061	-0.0031	325	10	10	6.53	0.89986	100	0.89425	0.78098	tram
3085	14-06-2015	4.67E+07	321796	5807699	-0.6538	6.1973	7.4503	-0.1404	0.0487	0.0467	-0.0947	-0.047	-0.0195	325	10	10	6.53	0.89986	100	0.89425	0.78098	tram
3086	14-06-2015	4.67E+07	321795	5807700	-0.4767	5.775	8.145	0.0484	0.0931	0.0414	0.0935	-0.0672	-3.00E-04	326	10	10	5.18	1.13195	100	1.11632	1.00921	tram
3087	14-06-2015	4.67E+07	321795	5807700	-0.5448	5.884	7.4912	-0.3485	0.1326	-0.2866	0.0797	0.0238	0.0363	326	10	10	5.18	1.13195	100	1.11632	1.00921	tram

Figure 16: State transition from walk to tram.

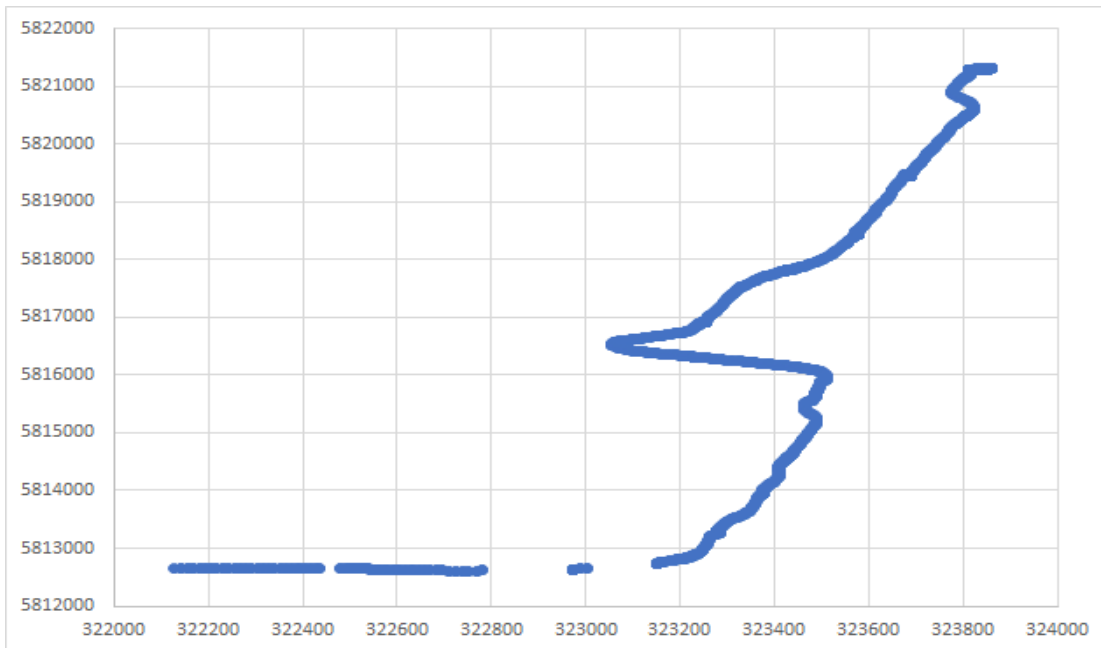


Figure 17: Signal gap in raw GPS trajectory (in projected coordinate system GDA94 zone 55).

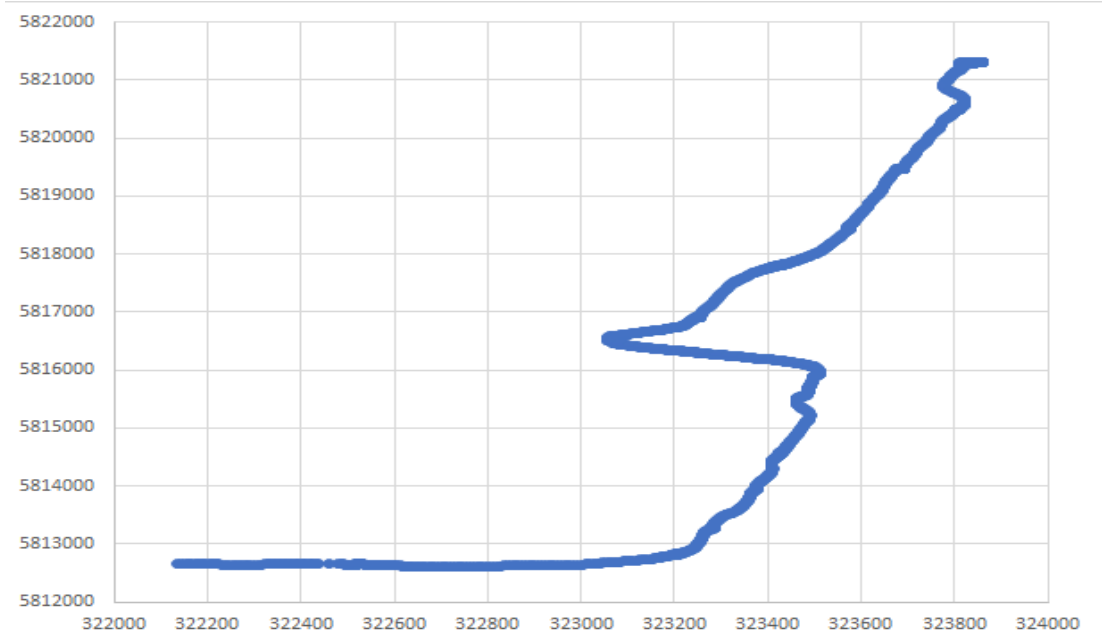


Figure 18: Interpolated trajectory.

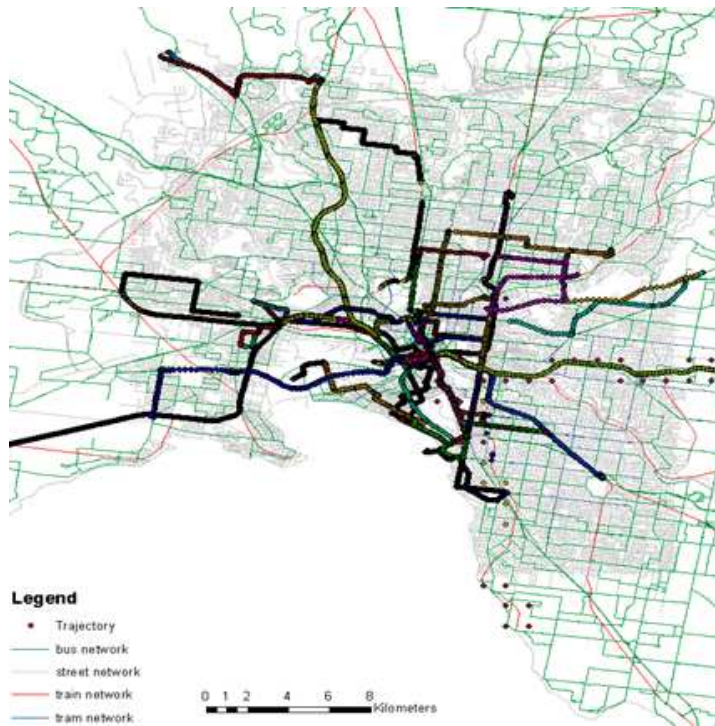


Figure 19: Data set 1: Low frequency (1Hz, 2Hz) GPS trajectories in Greater Melbourne.

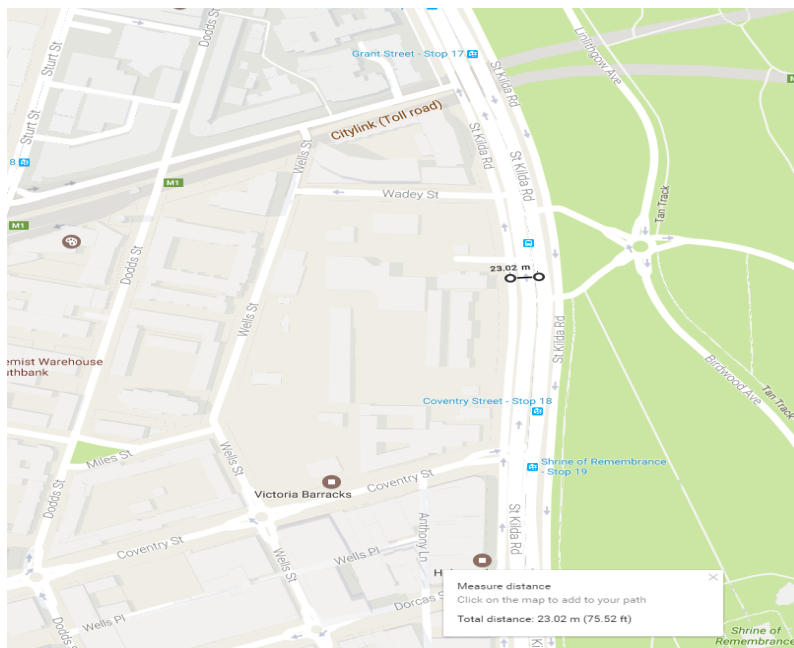


Figure 20: The tram network is 23.02 m away from a bus route which is within a GPS confidence ellipse with a radius of 40 m in urban environment.

Table 8: Data Model

<b>Attribute</b>	<b>Data type</b>
FID	Integer
Geometry	Point
Date	String
Time	String
Latitude	Double
Longitude	Double
Altitude	Double
Accuracy	Double
Number of satellites	Integer
Speed	Double
Bearing	Double
Acceleration (Magnitude in x, y, z direction)	Double
Linear acceleration (Magnitude in x, y, z direction)	Double
Gravity (Magnitude in x, y, z direction)	Double
Azimuth	Double
Roll	Double
Pitch	Double

Table 9: Modal specification

<b>Transport mode</b>	<b>GPS points</b>	<b>Duration (mins)</b>
<b>Bus</b>	91469	761.6
<b>Walk</b>	335802	2796.8
<b>Train</b>	76630	638.0
<b>Tram</b>	108474	903.3
<b>Total</b>	612375	5099.9

Table 10: Data set used in different models

Chapter	Model	Data set	Sensors used	Primary information
4	Context-sensitive activity model	Data set 1	GPS	Location
5	Fuzzy logic based offline model	Data set 1	GPS	Location, speed
6	Neuro-fuzzy based hybrid near-real time model	Data set 1	GPS	Location, speed
7	State-based bottom-up model	Data set 1, data set 2	GPS, accelerometer, gyroscope	Location, speed, angular speed, linear acceleration

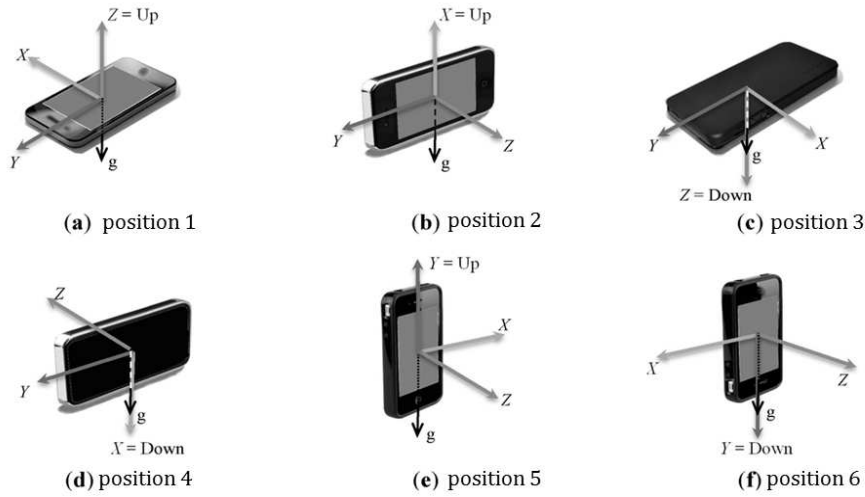


Figure 21: Smartphone axes in different directions. This figure has been reproduced from [Saedi and El-Sheimy \(2015\)](#).

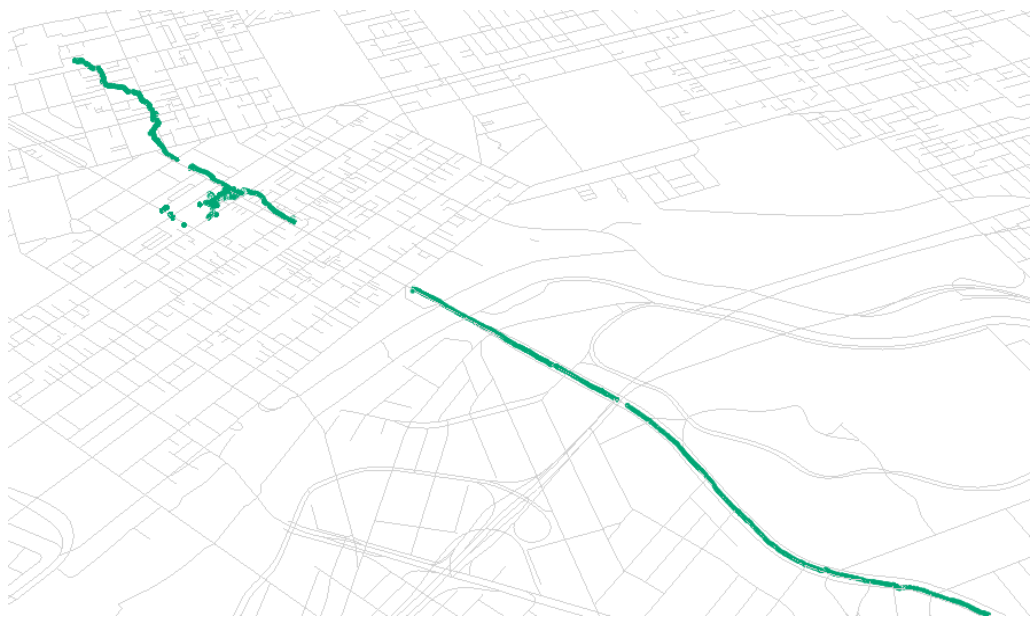


Figure 22: Signal gap present in a GPS trajectory.



## A CONTEXT-SENSITIVE ONTOLOGICAL FRAMEWORK FOR ACTIVITY MODELLING

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This chapter <sup>1</sup> presents the first contribution of this research that addresses the semantic gap present in the definition of *activity* approached by different application domains with a focus on activity knowledge discovery at different contexts from a motion trajectory. Human motion trajectories, however captured, provide a rich spatio-temporal data source for human activity recognition, and the rich literature in motion trajectory analysis provides the tools to bridge the gap between this data and its semantic interpretation. But activity is an ambiguous term across research communities. For example, in *urban transport-geography* activities are generally characterized around certain locations along with the time spent at that location, assuming the opportunities and resources are present in that location (Fig 23), and travelling happens between these locations for activity participation, i.e., travel is not an activity, rather a mean to overcome spatial constraints (Fig 23). In contrast, in *Human-Computer Interaction (HCI) research* and in *Computer vision research* activities taking place ‘along the way’, such as ‘reading on the bus’, are significant for contextualized service provision (Fig 24). On the other hand in *public health research and mode-specific transport management* main focus lies on low level physical body parts movements and different modes of transports people are using (Fig 25). Similarly activities at coarser spatial and temporal granularity, e.g., ‘holidaying in a country’, could be recognized in some context or domain.

Thus the context prevalent in the literature does not provide a precise and consistent definition of *activity*, in particular in differentiation to travel when it comes to motion trajectory analysis. Hence in this research, a thorough literature review studies activity from different perspectives, and develop a common framework to model and reason human behaviour flexibly across contexts. This spatio-temporal framework is conceptualized with a focus on modelling activities hierarchically. Three case studies will illustrate how the semantics of the term activity changes based on scale and context. They provide evidence that the framework holds over different domains. In turn, the framework will help developing various applications and services that are aware of the broad spectrum of the term *activity* across contexts.

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<sup>1</sup> The contribution presented in this chapter has been peer-reviewed and published as follows:  
Das, RD., Winter, S. (2016): A Context-Sensitive Conceptual Framework for Activity Modelling, *Journal of Spatial Information Science*, issue 12

#### 4.1 INTRODUCTION

With the emergence of pervasive and mobile computing, and especially location-based services, there has been a growing interest in a theoretical framework facilitating the processing and sharing of activity information more effectively between human and computer (Crease and Reichenbacher, 2013; Kaptelinin and Nardi, 2006; McDonald, 2000; Rasmussen, 1986; Raubal, 2001). While individual disciplines have worked towards their own frameworks, the research presented in this chapter will demonstrate that they are incompatible, and an overarching framework is still lacking.

In principle, activity, and synonymously action, requires agency, or a purposeful, goal-directed performance that is available to awareness (George Wilson, 2012). Based on the usage of the word *activity* in natural language, WordNet (Fellbaum, 1998) defines activity as any specific behaviour or an action or bodily function. In this view, travel, which is understood here as any purposeful, goal-directed change of location, is an activity (or action). Furthermore, any complex travel can be composed of simpler activities, some of them forming travel activities themselves (such as ‘taking the bus on the way to work’), and others are non-travel or stationary activities (such as ‘reading the papers on the bus’). In contrast to many other disciplines, human-computer interaction research (HCI) actually applies this understanding by modelling activity from a purely motivational, goal-oriented and operational perspective (Kaptelinin et al., 1995; Kaptelinin and Nardi, 2006, 2012) where the activity is motivational and oriented towards an objective, actions (which are subsumed by activity) required to perform the activity are oriented towards goals and realization of the entire phenomena happens through operations. HCI assumes activity as interaction of a subject with an object to fulfil certain needs through mediation which may involve the process of externalization and internalization (Kaptelinin and Nardi, 2006). Thus in HCI activity is characterized mostly by the why, what and how, but less so by the where (location) and when (time), despite most activities being generally constrained by space or time or both. Obviously this understanding can cope with travel as well as non-travel activities.

In pervasive computing, the common subject of research into activity recognition are human motion trajectories (Spaccapietra et al., 2008), whether captured, for example, from diaries (Stopher et al., 2003), social networks (Damiani et al., 2011), checkpoints or cordons (Duckham, 2013), GPS (Wolf et al., 2004; Zheng, 2015) or CCTV cameras (Rodríguez-Serrano and Singh, 2012). Accordingly, a variety of disciplines, from geography over data mining (Gutting et al., 2000; Moreira et al., 1999; Sellis, 1999; Sistla et al., 1997; Wolfson et al., 1998) to computer vision (Aggarwal and Ryoo, 2011), provide tools for motion analysis. But across these disciplines activity remains an ambiguous term, to the point of direct contradiction. For example, in (urban) transport research activity generally bears semantics related to times spent at home, work, restaurants or shops (Jovicic, 2001; Liao et al., 2005; Wolf, 2000), and is the cause for travel between the locations of these activities (Jovicic, 2001). In this view, travel is

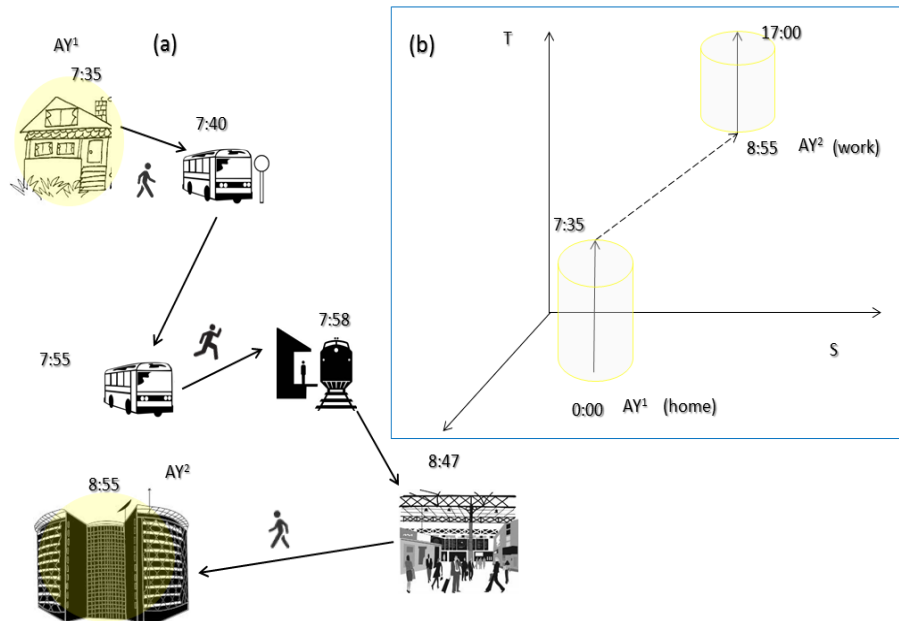


Figure 23: In transport geography *activity* involves time spent at a given location. In this figure a person has spent some time at home and then travelled to his office with the help different transport modes (a). The space-time geography shows two different activities (home and office) in the form of two vertical cylinders where as the line connecting those two cylinders are travel – which is not considered as an activity in itself (b).

not considered as an activity, rather an undefined mean to overcome spatial constraint (Shaw and Yu, 2009). In contrast, pervasive and mobile computing (e.g., in its desire to provide context-aware travel support) and similarly computer vision (in its desire of scene recognition) consider motion central: here activity generally refers to locomotion defined at a finer granularity such as walking, running or moving body parts (Bao and Intille, 2004; Shoaib et al., 2015; Aggarwal and Ryoo, 2011; Rao et al., 2002). Taking middle ground, trajectory data mining (from the data end, e.g., (Zheng, 2015)) and time geography (from the conceptual end, e.g., (Hägerstrand, 1970)), both taking a space-time approach to modelling, accept motion as well as stationary activities, and structure behavioural patterns by disruptive changes in the motion trajectory.

Furthermore, most, but not all disciplines share an understanding that more complex activities are composed of simpler activities (Aggarwal and Ryoo, 2011). The daily home-work commute, for example, which is for travel demand modelling an atomic activity with no further need for differentiation, is an aggregated (complex) activity in other disciplines. Time geography as well as HCI would see this commute trip as a concatenation of locomotion activities such as walking, taking a bus, and then a train, especially since HCI aims to provide purposeful information for each of these

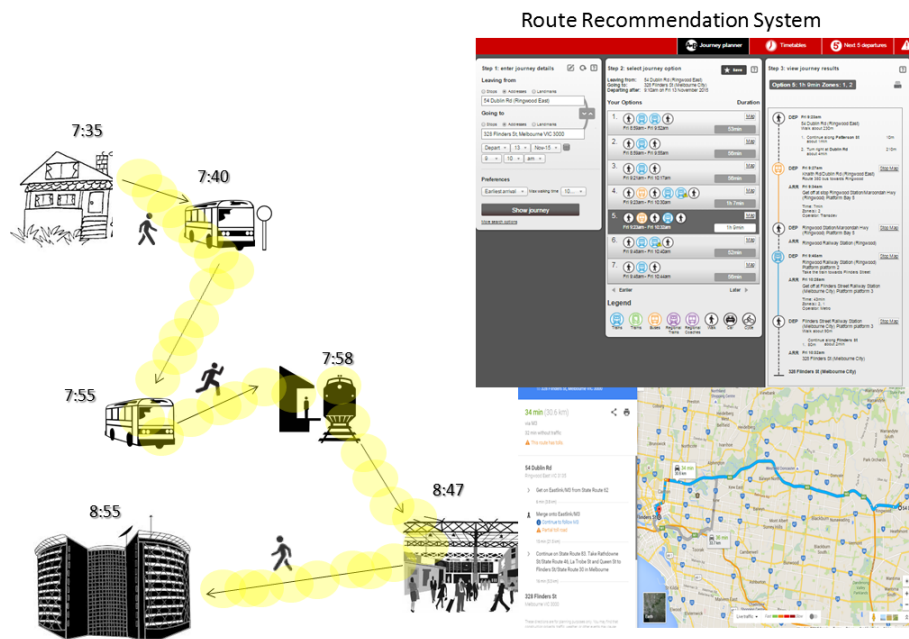


Figure 24: Depending on the origin, destination two different route recommendation system are suggesting two different set of activities (or actions)

commuting segments. This argument can be carried forward for an even finer level of granularity. There are other activities being part of the commute, such as buying a ticket for the public transport, buying and drinking a coffee while transferring from bus to train, waiting for the train at the platform, or reading a newspaper on the train. Again, HCI research is keen to capture these activities as well in order to provide appropriate information services, such as smart ticketing, recommendations of coffee places, or newsfeeds related to places of interest.

These examples illustrate a semantic gap in the notion of activity between the disciplines involved with human mobility in the city. This gap exists despite the vagueness inherent in all definitions. For example, whether a worker going out for lunch, a tourist strolling in a city, or a person jogging in the evening is travelling or pursuing an activity is not clear in travel demand modelling. And from an HCI perspective it is hard to decide whether a transfer between bus and train, or grabbing a coffee-to-go between, is an activity.

In the above examples, it is evident that the concept of activity depends on the context within which the analysis takes place, and the context determines an appropriate (default) level of granularity in space and time – always allowing for abstraction (zooming out) or refinement (zooming in) should a change of context require so. A closely related property of activities revealed by the examples above is their nestedness. A person can do a number of activities in sequence that form an aggregate activity (e.g.,

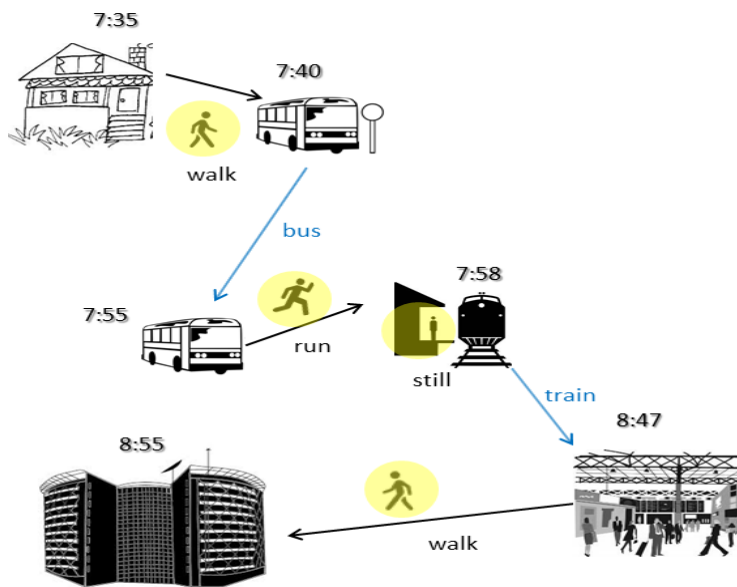


Figure 25: In public health research and near-real time mode specific travel demand modelling activity focus has shifted from a static location (home and office) to different types of bodily locomotion and boarding different transport modes.

the above described commuting trip as a sequence of walking and taking the bus), and even two activities at the same time (e.g., travelling by bus and reading a newspaper as part of the commute). Although WordNet does not draw any distinction between *activity* and *action* but there is a semantic gap in the conceptualization of activity structure in different domains including HCI, transportation science, cognitive science, public health research, mobile computing and context-aware location based services. This calls for a hierarchical approach to modelling activities, which will be provided by activities that consist of actions in one context, and in another context these actions becoming activities themselves consisting of actions.

Assuming a trajectory indicates the intention of the agent to participate in different spatio-temporal setups to fulfil certain needs, it is possible to model or retrieve activities from a given trajectory or parts thereof. However, this process is determined by context, which defines the semantics of need (and hence of the activity). In addition, there is no precise correspondence between the concept of activity and the mobility patterns extracted from motion trajectories. Hence, this research presents a conceptual analytical framework that aims to bridge the semantic gap between trajectories and activities on one hand, and the disciplines' understanding of activity on the other, the latter through integration of *activity theory* and space-time concepts in an urban environment. With the distinction of activity as an abstract concept oriented towards certain needs and actions defined at concrete granularities of space and time, it is

hypothesized that *the semantics of activity depends on the spatial and temporal granularity suggested by context. Shifts in granularity will enable processing motion trajectories and activity knowledge can be represented in various contexts facilitating flexible, appropriate and relevant information representation or provision and thereby develops a connected knowledge flow.* Here *granularity* relates to the concept of scale in space and time and also level of details in contextual perspective.

This research work contributes to the existing knowledge in the following ways, such as

- Currently there exists a trajectory ontology (Hu et al., 2013) that represents the knowledge of a trajectory conceptualization. There also exists few activity ontology in indoor (Lee et al., 2013) or based on its components (Kuhn, 2001). But there is no attempt made so far to model activities on trajectories at different contexts and how that can maintain a smooth and connected knowledge flow from one contextual level to another contextual level. Thus the proposed framework is novel and improving the existing work not by replacing them, rather by enriching them with more structured way.
- This research also goes beyond the existing trajectory ontology (Hu et al., 2013) by extending a trajectory ontology to activity ontology with *actor* as the key concept. Unlike earlier work (Hu et al., 2013) this research illustrates the entire ontology and its knowledge base through instantiating the relevant concepts and using few SPARQL queries.
- This research incorporates the concept of a set of needs defined in human-scale development (Max-Neef, 1991), and the notion of space and time in the existing *activity theory* in HCI. Thus the framework bridges the gap between the notion of *activity* in spatial science, transport geography, HCI and other domains.

The rest of the chapter is organized as follows. Section 4.1 introduces the problem definitions and the hypothesis behind the research presented in this chapter. Section 4.2 presents a brief overview of existing ontologies for trajectory modelling and activity reasoning. Section 4.3 presents the conceptual framework that models activities from a trajectory at different contexts through formal semantics and a reasoning scheme. Section 4.4 implements the model and illustrates different contexts as a function of granularity. Section 4.5 discusses the framework and its efficacy in different contexts followed by summary and future research direction in Section 4.6.

## 4.2 ONTOLOGIES IN TRAJECTORY MODELLING AND ACTIVITY REASONING

Ontologies are very efficient way to represent the domain knowledge in a formal way. Ontology can be defined as “explicit specification of conceptualization” (Gruber, 1993,

2009). Ontologies can be of different types by the nature of their knowledge representation. There are several top level ontologies developed through logical design patterns such as DOLCE (Gangemi et al., 2002) and BFO (Grenon and Smith, 2004) which are independent of any particular domain. On the other hand ontologies are also developed with a domain specific focus based on content patterns, such as the above mentioned semantic trajectory ontology (Hu et al., 2013). With the emergence of Linked Data and Semantic Web (web 3.0) enormous amounts of trajectory data sets are now generated, processed based on semantic relations between different entities and their properties over time (Hu et al., 2013; Kuhn, 2001).

While modelling a context-aware computing system with a focus on movement behaviour of an agent it is important to understand its context and the intention of the movement, and that can only be understood from the activity (and actions) the agent performs at a given location and time. Additional information such as a road network or a point-of-interest database is often used to enrich the trajectory to extract the activity information (Spaccapietra et al., 2008).

Lee and colleagues developed an indoor activity based ontology model to support shopping related information search based on user's location (Lee et al., 2013). They have developed their model in four stages. In the first stage a geocoding operation was performed based on character matching followed by shopping activity ontology development. In the third stage inferencing rules are defined for semantic query followed by a 3D topological model. However the model developed by Lee and others cannot model activity from different contexts in a hierarchical approach. Thus, the model fails to address different situations at different granularity.

In activity modelling domain Kuhn developed an ontology based on semantics of natural language in terms of activities and actions and different entailment relations among the verbs (Kuhn, 2001). Scheider and Janowicz suggested a framework for place reference system where the authors mentioned about the notion of actions agents perform to refer a given place (Scheider and Janowicz, 2014).

To the best of author's knowledge there has been no attempt made so far on modelling and formalizing activity from a semantic trajectory, but there has been work presented on a general content-based trajectory ontology (Hu et al., 2013), on which the proposed framework is based on. Especially the proposed framework extends (Hu et al., 2013) by fusing with an activity ontology, introducing a concept *actor* as a connecting concept. With the emergence of spatial intelligence in various domains there is a need to share and process the information between human and computer in order to capture and represent knowledge about a given context in a given domain.

Here especially relevant is the general content-based trajectory ontology by Hu and colleagues (Hu et al., 2013). Their flexible, self-contained and reusable semantic trajectory ontological design pattern is based on the atomic unit of fixes or spatio-temporal points. Based on the notion of fix and segments in a semantic trajectory (Hu et al.,

2013) , an ontological framework for activity is now presented that models activity at different contexts.

### 4.3 CONCEPTUAL ONTOLOGICAL FRAMEWORK

In this chapter a semantic trajectory based activity ontology framework has been developed with an *activity* as the central concept. The conceptual framework consists of an activity layer and a semantic trajectory layer with *actor* being the common concept between two layers. The concept *actor* used in this research is same with the concept *subject* used in HCI.

The framework has been developed based on a content-based ontology pattern which involves two independent ontologies: an activity ontology and a semantic trajectory ontology. The semantic trajectory ontology is based on the design pattern of (Hu et al., 2013) which is extended in this research, and applied not on trajectory semantics as such, but on activities. And also (Hu et al., 2013) develops rather a general content-based trajectory ontology that was not instantiated in different context. In the proposed model each concept has been instantiated with data properties and object properties and fused it with an activity ontology and developed a more complex ontology. In order to model any ontology, typical queries are considered that capture generic use cases (GUC) and guide the ontology design. The GUCs are assumed to be optimal for developing an ontology with a possibility of inferring new facts during reasoning phase. Here, the competency questions are as follows:

- What activity actor  $X$  has participated in context  $C_i$ ?
- What action(s) actor  $X$  has performed from time stamp  $t_1$  to  $t_2$  at a context  $C_i$ ?
- Extract the actions ( $AN_j^k$ ) involved in an activity  $AY_j$  at a context  $C_i$ ?
- Extract the trajectories that have at least one transfer at context  $C_i$ ?
- Extract the action(s) that are not spatially or temporally constrained?
- What action(s) have been performed over a segment  $S_i$ ?
- Extract the object(s) involved in an activity  $AY_j$  at a context  $C_i$ ?
- What are the action(s) embedded in a given semantic trajectory?

#### 4.3.1 Context-based recursive activity model

The semantics of activity depends on a context. Hence by changing the context the semantics of activity also changes recursively and represents a nested structure at different granularity. By changing a situation or shifting through granularity (hence



changing the context completely or partially), the object(s) of interests also changes vis-a-vis an activity structure. Action plays an important role in activity modelling. An activity (AY) is characterized by its objective (O), and an action (AN) is characterized by its goal (G). A shift in granularity or change in situation can transform an objective to goal(s) at finer granularity or a goal to an objective at a coarser granularity (Fig 26).

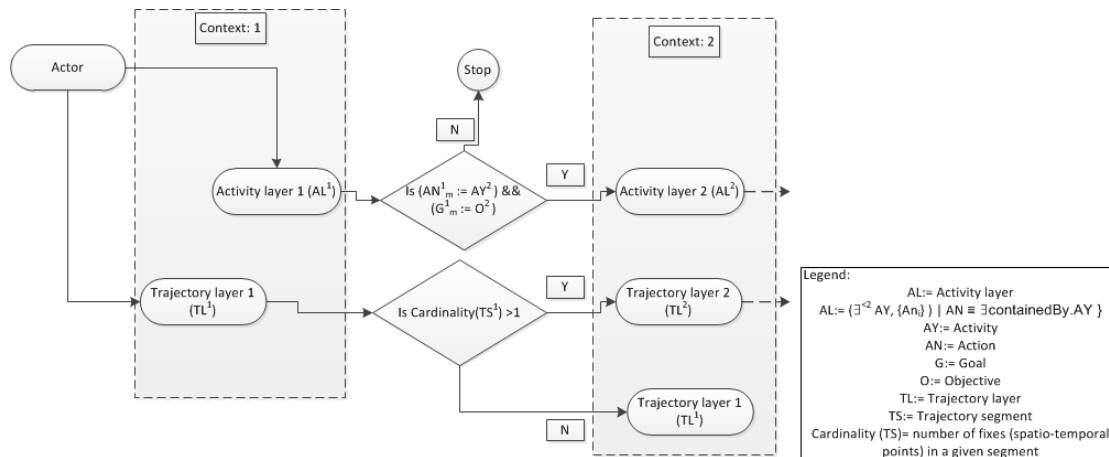


Figure 26: Context-based recursive activity model

#### 4.3.2 OWL Formalization

The ontology has been formalized and encoded in Web Ontology Language (OWL) which is based on Description Logic (DL). OWL has been successfully used in semantic web for knowledge representation and developing ontologies that can share information between a human and a machine. OWL is standardized by World Wide Web Consortium (W3C). OWL-DL has been used in previous literature as it is deemed to improve the readability, reasoning ability and compactness of concepts and relationships and enables an intelligent communication on semantic web.

DL provides the formal semantics to specify the meaning of an ontology (Krotzsch et al., 2014). The basic building blocks in DL are three entities such as concept, role and individual. A concept is a collection of individuals. A role is a binary relation between two individuals (or concepts). An individual is an instantiation of a respective concept. A DL ontology does not manifest the complete knowledge of the world, rather a partial knowledge of the world through a set of statements that must hold in a given situation (Krotzsch et al., 2014). Those statements are called axioms. In order to model a knowledge base DL provides three types of axioms such as A-Box axiom, R-Box axiom, T-Box axiom. A-Box axioms assert knowledge about the individuals and their concepts. R-Box axiom relates to individuals through a binary role. T-Box axioms provide knowledge about the concepts through concept equivalence or concept inclu-

sion. In this framework, the different boxes (namely- A-Box, R-Box and T-Box) are not explained in details but that are there in the knowledge base without specifying them explicitly. The reason was to focus on the contextual model rather than the intricacies of DL. Interested readers can refer to (Krotzsch et al., 2014) for basics of DL.

In the implementation phase, in order to address the above competency questions basic relations (roles) are developed based on any two entities from a set of concepts CS (see Table 11). Some of the key concepts are formalized as follows.

CS = {Actor, Activity, Objective, Need, Action, Object, Affordance, Constraint, Objective, Semantic\_trajectory, Segment, Fix, Device}

Table 11: Basic relations and their entity types

Competency Question	Relation	Entity Type	Semantics
1	hasParticipatedIn	Activity x Actor	An activity in which an actor has participated
2	hasPerformedBy	Actor x Action	Action(s) performed by an actor
3+4	hasAction	Action x Activity	Actions involved in a given activity
5	isMediatedBy	Object x Action	An action is mediated by an object
	isConstrainedBy	Constraint x Object	Constraint(s) of an object
6+8	traversedBy	Actor x Semantic_trajectory	A semantic trajectory traversed by an actor
	hasSegment	Semantic_trajectory x Segment	A segment of a semantic trajectory
	hasPerformedBy	Actor x Action	An action performed by an actor
7	isMotivatedBy	Objective x Activity	An activity motivated by an objective
	seeksAffordance	Affordance x Objective	An object of finding some affordance
	offersAffordance	Object x Affordance	Affordances offered by an object

#### 4.3.2.1 Actor

*Actor* is an agent that has an objective to fulfill, at least one need, and interacts with at least one object by performing respective actions that in turn enable the actor to participate in an activity. Actor can be instantiated by a specific person or a vehicle in an urban environment. The concept *actor* can be defined as a subclass of some *agent* having some need and objective and performs some actions and participating in an activity. The concept of *actor* can be formalized as follows:

##### **Axiom 1**

$$\text{Actor} \sqsubseteq \exists \text{subclassOf}.\text{Agent} \sqcap \exists \text{hasNeed}.\text{Need} \sqcap \text{hasObjective}.\text{Objective} \\ \sqcap \exists \text{isPerformedBy}.\text{Action} \sqcap \text{hasParticipatedIn}.\text{Activity}$$

#### 4.3.2.2 Activity

*Activity* is a contextual phenomenon in which an actor participates to fulfill its need(s). An activity consists of actions and motivated by an objective to satisfy the need(s) of the respective actor. *Activity* can be defined as having some action is motivated by some objective. A simple DL formalization of an *activity* concept can be expressed as follows:

##### **Axiom 2**

$$\text{Activity} \sqsubseteq \exists \text{hasAction}.\text{Action} \sqcap \exists \text{isMotivatedBy}.\text{Objective}$$

#### 4.3.2.3 Action

*Action* is one of the atomic units of the semantic trajectory based activity model. An action is contextual phenomenon that is embedded in an activity at a given context which is performed by an actor and directed by a goal and generally achieved by affordance. Actions involve a complex interaction of an actor to its surrounding objects and hence an action is generally mediated by a given object. An *action* can be defined as something that is performed by some actor and is directed by exactly one goal and mediated by objects and achieved by corresponding affordance. The concept of action can be formalized in DL as follows:

##### **Axiom 3**

$$\text{Action} \sqsubseteq \exists \text{isPerformedBy}.\text{Actor} \sqcap \exists \text{isDirectedBy}.\text{Goal} \\ \sqcap \text{isAchievedBy}.\text{Affordance} \sqcap \text{isMediatedBy}.\text{Object}$$

#### 4.3.2.4 Context

In this research a context must have exactly one actor and exactly one activity and one or more than one actions. The notion of context will be used to instantiate each concepts at different situations (For definition of context see Section 3.1.2). *Context* can be expressed as something that has exactly one unique actor and an activity. A context can be formalized in DL as follows:

##### Axiom 4

$$\text{Context} \sqsubseteq \exists! \text{hasActor}.\text{Actor} \sqcap \exists! \text{hasActivity}.\text{Activity}$$

#### 4.3.2.5 Object

*Object* is an entity of physical or cognitive existence that is perceived at a given context through at least one of its affordances. An *object* can be constrained in a given space or time or both. Following the definition of *actor*, the significance of an object is subjectively perceived through an interaction with an *actor* who is performing some action(s).

An *object* can be defined as something that offers a unique affordance and which may be constrained by some constraints.

An agent (*OtherAgent*) can be an object if it is relevant in a given context when an agent offers certain affordances for an *actor* to perform certain action(s):

##### Axiom 5

$$\begin{aligned} \text{Object} \sqsubseteq \exists! \text{offersAffordance}.\text{Affordance} \sqcap \text{isConstrained}\{(\text{true}), (\text{false})\} \\ \sqcap \exists \text{isConstrainedBy}.\text{Constraint} \end{aligned}$$

#### 4.3.2.6 Semantic Trajectory

A *semantic trajectory* consists of temporally indexed fixes in terms of  $(x_i, y_i, t_i)$  that represent an agent's (actor's) movement history supplemented by additional background information and domain knowledge. The definition of semantic trajectory varies in different research with additional knowledge to enrich the semantics. However the basic representation of a semantic trajectory involves a set of fixes and having an actor and activity. Here *having an actor and activity* means the semantic trajectory is the movement record of an actor in terms of fixes who is shifting its position in order to perform some activity. But in order to make the formalization simple, the concept *semantic\_trajectory* is formalized as follows:

##### Axiom 6

$$\text{Semantic\_trajectory} \sqsubseteq \exists! \text{hasActor}.\text{Actor} \sqcap \exists \text{hasFix}.\text{Fix} \sqcap \exists! \text{hasActivity}.\text{Activity}$$

#### 4.3.2.7 Segment

A *segment* is a part of a semantic trajectory that is traversed by an actor. A segment is represented by a starting fix  $(x_{i-n}, y_{i-n}, t_{i-n})$  and an ending fix  $(x_i, y_i, t_i)$  where  $\forall n, t_{i-n} < t_i$ . The starting fix of segment<sub>*i*</sub> is the ending fix of segment<sub>*i-1*</sub> if there is no semantic gap or hole (a deliberate gap) between *i* and *i-1*. A deliberate gap happens when the user turns off the GPS by her own from the concerns related to privacy or battery drainage or any other reason. A semantic gap is generally considered in this research when there is a signal loss in urban canyon or indoor environment such as a tunnel. The following formalization of a fix can be encoded as follows

#### Axiom 7

$$\text{Segment} \sqsubseteq \exists! \text{startsFrom.Fix} \sqcap \exists! \text{endsAt.Fix}$$

#### 4.3.2.8 Fix

A *fix* is another atomic unit in a semantic trajectory based activity model. A fix can be defined by its data property in the form of a spatio-temporal point  $(x_i, y_i, t_i)$ , and in a more abstract but understandable form such as a semantic name (home, restaurant, office) and a unique identification for a given semantic trajectory. A fix can be captured by a location or positioning sensor or by manual reporting. The formalization of a fix can be encoded as follows:

#### Axiom 8

$$\text{Fix} \sqsubseteq \exists \text{atTime.Time\_stamp} \sqcap \exists \text{hasAttribute.Attribute} \sqcap \exists \text{hasLocation.Position}$$

### 4.4 IMPLEMENTATION AND EVALUATION

The ontology has been implemented in Protege, an ontology editor supporting OWL-DL. The model has been encoded in Java in back end with each concept as a class. Unlike functional language (such as Haskell) Protege provides more expressiveness in terms of DL and flexibility through its graphical user interface and object-oriented paradigm. Protege also offers a distributed environment to share and query a knowledge base using Jena-Fuseki web server.

In order to develop the model, first a high-level content based ontology is developed through some concepts and object properties (Fig 27). The model is then instantiated in three different contexts (see illustration section). In this research each context is modelled separately. It is assumed that if a given query cannot generate a satisfactory result in one context then it will assess the next context until all the contexts are evaluated (without any conflict) or a search result is found. The ontology has been checked through HermiT Reasoner in Protege (Glimm et al., 2014). HermiT provides a subsumption checking and logical consistency checking in order to validate an ontology.

