UNIVERSITY OF TRENTO

DOCTORAL THESIS

Modelling and Recognizing Personal Data

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in the

Knowdive Group
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Declaration of Authorship

I, Enrico BIGNOTTI, declare that this thesis titled, “Modelling and Recognizing Personal Data” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date: March 30, 2018

"Have no fear of perfection - you'll never reach it."

Salvador Dali

Abstract

Modelling and Recognizing Personal Data

by Enrico BIGNOTTI

To define what a person is represents a hard task, due to the fact that personal data, i.e., data that refer or describe a person, have a very heterogeneous nature. The issue is only worsening with the advent of technologies that, while allowing unprecedented collection and processing capabilities, cannot *understand* the world as humans do. This problem is a well-known long-standing problem in computer science called the Semantic Gap Problem. It was originally defined in the research area of image processing as "... the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation..." [Smeulders et al. 2000]. In the context of this work, the semantic gap is the lack of coincidence is between *sensor data* collected by ubiquitous devices and the *human knowledge* about the world that relies on their intelligence, habits and routines.

This thesis addresses the semantic gap problem from a *representational* point of view, proposing an interdisciplinary approach able to **model and recognize personal data in real life scenarios**. In fact, the semantic gap affects many communities, ranging from ubiquitous computing to user modelling, that must face the issue of managing the complexity of personal data in terms of modelling and recognition.

The contributions of this Ph. D. Thesis are:

- *The definition of a methodology* based on an interdisciplinary approach that **can account for how to represent and allow the recognition of personal data**. The interdisciplinary approach relies on the entity-centric approach and on an interdisciplinary categorization to define and structure personal data.

- *The definition of an ontology of personal data* to represent human in a general way while also accounting their different dimensions of their everyday life;

- *The instantiation of the personal data representation* above in a reference architecture that allows implementing the ontology and that can exploit the methodology to account for how to recognize personal data.

- *The adoption of the methodology for defining personal data and its instantiation* in three real-life use cases with different goals in mind, proving that our modelling works in different domains and can account for several dimensions of the user.

Keywords: Knowledge Representation, Personal Data, Ubiquitous Computing, Pervasive Computing, Computational Humanism, Semantic Gap

Acknowledgements

As it is customary, before the (unfortunate) reader must begin the trailing task of reading my thesis, I should take the time to express my gratitude to those who helped me and supported me in this long and perilous journey.

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Enrico Bignotti
University of Trento
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- *the European Union's Seventh Framework Program (FP7) under grant agreement 600584, Smart Society - Hybrid and Diversity-aware Collective Adaptive Systems: Where People Meet Machines to Build Smarter Societies* http://www.smart-society-project.eu/

Contents

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Author's Contributions

What follows is the list of publications of the author that are relevant to the work presented in this thesis.

This paper, awarded with the Best paper at the MobiCASE'14 conference, presents the general Mainkofen scenario we base our model from in Chapter 9. It illustrates the initial data collection phase and outlines the possible improvements of adding semantic knowledge.

Bahle, Gernot et al. (2014). "Recognizing hospital care activities with a coat pocket worn smartphone". In: *Mobile Computing, Applications and Services (MobiCASE), 2014 6th International Conference on*. IEEE, pp. 175–181.

This paper presents how the modeling of context can be exploited in the area of robotic surveillance by adapting the notion of human context.

Giunchiglia Fausto, Bignotti Enrico and Zeni Mattia (2017a). "Human-like context modelling for robot surveillance". In: *Semantic Computing (ICSC), 2017 IEEE 11th International Conference on*. IEEE, pp. 360–365.

This paper presents the first formalization of our definition of context from Section 7.3 and the time diary adaptation from 10.2.2.

— (2017b). "Personal context modelling and annotation". In: *Pervasive Computing and Communications Workshops (PerCom Workshops), 2017 IEEE International Conference on*. IEEE, pp. 117–122.

This paper presents how the modeling of context can be exploited in the area of robotic surveillance by, in addition to adapting the notion of human context, also showing preliminary results in terms of sensor data collection.

Giunchiglia, Fausto, Mattia Zeni, and Enrico Bignotti (2017). "Human-like context sensing for robot surveillance". In: *International Journal of Semantic Computing*.

This paper refers to the Smartunitn One use case from Chapter 10. In this paper, the authors present the performance of the participants in identifying WiFi networks in the university buildings.

— (2018a). "Combining Crowdsourcing and Crowdsensing to Infer the Spatial Context". In: *PerCrowd'18 - International Workshop on Context-Awareness for Multi-Device Pervasive Computing (PerCrowd'18)*. Athens, Greece.

This paper refers to the Smartunitn One use case from Chapter 10. It presents a series of measures to analyze the impact of response biases in users' annotation in real life scenarios

Giunchiglia, Fausto, Mattia Zeni, and Enrico Bignotti (2018b). "Personal Context Recognition via Reliable Human-Machine Collaboration". In: *IQ2S'18 - 9th International Workshop on Information Quality and Quality of Service for Pervasive Computing (IQ2S'18)*. Athens, Greece.

This paper refers to the Smartunitn One use case from Chapter 10. In this paper, a new approach to evaluate how well users answer to real time annotation of their data is provided based on their consistency when referring to their home.

Giunchiglia, Fausto, Mattia Zeni, Enrico Bignotti, and Wanyi Zhang (2018). "Assessing annotation consistency in the wild". In: *ARDUOUS'18 - 2nd International Workshop on Annotation of useR Data for UbiquitOUs Systems (ARDUOUS'18)*. Athens, Greece.

This paper refers to the Smartunitn One use case from Chapter 10. It presents an evaluation of the impact of mobile social media on students by parametrizing social media usage in terms of interactions with the smartphone and academic performance. Results corroborate the literature on the negative correlations between social media usage and academic performance, while also underlining new insights, e.g., how academic performance of scientific students is more affected by their usage than students from humanities. .

Giunchiglia, Fausto, Mattia Zeni, Elisa Gobbi, et al. (2017). "Mobile Social Media and Academic Performance". In: *International Conference on Social Informatics*. Springer, pp. 3–13.

This paper refers to the Smartunitn One use case from Chapter 10. It extends the previous paper by considering also CFU as an academic performance measure, thus extending the coverage and depth of the analysis.

— (2018). "Mobile social media usage and academic performance". In: *Computers in Human Behavior*. URL: http://www.sciencedirect.com/science/article/pii/S0747563217307276.

This paper comes from the collaboration with members of the Digital Humanities research group at FBK. It presents an automatic approach for the extraction and visualisation of motion trajectories of famous people that can provide insights for studies in many fields, e.g., history and sociology.

Menini, Stefano et al. (2017). "RAMBLE ON: Tracing Movements of Popular Historical Figures". In: *EACL 2017*, p. 77.

Part I

General Notions

Chapter 1

Introduction

This Chapter introduces the work presented in this Ph.D. thesis. We begin by outlying a motivating example to ease the understanding of the methodologies and theories presented in this work in Section 1.1. Then, we present the context which provides the scope to position the work in Section 1.2, while Section 1.3 illustrates the problems we tackle, starting from the motivating example and the context. Section 1.4 proposes the solution to these problems, that is composed by an entity-centric modelling personal data and deploy them in a ubiquitous system used in three different use cases. Finally, Section 1.5 provides the reader with a structure of the thesis.

1.1 Motivating Example

Fausto has scheduled an appointment in the Trento city center at lunch and he cannot afford to be late (as he usually is). His personal application installed on his smartphone knows about this, because Fausto gave it permissions to check the agenda in addition to other personal information. At 11:30AM the application notifies Fausto that he has to leave for his appointment and proposes him the best route to cover to reach the parking lot. This apparently simple service that notifies about an appointment involves a lot of knowledge the system has to be aware of. First of all, the two locations: where Fausto is now and where he has to be for lunch. Knowing the locations, the system is able to calculate the time necessary for reaching the destination considering additional information such as real-time traffic conditions in the area. Not only this, the system is aware that Fausto has a specific self realization goal about his fitness, which is set as performing a total of 10.000 steps. Since today he didn't move much, the system wants to gently nudge Fausto to walk more and proposes a parking lot that is a bit further away. For this reason, the departure time from the office takes into account also this additional element. Additionally, the system has learned that Fausto always tends to be late and then adapted the departure time accordingly, anticipating it by 10 minutes. Fausto is having an amazing time at lunch and did not realize that the passage of time. In fact, he has a very important meeting with a professor coming from another university. Since the meeting is scheduled at 1PM but at 12:40AM Fausto is still at the restaurant, the system notifies him with the same service used in the morning, but this time Fausto decides he wants to finish the conversation and ignores the notification. At this point the system elaborates a strategy, based on a past experience, that involves sending an email to Mattia, one of Fausto's postdoc, communicating about his delay. One month before in fact, Fausto was in a similar situation and decided to send an email to inform about the delay and advice that the meeting could start without him.