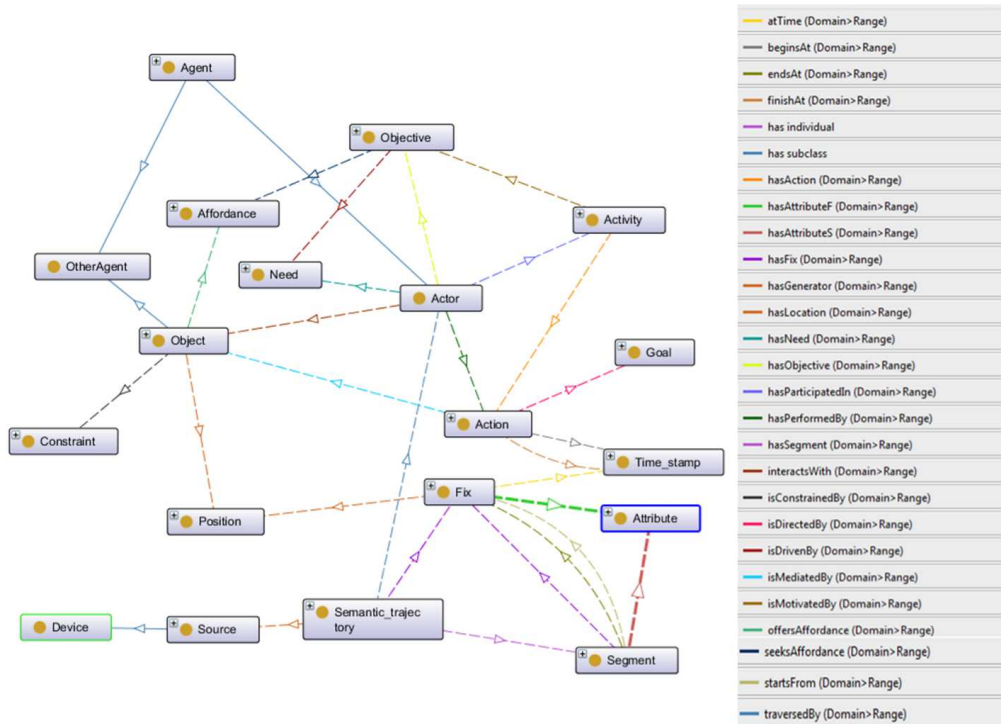


Figure 27: Semantic trajectory based activity ontology

The raw trajectory collected for this framework is first preprocessed in two steps- a) noise removal and , b) coordinate transformation. A raw trajectory can give only geometrical information. In order to semantically enrich the raw trajectory and convert it to a semantic trajectory, infrastructure information (route network), domain knowledge (opening time of market) and other situational aspects (focus of analysis at a given granularity) are considered. Figure 28 shows a flow chart how a raw trajectory is transformed into a semantic trajectory.

Figure 29 illustrates the implementation in terms of all the entities in the ontology. Each panel contains a set of entities (concepts, object properties, data properties and individuals). The arrow annotated with an alphabet shows the direct connection between different entity types. For example, connection *a* signifies a concept (in class hierarchy panel) may have individual(s). Connection *b* and *c* signify each concept is related to another concept or an individual by an object property. Connection *d* shows each individual and their data properties.

In this research, three contexts are considered based on three different situations on a same trajectory. Since these three sets of contextual information are extracted from the same trajectory, each context shows a given level of granularity.

A trajectory (Fig 30) shows Joe’s movement history from his home to market (00:00:00 AM to 11:48:00 AM), a part of his movement trajectory of the day. However the same

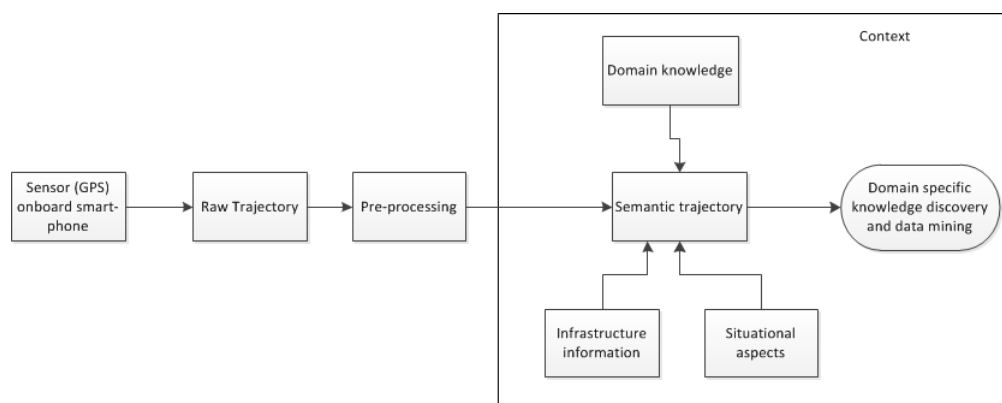


Figure 28: Raw trajectory to semantic trajectory conversion

approach can be used for an entire trajectory with defined context. Table 12 shows Joe’s travel diary on 13th June, 2015 from 00:00:00 AM to 11:48:00 AM.

Table 12: A portion of travel diary

start_time	end_time	Action/Activity	Transfer
0:00:00	10:08:00	Home	–
10:08:00	10:18:00	Walk	transfer_0
10:18:00	10:46:00	Bus	–
10:46:00	10:50:00	Walk	transfer_1
10:50:00	11:04:00	Train	–
11:04:00	11:09:00	Walk	transfer_2
11:09:00	11:48:00	Market	–

In each context the key concepts are instantiated by respective individuals with their data property, data type and value. Hence for three different contexts, three different sets of instantiations are made to develop three sets of knowledge base with a focus on activity. The examples illustrate how an action in one context is transformed to an activity in another context (Table 13,14,15) at a finer granularity. The same has also been depicted in Fig 31 which shows contextual recursive transformation of action into activity and vice-versa (Fig 31).

The model has also been tested by issuing SPARQL queries at different contexts. The queries are kept simple, for illustration purposes, but can easily be made more complex and nested based on information needs at a finer granularity and situations which is subject to the design of knowledge base in a given context.

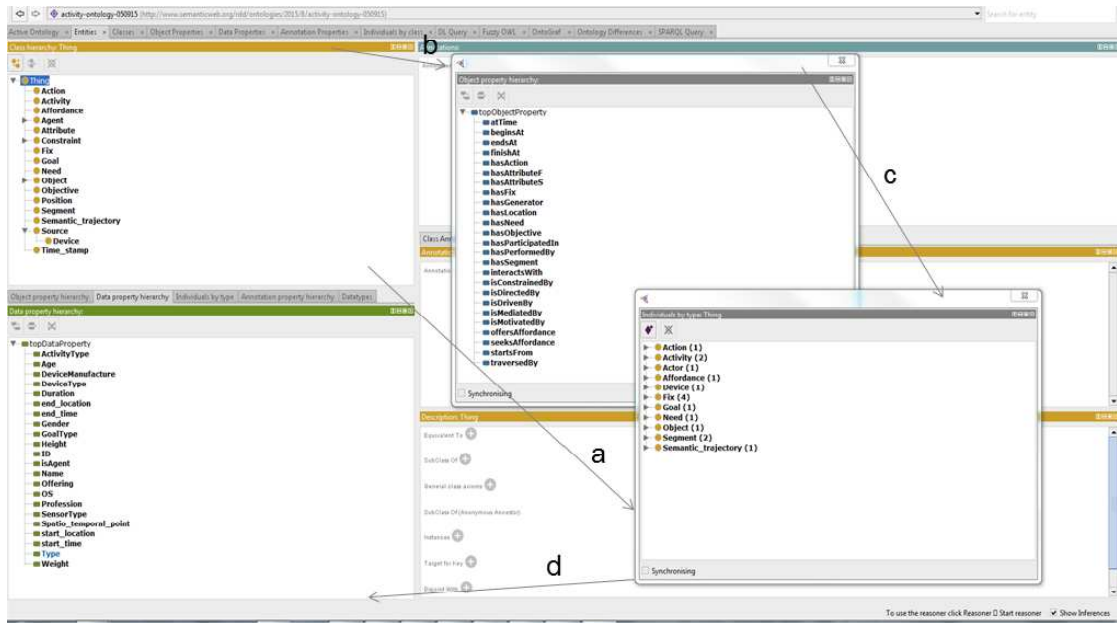


Figure 29: Ontology implementation in Protege

In Fig 31 AY indicates activity and AN indicates action. The Figure 31 shows how a singular (atomic) action ( $AN_0^1$ ) in context layer  $C_1$  (in Fig 31a) becomes activity ( $AY^0$ ) in context layer  $C_2$  which is broken down into four new actions  $AN_k^0$  where  $k$  ranges from 0 to 3 (in Fig 31b). One of the singular actions in  $C_2$  (in Fig 31b) is again transformed to activity in  $C_3$  with four new actions (in Fig 31c).

In order to make the activity (AY) and action (AN) defined in each context easily identifiable by the readers, the following notations are used.

$C_i\_AY^k = k^{th}$  activity in Context  $i$

$C_i\_AN_j^k = j^{th}$  action in  $k^{th}$  activity in Context  $i$

Context 1 (Fig 31a) reflects a travel survey type knowledge base captured for *travel demand analysis*, where time spent at a particular location (or place) is considered as an activity, which are *home* and *market* respectively in this case (“Where have you been today?” – “First at home, then I went to the market”). Travel demand analyses assume travel as a derived demand for activity participation. Hence, travel influences the chance of taking part in an activity which is not otherwise possible at a current location. However travel demand models do not consider travel as an activity or an action. Hence it grossly ignores time spent at certain locations during travel (such as transfer or having coffee or buying tickets) and does not give much emphasis on travel-based activities (activities embedded in a travel) or travel as action (Table 13). Conforming with the travel demand models, in Context 1 travel is a phenomenon of changing location from home to market over a given route network. Thus, in Context 1 two activities are presented in the knowledge base such as (being at) home



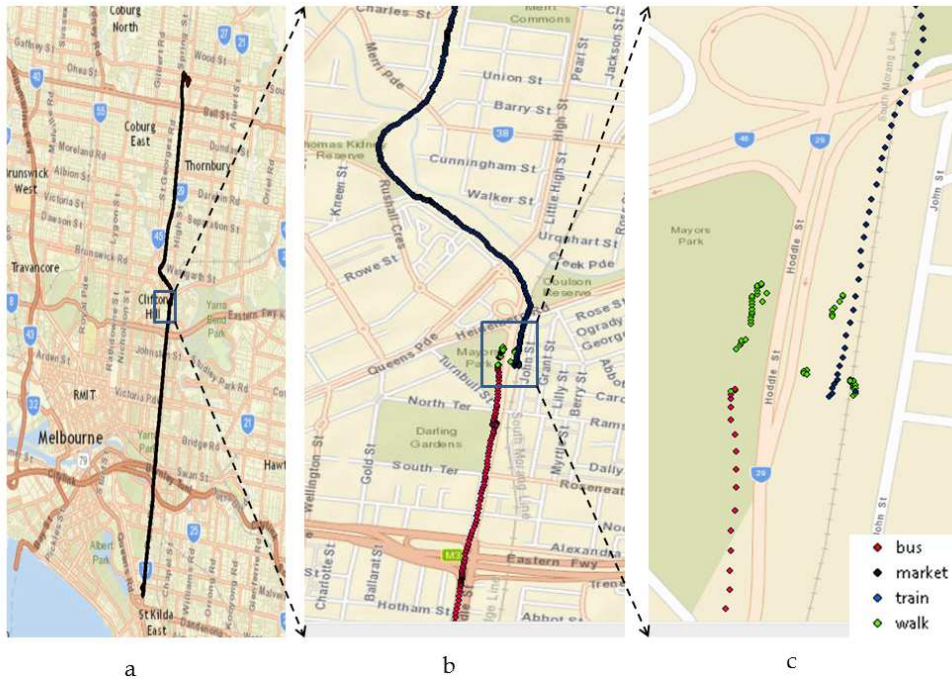


Figure 30: Joe's home to market travel record (Trajectory\_13062015). The shift in position over time is from south to north. The figure shows on refining the granularity from (a → b → c), more action knowledge is discovered. In a walking action is not properly visible. In b and Figure c walking action (in green dots) is visible which took place while Joe was changing from bus mode to train mode.

( $C_1\_AY^0$ ) and (shopping at) market ( $C_1\_AY^1$ ) without giving any treatment to *travel*, with an assumption that there is no other activity embedded in this travel and left it as a singular (atomic) action ( $C_1\_AN_0^1$ ). Figure 31a also shows some possible actions ( $C_1\_AN_1^1, C_1\_AN_2^1, C_1\_AN_3^1$ ) in the market place such as shopping at two different shops ( $C_1\_AN_1^1, C_1\_AN_3^1$ ) and changing the location from one shop to another within the market ( $C_1\_AN_2^1$ ). However, actions e.g., ( $C_1\_AN_1^1, C_1\_AN_2^1, C_1\_AN_3^1$ ) are not furnished in Table 13 for as these are not relevant from travel demand perspective. Generally, travel demand modelling focuses on significant time spent at a given location- not on the actions performed within that location.

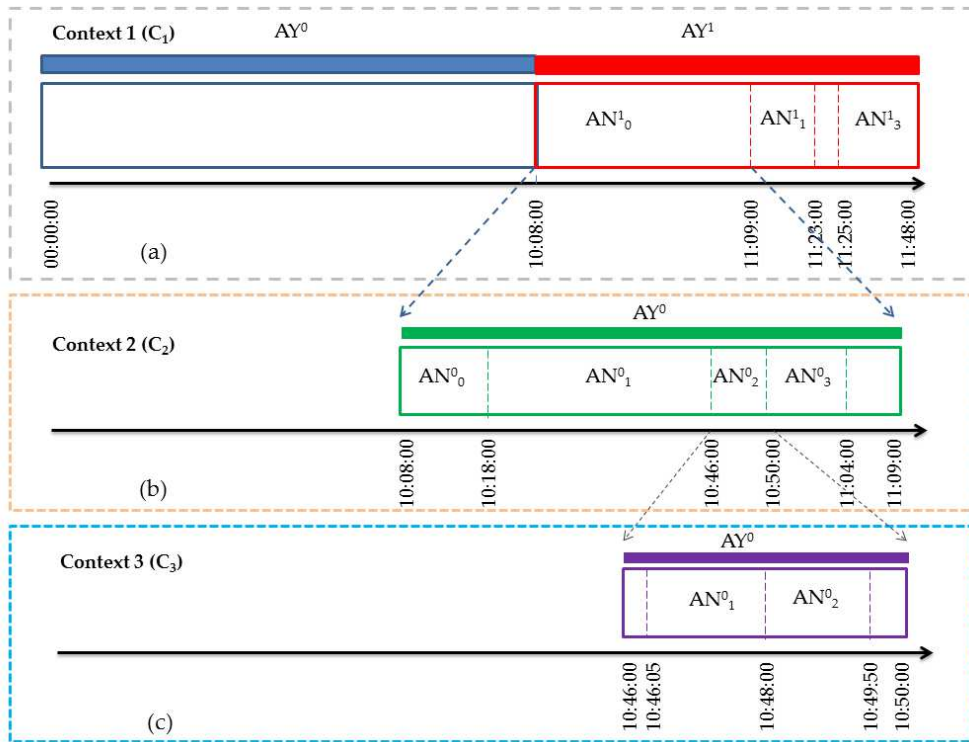


Figure 31: Context based recursive activity layers on temporal zooming.

Table 13: Knowledge base schema for Context 1

Context 1: Number of activity: 2			
Situation: Fill out a Travel Survey form for travel demand analysis			
Concept	Individual	Data Property	Value
Activity	Activity <sub>0</sub>	Name	Being at home
		ActivityType	semantic
		Duration	36480
		start_time	13062015_00:00:00
		end_time	13062015_10:08:00
		start_location	(-37.851795, 144.982711)
Activity	Activity <sub>1</sub>	Name	Shopping at market
		ActivityType	semantic

Continued on next page

Table 13 – Continued from previous page

Concept	Individual	Data Property	Value
		Duration	2340
		start_time	13062015_11:09:00
		end_time	13062015_11:48:00
		startLocation	(-37.739033, 145.001965)
		endLocation	(-37.739033, 145.001965)
Need	Need_0	Type	Subsistence
	Need_1	Type	Subsistence
Action	Action_0	Name	Travel
		startTimeStamp	36480
		endTimeStamp	40140
Goal	Goal_0	GoalType	Reaching at the market
Actor	Agent_0	Name	Joe
		ID	0
Segment	Segment_0	SegmentName	Home
	Segment_1	SegmentName	Market
Fix	Fix_0	Name	Home
		Spatio_temporal point	(-37.851795, 144.982711, 00:00:00 )
	Fix_1	Name	Home
		Spatio_temporal point	(-37.851795, 144.982711, 10:08:00 )
	Fix_2	Name	Market
		Spatio_temporal point	(-37.739033, 145.001965, 11:09:00)
Fix_3	Name	Market	
	Spatio_temporal point	(-37.739033, 145.001965, 11:48:00)	
Device	Device_0	SensorType	GPS
		DeviceType	Smartphone

Context 2 (Fig 31b) illustrates a knowledge base for *transport mode analysis* (“how did you go to the market?”) which is a refinement of Context 1, and may be an important facet in *urban analytics and various context-aware location-based services*.

Although the analysis is made on the same trajectory as that of Context 1, the information needs in both the contexts are different. Hence, there is a change in activity and action characterization between the contexts. In Context 2 the activity is the travel from home to market ( $C_2\_AY^0$ ) with actions are transfer\_o ( $C_2\_AN_0^0$ ), travel on train ( $C_2\_AN_1^0$ ), transfer\_1 ( $C_2\_AN_2^0$ ), travel on bus ( $C_2\_AN_3^0$ ) (see Fig 31b, Table 12, Table 14). Accordingly, for Context 2 information are captured at a finer granularity, especially the way Joe has changed his location over space and time in order to travel from home to market. The focus is now on transport modes and transfers as actions with different conscious goals (Table 14).

Table 14: Knowledge base schema for Context 2

Context 2: Number of activity: 1			
Transport mode analysis from home to market			
Concept	Individual	Data Property	Value
Activity	Activity_o	Name	Travel from home to market
		ActivityType	Semantic
		Duration	3660
		start_time	13062015_10:08:00
		end_time	13062015_11:09:00
		startLocation	(-37.851795, 144.982711)
		endLocation	(-37.739033, 145.001965)
Need	Need_o	Type	Subsistence
Action	Action_o	Name	transfer_o
		startTimeStamp	36480
		endTimeStamp	37080
Action	Action_1	Name	Travel on bus
		startTimeStamp	37080
		endTimeStamp	38760
	Action_2	Name	transfer_1
		startTimeStamp	38760
		endTimeStamp	39000
Action_3	Name	travel on train	

*Continued on next page*

Table 14 – Continued from previous page

Concept	Individual	Data Property	Value
		startTimeStamp	39000
		endTimeStamp	39840
	Action_4	Name	Walk to market
		startTimeStamp	39840
		endTimeStamp	40140
Goal	Goal_0	GoalType	Getting on the bus
	Goal_1	GoalType	Reaching the bus stop at the train station
	Goal_2	GoalType	Getting on the bus
	Goal_3	GoalType	Reaching the train station at the market
	Goal_4	GoalType	Getting to the market
Actor	Agent_0	Name	Joe
		ID	0
Segment	Segment_0	SegmentName	Home_to_bus_stop1
		startTimeStamp	36480
		startLocation	(-37.851795, 144.982711)
		endTimeStamp	37080
		endLocation	(-37.852669, 144.983735)
	Segment_1	SegmentName	Bus_stop1_to_bus_stop2
startTimeStamp		37080	
startLocation		(-37.852669, 144.983735)	
endTimeStamp		38760	
endLocation		(-37.788104, 144.994969)	
Segment_2		SegmentName	Bus_stop2_to_train_stop1
		startTimeStamp	38760
		startLocation	(-37.788104, 144.994969)
		endTimeStamp	39000
		endLocation	(-37.788112, 144.994975)

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Table 14 – Continued from previous page

Concept	Individual	Data Property	Value	
	Segment_3	SegmentName	Train_stop1_to_train_stop2	
		startTimeStamp	39000	
		startLocation	(-37.788112, 144.994975)	
		endTimeStamp	39840	
		endLocation	(-37.788639, 144.995391)	
	Segment_4	SegmentName	Train_stop2_to_market	
		startTimeStamp	39000	
		startLocation	(-37.788112, 144.994975)	
		endTimeStamp	40140	
		endLocation	(-37.739033, 145.001965)	
Fix	Fix_0	Name	Home	
		Spatio_temporal point	(-37.851795, 144.982711, 10:08:00)	
	Fix_1	Name	Bus_stop1	
		Spatio_temporal point	(-37.852669, 144.983735, 10:18:00)	
	Fix_2	Name	Bus_stop2	
		Spatio_temporal point	(-37.788104, 144.994969, 10:46:00)	
	Fix_3	Name	Train_stop1	
		Spatio_temporal point	(-37.788112, 144.994975, 10:50:00)	
	Fix_4	Name	Train_stop2	
		Spatio_temporal point	(-37.788639, 144.995391, 11:04:00)	
	Fix_5	Name	Market	
		Spatio_temporal point	(-37.739033, 145.001965, 11:04:00)	
	Object	Object_0	Name	Bus_stop
			isAgent	FALSE
Object_1		Name	Bus	

Continued on next page

Table 14 – Continued from previous page

Concept	Individual	Data Property	Value	
	Object_2	isAgent	FALSE	
		Name	Train_stop	
	Object_3	isAgent	FALSE	
		Name	Train	
	Object_4	isAgent	FALSE	
		Name	route_network	
	Affordance	Obj0_Affordanceo	Type	positive
			Offering	Embarking and disembarking
	Obj1_Affordanceo	Type	positive	
		Offering	Mediated travel	
	Obj2_Affordanceo	Type	positive	
		Offering	Embarking and disembarking	
	Obj3_Affordanceo	Type	positive	
		Offering	Mediated travel	
	Obj4_Affordanceo	Type	positive	
		Offering	Navigation	
Device	Device_o	SensorType	GPS	
		DeviceType	Smartphone	

Context 3 (Fig 31c, Table 15) demonstrates human movement behaviour during transfer which is analysed in order to support any potential non-travel activities along. A transfer involves at least disembarking from a vehicle, walking a given distance from point of arrival to point of departure, waiting for next connecting vehicle, and embarking on that vehicle.

Table 15: Knowledge base schema for Context 3

Context 3: Number of activity: 1			
Situation: Human movement behaviour analysis during modal transfer			
Concept	Individual	Data Property	Value
Activity	Activity_0	Name	transfer_1
		ActivityType	semantic
		Duration	240
		start_time	13062015_10:46:00
		end_time	13062015_10:50:00
		startLocation	(-37.788104, 144.994969)
		endLocation	(-37.788112, 144.994975)
Need	Need_0	Type	Subsistence
Action	Action_0	Name	Disembarking
		startTimeStamp	38760
		endTimeStamp	38765
	Action_1	Name	Walking
		startTimeStamp	38765
		endTimeStamp	38880
	Action_2	Name	Waiting
		startTimeStamp	38880
		endTimeStamp	38990
	Action_3	Name	Embarking
		startTimeStamp	38990
		endTimeStamp	39000
Goal	Goal_0	GoalType	Get down at the bus stop
	Goal_1	GoalType	Get to the nearest train station
	Goal_2	GoalType	Catching the next connecting train
	Goal_3	GoalType	Mediated travel to the market
Actor	Agent_0	Name	Joe

*Continued on next page*



Table 15 – Continued from previous page

Concept	Individual	Data Property	Value
		ID	0
Segment	Segment_o	SegmentName	Bus_stop2_to_train_stop1
		startTimeStamp	38760
		startLocation	(-37.788104, 144.994969)
		endTimeStamp	39000
		endLocation	(-37.788112, 144.994975)
Fix	Fix_o	Name	Bus_stop2
		Spatio_temporal point	(-37.788104, 144.994969, 10:46:00)
	Fix_1	Name	Train_stop1
		Spatio_temporal point	(-37.788112, 144.994975, 10:50:00)
Object	Object_o	Name	Bus_stop
		isAgent	FALSE
	Object_1	Name	Bus
		isAgent	FALSE
	Object_2	Name	Train_stop
		isAgent	FALSE
Object_3	Name	Train	
	isAgent	FALSE	
Affordance	Obj0_Affordanceo	Type	positive
		Offering	Embarking and disembarking
	Obj1_Affordanceo	Type	positive
		Offering	Mediated travel
	Obj2_Affordanceo	Type	positive
		Offering	Embarking and disembarking
Obj3_Affordanceo	Type	Positive	
	Offering	Mediated travel	
Device	Device_o	SensorType	GPS

Continued on next page

Table 15 – Continued from previous page

Concept	Individual	Data Property	Value
		DeviceType	Smartphone

In order to test the model, SPARQL queries are issued at different contexts. In Context 2, all the activities and corresponding action information are retrieved from the knowledge base (Fig 32). Since Context 2 contains only one activity, the output produces only one activity (*travel from home to market*) with corresponding five actions that are required to perform that activity.

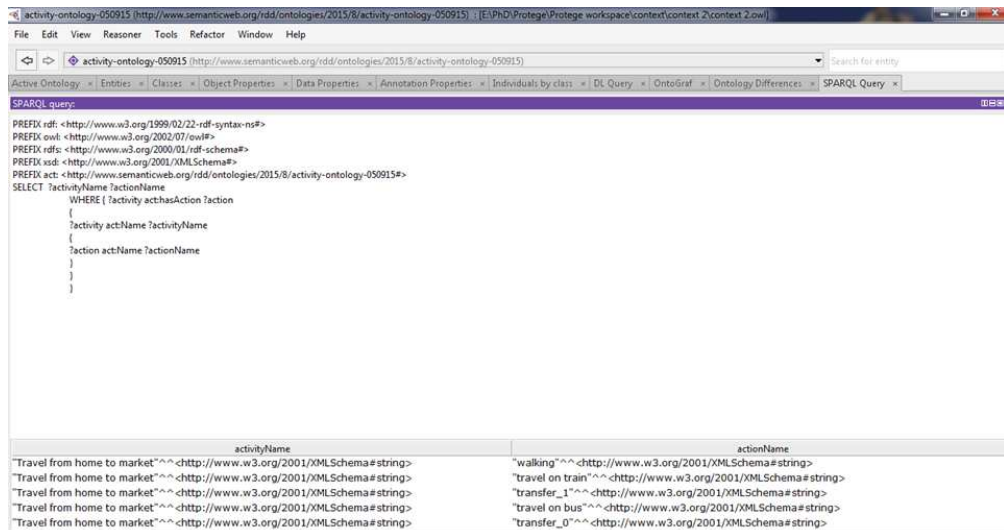


Figure 32: SPARQL query in Context 2: Extract all the activities and actions in Context 2

In context 3, a more complex query is issued to extract all the actions along Segment\_o (Fig 33).

From the illustration it is seen that Context 1 conforms with the transportation domain where understanding the causes behind people’s travel behaviour has been a long standing research endeavour (which is generally addressed by travel surveys in different sorts). Context 2 purports the domain of mobile computing and context-aware computing (along with transportation science) where one may be interested to know a person’s current active state in terms of modality and movement behaviour and customize different location based and context-aware services. Context 3 aligns with public health research where one is more interested in a person’s low level movement behaviour such as whether standing or walking or running.

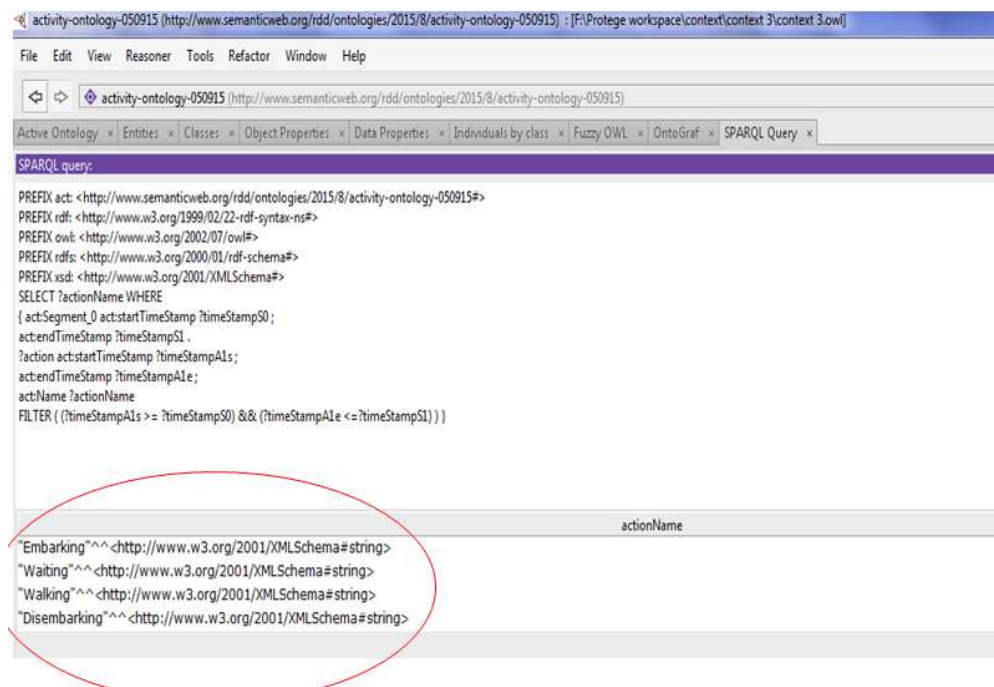


Figure 33: SPARQL query in Context 3: *Extract all the actions along Segment\_0*

Thus the model will work in all the domains based on the situational aspects, need and goal set by the actor. The model will also work in ambient assisted environment where the main focus lies in indoor activities such as brushing teeth, bathing, having coffee, watching television, cooking, talking on a phone- all can be addressed based on a need and corresponding actions with their goals defined at a given context and a granularity (level of details and space-time scale). For example, the activity *eating* can be modelled with need as subsistence, component actions such as taking food from bowl, using forks and spoons, chewing. This activity structure also involves different objects with given affordances such as bowl for containing the food, fork for cutting the food and spoon for lifting the food from the plate to mouth. The space-time information can also be populated in this case at a finer granularity (may be the spatial dimension can be transformed into a Cartesian coordinate in indoor or a qualitative information say Room 1 to Room 2).

Since the main interest of this research lies in trajectory based activity modelling in urban environment, three case studies are shown with their corresponding knowledge bases on a single trajectory at different contexts. The knowledge bases can easily be extended or shrunked at different spatial and temporal scope.

## 4.5 DISCUSSION

In this research, a framework of activities has been developed, implemented as an ontology, and tested for three different contexts.

The three contexts illustrate that activity can be modelled for different contexts with different semantics, or level of spatial and temporal granularity. The contexts presented in this research are all related to each other in terms of a common need. It has been shown how action in one activity layer (in one context) can be transformed to an activity in another layer (in another context). In terms of refinement of granularity the presented contexts are ordered in terms of space and time from coarsest to finest granularity (see Fig 31):

$$\text{Context 1} \prec \text{Context 2} \prec \text{Context 3}$$

The symbol " $\prec$ " indicates a binary granularity relationship between two contexts in terms of situational relevance. Since Context 3 represents knowledge within a smaller spatial and temporal scope with detailed information on mobility phase than that of Context 1, Context 3 can be viewed at a finer granularity than that of Context 1. The three contexts show how on refining the granularity more information is revealed at a given segment. For example, in Context 1, the most relevant information required is time spent at a given location (such as home or market) which is characterized as activity and hence any more detailed information pertaining to travel (such as modes and transfers) is irrelevant and is presented as single (atomic) action in the knowledge base (Fig 31a, knowledge base for Context 1). Whereas in Context 2, since the way of movement is now relevant, detailed information about transport modes and transfers are presented in the knowledge base, together with further object and affordance information (Fig 31b, knowledge base for Context 2). Context 3 shows again more details but here only for a shorter movement segment (within a constrained spatial and temporal scope), such as transfer (Fig 31c, knowledge base for Context 3).

Based on a context an activity is the interaction of an agent with its environment to satisfy some need(s). In order to satisfy a need, agent follows an objective. An objective is composed of goals set by the agent which are constrained by the affordances offered by object(s). Each activity contains one or more actions which are oriented towards an object (that offers affordance) to fulfill a given goal. However the concept of activity and action is highly context-sensitive. On spatial and temporal zooming and by changing the situation, the semantics and role of an activity or action changes in a given context.

Based on the illustration presented in this research (Fig 31), the concept of "activity and action" are very much aligned with "process and event" in spatial information science. An activity resembles to a process and an action contained in an activity resembles to an event as an action is like a snapshot and building block of a given activity. But as it is established context plays an important role in defining an activity or action

hence context would also affect the conceptualization of a process and event which both can be refined or simplified and change the semantics recursively (a process may transform into an event at a given context and vice versa) which is left for future work in the same line.

There has been a long standing question if *travel* is an activity or a need to participate in an activity and thus there exists an ambiguity in urban activity patterns while addressing the aspect of *travel*. It has been illustrated that the ambiguity lies in context-dependency. In Context 1 travel is not an activity (Table 13); rather it induces some activities that are not possible at a current location. Hence a travel can be viewed as an action in Context 1. Thus this bridges the gap between the notion of activity in HCI and activity in travel demand modelling.

However, at a different situation, travel can be viewed as an activity with embedded actions (see Context 2 in Table 14, Fig 31b) that also conforms some of the earlier literature where travel has been considered as activity (Hirtle et al., 2011). On a coarser granularity and a different context, say, for an activity “holidaying in Melbourne” with a need of recreation, travel can also be considered as an action. However changing position in a same campus (university or office) or indoor environment (one terminal to another terminal in an airport or train station, one floor to another floor in a same building) are left for further treatment in future which can be explained through scale of objects and situational aspects.

Representing activity knowledge is important at different contexts for knowledge sharing and reasoning purpose. Activity knowledge can be best represented and shared through activity ontology and a contextual knowledge base. In this research, activity is modelled based on some key concepts (see Table 13,14,15) at different contexts. However the main concepts are activity itself, an actor, a need for an activity, action(s), goal(s), and object(s). Each of the key concepts is instantiated with respective data type, data property and data value at a given context and linked together through an actor.

Figure 31 depicts how activity knowledge can also be represented visually on a temporal scale. Thus a change in context and shift in granularity in time (and space) can also affect activity knowledge representation with varied details and situational relevance.

This research shows a raw trajectory can be used for activity modelling and extracting different mobility based information at urban scale. A raw trajectory encodes agent’s movement behaviour and state of activeness (doing something) in the form of spatial information (coordinate) and temporal information (time stamp) with additional sensor signals at different granularity across a wide range of urban scale (holidaying in Melbourne, travelling from home to office, movement history inside office campus, movement history inside the office building over a given time period). A trajectory can be collected through different sources such as check-in points, static sensors or cordons laid in the environment (Duckham, 2013), continuous recording

through location and positioning sensors onboard a smartphone. A raw trajectory collected through different sources can be transformed to semantic trajectory by integrating number of domain specific information including route information (Spaccapietra et al., 2008) or indoor infrastructure information. Based on a given context a semantic trajectory can then be segmented in a number of segments where each segment can be used to represent an action or activity with a starting and ending fix (spatial and temporal information). Hence, a raw trajectory can be used for activity modelling of a respective actor based on segmentation strategy and context at hand.

This research also demonstrates the extensible nature of an earlier version of a content-based semantic trajectory ontology (Hu et al., 2013). In this research some of the concepts and relationships are borrowed from the earlier work while developing the semantic trajectory part such as “fix” and an extended version of “segment”. However this context-sensitive activity model has extended the earlier trajectory ontology and developed different sets of knowledge base to represent activity knowledge from trajectory data through instantiation of different concepts.

The relevance of three contexts is based on the given situations. For example for Context 1, the relevance is to gain insight of time spent at a particular place over a considerable duration which is important for modelling travel demands. For Context 2, the relevance lies in understanding the modality information to reflect agent’s preferences, location-based services and route recommendations. In Context 3 the relevance is focused on the agent’s movement behaviour during transfer for various context-aware computing services.

This research has shown affordance theory reasons the usability of an object to fulfill certain need(s) at a given context, which can be connected to activity theory, namely the mean that satisfies an objective of an activity or a goal of an action. In the framework presented in this chapter affordance has a place in relationship to the needs of a person and the properties of a location at a particular time, in the spirit – but not at the detail – of Raubal and Moratz (Raubal and Moratz, 2008).

In order to keep the model simple, the three contextual knowledge bases are rather basic. But the knowledge bases can be populated and extended with more detailed action information on getting more sensor signals especially indoor positioning sensors and inertial navigation sensors such as accelerometer, gyroscope or proximity sensor that in turn can give information at a finer level of bodily movement, and thus can model semantic activity (at a high level) as well as physical activity (at a low level).

In addition to that, in this research any atomic unit in the activity model is not discussed, however, action is used as the fundamental building block for an activity. An action can be broken down into sub-action. A sub-action can be broken down into sub-sub action. But this research, limits into only action and do not break an action into its subsequent parts. This research assumes a different context when an action is broken down into its components and the action then transforms into an activity in that given context. On the other hand, the concept of granularity is used

several places in this research. The granularity can be user defined (by relevance) or system defined (concerned with details of data-hardware and software configuration and external influences). In the same line, this research also admits the constraints involved with a given granularity. The constraints depend on the sampling frequency and the sensor configuration and also the level of details suited for the analysis. Since this work is on structuring and building a common knowledge base for activities in different contexts from a generic point of view and not to develop a new predictive model for activity recognition, this research does not illustrate much on the constraints on the granularity of the data. Granularity will only affect the extraction of knowledge, but not the design of the model.

#### 4.6 SUMMARY

In this chapter, a context-sensitive semantic trajectory based activity model has been developed at a conceptual level. A semantic trajectory based activity modelling will enable an efficient communication between human and machines and extracting relevant geographic information retrieval. This research demonstrates the notion of activity and action is contextual. A context defines a situation with a set of concepts, individuals and their properties. An activity can be modelled based on a given context. An activity is mainly characterized by an objective and a need whereas an action is characterized by a goal. An activity consists of action(s). A semantic trajectory shows movement pattern of an agent. Hence it is assumed that a trajectory contains agent's activity information. In this chapter, activity and action information are extracted from a portion of a given trajectory. In order to demonstrate the varied semantics of activity, three contexts are illustrated with three different situations. In the first context a travel survey type activity knowledge base is developed. In Context 2, a more detailed activity knowledge base is developed based on the same trajectory with action information and space time information in terms of fixes and segments. In Context 3, more detailed activity knowledge (transfer) is evaluated over a shorter time frame.

In order to demonstrate the validity of the hypothesis, an ontological framework is developed. The framework is implemented in Protege in OWL-DL. The model has also been tested using simple SPARQL queries. The illustrations presented in this chapter, are somehow demonstrate that the contexts are related to each other in terms of the need (subsistence in three cases) on the same trajectory. But in a more complex set up, the contexts can be entirely different such as reading newspaper (need: understanding), while travelling on the bus to work (need: subsistence).

The model proposed in this chapter considers a trajectory captured by a GPS sensor onboard a smartphone in order to illustrate the working of the ontological framework across contexts and levels of granularity. However, the approach can be used for trajectories captured by different sources such as trajectories of check-in points, generated by cordons, by static sensors, or from indoor tracking, where each method may have

its own granularity and context. The model can also address complex activity models at any level of granularity. Thus the approach presented in this research can be expected to be both flexible and scalable. This research also demonstrated the approach can be used to represent activity knowledge in different domains.

In this research the three different illustrative contexts are treated separately. Future research may connect different contexts in a single model (of variable granularity) based on situational relevance in order to structure more complex activities and extract different action and activity information (disjoint or joint) happening or overlapping on the same space-time window through temporal calculi (Ligozat, 2013) and context-sensitivity. As the focus of this thesis lies on how a person mediates during a travel, following three chapters (Chapter 5, Chapter 6, Chapter 7) will explore three different approaches to detect the transport mode information and trip information at different temporal granularities.



## A FUZZY KNOWLEDGE-DRIVEN APPROACH FOR TRANSPORT MODE DETECTION

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Transport mode detection is an emerging research area in different domains e.g., urban mobility, context-aware mobile computing and intelligent navigation. Current approaches are mostly data centric – based on machine learning approaches. However, the machine learning approaches require substantial training data and cannot explain the reasoning or infer procedure. Machine learning based approaches also fall short in providing different possibilities with varied certainty levels. To overcome such shortages, there is a need to develop a novel approach for transport mode detection: a knowledge-driven approach that can work without any training, based solely on expert knowledge and can generate multiple possibilities. This is useful particularly when the ground truth information or expert knowledge is limited. Thus in this chapter <sup>1</sup> a fuzzy multiple-input multiple-output (MIMO) knowledge-driven model is developed using kinematic and spatial information with a well explained fuzzy reasoning scheme through a fuzzy rule base. Different membership function combinations are evaluated in terms of accuracy and ambiguity. The results justify that the model performs best using a Gaussian-Gaussian combination, and is comparable to machine learning approaches.

### 5.1 INTRODUCTION

In order to travel, a wide spectrum of transportation modes are in use, which are broadly classified into motorized and non-motorized modes. Examples of the popular motorized modes are bus, car, motor bike, train and tram, and some of the non-motorized modes are walking, human-powered rickshaw, and bicycle. Transport mode information, i.e., the travel mode on each part of a travel, is valuable in order to understand the dynamics of people's movement behaviours and preferences as well as to develop various context-aware services (Ashbrook and Starner, 2003; Dey and Abowd, 2000; Schilit et al., 1994).

As described in Chapter 1 and Chapter 2, currently transport mode information is collected through manual travel survey methods with inherent quality issues (Stopher, 2004; Stopher and Collins, 2005; Wolf, 2000). In order to resolve the quality issues, automated surveys have been conducted deploying handheld GPS receivers with high

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<sup>1</sup> The research has been submitted and currently under review.

Das, RD., Winter, S. (2016): Fuzzy Logic based Transport Mode Detection Framework in Urban Environment, Journal of Intelligent Transportation Systems (under review)

accuracy (Wolf, 2000), which, however, is costly and cumbersome. Hence, recently various sensors on board of smartphones have been trialled for mobility surveys (Cottrill et al., 2013; Safi et al., 2013; Stopher et al., 2008). The raw data collected by smartphones requires an automatic (post-event) detection of transport modes. In this chapter, an attempt is made to explore the efficacy of the data provided by GPS sensors on board of smartphones to detect a given transport mode.

The existing researches in transport mode detection using velocity-based measures, or rigid threshold-based kinematic measures in urban environments (Bohte et al., 2008), cannot handle uncertainties present in an object's movement behaviour. The existing researches also fail typically when the speeds of different modalities are the same. In this regard, a wide range of transport mode detection work is based on machine learning (Byon et al., 2009; Hemminki et al., 2013; Reddy et al., 2010; Stenneth et al., 2011; Gonzalez et al., 2010; Zheng et al., 2009, 2008; Gong et al., 2012) that requires a substantial amount of training to develop a mode detection model. Machine learning models inherit the uncertainties embedded in any training data, but cannot represent the uncertainties in their own classification(s) – posing a gap in knowledge representation. This knowledge gap is the motivation of some of the recent works exploring knowledge-driven aspects in mode detection (Biljecki et al., 2012; Tsui and Shalaby, 2006). In this research a fuzzy logic based purely knowledge-driven model is proposed for mode detection. Purely knowledge-driven models do not require any training data. The models are developed based on expert knowledge in terms of a set of fuzzy rules. The models are applicable in different conditions provided the expert knowledge is sufficient enough to capture different movement behaviours. On the other hand hybrid knowledge-driven models require a training data to generate its initial knowledge base. This chapter investigates if a purely knowledge-driven model works effectively on historical trajectories.

In the context of transport mode detection, so far suggested fuzzy logic based knowledge-driven models in the literature are not easily comprehensible in human understandable format and lack the transparency in knowledge representation (see Chapter 2). They were designed to highlight a single rule for each (transport) modal class based on a multiple-input single-output (MISO) approach that assigns the mode of the maximum certainty factor (CF), i.e., of highest possibility. Thus existing fuzzy mode detection models are unable to address the fuzziness of belonging to different modal classes with different certainty levels. Say, if the speed profile of a particular trajectory is inconclusive between bus and tram, but this trajectory segment is spatially close to the bus network, then there is a 'high' chance that the travel mode of this segment would be a bus ride, and 'low' to be a tram ride. The existing models ignore such alternative possibilities. They will classify a given segment either as a bus ride or tram ride without any certainty factor. Similarly, they do not address the linguistic values with different degrees of certainties associated with each variable. In this chapter, a more robust and flexible multiple-input multiple-output (MIMO) model has been de-

veloped in order to lift the expressiveness. The transparency and comprehensiveness in the reasoning process can also generate relevant kinematic knowledge related to a given action (or activity) to enrich the ontological framework developed in [Chapter 4](#).

This research states that *a multiple-input multiple-output fuzzy logic based knowledge-driven approach is able to detect different transport modes effectively based on the expert knowledge from historical trajectories. The knowledge-driven approach will also model the uncertainties present in the movement behaviour in a transparent way.*

A trajectory may contain a number of trips with different transport modes. The trips are first detected based on a speed-based approach and then a particular modal state is predicted over each trip segment using a fuzzy inference process. The framework in this research is developed and tested for four transport modes: walk, bus, tram and train, but can be extended for additional modes by incorporating more rules. This work contributes to the existing mode detection researches in the following ways.

- The proposed model explores the efficacy of cheap GPS sensors onboard smartphones. Although the proposed model uses GPS sensors alone, but is easily extensible by incorporating other sensors available on smartphones (such as accelerometer).
- The proposed Mamdani fuzzy model is based on MIMO architecture. The model can explain the reasoning scheme in a more comprehensive way with an ability to quantify the cognitive certainty of being different modes with varied degree. Such comprehensiveness is missing in the existing fuzzy logic based models.
- This research investigates the efficacy of combining different membership functions rather than only a trapezoidal membership function which has been used in earlier researches.

The rest of the chapter is organized as follows. [Section 5.2](#) and [Section 5.3](#) present the fundamental concepts and fuzzy mathematics along with the proposed fuzzy logic based framework for travel mode detection. This framework is put to a test in [Section 5.4](#), which presents the experimental set up and the evaluation. In [Section 5.5](#), the results are discussed with regards to the novelty and the limitations of the framework. [Section 5](#) contains the summary and future research directions.

## 5.2 THEORY

### 5.2.1 Expert system

Expert systems emulate an expert's reasoning process and decision making ability through complex situations ([Buchanan and Duda, 1982](#)). The core of an expert system is based on IF-THEN rules. The IF part includes the fact or evidence, whereas THEN

part includes the hypothesis or conclusion. An expert system has two components, a knowledge base and an inference engine. The knowledge base contains the facts or evidences (e) whereas the inference engine contains the rules (R) and applies the rules to known facts to deduce new facts or arrive at a conclusion or hypothesis (h). A Mamdani fuzzy logic based model is a type of expert systems that can reason with uncertainty, and to represent their reasoning scheme (Shortliffe, 1975; Siler and Buckley, 2004; Nickles and Sottara, 2009). In this chapter a forward chaining fuzzy expert system is developed.

### 5.2.2 Fuzzy expert system

A fuzzy expert system is based on fuzzy set theory (Zadeh, 1965). Unlike a crisp set theory where an element is either present or absent in a given set, fuzzy set theory assigns a membership value to an element and, thus, introduces the concept of a partial membership of that element in a number of different set(s). If  $A$  is a fuzzy set defined on a universe of discourse  $U$ , then the membership of an element  $y \in A$  can be defined by a membership function (MF)  $\mu_A(y)$  within an interval of  $[0,1]$ . This can be mathematically expressed as follows.

$$A = \{(y, \mu_A(y)) | y \in U\}, \mu_A(y) : U \rightarrow [0, 1] \quad (5)$$

A fuzzy variable is expressed through a fuzzy set, which is attributed with a set of fuzzy values. Thus, a fuzzy variable  $A$  can be characterized by a set of fuzzy values, known as term set  $\{T\}$ , and a set of membership functions  $\{M\}$ , where:

$$T_A(y) = T_y^1, T_y^2, \dots, T_y^k \quad (6)$$

$$M_A(y) = \mu_y^1, \mu_y^2, \dots, \mu_y^k \quad (7)$$

There are two types of fuzzy models used in general: the Mamdani fuzzy model and the Takagi–Sugeno–Kang (TSK) fuzzy model (more popularly known as the Sugeno fuzzy model). In a Mamdani fuzzy model, both the antecedent (**IF**) and consequent (**THEN**) are fuzzy. The **IF** part contains the fact, and the **THEN** part contains the conclusion. In the case of a Mamdani fuzzy approach, both the fact and the conclusion are not certain, which occurs in most of the real-life situations due to limitations in system architecture, data acquisition, subjective perception of the user, the quality of data and the predicted outcome in a given context. The model developed in this chapter is based on Mamdani approach. A Mamdani fuzzy inference system (MFIS) is more transparent (compared to a Sugeno model) due to its ability to represent the fuzziness both in antecedent and consequent part in an offline scenario. Whereas a Sugeno approach is more suited where the antecedent part is fuzzy but consequent part is crisp. This chapter develops a Mamdani approach for transport mode detection on historical trajectories whereas Chapter 6 investigates whether a Sugeno approach works better than a Mamdani approach in near-real time.

### 5.2.3 Mamdani fuzzy inference systems

An MFIS fuzzy inference system comprises a fuzzifier, a rule base, an inference engine, and a defuzzifier (Iancu, 2012). A fuzzifier takes an input feature vector, and maps each numerical value to a fuzzy membership value. To develop the rule base, each rule consists of a number of facts related to the kinematic and proximity measures (e.g., speed, closeness to the bus route). The facts are combined using a t-norm or t-conorm or a negation operator. In this research the rule bases developed are all based on a t-norm operator. On firing a given rule, a *MIN* operator is used to select the minimum membership value from a number of fuzzy antecedent variables ( $A_i$ ) to obtain the corresponding consequent ( $C_i$ ) lamina in the consequent function. Once all of the rules are fired, all of the selected consequent lamina are aggregated; in order to generate the final (crisp) output value from the combined consequent lamina, which corresponds to the *centre of gravity* (cg) of the combined consequent lamina. Figure 34 illustrates how each rule is fired, and the consequent lamina are combined once all of the rules are fired. In Figure 34, two rules are shown where the rules state,

$R_1$  : **IF**  $A_1$  is  $T_1$  and  $A_2$  is  $T_2$ , **THEN**  $C_1$  is  $T_1$ .

$R_2$  : **IF**  $A_1$  is  $T_1$  and  $A_2$  is  $T_3$ , **THEN**  $C_2$  is  $T_2$ .

For given inputs, when fuzzy variable  $A_1 = y_1$  and  $A_2 = y_2$ , each rule is fired, and the corresponding fuzzy consequent is inferred. In order to defuzzify the consequent part and to obtain the final output ( $F_o$ ) a *centre of gravity*' method is used as follows.

$$F_o = \frac{\sum u_i \cdot y_i}{\sum u_i} \quad (8)$$

### 5.3 A MAMDANI FUZZY INFERENCE SYSTEM FOR MODE DETECTION

In a mode detection model, each consequent variable is a modal state. The linguistic values of different consequent variables represent *low*, *moderate*, and *high* certainties. Each linguistic value is quantified over a range of 0 to 100.

Based on the observations and common sense knowledge 74 fuzzy rules have been developed (see first 74 rules in Appendix A), with five antecedent variables and four consequent variables in each rule statement. The notion behind the multiple consequent parts is that a given set of facts (antecedent part) may indicate different modes with varied degree of certainty. The evidences (inputs) in an antecedent part are fuzzified using a given fuzzy membership function, which are aggregated using an AND operator and fed to a fuzzy inference engine containing the rule base for generating conclusions as consequent variables with different values. The consequent variables are also combined using an AND operator. Then a defuzzification is performed to generate the crisp certain factor for each consequent part. Finally, the modal state with the maximum certainty factor is chosen as the predicted class for a given input feature

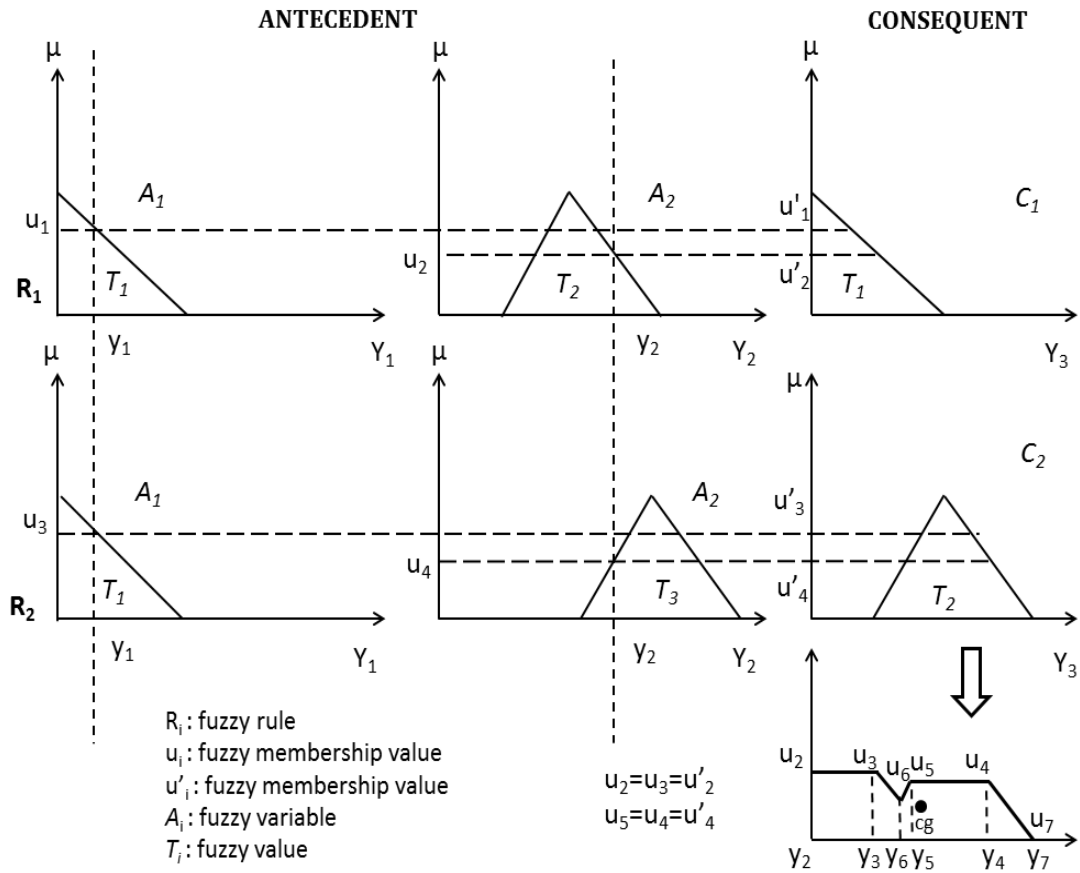


Figure 34: A Mamdani fuzzy inference system with two rules.

vector (Fig 35). Some of the fuzzy rules are as follows. Due to space limitation all rules are not shown here (for the complete set of rules refer Appendix A).

R1: If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)

R2: If (avgSpeed is high) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is moderate)

R3: If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is high)

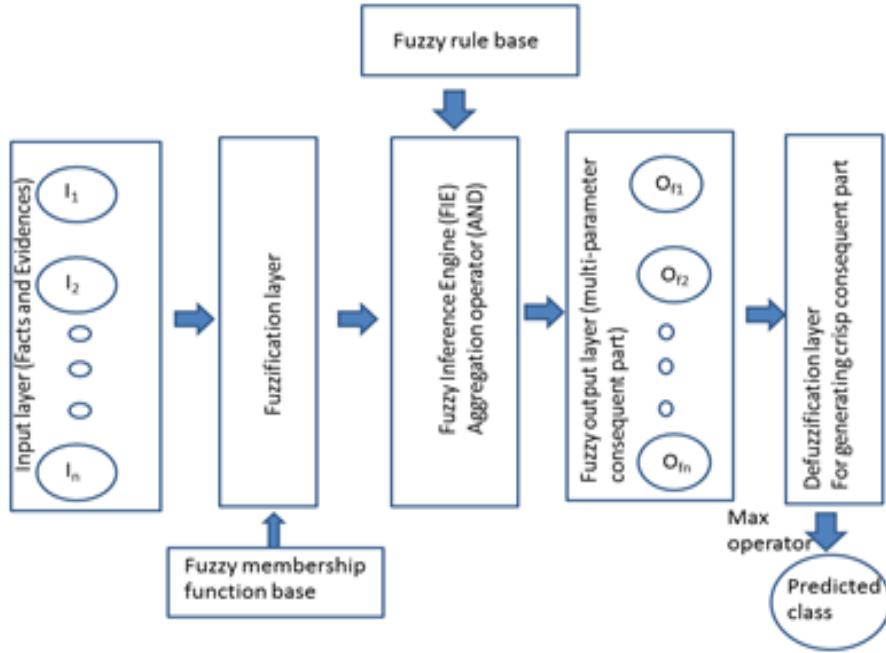


Figure 35: A MIMO Mamdani fuzzy inference system for mode detection.

Since choosing a proper membership function is a challenge in designing a fuzzy model, this research evaluates different membership function combinations (antecedent-consequent) by considering three basic mathematical functions, e.g., a) Triangular (T); b) Gaussian (G); c) Trapezoidal (Trap), which can be expressed as follows. The parameters for each function are based on the heuristics and trial-and-error similar to previous studies (Biljecki et al., 2012).

#### TRIANGULAR FUNCTION

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \quad (9)$$

#### TRAPEZOIDAL FUNCTION

$$\mu(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d) \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \end{cases} \quad (10)$$

## GAUSSIAN FUNCTION

$$\mu(x) = \exp \frac{-(x - c)^2}{2\sigma^2} \quad (11)$$

## 5.4 EVALUATION

### 5.4.1 *Data set*

In order to evaluate the model a data set is collected in Greater Melbourne, Australia (see Section 3.2). Unlike the current telephone or web-based surveys relying on people's memories (Doherty et al., 2006; Stopher and Collins, 2005), the groundtruth of transport mode information is highly reliable as it was recorded instantly on the fly on a paper diary with start time, end time and modal state. During the data collection it is observed that there is a GPS update delay each time when getting off any motorized mode, and occurrence of signal loss for a certain duration, which may be caused by a certain implementation of the sampling in the Android app. This update process typically takes 8 s-10 s which creates semantic gaps in the location information for certain duration.

The speed distribution shows that in this survey buses generally maintain an average speed of 25 km/h with a maximum speed around 60 km/h with occasional higher speed (>100 km/h) especially on the expressways (Fig 38). Trains show an average speed of 40 km/h with maximum speed around 80 km/h in the inner city. Trams show an average speed of 20 km/h with a maximum speed of 60 km/h occasionally (mostly in the night and during off peak hours). However, average walking speed was recorded around 9 km/h with occasional spikes exceeding 15 km/h either due to brisk walking or momentary running or multipath effect (Fig 36). Table 9 presents the temporal distribution of different modes.



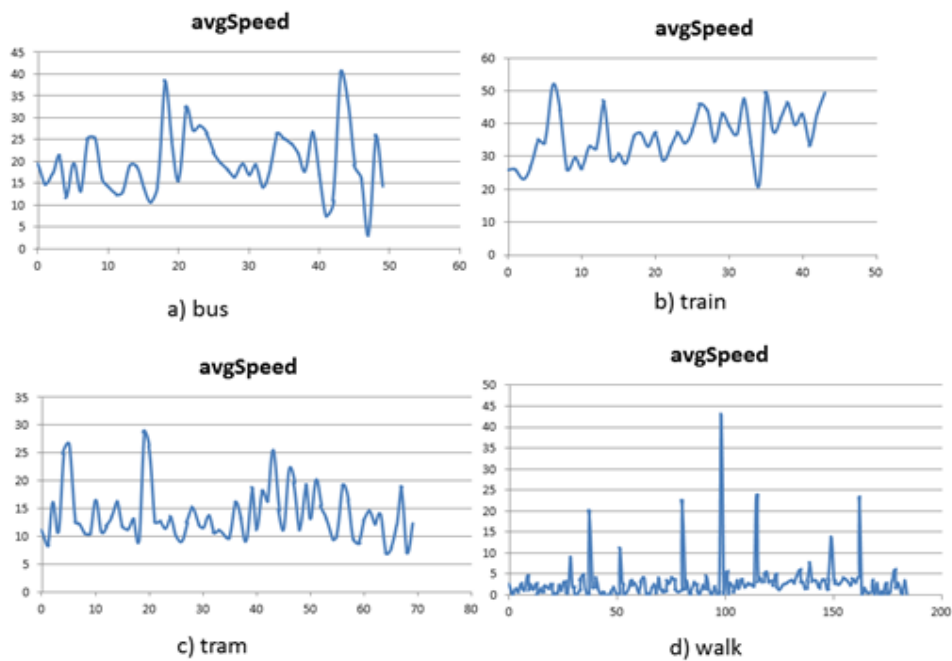


Figure 36: Average speed profile for different modes (derived from raw location information before filtration).

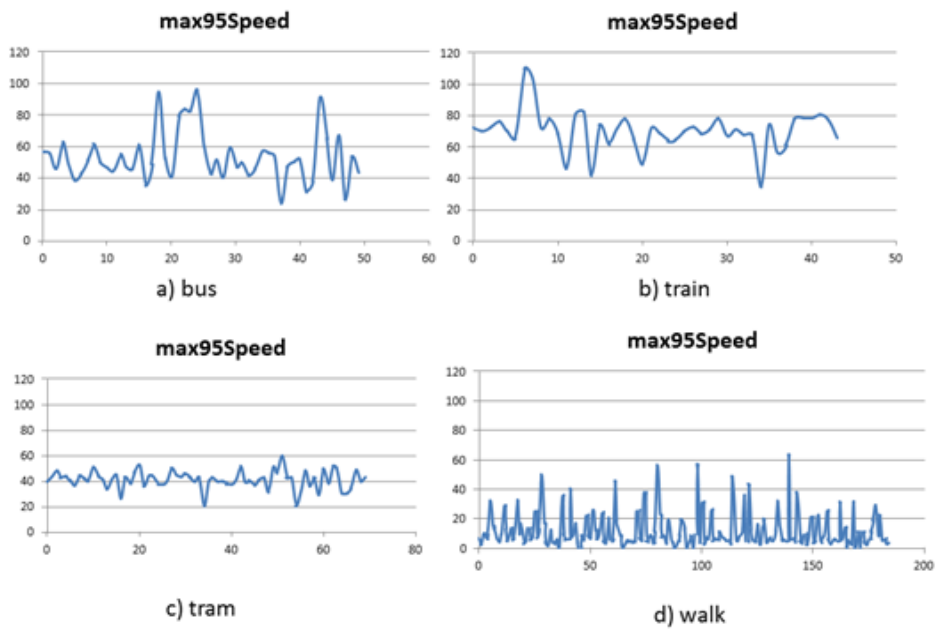


Figure 37: Maximum speed profile for different modes (before filtration).

### 5.4.2 Data preprocessing

Data preprocessing is performed as follows.

- GPS data pruning (noise removal) is done based on positional (in)accuracy. Any GPS sample point with accuracy less than 40 m is removed.
- Followed by the pruning a smoothing operation is performed on the trajectories using a spatial linear interpolation technique. Linear interpolation estimates the coordinate of an unknown location using the coordinates at two known locations along a straight line. Prior research have shown and tested the efficacy of linear interpolation technique due to its simplicity (Long, 2016; Nelson et al., 2015; del Mar Delgado et al., 2014; Wentz et al., 2003), and usefulness in comparatively on a fine grained trajectory.

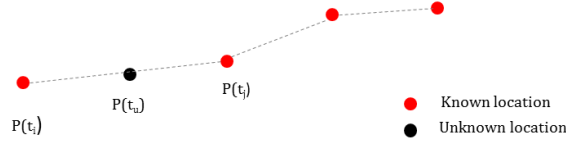


Figure 38: Linear interpolation at time  $t_u$

A linear interpolation estimates the coordinate at an unknown location  $P(t_u)$  at time  $t_u$  using two known locations  $[P(t_i), P(t_j)]$  recorded at time  $t_i$  and  $t_j$ , where  $t_i < t_u < t_j$ . In this research  $Z$  is composed of  $(x,y)$  in  $R^2$  space. Figure 39 shows how the linear interpolation operation populated the missing locations of a GPS trajectory.

$$P(t_u) = P(t_i) + \frac{t_u - t_i}{t_j - t_i} [P(t_j) - P(t_i)] \quad (12)$$

- Once the trajectories are interpolated, a speed-based filtering is done with the assumption that no high speed point should lie in between two low speed point and vice-versa with a 9 km/h low speed threshold. This ensures removing any sudden inaccurate GPS points for walking or waiting or moving in a vehicle. In order to perform spatial computation, especially proximity analysis, the trajectories are projected onto GDA94 coordinate system (zone 55) from WGS84. Following this, a walking-based segmentation segments a trajectory into a number of low speed and high speed segments. Over each segment, features are computed and then fed to a fuzzy inference system (FIS). A particular modal state is predicted based on maximum certainty factor. Figure 40 shows the entire workflow.



Figure 39: A raw trajectory with occasional signal loss (a), an interpolated smoothed trajectory after linear interpolation (b).

In this research five features are considered: average speed, 95th percentile of maximum speed, average spatial proximities to bus network, to tram network, and to train network.

### 5.4.3 Experiment

In order to compare the accuracies using only kinematic versus kinematic along with spatial information, different experiments are set up. Since earlier work (Bohte et al., 2008; Schuessler and Axhausen, 2009; Tsui and Shalaby, 2006) used velocity-based features to predict transport modes, the first experimental setup is designed with velocity-only features.

In the second experimental setup, spatial information is incorporated with kinematic information. In order to strengthen the reasoning process, spatial proximity of each GPS point in a trajectory to its nearest route network is evaluated. Walking is a very flexible type of transport mode taking place anywhere along any network except train networks, the proximity information to the different networks does not give much distinct information for the walking mode (Fig 36d). Hence while reasoning for walking, the focus was on speed as the average speed of walking is low. For trams the speed is *low* to *moderate* and close to the tram network. Bus and tram networks can occasionally coincide in inner city environments. However, the maximum speed of trams is less than the maximum speed of a bus in the observed environment. For

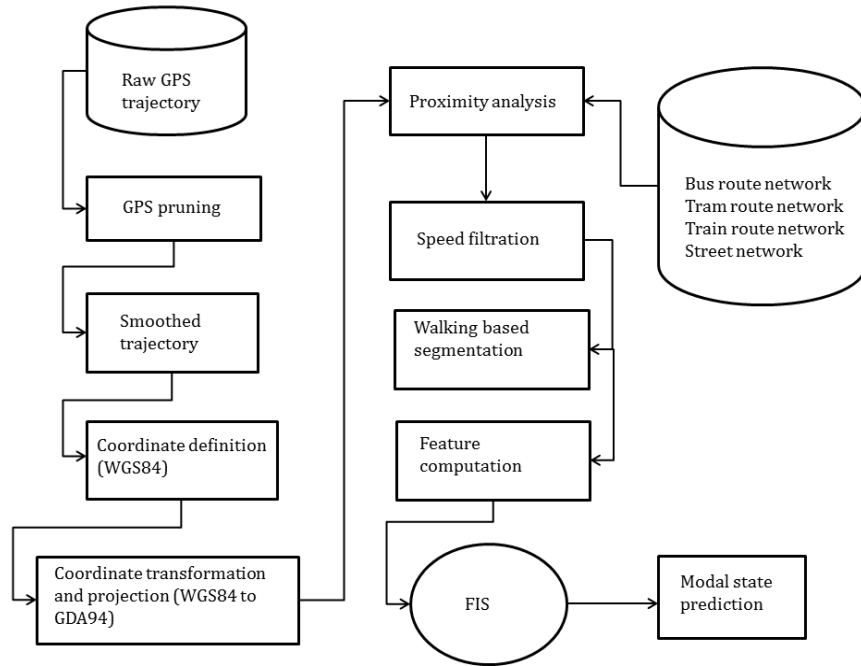


Figure 40: A workflow for MIMO Mamdani fuzzy inference system for mode detection.

trains, average speeds range from *moderate* to *high* and close to the train network, with less signal loss or multipath effects. In the second experimental setup 74 fuzzy rules are used.

it has been observed that due to signal loss and positional inaccuracy, sometimes proximity information is not useful. In order to address this issue a third experimental setup was designed consisting of 76 (74+2) fuzzy rules.

#### 5.4.4 Results

In order to measure the accuracy of the models, precision accuracy, and recall accuracy are used, which are based on true positives (tp), false positives (fp), true negatives (tn), and false negatives (fn). An F1-score is also used that combines the precision and recall together. The formula for precision accuracy, recall accuracy and F1-score are provided as follows:

$$\text{precision} = \frac{tp}{tp + fp} \quad (13)$$

$$\text{recall} = \frac{tp}{tp + fn} \quad (14)$$

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \quad (15)$$

For first experimental setup, two linguistic variables (features), average speed and the 95th percentile of maximum speed, are considered with the linguistic values high, moderate and low. The average accuracy ranges from approximately 56.68% to 52.91%. This happens as some of the modes show similar movement behaviours especially due to traffic congestion or GPS signal loss.

In the second experimental setup, the average recall accuracy is 70.98% and precision accuracy is 79.92%. The F1-score for walk is 0.81, for bus is 0.65, for train is 0.62, and for tram is 0.78. Most of the train trips are misclassified as bus trips and walking trips (Table 16).

Table 16: Confusion matrix of second experimental setup

Actual	Walk	Bus	Train	Tram
Predicted				
Walk	148	7	1	31
Bus	8	61	3	7
Train	13	24	37	6
Tram	15	99	0	14

In the third experimental setup when adding two more new rules (rule 75, 76) in the rule base, the accuracy has improved (see Appendix A, Table 17). In terms of average recall accuracy a G-G combination outperforms other combinations (Fig 42). In this experimental setup three different combinations are tested: G-G, Trap-Trap, and T-T.

*for function  
acronyms see  
Section 5.3*

The basic assumption for developing the rule base is that a given GPS point that belongs to a given transport mode should be located closer to the respective route network than that of the other networks. For example the GPS points during a bus trip should be closer to a bus route than that of a tram or train route. In terms of speed, train should show the highest speed compared to bus and tram, followed by walk. But this can only be comprehended in the presence of consistent and good-quality GPS signals. Figure 41 shows a distinct speed profile and proximity behaviour by three different transport modes in a given trajectory.

Figure 42 and Figure 43 demonstrate performance measure of the fuzzy model. The average recall accuracy ranges from 68% to 75% whereas the precision accuracy is 81% for all the combinations. However, in some cases for some feature vectors over given segments the predicted class scores for each mode were equal (50, 50, 50, 50). Such ambiguous segments reduce the recall and precision accuracy for a given mode. A G-G combination show no ambiguity whereas Trap-Trap and T-T combination show 25 ambiguous trips. In terms of individual modal accuracy, G-G combination produces maximum recall accuracy (90%) for the walk mode, followed by bus (78.48%), tram (69.76%) and train (61.72%). On the other hand, a T-T combination yields 100% preci-

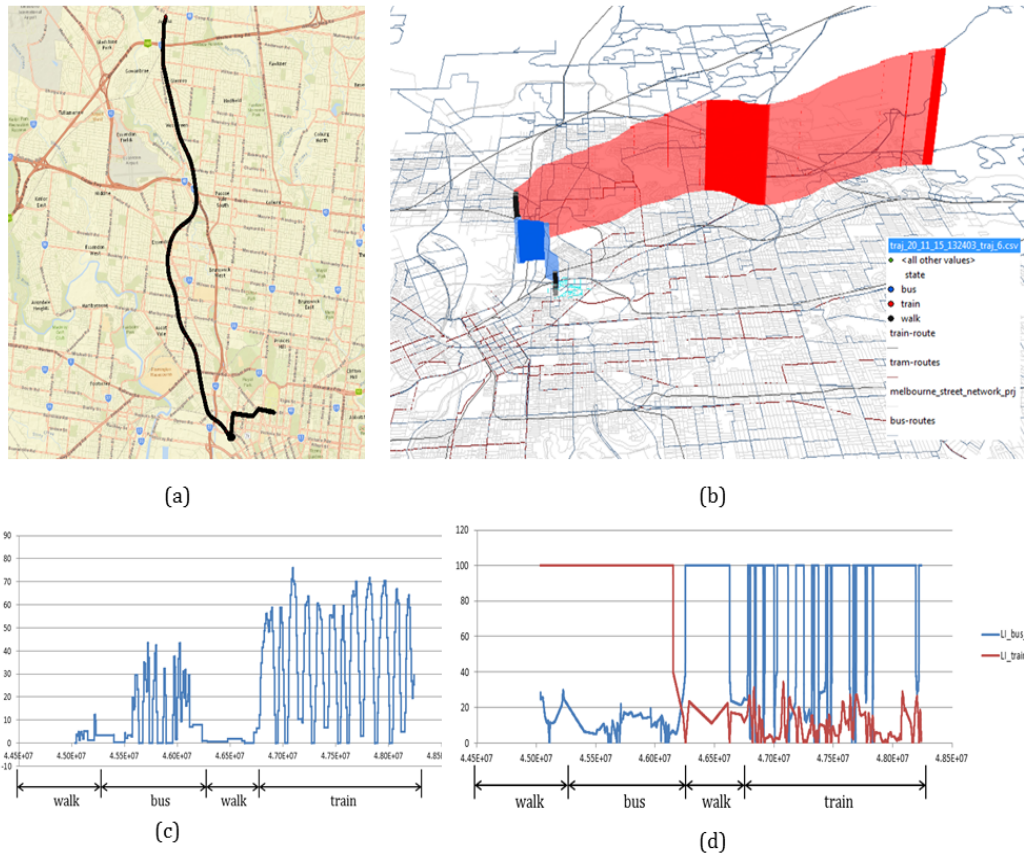


Figure 41: A trip from the University of Melbourne in the CBD to Jacana train station. Figure (a) shows the interpolated trajectory, (b) shows the space-time lamina to indicate how time elapsed during the travel, (c) exhibits different speed profile for walking, bus and train, and (d) exhibits the proximity to the respective route network during bus and train trip.

sion accuracy for train, followed by tram (88.88%), walk (72.36%) and bus (66.31%). For G-G and Trap-Trap combinations, the pattern is also same (Fig 43). Figure 44 shows the accuracies for all the combinations in terms of F1-score are always higher for walk mode .

The recall accuracy for bus is approx 78% in three combinations (Table 18). On the other hand, the precision accuracy for bus varies from 65% to 70%. For the train mode, recall accuracy varies from 39% to 61% whereas the precision accuracy is quite high, varying from 97% to 100% (Table 19). That means the rules developed for train mode are not exhaustive enough to retrieve all the train trips but the rules are accurate enough to detect train trips as true positives from the retrieved information. However, due to multipath effect and signal loss in some cases, train route proximity was too distal owing to difficulty to identify train modes. For tram mode, recall accuracy varies

from 58% to 69%, and precision accuracy varies from 87% to 89%. For walking, the recall accuracy varies from 85% to 90% and precision varies from 69% to 73%. Some of the non-walk modes are misclassified as walking especially during low speed condition subject to Type I error for walking. The rules, however, developed for train mainly emphasize on the fact that, in order to be a *train* mode a given moving object should move in close proximity to the train network with a high speed profile. This assumption is found to be true with most of the predicted train classes. This results in less Type I error for train mode compared to the other modes (Table 17). In order to measure the combined accuracy a  $F_1$ -score is computed for each mode which shows for walk mode  $F_1$ -score is highest for G-G and Trap-Trap combination which 0.81 and 0.76 respectively, and for T-T combination for walk and tram similar  $F_1$ -score (Table 20).

The results signify that appropriate selection of membership functions and their shape is important. The results also demonstrate the proper rule(s) inclusion is necessary to detect a given modal state. For example, using 74 fuzzy rules, 25 train trips and 19 train trips are misclassified as bus and walk respectively. But after including two additional fuzzy rules that can handle the proximity issue, the accuracy for train mode has increased with less Type II error with a drop in false bus mode from 25 to 12. To see the detailed rule base refer to [Appendix A](#).

Table 17: Confusion matrix of third experimental setup using 76 fuzzy rules (G-G combination)

Actual	Walk	Bus	Train	Tram
Predicted				
Walk	171	15	0	4
Bus	10	62	0	7
Train	19	12	50	0
Tram	32	7	0	90

Table 18: Recall accuracy using 76 fuzzy rules

Function Combination	Walk	Bus	Train	Tram	Avg
G-G	90.00	78.48	61.72	69.76	74.99
Trap-Trap	85.78	77.21	55.55	58.91	69.36
T-T	86.84	79.74	39.5	68.21	68.57

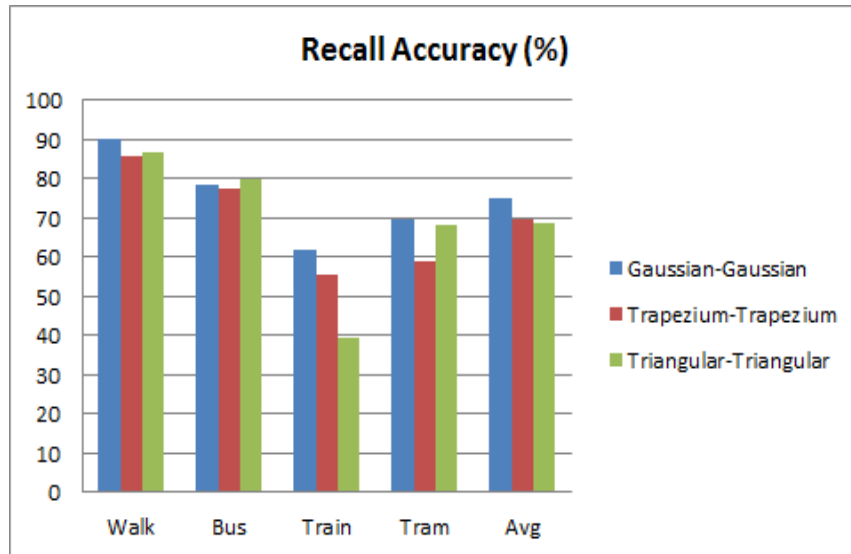


Figure 42: Average recall accuracy (vertical bars indicate accuracy measures for different transport modes. Different colours indicate different membership function combinations).

Table 19: Precision accuracy using 76 fuzzy rules

Function Combination	Walk	Bus	Train	Tram	Avg
<b>G-G</b>	73.70	65.26	98.03	89.10	81.52
<b>Trap-Trap</b>	69.36	70.93	97.82	87.35	81.36
<b>T-T</b>	72.36	66.31	100.0	88.88	81.89

## 5.5 DISCUSSION

In this research, a fuzzy logic based transport mode detection framework is developed and evaluated on a multi modal dataset collected across Greater Melbourne. The main contribution is developing a MIMO-Mamdani fuzzy inference model and testing different membership function combinations. The model is developed based on kinematic and non-kinematic (spatial) information.

Extending existing fuzzy models, a MIMO fuzzy model has been developed assuming a segment may contain possibility of different classes (modes) with varied certainty level. Earlier fuzzy models do not consider the fuzziness in their consequent part based on cognition in terms of linguistic labels and alternative possibilities. The earlier models directly quantified the consequent part based on rule firing without considering



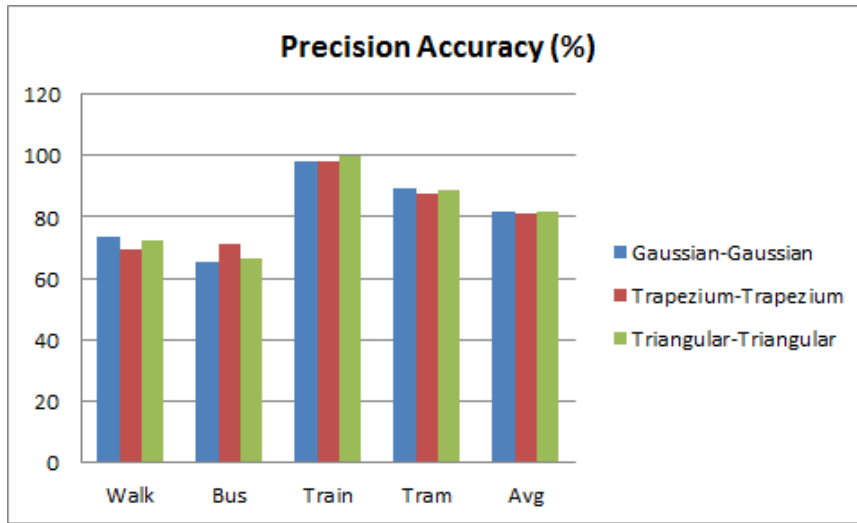


Figure 43: Average precision accuracy (vertical bars indicate accuracy measures for different transport modes. Different colours indicate different membership function combinations).

Table 20: F1-score using 76 fuzzy rules

Function Combination	Walk	Bus	Train	Tram
<b>G-G</b>	0.81	0.71	0.75	0.78
<b>Trap-Trap</b>	0.76	0.73	0.70	0.70
<b>T-T</b>	0.78	0.72	0.56	0.77

any linguistic value assigned to a consequent part. But this research expresses the varied degrees of certainty for a given modal class.

The results show that incorporating spatial information can increase accuracy significantly from 56% to 81%. However, by combining different membership functions in terms of number of ambiguous modal classes, a Gaussian-Gaussian combination works best compared to other combinations. The reason behind this is that for other membership functions (e.g., Trapezoidal, Triangular) the function itself is crisp in nature over a given range for a given linguistic value, and hence any value falling outside that range gets a membership value of zero. Thus in some cases, the model gets confused when the given input feature vector does not fall within the range defined by given membership functions owing to similar certainty value for four modes. Ambiguous results are also produced when the knowledge base is insufficient to capture

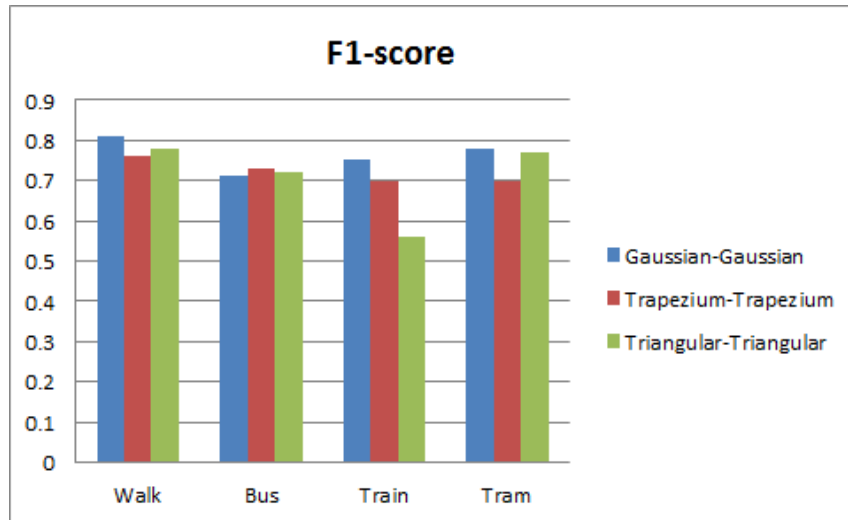


Figure 44: F1-score for different mode detection by different membership function combination.

different movement behaviour in terms of limitation in expert knowledge or sensor information.

Since a raw GPS trajectory involves occasional signal loss, it is important to smooth the trajectory using an interpolation technique. In this research a linear interpolation has been implemented (see Section 5.4.2). A linear interpolation works satisfactorily only when the signal gap is not very large as the interpolated points are plotted along a straight line between two known locations. In the case of a bigger signal gap, the uncertainty is higher and a simple linear interpolation would result in misleading location information. This particularly affects the proximity measurement which in turn will trigger the rules in improper way resulting in high Type I and Type II error. For example, during a train trip in the underground metro tunnel in the CBD, there was a signal gap for a certain period (Fig 45a). A linear interpolation has produced location information during that train trip. However, due to the geometrical nature of the interpolated GPS points, they show closer proximity to bus network which is 31 m for a queried point (see Fig 45b) and 191 m from the train network (Fig 45c). Whereas in reality the point is supposed to be closer to the train network. In order to deal with this kind of problem, more robust interpolation methods can be implemented in the future work such as a kinematic interpolation that relies on velocity measure at two known locations (Vishen et al., 2015), or a Bezier curve which assumes a curvilinear movement rather than a beeline movement (Long, 2016), or other probabilistic estimation techniques (Koyama et al., 2009).

Although the results show strong evidence supporting the hypothesis, the model still has some limitations at this stage. First of all, since the model is based on GPS

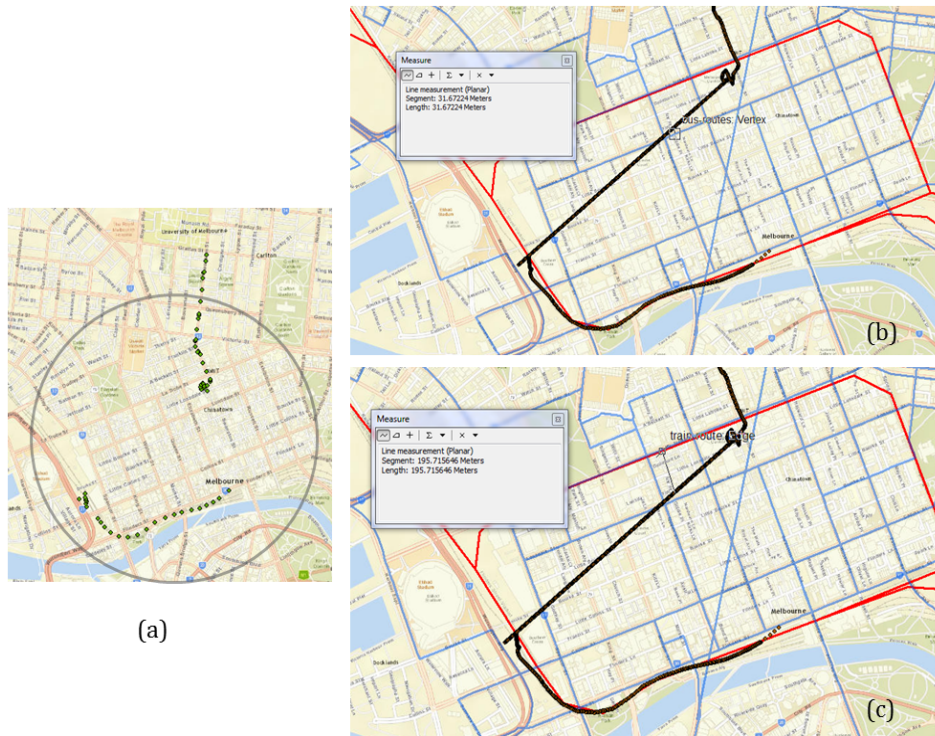


Figure 45: A train trip in the Melbourne CBD with occasional signal loss (a), proximity to bus network (b), proximity to train network (c).

readings only, it generates false positives and false negatives for different modalities during signal loss or in urban canyons. For example, sometimes the observed walking speed is unnaturally high due to multipath effects or passing through indoor environments. In urban environment in low speed condition where the vehicles are moving slowly, it is important to incorporate spatial proximity information. Though in a freeway when a bus moves at a high speed, there is a signal loss or noisy GPS measurement, it would be difficult to distinguish between bus and train modes.

That said, since the model is heavily dependent on speed and proximity, if both of these indicators pose ambiguous behaviours, additional information is required to resolve the ambiguity. For example, evidence of walking can be strengthened in indoor by measuring the radio signal strength (RSS) of nearby known hotspots or Bluetooth devices. The model has limitations with the average speed value calculated from two consecutive coordinates. This happens because of the noisy nature and semantic gap in the trajectories. This problem can be addressed by incorporating other infrastructure and inertial sensor information along with additional expert rules.

In this research, a speed based walking based segmentation is performed to segment a given trajectory into a number of low speed and high speed segments which are then

used to compute several kinematic and spatial features. The basic assumption behind such an approach is people need to walk in between two motorized or bicycle modes. But walking is context-sensitive and subjective which poses problem while setting the appropriate low speed threshold and distance threshold (for detailed discussion refer to [Chapter 7](#)).

The knowledge-based fuzzy model developed in this chapter is solely based on expert knowledge. The fuzzy rules are based on real world observations. As mentioned earlier in this Chapter, three different fuzzy membership functions are modelled manually through a trial and error method motivated by earlier work in the same line ([Biljecki et al., 2012](#)). Eventually, this is one of the limitations of a fuzzy knowledge driven approach where the model lacks adaptivity and automation. In order to automate the derivation of the sets and the rules, the fuzzy knowledge driven approach has been integrated with a machine learning based approach (neural network) and a hybrid neuro-fuzzy model (MLANFIS) is developed in [Chapter 6](#), which is more adaptive and at the same time, can explain its reasoning process through the rule based generated automatically. Since a hybrid model can learn from the training data, the membership functions are automatically tuned to their best possible configuration.

## 5.6 SUMMARY

Existing models on transportation mode detection are primarily based on machine learning algorithms, which require a considerable amount of training and falls short in representing the knowledge base and reasoning scheme. In order to address the incapability to handle the uncertainties and vagueness in the human thought process, a MIMO Mamdani-type fuzzy mode detection model is developed in this chapter. The model demonstrates that a fuzzy approach can yield 81% precision accuracy and 75% recall accuracy, which is at par with machine learning models, but without any requirement for a priori training. The results demonstrate that the way rules are developed can influence the mode prediction. For example, during signal gap or multipath effect some of the train modes do not show close proximity to the train network which has been handled by Rule 75 and 76 (see [Appendix A](#)).

The fuzzy model developed in this research shows that incorporating spatial information with kinematic information can improve the mode detection accuracy. The model also demonstrates its ability to model the kinematic uncertainties and the reasoning process in a human understandable format. In order to evaluate the model, a test runs with four modalities (walk, train, tram, bus) in an urban environment. However, the model can easily accommodate more modalities by extending the fuzzy inference engine in terms of variables and rules. The model can also allow integrating more sensor information. The fuzzy model presented in this chapter is a purely knowledge-driven model, which works effectively once the entire travel is complete.

Further investigations are required to understand how a purely fuzzy logic based knowledge-driven model behaves in near-real time.



## DETECTING URBAN TRANSPORT MODES USING A HYBRID KNOWLEDGE-DRIVEN FRAMEWORK

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Existing mode detection approaches extract travel information by interpreting the historical GPS trajectories. The existing approaches provide information in offline, once the entire travel is complete. Thus, the existing approaches are limited in terms of generating just-in-time mobility information. A just-in-time information can assist in understanding various dynamic phenomena e.g., real time mode specific patronage estimation. As mentioned in [Chapter 5](#), in order to detect the transport modalities from GPS trajectories, various machine learning approaches have already been explored. But majority of them produce only a single conclusion from a given set of evidences, ignoring the uncertainty of any mode classification (see [Chapter 5](#)). Also, the existing machine learning approaches lack the expressiveness. In contrast, a fuzzy knowledge-driven model can explain its reasoning scheme in a human readable format along with a provision of inferring different outcome possibilities, but lacks the adaptivity and learning ability. In this research<sup>1</sup>, a novel hybrid knowledge-driven framework is developed by integrating a fuzzy logic and a neural network to complement each other's limitations. Thus the aim of this research is to automate the tuning process in order to generate an intelligent hybrid model that can perform effectively in near-real time mode detection using GPS trajectory. Tests demonstrate that a hybrid knowledge-driven model works better than a purely knowledge-driven model and at par the machine learning models in the context of transport mode detection.