In such a scenario as the one just described above, which is common with many users and system, the system must have knowledge of the user preferences and habits among other heterogeneous information, e.g., his surroundings, in order to provide the appropriate service at the right time. To have such knowledge and successfully exploit it, is not an easy task.

1.2 The Context

Understanding what people are doing in a context-aware manner and react accordingly is an active field both from a research but also an industrial point of view. The final goal of this task is to provide services that are highly personalized on the user and that ultimately will improve her quality of life.

This field is gaining more and more interest in recent years especially thanks to the diffusion of smart devices that possess increasing computational capabilities and are becoming more and more intertwined with our lives. The main smart device is the smartphone; its impact and relevance can be properly evaluated thanks to two measures. The first one is the Smartphone Penetration Rate (SPR), which is *the measure of the number of users that own and use at least one smartphone*. There are yearly conducted surveys that show an amazing 30,9%[1] of worldwide smartphone adoption in 2017, that corresponds to 2.5 Billion people. The second one is the Smartphone Usage Statistics (SUS), which is *the amount of time spent using smartphone in specific situations*. A person uses the smartphone for an average of 3 hours[2] per day; if we ignore the sleeping time, it corresponds to almost 19% of the time available during the day. In addition to the time spent using the phone, there are other interesting dimensions that should be considered. For example, 52%[3] of UK owners look at the device within 15 minutes after wake up in the morning, which increases to 86%[3] within one hour. Similar values can be found considering the time interval between when the user looks at the phone and when he goes to sleep, with a 43% within 15 minutes that raise up to 77%[3] within one hour.

Applications are the main element that contributes to smartphone success. According to a recent report from App Annie[4], smartphone user access over 30 apps on a monthly basis. These 30 apps work out to being roughly one-third to one-half of the apps users have installed on their smartphones. And using those apps is a daily habit, as people now launch an average of at least 9 apps per day [4]. In terms of time spent on apps, users in the U.S. spend an average of over 2 hours and 15 minutes[4] in apps every day, which amounts to over

[1] http://goo.gl/5qGJBZ
[2] http://goo.gl/ctXFLv
[3] http://goo.gl/t9krFC
[4] https://goo.gl/Fyv8sH

one month out of the year. In South Korea, Brazil, Mexico and Japan, that number is even higher, with users averaging around 3 hours daily[4].

Some type of applications are also becoming more and more pervasive in use, especially those related to fitness and health care. According to the Pew Research Center's Internet & American Life Project[5], as of 2013 69% of U.S. adults kept track of at least one health indicator such as weight, diet, exercise routine, or symptom. Among them, 16% of 18-29 year-old use an app or other tool on a mobile phone or device, compared with 9% of 30-49 year-old, 3% of 50-64 year-olds, and 1% of trackers ages 65 and older. More recently, a survey found[6] that 29% of those aged 18 to 29 years utilize a fitness app regularly, compared to only 12% of those aged 61 years and older.

These statistic show us that, for a system that is capable of working in a way similar to the one described in the previous scenario, smartphone are indeed the best candidate technology but to work they require access and exploit data from their users. In fact, a device that is always with the user and that is powerful and flexible enough to run custom application can be used to collect huge amounts of data and to provide the results of the analysis in terms of context aware personalized services. Furthermore, they also show that the exploitation of data appears to be very specialized or vertical; however, to obtain and implement the motivation example, a more comprehensive understanding of the user's life is needed.

1.3 The Problem

Starting from the motivating example of Section 1.1 and within the context described in Section 1.2 the problem this thesis addresses is part of a long standing problem in computer science defined as *the semantic gap problem* (Smeulders et al. 2000). Within the context of this thesis, we can refer to it as the lack of coincidence between the sensor data collected by the machine and the fundamentally different understanding of the situation that the user and the machine have. In fact, due to a series of factors such as habits, routines and ultimately her intelligence, the user has a completely different understanding of the world with respect to a machine. The reason can be explained by the fact that the same sensor values can refer to multiple situations if no contextual information is provided. This is even more evident if we consider that two very similar situations can be perceived as very different to a person. If a person is very close to the door of a room, it is very different if she is inside or outside it. If she is inside, she can be attending a meeting, while if she is outside, probably she is at the copy machine one meter away from the door. From a machine point of view, the two positions can be assimilated with a unique point in space, due to the accuracy and errors in the measurement.

Within this general problem in the area of computer science, we want to focus on the specific issue of *representing* personal data, be they provided by users or sensors. Consider for instance an application that collects location

[5] https://goo.gl/ndL6Ja
[6] https://goo.gl/f9mzX7

points about the places visited by the user and asks the user to input the label, allowing then the user to share them. From an human perspective, the same location points collected by the machine in terms of coordinates can be interpreted very differently depending on the context. If the user has to communicate where she works to a new person met in a conference, she cannot reply with "I work in my office" but rather she will say something like "The University of Trento in Povo (TN)". On the other hand, if a user's friend asks where she is, she may reply using "The University of Trento in Povo (TN)" still, but it is more likely that she would prefer saying "I'm in my office". This situation shows that, depending on the context, a different output is enabled starting from the same sensor inputs, i.e., the physical coordinates of the University. This representational issue leads many communities, especially the ubuiquitous computing one, to avoid *representing* personal data as a whole, but rather focus on specific, *vertical* dimensions which are easier to manage in terms of complexity, although of course not trivially so, like healthcare for the Quantified Self (Haddadi et al. 2015) or activities in smart homes (Rodríguez et al. 2014).

From this problem, we identified the following sub-problems:

1. **Personal Data Definition** It is not easy to define which are personal data and how they relate to the actual users. The *psychological and social implication* of such an operation must be considered. Moreover, the privacy requirements for personal data are becoming more and more strict;

2. **Personal Data Representation** Having defined what personal data are, the issue is then how to represent them. This means understanding which is the best way to represent them and identify their sources, their availability and how they interact with each other;

3. **Knowledge Generation.** Analyzing the sensor data in a context aware manner is not an easy task and this is why the semantic gap problem is still unsolved, especially in open domain scenarios. There is the need to represent the different elements of the context involved in the analysis and create the appropriate methodologies to process personal data;

1.4 The Solution

This Ph. D. Thesis wants to find a solution to the semantic gap problem from a representational point of view. This means providing a representation of a person in a general, holistic way that can be applied to different real life scenarios. The main goal is therefore to overcome the verticality of current solutions, especially with respect to the quantified self movement, and model personal data in a way that is understandable to humans and machines alike.

The contributions of this Ph. D. Thesis are:

- *The definition of a methodology* based on an interdisciplinary approach combining philosophy, sociology and computer science to **categorize**

and recognize personal data. The methodology is based on the entity-centric approach and based on two fundamental criteria to define and structure personal data to address the issues of open domains and verticality of application scenarios.

- *The definition of an ontology of personal data* to represent human in a general way while also accounting their different dimensions of their everyday life;
- *The instantiation of the personal data representation* above in a reference architecture. In order to align the ontology with real world, we rely on an internal system architecture to collect the streaming data from the users devices (smartphone and others) using a mobile application developed for this scope called i-Log (Zeni, Zaihrayeu, and F. Giunchiglia 2014) and store them in a distributed database system;
- *The adoption of the methodology for defining personal data and its instantiation* in three real-life use cases with different goals in mind, proving that the our modelling works in open domains and can account for several dimensions of the user.

1.5 Structure of the thesis

The remainder of this thesis is organized as follows:

Chapter 2 presents the related work in different areas that are connected with the work presented in this thesis. Given how interdisciplinary our solution is, this Chapter will cover very different research communities;

Chapter 3 analyzes in detail the different elements of the problem of representing in a general way personal data in order to account for open domains;

Chapter 4 describes the entity-centric approach that will be used to model personal data;

Chapter 5 presents how proposal to model personal data as the Person Etype, in addition to our categorization of personal data.

Chapter 6 describes the methodology we developed to solve the problems related to the knowledge exploitation for providing context aware services to the users that are meant to improve their quality of life;

Chapter 7 describes in details the architectural solutions related to the exploitation of the generated knowledge to provide services to the users;

Chapter 8 provides an overview of the architectural solutions related to the collection, recognition and exploitation of personal data to provide services to the users;

Chapter 9 illustrates how we used our modelling of personal data in a use case within the EU project SmartSociety for modelling nurses and their routines in a geriatric hospital;

Chapter 10 illustrates how we used our modelling of personal data in a use case run on the students of the University of Trento called SmartUnitn;

Chapter 11 illustrates how we used our modelling of personal data in a use case within the EU project QROWD involving the citizen of the Municipality of Trento;

Chapter 12 concludes and summarizes the relevance of the thesis;

Chapter 13 presents future research directions following this work

Chapter 2

State of the Art

The work presented in this Ph.D. thesis has a strong interdisciplinary component; in fact, people have been studied in different areas. Among the many, we focus on ubiquitous computing, context-aware systems, knowledge management, user modelling, computational social sciences, the Quantified self movement, psychology, and sociology. This Chapter presents the state of the art in the different research communities.

2.1 User Modelling

User modeling is defined as "designing a model for representing and retrieving information about a user"(Kobsa 2001). The most common names for models of users are called either *user models* or *user profiles*[1]. Generally speaking, user modeling is either knowledge-based or behavior-based. Knowledge-based approaches create models and adapt users' information to them, whereas behavior-based approaches rely upon users' behavioral patterns as a model, usually via machine-learning techniques. Ontology-based modeling has attracted increasing attention within the area of user modeling, mainly because of its interoperability facets and ability to enable knowledge sharing and reuses across several application domains (Pan et al. 2007). Furthermore, as (Knappmeyer et al. 2013) claim, ontological modeling is more appropriate for ubiquitous computing environments.

The OntobUM Ontology (Razmerita, Angehrn, and Maedche 2003) is a generic ontology-based architecture for user modeling in the context of Knowledge Management Systems (KMS). The model is generated through two different ways. The first one is explicit and requires using a user profile editor so that the user has to provide some information. The second one is implicit so that the information maintained by several intelligent services, which not only maintain and update user information accounting for his or her behavior with the services but also provide adapted services based on user's preferences. The ontology architecture consists of three components: *i)* the User Ontology, which structures the different characteristics and preferences of the user, *ii)* the Domain Ontology, which defines several concepts about the domain, and *iii)* the Log Ontology, which manages the semantics of the interaction between the user and the whole system. Authors identify several users' characteristics that are relevant for a KMS under the Behavior concept.

[1] http://www.w3.org/WAI/RD/wiki/User_modeling

(Golemati et al. 2007) present an ontology which, while considering past literature solutions, aims to reduce the intrinsic problems of user modeling: ad-hoc modeling processes, the required amount of work to model users and the possibility of errors by omitting several user's characteristics. To this end, the authors present an extensible, comprehensive and general ontology which design is addressed through a top-down approach by firstly collecting static information about the user. According to this work, the main classes shared by the various ontologies tend to be:

Person: basic user information like name, date of birth, e-mail;

Characteristic: general user characteristics, like eye color, height, weight, and so on;

Ability: user abilities and disabilities, both mental and physical;

Living Conditions: Information relevant to the user's place of residence and house type;

Contact: Other persons, with whom the person is related, including relatives, friends;

Preference: User preferences, for example "loves cats", "likes blue color" or "dislikes classical music";

Interest: User hobby or work-related interests. For example, "interested in sports", "interested in cooking";

Activity: User activities, hobby or work related. For example, "collects stamps" or "investigates the 4thCrusade";

Education: User education issues, including for example university diplomas and languages;

Profession: The user's profession

A different approach is implemented by (Henricksen, Indulska, and Rakotonirainy 2002). Divided into four main groups (emotional state, personality, characteristics and physiological state), the authors present GUMO, an ontology model to characterize users capabilities within adaptive environments. GUMO divides the user model dimensions into three parts: auxiliary, predicate and range. Therefore if one wants to say something about "the user's interest in football", one could divide this into the auxiliary (has interest), the predicate (football) and the range (low-medium-high). The Basic User Dimension entails the information related to the physical and psychological user conditions. The classes which are contained in this dimension are: Contact Information, Demographics, Abilities, Personality, Characteristics, Emotional State, Physiological State, Mental State, Motion, Role, Mood, Nutrition, Facial Expression, Relationships and Basic Human Needs. The Context Dimension defines classes regarding the user's environment or product used as: Location, Physical Environment, Social Environment, Sensor Dimensions, Product

Information and Travel Contexts. Finally, the Domain Dependent Dimension reflects classes of Interest, Knowledge, and Preference. The auxiliaries employed by GUMO are: hasBelief, hasDone, hasInterest, hasKnowledge, hasLocation, hasPlan, hasPreference, hasRated, hasExperience, hasRegularity, and hasGoal.

Within an application personalization within mobile environments (Skillen et al. 2012) present a User Profile Ontology which is able of modeling dynamic components. The ontology considers both static and dynamic aspects of the user mainly focused on his/her behavior changes. In this work user capabilities are also taken into account for the user profile. Capabilities are defined as the extent to which the user has an ability, i.e., physical, emotional or cognitive, to carry out some activities. User's interests and several context parameters are also considered in the ontology to cover context-aware environments. This usually depends either on the developer, because of his/her experience, or in the system's technical characteristics. For example, if the system can perform inference with the user data an ontology-based representation could be more helpful than an object-based one.

Ontological user modeling is also widely used in the field of Ambient Assisted Living (AAL). (Sutterer, Droegehorn, and David 2008) introduced the concept of dynamic user profiles by developing the User Profile ontology with Situation-Dependent Preferences Support (UPOS). The main idea behind this ontology is supporting the situation-dependent personalisation of user services in pervasive environments; unfortunately, no further progress has been done with this approach. Similarly, the Unified User Context Model (UUCM) (Viviani, Bennani, and Egyed-Zsigmond 2010) aims at providing cross-system personalisation. This work presented an extensible user model that could be used for modeling various characteristics of the user and their situations (i.e., the user context) along different 'dimensions.' While this approach demonstrated benefits in allowing different applications to use the same profile, the lack of a standardized approach to the building of a general user profile affected the model maintenance.

2.2 Context and Context-Awareness

A fundamental notion for any modeling of user, and hence a person, is context. One of the earliest proposals is provided by (Dey, G. D. Abowd, and Wood 1998), defining context as "the user's physical, social, emotional or informational state"; nonetheless, (G. Abowd et al. 1999) definition of context is widely cited in the literature. It claims that context "is any information that can be used to characterize the situation of an entity. An entity is a person, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". Overall, as noted in (W. Liu, Li, and Huang 2011; Knappmeyer et al. 2013), despite more than a decade of research in the area, the most accepted definition of context is still the one from (G. Abowd et al. 1999), which shows how addressing the what context is and how to exploit it is still a challenging endeavor.

As specified by Pentland in (A. Pentland 2000), machines have to be aware of the context in which the user is involved to work autonomously. (Knappmeyer et al. 2013) provides a survey on the current work in the research community that deals with context-awareness. The authors claim that the context is an element that only humans can see, interpret and use and is constituted by "implicit situational information" that are used to "increase the conversational bandwidth". The main element that allows to the context to exist is the fact that humans have a global vision of how the world and society work. Moreover, the goal of context-aware systems is to simplify the interactions between the user and the machine: the user no longer becomes responsible for choosing which information is relevant and which is not. If computers were to access context information, we could improve the quality of their output and their services. (Schilit and Theimer 1994) first addressed the notion of context-awareness almost 20 years ago by claiming that the context is provided as "location, identities of nearby people and objects, and changes to those objects". (G. Chen, Kotz, et al. 2000) provide an active and passive definition of context-aware computing:

- **Active context awareness:** it is when an application automatically adapts to discovered context, by the changing in the application's behavior
- **Passive context awareness:** it is when an application presents the new or updated context to an interested user or makes the context persistent for the user to retrieve later."

Also, (G. Chen, Kotz, et al. 2000) are among the first to underline the importance of time as a context feature for many applications. In fact, they introduce the term "context history", which is an extension of the time feature recorded across a time span.

2.3 Context Modelling

Notwithstanding the issues in defining what context is, a major area of research is exploiting it by represent and modeling it via different formalisms. (Schmidt, Beigl, and Gellersen 1999) consider several issues about context modeling emphasizing the excess of abstraction about context-aware systems and environments which causes a lack of models to be compared. According to (Knappmeyer et al. 2013), the ontological representation of context is theoretically the best modeling approach; nonetheless, "full-featured ontological representations tend to decrease the inference performance."

(Henricksen, Indulska, and Rakotonirainy 2002) provide some caveats on modeling context, focusing on its role in pervasive environments:

1. Context information shows temporal characteristics, thus agreeing with (G. Chen, Kotz, et al. 2000). Context information can be static, e.g., one's birthday or dynamic, e.g., one's position; this latter type of information can change very rapidly. Thus, (Henricksen, Indulska, and Rakotonirainy 2002) argues that static context should be provided by the user,

while the dynamic one should be gathered by sensors. Historical account of the context information should also be considered as a description of the context.

2. Context information is often inaccurate, imperfect, or inconsistent, which may be due to several reasons. For instance, information can change so fast that it may be invalid once it is collected, and the collection mediums themselves may fail at any time.

3. Context can be represented in multiple ways, also at the machine level, e.g., the different representation of location from the GPS and what Google Maps represents.

4. Collected context information *per se* lack inherent structure and association. I may refer to my context as "work", but the basic information may be simply a person sitting on a desk typing, which require an abstraction step to be added.