### 6.1 INTRODUCTION

The majority of transport mode detection research uses offline inference strategies on historical GPS trajectories (Section 2.3.3). In contrast, near-real time transport mode detection from a GPS trajectory is comparatively a new concept. Transport mode detection, being a classification problem, has been approached by artificial neural networks (ANN), support vector machines (SVM), decision trees (DT) and several other machine

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<sup>1</sup> The initial findings from this research was presented in the following conference workshop.  
Das, RD., Winter, S. (2016): A Neuro-Fuzzy based Hybrid Intelligent Framework for Transport Mode Detection, ACM SIGSPATIAL Workshop on Mobile Entity Localization, Tracking and Analysis, Burlingame, USA

An extended and revised version of this research is later published as follows:  
Das, RD., Winter, S. (2016): A Hybrid Knowledge-driven Framework for Urban Transport Mode Detection from GPS Trajectory, ISPRS International Journal of Geo-information, 5(11)

learning techniques so far (Byon and Abdulhai, 2007; Byon et al., 2009; Gonzalez et al., 2010; Reddy et al., 2010; Stenneth et al., 2011; Zheng et al., 2010, 2008), and less so by knowledge-driven models (Biljecki et al., 2012; Tsui and Shalaby, 2006). However, traditional machine learning techniques used in existing mode detection research provide limited functionality to express the uncertainties in a user's movement behaviour.

Besides, a machine learning model needs to be trained every time with a new training sample when there is a need to upgrade the model. A machine learning approach also lacks the transparency and expressiveness in its reasoning mechanism. On the other hand a knowledge-driven expert system approach is more expressive and allows semantic extraction from a given trajectory based on the kinematic observations.

In a near-real time scenario a purely knowledge-driven approach (see Chapter 5) does not perform well as the (expert) rule base may not capture all the possible situations. To address this issue, in this research, a hybrid knowledge-driven model is proposed that can bridge the trade-off between the learning ability and the expressiveness. The hybrid model proposed in this chapter is based on a Sugeno-type fuzzy inference process. Since a knowledge-driven (expert system) model can explain its reasoning scheme, the model can also reflect any anomaly in user's movement pattern or his/her driving behaviour based on the set of rules that are fired for a given set of input features, which is not very prominent by a machine learning model.

Although fuzzy logic based models are transparent and works based on an expert knowledge, but the success of a fuzzy knowledge-driven model lies in its proper selection of membership functions and their parameters. In case of a fuzzy logic based knowledge-driven model the membership functions and their parameters are selected manually. Thus, the model lacks the self-adaptivity and provide limited capacity under varying conditions, especially when there are large numbers of fuzzy variables (Siler and Buckley, 2004). Applied to trajectory interpretation, fuzzy models may not be of consistent quality with their given rule sets along with their membership function(s) over a given travel due to GPS multipath and signal loss, especially on shorter segments in the context of near-real time mode detection. Thus, a fuzzy inference model needs an automation to select its membership function parameters automatically by learning from a given input-output mapping. This is accomplished by integrating machine learning with a fuzzy system: only a neuro-fuzzy system is capable of developing a fuzzy expert system automatically with the provision of making modifications by experts in later phases without having proper training data.

Therefore, this research proposes an integrated multi-layered hybrid neuro-fuzzy framework for transport mode detection in the interest of public transport infrastructure. The framework combines an artificial neural network (ANN) with a Sugeno-type fuzzy logic (see Section 5.2.2) in order to enable the fuzzy inference system (FIS) to tune its parameters through an iterative learning process. At the same time, the model also makes the ANN more transparent by expressing the fuzzy knowledge base and reasoning scheme. The aim of this chapter is to develop a novel multi-layered neuro-



fuzzy-based hybrid intelligent knowledge-driven model that can perform better than Mamdani-type fuzzy models (see Section 5.2.2) and work at par with some of the state-of-the-art machine learning models, but has the ability to explain the reasoning scheme for near-real time mode detection. Thus, this research hypothesizes that *a hybrid neuro-fuzzy approach will bridge the gap of ability to represent knowledge and learning capacity in an uncertain condition and compensate the trade-off between a machine learning-based approach and a fuzzy logic expert system and can develop a more robust and transparent classification than that of its counterparts in transport mode detection in near-real time.*

The contributions of this chapter are as follows:

- (a) To the best of the author's knowledge, this is the first work in the field of transport mode detection where a hybrid intelligent model is developed using a machine learning approach and a fuzzy expert system.
- (b) This work investigates the performance of a hybrid knowledge-driven model compared to a purely knowledge-driven model and machine learning models.
- (c) This research also presents a novel approach to deal with multi-class problems, using a multi-layered neuro-fuzzy model. Most of the hybrid models used in other areas of transportation research so far, deal with regression problems such as travel time estimation, demand estimation, mode choice behaviour or flow behaviour. However, this research develops an adaptive and multi-layered hybrid intelligent model to address the transport mode classification problem.

In this research, the term "near-real" time has been introduced for the first time in transport mode detection research. Detecting transport modes in near-real time resembles to activity recognition on a second-by-second basis in pervasive and mobile computing (Bao and Intille, 2004; Bulling et al., 2014). However, for practical reasons, activity recognition (in the context of body part movement and gesture recognition) at a finer granularity based on inertial sensor data can be performed comparatively within a shorter time window (typically in the order of 1 s–10 s) than the length required for transport mode detection using GPS (typically in the order of 60–120 s). This temporal difference is due to the temporal delay in GPS signal updates typical on commercial smartphones. Thus, instead of using the term "real time", this research uses the term "near-real time" to indicate the granularity of the query window in a qualitative way. The model presented in this research is compared with a multiple-input multiple-output (MIMO) Mamdani fuzzy inference system (MFIS) and some machine learning models, and the results demonstrate the efficacy of the model in terms of its consistency in performance and reasoning ability.

The remainder of the chapter is organized as follows. Section 6.2 presents a brief theory of the fuzzy and neuro-fuzzy model. In Section 6.3, a near-real time mode detection architecture is presented, followed by an implementation and evaluation in Section 6.4. A discussion is presented in Section 6.5. In Section 6.6, summary and possible future research directions are presented.

The hybrid approach has been successfully used in other contexts already, such as in traffic modelling, different transportation control systems and people's mode choice behaviour.

For example, Panella and colleagues developed a neuro-fuzzy model to address vehicular traffic flow in an urban environment. They developed a centralized system where the vehicular movement data are transmitted and based on the kinematics, a particular flow state is determined. They used a hyper-plane clustering technique in the training stage (Panella et al., 2006). Neuro-fuzzy systems have been also used in traffic control in different types of intersections. Henry and colleagues show a neuro-fuzzy model working satisfactorily at intersections with simple and medium complexity. At more complex intersections, a neuro-fuzzy model needs integration with an optimal control (Henry et al., 1998). Wannige and colleagues developed a neuro-fuzzy-based traffic control system in their simulated study. They used two four-way traffic junctions and a road connecting both the junctions. They have investigated how traffic behaviour changes on that particular road segment between the two junctions and how the traffic system adapts with varying conditions. Their study shows that a neuro-fuzzy logic-based traffic control system works better than a fixed-time signal control system. The model also minimizes the delay time significantly during red light phases at each junction. Wannige and colleagues also showed how traffic lights at both of the junctions synchronize adaptively when the volume of traffic increases significantly at one of the two junctions (Wannige and Sonnadara, 2009). In a slightly different work, Dell'Orco and colleagues developed a neuro-fuzzy model to predict users' decisions in transport mode choice (Dell'Orco et al., 2008). Their assumption is based on the uncertainty and imprecision in data in an urban environment. Using simple fuzzy rules, they have demonstrated how users' perception can be encoded in linguistic attributes. The model performs better in forecasting users' mode choice behaviour than that of a random utility-based model.

Although neuro-fuzzy models have been used in regression problems e.g., traffic estimation, but the models have not been used to solve transport related classification problems yet, for example, travel mode detection. Due to the particularities of travel modes, the presented model will have some distinctive properties, which are discussed in the subsequent sections.

## 6.2 THEORY

In this section, some basic concepts are presented related to the proposed hybrid model presented in this chapter.

### 6.2.1 Near-real time mode detection

In contrast to a real-time mode detection, this research deals with a near-real time mode detection. The difference between the two concepts lies in the delay in response time. For a real-time detection the location information is pinged on a second-by-second basis or at a very fine granularity. The commercial Android-based smartphones, however, suffer from battery drainage on heavy usage of GPS. In addition to that, in an urban environment, the GPS trajectory involves frequent signal gaps and multi-path effects, which make a fine-grained sample unreliable for detecting the modes. On the other hand, in contrast to body part movement in the context of activity recognition in pervasive and mobile computing (Bao and Intille, 2004), the transport mode does not change so frequently within a few seconds, and thus, a comparatively more coarser-grained time window containing more than one piece of GPS location information is deemed to be useful for detecting modes in the interest of close to real-time information retrieval for various mobility-based service provisions. Figure 46a shows a real-time mode detection concept where the smartphone continuously pings its location information to a central server on a second-by-second basis (or at an interval set by the sampling frequency), whereas Figure 46b shows for a near-real time scenario a shorter sequence of GPS points being sent to the central server over a given time window containing richer kinematic information for mode detection.

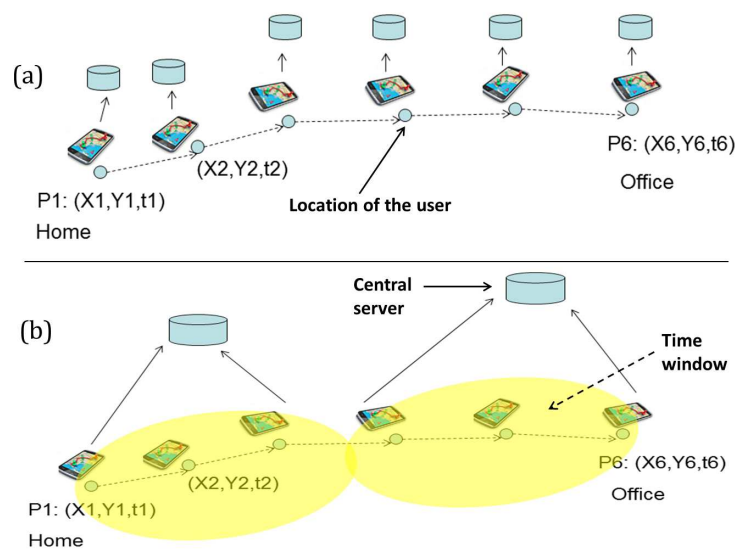


Figure 46: This figure illustrates how the location information is pinged at a real time scenario (a) and at a near-real-time scenario (b), while travelling from home to office.

Chapter 5 presents a Mamdani fuzzy logic based framework to detect transport modes on historical trajectories. In contrast, in this chapter a Sugeno fuzzy model is

developed to detect transport modes in near-real time. The model is also compared with a Mamdani based model in near-real time. A Sugeno fuzzy model involves a fuzzy antecedent and a crisp consequent part, which is generally expressed in terms of a polynomial function of order 'n'. A Sugeno fuzzy rule can be represented as follows.

$R_{s1}$  : **IF** avg\_speed is high and avg\_acceleration is uniform, **THEN** delay\_time is 10 sec.

Unlike Mamdani fuzzy model, in the case of a first order Sugeno fuzzy model, on firing each, rule the consequent part takes on a crisp value in terms of a number of coefficients (p, q, r) based on a given function. For example, in the previous example, in Rule 1, when  $A_1 = y_1$  and  $A_2 = y_2$ , the output  $C_1=f(y_1, y_2)$ , where:

$$f(y_1, y_2) = py_1 + qy_2 + r \quad (16)$$

Each rule ( $R_i$ ) weighs its output by a firing strength  $w_i$ . Once all of the rules are fired, a weighted average is used to generate  $F_o$  for a given Sugeno model.

$$F_o = \frac{\sum w_i.C_i}{\sum w_i} \quad (17)$$

In the case of a zero order Sugeno model, p and q essentially become zero. Both the conventional Mamdani and Sugeno fuzzy models are dependent on proper rule base and membership functions. Often, it is difficult to choose a proper membership function along with its characteristic parameters for a given fuzzy set. Fuzzy expert systems also cannot learn in varying conditions and need a human expert intervention for modification. In order to select the membership function parameters automatically and in turn construct the rule base, a hybrid knowledge-driven technique, such as an adaptive neuro-fuzzy inference system (ANFIS), is required.

### 6.2.2 Adaptive neuro-fuzzy inference system

An adaptive neuro-fuzzy inference system (ANFIS) is a neuro-fuzzy-based hybrid model that is equivalent to a Sugeno fuzzy model by its operation and reasoning process, whereas it is equivalent to a neural network (with a connectionist structure) by its architecture and learning ability (Negnevitsky, 2002). ANFIS requires a training phase that initializes the knowledge base with a set of rules and membership functions with automatically-selected function parameters. The training takes place through a number of iterations. A standard ANFIS model follows a hybrid learning using a forward and backward pass (Jang, 1993). An ANFIS model consists of five layers.

Layer 1 is a fuzzification layer. The inputs are fuzzified in this layer based on the respective membership functions. In Figure 47, the nodes  $A_i$  and  $B_i$  are linguistic values of input  $x$  and  $y$ , respectively. The parameters involved in the given membership function are called antecedent parameters. The nodes in Layer 1 are adaptive nodes

in the sense that the nodes will keep on changing the antecedent parameters during the training stage to achieve minimum errors. Layer 2 contains the rule base with a t-norm operator which is generally considered as equivalent to a MIN or a product operator (Bobillo and Straccia, 2011). The nodes in Layer 2 are all fixed nodes. Each node in Layer 2 emits a firing strength ( $w_{li}$ ) of the corresponding rule, where ( $w_{li}$ ) can be expressed as:

$$w_{li} = \prod_i^V \{\mu_A(x_i)\} \quad (18)$$

where  $\mu_A(x_i)$  is the membership function of fuzzy set A for a linguistic variable i for a given rule r, assuming the total number of linguistic variables is V. The firing strengths are then normalized by the nodes in Layer 3 as follows:

$$s_r = \frac{w_{li}}{\sum_l^n w_{li}} = \frac{\prod_i^V \{\mu_A(x_i)\}}{\sum_l^n \prod_i^V \{\mu_A(x_i)\}} \quad (19)$$

where l is the layer number, and r is the node number in a given layer and n is the total number of nodes in Layer l.

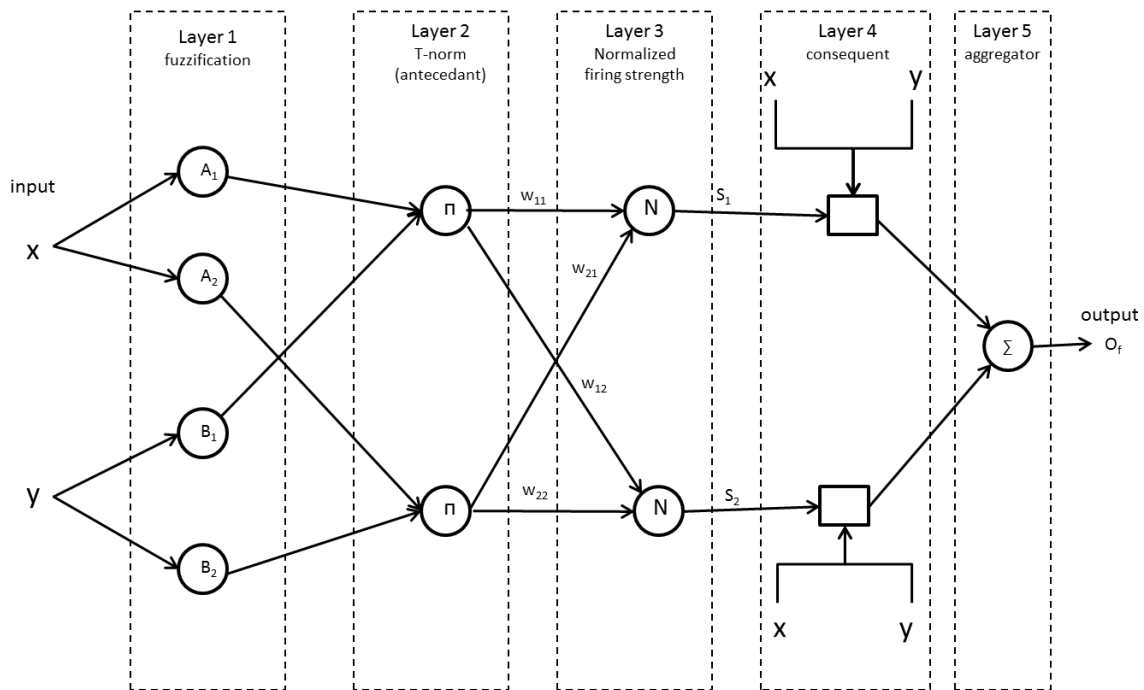


Figure 47: A basic adaptive neuro-fuzzy inference system (ANFIS) architecture.

Layer 4 computes the consequent part of each rule based on the firing strength. An ANFIS model is based on a Sugeno architecture for computing its consequent part. A first order Sugeno model computes a consequent part as follows:

$$O_r = s_r(a_r x + b_r y + p) \quad (20)$$

where  $O_r$  is an output in a consequent part for rule  $r$ ,  $s_r$  is the normalized firing strength and  $a_r$ ,  $b_r$  and  $p$  are consequent parameters. Layer 5 aggregates all of the individual consequent parts from of the respective rules and defuzzifies to generate the overall output ( $O_f$ ):

$$O_f = \sum s_r f_r = \frac{\sum_r^n s_r (a_r x + b_r y + p)}{\sum_r^n s_r} \quad (21)$$

In the case of a zero-order Sugeno model, the consequent part simplifies into  $p$ . The consequent parameters are tuned in a forward pass using a least square estimation where the error term ( $E$ ) can be expressed as:

$$E_k(a, b) = \sum_{t=1}^N (T_k - (a_k x + b_k y + p))^2 \quad (22)$$

where  $E_k(a, b)$  is the error term for the  $k$  – th entry in the training data,  $T_k$  is the target output for the  $k$  – th entry, and  $N$  is the total number of iterations. Thus, the overall error is:

$$E = \sum E_k \quad (23)$$

The objective is to minimize  $E_k(a, b)$ , and hence, the objective functions can be mathematically expressed as

$$\frac{\partial(E_k(a, b))}{\partial a} = 0, \frac{\partial(E_k(a, b))}{\partial b} = 0 \quad (24)$$

In order to determine the antecedent and consequent parameters a hybrid back propagation technique is used. The consequent parameters, are determined through a least square estimation in a forward pass, whereas the antecedent parameters are determined using a gradient descent technique in backward pass. The rules can be generated in one of three ways: grid partitioning, subtractive clustering or fuzzy c-means clustering (FCM). In this research, a grid partitioning technique has been used to search the entire input space and generate all of the possible rules. Hence, if  $V$  is the number of linguistic variables, and  $m$  the number of linguistic values for each variable then the total number of rules  $n$  is:

$$n = V^m \quad (25)$$

### 6.3 KNOWLEDGE-DRIVEN FRAMEWORKS FOR NEAR-REAL TIME TRANSPORT MODE DETECTION

In this section, two fuzzy logic-based knowledge-driven models are developed. In the first framework, a MIMO Mamdani fuzzy inference system (MFIS) is developed, which is based on a priori expert knowledge (without any training). In the second framework, a hybrid knowledge-driven model is developed using a neuro-fuzzy approach.

#### 6.3.1 Framework 1: Multiple-input multiple-output Mamdani fuzzy model

The MIMO MFIS presented in this research consists of a fuzzy inference engine consisting of 76 fuzzy rule sets (rule base). The antecedent part contains five fuzzy variables with three fuzzy values for each of the variables (Table 21). The consequent part consists of four alternative solutions (*bus, train, tram, walk*) with their corresponding certainty factors (CF) ranging from 0 to 100. The rules are developed in such a way that they can handle different quality (inaccuracy level) in positional information and different kinematic behaviour shown by a given transport mode. In order to combine different facts in the antecedent and consequent part, a t-norm operator (AND) is used. The fuzzy variables in the consequent part are independent of each other; however, their certainty value (CF) depends on the rule firing and a given input feature vector. In order to defuzzify the consequent outputs, a center of gravity method is implemented. The membership functions are all selected manually. Figure 48 shows a MIMO MFIS model developed in this research. Some of the fuzzy rules (out of 76) are as follows.

**R1:** IF avgSpeed is low AND maxSpeed is low AND avgBusProx is far AND avgTrainProx is far AND avgTramProx is moderate, THEN CF for walk is high AND CF for bus is low AND CF for train is low AND CF for tram is low.

**R2:** IF avgSpeed is moderate AND maxSpeed is moderate AND avgBusProx is near AND avgTrainProx is far AND avgTramProx is far, THEN CF for walk is low AND CF for bus is high AND CF for train is low AND CF for tram is low.

**R3:** IF avgSpeed is moderate AND maxSpeed is moderate AND avgBusProx is moderate AND avgTrainProx is far AND avgTramProx is moderate, THEN CF for walk is low AND CF for bus is moderate AND CF for train is low AND CF for tram is high.

**R4:** IF avgSpeed is high AND maxSpeed is high AND avgBusProx is far AND avgTrainProx is near AND avgTramProx is far, THEN CF for walk is low AND CF for bus is moderate AND CF for train is high AND CF for tram is moderate.

**R5:** IF avgSpeed is moderate AND maxSpeed is high AND avgBusProx is far AND avgTrainProx is far AND avgTramProx is far, THEN CF for walk is low AND CF for bus is high AND CF for train is low AND CF for tram is low.

Table 21: Fuzzy variables and their fuzzy values for MIMO Mamdani fuzzy inference system (MFIS).

Fuzzy Variable	Fuzzy Value
<b>Antecedent</b>	
Average speed (avgSpeed)	low, moderate, high
Maximum speed (maxSpeed)	
Average proximity to the bus network (avgBusProx)	near, moderate, far
Average proximity to the train network (avgTrainProx)	
Average proximity to the tram network (avgTramProx)	
<b>Consequent</b>	
CF for bus	low, moderate, high
CF for train	
CF for tram	
CF for walk	

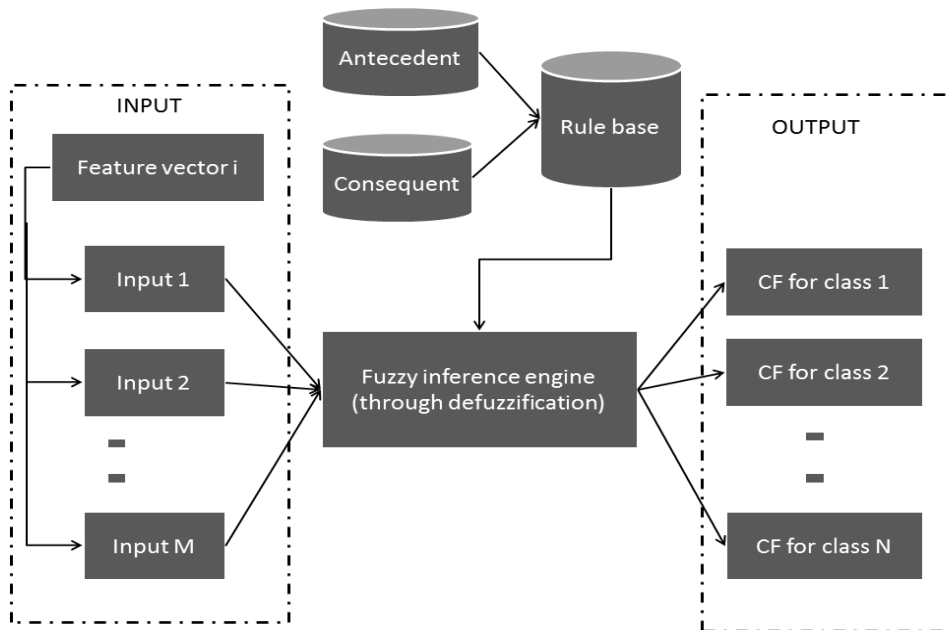


Figure 48: A MIMO MFIS model with M number of input and N number of classes with their varied certainty values. In this research, M = 5 and N = 4.



### 6.3.2 Framework 2: Multi-layered adaptive neuro-fuzzy model (MLANFIS)

In existing transportation research and traffic control systems, ANFIS models deal with regression-type problems. In contrast, in this research, a multi-class problem has been posed, requiring to developing a multi-layered ANFIS (MLANFIS) model in order to provide a near-real time transport mode detection framework (Fig 49). The core of the framework is a processing layer that contains a number of ANFIS modal blocks in parallel connection, where each ANFIS modal block corresponds to a given class. If there are  $K$  numbers of classes, then there will be  $K$  numbers of ANFIS modal blocks. Hence, the cardinality of the framework is  $K$ . Since each ANFIS modal block is trained in parallel without any direct connection in between them, each ANFIS modal block contains its own rule base.

In this research, transport modes are categorical in a classification problem, which is not possible to deal with in a standard neuro-fuzzy approach due to its very nature of generating continuous real values. Hence, the classification problem is converted to a regression problem first, where each ANFIS modal block deals with a binary evaluation of a given modal class. An ANFIS modal block is attributed by a specific modal class (categorical value) it deals with and a level of certainty (real value) of being a given modal class. For each modal class, a separate set of training samples (training instances) and an ANFIS model are developed. In each training set, each feature vector is of a certainty factor (CF) of either zero or one, which quantifies the belongingness of that given feature vector to a given class. Hence if there are  $K$  numbers of modal classes, then there are  $K$  numbers of training sets, where each set of training samples contains the same set of feature vectors, but different output patterns. For example, the modal class *bus* contains samples in the given feature vector that are segments of a trajectory representing a bus ride, then the output is quantified in terms of a CF of one (see Section 5.2.2). If the feature vector is not of a bus ride, then the output CF is quantified as zero. This process is iterated for all of the instances in each training set for  $K$  modal classes. The logic behind such certainty quantification is that each ANFIS block (corresponding to a given modal class) will be trained in such a way that if it ( $ANFIS^T$ ) is fed with a test sample ( $fv_t$  : testfeaturevector), it will assign some CF as an output through its reasoning process depending on the input feature vector. If the sample represents a given modality, it will get the maximum CF corresponding to that ANFIS modal block.

The framework consists of four layers (Fig 49). Layer 1 is the input layer, which contains the input feature vector. Layer 2 is the processing layer, which consists of trained ANFIS modal blocks ( $ANFIS^T$ ), one for each class. Layer 3 is the output layer for each ANFIS modal block. Layer 4 is the evaluation layer where all of the CF outputs are aggregated and evaluated using an *argmax* operator to select the maximum value. The predicted class for that given input feature vector is then determined based on the maximum CF generated by the respective trained ANFIS modal block. Thus, in

near-real time each query is assessed in parallel in different ANFIS modal blocks, and a modal class is predicted based on the maximum CF value.

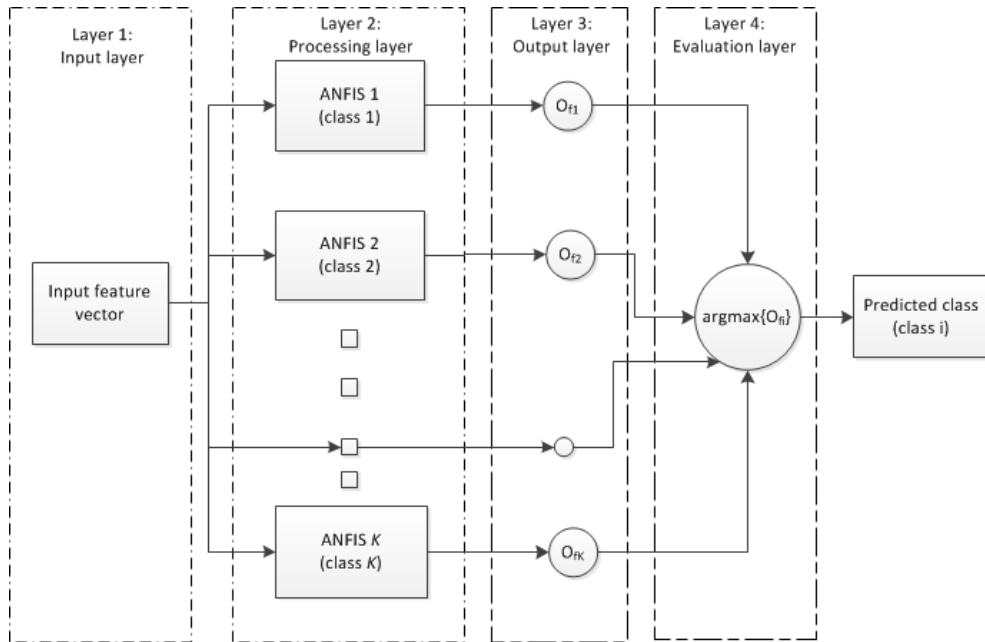


Figure 49: Multi-layered ANFIS framework for mode detection (MLANFIS).

## 6.4 EVALUATION

### 6.4.1 Data set

In order to evaluate the hypothesis and test the model, a GPS dataset had been collected in Greater Melbourne, Australia, for 85 h which covers four modalities, *bus*, *train*, *tram* and *walk*, which are four common public modalities in an urban environment (see 3.2, Fig 19).

The data set covers modalities of similar features on different routes, as well as different modalities on overlapping routes e.g., portion of the bus network overlaps with the tram network (Fig 14). Since in this research, a near-real time mode detection is performed, i.e., no prior segmentation can be produced, there is a possibility that within any given time window, two modalities may exist together. In this case, it is assumed that always one of them is walking, as only a walk connects between two different non-walking modalities. For this to hold always true, the extent of the time window must be chosen smaller than any individual walking segment. That co-existing modes over a given time window is termed as a *composite* mode. From observation within a shorter temporal window (say 60 s to 120 s) there could be a maximum of two co-

existing modes, one of which must be *walk*. Hence, all of the *composite* modes in this research are labelled as *walk*.

#### 6.4.2 Preprocessing and feature preparation

Before generating the feature vectors, each trajectory is pre-processed. A preprocessing stage involves filtering a trajectory based on positional accuracy, where any GPS point with positional accuracy  $<40$  m (i.e., the major axis of the confidence ellipse is  $> 40$  m) is considered as noise and eliminated from the trajectory. The raw GPS data were collected in WGS84 coordinates. In order to perform spatial analysis, the dataset was projected onto the GDA94 coordinate system followed by feature computation.

In this framework, five features are computed: *average speed*, *maximum speed* (which is actually 95th percentile of maximum speed), *average proximity to bus network*, *average proximity to tram network*, and *average proximity to train network*. Since walking can take place anywhere (say close to a bus route or a street or a train network during transfer) the nearness to the street network is not utilized in this research. Proximity values are computed using a spatial buffer of 40 m (assuming standard GPS positional accuracy in this research) of each GPS point to its nearest bus network, train network and tram network. In case there is a network absent within a 40 m radius, the proximity value to that network from a given GPS point is assigned as 100 m to avoid a null value, or zero proximity. The data set is split up into training, checking and testing data sets. The trajectories selected as the training data set are of higher travel time duration than the trajectories used to generate checking and testing data set, and hence the number of features for training is always higher than the checking (and testing data) in all the experimental setups (Table 22). After training the four ANFIS modal blocks, each of them generates 243 distinct fuzzy rules.

#### 6.4.3 Experiment

Five sets of experimental setups are designed based on growing time window size starting from 30 s, 40 s, 50 s, 60 s and 120 s. In order to compare the performance of the proposed framework (MLANFIS) a number of machine learning models are also developed based on a multi-layered perceptron neural network (MLP), a radial basis function-based neural network (RBF), a decision tree (DT), K-nearest neighbor (KNN), and a naive Bayes (NB). The result shows at a 60 s and a 120 s time window that MLANFIS yields significant accuracy for detecting different transport modes in near-real time.

In order to evaluate, the same training and testing data have been used for the MLANFIS model and all of the machine learning models. Since MFIS does not require to be trained, hence an MFIS model evaluated using only a testing dataset, which has been used to test the predictive ability of MLANFIS and the machine learning models.

A checking dataset is used while building the MLANFIS model in order to make sure the model does not get over-fitted. Table 22 shows the number of features used as training, checking and testing datasets for different models. Figure 50 shows how checking error and training error vary with the number of iterations (epochs). A total of 200 iterations are performed for each MLANFIS modal block building. A training error shows a gradual decrease in magnitude over 200 iterations. On the other hand, the checking error shows a gradual decrease in magnitude up to a certain epoch followed by a sudden increase in magnitude. That critical epoch point indicates the moment when the model starts getting over fitted. The membership function parameters are selected at that particular given epoch before the checking error gets increased.

In order to measure the accuracy of the models, precision accuracy, and recall accuracy are used, which are based on true positives (tp), false positives (fp), true negatives (tn), and false negatives (fn).

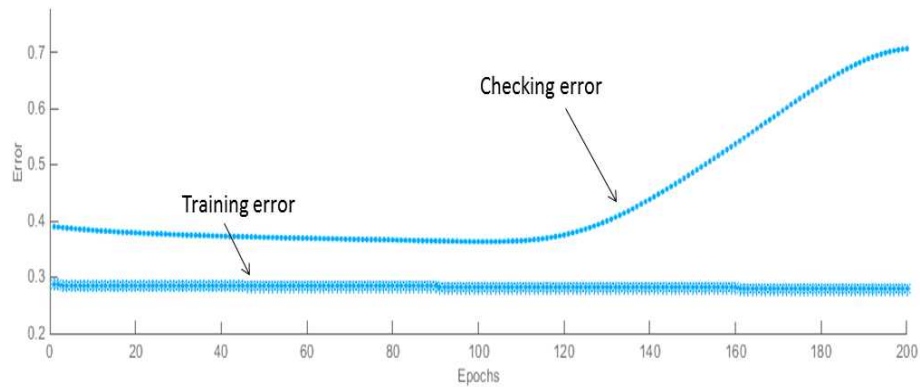


Figure 50: An over-fitting in *walk* modal block in MLANFIS.

Tables 23 and 24 show recall and precision accuracy of seven different predictive models, including an MLANFIS and MFIS at 60 s time window. In terms of recall accuracy, MLANFIS outperforms the MFIS model and performs on par with the machine learning models for *walk*, *train*, *tram* mode. On the other hand, MLANFIS performs poor in terms of recall accuracy for *bus* when compared to the machine learning models. On the other hand, the MFIS model performs better than MLANFIS and other machine learning models in terms of precision accuracy, particularly for *train* (96.86%) and *tram* (87.91%). MLANFIS works best and very close to an RBF model in terms of precision accuracy for *bus* (92.19%). This suggests the rules generated for bus ANFIS block in MLANFIS model are properly tuned and thus giving rise to less Type I error for *bus* when evaluated by a MLANFIS. However, the rules in the *bus* ANFIS block are not sufficient enough to capture all of the kinematic behaviour and signal quality during a bus ride, and hence, although MLANFIS generates less Type I error, but higher Type II error for *bus*, that led to low recall accuracy for *bus* mode, when compared

Table 22: Number of features used for training, checking and testing.

Time Window (s)	Features Type	MLANFIS	Machine Learning	MFIS
30	Training	21,279	21,279	-
	Checking	13,459	-	-
	Testing	10,099	10,099	10,099
40	Training	15,665	15,665	-
	Checking	9894	-	-
	Testing	7433	7433	7433
50	Training	12,390	12,390	-
	Checking	7814	-	-
	Testing	5876	5876	5876
60	Training	10,243	10,243	-
	Checking	6456	-	-
	Testing	4859	4859	4859
120	Training	5011	5011	-
	Checking	3132	-	-
	Testing	2371	2371	2371

with the machine learning models. Since different predictive models perform differently for different modes in terms of precision and recall, hence in order to evaluate the overall performance of the models, an F1-score (F) is considered, which combines the precision and recall together.

In terms of F1-score, MLANFIS performs similarly as MLP and DT for walk mode detection and outperforms a MFIS and all other machine learning models (Fig 51). MLANFIS outperforms all other models for train mode detection. For train mode detection, MLANFIS yields 0.91 F1-score followed by 0.88 by MLP, which is the highest F1-score generated by any machine learning model. For tram mode, MLANFIS yields 0.82, which is very close to MLP, which yields 0.84, and a DT model, which generates a 0.81 F1-score. On the other hand, for bus mode detection, MLANFIS generates 0.76 F1-score, which is less than the machine learning models, but higher than the MFIS model (Fig 51).

Table 23: Recall accuracy (%) at a 60 s time window.

Mode	MLANFIS	MFIS	RBF	MLP	NB	KNN	DT
Walk	92.58	93.47	85.60	91.10	83.80	88.60	89.30
Bus	65.21	61.20	69.60	77.60	74.90	77.30	74.70
Train	93.33	61.77	93.80	93.30	91.30	88.60	95.30
Tram	84.16	60.06	79.30	85.10	89.80	79.50	82.60

Table 24: Precision accuracy (%) at a 60 s time window.

Mode	MLANFIS	MFIS	RBF	MLP	NB	KNN	DT
Walk	88.94	80.33	88.40	91.90	92.80	90.10	91.30
Bus	92.19	65.12	92.00	85.00	87.50	80.10	85.60
Train	89.74	96.86	73.10	80.90	85.80	82.20	77.40
Tram	80.78	87.91	70.30	84.10	64.80	77.20	79.40

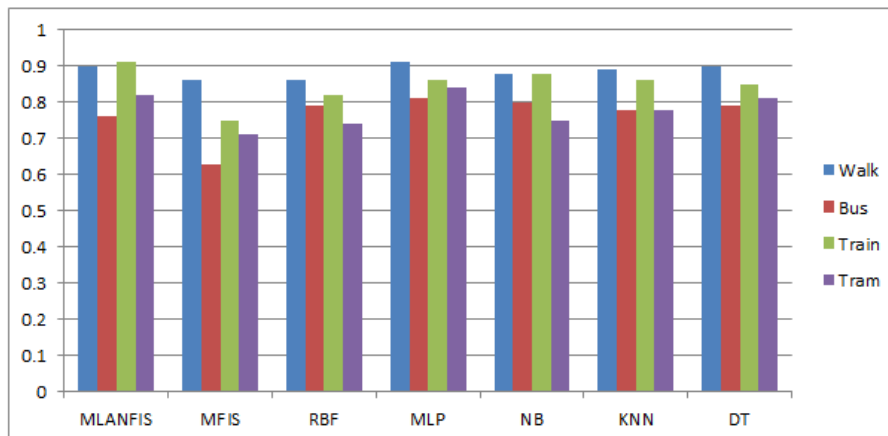


Figure 51: F1-score at a 60 s time window.

When evaluated within a 120 s time window, MLANFIS shows the same pattern in terms of recall and precision accuracy, as well as the F1-score. MLANFIS yields the highest recall accuracy for *walk* mode, which is 92.87%, seconded by MFIS and DT, which are approximately 91.4%. For *train* mode detection, RBF yields the highest recall accuracy, which is 99.10%, whereas an MLANFIS generates 94.31% accuracy. On the other hand, an MFIS generates 74.40% accuracy for *train* mode detection showing worse performance than MLANFIS and the machine learning models. MFIS also

performs poor compared to MLANFIS and the machine learning models in terms of recall accuracy for *bus* and *tram* mode detection. In terms of precision accuracy for *train*, MFIS works best, generating 94.57% accuracy, followed by MLANFIS, which generates 89.23% accuracy, whereas the highest precision accuracy was generated by the machine learning model (NB in this case), which is 87.70% (Table 25). However, in terms of F<sub>1</sub>-score, MLANFIS outperforms all of the predictive models for *train* mode detection, whereas it works on par with the machine learning models (and outperforming a MFIS) for *walk* mode, detection (Fig 52). For *tram* mode MLANFIS yields 0.84, which is very close to MLP (0.86) and DT (0.83) and outperforms MFIS (0.74), RBF (0.78), NB (0.76) and KNN (0.80).

Table 25: Precision accuracy (%) at a 120 s time window.

Mode	MLANFIS	MFIS	RBF	MLP	NB	KNN	DT
Walk	92.05	86.12	94.10	96.10	95.80	92.30	93.50
Bus	85.93	66.14	88.10	85.60	86.80	80.40	88.10
Train	89.23	94.57	73.90	76.50	87.70	77.70	83.90
Tram	84.08	83.13	75.10	84.00	66.50	79.80	82.00

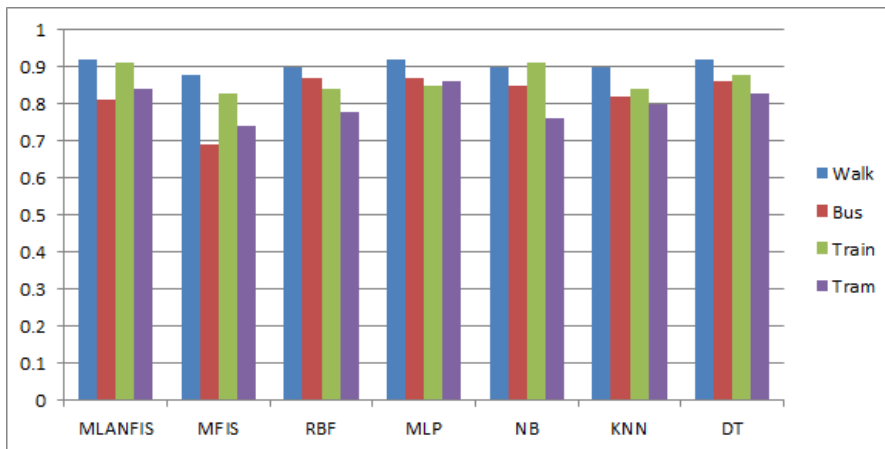


Figure 52: F1-score at a 120 s time window.

When a comparison is made only between two different types of knowledge-driven models (e.g., MLANFIS and MFIS), the results suggests MLANFIS performs better than MFIS (Figs 51 and 52). For a 60 s time window MFIS generates high Type II error for *bus*, *train* and *tram* mode compared to a MLANFIS. Thus an MFIS shows a drop in recall accuracy for different transport modes except *walk* (Table 23). On the other hand, an MFIS model yields higher precision accuracy for *train* and *tram* mode

(Table 24) than that of the MLANFIS model, whereas MFIS performs worse compared to MLANFIS in terms of *bus* and *walk* mode detection. This can be justified as due to the particularities in rule base to capture the different kinematic behaviour in the MFIS model typically at a low speed condition, and *near* to *moderate* proximity to the tram network or train network, some portion of the actual tram or train trip is detected as *walk*. Most of the retrieved *tram* and *train* instances are correctly detected owing to high precision accuracy in *train* and *tram* mode detection. The MFIS rule also does not work well when there is an overlap between tram network and a bus network. A MLANFIS can typically work better than the MFIS model in such ambiguous situations and shows an overall better performance than that of the MFIS model (Fig 51). Some of the fuzzy rules (out of 243) generated by the MLANFIS bus modal block are as follows:

R1: **IF** avgSpeed is low AND maxSpeed is low AND avgBusProx is low AND avg-TrainProx is low AND avgTramProx is low, **THEN** CF for Bus is out1mf1;

R2: **IF** avgSpeed is low AND maxSpeed is low AND avgBusProx is low AND avg-TrainProx is low AND avgTramProx is moderate, **THEN** CF for Bus is out1mf2;

Where out1mf<sub>j</sub> is the CF value for the  $i^{\text{th}}$  consequent part for  $j^{\text{th}}$  fuzzy rule.

Table 26 shows a confusion matrix for MLANFIS at a 60 s time window. The confusion matrix illustrates that most of the Type II error for non-walk modes are misclassified as *walk*, and that happened during signal loss or typically at a low speed condition. This suggests a more rigorous rule formation by incorporating more sensor information, such as an accelerometer.

Table 26: Confusion matrix for MLANFIS at a 60 s time window.

Actual	Predicted			
	Walk	Bus	Train	Tram
Walk	2711	19	37	161
Bus	192	390	1	15
Train	25	4	420	1
Tram	120	10	10	744

The MLANFIS framework developed in this research can also produce alternate solutions with varied degrees of confidence. For a given feature vector where the average speed is 64.6 km/h, the maximum speed is 73.9 km/h, the average proximity to bus network is 88.4 m, the average proximity to train network is 7.15 m, and average proximity to the tram network is 88.4 m, MLANFIS produced a certainty factor for being a *train* as 0.782 (Fig 53a) and for being a *bus* as 0.106 (Fig 53b). Due to the space limitations, Fig 53 shows only 29 rules out of 243 rules for each *train* and *bus* ANFIS modal block. This also explains the explanatory power and multiple output possibility from the proposed MLANFIS framework, which is missing in machine learning models.



Since choosing the appropriate membership function is important while developing a knowledge-driven model, two different fuzzy membership functions e.g., a Trapezoidal function and a Gaussian function are tested while developing MLANFIS and MFIS models. However, due to crisp geometrical nature of Trapezoidal function, there are cases when an input feature may fall outside a given range of fuzzy membership function and thus may bear a zero membership value owing to low performance in its predictive process. On the other hand since a Gaussian function is asymptotic in nature, it guarantees to generate a certain membership value  $\mu$  always in the range of  $[m, 1]$  where  $\lim_{m \rightarrow 0}$ . A trapezoidal membership function is characterized by four characteristic points (upper left, upper right, lower left and lower right), whereas a Gaussian membership function is characterized by only two characteristic parameters such as the center ( $c$ ) and the width ( $\sigma$ ). Table 27 shows different parameters for MLANFIS which are selected automatically based on a hybrid learning involving a gradient descent and least square estimation whereas the parameters for MFIS chosen manually resulting higher ambiguity and low performance in near-real time scenario. Figures 54 and 55 show two sets of three different Gaussian membership functions for average proximity to the train network in MLANFIS and MFIS respectively. Figure 56 shows how the certainty factor changes with two different fuzzy variables. The figure shows a prominent contrast between change in CF for a *bus* and *train* when considering the same fuzzy variables such as average proximity to the bus network and average speed (Fig 56a,b). Since walking can take place anywhere hence in this research nearness to the street network is not used as the streets in Melbourne show a significant overlap with the tram and bus network. Thus in order to detect the walking mainly a low speed behavior is considered (Fig 56d).