Furthermore, the following elements should be addressed when analyzing a context scenario: *i)* a person's activities, *ii)* the person's device(s), *iii)* the resources, and *iv)* the social relations.

(Almeida and López-de-Ipiña 2012) consider two common problems concerning the ambiguity in context modeling: the uncertainty and the vagueness. The uncertainty models the likeness of a certain fact, while the vagueness represents the degree of membership to a fuzzy set. The uncertainty is represented by a certainty factor. Due to the nature of the process of collecting data from the environment, they propose an ontology designed to support two types of uncertainty: *i)* uncertain data, i.e., uncertainty generated from the collection of data from sensors due to the imperfect nature of the devices, and *ii)* uncertain rules, i.e., uncertainty in the execution of the rules. To reason over the ambiguous information, the JFuzzy Logic Open Source fuzzy reasoner has been adapted to support uncertainty information.

In terms of actual context models, one of the first context modeling systems is CoBrA (H. Chen, Finin, and Joshi 2003), an agent-based infrastructure, designed for campus spaces, capable of performing several context operations such as modeling, reasoning, and knowledge sharing. A fundamental element of this architecture is the context broker, which maintains and manages a shared context model between agents (applications, services, web services, etc.) within the community. The main application for CoBra is managing Intelligent Meeting Rooms.

SOCAM (Gu, Pung, and Zhang 2004) is a service-oriented context-aware middleware architecture for designing and prototyping applications in an Intelligent Environment. Its context ontologies are described via OWL. Since the pervasive computing domain can be divided into smaller sub-domains, the authors also divided the designed ontology into two categories: *i)* an upper ontology, which captures high-level and general context knowledge about the physical environment, and *ii)* a low-level ontology,which is related to each sub-domain and can be plugged and unplugged from the upper ontology when the context changes. Thus, the upper ontology considers person, location, computational entity and activity as context concepts.

CONON (X. H. Wang et al. 2004) focuses on modeling locations by providing an upper ontology and lower domain-specific ontologies organized into a hierarchy.

PiVOn (Hervás, Bravo, and Fontecha 2010) consists of four independent ontologies (users, environment, devices, and services), used to describe smart environments. The users perform tasks that have a goal and use some services, while the device ontology defines specifications of devices. Lastly, the environment ontology represents the position of objects and their type of location.

(Yamabe, Takagi, and Nakajima 2005) present the CITRON framework for personal devices which gathers context information about the user and his/her surrounding environment. Muffin, a personal sensor-equipped device is designed to collect several context parameters. Also, sensor information can be exploited for evaluating high-level context information. For example, accelerometer readings might recognize a walking or running activity, shaking and rotating, etc. There are two types of context acquisition: the user and the environment. For the user, several issues are analyzed. For example, activities recognition requires the user to use the device in specific ways (it is not the same to use it with hands or waist-mounted). Another problem the authors had to face is the long time required in processing an event from when the event is captured to when it is validated. Another relevant issue is how to address the complexity and ambiguity of context information. Unfortunately, Muffin suffered from several heat problems due to the sensors sensitivity to environment temperature, which affected the validity of its readings.

CaCONT (Xu et al. 2013) defines several types of entities, focusing on locations. It provides different levels of abstraction for specifying information about the location of entities, e.g., GPS and location hierarchies.

Finally, the Mining Minds Context Ontology (Villalonga et al. 2015) represents contexts defined as a triple of locations, activities, and emotions, that in turn are grouped according to an aggregating element, e.g., amusement, housework, commuting and so on.

2.4 Ontology Based activity recognition

Ontologies are also being successfully employed in the area of activity recognition. This research area focuses on the recognition of human activities and has traditionally favored statistical approaches (Rodríguez et al. 2014). These approaches exploit a range of different stochastic techniques to recognize anomalies and build a behavior model based on sensor information. However, while these systems can handle noise, uncertainty, and incomplete sensor data (L. Chen and C. Nugent 2009), they suffer the following drawbacks (L. Chen, C. D. Nugent, and H. Wang 2012):

1. **Cold-start problem:** requiring a large representative dataset to support model training for each activity.

2. **Model applicability:** multiple models must be trained for each activity, especially if it can be performed in different ways.

3. **Model reusability:** it is difficult to apply activity models to different users

The main area for employing ontologies in activity recognition is AAL. Similarly to user modeling in the same field, ontologies have the main advantages of adopting ontologies in the are interoperability, and knowledge reuse (L. Chen, C. Nugent, and Okeyo 2014), coupled with reasoning for deriving implicit information from the available context. Finally, unlike statistical data, ontologies based approaches "allow previous activity recognition models to be used; updating only the affected context rules is enough to recognize the adapted activity" (Riboni, Pareschi, et al. 2011).

(Cheng 2013) presents a new approach that does not need training samples and therefore can recognize unseen complex activities. The solution consists of a framework that uses human knowledge to identify the hierarchies of human activities. These activities are decomposed into atomic units that are then individually recognized and used with their sequential order to recognize the original complex activity.

(Riboni and Bettini 2011) propose a framework called COSAR for the recognition of activities by following a hybrid approach that combines data-driven and ontology-driven approaches. COSAR combines mobile sensor data with the structured knowledge provided by the Pal-SPOT ontology[2]. This allows for the recognition of the activity performed by the user, increasing the overall accuracy with respect to only data-driven methods. Moreover, the ontology presented assists the system in recognizing complex activities that otherwise will not be recognized. To do so, the system uses ontological reasoning on locations only, e.g., filtering uncertain activities checking in the ontology whether they can be performed in a certain location. As (Rodríguez et al. 2014) notes, the main disadvantage of localizing activities is that it may be difficult for recognizing activities performed in small spaces.

Other researches in this field do not refer to personal user data collected by general purpose mobile devices. For instance, (L. Chen and C. Nugent 2009) presents an innovative system that facilitates the domain knowledge reuse and exploits semantic reasoning for activity recognition with an interesting result in the final recognition accuracy of 94.44%.

2.5 Quantified Self

The first mention of the term "quantified self" defines it as "a collaboration of users and tool makers who share an interest in self-knowledge through self-tracking"[3]. According to (Marcengo and Rapp 2014), the quantified self movement "aims to use the increasingly invisible technology means to acquire and collect data on different aspects of the daily lives of people." This idea of

[2] http://everywarelab.di.unimi.it/palspot
[3] http://quantifiedself.com/

using technologies to quantify people is also similar to other areas of research, e.g., "Personal Informatics" [4], "Living by Numbers," and so on. In the last years many works in the research community started focusing on it, such as (Lupton 2016), (Swan 2013), (Fox and Felkey 2016), (Swan 2012a) and (Swan 2012b).

A major application of quantified self has been in health and wellness improvement. Many devices and services help with tracking physical activity, caloric intake, sleep quality, posture, and other factors involved in personal well-being. Commercial solutions, which also prove the increasingly growing industry, are FitBit,[5] Nike+ FuelBand,[6], Jawbone[7] among others.

A very similar field to the quantified self is lifelogging, i.e., "a form of pervasive computing consisting of a unified digital record of the totality of an individual's experiences, captured multimodally through digital senors and stored permanently as a personal multimedia archive" (Dodge and Kitchin 2007). (Rawassizadeh et al. 2013) presents an innovative Lifelogging system called UbiqLog. The authors claim that unlike context-aware applications, lifelogging needs to store the collected information for a much longer period, e.g., at least the life of a person, with a need to focus on privacy and annotation. This work proposes an interesting approach: to configure the sensors and provide high flexibility to the data structure, to allow the addition of other sources of information later.

2.6 Computational Social Sciences

Understanding behavior via computational means has been gaining momentum in the last decade, leading to the creation of increasingly large and complex datasets built by collecting various sources of data to extract behavioral patterns.

The earliest work is the Reality Mining study (Eagle and A. S. Pentland 2006), which collected data from mobile phones of business school students for nine months to explore how smartphones could be used to investigate human interactions.

The Social Evolution experiment (Madan, Cebrian, Lazer, et al. 2010) was conducted to closely track the everyday life of a whole undergraduate dormitory from October 2008 to May 2009. Proximity, location, and call log, were collected through a cell-phone application scanning nearby Wi-Fi access points and Bluetooth devices every six minutes. Also, surveys were used to obtain data about relationships, and attitude towards various aspects of student life, ranging from political opinions, fitness (e.g., smoking behavior and exercising), to confidence and anxiety level. Based on these data, (Madan, Cebrian, Lazer, et al. 2010) was able to track stress, sadness, and flu by looking at how the subjects moved around, how much they talked to the others,

[4] See http://www.personalinformatics.org/ for a list of Personal Informatics tools.

[5] http://www.fitbit.com

[6] http://www.nike.com/us/en_us/c/nikeplus-fuelband

[7] https://jawbone.com

and when they talked to others, while (Madan, Cebrian, Moturu, et al. 2012) studied the adoption of political opinions.

Although not focusing only on students, the Friends, and Family study (Aharony et al. 2011), investigated graduate students and their partners to study how decisions are made and how to support people when making them. Like the Social evolution experiment, it collected both sensor data, through a mobile sensing platform, and surveys.

The Student Life study (R. Wang, F. Chen, et al. 2014) used Android phones to assess the impact of workload on stress, sleep, activity, mood, sociability, mental well-being and academic performance of a class of 48 students across a 10ten-week term at Dartmouth College. Moreover, the SmartGPA study (R. Wang, Harari, et al. 2015) uses the data from (R. Wang, F. Chen, et al. 2014) to show that there is evidence of a link between the students' GPA and their behavioral patterns.

Currently, the Copenhagen Networks Study (Stopczynski et al. 2014) is collecting data on 1,000 students by coupling smartphone data with face-to-face interactions and Facebook usage, together with answers to a survey on several metrics deployed every six months. By also considering web-based interactions, i.e., Facebook usage, the authors are therefore able to analyze a bigger picture than other studies based on only smartphone data.

As (Centellegher et al. 2016) notes, the majority of the work in this area has been focusing on students as a particular sample of the population to investigate, given the fact that they are very susceptible to smartphones' pervasiveness. However, relying on students can severely limit the range of behaviors (e.g., studying, attending classes, hanging out with friends, doing sport, etc.) and the range of places (e.g., cafeteria, canteen, library, etc.); this makes it harder to generalize the results. Thus, (Centellegher et al. 2016) proposes the Mobile Territorial Lab, which is a longitudinal living lab which has been sensing the lives of more than 100 parents in different areas of the Trentino region in Northern Italy. In addition to collecting call and SMS logs and location data from each participant's phone, each participant filled out several questionnaires to collect information about her/his psychological traits and dispositions. The first results after two years of experimenting are that, despite differences among parents in terms of incomes and working habits, their movements are concentrated in the city of Trento, and they tend to visit the same number of places during the week. Furthermore, data suggests that travel, spending and social relations are modulated by personality.

2.7 Time diaries

In this section, we discuss which are the main tools sociologists use for their researches in analyzing the human behavior. Among them, one of the most important and most used ones are those that allow researchers to study time allocation, i.e., how people use their time. Time-use research is defined as an interdisciplinary field of study dedicated to learning how people allocate their time during an average day. The comprehensive approach to time-use research addresses multiple issues, i.e., political, economic, social, and cultural ones.

The main tool for time use research is time diaries (Sorokin and Berger 1939), where respondents are asked to indicate three main dimensions of their everyday life: *i)* the activities they perform (sometimes indicating also secondary activities, i.e., activities that the respondent reports being done at the same time as the diary (primary) activities (Juster and Stafford 1991)), *ii)* the locations they visit and *iii)* the people around them. Usually, diaries consist of tables divided by time intervals of 10 minutes (Romano 2008), covering the whole day, where each interval is an entry divided into the corresponding dimensions. Also, time diaries may be either open or structured. Open time diaries allow respondents to record activities and events in their own words, which requires manual decoding by a uniform classification criteria, where activities are ordered in mutually exclusive groups (J. P. Robinson 1985). In structured time diaries, all activities are based on pre-coded categories, so it is the user who decides which activities to report (Hellgren 2014). Additionally, time diaries can be administered either as "leave behind diaries," where the respondents fill the data in real time as the day progresses (Juster and Stafford 1991), or as "recall diaries," where respondents have to recall their activities for the previous day (W. E. Pentland et al. 1999). A major drawback for time diaries is that they are expensive and time-consuming, especially for the amount of work required to process the data collected, e.g., the correct coding of open answers by dedicated coders (Hellgren 2014).

Sociologists have only recently begun to explore the use of smartphones with time diaries. The first (and only) pilot study using smartphones as a survey tool (Sonck and Fernee 2013) developed a diary app where a selected sample of about 150 people was asked to record their activities for two days, i.e., a Wednesday and a Saturday, by selecting them from a list of 41 activities from the Harmonized European Time Use Survey (HETUS) (EUROSTAT 2009). Respondents could also retrospectively record their activities the following day. Smartphones were used to collect the respondents' positions via GPS every 10 minutes in addition to log-data of their calls and SMSs. This work allowed to establish that smartphone-based diaries do not differ substantially from other time diaries in terms of number of answers provided. In this thesis, time diaries are relevant since they are an integrating part of the way to elicit personal data from people and even allow users to provide additional information as annotations of their own data, as it will be shown in Chapter 8 and in the SmartUnitn use case 10.

2.8 Person Representation Standards

Deciding which are the defining properties of a person has been tackled in many ways, as we shown in this chapter. One additional source of comparison is *de re*, or *de facto* standards for representing personal information used not only within the research community but also in other major areas such as business or healthcare. In this section, we will present a handful of relevant and as context-independent as possible standards we used as a resource for personal information, focusing on those used in the Web.

A commonly used framework for representing personal information is vCard, also known as VCF (Virtual Contact File). It is a file format standard for electronic business cards, whose latest version is the 4.0[8]. vCards are often attached to e-mail messages, but can be exchanged in other ways, such as on the World Wide Web or instant messaging. They can contain name and address information, telephone numbers, e-mail addresses, URLs, logos, photographs, and audio clips. vCard is used as a data interchange format in Personal digital assistants (PDAs), Personal information managers (PIMs) and Customer relationship management (CRMs). In addition to version 4.0, several dedicated specifications have been developed to extend it, e.g., RFC6715[9] add expertise and hobbies synchronizing with the Open Mobile Alliance (OMA) Converged Address Book group. There are several variants that adapt vCard to different formats and platforms. For instance, since vCard information is commonly used in web pages, there has been work to make some of its values, which may be free text, from human-readable to machine-readable. Thus, the hCard was developed to allow a vCard to be embedded inside an HTML page. It makes use of CSS class names to identify each vCard property. Normal HTML markup and CSS styling can be used alongside the hCard class names without affecting the webpage ability to be parsed by a hCard parser[10].

The (Friend-of-a-Friend) FOAF project[11] is devoted to linking people and information using the Web and is considered a *de facto* standard in the Semantic Web. FOAF integrates three kinds of network:

1. social networks of human collaboration, friendship, and association;
2. representational networks that describe a simplified view of this domain in factual terms,
3. information networks that use Web-based linking to share independently published descriptions of this inter-connected world.

FOAF provides an approach in which different sites can tell different parts of the same world, and by which users can retain some control over their information in a nonproprietary format. FOAF provides an RDF/XML vocabulary to describe personal information, including name, mailbox, homepage URL, friends, and so on. The most important component of a FOAF document is the FOAF vocabulary, which is identified by the namespace URI[12]. The FOAF vocabulary defines both classes (e.g., foaf:Agent, foaf:Person, and foaf:Document) and properties (e.g., foaf:name, foaf:knows, foaf:interests, and foaf:mbox) grounded in RDF semantics. In contrast to a fixed standard, the

[8] `https://tools.ietf.org/html/rfc6350`
[9] `https://tools.ietf.org/html/rfc6715`
[10] `http://microformats.org/wiki/h-card`
[11] `http://www.foaf-project.org/`
[12] `http://xmlns.com/foaf/0.1/`

FOAF vocabulary is managed in an open source manner, i.e., it is not stable and is open for extension by design.[13]

Another standard in the Semantic Web is the ISA Programme Person Core Vocabulary[14], which provides a minimum set of classes and properties for describing a natural person, i.e. the individual as opposed to any role they may play in society or the relationships they have to other people, organizations, and property; all of which contribute significantly to the broader concept of identity. It was developed under the ISA Programme of the European Union[15], with the final aim to public help public administration to: develop new systems from a conceptual and logical data model, enable the information exchange between systems, integrate data from various sources, and publish data in a common export format.

Schema.org[16] is a collaborative, community activity with a mission to create, maintain, and promote schemas for structured data on the Internet, on web pages, in email messages, and beyond.The aim of the Schema.org is to help search engines to interpret information on web pages so that it can be used to improve the display of search results, making it easier for people to find the information they are looking for. To do this, content publishers insert machine-readable information into the HTML of web pages that helps search engines understand the significance of the text on those pages. This information allows human-readable resource descriptions to double up as machine-readable metadata, or what Google calls structured data. Schema.org has two components. The first one is the ontology, i.e., a vocabulary for naming the types and characteristics of resources, their relationships with each other, and constraints on how to describe these characteristics and relationships. This vocabulary can easily be extended through a well-documented extension model. The second component is the expression of ontological information in machine-readable formats such as microdata, RDFa Lite, and JSON-LD. The schema.org documentation lists a hierarchical set of types and their properties. The top level of the hierarchy, the most generic type, is Thing, subtypes of this include CreativeWork, Event, and of course Person. Over 10 million sites use Schema.org to markup their web pages and email messages. Many applications from Google, Microsoft, Pinterest, Yandex and others already use these vocabularies to power rich, extensible experiences. Founded by Google, Microsoft, Yahoo, and Yandex, Schema.org vocabularies are developed by an open community process, and it is becoming a more and more *de facto* standard for representing people information (and more) in the Web.