Figure 53: Certainty factors for train (a) and bus (b) for a given feature vector.

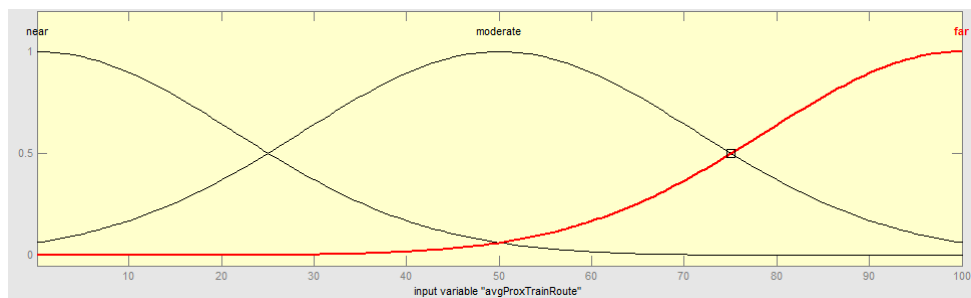


Figure 54: Fuzzy membership functions for average proximity to the train network in MLAN-FIS.

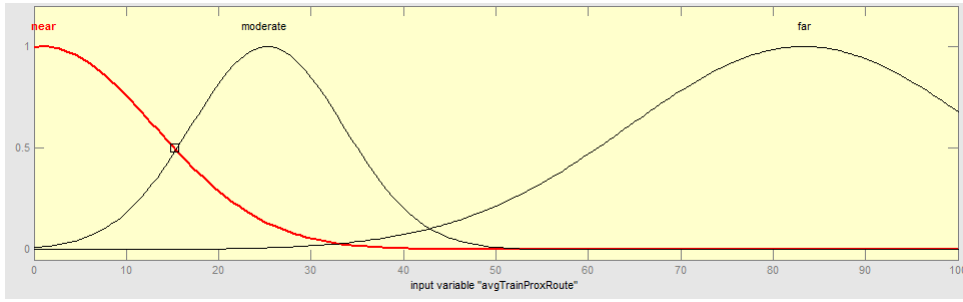


Figure 55: Fuzzy membership functions for average proximity to the train network in MFIS.

For trapezoidal membership function, the recall accuracy at the 60 s time window for MLANFIS and MFIS drops significantly. For MLANFIS, for *walk*, recall accuracy drops from 92.58% down to 89.31%, for *bus* accuracy, drops from 65.21% down to 57.52%; for *train*, from 93.33% down to 88%; for *tram* accuracy; down from 88.94% down to 85.42%. For MFIS, the drop is more prominent. For MFIS, recall accuracy for *bus* drops from 61.20% down to 51.67%; for *train*, it drops from 61.77% down to 40.22%, and for *tram* the accuracy drops from 60.06% down to 35.74%. Thus, the result suggests that a Gaussian function is better than a trapezoidal membership function for near-real time mode detection using fuzzy logic-based knowledge-driven models. The results also suggest a hybrid neuro-fuzzy (MLANFIS) works better than a purely knowledge-driven fuzzy logic-based MFIS model and performs on par with some of the state-of-the-art machine learning models, and even sometimes outperforms them for many places (Fig 51).

## 6.5 DISCUSSION

Transport mode classification is an emerging research problem approached by different research communities. In this research the concept of a near-real time transport mode detection have been introduced. We have developed a multi-layered neuro-fuzzy based model (MLANFIS). In order to choose the optimal temporal window in near-real time, five sets of experiments were performed. Based on the results a 60 s time window is selected as an optimal window which can generate satisfactory accuracy, however, deciding an optimal temporal window is subjective and may vary from one service domain to another. For example, a traffic management organization may accept a longer temporal window ( $>120$  s) if the main objective is to understand mode preference and patronage over a given route type (say, train route) assuming the downside that, there may be some quick transfers with in 2 min which may be missed by the proposed model when evaluate over a longer time window.

On the other hand for an emergency service provider or location-based e-marketing organization a shorter time window ( $\leq 120$  s) is required since the main focus is to communicate with the user in awareness of their current travel mode (say, a gas station

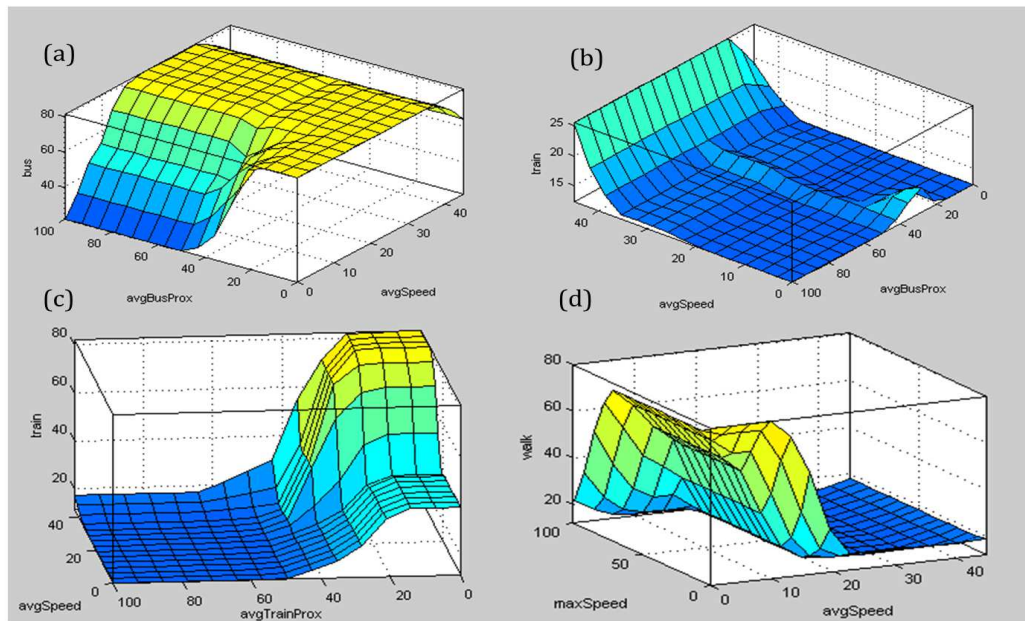


Figure 56: illustrates how CF for a given class changes with any two different fuzzy variables. z-axis indicates CF value whereas  $xy$  plane indicates fuzzy variable space. The figure shows how CF for bus changes with change in average proximity to the bus network and average speed (a); The figure also shows how CF changes for a train mode when considering the same fuzzy variables that is average proximity to the bus network and average speed (b); followed by the CF for train with average speed and average proximity to the train network (c); A change in CF for walk is shown with change in average speed and maximum speed (d).

wants to advertise some discounted gas coupons to all private cars within 1 km). The shorter temporal window is necessary for all context-aware systems that relate to the current travel modality (say, auto-answering an incoming phone call while the called person is driving). Compared to the ANN model by Byon and colleagues who used longer time windows (in the order of 5 min and 10 min) (Byon et al., 2009), this research is an improvement allowing shorter time windows of 1 min or 2 min using GPS only samples and infrastructure information. It is observed that by using GPS only samples it is not feasible to get a shorter temporal window than that of indoor activity recognition due to hardware and software limitations of the sensing system (and also to preserve the battery). Table 26 shows the accuracy of MLANFIS drops mainly due to the fact that all the non-walk modes are most of the times misclassified as *walk* mode during signal loss or at a low speed condition, which can be resolved in the future by integrating different inertial sensors, which can sense at significantly higher sampling rates than a GPS sensor on board of smartphones.

Table 27: Different parameters for MLANFIS and MFIS for a Gaussian function at a 60 s time window.

Fuzzy Variable	Fuzzy Value	MLANFIS			MFIS		
		$\sigma$	$c$	Range	$\sigma$	$c$	Range
avgSpeed (km/h)	low	23.32	-0.21		5.30	0.21	
	moderate	23.68	55.29	0-110.9	7.81	21.9	0-45
	high	24.30	110.6		5.54	44.00	
maxSpeed (km/h)	low	23.29	-0.48		13.19	2.65	
	moderate	24.26	54.17	0-110.9	14.74	45.90	0-100
	high	24.26	109.5		13.20	97.93	
avgProxBusRoute (m)	near	20.73	-0.3		10.59	1.02	
	moderate	20.96	49.92	0.03-100	8.28	25.25	0-100
	far	21.36	99.91		20.33	83.80	
avgProxTrainRoute (m)	near	21.17	0.19		12.04	1.02	
	moderate	21.3	50.03	0.06-100	8.28	25.25	0-100
	far	21.20	100		18.99	83.30	
avgProxTramRoute (m)	near	21.14	0		11.23	1.02	
	moderate	21.02	49.95	0.03-100	7.36	25.30	0-100
	far	21.29	99.93		25.15	83.30	

MLANFIS shows a performance improvement for some of the modes on increasing the time window in particular for *walking*, and *tram*. The model also demonstrates different accuracy while choosing different membership functions. This research also shows how knowledge-driven (MFIS) and hybrid knowledge-driven model (MLANFIS) can explain their reasoning scheme unlike conventional machine learning models.

The success of MFIS depends on the number of fuzzy rules and their relevance. The success of MFIS also lies in proper membership functions and their shape, which can be automatically handled by a MLANFIS. However, the MLANFIS model developed in this research is based on a grid partitioning approach, which exhaustively searches the entire input space. Thus increasing the number of features (fuzzy variables) along with their term set will also increase the number of rules, which raises scalability issues (Jang, 1993). Although in this research complexity associated with the models is not addressed, in general a grid partitioning suffers from higher temporal complexity and memory usage. This issue can be addressed in more complex

hybrid models by adopting a subtractive clustering or fuzzy c-means clustering (FCM) approach.

## 6.6 SUMMARY

This chapter addresses the challenges of detecting transport modes in near-real time particularly for real time travel demand estimation in the interest of public transport authorities and different context-aware service provisions. This research presents a neuro-fuzzy based hybrid knowledge-driven framework for an inference system in the context of urban mobility. Since this research is focused on a near-real time approach, there is no need to segment the trajectories like the existing practice in transport mode detection on historical trajectories; and thus this approach will reduce the computational overhead and response time. To the best of the authors' knowledge this is the first work where a hybrid, multi-layered ANFIS (MLANFIS) model is developed to address the classification problem of transport mode detection. In this research an optimal time window is also suggested for querying in near-real time. We have also drawn a comparison in performance between a number of knowledge-driven models and a number of machine learning models.

The result shows in some cases some of the machine learning models perform well but they act like a black box and lack the capacity to explain their reasoning process. A DT based model can explain the reasoning process in a more deterministic way based on some threshold at each level which however varies in different conditions and cannot represent a generic kinematic behavior in a linguistic way for human understanding. On the other hand, MFIS is based on predefined generic rule sets which is understandable by a machine and a human, but since the process involves expert knowledge in constructing the rule base and the membership functions, a MFIS model fails in the situation, which is not explained to the model by the expert or in a situation where the expert knowledge is outdated. This problem is mitigated by the suggested multi-layered neuro-fuzzy based model with its capacity to encode knowledge through n-ary relationships through different t-norm operators and expressed in a human readable format. Thus a neuro-fuzzy model is more robust and effective than that of a fuzzy model. The results demonstrate that a neuro-fuzzy model can perform at par with machine learning algorithms for most of the modalities while outperforming a traditional fuzzy logic model (Fig 51). The hybrid model presented in this research is capable of generating alternate possibilities with different certainty factors. The reasoning scheme can also explain the driving behavior of a person and deviation from regular behavior based on the type of rules fired, which can then trigger various mode specific context-aware service provisions. The result also demonstrates a knowledge-driven approach (fuzzy and neuro-fuzzy) can also achieve a higher accuracy with a transparent reasoning scheme (Tables 23 and 24). Table 24 shows MLANFIS outperforms all the machine learning models in terms of precision accuracy for *bus* at 60 s

time window. In the same line, a MFIS also outperforms the machine learning models in terms of precision accuracy for *train* and *tram*.

At 60 s time window, MLANFIS yields 83% average accuracy which is at par with a RBF, DT, and a NB model and outperforms a purely knowledge-driven fuzzy model, which generates only 69% average accuracy. However, an MLP based neural network model generates 87% average accuracy, which is higher than the neuro-fuzzy model developed in this research. But at the same time the neuro-fuzzy framework developed in this research can explain its reasoning process, which is missing in an MLP or RBF or even in a DT based model. In addition to that, a conventional fuzzy model cannot learn adaptively and thus is not robust to noise. In contrast, the presented neuro-fuzzy model can tolerate noise and adapt to varying conditions. The neuro-fuzzy model developed in this research shows more consistent performance than that of a fuzzy logic based model in near-real time scenario. The neuro-fuzzy model is also tested against some other machine learning models (e.g., SVM) where the model shows better performance than those machine learning approaches.

The framework shows that a MLANFIS model can learn and explain its reasoning scheme, which overcomes limitations of a conventional MFIS type fuzzy expert systems developed by (Biljecki et al., 2012; Xu et al., 2010) as well as machine-learning models (e.g., neural network) (Byon et al., 2009; Gonzalez et al., 2010). In this research four urban transport modes are used for testing the MLANFIS model, where the *train*, *tram* and the *walk* modes are detected with high accuracy, followed by *bus* mode. However, the model can easily be extended for more modalities along with more input features. This may increase the ambiguity especially when two modalities show similar movement patterns and share the same network (say, a car and a bus are moving on an express way with the same high speed). In such situations more features are required such as stop rate, heading change rate, vibration and ambient sound profile: All of these can easily be incorporated in the model.

Future research will investigate how the model behaves on integrating different sensor signals such as accelerometer, gyroscope and GPS. This integration also leads to new challenges as how to fuse sensors with their different data quality and ability to sample at different frequency. Future research will also look into how a Sugeno-based rule set can be converted to a MIMO Mamdani-type fuzzy rule set in order to improve the expressiveness. In the same line, future research could investigate the top-k most relevant rule sets for each modal block in an MLANFIS model in the context of travel mode detection. Although the hybrid knowledge-driven model presented in this chapter is more adaptive than that of a purely knowledge-driven model in near-real time but the hybrid model poses scalability issues. Chapter 7 has picked up these issues, and proposed a more adaptive and sophisticated model.





## AUTOMATED URBAN TRAVEL INTERPRETATION: A BOTTOM-UP APPROACH

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This chapter investigates how travel behaviour information can be extracted from smartphone sensor traces in a more adaptive way. Sensor traces can be used to interpret travel modes, both for generating automated travel diaries as well as for real-time travel mode detection. Current approaches segment a trajectory by certain criteria, e.g., drop in speed. However, these criteria are heuristic, and, thus, existing approaches are subjective and involve significant vagueness and uncertainty in activity transitions in space and time. Also, segmentation approaches are not suited for real time interpretation of open-ended segments, and cannot cope with the frequent gaps in the location traces. In order to address all these challenges in this chapter<sup>1</sup> a novel, state-based *bottom-up approach* is proposed. This approach assumes a fixed atomic segment of a homogeneous state, instead of an event-based segment, and a progressive iteration until a new state is found. The research investigates how an atomic state-based approach can be developed in such a way that can work in real time, near-real time and offline mode and in different environmental conditions with their varying quality of sensor traces. The results show the proposed bottom-up model outperforms the existing event-based segmentation models in terms of adaptivity, flexibility, accuracy and richness in information delivery pertinent to automated travel behaviour interpretation.

### 7.1 INTRODUCTION

Travel is an inevitable part of human life, required in order to perform an activity which is not possible at a current location. Changing the perspective, as evident from [Chapter 4](#) travel itself can become an *activity* in its own right, and again changing perspective, travel can be conceived as a *sequence of activities*, each consisting of a segment travelled in a single mode. This chapter focuses on the automatic interpretation of a travel as a sequence of activities, i.e., segments travelled in a single mode of travelling, from sensor traces collected on smartphones (Section [3.1.4](#)). In particular, the role of granularity will be highlighted (e.g., between *getting on board of a bus*, *taking the bus*, or *going to work*), along with the ambiguity about the mode that comes along with it ([Chapter 4](#)). The elementary trips of a travel are connected by transfers, at certain gran-

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<sup>1</sup> The contributions presented in this chapter has been peer-reviewed and published as follows.

Das, RD., Winter, S. (2016): *Automated Urban Travel Interpretation: A Bottom-up Approach for Trajectory Segmentation*, *Sensors*, 16(11)

ularities. Travel can be mediated by moving objects in the form of different transport modes, but this research explicitly include unsupported body movement (walking, running, stationary) as a mode. Since any mode is mixed with unrelated movements, e.g., walking through a bus, taking a smartphone out of a pocket while sitting on a bus, or turning the head while cycling, the interpretation of sensor traces has to deal also with other noise than only from the sensor characteristics.

Identifying trips automatically is important for understanding the travel demand in a city, people's movement behaviour, modal preferences, route choice, patronage, and for enabling various personalized context-aware service provisions.

In order to understand people's travel activities, traditional methods rely on paper-based, telephonic or face-to-face travel survey techniques in order to generate travel diaries. A travel diary contains the mobility information of a person in terms of trips, with their start time, end time, origin, destination and transport mode(s). Current travel diary generation process is manual and involves lack of detailed (and accurate) travel information. With the recent emergence of smartphones equipped with positioning and other location sensors along with inertial measuring units (IMU) it has been now possible to continuously track an individual across any mode of travelling and thus it is possible to provide detailed and more accurate information (Cottrill et al., 2013).

The remaining challenge is to automatically interpret these sensor traces for travel activities (single mode trips) and transfers. In the current state-of-the-art, a trajectory is top-down segmented based on some critical events (e.g., a drop in speed) and then activity states are detected for each segment (Rocha et al., 2010; Zheng et al., 2008). However, segmenting a trajectory based on some heuristics is subjective and involves vagueness and uncertainty in activity transition in space and time, and thus, obscures the recognition and modelling of transfers. Prior work, discovering activities (including transfers) using clustering techniques, has to deal with clusters of any shape and any size, and hence comes with a significant uncertainty and ambiguity as to where a transfer begins and ends along with a trip start and end. In contrast, the present work assumes that within a very fine grained space-time frame the activity state will remain same: A finer kernel involves less uncertainty than that of a longer segment, and the trip end of one segment becomes the trip start of the next segment. The common point in time defines a transfer precisely in space and time, and thus involves less ambiguity than that of a clustering-based approach. The research presented in this chapter hypothesizes that *a state-based bottom-up approach is more adaptive than any top-down approach, and in addition it will be flexible enough to detect activity states in a progressive manner at different temporal granularity.*

This translates into the temporal uncertainty depending on the length of space-time kernel. The shorter the kernel the less is the uncertainty, but at a cost of overall detection accuracy.

In the state-based bottom up approach an atomic kernel is ran over the entire sensor trace and a particular activity state is detected iteratively. The assumption behind this approach is, shorter the temporal kernel more homogeneous the activity state will be. A transfer is then modelled with a given temporal uncertainty when there is a change in the activity state. The approach can be extended to a multi-grained atomic kernel approach to drill down the activity states, e.g., first detecting the travel activities, then the finer grained activity states during any transfer. The hypothesis has been tested on two different data sets: A trajectory data set of multi-modal inner-urban trips, and also a data set of inertial measurement unit (IMU) observations on-board a smart-phone (without location information). The experiments prove that the new approach is not only more expressive in terms of richer travel information, but also capable of near-real time trip analysis as required for context-aware services. The contributions of this chapter are as follows.

(a) Unlike the earlier approaches which are mostly behaviour-based depend on a particular event(s) (say, drop in speed), this research presents a novel state-based bottom-up framework to segment the trajectories in a progressive way at different granularity.

(b) The aspect of temporal uncertainty in activity transition is explored and modelled using Allen's temporal calculus (Allen, 1983)—which was missing in the earlier trajectory segmentation, trip generation and transport mode detection research (Fig 57).

(c) The framework presented in this research is modular, adaptive, flexible and robust, and yet accurate. Since the framework uses an atomic kernel of definable length, it can work in different granularities (e.g., for travel mode or transfer interpretation), and even in near-real time (defined by the kernel length). The framework can also handle varying data quality and richness in information content in the sensor trace.

Thus, in case of a top-down approach depending on a certain behaviour or event, a trajectory is first segmented into a number of segments; and then an activity state is detected over each segment. On the other hand, for a bottom-up approach, a given activity state is detected within a short temporal kernel without considering any change in behaviour of the moving object. Then the subsequent states are discovered iteratively, and a progressive segmentation takes place along the given trajectory.

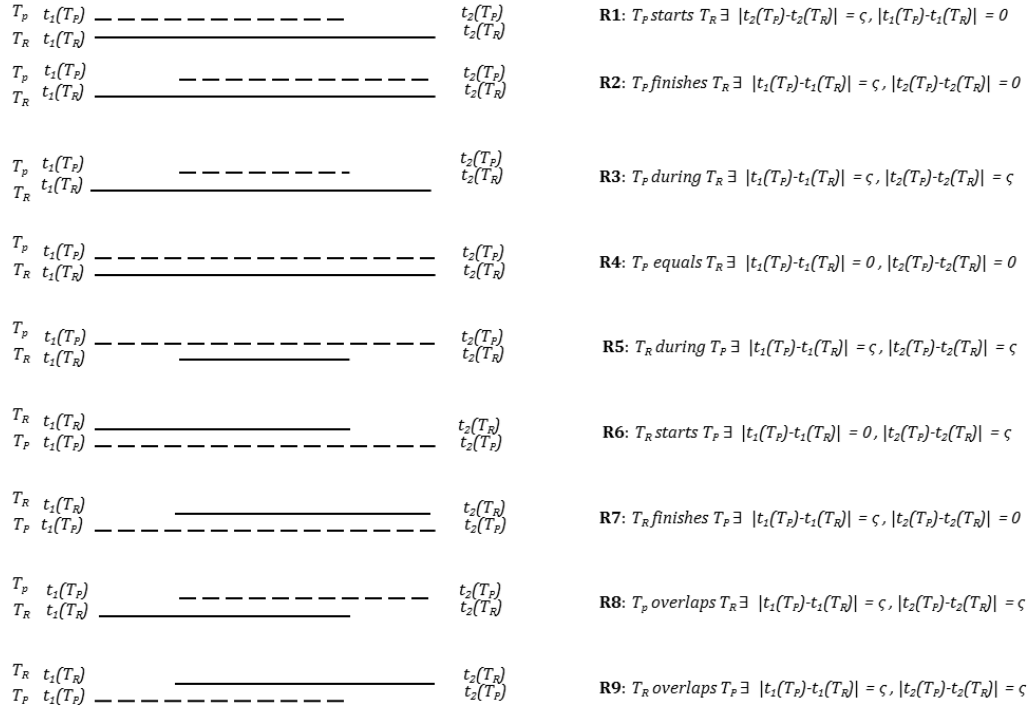


Figure 57: Trip uncertain temporal relationships between a reported trip ( $T_R$ ) and predicted trip ( $T_P$ ) based on Allen's temporal calculus. In this figure  $t_1$  and  $t_2$  are the start time and end time of a given trip respectively.

Existing top-down segmentation approaches first segment the trajectory based on either a stop episode or a low speed or walking episode, and then attempt to detect a particular activity state or travel behaviour over other segments. But as mentioned in Section 7.1, this approach is subjective and creates spatial and temporal ambiguity (Cich et al., 2016), and thus, if each of the segments is viewed as a specific trip then there is a temporal uncertainty (or misalignment) of trip start and end (from segmentation perspective) and uncertainty of activity state (e.g., transport mode) along a given trip (from activity detection perspective). A vast majority of literature on transport mode detection and trip generation does not address this ambiguity during the trajectory inference process. In this research four different types of trips have been figured out that may be possible during a single mobility-based action and their temporal inter-relationships.

In order to detect mobility-based activities in real time other researchers developed a temporal window-based approach (Hemminki et al., 2013). Reddy and colleagues integrated an accelerometer and a GPS sensor to detect the modality in 1 seconds (Reddy et al., 2010). Byon and colleagues used comparatively higher time window (10 min) to detect modalities without segmenting the GPS trajectories (Byon et al., 2009).

A similar approach has also been developed in detecting micro-level activities involved with body parts movement or small scale locomotion in an indoor environment (Kautz et al., 2003; Krumm and Horvitz, 2006; Choudhury et al., 2008; Shoaib et al., 2016). Thus the existing research in real time urban transport mode detection as well as most of the activity recognition research in public health and mobile computing attempt to detect the activity within a queried time window and do not attempt to model the uncertainty of the continuity of a given activity. That means, the existing activity recognition research lacks in providing the information on activity start and end.

In this research an existing temporal window (kernel)-based approach will be used but with an introduction of iterative temporal merging in order to detect an activity in real to near real time as well as detecting activity transition at different granularity using different sensor combinations. In contrast to the existing real time approaches (Hemminki et al., 2013; Reddy et al., 2010; Byon et al., 2009), where a time window is given and an activity state is to be detected, the framework presented in this chapter has extended that approach and can detect an activity within a given time window as well, and given an activity the model can detect its start time and end time. In contrast to the offline approaches on trajectories where a subjective segmentation is performed, this chapter presents a simple yet effective approach for segmenting the trajectory based on activity states in a fine grained time window. In this research it is also investigated how activity detection accuracy varies with different sensor combinations and different feature types. The state-based bottom-up framework proposed in this chapter is also a hybrid model in the sense it combines a machine learning and deterministic (crisp) rules for further refinement unlike a neuro-fuzzy based hybrid knowledge-driven model (Chapter 6), which is a combination of a machine learning (ANN) and fuzzy rules.

Allen's temporal predicates are qualitative in nature. Thus, the temporal mismatch of predicted trip (or trip leg) with the reported trip can be qualitatively modelled using Allen's temporal predicates. Such a qualitative representation can enrich the activity knowledge base in a qualitative way and it would be useful for a context-aware service provision that leverage the activity ontology at different contexts (where the temporal mismatch may vary quantitatively), particularly during trip start, trip end or transfer from one travel segment (trip) to another travel segment (trip) where the knowledge of dwell time is critical for various service provisions (e.g., recommending next connecting vehicle, recommending nearest POI for a specific activity). However, this thesis has delimited the temporal uncertainty within a crisp temporal bound, which is, however, subjective and context-sensitive. That said, Allen's qualitative temporal relationships used in this thesis will remain same and thus can be implemented in different mobility applications in different environments.

The remainder of the chapter is organized as follows. Section 7.1 gives an overview of the current state of knowledge and research gap. Section 7.2 defines some key

concepts used in this research. Section 7.3 outlines the methodology used for data pre-processing and model building. Section 7.4 presents the experiments and results. Section 7.5 reflects on the framework, which is followed by a summary in Section 7.6.

## 7.2 THEORY

This section will introduce the proposed bottom-up framework along with some key concepts.

### 7.2.1 *Uncertainties in trips*

Trips are characterized by start and end time locations, and a travel mode. Each of these characteristics can vary between the reported trip, the scheduled trip, the actual trip, and the predicted trip, leading to temporal, spatial and semantic uncertainties. These uncertainties may occur due to synchronization problems between clocks (such as the smartphone's and the transport provider's) or the memory or attention of the traveller when reporting a trip. The uncertainties also stem from the varied ontological commitments and cognitive perceptions of trip starts and transitions in actions (e.g., resolving a transfer into subsequent actions). The uncertainty can also arise from actual travel times other than the scheduled time, wrong inferences from the predictive model on the mode, and also uncertainties in sensor signal information (e.g., signal loss or multipath effects in case of a GPS trajectory).

### 7.2.2 *Trip uncertain temporal relationships*

The experiment below is designed with trips reported in-situ, not from memory in hindsight. These reported trips will form the ground truth in the experiment, i.e., they are assumed to be correct representations of the actual trips. In this case it is difficult to model the temporal uncertainty between the reported trip and actual trip, although it must exist. Temporal deviations will also occur between the reported trip and the predicted and the scheduled trip. Such temporal uncertainties can be modelled qualitatively by using Allen's interval calculus (Allen, 1983). Figure 57 shows nine possible relationships between a predicted trip ( $T_P$ ) and a reported trip ( $T_R$ ) where  $\sigma$  is the crisp uncertainty for time observations predefined at a given context. It will be shown later how the inference accuracy varies by varying the  $\sigma$  value. The relationships also hold between a reported trip ( $T_R$ ) and a scheduled trip ( $T_S$ ), or a scheduled trip ( $T_S$ ) and a predicted trip ( $T_P$ ).

### 7.2.3 Predictive model

A predictive model is a module in this framework in Layer 1 in the processing phase (Fig 58) that detects a given activity state. A predictive model is basically a classifier constructed based on a number of features (Section 7.3.3.4). In this chapter a number of machine learning algorithms have been investigated to construct the best predictive model in Layer 1 which is explained in Section 7.4.

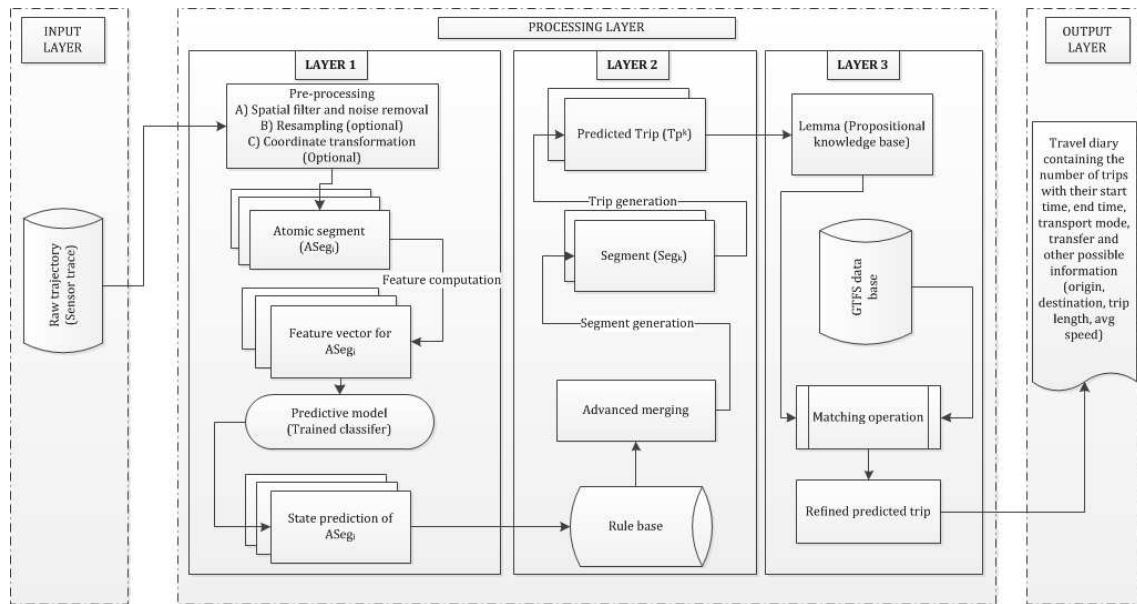


Figure 58: A state-based bottom-up framework for travel diary generation.

## 7.3 TRAJECTORY SEGMENTATION FRAMEWORKS

In this section the existing trajectory segmentation frameworks will be presented that detect the trips based on different criteria. Then the novel state-based trip detection framework is presented, which detects the trips more adaptively along with rich behavioural information (e.g., transport mode state).

A trip can be modelled as a particular segment with a homogeneous state and distinct behaviour. Trajectory segmentation approaches can be classified into two broad categories: behaviour-based and state-based approaches. Behaviour-based approaches segment a trajectory into meaningful parts and then infer a state for each segment. Thus, these approaches are top-down. The number and type of segmentation operations is context dependent. In contrast, the state-based approach developed in this chapter extracts an atomic segment assuming the state will remain constant in that fine grain, and then the state is detected using a hybrid approach (machine learning and heuristic rules), whereupon homogeneous segments are generated using an advanced

merging operation, which will generate the trips. Thus, the second approach is richer in information content and more adaptive. This approach is bottom-up. This chapter presents the novel state-based bottom-up approach, which is compared with the two state-of-the-art top-down approaches: a walking-based approach and a clustering-based approach (and its variants), which is basically a realization of the SMoT algorithm (Alvares et al., 2007; Spaccapietra et al., 2008). Based on the literature and current research trajectory segmentation approaches has been categorized in Figure 59.

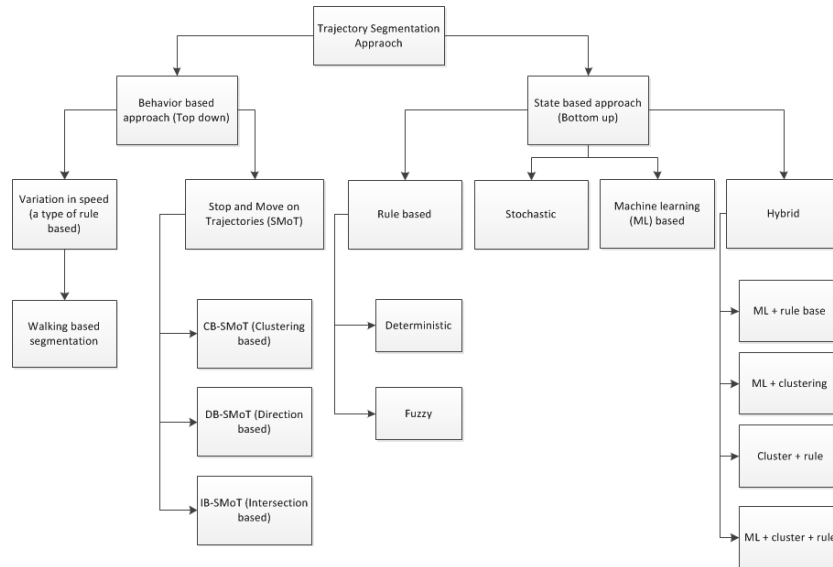


Figure 59: Different types of trajectory segmentation strategies.

### 7.3.1 Trip detection by a walking-based approach

A walking-based approach is a variant of the behaviour-based approaches where the behaviour is attributed to drop in speed. It is generally used in order to segment a trajectory in the context of transport mode detection.

The assumption behind a walking-based approach is that people need to walk in between two different transport modes (Zheng et al., 2008). In this regard, a walking segment is detected by deterministic rules where the key parameters are speed ( $\frac{dl}{dt}$ ), merging distance ( $\delta l$ ), and total distance ( $L$ ) travelled over a segment. However, by relying on these parameters this approach is subjective and thus it is difficult to set the threshold parameters.

Since a GPS trajectory is prone to signal loss and multipath effect, a walking-based approach needs a thorough pre-processing of the raw trajectory. The trajectory is filtered in such a way that no high speed points remain in between two low speed points and vice-versa. The filtering process should also remove points with high DOP values



(or spatial uncertainties). In this research the speed threshold is considered 9 km/hr based on prior research (Minetti, 2000), and the merging distance is 20 m based on trial and error. The total distance threshold for a segment to qualify as a walking segment is iteratively tested from 10 m to 200 m. Algorithm 1 presents a two stage pre-processing operation where a GPS trajectory is first filtered based on spatial uncertainty (Spatial\_Filter) followed by speed outliers (Velocity\_Filter). The walking-based technique is then presented in Algorithm 2.

---

**Algorithm 1** Preprocessing of a GPS trajectory in two stages

---

```

1: INPUT 1) $\Pi_R$  : rawTlist(), 2)lowSpeed: LST
2: OUTPUT  $\Pi_P$  [spatialFiltered: sfTlist(); velocityFiltered:vfTlist()]
3: PROCEDURE Spatial_Filter()
4: rawTlist.size() =  $k_1$ 
5: for  $i=0$  to  $k_1-1$  do
6:   if rawTlist.get(i).getAccuracy() > 40 then
7:     sfTlist.add( $P_i$ ) {rawTlist.get(i)= $P_i$ , where  $P_i$  is a GPS point in raw trajectory
       $\Pi_R$ }
8:   end if
9: end for
10: END PROCEDURE
11: PROCEDURE Velocity_Filter()
12: sfTlist.size() =  $k_2$ 
13: for  $i=1$  to  $k_2-1$  do
14:   if sfTlist.get( $i-1$ ).getSpeed() > LST||sfTlist.get( $i+1$ ).getSpeed() > LST then
15:     vfTlist.add( $P_i$ )
16:   else
17:     if sfTlist.get(i).getSpeed() < LST then
18:       if sfTlist.get( $i-1$ ).getSpeed()  $\leq$  LST||sfTlist.get( $i+1$ ).getSpeed()  $\leq$  LST
        then
19:         vfTlist.add( $P_i$ )
20:       end if
21:     end if
22:   end if
23: end for
24: END PROCEDURE

```

---

---

**Algorithm 2** Trip generation using walking-based approach

---

```
1: INPUT 1)  $\Pi_P$  : pTlist(), 2) lowSpeed: LST, 3) mergingDistance:  $\delta l$ , 4) totalDistance: L

2: OUPUT a set of trips
3: PROCEDURE Trajectory_Segmentation()
4: pTlist.size() =  $k_3$ 
5: for i=0 to  $k_3-1$  do
6:   if pTlist.get(i).getSpeed()  $\leq$  LST then
7:     templist.add( $P_i$ )
8:   else
9:     if pTlist.get(i).getSpeed() > LST then
10:      if templist.size() > 0 then
11:        seglist.add(newlist(templist))
12:        templist.clear()
13:      end if
14:    end if
15:  end if
16: end for
17: END PROCEDURE
18: PROCEDURE getPotential_Walking_Segments()
19: if seglist.hasMergeableSegments( $\delta l$ ) then
20:   mergedSeglist = segmentMerging(seglist) {merging all the mergeable short
    low speed segments}
21: end if
22: mergedSeglist.size() =  $k_5$ 
23: for i=0 to  $k_5-1$  do
24:   if mergedSeglist.get(i).getLength  $\geq$  L then
25:     walkingSeglist.add(mergedSeglist.get(i) {walking segments are detected})
26:   end if
27: end for
28: nonWalkingSeglist = getNonWalkSegments(walkingSeglist) {non walking
    segments are extracted}
29: END PROCEDURE
```

---

### 7.3.2 Trip detection based on clustering-based approach

A clustering-based technique is another popular approach for trajectory segmentation. Since a clustering technique is based on proximity of GPS points, the clusters generated over a trajectory bear a semantic significance, for example, where the traveller has been stationary or had limited body movement for a certain time period. The notion

behind a clustering-based approach is that during traveling on different modes people transfer or do some static activity (say, in a station, office, or home) where the GPS points are located very close to each other and tend to form a dense cluster (Fig 60). In this research the clusters are assumed as the extent in space and time where a transfer takes place in order to change from one transport mode to another.

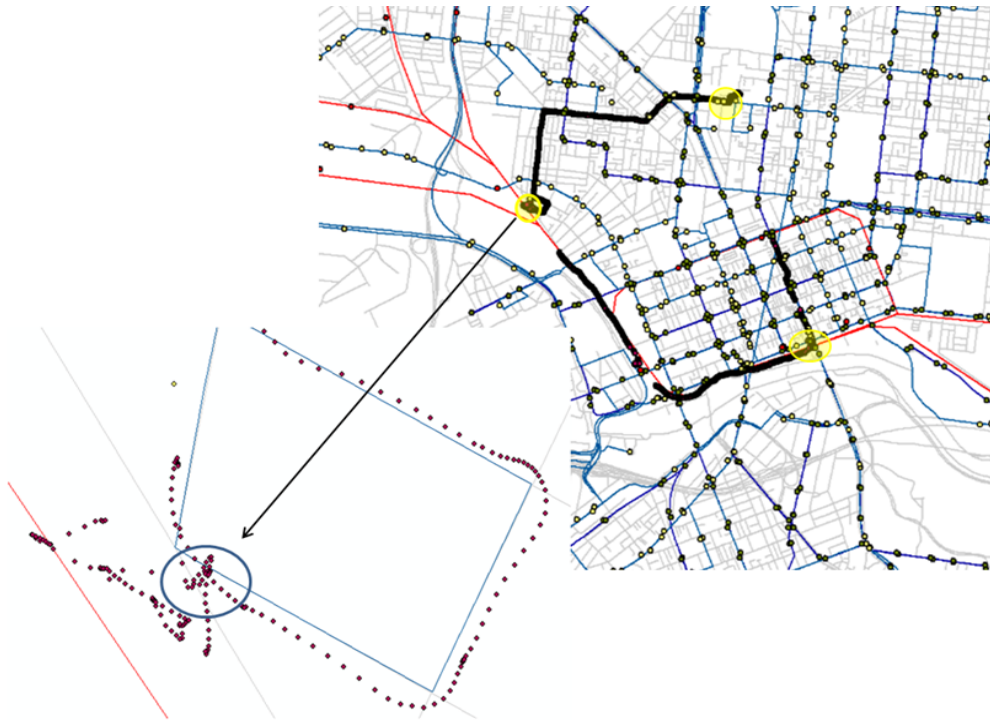


Figure 60: Spatial proximity of the GPS points during transfer.

A clustering-based algorithm is implemented using a spatial clustering application with noise (DBSCAN). DBSCAN is initialized with an arbitrary point ( $P_i$ ) in the trajectory. The algorithm then searches for neighbor points ( $N$ ) within an  $\epsilon$ -neighborhood of point  $P_i$ . If  $N \geq \text{minPts}$  then  $P_i$  is defined as core point. The parameter 'minPts' is the minimum number of points to be present in the neighborhood of any given point in order to qualify that point as a core point. The algorithm then evaluates the next point and grows the cluster(s) until all the points are visited.

Once the clustering operation is performed there may be a number of clusters of different shape and size. In order to extract the most potent clusters (in the context of trip detection) a merging operation is performed followed by a relevance measure check. The merging operation is performed based on inter-cluster spatial distance threshold (ICSD) and inter-cluster temporal duration threshold (ICTD). However, a spatial clustering may raise the risk of clustering the to and from points together and thus leading to erroneous trip modelling. In order to deal with this issue a temporal proximity (td-

iff) is used along with the spatial proximity ( $\epsilon$ ) to modify the basic DBSCAN into spatio-temporal DBSCAN (ST-DBSCAN).

There may also be some clusters that form without characterizing a transfer, for example, due to vehicle stops for pickup or drop-off or at traffic lights, or over a walking trip where the speed of walking is low, such as a stroll in a park or moving in a crowd. In order to filter such irrelevant clusters a temporal relevance check is performed over all the clusters. If the duration ( $\Phi$ ) of the cluster is greater than or equals to a temporal threshold then that cluster qualifies as a relevant cluster or a potential transfer zone. That said, clusters can be of any shape and size and hence from ontological point of view it is difficult to model the trips with their start and end in space and time. Algorithm 3 demonstrates a spatio-temporal clustering on trajectories to retrieve the transfer information.

---

**Algorithm 3** Spatio-temporal clustering on trajectories

---

```

1: INPUT 1) $\Pi_R$  : rawTlist(), 2)Neighbors: minPts, 3)search radius:  $\epsilon$ ,
2: INPUT 4)temporal proximity: tdiff, 5)ICSD, 6)ICTD
3: OUPUT a set of clusters denoting possible transfers in a trajectory  $\Pi_R$ 
4: PROCEDURE ST_Clustering()
5: clusterlist=getST_DBSCAN (rawTlist, minPts,  $\epsilon$ , tdiff)
6: clusterlist.size() $=k_1$ 
7: for i=0 to  $k_1-1$  do
8:   if spatialDistance(clusterlist.get(i),clusterlist.get(i + 1))  $\leq$  ICSD then
9:     if temporalDistance(clusterlist.get(i),clusterlist.get(i + 1))  $\leq$  ICTD then
10:      clusteri = merge(clusterlist.get(i),clusterlist.get(i + 1))
11:      clusterlist.remove(i,i+1)
12:      clusterlist.add(clusteri)
13:     end if
14:   end if
15: end for
16: clusterlist.size() $=K_2$ 
17: for i=0 to  $K_2-1$  do
18:   if clusterlist.get(i).getDuration  $\geq$   $\Phi$  then
19:     clusteri = clusterlist.get(i)
20:     transferlist.add(clusteri)
21:   end if
22: end for
23: END PROCEDURE

```

---

In this chapter two existing top-down approaches (walking-based and clustering-based) have been implemented along with the proposed state-based approach for a comparative study. Although there could be different variations of the two above men-

tioned top-down approaches, but in general such approaches are inadequate in certain circumstances. For example, the walking-based approach requires a consistent and good quality GPS signal, it cannot handle IMU information, and it completely fails when there is no GPS signal for a prolonged period of time. On the other hand the clustering-based approach is robust to GPS noise, but also cannot deal with the IMU information, and does not work very well on sparse GPS trajectory data. More significantly, the clustering-based approach suffers from the ontological ambiguity about start and end of a trip.

### 7.3.3 *Trip detection using a state-based bottom-up approach*

In order to address these issues a more robust and adaptive state-based bottom up approach is proposed. The proposed approach can handle GPS noise as well as IMU information. The proposed approach is less subjective than the walking-based approach, and at the same time tends to generate activity transitions with a clear provision of trip start and end, which is missing in the clustering-based approach. A state-based bottom-up approach also generates rich activity information (in terms of transport mode along a given trip) and thus this proposed approach is more effective in terms of generating travel diaries at different granularity with different level of uncertainty.