[13]As the time of writing, The lastest FOAF specification only lists one stable term, i.e., homepage', and leaves many others in testing' or unstable' stages.

[14]https://www.w3.org/ns/person

[15]https://ec.europa.eu/isa2/home_en

[16]http://schema.org/

Chapter 3

The Problem

The goal of this thesis is to define a framework to represent and recognize personal data in the context of ubiquitous systems like smartphones. This framework will account for several dimension not only of persons *per se* but also their surroundings and everyday life in general.

To reach our goal, we are required to address a long-standing problem in computer science, i.e., *the semantic gap problem*. The original definition comes from the area of image processing, and it is as follows: "the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation" (Smeulders et al. 2000). The same issue applies to the work of this thesis since the two sources of information that we rely on are humans and sensors. These two sources represent the world very differently, and their representations are neither consistent neither coherent. This makes it very hard, if not impossible, to understand that they represent the same real world. Consider for instance how both sensors and humans represent a location:

- **Sensors:** a location can be reduced to (a set of) coordinates, which may also be collected with different sensors with varying degree of granularity and noise. For instance, rooms within buildings are hard to be represented with current technologies embedded in smartphones with the same granularity of external buildings, which are easily detectable using the Global Positioning System (GPS) (Ladd et al. 2004).

- **Users:** Humans understand their surroundings via *context*, i.e., "a theory of the world which encodes an individual's subjective perspective about it" (F. Giunchiglia 1993), which relates and make sense of different elements of humans' environment(s). In the case of locations, humans distinguish between different types of locations not only in terms of functions, e.g., my house vs. my workplace but also about other elements such as social circles, e.g., family vs colleagues.

The misalignment between these two representations is because the same sensor values can ideally refer to multiple situations in reality if no further contextual information is provided. This is even more evident if we consider that for a person two very similar situations can be perceived as very different. In fact, sensors always collect position with a certain error, e.g., being in front of a door vs. being inside, which for humans implies radically different situations, e.g., standing by the coffee machine in a lounge vs. walking down in the street.

This semantic gap affect not only humans and machines but also humans between themselves, which is due to many issues arising from social, linguistic and cultural factors. For instance, imagine that I meet a person at a conference. If I were to say to this person where I work, considering we just met and maybe she is not from my area, I could not say something like "I work in my office"; rather, I could say something like "The University of Trento", possibly stating additional information like, "My department is in a suburb called Povo" and so on. Instead, if a friend of mine were to call me during office hours and ask me where I am, I would rather say "I'm in my office" that replying with "The University of Trento in Povo (TN)." This additional layer of complexity only worsens the fact that, from the point of view of sensors, a different output is enabled starting from the same sensor inputs.

However, to address the whole issue of the semantic gap is outside the scope of this work — we aim at addressing its *representational* aspect in the area of ubiquitous computing. As such, we deal with the semantics behind users' understanding of the world and how they can be recognized by ubiquitous devices such as smartphones. Our problem has two main dimensions:

1. **Open vs closed domains:** While discussing the general issue of the semantic gap, (Smeulders et al. 2000) discuss the limited solvability of the semantic gap problem in broad domains, where a broad domain is defined as having "an unlimited and unpredictable variability in its appearance even for the same semantic meaning." In our view, we define broad domains as *open domains*, namely domains which allow for unpredictable variations in the way the world appears, extended to allow also for unpredictable variations in how the user perceives the world. In open domains, it is impossible to predict, and hence model, how the world will present itself (F. Giunchiglia 2006). This requires managing, at run-time, unexpected obstacles and changes of the environment (F. Giunchiglia, E. Giunchiglia, et al. 1996) and also deciding what is relevant to the state of affairs the user is in at that time (Bouquet and F. Giunchiglia 1995). On the contrary, *closed domain* are limited regarding complexity and known in advance, which allows for the (partial) solvability of the semantic gap. Overall, this dichotomy between open and closed domain arises when the representation is only limited by choosing or relying on a simplified view of the domain of investigation.

2. **Comprehensive vs. vertical representation:** While smartphones can be employed both in open and closed domains, their more "natural" setting is former, since we carry them with us everywhere. The second dimension of our problem affects smartphones in a similar pattern to the first one, in the sense that current solutions, to reduce the complexity and variability of the world, generally opt for a limited, *vertical* element of a person's life to investigate, e.g., fitness or mood. However, the progressive blurring of the border between humans and machines

requires mutual interaction in a seamless, holistic way. In fact, only big companies are working towards personal assistant software such as Google Assistant[1] or Apple's Siri[2]. However, to move towards an improved, all-round personalization of applications and services for users' everyday life, an even better understanding of human context is required. Acquiring this type of knowledge cannot be done by relying on sensor data alone — it requires involving humans and representing their knowledge. Overall, the dichotomy holistic vs. vertical arises regarding representation because both humans and sensors as sources of information must be accounted for when representing humans and their surroundings

When considering state of the art from Section 2, the issue of the open domain affects several research areas in different ways. In the case of user modeling, the main issue is that the majority of (ontological) user and context modeling tends to be used in relatively closed domains. While they may not focus only on static elements of users and thus account for dynamic data, context modeling often favors closed domains. Similarly, in the case of ontology-based activity recognition, the approaches are tailored to work within closed domains, where the range of possible contextual elements to be modelled and recognized is greatly reduced and defined *a priori*. Furthermore, they can rely on the pervasiveness of sensors to mitigate representational issues, since there is a constant improvement of the sensory technology to be deployed in these domains.

As for the issue of verticality, computational social science, while they do work in open domains since they need realistic data, they only work in a bottom-up way. The main issue concerning verticality is that they work in more of a "shoot first, ask questions later" and usually focus on specific dimensions that can be obtained via sensor data. Given the relatively recent development of this research area, there is more of a focus on the data and their limits in terms of what can be collected rather than what is wanted to obtain from humans. As for the Quantified self-movement, the issue of verticality is due to the ever-increasing staleness in focusing only on healthcare. In fact, the importance of health in the individual context has overshadowed other aspects of the Quantified Self movement to the extent that some believe that health is the only objective of this movement (Haddadi et al. 2015). Many seem to be happy enough to limit themselves to plots of their daily step counts, and eventually simply abandon their wearable device due to lack of more useful feedback. Having narrowed down the person as simply a set of biometrics, may Quantified Self approaches lose sight of the person as a whole.

In terms of person representation standards, these standards often suffer from the fact that they are may not be applicable outside of a certain country or that they treat a very specific subset of personal information. Thus, they may suffer from both issues at the same time. For instance, the NHS in Scotland and Italy describe the same portion of reality, i.e., the healthcare domain;

[1]https://assistant.google.com/intl/en/

[2]https://www.apple.com/ios/siri/

however, their representation of different roles, e.g., patient and doctor, do not align. Furthermore, all these standards account for the static type of data, which makes their adoption in ubiquitous computing, and hence real-life scenarios, very limited.

Therefore, the main challenge is how to devise a model, or rather a general modeling framework that focuses on personal data representation in *open domains*, which accounts both for how humans and machines represent them and for their collection and recognition.

Chapter 4

The Entity-centric Approach

This chapter is intended to illustrate the entity-centric approach we will use for modeling personal data and the general modeling of other entities.

4.1 The eType Model

In the past decade, ontologies have been used as core in most knowledge-based applications (Kharbat and El-Ghalayini 2008). In the literature, several definitions of ontology are available. Among them the probably most relevant definition of ontology was proposed by Guarino (1998): *a set of logical axioms designed to account for the intended meaning of a vocabulary* (Guarino 1998). In this definition, Guarino emphasized the role of logic as a way of representing an ontology. We believe that ontology has an important role to play in the general task of managing diverse information. In particular, ontology can ensure coherent and correct conceptualization of the real-world entity providing the subject matter of the information to be handled. For example, road, highway, path, route are often used more or less interchangeably, but they can have different intended meaning using ontology in the model help to minimize this confusion.

To model multivariate data, we choose an **entity-centric approach** to collocate all information in one place. We group real world entities as sets of *eTypes* (or in short *eTypes*). FGDC (Federal Geographic Data Committee) defines *eTypes* as *"the definition and description of a set into which similar entity instances are classified (e.g. bridge)"* (Committee 2015). An *eType* provides a schema and set of rules for the creation of a conceptual representation of a real world entity (e.g. a person, a building, an organization). We define an *eType* as the quadruple,

$$eType = (ID, EC, NS, \{AD\}) \tag{4.1}$$

Where

- *ID* is a unique identifier
- *EC* is a concept denoting the class of the eType;
- *NS* is a name of the eType;
- *AD is a non-empty set of Attribute Definitions*

Notice that the *eType* components name:NS (e.g. building), class:EC (e.g. restaurant, government building), attribute definition:AD (e.g. height, date of construction, roofing material) and qualitative attribute:QA are connected with the concept.