A state-based bottom-up approach is a hierarchical framework consisting of three layers (Fig 58). The first layer is the input layer where a raw trajectory is fed in. The second layer is the processing layer that consists of further three sub-layers (LAYER 1, LAYER 2, LAYER 3), where the third layer is the output layer that generates the travel diary containing the trip information. In the first processing layer (LAYER 1) an atomic kernel is ran over the trajectory based on the query time that detects the activity states using a set of machine learning algorithms over each atomic segment. Thus, the first layer can also infer activity states (transport mode in this case) in near-real time. In the second processing layer (LAYER 2) an advanced merging operation is performed based on a set of heuristic rules. This will merge the consecutive atomic segments with similar activity states and predict the trips. In order to raise the confidence and strengthen the inference process, especially on trip start and trip end along with the transport mode used in that particular trip, a general transit feed specification (GTFS) information is used to evaluate the initial predicted trips in the third processing layer (LAYER 3). Figure 9 illustrates how the atomic kernel bounded in time  $[t_{k-1}, t_k]$  of duration  $(t_k - t_{k-1} = \eta \mid k \geq 1)$  is ran over the trajectory and how different trips are inferred based on given transport modes. In the following section each layer is explained in detail. The model presented in this chapter is a hybrid approach that leverages the machine learning algorithm(s) for the initial activity state prediction followed by processing the rule base.

#### 7.3.3.1 LAYER 1: Near-real time activity state detection

Since a trip is characterized by a set of time-ordered homogeneous sensor data points (that may include GPS data points), in the first layer a predictive model is developed that will detect the activity state based on a classifier. In order to train the classifier different types of kinematic and spatial features are computed using sensor signals.

In this context the *activity state* is traveling on a given transport mode, and the *transport mode* is the mediation of this activity. In order to detect the transport mode an atomic kernel is applied (with 50% overlap) over the trajectory (or sensor trace) to extract a set of atomic segments. Then a number of features are computed within each atomic segment and a feature vector is created. Thus, if there are N atomic segments then there will be N feature vectors for a given trajectory. In some literature the atomic kernel is termed as sliding window or sliding kernel. The overlap is necessary in order to capture all the possible kinematic behaviour especially during state transition and sudden change in behaviour. Once the feature vectors are generated training is performed on a number of classifiers. Then all the classifiers are evaluated using testing trajectories separately. Once all the atomic segments are inferred (from all the test trajectories) an advanced merging operation is performed to generate longer segments of homogeneous activity states, which will turn into predicted trips. The six machine learning-based classifiers are chosen based on prior research in transport mode detection and trajectory analysis.

#### 7.3.3.2 LAYER 2: Advanced merging operation and potential segment generation for trip detection

In the second layer the atomic segments are merged sequentially based on similarity in their predicted transport mode (queried from Layer 1). The assumption behind such a merging operation is that all the points in a sensor trace or a portion of GPS trajectory that form a particular trip will bear a uniform activity state: travelling on one transport mode along one and the same trip from a given origin to a (temporary or final) destination. Thus, when there is a change in activity state, a new trip has started. The point in time and space where the transition occurs is the transfer point.

In the first stage in Layer 2, an initial merging operation is performed based on the initial transport mode inference. However, due to the diverse performance of classifiers and depending on the data quality and uncertainties in movement behaviour there may be false positives. In order to address this issue a set of rules refines the merging operation of the consecutive atomic segments (Algorithm 4).

#### 7.3.3.3 LAYER 3: Trip refinement using GTFS and spatial information

Once the merged segments (predicted trips) are generated from Layer 2 a further refinement operation is performed using GTFS and other spatial information realizing the following five lemmas. In this layer a matching is carried out that matches the

predicted trips with the scheduled trips based on spatial and temporal information along with the trip start and trip end with the scheduled stop information. For the following lemma an  $i^{\text{th}}$  predicted trip ( $T_p$ ) is represented by a tuple of trip origin ( $O_p^i$ ), trip destination ( $D_p^i$ ), and predicted mode over trip  $i$  ( $M_p^i(T_i)$ ). However, in order to match against the scheduled transit information the framework requires predicted stop and route information. Thus, a pair of stops at predicted trip origin ( $S_p^i(O)$ ) and destination ( $S_p^i(D)$ ) are queried using a variable search radius of 50 m, 100 m and 300 m progressively until at least one stop is retrieved around the trip origin point ( $O_p^i$ ) and trip destination point ( $D_p^i$ ). This information is then used to match the predicted trips with the scheduled trips and refine the prediction through the following lemmata.

Figure 61 shows different component tables of GTFS schema with their common primary keys (*pkey*) and a consistency check between the predicted trip generated from Layer 2 in processing layer (with stop information at trip start and end) and a suitable scheduled trip, which is retrieved from the GTFS data.

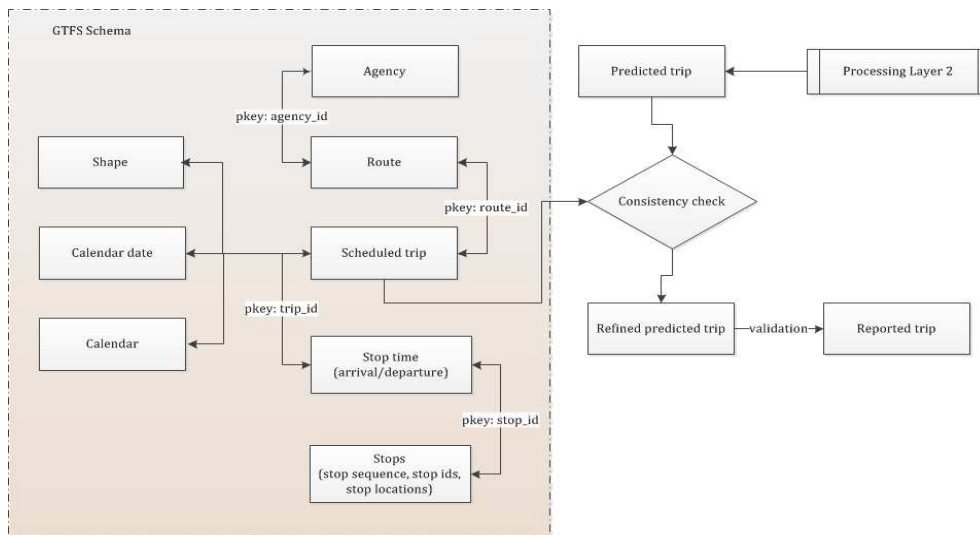


Figure 61: General transit feed specification (GTFS) schema and consistency check between the predicted trip and the scheduled trip.

- **Lemma 1: Stop type similarity**

Since a trip is a segment of the trajectory, which consists of sensor data points that bear the same transport mode state ( $M_p^i$ ), the stops at trip start and end must be of type ( $M_p^i$ ). For example if a trip is made by a tram then the start stop and end stop of this trip must be two tram stops.

$$M_p^i(S_p^i(O)) = M_p^i(S_p^i(D)) \quad (26)$$

- **Lemma 2: Disjoint stop relationship**

Since the GPS signal is prone to multipath effects and occasional signal loss due to obstruction must be expected, not all GPS points are recorded, and instead of updates in the GPS feed successive points will be recorded as the last known point. However, technically the stop at the trip start and end must be spatially different if it is not a return trip.

$$S_p^i(O)_t \neq S_p^i(D)_t \quad (27)$$

$$\implies (X_{S_p^i(O)}, Y_{S_p^i(O)}, Z_{S_p^i(O)}) \neq (X_{S_p^i(D)}, Y_{S_p^i(D)}, Z_{S_p^i(D)}) \quad (28)$$

- **Lemma 3: Stop sequence (un)ambiguity**

No pair of trip origin and destination stop may be the members of more than one scheduled trip. That said, two scheduled trips may have a portion of their routes overlapping with each other. There may also be two routes with the same pair of origin and destination stops but in reverse order (which is a typical case in a return travel along the same route but in different direction). In this case routes may overlap. Figure 62 illustrates some of these ambiguities in stop sequences for different routes.

For the time being the first case in lemma 3 will be ignored. In order to address the latter case the following proposition should be followed.

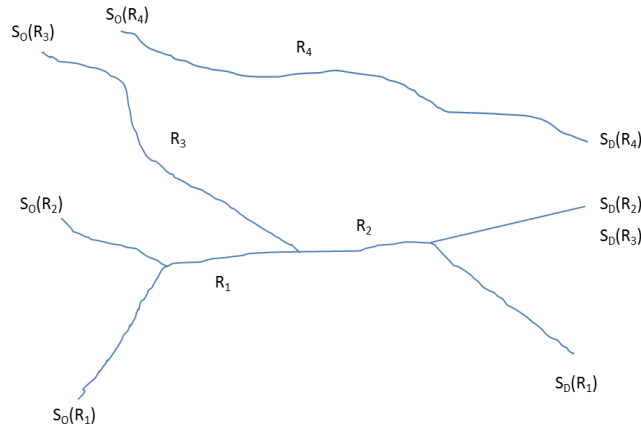


Figure 62: Some possible stop sequence ambiguity along different routes:  $S_O(R_i)$  and  $S_D(R_i)$  denote an origin and destination stop along route  $R_i$ . In order to hold the lemma 3, departure time at  $S_O$  must be earlier than arrival time at  $S_D$ .

**Proposition L3.1:** The end stop or destination stop ( $S_p^i(D)$ ) should occur after start or origin stop ( $S_p^i(O)$ ) in terms of time of visit ( $t$ ).

$$S_p^i(O)_t > S_p^i(D)_t \quad (29)$$



- **Lemma 4: Closest time selection**

The arrival and departure time at predicted origin and destination stops should be close to the scheduled stops in that location. However, there always exists a temporal uncertainty that makes the predicted trip start and end time deviate from the scheduled trip start and end time. For this purpose a temporal threshold ( $\delta t$ ) is used. For origin stops this can be expressed as follows, and similarly for destination stops. This will also conform with the first case in Lemma 3.

$$|S_p^i(O)_t - S_s^i(O)_t| = \delta t \quad (30)$$

- **Lemma 5: Use of  $WT_{i\pm 1}$  OD information**

Due to signal loss and uncertainties in the inference process in Layer 1, some (predicted) non-walking trips may have wrong trip start and end time. And these trip origin and destination stops may not have any scheduled trips in common within a given temporal threshold ( $\delta t$ ). To address this issue following proposition is made.

**Proposition L5.1:** If there is no scheduled trip ( $T_s$ ) found in the GTFS data base that matches a predicted trip  $i$  ( $T_p^i$ ) in terms of the mode type ( $M$ ) or temporal information (arrival/departure time) then the mode type ( $M_p^i(S_p^{i-1}(D))$ ) at the destination stop of the previous predicted trip ( $T_p^{i-1}$ ) or mode type ( $M_p^i(S_p^{i+1}(O))$ ) at the origin stop of the next predicted trip ( $T_p^{i+1}$ ) stops are considered, whichever is a walking trip ( $WT$ ) in between  $T_p^{i-1}$  and  $T_p^{i+1}$ .

The lemmata developed in this chapter are not exhaustive. Depending on the situation new lemmata can be added. However, the lemmata presented are sufficient enough to deal with different spatio-temporal and predictive uncertainties of trip patterns. That said, the thresholds set to quantify the lemmata and length of the temporal kernel depend on the type of data quality, sampling frequency and mode types to be distinguished. For temporal kernels the length has been evaluated starting with the shortest possible duration depending on the sampling frequency. Empirically the length of the temporal kernel must be greater than the minimum sampling rate used to capture the sensor trace.

---

**Algorithm 4** Rules for segment merging

---

```
1: INPUT All the atomic segments in a given trajectory (seglist), temporal threshold:  $\Psi$ 

2: OUTPUT a set of merged segments (mergedSeglist)
3: PROCEDURE Segment_Merging()
4: seglist.size() = k
5: boolean flag = false
6: for i=0 to k-2 do
7:   current_seg = seglist.get(i)
8:   next_seg = seglist.get(i + 1)
9:   RULE 1:
10:  if current_seg.mode_type == next_seg.mode_type && next_seg.duration  $\leq$ 
     $\Psi$  then
11:    merge_seg = merging(current_seg, next_seg)
12:    mergedSeglist.add(merge_seg)
13:    flag = true
14:  end if
15:  RULE 2:
16:  if current_seg.mode_type == next_seg.mode_type && next_seg.duration >
     $\Psi$  then
17:    merge_seg = merging(current_seg, next_seg)
18:    mergedSeglist.add(merge_seg)
19:    flag = true
20:  end if
21:  RULE 3:
22:  if current_seg.mode_type != next_seg.mode_type && next_seg.duration  $\leq$   $\Psi$ 
    then
23:    merge_seg = merging(current_seg, next_seg)
24:    mergedSeglist.add(merge_seg)
25:    flag = true
26:  end if
27:  RULE 4:
28:  if flag == false then
29:    mergedSeglist.add(current_seg)
30:    mergedSeglist.add(next_seg)
31:  end if
32: end for
33: END PROCEDURE
```

---

#### 7.3.3.4 Feature computation for detecting near-real time activity states in layer 1

In order to construct the predictive model, a number of features are generated using different machine learning classifiers, inferring the activity state on a queried trajectory using a given kernel length ( $\eta$ ) over  $I_n$  number of data points. Three different case studies are presented (Context 1 Scenario 1, Context 1 Scenario 2, and Context 2) depending on the quality and granularity of data using different sensor combinations (e.g., GPS, 3-axis accelerometer, gyroscope and gravity sensor). Prior work has investigated the aspects of sensor calibration in the context of activity recognition (Saeedi and El-Sheimy, 2015). However, in real to near-real time scenario the sensor information can come from different (unknown) smartphone sources owned by different users to a centralized server where the inference model is running. In such situation it is not always possible to get the hardware type, or mobile manufacturer information and thus poses difficulty in calibrating the particular source(s). To emulate the real world condition, thus in this work no attempt has been made to calibrate the sensors. However, a low pass filter has been used to remove the noise present in the IMU signals used in the proposed framework (see Section 7.4). For different orientation of the phone readers are referred to Figure 21.

A total of 34 features are computed using different sensor signals, based on acceleration in three directions such as (X:  $A_x$ , Y:  $A_y$ , Z:  $A_z$ ), rotational vectors in three directions (X:  $r_x$ , Y:  $r_y$ , Z:  $r_z$ ), pitch ( $r_x$ ), yaw ( $r_z$ ), roll ( $r_y$ ), speed ( $v$ ), and spatial proximity to the nearest route network using latitude, longitude information from a GPS sensor. In order to eliminate the gravity component a linear acceleration in three axes is chosen (X:  $a_x$ , Y:  $a_y$ , Z:  $a_z$ ). The features generated are as follows:

- Average of linear acceleration in X-direction ( $Avg a_x$ ), Y-direction ( $Avg a_y$ ) and Z-direction ( $Avg a_z$ )

$$Avg a_x = \frac{\sum a_x}{I_n} \quad (31)$$

$$Avg a_y = \frac{\sum a_y}{I_n} \quad (32)$$

$$Avg a_z = \frac{\sum a_z}{I_n} \quad (33)$$

- Average of resultant linear acceleration ( $Avg a_{xyz}$ )

$$Avg a_{xyz} = \frac{\sum a_{xyz}}{I_n} \quad (34)$$

- Average of resultant rotational vector ( $Avg R_{xyz}$ )

$$\text{AvgR}_{xyz} = \frac{\Sigma r_{xyz}}{I_n} \quad (35)$$

- Average of rotational vectors in X-direction ( $\text{Avg}r_x$ ), Y-direction ( $\text{Avg}r_y$ ) and Z-direction ( $\text{Avg}r_z$ )

$$\text{Avg}r_x = \frac{\Sigma r_x}{I_n} \quad (36)$$

$$\text{Avg}r_y = \frac{\Sigma r_y}{I_n} \quad (37)$$

$$\text{Avg}r_z = \frac{\Sigma r_z}{I_n} \quad (38)$$

- Variance of linear acceleration in X-direction ( $\text{Var}a_x$ ), Y-direction ( $\text{Var}a_y$ ), Z-direction ( $\text{Var}a_z$ ) and resultant linear acceleration ( $\text{Var}a_{xyz}$ )

$$\text{Var}a_x = \frac{1}{I_n - 1} \sum (a_x - \text{Avg}a_x)^2 \quad (39)$$

$$\text{Var}a_y = \frac{1}{I_n - 1} \sum (a_y - \text{Avg}a_y)^2 \quad (40)$$

$$\text{Var}a_z = \frac{1}{I_n - 1} \sum (a_z - \text{Avg}a_z)^2 \quad (41)$$

$$\text{Var}a_{xyz} = \frac{1}{I_n - 1} \sum (a_{xyz} - \text{Avg}a_{xyz})^2 \quad (42)$$

- Variance of rotational vector in X-direction ( $\text{Var}r_x$ ), Y-direction ( $\text{Var}r_y$ ), Z-direction ( $\text{Var}r_z$ ) and resultant rotational vectors ( $\text{Var}r_{xyz}$ )

$$\text{Var}r_x = \frac{1}{I_n - 1} \sum (r_x - \text{Avg}r_x)^2 \quad (43)$$

$$\text{Var}r_y = \frac{1}{I_n - 1} \sum (r_y - \text{Avg}r_y)^2 \quad (44)$$

$$\text{Var}r_z = \frac{1}{I_n - 1} \sum (r_z - \text{Avg}r_z)^2 \quad (45)$$

$$\text{Var}r_{xyz} = \frac{1}{I_n - 1} \sum (r_{xyz} - \text{Avg}r_{xyz})^2 \quad (46)$$

- Signal magnitude area in 2-channels (SMA2) and 3-channels (SMA3) respectively

$$SMA2 = \frac{1}{I_n} \sum (a_x + a_y) \quad (47)$$

$$SMA3 = \frac{1}{I_n} \sum (a_x + a_y + a_z) \quad (48)$$

- Average of Fourier coefficients of the resultant acceleration ( $FFT_A$ ) over kernel length  $\eta$

$$FFT_A = \text{fft}(\{A_{xyz}\}) \quad (49)$$

- Average of Fourier coefficients of the resultant acceleration ( $FFT_R$ ) over kernel length  $\eta$

$$FFT_R = \text{fft}(\{R_{xyz}\}) \quad (50)$$

- Number of zero crossings along in linear acceleration over  $\eta$  in X-direction ( $za_x$ ), Y-direction ( $za_y$ ), Z-direction ( $za_z$ )
- Average speed (AvgV) and 95th percentile of maximum speed (MaxV)
- **Correlation of linear acceleration in X-Y direction ( $corr_{xy}$ ), Y-Z direction ( $corr_{yz}$ ) and X-Z direction ( $corr_{zx}$ )**
- Entropy of resultant rotational vector (ER) and linear acceleration (EA) based on normalized power spectrum density (PSD) of resultant rotational vectors ( $p_{ri}$ ) in the time domain and normalized PSD of resultant acceleration ( $p_{Ai}$ )

$$ER = \sum -p_{ri} \log_2 p_{ri} \quad (51)$$

$$EA = \sum -p_{Ai} \log_2 p_{Ai} \quad (52)$$

- Average spatial proximity (Euclidean distance) to the bus network (avgBusProx), tram network (avgTramProx), train network (avgTrainProx), street network (avgStreetProx)

Table 28 gives an overview of the different features that are used in different contexts to detect the activity states over atomic segments that leads to trip detection after further merging and refinement.

Table 28: Feature selection in different contexts. A  $\bullet$  denotes the corresponding feature is selected under the given context. Likewise  $\circ$  denotes the feature is not selected.

FID	Feature	Context 1	Context 1	Context 2
		Scenario 1	Scenario 2	
1	$Avg a_x$	$\bullet$	$\circ$	$\bullet$
2	$Avg a_y$	$\bullet$	$\circ$	$\bullet$
3	$Avg a_z$	$\bullet$	$\circ$	$\bullet$
4	$Avg a_{xyz}$	$\bullet$	$\circ$	$\bullet$
5	$Avg r_x$	$\bullet$	$\circ$	$\bullet$
6	$Avg r_y$	$\bullet$	$\circ$	$\bullet$
7	$Avg r_z$	$\bullet$	$\circ$	$\bullet$
8	$Avg R_{xyz}$	$\bullet$	$\circ$	$\bullet$
9	$Var a_x$	$\bullet$	$\circ$	$\bullet$
10	$Var a_y$	$\bullet$	$\circ$	$\bullet$
11	$Var a_z$	$\bullet$	$\circ$	$\bullet$
12	$Var a_{xyz}$	$\bullet$	$\circ$	$\bullet$
13	$Varr_x$	$\bullet$	$\circ$	$\bullet$
14	$Varr_y$	$\bullet$	$\circ$	$\bullet$
15	$Varr_z$	$\bullet$	$\circ$	$\bullet$
16	$Var R_{xyz}$	$\bullet$	$\circ$	$\bullet$
17	$FFT_A$	$\bullet$	$\circ$	$\bullet$
18	$FFT_R$	$\bullet$	$\circ$	$\bullet$
19	SMA2	$\bullet$	$\circ$	$\bullet$
20	SMA3	$\bullet$	$\circ$	$\bullet$
21	$z a_x$	$\circ$	$\circ$	$\bullet$
22	$z a_y$	$\circ$	$\circ$	$\bullet$
23	$z a_z$	$\circ$	$\circ$	$\bullet$
24	$corr_{xy}$	$\circ$	$\circ$	$\bullet$
25	$corr_{xz}$	$\circ$	$\circ$	$\bullet$
26	$corr_{yz}$	$\circ$	$\circ$	$\bullet$
27	EA	$\bullet$	$\circ$	$\bullet$
28	ER	$\bullet$	$\circ$	$\bullet$
29	AvgV	$\bullet$	$\bullet$	$\circ$
30	MaxV	$\bullet$	$\bullet$	$\circ$
31	avgBusProx	$\bullet$	$\bullet$	$\circ$
32	avgTramProx	$\bullet$	$\bullet$	$\circ$
33	avgTrainProx	$\bullet$	$\bullet$	$\circ$
34	avgStreetProx	$\bullet$	$\bullet$	$\circ$

## 7.4 EVALUATION

In order to evaluate the developed approach, two different types of data sets have been used, each on one context. Data set 1 consists of low frequency sensor data including GPS and IMU sensor signals. Data set 2 consists of a high frequency IMU signal without location information.

### 7.4.1 *Context 1: Availability of location and speed information along with IMU signals sampled at a coarser granularity*

In the first context, a low frequency (1 Hz, 2 Hz) sensor trace containing GPS and IMU has been used. This is the typical context of smartphone based travel surveys, which generally sample at a low frequency to preserve battery power, as well as to capture real life kinematic behaviour during signal loss and in urban canyons.

Since Data set 1 contains GPS points, this data set is well suited for testing also the two existing methods (*walking-based* and *clustering-based*). In the subsequent section a comparative study is performed showing how the three methods perform on the same data set.

#### 7.4.1.1 *Data Set 1: Low frequency GPS and IMU data*

The first data set that is used in this research contains a low frequency GPS and IMU sensor information that covers different parts of Greater Melbourne, Australia (Fig 19). The data set mainly covers tram route, train route, bus route and different portions of street network.

The data set has been pre-processed using a spatial filter that removes any noise point where the positional inaccuracy is more than 40 m. The data set is collected in the WGS84 coordinate system, which is then projected on to GDA94 zone 55 reference system in order to perform spatial computation on the trajectories in an Euclidean space.

#### 7.4.1.2 *Experimental setup and results*

In Context 1, two different scenarios are tested. In the first scenario, the full sensor trace is used (GPS and IMU), whereas the second scenario investigates how the model behaves with GPS only signal and how the accuracy improves when the semantic gap created by the signal loss is bridged by a set of IMU signals sampled at a coarser granularity. A GPS feed sampled at a frequency of  $\geq 1$  Hz is state-of-the-art practice in smartphone based travel surveys (Cottrill et al., 2013; Forrest and Pearson, 2005; Gonzalez et al., 2008) and various location based context-aware service provisions (Zheng et al., 2008). Hence, although the IMU is sampled at a lower frequency, the framework is able to detect the trips and the transfers in between the trips effectively. A prior study

on stop detection from smartphone-based travel surveys that also includes GSM trajectories and 3-axis accelerometer signals sampled at a lower frequency demonstrates the efficacy of such sampling strategy (Zhao et al., 2015). The sampling rate is sufficient for trip or transfer detection, which are phenomena of significantly coarser temporal granularity.

In order to evaluate the framework, 56 trajectories are used as the training sample and 49 trajectories are used as the testing sample for both the scenarios in Context 1. The experiments are realized in three stages. In the first stage (LAYER 1) an atomic kernel of time length  $\eta$  is run over each trajectory to generate atomic segments. Each atomic segment is then used to compute a number of features to train a predictive model in Layer 1. In this stage, a near-real time mode detection is performed in order to infer the given activity state. In the second stage (LAYER 2) the atomic segments are merged based on a rule base, where the primary goal is to merge the consecutive atomic segments that bear the same activity state (see Section 7.3.3.2). This stage generates potential predicted trips. In the third stage (LAYER 3) the predicted trips are further refined based on GTFS information and the lemmata. The basic assumption behind such modular approach is the higher the consistency in mode detection accuracy in Layer 1 the better the inference performance for trip detection in Layer 3.

In order to select the best predictive model in terms of average accuracy and consistency in Layer 1 six different machine learning based classifiers are constructed through supervised learning: a decision tree (DT), a multi-layered perceptron artificial neural network (MLP), a random forest (RF), a K-nearest neighbor (KNN), a naive Bayes (NB) and an ensembled meta classifier (EC-Voting). An EC-Voting based method predicts through majority voting by combining three learning algorithms together (e.g., RF, KNN and MLP) to construct the meta-classifier. These classifiers are tested against each test trajectory separately. The classifiers are chosen based on prior studies on transport mode detection and activity recognition. There are ten experiments performed for each of the classifiers using different kernel lengths with different time windows  $\eta$ . Table 29 presents the number of total instances used as training and testing in ten experimental setups by changing the kernel length. Table 30 shows the average accuracy of near-real time mode detection for each atomic segment for all the test trajectories in Layer 1 at different  $\eta$ .



Table 29: Total number of instances used for training and testing at different kernel length

$\eta$	Training instances	Testing instances
10	87063	70260
20	38646	31188
30	24818	20022
40	18262	14733
50	14438	11645
60	11935	9626
120	5824	4693
180	3831	3090
240	2845	2294
300	2258	1812

Table 30: Average accuracy (%) in Layer 1 for near-real time mode detection using GPS, inertial measuring units (IMU) and spatial information.

Classifier	Kernel length $\eta$ in s									
	10	20	30	40	50	60	120	180	240	300
<b>DT</b>	80.47	83.11	83.48	84.19	83.67	83.91	91.01	90.93	90.63	89.72
<b>MLP</b>	83.25	85.25	85.21	88.04	85.55	89.21	92.32	93.25	91.05	91.13
<b>RF</b>	86.47	87.53	88.42	89.67	90.12	90.37	92.48	93.48	93.94	93.83
<b>KNN</b>	79.74	81.36	82.11	82.25	83.21	84.09	86.03	86.92	86.08	86.92
<b>NB</b>	55.84	56.08	57.89	57.69	59.61	57.57	59.87	60.59	62.63	63.58
<b>EC-Voting</b>	83.61	85.73	86.01	86.79	86.85	87.55	92.51	93.41	91.04	91.95

Average accuracy reflects the representative measure of each classifier’s prediction accuracy. In order to measure the consistency of the performance of each classifier standard deviation of average accuracy is computed for each kernel length for the same set of test trajectories (Table 31). The result shows a RF based classifier generally yields the maximum accuracy in all the ten experiments with least standard deviation followed by MLP and EC-Voting. A low standard deviation value essentially indicates high consistency with less variation in the accuracy value. However, the difference in average accuracy between a RF based classifier and an MLP based classifier (Table 30) is less. In order to evaluate the statistical significance of their performance measure a paired t-test is performed using the individual prediction accuracy made on all

the test trajectories. It shows the difference in performance between RF and MLP is statistically significant in eight experimental setups (from 10 s to 60 s and then from 240 s to 300 s) out of 10 experiments (Table 32). This draws a clear contrast between a RF based and MLP based classifier. The result also suggests a RF based classifier outperforms all other learning algorithms used in this research to infer the activity state (transport modes) in near-real time when using GPS and IMU signal to generate the feature vectors. Figure 63 shows how six different classifiers perform at 10 s and 60 s kernel lengths on all the test trajectories. Table 33 and 34 show two confusion matrices to demonstrate the classification accuracy of an MLP and RF classifier at 60 s window when evaluated on all the test samples together by combining all the test trajectories.

Table 31: Measure of standard deviation at different kernel length by different classifiers in Context 1, Scenario 1.

Classifier	Kernel length $\eta$ in s									
	10	20	30	40	50	60	120	180	240	300
DT	3.31	2.8	1.76	1.66	2.73	2.59	0.61	1.05	0.81	2.65
MLP	3.79	3.12	2.73	1.83	3.58	1.53	0.88	1.27	2.1	0.75
RF	<b>1.88</b>	<b>1.72</b>	<b>1.61</b>	<b>1.48</b>	<b>1.51</b>	<b>1.29</b>	<b>0.86</b>	<b>0.72</b>	<b>0.71</b>	<b>0.74</b>
KNN	3.34	3.22	3.28	3.36	3.13	3.27	2.85	2.74	2.57	1.83
NB	3.67	3.72	3.48	3.62	3.63	3.72	3.71	4.18	4.26	3.46
EC-Voting	3.51	3.24	3.05	2.84	3.02	2.85	0.63	0.82	2.27	0.67

Table 32: Context 1, Scenario 1: Measuring statistical significance of prediction accuracy between MLP and RF based classifiers at 5% significance level. A  $p$ -value  $\leq 0.05$  and  $h$ -value=1 signifies the result is statistically significant.

Kernel length in s	$p$ -Value	$h$
10	$6.65 \times 10^{-7}$	1
20	$2.14 \times 10^{-5}$	1
30	$2.55 \times 10^{-10}$	1
40	$5.37 \times 10^{-6}$	1
50	$9.50 \times 10^{-13}$	1
60	$9.74 \times 10^{-5}$	1
120	$3.5 \times 10^{-1}$	0
180	$2.8 \times 10^{-1}$	0
240	$1.18 \times 10^{-14}$	1
300	$4.33 \times 10^{-32}$	1

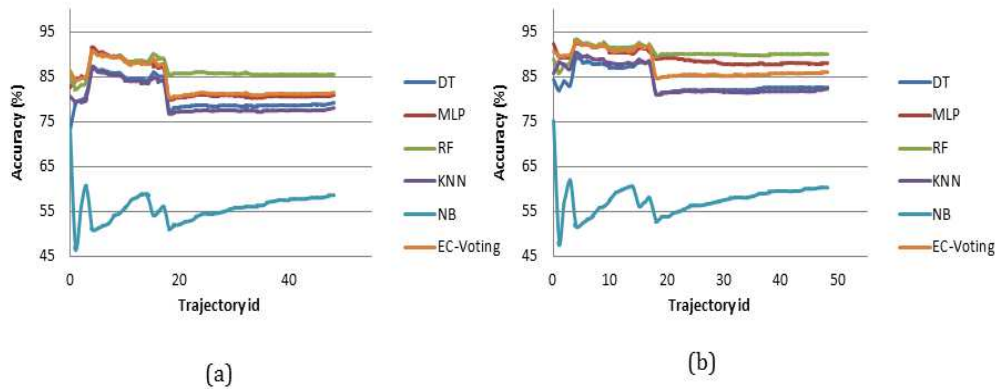


Figure 63: Performance of various classifiers in Layer 1 when using GPS and IMU information at 10 s (a) and 60 s (b).

In Context 1 Scenario 2 when a sensor trace consists of GPS only information, the performance of different classifiers are evaluated at different kernel lengths. The result shows an MLP based classifier outperforms an RF based classifier in terms of average accuracy (Table 35). In terms of consistency of performance MLP and RF based classifier behave close to each other, however the average accuracy of a RF based classifier is less than that of an MLP based classifier (Table 36). The result also demonstrates that the difference in performance of RF and MLP is statistically significant (Table 37) in nine experiments, except the 240 s window.

Table 33: Confusion matrix by MLP based classifier using GPS and IMU information at 60 s

Predicted	Bus	Train	Walk	Tram	Composite
<b>Actual</b>					
<b>Bus</b>	<b>1245</b>	14	269	72	0
<b>Train</b>	14	<b>1023</b>	61	36	0
<b>Walk</b>	31	53	<b>4723</b>	303	0
<b>Tram</b>	95	16	164	<b>1476</b>	0
<b>Composite</b>	4	3	19	5	<b>0</b>

Table 34: Confusion matrix by RF based classifier using GPS and IMU information at 60 s

Predicted	Bus	Train	Walk	Tram	Composite
<b>Actual</b>					
<b>Bus</b>	<b>1477</b>	6	76	41	0
<b>Train</b>	14	<b>1046</b>	43	31	0
<b>Walk</b>	122	64	<b>4747</b>	177	0
<b>Tram</b>	56	10	133	<b>1552</b>	0
<b>Composite</b>	3	4	18	6	<b>0</b>

Table 35: Average accuracy (%) in Layer 1 for near-real time mode detection using GPS and spatial information.

Classifier	Kernel length $\eta$ in s									
	10	20	30	40	50	60	120	180	240	300
<b>DT</b>	77.81	83.38	85.02	85.24	81.46	84.45	89.61	91.21	91.54	90.85
<b>MLP</b>	82.99	84.36	87.38	87.28	89.15	90.28	93.03	93.37	92.91	91.86
<b>RF</b>	76.95	79.12	84.62	85.82	87.13	89.24	91.07	92.69	93.01	92.71
<b>KNN</b>	75.26	77.51	78.75	79.02	84.71	86.43	89.05	86.21	90.28	89.61
<b>NB</b>	76.07	81.93	83.93	84.88	85.67	86.62	90.76	92.56	92.69	92.76
<b>EC-Voting</b>	77.86	79.65	81.78	82.36	87.28	89.05	91.83	93.16	93.65	92.52

Table 36: Standard deviations at different kernel lengths by different classifiers in Context 1, Scenario 2.

Classifier	Kernel length $\eta$ in s									
	10	20	30	40	50	60	120	180	240	300
DT	4.11	1.59	1.31	1.19	4.41	3.81	1.07	1.11	0.79	1.05
MLP	2.08	1.27	1.53	1.84	1.26	1.35	1.26	1.08	0.84	0.84
RF	4.55	4.55	1.28	1.11	1.01	1.21	0.86	0.97	0.79	0.77
KNN	4.18	3.93	4.02	3.79	1.27	1.51	0.88	3.47	1.53	1.29
NB	3.95	2.23	2.12	1.93	1.98	1.96	1.58	1.41	1.01	0.95
EC-Voting	4.83	3.93	4.31	3.94	0.87	1.23	0.58	0.69	0.73	0.82

Table 37: Context 1, Scenario 2: Statistical significance of prediction accuracy between multi-layered perceptron artificial neural network (MLP) and random forest (RF)-based classifiers at 5% significance level. A  $p$ -value  $\leq 0.05$  and  $h$ -value =1 signifies the result is statistically significant.

Kernel length in s	$p$ -Value	$h$
10	$3.26 \times 10^{-13}$	1
20	$9.22 \times 10^{-12}$	1
30	$8.29 \times 10^{-16}$	1
40	$7.15 \times 10^{-6}$	1
50	$7.05 \times 10^{-14}$	1
60	$1.19 \times 10^{-4}$	1
120	$2.81 \times 10^{-14}$	1
180	$1.50 \times 10^{-3}$	1
240	$4.77 \times 10^{-1}$	0
300	$1.75 \times 10^{-6}$	1

Once the atomic segments are generated with a given activity state (transport mode) a rule-based merging operation is performed to generate a set of homogeneous segments for each queried trajectory. Then a pair of stops is retrieved using a ring buffer corresponding to the beginning and ending of the segment. Following that, the segments are now transformed to potential predicted trips with trip start and end in space-time with their stops. These trips are then fed to the Layer 3, where a spatio-temporal consistency check is performed and a refinement process takes place which

generates the final trips with their start time and end time, start stop and end stop along with the given transport mode taken during that trip.

For validation purposes in Context 1, the final predicted trips are compared with the reported trips based on trip start time, end time, and the mode. The origin and destination is not validated in this research as the reported trips did not have the complete origin-destination information, but a detailed information on trip start time, end time, and transport mode. However, the framework has a provision to validate the origin, destination and route information if needed (or if the reported data incorporates such detailed ground truth data).

Since there is a temporal uncertainty (Fig 57) associated with the trips due to several reasons (from data end, user end, device end, service end, inference end, and the environmental aspects including the noise and signal loss introduced in the data), while validating the final predicted trips against the reported trips two temporal uncertainty bounds  $\sigma$  are used. Table 38 shows at 10 s kernel length MLP outperforms an RF based classifier in terms of trip detection. But with the growing window RF outperforms MLP in terms of precision and recall accuracy both when  $0 \leq \sigma \leq 3$  and  $0 \leq \sigma \leq 4$ .

Figure 64 shows an RF based classifier performs better in general over an MLP classifier—and other classifiers, which is not shown here but evident from the performance in their respective Layer 1 (Table 30). The result shows that with growing upper bounds of temporal uncertainty ( $\sigma$ ) the accuracy improves significantly especially for an RF based classifier, where the precision jumps from 57.96% to 65.50% at  $\eta$  of 10 s, 70.30% to 76.36% at 20 s, 72.18% to 79.30% at 60 s and 82.78% to 88.07% at 120 s. Table 38 also demonstrates there is a significant improvement in recall when  $\sigma$  is increased from 3 min to 4 min. Figure 65 shows the false discovery rate (thus the Type I error) of a RF based classifier also decreases with growing time window, suggesting that the uncertainty is reduced with growing the kernel length (vis-a-vis the window size). The result also shows when the upper bound of temporal uncertainty is raised from 3 min to 4 min the Type I error has reduced for each kernel length. Since the temporal uncertainty may vary from 3 min to 4 min in this research atomic segments with kernel length of 2 min have been tested assuming there is no change in activity state within that shorter window. The result shows the maximum accuracy is reached at a 120 s window, which is followed by a 60 s window. However, in some situations a quick transfer may take place within 60 s which may be difficult to detect.

Table 38: Context 1, Scenario 1: Trip detection accuracy by RF and MLP based classifier using GPS, IMU and spatial information.

Classifier: RF		$0 \leq \sigma \leq 3$			$0 \leq \sigma \leq 4$		
$\eta$	Precision (%)	Recall (%)	F1-Score	Precision (%)	Recall (%)	F1-Score	
10	57.96	59.01	0.58	65.50	65.60	0.65	
20	70.30	75.32	0.72	76.36	81.81	0.78	
30	70.10	77.27	0.73	74.70	82.16	0.78	
40	67.25	74.67	0.71	76.02	84.41	0.79	
50	72.50	75.32	0.73	79.37	82.46	0.81	
60	72.18	79.20	0.75	79.30	87.01	0.82	
120	82.78	81.16	0.81	88.07	86.36	0.87	

Classifier: MLP		$0 \leq \sigma \leq 3$			$0 \leq \sigma \leq 4$		
$\eta$	Precision (%)	Recall (%)	F1-Score	Precision (%)	Recall (%)	F1-Score	
10	65.86	71.42	0.68	71.85	77.90	0.74	
20	64.28	75.97	0.69	67.03	79.22	0.72	
30	63.74	70.77	0.67	69.00	76.60	0.72	
40	63.63	72.72	0.67	69.31	79.22	0.74	
50	65.53	75.32	0.70	81.16	70.62	0.75	
60	57.22	66.88	0.61	63.88	74.67	0.68	
120	74.25	80.51	0.77	76.64	83.11	0.79	

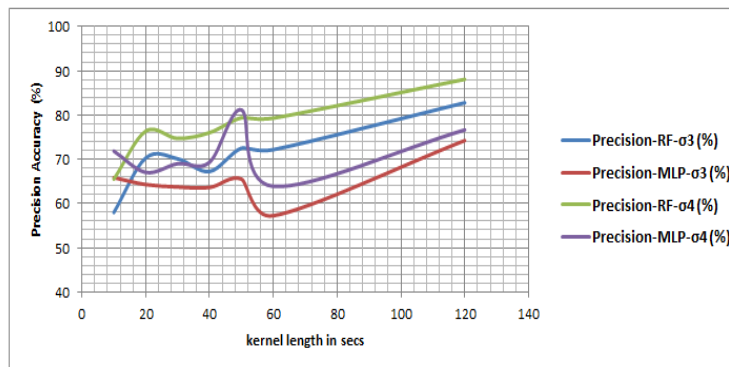


Figure 64: Precision of RF and MLP classifier at different temporal uncertainties.

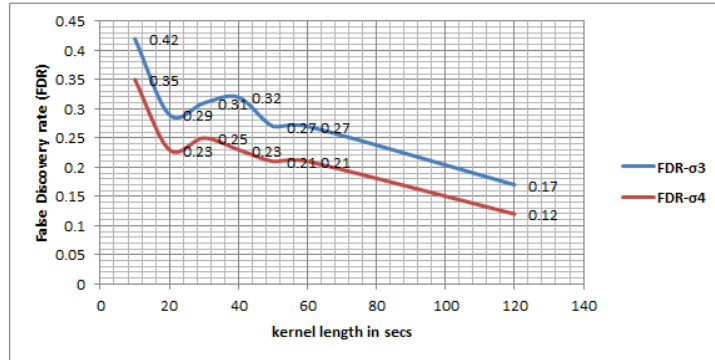


Figure 65: False discovery rate (FDR) of a RF based classifier for trip detection at different  $\sigma$  using a state based bottom up approach.

In Scenario 2, Context 1, in absence of the IMU signal the detection accuracy drops significantly than that of Scenario 1, Context 1. When the sensor trace consists of only GPS based location information without further IMU observations an MLP based classifier performed better in processing Layer 1 as well as in processing Layer 3 and detects trips more accurately than that of a RF based classifier (Table 39). The results in Scenario 1 clearly indicate that although IMU information is sampled at a low frequency this information can bridge the gap present in a GPS trajectory to some extent and helps in detecting the trips. In Scenario 2 using a GPS-only data set the maximum recall and precision obtained using a RF based classifier are 70.77% at 60 s and 64.93% accuracy respectively when  $0 \leq \sigma \leq 3$ , and 79.22% recall at 60 s and 72.72% precision at 120 s when  $0 \leq \sigma \leq 4$ . On the other hand an MLP based classifier yields 75.32% recall and 72.51% precision at 120 s when  $0 \leq \sigma \leq 3$  and 83.76% recall at 50 s and 75.01% precision at 120 s when  $0 \leq \sigma \leq 4$ .

In order to compare with the existing trajectory segmentation and trip detection approaches the data set has also been evaluated using a *walking-based* and *clustering-based* approach. Walking can take place anywhere (along the street, along the train station, close to the bus stop or tram stop) or over any distance (Fig 66). In order to find the most suitable walking distance threshold (L) for the given data set a set of eleven experiments are performed starting with 10 m to 100 m incremented by 10 m, and 200 m separately. The existing walking-based approach segments a trajectory into either a walking or non-walking mode. Thus, for validation purposes any motorized mode is labelled as non-walk. The validation is also performed by measuring the difference between predicted trip start and end time (inferred from *walking based* model) with the reported trip start and end time. Like the state-based bottom-up approach, if the difference for start and end of the trip falls within a given temporal uncertainty then that predicted trip is considered as a true positive.

Table 40 shows for the given data set and given movement that behaviour maximum accuracy is obtained when the distance threshold (L) ranges from 60 m to 70



Table 39: Context 1, Scenario 2: Trip detection accuracy by RF and MLP based classifiers using GPS and spatial information.

Classifier: RF		$\sigma \leq 3$			$\sigma \leq 4$		
$\eta$	Precision (%)	Recall (%)	Type I	Precision (%)	Recall (%)	Type I	
10	32.41	38.31	123	44.51	52.59	101	
20	35.38	44.81	126	47.17	59.74	103	
30	39.11	51.29	123	48.51	63.63	104	
40	38.74	48.05	117	48.16	59.74	99	
50	47.33	57.14	98	59.13	71.42	76	
60	60.55	70.77	71	67.77	79.22	58	
120	64.93	64.94	54	72.72	72.72	42	

Classifier: MLP		$\sigma \leq 3$			$\sigma \leq 4$		
$\eta$	Precision (%)	Recall (%)	Type I	Precision (%)	Recall (%)	Type I	
10	40.41	50.64	115	46.11	57.79	104	
20	46.96	60.38	105	52.52	67.53	94	
30	52.42	70.12	98	60.19	80.51	82	
40	49.46	60.38	95	58.51	71.43	78	
50	60.21	72.72	74	69.35	83.76	57	
60	62.92	72.72	66	70.78	81.81	52	
120	72.51	75.32	44	75.01	77.92	40	

m. When  $\sigma \leq 3$  the maximum precision accuracy by the walking-based approach is 66.85% and recall accuracy is 75.97% at 70 m distance threshold. The walking-based approach generates many irrelevant segments for shorter distance thresholds, denoting false positive trips when a motorized mode moves very slowly in traffic. On the other hand, a longer distance threshold would miss some true positive walking trips owing to reduction in precision accuracy. However, in this research while implementing the walking-based approach the models starts with a very short distance threshold—10 m to 100 m (based on heuristics). Prior studies found a critical distance threshold (>100 m) for effective trajectory segmentation in cities like Beijing (Zheng et al., 2008). The result shows a shorter distance threshold tends to over-segment the trajectory and gives rise to high FDR and thus to reducing the accuracy of the model (Fig 67). When comparing between the proposed state-based bottom-up model and the walking-based model, it is evident that a walking-based model generates high Type I error owing to

high FDR (Fig 65 and Fig 67). For a state-based bottom-up model the maximum FDR obtained is 0.42 (at  $\sigma \leq 4$ ) and the minimum is 0.12 (at  $\sigma \leq 3$ ) (see Fig 65), whereas for walking-based model the maximum FDR is 0.71 and the minimum is 0.32. Both the max-min FDR generated by walking-based approach is higher than the state-based bottom up model. Thus, it is clear the proposed approach is less context-sensitive and less subjective and can work in any environment with a diverse topology of different region of interest (say, transfers between a train stop to the nearest bus stop may be different between cities, which is difficult to model by a walking-based approach but can be effectively detected by the proposed method in this research).

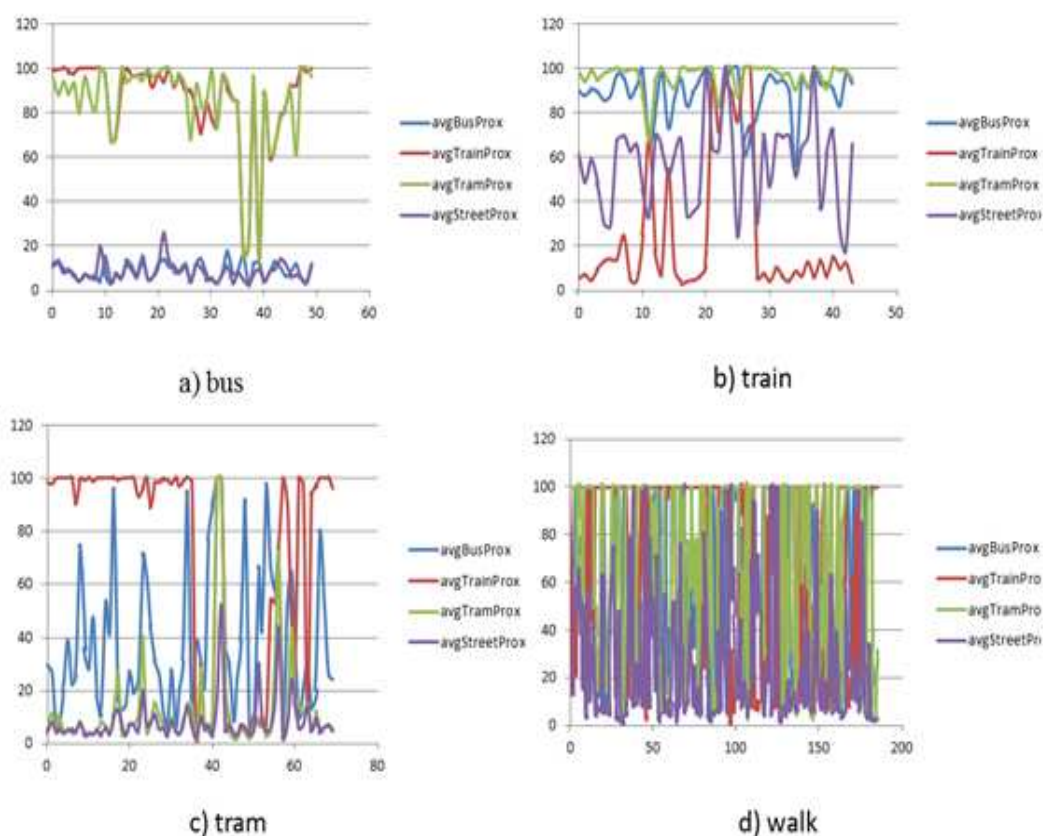


Figure 66: Average proximity of some of the trips to different route types. Although there is an overlap by the routes of different public transport modes, a trip with a given mode type (for bus (a); train (b); tram (c)) shows a distinct proximity behaviour to the given route type. However, since walking can happen anywhere for walking trips, there is no discernible visual pattern for walking (d).

Table 40: Accuracy measure of trip detection by walking-based approach.

L (m)	$\sigma \leq 3$			$\sigma \leq 4$		
	Precision (%)	Recall (%)	F1-Score	Precision (%)	Recall (%)	F1-Score
10	28.98	51.94	0.37	33.69	60.38	0.43
20	37.65	60.38	0.46	40.98	65.58	0.5
30	50.47	68.83	0.58	53.33	72.72	0.61
40	55.94	73.37	0.63	58.41	76.62	0.66
50	61.45	76.62	0.68	63.02	78.57	0.69
60	65.53	75.32	0.70	67.23	77.27	0.71
70	66.85	75.97	0.71	67.42	76.62	0.71
80	66.67	74.02	0.70	67.83	75.32	0.71
90	63.58	71.42	0.67	64.73	72.72	0.68
100	61.21	65.58	0.63	62.42	66.88	0.64
200	61.78	49.35	0.54	61.78	49.35	0.54

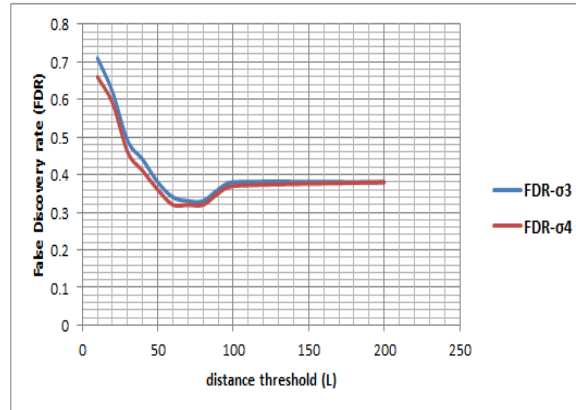


Figure 67: False detection rate (FDR) generated by the walking-based model.

For illustration a test trajectory and its inference process is explained in Figure 68. Table 41 presents a comparison between the reported trips and the predicted trips generated by an RF classifier with 60 s kernel length on trajectory ID 150615\_1. Using a state-based bottom-up approach six out of six trips are correctly detected with trip start and end time and respective transport modes. Using the walking-based method only four out of six trips are detected, and with less detailed mode information (Table 42). The raw trajectory is shown in 2D; except location information no other semantics is

known (Fig 68a), whereas in Figure 68b the same trajectory is shown in 3D in the form of a space-time path with inferred semantics such as different trips with different modes, trip start and end in space and time. In that figure (Fig 68b) the X-Y space denotes the geographical space and Z the time. From the space-time path it is also evident that there are two semantic gaps in the trajectory due to signal loss. The existing approaches such as the walking-based or the clustering-based approach tend to generate misleading information within such gaps. However, the state-based approach bridges these gaps since it is able to handle IMU information. The IMU signals show a distinct kinematic behaviour for the different modes (Fig 69).

The data set is also tested with a clustering-based approach. A clustering-based model has been developed that produces the geometric clusters of points based on the spatial proximity between the GPS points. The clusters are not semantically enriched. Based on the neighborhood ( $\epsilon$ ) and the dwell time ( $\phi$ ) over each cluster three sets of experiments (based on  $\phi$ ) are performed where each of the sets contains further ten sets of setups (based on  $\epsilon$ ). The minimum number of neighbor points are considered as three, so the total number of points to form a cluster is the core point itself and at least three neighbors. The value of  $\epsilon$  is chosen from 1 m to 10 m assuming the GPS inaccuracy will vary from 1 m to 10 m and beyond in the urban environment using cheap commercial smartphone GPS receivers. However, in real world applications where the location information comes only from GPS feeds (without other location sources such as GSM, Wi-Fi, checkpoints installed in the environment, or from social media) and without semantic enrichment of the clusters, it is evident that the temporal uncertainty is quite high between the predicted trips and the reported trips leading to a low accuracy for all the clustering based experiments (Table 43). The result shows that using a clustering-based method without any semantic enrichment (i.e., without considering the intersected point of interest or other contextual information) a state-based approach outperforms a clustering-based model.

Table 41: Trip comparison between reported trips and predicted trips in an automated travel diary generated by a state-based bottom-up approach (TrajectoryID150615\_1).

Reported				Predicted			
Trip ID	Trip Start	Trip End	Mode	Trip ID	Trip Start	Trip End	Mode
1	12:48:00	12:49:00	walk	1	12:48:45:412	12:49:43:413	walk
2	12:49:00	12:58:00	bus	2	12:49:43:413	12:58:10:913	bus
3	12:58:00	13:03:00	walk	3	12:58:10:913	13:03:00:913	walk
4	13:03:00	13:14:00	train	4	13:03:00:913	13:14:22:413	train
5	13:14:00	13:16:00	walk	5	13:14:22:413	13:16:03:912	walk
6	13:16:00	13:27:00	train	6	13:16:03:912	13:26:56:413	train

Table 42: Trips generated by a walking-based method on Trajectory ID 150615\_1.

Trip ID	Trip Start	Trip End	Mode
1	12:48:16:412	12:49:53:413	walk
2	12:49:53:413	12:57:52:912	non-walk
3	12:57:52:912	13:03:00:413	walk
4	13:03:00:413	13:26:59:412	non-walk

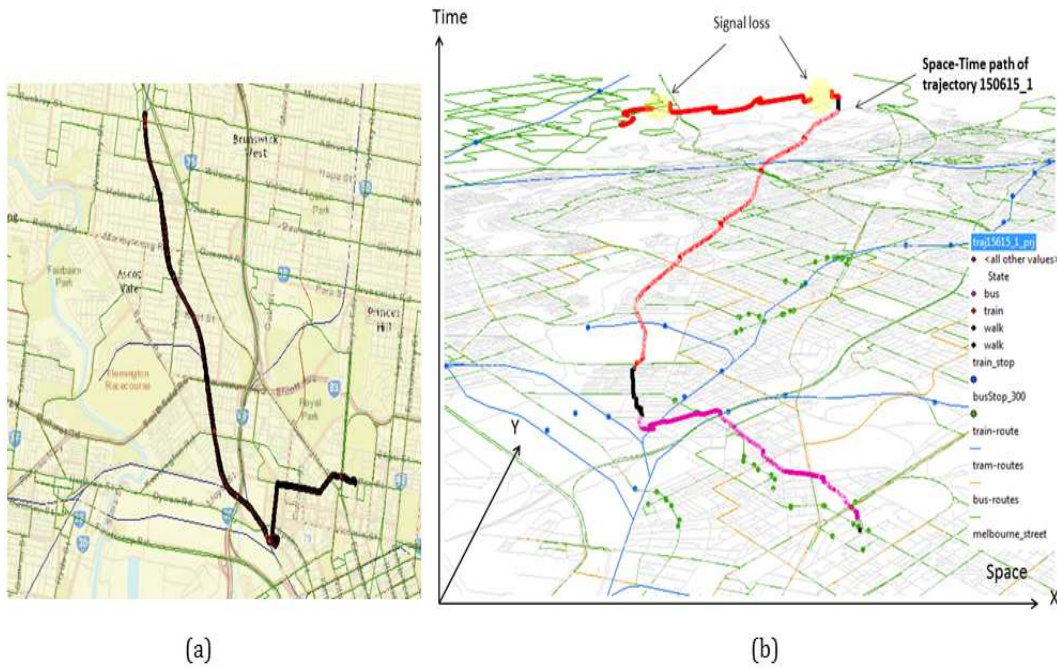


Figure 68: A raw trajectory ID 150615\_1 in 2D without any semantic information (a); and in 3D as a space-time path with semantic information such as different trips with their start and end in space-time, modes used, travel direction, signal gap, and travel speed (b).

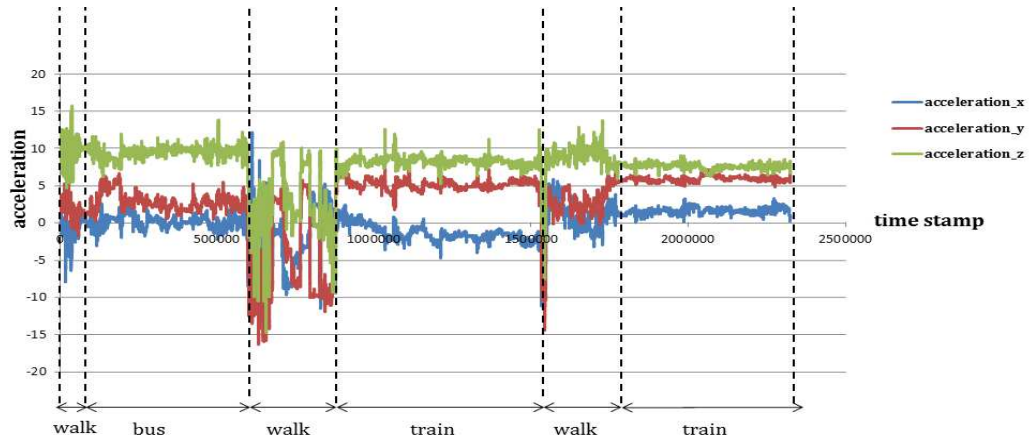


Figure 69: A continuous acceleration profile showing distinct behaviour of different transport modes even through the semantic gap due to GPS signal loss on the (TrajectoryID150615\_1).

Table 43: Trip detection accuracy by a geometric clustering-based model.

total minPts = (3 + 1) = 4;							
$\phi = 60$ s							
$\sigma \leq 3$				$\sigma \leq 4$			
$\epsilon$ (m)	Precision (%)	Recall (%)	Type I	Precision (%)	Recall (%)	Type I	
1	48.01	15.58	26	48.01	15.58	26	
2	46.15	15.58	28	46.15	15.58	28	
3	40.32	16.23	37	40.32	16.23	37	
4	44.61	18.83	36	46.15	19.48	35	
5	41.42	18.83	41	42.85	19.48	40	
6	38.15	18.83	47	40.78	20.12	45	
7	36.25	18.83	51	38.75	20.12	49	
8	36.71	18.83	50	39.24	20.12	48	
9	35.71	19.48	54	38.09	20.78	52	
10	34.48	19.48	57	36.78	20.77	55	
total minPts = (3 + 1) = 4;							
$\phi = 120$ s							
$\sigma \leq 3$				$\sigma \leq 4$			
$\epsilon$ (m)	Precision (%)	Recall (%)	Type I	Precision (%)	Recall (%)	Type I	
1	46.93	14.93	26	46.93	14.93	26	
2	46.93	14.93	26	46.93	14.93	26	
3	48.97	15.58	25	48.97	15.58	25	
4	44.23	14.93	29	44.23	14.93	29	
5	43.13	14.28	29	43.13	14.28	29	
6	43.39	14.93	30	43.39	14.93	30	
7	42.59	14.93	31	42.59	14.93	31	
8	42.59	14.93	31	42.59	14.93	31	
9	43.63	15.58	31	43.63	15.58	31	
10	43.85	16.23	32	43.85	16.23	32	

#### 7.4.2 Context 2: Fine granular inertial sensor information in unknown location

Existing approaches (walking-based and clustering-based) rely on the consistent availability of location information. But a GPS signal is not available everywhere and also the GPS receiver on the smartphone draws on significant amount of energy, hence in Context 2 it has been investigated how the proposed state-based bottom-up approach behaves without location information. It turns out to be adaptive to different contexts, while the existing approaches are not applicable due to lack of location and speed information. Context 2 is also applicable to public health research where one needs to know the current activity state of the user at an even finer granularity (including body movements). As the location information is unknown and a normal body movement frequency is generally 20 Hz (Karantonis et al., 2006; Xia et al., 2014) the sampling frequency is chosen as 50 Hz (which is roughly double of 20 Hz) which also aligns with the prior studies in intelligent transportation systems (Xia et al., 2014). Such a high frequency is required mainly due to the lack of location information in the sensor trace. The inference process will solely rely on the IMU signals.

##### 7.4.2.1 Data Set 2: High frequency IMU Only data

In order to evaluate the model a high frequency IMU only data set has been used (see Section 3.2). Most of the prior transport mode detection research that used IMU signals did not attempt to distinguish between different motorized modes (Reddy et al., 2010; Xia et al., 2014), and only detected pedestrian modes and motor modes. Prior studies also used additionally speed information using a GPS receiver. Here, the inference process is solely based on accelerometer and gyroscope.

##### 7.4.2.2 Experimental setup and results

In order to detect the trips using only high frequency IMU data, nine sensor traces are used as training data and nineteen sensor traces are used as testing data. The experiments are performed in two setups. In the first setup a 5 s kernel is run over each sensor trace, and feature vectors are computed from the extracted atomic sensor segments with 50% overlap after passing the atomic segments into a first order low pass filter (LPF) in order to remove any sudden jerk or noise. In the second setup a 10 s kernel is used to generate the feature vectors. In order to avoid the correlation effect (and thus the overfitting of the model) training and testing sensor traces are used separately. The result shows that without using speed information, a sensor trace containing only accelerometer and gyroscope cannot yield very high accuracy due to the ambiguity in groundtruth information (which is in line with a prior research (Wang et al., 2010)). For example, a reported tram trip with its trip start and end may have several waiting events in between (at stops), which may not be reported and thus can be misclassified. Also, the vibration of trams and trains may produce similar effects,

especially when the train and tram move at a similar speed. During walking changes of speed can happen more abruptly compared to other modes of transport, and thus there is a sharp distinction between walk and non-walk modes in their acceleration profile. Figure 70 shows the accuracy in processing Layer 1 for mode detection on IMU sensor traces. The result shows an RF classifier generally works better than other classifiers and yields accuracies from 60% to 78%. In order to train different classifiers a total 2285 feature vectors are used, whereas a separate set of feature vectors are used for each of the test sensor traces to infer the trips for each of those testing sensor traces. The number of feature vectors ranges from 190 (very short sensor trace) to 1571 .

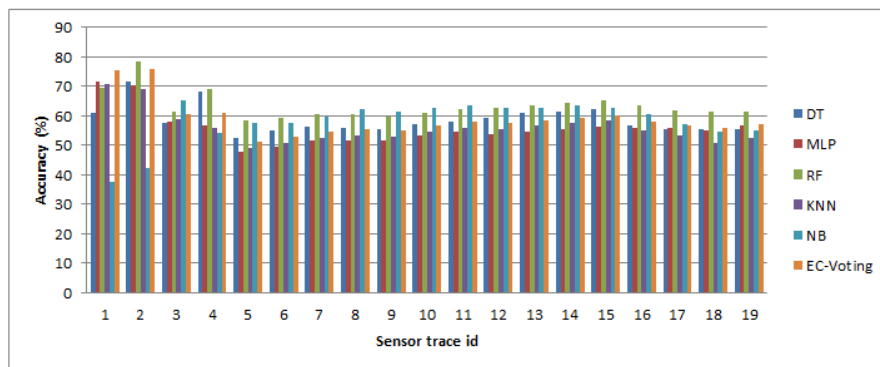


Figure 70: Transport mode detection accuracy using a 5 s kernel over different test sensor traces.

In Context 2, once the activity states (transport modes) are detected, the atomic sensor segments are fed to Layer 2 where a rule based advanced merging is performed and potential predicted trips are generated. Since in this case the location information is missing, the predicted trips are not further fed to Layer 3 for location consistency checking. Rather the predicted trips generated by Layer 2 are treated as the final predicted trips. Since there is no consistency check, there are ambiguities in detecting motorized modes, however the models can correctly distinguish between a walking and non-walking mode (bus, train, tram). Hence during validation for the trips generated by IMU only sensor trace, only the predicted trip start and trip end time is matched with the reported trip excluding the activity state (transport mode) at a given temporal uncertainty. When  $0 \leq \sigma \leq 3$  the recall accuracy for trip detection is 71.05% and precision accuracy is 67.50% using a 5 s kernel.

## 7.5 DISCUSSION

In this chapter a novel state-based bottom-up framework is proposed that can interpret a raw sensor trace and can generate an automated travel diary containing a rich travel information from smartphone based sensor information. A travel diary gener-



ated through this framework contains the number of trips, their start and end time, and the particular transport mode used during that trip(s). The model presented in this research is adaptive and modular in nature. The model is adaptive because it can be applied in different contexts with different types of sensor data and different granularity. The model can generate the activity state information based on a user defined kernel length. The model consists of three phases: an input phase, a processing phase and an output phase. The core of this model is the processing phase which consists of three layers. Depending on the situation each of the layers can be activated or deactivated. For example, if the interest lies in near-real time activity detection (transport mode in this case) then the Layer 1 will be activated and the subsequent layers (Layer 2 and Layer 3) can be deactivated. On the other hand, if one is interested in trip detection from GPS trajectories all three layers can be activated. On the other hand, if the same task (trip detection) is to be performed based on IMU only then the third layer is no longer required—thus the model can adapt depending on the requirements and workload effectively.

In this research the concept of temporal uncertainty ( $\sigma$ ) is introduced while modelling the trips using Allen's temporal calculus (Allen, 1983). The upper bound of  $\sigma$  is considered to vary from 3 min to 4 min depending on the observation for this particular research. The quantification of such temporal uncertainty is done from the fuzziness in traveller and driver behaviour, uncertainties in hardware performance (sensors and clock), and the uncertainty present in user's perceptions of activities while reporting the trips. Since in this research the precision used in temporal information on reported trips is limited to minutes and not seconds, there is always an uncertainty of at least 59 s. Thus, the minimum temporal uncertainty that can be improved in future research will be 2 min by shortening the 3 min minimum uncertainty modelled in this research, which can be further improved if a finer temporal precision is available while recording the ground truth.

In order to illustrate the efficacy and performance of the proposed model for trajectory segmentation and trip generation, it has been compared with two state-of-the-art approaches (walking-based and clustering-based). A walking-based approach is subjective and context-sensitive and thus subject to proper functioning in different situations and for different users. The success of a walking-based approach depends on proper selection of walking speed, distance merging threshold and total distance threshold, which are difficult to set. On the other hand a clustering-based approach depends on the minimum number of points to form a potential cluster based on their spatial proximity. A potential cluster can be treated as a stop or slow walking trip depending on the chosen  $\epsilon$ . The relevance of a cluster can be measured based on the dwell time and other contextual information. In this research, the clusters formed are simple geometric clusters without any semantic enrichment but limited by spatial-temporal constraints. The clusters can be of any shape and size, thus raising more uncertainty especially when there is frequent signal gap and randomness in GPS loca-

tions. Since both the methods work only when there is a consistent location information (say from a GPS feed) with reasonable accuracy they do not perform well in sparse GPS trajectory data (Context 1) and cannot cope without location information (Context 2). The state-based bottom-up method presented in this research can incorporate different IMU information, and hence can work in diverse situations with a reasonable accuracy for mode detection as well as trip detection. The proposed model can also work on a low frequency GPS, combination of GPS and IMU signals, and a high frequency IMU only signal. The model can be made more robust and more intelligent by extending the layers in its processing phase to deal with more diverse and challenging situations, for example, detecting trips and modes on a GSM trajectory, which is generally coarser and more uncertain than that of a GPS trajectory depending on the distribution of cell phone towers.

Despite of the richness in mobility-based activity information the proposed model has some limitations. For example, in Layer 3 while performing the consistency checking an alternate possibility checking is missing at this moment, and that is due to the fact that machine learning algorithms cannot generate an alternate prediction in a human understandable format.

This research also investigated the optimal kernel length for detecting transport mode in near-real time. The length of kernels ranging from 5 s to 300 s conforms with the prior studies that attempt to detect mobility-based activities from different perspectives (Byon et al., 2009; Xia et al., 2014). The results show that an RF-based classifier performs better than the other classifiers, and an optimal kernel length can be 60 s to 120 s. However, since some activities, e.g., a transfer, can take place within a 120 s interval, the kernel length can further be reduced to 10 s with the given accuracy. The experimental results show that the performance of the model drops in high frequency IMU only information. This is because the public transport modes (bus, train and tram) can stop at different locations due to traffic signals, congestion, passenger drop off and pick up. During all these events the traveller was most likely being stationary and sitting (or standing) in the vehicle, and the acceleration profile would show a momentary drop during that period. But while reporting the trips, it is difficult to get such a fine ground truth information including how many times a vehicle stopped during a given trip and why. The reported trip is generally annotated as trip start and end time with origin, destination information with a single trip mode type. Thus, if a reported trip mode is *bus*, all atomic segments of the trip are labelled so, although some of them may be actually stationary. This can cause miss-classification as well when the predictive model is wrongly trained and detects some of the stationary atomic segment as *bus* and others as *train* or *tram*. When merging the segments in Layer 2, due to this issue some of the trajectories show unreasonable travel behaviour, especially Trip ID 1 to 3 (Table 44), where a *bus* mode has been detected in between two *tram* modes, which is not realistic due to the two reasons: (a) if the trip duration ( $|t_3 - t_2|$ ) is very short that means it was actually a continuation of tram trip, but some portion of that

particular tram trip has been wrongly detected as *bus*; (b) For some reason if the given trip (Trip ID: 2) is a bus trip then there has to be two walking trips before and after the bus trip as walking can only connect two motorized (or bicycle) modes, which is missing in this case (Table 44).

Table 44: Unreasonable trips.

Trip ID	Trip Start	Trip End	Mode
1	t1	t2	tram
2	t2	t3	bus
3	t3	t4	tram
4	t4	t5	walk

Such ambiguity can be resolved in a number of ways. In the first approach all the consecutive non-walk trips can be merged together until a discontinuity in activity state occurs or a walk trip is encountered (assuming walking is necessary between two non-walking modes). The first approach is used in this research.

There may be some cases when a quick transfer may take place shorter than the kernel length, which will generate a Type I error, and wrongly detects a trip with its end time higher than the end time in reported trip. The second approach is collecting even finer ground truth data that should contain intermittent stationary states at different locations (stop, traffic light, congestion, driver fatigue), while travelling in a particular mode in order to train the classifier accordingly. Then while predicting the trips, all the consecutive stationary atomic segments will be merged together until a non-stationary atomic segment is found. The merged segment will be labelled as the immediate non-stationary mode found. However, this approach is tedious, puts cognitive burden on the travellers keeping records for groundtruthing, and also deviates these travellers from their normal travel behaviour. The third approach can be using a phased sampling strategy (whenever a there is a drop in speed a higher sampling rate can be deployed to record the movement behaviour). And lastly the IMU information can be supplemented by speed information from a GPS sensor. Prior studies show using speed information along with the acceleration profile improves mode detection accuracy (Reddy et al., 2010).

## 7.6 SUMMARY

Understanding travel behaviour is important for developing different context-aware services that can enrich mobility as a service (MaaS). Understanding travel behaviour is also critical for urban planning and traffic management. Mobility-based activities

can also generate information in the interest of public health, analysing a person's movement behaviour at a finer granularity.

In this chapter a novel and adaptive state-based bottom-up approach for travel diary generation is proposed, which can detect individual trips with their trip start and end in space and time and the transport mode used to mediate the trip. The approach presented in this chapter first detects the activity state on a finer segment (which is called an atomic segment) and then progressively models the trips based on the consistency in the activity state. The reasoning process incorporates a set of machine learning algorithms, heuristic rules and transit feed information. The model is also compared with existing approaches.

In order to test the model, three situations were evaluated using two different real word data sets. The model shows that an RF-based model outperforms other machine learning models in the presence of GPS and IMU information with 0.75 F1-score at  $0 \leq \sigma \leq 3$  and 0.82 F1-score at  $0 \leq \sigma \leq 4$  using a 60 s kernel length. On the contrary an MLP-based model works better compared to an RF-based model in absence of IMU information but with a low frequency GPS information, yielding 72.72% and 81.81% recall accuracy at  $0 \leq \sigma \leq 3$  and  $0 \leq \sigma \leq 4$  respectively. The model also demonstrates its efficacy in a high frequency IMU only context in absence of location information with accepted loss in granularity in trip information (missing or ambiguous trip mode type). The model also contributes to the knowledge in travel behaviour analysis by modelling different types of trips possible at an abstract level (such as actual trip, reported trip, predicted trip and scheduled trip) with their different level of granularity. The results show the proposed model performs better in different situations on different types of data. The model works well even when the existing approaches completely fail especially in absence of location information. The model can also detect a return travel and its direction (Fig 68).

Future research will investigate the notion of alternate solutions in Layer 1. The model also can be improved by more intelligent reasoning schemes to be incorporated during merging operations and consistency checking, such as introducing the longest common subsequence strategy while matching the stop behaviour. The model can also be strengthened by implementing a phased sampling strategy to detect finer mobility based activity states especially in the absence of location information. The core of the framework developed in this chapter is a hybrid approach which is based on machine learning and a set of heuristics, which can be further enhanced by introducing a further clustering concept whenever there is a consistent location information. Future research can also test other contexts such as on a trajectory with the location information with varied accuracy (e.g., when the source is not only a GPS but also GSM and Wi-Fi).

## DISCUSSION

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This chapter presents a critical reflection on all the models that are developed within the scope of this thesis. The section first discusses the research questions that were framed in order to investigate the primary hypothesis in [Chapter 1](#). Then a high level discussion is presented that revolves around the four major contributions in [Chapter 4](#), [Chapter 5](#), [Chapter 6](#), [Chapter 7](#). This chapter also highlights the limitations of this work, which can be addressed in future.

### 8.1 ADDRESSING THE RESEARCH QUESTIONS

#### 8.1.1 *Overarching research question*

##### **How the knowledge gap in activity definition can be bridged while interpreting a trajectory at different granularities?**

The knowledge gap in activity definition can be bridged by developing an overarching activity ontology that can integrate different disciplines by defining activity at different contexts. The knowledge gap can also be bridged by interpreting trajectories using a (hybrid) knowledge-driven model (see [Chapter 4](#), [Chapter 5](#), [Chapter 6](#), [Chapter 7](#)). In order to address the overarching research question, a number of secondary research questions are answered as follows.

#### 8.1.2 *Research question 1*

##### **What is an activity? How can an activity be modelled at different contexts on motion trajectories? Is travel an activity?**

As developed in [Chapter 4](#), an activity is a recursive phenomenon where an agent satisfies some need by interacting with an object in the environment. One of the motivations of this thesis is to develop a framework that can improve the context-awareness of a (mobile) computing device. A context-aware device can improve the user experience by assisting a user while performing an activity. However, in order to assist effectively the device needs to understand the user's activity state at a given context. That said, it is already shown in this thesis ([Fig 2](#)) that the notion of activity depends on the context, which requires an adaptive framework that will model an activity in different contexts in a structured way.

[Chapter 4](#) has proposed an ontological framework that is capable to model an activity at different contexts from a motion trajectory. The ontology presented in this

research consists of two parts – a trajectory part and an activity part with an *actor* as the common concept. The framework developed in this research assumes an activity is composed of at least one action. Depending on the context an activity can become an action or an action can be lifted to an activity (Fig 26).

For example, when the focus lies on route recommendations, depending on the origin and destination, a number of trips with different transport modes can be formed where making a trip itself is an action that contributes to perform the activity *travelling from a given origin to a destination*. From the perspective of mode specific patronage estimation it is important to know the transport mode information and people's mode choice behaviour. In this context *making a trip on a given mode* can be viewed an activity by itself, whereas transferring from one mode to another is an action in this case. Again in another context, say assisting people in wayfinding during transfer the focus lies on bodily movements between trips. In this context *transfer* is an activity that is composed of a number of actions e.g., alighting from a given transport mode, navigating to the next stop, waiting and boarding the next connecting transport mode.

While modelling an activity some of the key concepts used in this research are *actor, activity, action, object, need, fix, segment* (Fig 27). As an activity is motivated by a user's need, the framework has suggested one of the nine fundamental needs (Max-Neef, 1991) to be used while modelling a specific activity. However, the framework is evaluated using a *subsistence* need throughout. But other types of needs can be addressed by the framework. This research has also demonstrated that a shift in granularity plays an important role while modelling an activity from a motion trajectory at a given context.

Depending on the context *travel* can be viewed either as an activity or an action (Fig 31). When the focus lies on how a person mediates between two different locations, *travel* becomes an activity. On the other hand when the focus lies on how a person interacts with an object situated at a given location over a considerable time, the interaction between the person and the object becomes an activity. In the latter case *travel* can be viewed as an action that facilitates that interaction.

Thus an activity can be modelled from a motion trajectory in a recursive way at different contexts by shifting the granularities. This research has contributed to the state-of-the-art by proposing a novel context-sensitive framework that can model a hierarchical (activity) knowledge base (see Chapter 4). The knowledge base has an ability to provide relevant contextual cues to a context-aware device while perceiving a user's need so that the device can trigger service(s) to the user in awareness relevant to the given context.

### 8.1.3 Research question 2

**How can a raw trajectory be analysed to extract transport mode information automatically at different granularities?**

Transport mode information being a critical component of travel behaviour has been an interest for urban and transport planners, and various personalized mobility service providers. This research primarily focuses on extracting transport mode information at different temporal granularities from raw trajectories. Depending on the information need the temporal granularities can be modelled in three different ways as follows (Fig 4).

- **Offline interpretation:** In case of an offline interpretation, the inference takes place over a raw trajectory once the entire travel is complete. A segmentation operation is performed that breaks the entire trajectory into a number of segments where each segment bears a homogeneous modal state. The segments resemble to a number of distinct trips.

Following that, a number of transport modes are detected over the segments generated from the segmentation operation. [Chapter 5](#) developed a knowledge-driven framework to detect a transport mode over a given trip through an offline interpretation process. An offline interpretation is particularly useful in order to understand a user's historical travel behaviour over several days.

- **Near-real time interpretation:** In near-real time interpretation, the inference process takes place on the go by using a temporal kernel. A near-real time interpretation is relevant for an urban traffic management system that requires dynamic travel demand estimation. In order to extract mode information in near-real time, a temporal query of different length is issued and a modal state is predicted within that query window. Two different types of models have been developed in this thesis. The first one is a hybrid knowledge-driven model (MLANFIS) that works satisfactorily on GPS only data (see [Chapter 6](#)) by combining a machine learning approach and a fuzzy inference process. The second type of model is also a hybrid one, but based on a machine learning approach followed by a number of crisp rule integration. The second model can work on GPS as well as IMU data.

The results obtained in [Chapter 7](#) suggested that the optimal response time in near-real time is 120 s using GPS only information and 60 s using GPS and IMU information when sampled at 1 Hz to 2 Hz.

- **Real time interpretation:** In this case the interpretation process takes place on the go but based on a comparatively shorter temporal kernel than that of a near-real time strategy. A real time interpretation is essential to realize various personalized mobility services in real time. [Chapter 7](#) proposed an optimal response time in real time could be 5 s using IMU only signals sampled at 50 Hz. However, the proposed model yields lower accuracy in real time compared to the accuracy produced in near-real time (see [Chapter 7](#)). The reason behind such discrepancy can be justified due to the lack of finer details in the groundtruth information

recorded for training and validation purpose (see Section 7.5 for the detailed explanation).

This research suggested that the finer and more accurate the sensor information is, the more effective the model is in terms of response time and prediction accuracy. The detection process also depends on types and number of features computed from the trajectory (or a sensor trace). A trajectory interpretation process can be influenced by the following factors.

- Types of sensors used
- Quality of sensor signals
- Sampling frequency
- Availability of domain specific information
- Design of the background intelligence framework

Getting back to the research question 2, this research has shown a trajectory can be analysed to extract transport mode information at different temporal granularities. This thesis has contributed to the knowledge by proposing three different mode detection models from three different angles. The first one is a knowledge-driven model that works offline (Chapter 5). The offline model expects a number of trips as inputs. The trips are deduced by segmenting a trajectory based on the similarity in the kinematic observation(s). The second one is a hybrid model that works in near-real time (Chapter 6), which does not require any segmentation. Instead, the near-real time model uses a temporal kernel over the trajectory on the fly. The third one proposed in Chapter 7 is deemed to be more flexible and adaptive compared to the previous ones (Chapter 5, Chapter 6). The three models developed in this research demonstrate that the objective of semantic extraction has been achieved at different temporal granularities. The models also demonstrate that it can be possible to interpret a raw trajectory automatically either by using a predefined knowledge base (Appendix A) or supervised predictive model or by integrating a rule base to a supervised model in its post-prediction stage to raise the confidence and transparency in the interpretation process (see Section 7.3.3.3).

#### 8.1.4 *Research question 3*

**What are the different uncertainties that exist in a trajectory interpretation process especially in transport mode detection? How can such uncertainties be modelled?**

This research has primarily modelled two types of uncertainties e.g., kinematic uncertainties and temporal uncertainties that may exist during a trajectory interpretation process. The uncertainties may be influenced by several factors. While developing and



evaluating the three mode detection models developed in [Chapter 5](#), [Chapter 6](#), [Chapter 7](#), the following factors have been identified.

- **Uncertainties introduced by the sensing:** The quality of a GPS trajectory is subject to signal availability especially in the urban canyons. The quality also degrades depending on the atmospheric condition and the seasonal variation which have not been studied within the scope of this research. But these factors contribute to the positional uncertainties.

In terms of sampling frequency the cheap GPS sensors installed on the smartphones cannot sample at a higher frequency due to hardware and software limitations. On the other hand, inertial sensors can sample at a higher rate but the quality of the signal is subject to body parts movements and the orientation of the phone.

- **Uncertainties due to data logging and sampling frequency:** The quality of a trajectory is also affected by the way data is logged and the precision used while logging the data. The sampling frequency is another aspect while recording the movement behaviour. A GPS trajectory sampled at 1 Hz to 2 Hz is deemed to be of reasonable quality for mode detection, provided it does not have longer and frequent signal gaps. A trajectory captured at a coarser granularity may save memory but at a cost of higher response time for information delivery and low accuracy in near-real time scenario.

From observation it is also found that in commercial smartphones cannot ensure that the sensors will log the observation(s) at a prescribed sampling interval. In particular, for GPS sensors the actual timestamp of logging an observation may differ from the predefined sampling interval by a few seconds to a few minutes depending on the signal reception.

In the context of near-real time it is assumed that a query can come at any time. However, there may be a signal gap or lack of sufficient samples within a given query window. The state-of-the-art interpolation technique such as inverse distance weightage works well on historical trajectories ([Schuessler and Axhausen, 2009](#)). But an inverse distance weightage technique cannot be realized in real to near-real time applications due to data insufficiency. In order to avoid the gap in a trajectory, the data has been recorded continuously. When there is a signal gap encountered, the last known location has been recorded as the new locations until a new observation is sensed.

- **Temporal uncertainties due to user's perception:** Temporal uncertainties may exist during groundtruth collection or validation process. The uncertainties mainly come from user's perception about an event and their ability to report the event with the appropriate details. For example, while recording a start time of an action for groundtruth, it is difficult to capture the exact time when a shift occurs

from one action to another action, e.g., between standing at a tram stop and riding a tram.

The temporal uncertainties also exist for trip inference with a temporal shift in start time and end time between a predicted trip, reported trip, and scheduled trip (see [Chapter 7](#)). The temporal uncertainties may also exist due to asynchronous clocks of the person recording the groundtruth, the clock used by the respective vehicle in order to keep to schedule, and GPS time.

- **Temporal uncertainties from service providers:** Due to unforeseen events a particular transport service can be slowed down, cancelled, or re-routed. In this situation using predefined information such as (static) GTFS is not well suited for trajectory interpretation. Figure 71 shows a temporal deviation of a scheduled train trip from North Melbourne to Sunbury Station in Greater Melbourne. On the other hand, a vehicle can also move ahead of scheduled time due to particular driving behaviour or during late night when traffic is very low.



Figure 71: Temporal uncertainties from the service provider. The train is initially scheduled at 2:46 pm but delayed by few minutes. The time stamp 2:44:21 pm shown in the bottom right corner is the current time when the scene was recorded.

In this research, temporal thresholds of 3 mins and 4 mins have been used to quantify the temporal uncertainties that may exist in the trip detection process ([Chapter 7](#)). This means a near-real time mode detection using a query window

less than 180 s can fall within the temporal uncertainty and may affect a context-aware service that leverages the mode information within that time period.

This is also required to model the transfer effectively. From an ontological perspective, a transfer can be defined at different granularities. However, at the finest granularity a transfer (with its start and end) that happens within such quantified temporal uncertainty zone may not be precisely detected in time (and space).

Thus a quantification of temporal uncertainty can provide a reliability measure for a context-aware computing service for certain application where time is being a critical factor.

- **Uncertainties due to movement behaviour:** Assuming movement is subjective, the kinematic uncertainties may also take place due to a respective user's movement behaviour depending on personal walking speed, personal preference of transport modes.

The uncertainties also exist due to a specific driving behaviour or road condition. For example, during traffic a bus may move very slowly owing to a false impression of walking and delay in arriving at the next destination.

This research has modelled the kinematic uncertainties through a purely knowledge-driven model in a human understandable format in [Chapter 5](#). The uncertainties are captured through an expert knowledge and expressed through a number of linguistic values in a fuzzy knowledge base. Similarly, in [Chapter 6](#), a hybrid knowledge-driven model is presented that can capture the kinematic uncertainties automatically from the training data and then develop a fuzzy rule base.

On the other hand, the temporal uncertainties during a trajectory interpretation process has been modelled using Allen's interval algebra from a qualitative perspective ([Allen, 1983](#)). [Chapter 7](#) has explained nine different temporal relationships that may exist between a scheduled trip, reported trip and a predicted trip. [Chapter 7](#) has also suggested quantifying temporal uncertainties during a trajectory interpretation process is essential to measure the reliability of an inference process.

In this research kinematic and temporal uncertainties have been modelled. Modelling the uncertainties enables action (or activity) specific semantic extraction from a given trajectory at a given context. Depending on the kinematic uncertainties present in an object's movement behaviour [Chapter 5](#) and [Chapter 6](#) have proposed the concept of alternate possibilities of being different transport modes at different certainty levels. The temporal uncertainties are quantified within a crisp temporal bound that limits temporal uncertainties in activity (or action) transition in space and time. While addressing the uncertainties a number of contributing factors are discussed. However, there may be other factors from statistical perspective which are out of the scope of this thesis.

#### 8.1.5 *Research question 4*

**What are the advantages and disadvantages of a machine learning approach and a knowledge-driven approach while detecting transport modes from the raw trajectories? How can the trade-off between a machine learning model and knowledge-driven model be bridged so that it is possible to represent the reasoning scheme of a predictive model that works on motion trajectories and at the same time the model is able to self-adaptation?**

Transport mode detection is mostly addressed by machine learning approaches and less so by knowledge-driven approaches. However, both of these approaches have their advantages and disadvantages. Machine learning approaches are data specific. Their performance depends on the way the model is trained. For transport mode detection speed, acceleration profile, and spatial proximity to different route types and their derived features are some of the critical indicators, which can be handled by machine learning models. Machine learning models can also handle complex features e.g., signal magnitude area of triaxial accelerometer signals, or entropy. However, machine learning approaches are limited in terms of expressing the reasoning mechanism, which poses difficulty in semantic extraction of action specific behaviours. A machine learning approach provides limited flexibility to incorporate heuristics in the post-processing phase in order to refine the prediction results ([Chapter 7](#)).

That said machine learning models can handle a wide range of feature types with their inherent complexity. During signal gap the models can still leverage the signals generated by inertial sensors and predict a given modal state (and other mobility-based information as required).

On the other hand, knowledge-driven models do not need to be trained. The knowledge-driven models operate solely based on the rule base developed by a domain expert. Since a knowledge-driven model is based on the set of rules that encodes the perception about the world, the model in particular, a fuzzy logic based model offers more flexibility and ability to model uncertainties compared to a machine learning model. A knowledge-driven model can also include crisp rules (based on common sense) to raise the confidence of an interpretation process.

However, from observation, a rule based model is limited in an urban environment where bus routes, tram routes and street networks are located close to each other or even overlap. In an urban environment if an object moves at a moderate speed and very close to a bus network and a tram network, it could be a tram with a certainty as much as a bus ([Fig 20](#)). In such ambiguous conditions stop rates at given POIs play an important role in discriminating different modes: a bus will stop at the given bus stops, and a tram will stop at the given tram stops. Only due to the unreliability of positional information it may be difficult to use proximity to a given POI. This approach is also subject to availability of infrastructure information (route information, stop location, and schedule information). In order to address these challenges inertial sensor infor-

mation is deemed to be useful. The use of an inertial sensor in this situation can be justified as an inertial sensor can sample at a higher frequency and can capture finer kinematic details. However, as described earlier in this chapter due to limited knowledge of the domain expert (who will setup the rule base), it is difficult to incorporate the inertial sensor information in a conventional fuzzy logic based knowledge-driven model.

Although for a sufficiently long segment a fuzzy logic based knowledge-driven model may work effectively (Chapter 5), it may not work well over a shorter segment as required in near-real time scenarios (Chapter 6). On the other hand, a machine learning based model can work in near-real time and can handle different types of features but lacks the expressiveness.

To bridge the trade-off between a machine learning model and a knowledge-driven model a hybrid neuro-fuzzy model has been proposed in this research (Chapter 6). The hybrid model can work better than a traditional Mamdani-type fuzzy logic based knowledge-driven model and at par with some of the state-of-the-art machine learning models. However, the neuro-fuzzy based hybrid model (MLANFIS) presented in Chapter 6 suffers from the scalability issue. A more sophisticated and adaptive hybrid model has been developed in Chapter 7 using a machine learning approach integrated with a number of crisp rules.

Thus this research has investigated the advantages and disadvantages of a machine learning and a knowledge-driven approach. The research has shown although a knowledge-driven model works effectively offline it may not work well in near-real time. This research has also explained the trade-off between a knowledge-driven model and a machine learning model in terms of their expressiveness and performance. Two hybrid models have been proposed in this research to bridge the trade-off while interpreting the raw trajectories for transport mode detection.

## 8.2 EVALUATION OF THE HYPOTHESES

This research has investigated the primary hypothesis (Hypothesis 1) that *hybrid models allow a consistent and adaptive interpretation of activities from smartphone trajectories*. In order to address the primary hypothesis four major research questions (Section 8.1) and a number of sub-hypothesis had been formulated. Some of the research questions correspond to more than one sub-hypothesis. Based on the illustrations and evaluations in Chapter 4, Chapter 5, Chapter 6, Chapter 7 this section will justify the sub-hypotheses.