Concept =>{EC, NS, AD, QA}

Notice also that a concept has a *semantic relation* (e.g. is-a, part-of, component-of) with its parent/child concept (e.g. building is-a structure). Concept also used for *synset*. *Synset* (i.e. sets of cognitive synonyms) contains terms (e.g. building, edifice) associated with the particular concept. A *Lexical relation* (e.g. synonym) show the relation between terms within a *synset*. *Semantic lexical relation* (e.g. hyponym, hypernym) is used to denote relation between synset. *Gloss* provides natural language description (e.g. building: *"a structure that has a roof and walls and stands more or less permanently in one place"*) of the concept. It helps to eliminate issues related with *heterogeneity in meaning*.

In our modelling approach, the class of an *eType* is the most specific class which can be used to describe a specific instance of an *eType*. An entity can only have one class. Thus for instance "pizzeria" and "restaurant" could be two classes for two entities of *eType* building. Notice that the entity-centric approach allows for modelling eTypes also only as a class (and hence a concept) in case of the lack of charactheristic data.

AD determines the set of attributes that can be associated to instance of a certain *eType* and thus constraints the possible values the attribute can have. An Attribute Definition is a tuple,

$$AD = (ID, AN, DT) \tag{4.2}$$

Where,

- *ID* is a unique identifier
- *AN* is the concept denoting the attribute name
- *DT* is a DataType, i.e., descriptor of a set of values according to ISO/IEC 11404:2007[1].

With respect to Data Types, our modelling approach uses, in addition to the standard ones, the following data types:

Natural language string (NLString): it allows the assignment of a String in a natural language.

Concept: A special case of SString, where the value is exactly one Concept.

Semantic string (SString): allows the assignment of a semantic enabled value with semantics (possibly) computed from a string in a language.

Entity: A special case of SString, where the value is exactly one Entity.

[1]https://www.iso.org/standard/39479.html

ComplexType: It is a structure attribute. It is formed by nesting composite attributes and multi-valued attributes in an arbitrary way [2].

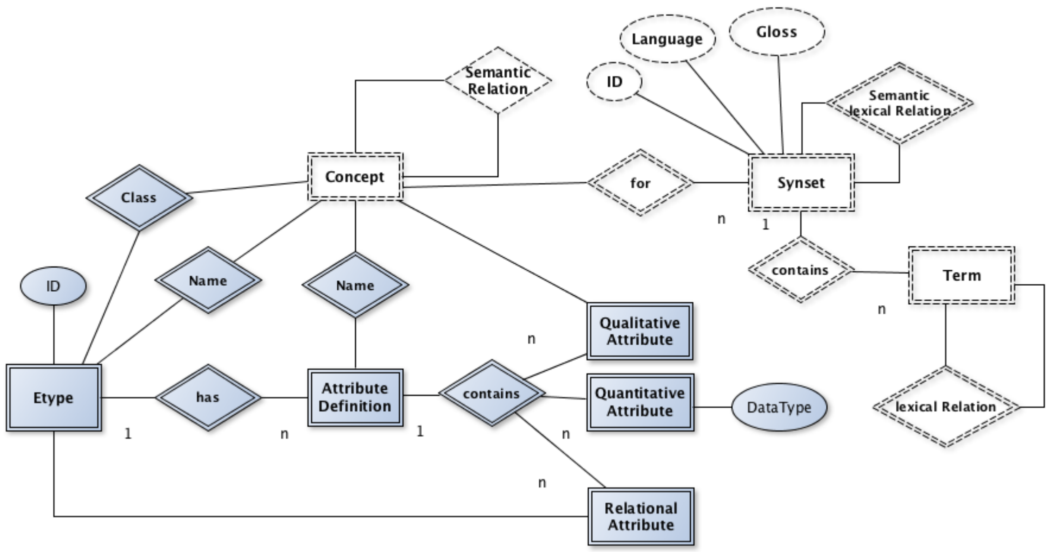


FIGURE 4.1: eType Metamodel

The full meta-model of the *eType* is illustrated in Figure 4.1. Notice that the meta-model clearly structures the *eTypes* model in two parts: (i) the one part centered on the *eType* which defines how to structure the schema(ii) the second part centered around the concept which defines how to structure the vocabulary. Notice how the two parts are coupled via "concept." In fact, notice that concept is used to capture and link to all the linguistics elements of the schema. This gives maximum flexibility in adaptivity and to all the terminology described. Hence, for instance, a word in one language schema can be represented in another language specified by vocabulary. In fact, to capture all simple terms used in the schema.

4.2 Top Level eTypes

In addition to this approach, we will base our modeling on the preexisting eTypes. Some remarks about the notation that will be followed throughout the thesis. Entity is the root of the eType. Thus all other eTypes inherit Entity's attributes, which we will not list in their respective tables to avoid repetition. When displaying a datatype, <Entity> means a relation to that entity type, while [] means that the attribute is multivalue, e.g., Integer [].

Entity: An entity is any object so important to be denoted with a name. For example, a person, a place or a document (indicated by its title). The attributes are shown in Table 4.1.

[2] http://databasemanagement.wikia.com/wiki/Category:Complex_attribute

TABLE 4.1: Entity etype

Attribute Name	Description	DataType
Name	The name by which an entity is known	NLString
Description	The description of the entity	SString
Part of	Defines the connection from the part to the whole, e.g. locations to their administrative division	<Entity>
Class	The class of the entity	Concept
Duration	The duration of existence of an entity	Long
Start	The moment in time an entity started to exist	Date
End	The moment in time an entity ceased to exist	Date

Location: It represents a point or an extent in space. The attributes are shown in Table 4.2. Notice that Geographical Name ovverides Name.

TABLE 4.2: Location eType

Name	Description	DataType
Coordinate	a number that identifies a position relative to an axis	Geometry

Administrative Unit: A Unit of administration, dividing areas where the Member States have and/or exercise jurisdictional rights, for local, regional and national governance, separated by administrative boundaries. It is a child of Location and hence inherits its attribute

TABLE 4.3: Administrative unit eType

Name	Description	DataType
Country code	country code as per ISO standard	String
Surface	the extended two-dimensional outer boundary of a three-dimensional object	Geometry
National level	number according to National level. (e.g. 1-5)	Integer
Area	the extent of a 2-dimensional surface enclosed within a boundary	Float
Population	the number of inhabitants in a given place	Integer

Event: it represents something that happens at a given place and time. The attributes are shown in Table 4.4.

Organization: it represents a group of people or a collective who work together. The attributes are shown in Table 4.6.

TABLE 4.4: Event Etype

Attribute Name	Description	DataType
Location	the place where the event occurs	Location []
Person	someone who takes part in an activity	Person []

TABLE 4.5: Organization Etype

Attribute Name	Description	DataType
Location	the place where the event occurs	Location []
Member	member(s) of the organization	Person []
Founder	person that founded the organization	Person []

Role: it represents a role, which is played by a person to perform an action and carry out a goal. Roles depend on the person playing them since they are constrained by time, place and social contexts for their effectiveness. In the entity-centric approach, Role is a child of the Entity eType, and its attributes are showed in Table 4.5.

TABLE 4.6: Role Etype

Attribute Name	Description	DataType
Role	the type of role played by the person	Person []
Membership	the social or relational framework within which the role is played	Organization

Artifact: it represents all man-made objects and construction (e.g. building, structure). The attributes are showed in Table 4.7.

TABLE 4.7: Artifact Etype

Attribute Name	Description	DataType
Creator	The entities (persons or organizations) that participated to the creation of the artifact	Entity []
Length	The longest vertical dimension of extension	Float
Width	The extent of something from side to side	Float
Depth	The extent downward or backward or inward	Float
Weigth	The vertical force exerted by a mass as a result of gravity	Float
Color	The visual attribute of things that results from the light they emit or transmit or reflect	Concept

Part II

From Modelling to Recognition

Chapter 5

Personal data modelling

In this chapter, we present our solution from the representational point of view, i.e., an entity-centric modeling of personal data. By relying on the entity-centric approach, our solution addresses the issue of modeling humans and the most relevant entities of their environment.

The structure of the chapters is as follows. Section 5.1 provides a definition of person and personal data, while Section 5.2 illustrates the two main dimensions of personal data that are used to categorize them as showed in Section 5.3. Finally, Section 5.4 summarizes the chapter.

5.1 Definitions

Given their relevance, we provide a general definition of two closely related concepts that will be used in this thesis:

Personal data: While there are almost 20 years between the General Data Protection Regulation 2016/679 (GDPR) (Regulation 2016) and the Directive 95/46/EC (Parliament 1995), they both define personal data as "any information relating to an identified or identifiable natural person ("data subject"), where an identifiable person is one who can be identified, directly or indirectly, in particular by reference to an identification number or one or more factors specific to his physical, physiological, mental, economic, cultural or social identity". More generally, (Kang 1998) defines personal data as "data that are authored by an individual, describe an individual, or can be mapped to an individual". In this thesis, we will take this definition as the general understanding of personal data as any information about a person.