### 8.2.1 Hypothesis 1.1

*The semantics of activity depends on the spatial and temporal granularity suggested by context. Shifts in granularity will enable processing motion trajectories and activity knowledge can*

*be represented in various contexts facilitating flexible, appropriate and relevant information representation or provision and thereby develops a connected knowledge flow.*

Chapter 4 has shown the semantics of activity varies from context to context. Figure 31 depicts how a motion trajectory can be processed at different granularities to explore activity and action information at different contexts. Based on the context-adaptive framework (Fig 27) it is evident that it is possible to develop different contextual knowledge bases only by instantiating each of the concepts every time a new context is perceived. But the structure of the framework and relationships between the different concepts will remain same. The three tables (Table 13, 14, 15) illustrate three different contextual knowledge bases can develop a connected knowledge flow in different contexts by altering the granularity. Due to this recursiveness of the framework any phenomenon can be modelled as an activity or action depending on the given situation. As discussed earlier (Section 8.1.2), the framework uses a modular approach – a portion to model a trajectory and a portion to model an activity. Thus the framework provides enough flexibility and can bridge the gap while defining an activity from different perspectives.

The information extracted from a particular knowledge base is relevant and appropriate in a given context. For example, Figure 32, 33 provide a number of information which are relevant to Context 2 and Context 3 respectively.

Thus this research has established Hypothesis 1.1 by illustrating a motion trajectory. Although this research has primarily used GPS trajectories and IMU information to evaluate the subsequent hypotheses but the ontological framework developed in this research (Fig 27) can be used to extract activity (or action) information from motion trajectories collected not only by a GPS sensor but also other sources.

### 8.2.2 Hypothesis 1.2

*A multiple-input multiple-output fuzzy logic based knowledge-driven approach is able to detect different transport modes effectively based on the expert knowledge from historical trajectories. The knowledge-driven approach will also model the uncertainties present in the movement behaviour in a transparent way.*

While addressing the second research questions (Section 8.1.3) it is already explained a knowledge-driven model performs effectively on historical trajectories. The results (Section 5.4.4) and the rule base (Appendix A) provide evidence that the Hypothesis 1.2 will hold in offline given the GPS trajectories are sampled comparatively at a reasonable granularity (in the order of 1 Hz-2 Hz). Chapter 5 shows how a knowledge-driven approach can reason based on the expert knowledge. Initially, by using 74 rules the train accuracy was low. However, by adding two new rules (Rule 75, 76) the accuracy has increased. This suggests that more the expert knowledge brought in the model, better the accuracy is achieved.

In order to evaluate the Hypothesis 1.2 it is already described in the third research question (Section 8.1.4) that a knowledge-driven approach is more flexible than a machine learning based approach while modelling the kinematic uncertainties. The rule base shown in Appendix A demonstrates that a Mamdani-type multiple-input multiple-output knowledge-driven approach models different kinematic uncertainties through simple IF-THEN rules in a human understandable format. The proposed multiple-input multiple-output approach also demonstrates its ability to provide alternate predictions with varied degree of certainties which was missing in the earlier knowledge-driven models (Xu et al., 2010; Biljecki et al., 2012).

### 8.2.3 Hypothesis 1.3

*While detecting transport modes in near-real time, a neuro-fuzzy based hybrid knowledge-driven framework will perform better than a purely knowledge-driven model. The hybrid model will also bridge the trade-off between a purely knowledge-driven model and machine learning model in terms of expressiveness and learning ability.*

The quality of a GPS trajectory may be affected by several factors (see Section 8.1.4) that lead to varied kinematic uncertainties and lack of location information in the trajectory. A purely knowledge-driven model, for example, the knowledge-driven model developed in Chapter 5 cannot capture all the uncertainties within a shorter temporal period. To address this issue a neuro-fuzzy based hybrid knowledge-driven model is developed, which is self-adaptive (Chapter 6).

In order to evaluate the hypothesis a set of experiments are performed. The results (Table 24) show that although a knowledge-driven model (Chapter 5) achieves higher precision accuracy it suffers from lower recall accuracy (Table 23). This can be justified by the fact that the rules in a purely knowledge-driven models can only reason a portion of the several possibilities. However, the rules are not exhaustive enough to capture all the kinematic possibilities from the GPS trajectories. On the other hand, a hybrid model performs consistently better than a knowledge-driven model in near-real time. As shown in Table 24 and Table 23 the results show the hybrid knowledge-driven model can perform at par with the machine learning models. As addressed in the fourth research question (Section 8.1.5) a hybrid knowledge-driven model is expressive in one hand and adaptive on the other hand, showing a clear evidence that the Hypothesis 1.3 has been justified.

### 8.2.4 Hypothesis 1.4

*A state-based bottom-up approach is more adaptive than any top-down approach, and in addition will be flexible enough to detect activity states in a progressive manner at different temporal granularity.*

In order to evaluate Hypothesis 1.4 a number of experiments are performed emulating different situations (Chapter 7). The results (Section 7.4.1.2) demonstrate that the existing top-down approaches (e.g., walking based approaches) are subjective and do not work well in the absence of location information. Likewise, a clustering based approach is also deemed to be dependent on a fine-grained GPS trajectory – and gives rise to high spatial-temporal uncertainty because of its very nature of producing clusters of arbitrary geometrical shape and size.

In order to make the model flexible the processing layer (Fig 58) is developed in such a way that depending on the information need and the data type (in presence or absence of location information), the modules can be activated or deactivated. This provides evidence that the model is adaptive enough. In addition to that, the temporal kernel used to detect the atomic state(s) is user defined and thus it can grow or shrink depending on the sampling frequency and type of sensor information that makes the model highly flexible.

The framework is developed based on a basic assumption that the activity state will remain the same within a shorter temporal window and thus a progressive merging based on homogeneity of the activity state will result in information extraction at different temporal granularities. The results (Section 7.4.1.2) demonstrate that the assumption was reasonable and thus the aim is achieved.

### 8.2.5 Hypothesis 1

Based on the evaluation of the four hypotheses there is enough evidence that supports the primary hypothesis (Hypothesis 1). The ontology (Fig 27) supports an adaptive modelling of activities at different contexts whereas the two predictive models (Fig 49, 58) demonstrate hybrid models are able to interpret smartphone trajectories in a consistent manner.

## 8.3 RELEVANCE OF THE RESEARCH CONTRIBUTIONS

This research has addressed two different semantic gaps – one in the activity definition and the other one related to the activity detection through trajectory interpretation. The major contributions of this research (Section 9.2) are presented in Chapter 4, Chapter 5, Chapter 6, Chapter 7. This section will present an overall discussion of the four models and how they are connected to the state-of-the-art.

### 8.3.1 Context-sensitive ontological framework

The framework proposed in Chapter 4 can help a context-aware mobile device to understand semantics of different activities (or actions) in different situations and act



accordingly. The framework extends an existing trajectory ontology developed by (Hu et al., 2013) through instantiating the concepts and fusing an activity part. On the other hand, the framework enriched existing activity ontologies (Nardi, 1995; Kuhn, 2001; Chen et al., 2014; Meditskos et al., 2013) by adding space-time dimension.

Previous works have used a set of temporal zooming operators to refine or abstract a user's movement history from time-geography aspect (Hornsby, 2001; Hornsby and Egenhofer, 2002). The proposed framework (Chapter 4) uses the similar concept of temporal zooming to extract activity information at different granularities. The ontological framework presented in this research also aligns with the concept of process and event in terms of recursiveness and context dependency suggested by previous researchers (Abler et al., 1971; Yuan, 2001; Worboys, 2005; Galton, 2006, 2015; Hornsby and Cole, 2007).

The framework suggests *need* is the key concept that defines an activity. A need can be satisfied through a given affordance. Although this research does not differentiate the type of affordances, but the framework is flexible enough to link with an existing relational-functional model for affordance based agent framework (Raubal and Moratz, 2008). The framework also enriches an earlier mobility-based model for information retrieval from motion trajectories (Hirtle et al., 2011) by introducing the concept of context.

The granularity addressed in this research while modelling an activity is represented in terms of space-time scales and amount of relevant information retrieval. As discussed in Section 4.5, the granularity and information extraction may be hindered during signal gaps – but that does not affect the ontological structure of the model. This only affects the details of information retrieval. Although, the framework is evaluated on a GPS trajectory, motion trajectories captured by other sources such as cordons or check-ins (Duckham, 2013), smart-cards (Sun et al., 2012), or Wi-Fi (Li et al., 2015) can also be used.

As mentioned earlier, the model can be applied both in outdoor and indoor and thus is general enough to apply in any application domain where activity is a key facet. The ontology has been developed in a modular way by integrating two sub-modules – one is the activity part, and the other is a semantic trajectory part with an actor as a common concept. Thus, the framework can be applied to a trajectory collected by a GPS, GSM, Wi-Fi, smart-card or other infrequent sources such as credit card transactions, check-in on social media, or a self-reported diary with a varying activity details.

There are still challenges as how to model different activities in indoor and outdoor from similar action sequences. For example, the following sequence of actions has been detected:

*[walking > entering into a cafe > sitting on a chair > leaving the cafe]*

One possible need for this sequence of actions is to have a cup of coffee which falls under a broader need of *subsistence*. An alternative need is to meet someone in the cafe which can fall under a broader need of *participation*. The framework developed in this research has a capacity to distinguish these two different activities (based on two different needs) from the same set of action sequences and location information, provided the subsequent actions in the cafe are captured by the available sensors. For example, a need *participation* can be attributed by actions such as *expressing an opinion, cooperating or interacting with others* whereas a *subsistence* need can be attributed by actions such as *feeding or resting* (Max-Neef, 1991). Such actions can be understood on getting different types of sensor information inside the cafe. Such a need-based activity categorization with similar action sequences are interesting to interpret for understanding an individual's activity patterns to enable personalized service provisions.

### 8.3.2 *A Knowledge-driven approach for transport mode detection*

The knowledge-driven model proposed in Chapter 5 investigated different membership function combinations. The results suggested a Gaussian-Gaussian combination works best in offline. Unlike the earlier models (Tsui and Shalaby, 2006; Schuessler and Axhausen, 2009), the proposed knowledge-driven model (Chapter 5) has shown that using kinematic-only features, the accuracy decreases compared to the cases when spatial information and the kinematic information both are included. The results demonstrated that the proposed knowledge-driven offline model works at par with some of the existing machine learning based models and more expressive than any machine learning models (Zheng et al., 2008; Byon et al., 2009; Wang et al., 2010) and some of the existing rule-based models e.g., (Tsui and Shalaby, 2006; Bohte et al., 2008; Schuessler and Axhausen, 2009; Xu et al., 2010; Gong et al., 2012; Biljecki et al., 2012). The proposed model is also an improvement over the existing knowledge-driven models in terms of expressiveness and alternate predictions (Xu et al., 2010; Biljecki et al., 2012). The developed model can detect four modalities (walk, bus, tram, train) with a possibility to incorporate other modalities (Chapter 5) e.g., car, bike, or taxi, and other variables e.g., stop rate, proximity to a given POI, vibration, or heading rate change.

### 8.3.3 *Hybrid Knowledge-driven framework for transport mode detection in near-real time*

It has been already demonstrated in this research that a fuzzy logic based knowledge-driven model performs well offline (see Chapter 5) but the model provides limited performance in real- or near-real time (see Chapter 6). A knowledge-driven model also suffers from tuning its membership function parameters.

To address the shortcomings of a knowledge-driven model, Chapter 6 has presented a neuro-fuzzy based hybrid model that can adapt and learn from the historical movement data. Although the hybrid model uses only five fuzzy variables (average speed,

95th percentile of maximum speed and average proximity to bus network, train network, and tram network), other features can easily be incorporated in the model. As described in [Chapter 6](#) in order to generate the fuzzy rules automatically currently a grid partitioning approach is used in this research, which is an expensive strategy in terms of processing time and memory usage. Despite the limitations, the hybrid model developed in this research outperforms some of the machine learning based models e.g., an RBF, DT, KNN based models and a knowledge-driven model in near-real time.

The proposed hybrid model ([Chapter 6](#)) yields 88% average precision accuracy at 60 s time window which is an improvement over the earlier work by Byon and colleagues ([Byon et al., 2009](#)) in terms of response time. The proposed model is also an improvement over the previous knowledge-driven attempts in terms of adaptivity in varying conditions ([Tsui and Shalaby, 2006](#); [Schuessler and Axhausen, 2009](#); [Xu et al., 2010](#); [Biljecki et al., 2012](#)).

Although the complexity of the hybrid model could be a critical factor in near-real time implementation, however, it is observed that the hybrid model is computationally expensive at this moment due to its very nature of exhaustive search while constructing the rule base. However, as the main interest of this thesis lies in GIScience rather than computational science, thus, the complexity is only qualitatively mentioned in the text and not investigated in-depth. The experiments evaluated a trade-off between the detection accuracy and different time windows in near-real time predictions. This partly gives an idea about the performance and complexity (in terms of response time during inference) of the models. A future study will investigate the complexity of the algorithms used in terms of execution time and memory usage.

#### 8.3.4 *Automated urban travel interpretation through a state-based bottom-up approach*

[Chapter 7](#) develops a hybrid state based adaptive framework that can handle the trajectory segmentation challenges caused by a walking or a clustering based approach. The result ([Section 7.4.1.2](#)) shows that the performance of the framework stretches on a wide temporal range – from a very fine temporal granularity (5 s) to a moderate granularity (300 s) or even more that approaches to the completion of the travel. Thus the framework also conforms the earlier works which have been done separately for transport mode information retrieval at different response time ([Byon et al., 2009](#); [Hemminki et al., 2013](#); [Xia et al., 2014](#)).

In this research due to the nature of groundtruth collected spatial uncertainty of a trip origin and destination is not explored, rather the temporal uncertainties are modelled ([Fig 57](#)) through Allen's interval algebra ([Allen, 1983](#)). The model can work on the different quality of movement data such as GPS only, GPS and IMU and IMU only sampled at coarser to finer granularity (see [Chapter 7](#)).

Currently in the processing layer ([Fig 58](#)) there is no provision for alternate prediction(s). But considering the uncertainties involved in the kinematic behaviour of a

moving object (user or the vehicle carrying the user), more rigorous merging operation can be performed on getting an alternate solution through a neuro-fuzzy based hybrid knowledge-driven technique. [Chapter 7](#) has also shown while developing a predictive model using a supervised learning approach the precision and quality of groundtruth is to be taken into account.

In this research to the best of the author's knowledge, GTFS information is used for the first time for modelling the temporal uncertainty while detecting the trips and travel modes. When GTFS information will not be available a more advanced predictive modelling should be developed.

#### 8.4 OVERALL LIMITATIONS

Despite the efficacy of the models developed in this research ([Chapter 4](#), [Chapter 5](#), [Chapter 6](#), [Chapter 7](#)) there are some limitations as follows.

- The context-sensitive ontological framework developed in this research ([Chapter 4](#)) is limited while explaining a composite activity at this moment. For example, the ontology will provide limited reasoning ability while resolving two composite activities occurring concurrently – reading newspaper while traveling. Thus the framework may pose challenges while satisfying a user's more than one needs at the same time. Although each of the component events that occur concurrently, can be modelled separately based on their respective objectives or goals but the model offers a limited explanation if there is any connection between those concurrent events happening at the same time by the same actor.

The ontological framework mainly uses a temporal zooming to distinguish different activities of varied entailments (actions, operations). Thus the contexts laid out in this research are inherently connected to granularity in terms of time and details of information, which are relevant to a given situation. The model provides limited capacity to detect a particular *need* that motivates to do an activity. This will require analysis of different sensor information in outdoor and indoor at varied granularity to develop a sequence of action chain.

The ontology has been evaluated through Hermit Reasoner embedded in Protégé and illustrated using a real GPS trajectory along with a number of SPARQL queries, however, the framework has not been implemented in reality and thus it is not tested how the quality of a trajectory can affect the performance of the ontology. The reliability of the ontology depends on the level granularity adopted while developing the concepts, their object properties and data properties. The reliability also depends on the intricacies in the competency questions that are to be formulated in the conceptualisation stage.

Although in this thesis the framework is evaluated using three different contexts at three different granularities, the framework can be extended to any number of

contexts in a recursive way. That said, the instantiation of various concepts at a given context depends on the application domain – but the functionality and the relationships between different concepts will remain same.

- In this research three different types of knowledge bases are considered as follows.
  - The first one is the contextual activity knowledge base (Chapter 4) that contains the concepts and the properties related to an activity at a given context.
  - The second one is the fuzzy knowledge base (Chapter 5, Chapter 6) that contains the fuzzy rules to model and reason an object’s mobility-based activities (or actions).
  - The third one is the crisp knowledge base represented in terms of a number of lemmata (Chapter 7), which is used to refine the prediction results during the trajectory interpretation process.

The ontological framework developed in Chapter 4 is based on (crisp) DL-OWL, which provides limited functionality to handle the fuzziness in space and time. This poses a gap in between the contextual activity knowledge base and the fuzzy knowledge base. In order to bridge the gap a fuzzy-DL reasoner (Bobillo et al., 2012) is to be implemented while developing the ontological framework in future work.

- The offline fuzzy logic based model and a near-real time hybrid model developed in Chapter 5 and Chapter 6 respectively work best on a relatively finer GPS trajectory sampled at 1 Hz to 2 Hz. But assuming location information can come from other sources such as GSM, Wi-Fi, check-ins, user-generated contents (UGC) with varied level of positional accuracy and semantic gaps, there is a need to develop more robust and adaptive model. In order to find the missing locations during signal gap, currently a linear interpolation is performed in the offline based model due to its simplicity (Long, 2016). But during a longer semantic gap or in presence of GSM trajectory where the positional uncertainty is higher (see Fig 72) in such situations a linear interpolation may not be a good choice. In these scenarios more advanced interpolation and filtering strategy, for example, a Kalman filter could be used.
- The hybrid model developed in Chapter 6 currently uses a grid partitioning to search its input space to generate the rule base. This is an expensive strategy and due to the “curse of dimensionality” (Bellman, 2003; Keogh and Mueen, 2010) the model fails when the number of fuzzy variables are more (Jang, 1993). Currently, the hybrid model is based on Sugeno-type fuzzy inference system, where the antecedent part is fuzzy but the consequent part is not fuzzy in itself. Thus

the model offers limited expressiveness in its output part. Currently the model generates all the rules that can be possible from a combinatorial approach. The model is not able to discover the most relevant or top-k fuzzy rules based on the input features which is required for extracting the behavioural knowledge that is relevant to a given context.

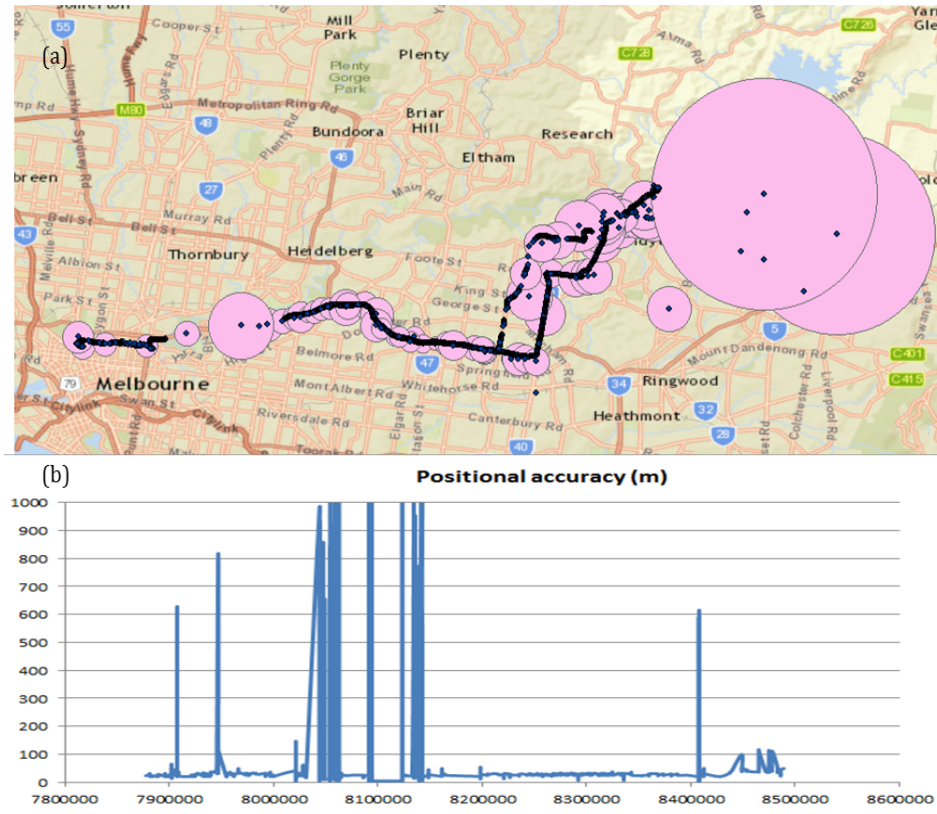


Figure 72: A mixed location trajectory using GPS and GSM network with varied buffer size for different accuracy level around the respective spatio-temporal point (a); the positional accuracy varies from 10 m to more than 1000 m. Particularly for GSM locations, the inaccuracy is more than 300 m and sometimes even greater than 1000 m (b).

- The hybrid state based bottom-up trajectory segmentation model ([Chapter 7](#)) lacks the ability to provide the alternate prediction. The model currently uses a simple low pass filter to preprocess the accelerometer signal information to get rid of the noise. But in practice, a sudden jerk may take place during transfer which may indicate a change in state. Such high frequency signal components need to be further investigated. The model does not consider the energy consumption of different sensors while collecting a trajectory, which has been a

critical issue in mobile computing and smartphone based travel surveys (Cottrill et al., 2013; Yu et al., 2014).





## CONCLUSIONS

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Understanding people's travel behaviour is essential to enable different mobility service provisions e.g., personalized activity recommendations based on a user's travel behaviour, or transport planning at an aggregate or disaggregate level. Currently, paper-based or telephonic manual travel surveys are capturing information related to various mobility-based activities by asking respondents about their travel patterns. But such approaches are subject to miss-reporting and under-reporting due to a memory-based reconstruction process. To cope with these issues smartphone travel surveys are emerging (Cottrill et al., 2013). A smartphone-based travel survey records people's travel behaviour and provide improved data quality. Beyond these surveys, large corpora of smartphone-based trajectory data sets emerge, in silos of commercial service providers. With regard to travel demand these latter trajectory data sets are typically limited to a singular mode, but on the other hand, they have the tendency to sample the population instead of small numbers of survey participants. In the future, however, a continuous and volunteered, incentivized provision of smartphone-based mobility data – of all mobility modes – can be envisioned, and then the challenge of mode detection arises at a massive scale and for multiple purposes, some offline, some real-time. A smartphone-based mobility data set leverages the location and other motion sensors installed on a smartphone to capture a person's travel behaviour and activity patterns, which are recorded as a sequence of spatio-temporal points.

Current context-aware mobility applications consider *location information* as one of the primary contextual cues. Moving one step further, this research has proposed *transport mode information* as another contextual dimension to be used by a context-aware application while perceiving a user's activity state. Thereby the research has made an attempt to improve the intelligence of the context-aware mobility applications by interpreting the raw trajectories. This research aims to understand how a user mediates between two locations from her trajectory.

As described earlier in [Chapter 1](#) the raw trajectories can only provide the location information and lack the semantics related to different mobility-based activities performed by a user e.g., transport modes used during a travel, trips made on the way. Thus, the raw trajectories need further enrichment to reconstruct semantics related to various activities and actions. This thesis has approached the challenge of reconstructing semantics from trajectories from four angles.

- The first one was a context-sensitive ontology of activities and actions that can adapt in different situations ([Chapter 4](#)).

- The second one was a fuzzy logic based knowledge-driven model to handle the kinematic uncertainties and extracting semantics of activities or actions related to a user's mediation of travel ([Chapter 5](#)).
- The third one addressed the limitations of a knowledge-driven model in near-real time by suggesting a hybrid knowledge-driven model bridging a fuzzy reasoning and a machine learning aspect ([Chapter 6](#)).
- The fourth one interpreted raw trajectories in near-real time, overcoming the limitations of most approaches that are actually doing retrospective analysis of semantics ([Chapter 7](#)).

## 9.1 OVERALL SUMMARY

As described in [Chapter 1](#), the semantics of activity is context-dependent. Since activity is understood differently in different disciplines (and application domains), there is a semantic gap in the definition of activity across different domains. While developing a context-aware service it is essential to understand the semantics of activities at different contexts to provide relevant services in different situations. In order to address this challenge an overarching ontological framework is proposed in [Chapter 4](#).

In order to interpret the smartphone trajectories, current background intelligence relies on machine learning based approaches. Although the machine learning based transport mode detection approaches have proven satisfactory performance in the past ([Zheng et al., 2008](#); [Byon et al., 2009](#); [Reddy et al., 2010](#); [Stenneth et al., 2012](#); [Hemminki et al., 2013](#); [Xia et al., 2014](#)), they cannot extract semantics related to a given mobility-based activity (or action). On the other hand, knowledge-driven approaches provide transparency and can extract semantics related to a particular activity (or action) in varied contexts ([Rodríguez-Serrano and Singh, 2012](#)). As understanding the meaning of an activity (travelling on a particular transport mode) is essential to enable a context-aware service, this research has primarily investigated the knowledge-driven approaches for mode detection at different temporal granularities. Existing knowledge-driven approaches for transport mode detection ([Tsui and Shalaby, 2006](#); [Xu et al., 2010](#); [Biljecki et al., 2012](#)) lack the transparency. To address this challenge, a novel Mamdani-type fuzzy logic based knowledge-driven model is presented in [Chapter 5](#), which is an improvement over the existing models presented in the literature.

Although, the knowledge-driven model proposed in [Chapter 5](#) is transparent enough, but it lacks the capacity of self-adaptation. In order to bridge the trade-off between self-adaptation and expressiveness [Chapter 6](#) suggested a hybrid knowledge-driven model.

The state-based bottom-up model presented in [Chapter 7](#) introduces the concept of segmentation of a trajectory through progressive merging of homogeneous mobility state. Assuming temporal granularity is a critical aspect in information retrieval,

the proposed knowledge-driven model interprets a trajectory once the travel is complete and thus requires the longest response time among the three proposed models (Chapter 5, Chapter 6, Chapter 7). The hybrid knowledge-driven model developed in Chapter 6 requires shorter response time compared to the offline model proposed in Chapter 5. On the other hand the model proposed in Chapter 7 is flexible and can provide information at different temporal granularities (ranging from 5 s to 300 s).

In this research different uncertainties related to a motion trajectory and interpretation process have also been addressed. In particular, the state based bottom-up model presented in Chapter 7 has addressed the temporal uncertainties that may exist during a trajectory interpretation process. Quantifying temporal uncertainties can serve as the reliability (or uncertainty) measure(s) in a trajectory interpretation while retrieving information at different contexts. Considering semantic gaps present in a GPS trajectory due to signal gaps, an investigation is made whether incorporating low sampled IMU information in a GPS trajectory can improve the prediction accuracy. The results (Section 7.4.1.2) confirm a trajectory enriched with location information along with the IMU information even sampled at a low frequency can improve the accuracy.

The primary data set (Section 3.2) used in this research covers four different transport modes. However, while recording the groundtruth any activity performed on the feet is labelled as *walking*. For example, *being stationary in indoor or outdoor*, *brisk walking*, *slow walking* – these are all recorded as *walking*. Some of the stationary activities take a longer duration from 30 mins to 2 h, e.g., *waiting during transfer*, *shopping*, *working at the office*. Thus the total duration of walking is longer than the other modes. But the data set is spatially well distributed and covers different kinematic uncertainties.

In the beginning of this research a use case was provided (Fig 2) in order to illustrate the semantic gap between a raw trajectory and the description of a user's travel behaviour. Based on the models developed in this research it is now possible to extract the portions of the trajectory (Fig 73), where Joe used a train, or a tram or walked on his feet. It is also possible to understand where (and when) Joe transferred from one transport mode to another mode. Extracting such mobility-based activity information on multiple users can generate mobility patterns at an aggregate level. This aggregated information can be further used for urban transport management and policy making. Returning to Section 8.2 this research has introduced novel trajectory interpretation approaches with more transparency and adaptivity. From the evaluations and results it can be inferred that the research has provided evidence that hybrid models are more effective and expressive while interpreting raw trajectories and thereby justifies the primary hypothesis (Section 8.2.5).

## 9.2 MAJOR CONTRIBUTIONS

The major contributions of this thesis are as follows.

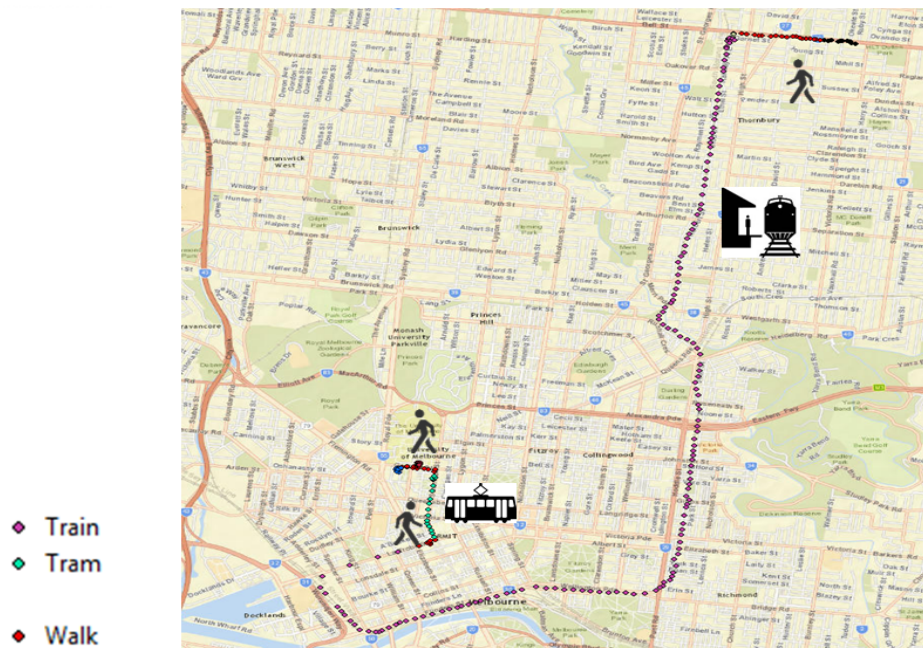


Figure 73: Raw trajectory is semantically enriched and different transport mode information along with the trip information are discovered.

- As addressed in the first research question (Section 8.1.2), this research has contributed to the knowledge by introducing an ontological framework for modelling activity at different contexts from motion trajectories. The ontology is capable of developing a connected knowledge base that can bring different application domains on a common ground while modelling an activity (Chapter 4).
- This research has developed a more transparent knowledge-driven model that is capable of providing alternate predictions with varied certainty factors in comparison to the previous works that provides limited transparency. Such a knowledge-driven approach will help in perceiving the characteristic behaviour of different modal states in different conditions while modelling the kinematic uncertainties (Section 8.1.3).
- In addition to that, the fuzzy knowledge base can supplement an activity knowledge base, which can be shared across different applications (Chapter 5).
- As pointed out in the third research question (Section 8.1.4), this research has introduced the concept of near-real time transport mode detection from GPS trajectories.
- To detect transport modes in near-real time a multilayered neuro-fuzzy based hybrid knowledge-driven model (MLANFIS) has been developed (Chapter 6)

that can bridge the trade-off between the expressiveness and adaptivity (Section 8.1.5).

- This research identified different uncertainties that may exist in a trajectory interpretation process (Section 8.1.4). The temporal uncertainties are first modelled in a qualitative way followed by a quantification of such temporal uncertainty to measure the reliability of a trajectory interpretation result.
- Existing trajectory segmentations are subjective, requires a consistent GPS trajectory (with less signal gaps), and generally works retrospectively, i.e., once the entire travel is complete. In contrast, in this research a novel state-based bottom-up approach is proposed, which is more adaptive and flexible and can fetch information at different temporal granularities (Chapter 7).

### 9.3 PRACTICAL IMPLICATIONS

Over the last few years there has been a considerable effort put forward to improve the performance of the context-aware devices (e.g. smartphones) that can assist in different mobility-based activities (Prekop and Burnett, 2003). A context-aware device needs to perceive a user's activity state and his need at a given context. In order to address this issue Chapter 4 presents an ontological framework that provides a more structured and flexible framework to model a user's activity states at different contexts from motion trajectories. The ontological framework impacts on the context-aware application design in two ways.

- **Reusability:** The ontological framework proposed in this research enables different context-aware mobility applications to use the concepts and their relationships (Chapter 4) with different entailments and data properties (see Table 13, 14, 15). This will save time and effort while developing the theoretical framework for a new user-specific context-aware mobility application.
- **User experience:** Instead of using multiple applications at different contexts, the framework allows using a single application that can adapt at different contexts. Thus the user does not need to be familiarised with different interfaces, rather a single interface can serve different needs of a user during her travel. This will in turn improve user experience while interacting with the application.

While reconstructing the semantics related to a user's mobility behaviour this research impacts on urban planning and transport management in the following ways.

- **Understanding the urban dynamics:** The models proposed in Chapter 6 and Chapter 7 can provide mode-specific patronage information in near-real time. This will help transport planners to identify the most demanding routes, most demanding modes, and urban dynamics. Based on a just-in-time information

ad-hoc decisions can be made to better utilize the transport resources. A near-real time application can also be useful for providing emergency services as and when necessary.

- **Long term transportation planning:** The knowledge-driven model proposed in [Chapter 5](#) generates historical travel behaviour at an aggregate or disaggregate level. The travel behaviour may include people's trip making patterns and mode specific patronage information. These information can be useful for long term urban policy making to meet travel demands.
- **The rise of mobility-as-a-service:** In order to improve the users' travel experience many countries have already integrated different modes of public transport. Users can use different applications (web-based or smartphone-based) to plan their travel and pay from their smart-cards, e.g., Myki card in Melbourne<sup>1</sup>, Oyster card in London<sup>2</sup>. However, the current options from an integrated mobility service offer only public modes of transport. Moving one step further, the emerging concept of *mobility-as-a-service* integrates not only public transport modes (bus, train), but also private modes e.g., tram, car, bike. MaaS provides multiple travel options given an origin and destination, with a cardless payment system. A user can choose an integrated travel plan from a monthly subscription or pay-as-you-go option<sup>3</sup>. In one hand, MaaS integration improves user's satisfaction and resource optimization. On the other hand, this integration opens up new business opportunities by connecting different stakeholders ranging from public and private transport providers, telecommunication and IT companies, payment processors, local and regional transport authorities ([Hietanen, 2014](#)).

While MaaS is still in its early stage, the new business model requires insight about people's mobility-based activities and their mode preferences. The contributions presented in this research has a potential to unravel people's transport choice behaviour from historical trajectories ([Chapter 5](#)) and real time information delivery ([Chapter 7](#)). For example, a smartphone-based MaaS application can inform a user if the next connecting vehicle is delayed and at the same time the application can recommend an alternative based on the user's previous travel behaviour (and mode choice). Thereby the travel will become more seamless, user-friendly, and sustainable.

By introducing the aspect of knowledge representation, certainty factors and temporal uncertainty during a trajectory interpretation process, this research is an improvement over the existing data specific interpretation models. While proposing the

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<sup>1</sup> For more information refer to (last accessed: April, 2017)

<https://www.ptv.vic.gov.au/tickets/myki>

<sup>2</sup> <https://oyster.tfl.gov.uk/oyster/entry.do>

<sup>3</sup> <https://dupress.deloitte.com/dup-us-en/deloitte-review/issue-20/smart-transportation-technology-mobility-as-a-service.html>

knowledge-driven mode detection model, the research provides a way to explore trajectory data where the groundtruth information is limited. This research also presents more adaptive and flexible models to interpret motion trajectories to extract people's transport mode information, which can be used as a critical information to enable MaaS.

#### 9.4 FUTURE RESEARCH DIRECTIONS

Though the results demonstrate that the research objective has been achieved but the proposed models suffer from a number of limitations (Section 8.4). There are several areas that need further improvements in future.

- The ontological framework developed in Chapter 4 can be extended to model composite activities that are occurring concurrently with some degree of overlap. Currently, the model uses a temporal zooming to distinguish between different activities. Future research will seek to model the inter-relationship between different activities. Moving away from an individualistic view, addressing activity system models (Engstrom, 1987) is also required to understand group activity patterns from motion trajectories of different users (Laube et al., 2005; Duckham, 2013; Miller et al., 2016). The ontological framework currently cannot cope with the uncertainties that may exist while modelling and detecting an activity. A future research should look into integrating the fuzziness that exists in a motion trajectory to the activity ontology.

While modelling complex mobility-based activities the ontological framework requires more rigorous activity constraints to improve the reasoning capability. For example, a person cannot travel by a car and a train at the same time. On the other hand, it is possible that a person can travel by a car and can talk on a phone concurrently. In order to model complex activities the ontology presented in this thesis should incorporate temporal reasoning (Brush et al., 2010; Ligozat, 2013) in future.

- The concepts of *process* and *event* are important in spatial science, while explaining any phenomena and its dynamics (Galton, 2006, 2015). In this regard, an *activity* and *action* can resemble to a *process* and an *event* respectively. A future research can look into such ontological resemblance to align the aspects of human interactions in *activity theory* with the temporal dynamics.
- The knowledge-driven models developed in this research represent the knowledge base that is either defined by an expert or through an exhaustive combinatorial search. However, in practice, the rules may not all be relevant. In other words, the rules may be relevant to different degrees. Future research should investigate

the sensitivity for the individual rules, and mechanisms that select a portion of the knowledge base which is relevant to a given situation (or a context).

- The membership functions used in both the fuzzy models developed in [Chapter 5](#) and [Chapter 6](#) are crisp in nature. Future research will look into higher order fuzzy modelling where the membership function itself is fuzzy in nature ([Mendel et al., 2006](#); [Pedrycz, 2015](#)).

The hybrid model proposed in [Chapter 6](#) currently uses a grid partitioning to generate its rule base. This is an expensive strategy and thus poses scalability issues. Future research will address this disadvantage by implementing other strategies e.g., a subtractive clustering or a fuzzy c-means clustering approach.

- The state-based bottom-up model developed in [Chapter 7](#) can be made more robust and intelligent by incorporating more information. Currently, the model primarily relies on GTFS information for consistency checking. But GTFS may not be available everywhere. This raises the concern how to make the model more robust in absence of GTFS information. One way could be increasing the sampling frequency at a cost of higher energy consumption and computational overhead. Future research should develop a strategy that can balance these issues.
- The research uses a reasonable quality GPS data set sampled at 1 Hz to 2 Hz to evaluate the models. But in reality, while dealing with a massive trajectory data the location information may come from different sources with varying positional uncertainties. This will require more adaptive analysis strategies. Although the research suggests using inertial sensor information in tandem with the location information can cope with the signal loss, but the quality of the inertial sensor signal is subject to orientation of the phone. Future research should address how the detection accuracy varies depending on the phone's orientation and position.
- The models presented in this research can be used as a background intelligence for smartphone based travel surveys or any large scale movement data analysis. The analysis could be transport mode detection at different temporal granularities, transfer detection, and trip detection. With the growing advanced ICT and various OGC standards there is an unprecedented amount of movement data being generated from different sources at different granularities, with varying quality. Future research can explore how such dynamic, fast paced movement data with different quality can be used to model the complex dynamic processes in an urban space.



## 9.5 CONCLUDING REMARKS

The introduction of Web 2.0 has generated a volume of movement data over the years through ubiquitous location sensing technologies and IoT (such as GPS, GSM, Wi-Fi enabled smartphones, check-ins, smart-cards, geo-tags and geo-tweets). This data can be used to reconstruct semantically meaningful movement patterns at different spatial and temporal resolutions. In particular, the concept of smartphone travel surveys is gaining popularity over manual (paper-based or telephone based) surveys due to its flexibility, ubiquity, and richness in information content. On the other hand, with the technological evolution, the activity pattern is changing from a physical space to even a larger and abstract virtual space increasing the complexity in activity patterns (Shaw and Yu, 2009; Sveda and Madajova, 2012). The accessibility of an object (relevant to an activity) is transforming from *something, somewhere, sometime* to *anything, anywhere, and anytime* (Couclelis, 1996). For example, people can participate in a distant business meeting or enjoy watching the Niagara Falls sitting at home in front of a computer without actually travelling to the given locations. And with that, the concept of "death of distance" (Couclelis, 1996, 2004) is becoming more pronounced over time. As shown in this thesis an integrated sensor based approach (GPS and IMU) will help in detecting activities (and actions) in a more effective and accurate manner. Although this research has primarily used a smartphone-based GPS, accelerometer and a gyroscope, given a diverse smartphone manufacturing market (in terms of number of different sensors available on a phone and their quality), there are issues with choosing the proper sensor combination, orientation of the sensor, sampling frequency and the scale of analysis in the light of context-aware activity modelling.

This leads to further future research questions:

- How can complex activity patterns be modelled from an ontological perspective?
- What type of trajectory data is required to address different complex activity patterns that spread across a physical and virtual space?
- How different mobility-based activity state can be detected from a multiple IMU sources sampled at different frequencies?
- How the detection accuracy may vary with different orientations and positions of the phone?
- How an advanced phased sampling approach can be implemented that can leverage a user's activity state (stationary/moving) as well as her spatial surroundings (indoor/outdoor)?
- How composite activities can be distinguished using IMU and GPS sensors on board a smartphone in a given temporal period (detecting travelling on a train while reading news on the smartphone)?

With the paradigm shift from paper-based travel surveys to smartphone travel surveys, there has been a constant improvement in terms of understanding behavioural information at a finer granularity with increasing flexibility. But these surveys use a predefined design, a software and hardware architecture targeted for a particular type of trajectory data, and are also limited to a specific spatial-temporal region and typically small numbers of respondents. In the age of *big data*, there is a significant scope to fuse different information sources such as GPS, GSM, IMU, smart-card, geo-tweets to reflect the location and body parts movement information at different granularities. The concept of fusing data sources will enrich a movement data. This is also useful when GPS signal is lost in one hand and supplementing an inertial signal with location information on the other hand. Such an enriched movement data will not only provide the clues on *where* and *when*; but also other contextualized information on *how*, *why*, and *what else*. This will in turn help to undertake more informed decisions in urban planning and realize more intelligent contextualized service provisions where *mobility* is the primary aspect.

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Part I

APPENDIX

This section contains additional information relevant to this thesis.



## THE SET OF FUZZY RULES USED IN MIMO MAMDANI FUZZY LOGIC BASED MODEL

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1. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)
2. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
3. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
4. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is moderate)(train is low)(tram is high)
5. If (avgSpeed is high) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is moderate)
6. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
7. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is low)(bus is high)(train is low)(tram is low)
8. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is low)(tram is high)
9. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is low)(bus is moderate)(train is low)(tram is high)
10. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is low)(bus is high)(train is low)(tram is low)

11. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is low)(bus is high)(train is low)(tram is moderate)
12. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
13. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
14. If (avgSpeed is high) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is moderate)
15. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is moderate)
16. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is low)(bus is moderate)(train is low)(tram is high)
17. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is moderate)
18. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
19. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is moderate) then (walk is low)(bus is low)(train is high)(tram is low)
20. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)
21. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
22. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)

23. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is low)
24. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is low)
25. If (avgSpeed is high) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is moderate) then (walk is low)(bus is moderate)(train is high)(tram is moderate)
26. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is moderate)
27. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
28. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
29. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
30. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is low)(bus is moderate)(train is low)(tram is high)
31. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is moderate)(train is high)(tram is low)
32. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is moderate)(train is high)(tram is low)
33. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is moderate) then (walk is low)(bus is low)(train is high)(tram is low)
34. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)

35. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is moderate)
36. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is proximal) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is high)(bus is moderate)(train is low)(tram is low)
37. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is moderate) then (walk is high)(bus is moderate)(train is low)(tram is low)
38. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is moderate)
39. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is high)(bus is low)(train is moderate)(tram is low)
40. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is moderate)(train is low)(tram is low)
41. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)
42. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)
43. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is moderate)(train is low)(tram is high)
44. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is moderate) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
45. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is moderate)(train is low)(tram is high)
46. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is high)



47. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is high)
48. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
49. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is moderate) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
50. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is proximal) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is low)(bus is high)(train is low)(tram is low)
51. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
52. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
53. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is moderate) then (walk is low)(bus is low)(train is high)(tram is low)
54. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is moderate) and (avgTramProx is far) then (walk is low)(bus is low)(train is high)(tram is low)
55. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is proximal) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is low)
56. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
57. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is low)(tram is high)
58. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is moderate) then (walk is low)(bus is low)(train is low)(tram is high)

59. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is moderate)(tram is high)
60. If (avgSpeed is low) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is low)(tram is high)
61. . If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is low)(tram is high)
62. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is moderate)(tram is high)
63. If (avgSpeed is low) and (maxSpeed is moderate) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is moderate)(tram is high)
64. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is moderate)(tram is high)
65. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
66. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
67. If (avgSpeed is moderate) and (maxSpeed is moderate) and (avgBusProx is moderate) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is low)(bus is low)(train is moderate)(tram is high)
68. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
69. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is proximal) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is high)(train is low)(tram is low)
70. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is proximal) then (walk is high)(bus is low)(train is low)(tram is moderate)

71. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is proximal) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
72. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is moderate) and (avgTramProx is moderate) then (walk is high)(bus is low)(train is low)(tram is low)
73. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
74. If (avgSpeed is low) and (maxSpeed is low) and (avgBusProx is moderate) and (avgTrainProx is far) and (avgTramProx is far) then (walk is high)(bus is low)(train is low)(tram is low)
75. If (avgSpeed is high) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is low)
76. If (avgSpeed is moderate) and (maxSpeed is high) and (avgBusProx is far) and (avgTrainProx is far) and (avgTramProx is far) then (walk is low)(bus is moderate)(train is high)(tram is low)



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