Person: To define what a person represents a hard task. In this work, we treat a person as a physical being that has certain capacities or attributes either cognitive or physical, such as reason, consciousness or self-consciousness, performing activities and experiencing her surroundings. Also, since no man is an island, a person is a part of a culturally established form of social relations, such as kinship, in the form of social norms, habits, and routines. Nonetheless, the defining features of personhood and consequently what makes a person count as a person differ widely among cultures and contexts. Throughout the work, we will also refer to different roles of a person interchangeably to refer to a person, e.g., a user or a citizen.

This distinction of personal data and person is motivated by two factors. Firstly, it shows that a person may not be the mere sum of whatever can be attributed to her and that there are many ways to describe a person. Secondly, it shows that modeling personal data does mean modeling for humans *per se*, but it also requires consider other types of entities. For instance, contextual data about a person's transportation routine is not about her alone, since it requires to account for transportation means in her city. Even a person's name is not "hers" inasmuch once considers that it is something that was bestowed upon her. Overall, a person cannot be isolated entirely from her world.

5.2 Dimensions of Personal Data

To model personal data, a general understanding and categorization of them must be provided. We accomplish this by considering two dimensions that classify personal data:

1. **Quantifiabilty:** This dimension refers to whether the type of personal data that can be *measured*. "Measureabilty" refers to anything that changes in varying degrees of time collectable via any technological mean.

   From an entity-centric approach point of view, this means that the attribute definition requires accounting for values, i.e., the datatypes, that can be modeled and recognized starting from data that can also be collected or measured by different sensors or devices in general.

   The heart of this distinction is to separate between *static* and *dynamic* attributes. In fact, static data are those data that never change (e.g., one's birth date and place) or that change very slowly and in a context-independent way. Static data change mainly because of (slow) natural evolution (e.g., height) or because of the conscious decision (eg., becoming a Facebook user, changing address, getting a new Identity card, enrolling in the Tennis Club, and so on). Static data changes usually correspond to a change of state in the life of a person. On the other hand, dynamic data are those data that in ubiquitous computing are usually collected via smartphones or other (smart) devices, e.g., physiological states such as heart rate or blood pressure or even physical features as observable by a physician. Dynamic data, therefore, provide information not only on the person as a physical entity but also in terms of mental states, since emotions, feelings and in general the state of mind of a person can vary very quickly, e.g., receiving sudden good news can radically and quickly change one's mood. While they may not be directly "measurable" as physical states, there a still ways to evaluate and quantify them, albeit indirectly, such as using Likert-like scales or PHQ-9 (R. Wang, F. Chen, et al. 2014). Finally, dynamic data also provide information about context as a whole in terms of surroundings, based on different sensing strategies, e.g., GPS sensing locations and sound detecting activities or people.

2. **Application dependence:** This dimension accounts for those attribute whose values are affected by the application scenario a person is currently in. By application scenario, we refer to any domain of life where a person may be involved in and where a dedicated application in a quantified self-like fashion may be developed. Therefore, the difference with respect to “quantifiability" is that the change is mainly in terms of *values*.

   From an entity-centric approach point of view, this means that the attribute name is likely to stay the same but that the values that can be modeled and recognized are a subset of all possible values. In other words, the expected and recognizable personal information can be somewhat limited depending on the domain where it is to be modeled and recognized. For instance, when considering an urban mobility scenario, the type of activity that is relevant to understand would be any movement, while other activities, e.g., cooking or self-care, would not be as relevant. Therefore, all the main entities such as locations, events, people, and objects are highly context-dependent, since they change very frequently.

Notice that this distinction is also intuitive in the sense that combining the two dimensions helps to understand the most likely source of information. As we said, our work aims to account in terms of representation of the differences between humans and machine and also how they can provide their own representation of the world. Based on our distinction, we can see that those type of data that are supposedly easier to represent and recognize for a machine, since they can be captured via sensors. On the other hand, data that are more static and less dependant on sensors imply human knowledge.

From a modeling point of view, notice how the dynamic/static distinction is the one that acts as an actual categorization criteria, i.e., *inter-category*. In fact, it allows us to create different categories of attributes that are exclusive. Instead, since the application dependence distinguishes the possible attribute values within each category of attributes, it represents the difference *intra-category*, thus it does not generate new classes.

5.3 Categories of Personal data

Based on this distinction and the state of the art of personal data standards in Section 2.8, we define the following categories of attributes to represent the general dimensions of personal information:

Identity: A fundamental notion for humans is the notion of identity, i.e., the necessary and sufficient conditions under which a person at one time and a person at another time can be said to be the same person, persisting through time.[1] It has been a long-standing issue in areas such as philosophy and sociology what it is the essence of a self-conscious person allowing him or her to be uniquely what him- or herself, making him or her the same entity at different times.

In this work, we model the element of identity focusing on the need of disambiguating between via *names*, which are one of the tenants, although not without their issues, of the notion of identities. Also, we will exploit the work of (Fernandez and Ignacio 2012) for handling identities within our architecture in Chapter 8.

Demographics: Demographics refers to that type of personal information that concerns the statistical characteristics of human populations, e.g., by considering the age, nationality and so on. Demographics tend to be very stable, and their granularity can vary depending on the research.

In this work, we model four main areas of demographics: *i)* existence, which refers to life and death of a person, *ii)* residency, which refers to the relation between a person and her location(s), *iii)* job, which refers to the occupational information of a person, and *iv)* education, which refers to the information about a person's learning process.

Goals: A goal is an idea of the future or desired result that a person envisions, plans and commits to achieve. Goals are hardly quantifiable and tend to be extremely complex, requiring extremely different degrees of time to be completed.

In this work, we model goals as a change of state desired by a person, which may either affect the person herself or her surroundings, e.g., getting more fit or moving to a new city.

Contact: Contacts represents the means people can use to reach and interact with each other. Current technologies allow us to be always available and capable of reducing great distances to a monitor.

In this work, we consider different types of contacts based on different technologies that enable them.

Knowledge: Knowledge is an extremely complex dimension of a person, which, much like identity, is a hot topic in philosophy, to the point of having a dedicated field of research called epistemology. Knowledge refers to the understanding of someone or something, such as facts, information, descriptions, or skills, which is acquired through experience or education by perceiving, discovering, or learning.

In this work, we consider theoretical or practical knowledge, the former representing interest and preferences while the latter representing competencies. We also consider language as its own type of knowledge, as it is the main way humans access it

[1] https://plato.stanford.edu/entries/identity-personal/

Activity: It refers to those actions consciously carried out by a person, e.g., locomotion or cognitive processes like thinking or studying, which are usually described in natural language via transitive verbs, e.g., eating or moving.

In this work, we represent activities as concepts, and exploit semantic relations to structure them and understand how to recognize them.

State: refers to those modes of being of a person that natural language describes via adjectives and usually refers to stative verbs, e.g., feelings and physiological conditions; furthermore, it refers to those elements on which a person has little or no control over.

In this work, we represent states in a variety of modeling choices, from concepts for mental states to events for conditions.

Context: As we noted in Section 2.3, to define context is no easy task and there is a lack of agreement in the literature. From the point of view of quantifiability, context can be quantified in terms of information, e.g., environmental sensors, but its actual purpose, i.e., to weave together (as the Latin origin of the name suggests), cannot be represented easily by sensors, as also noted by (Henricksen, Indulska, and Rakotonirainy 2002).

In this work, we treat context as a mechanism humans use to make sense of their surroundings, which are constituted of other entities, namely locations, activities, people, and objects.

TABLE 5.1: The relationship between our dimensions and personal data.

Dimension / Data	**Quantifiability**	**Application Dependence**
Identity	Static	Low
Demographics	Static	Low
Goals	Static	Medium
Knowledge	Static	Medium
Activity	Dynamic	High
State	Dynamic	High
Context	Dynamic	High

Table 5.1 shows how our two dimensions divide the categories of personal data. Static data account for 4 categories: *i)* identity, *ii)* demographics, *iii)* goals, and *iv)* knowledge. The first two are considered low on application dependence since they account for data that are required to describe a person in any type of situation and vary very little. As for goals and knowledge, they may change much more, since different application scenarios may require different expertise and different granularity in objectives. For instance, when considering a domain like mobility, the type of goals may be limited to reaching a destination and the expertise required could be having a certain type of

license, while the identity of the person would be the same in this scenario and also in, e.g., when she's at work. Dynamic data account for three categories: *i)* activity, *ii)* state, *iii)* context. All of these highly depend on the application scenario and the degree of quantifiability, since the range of possible activities and states, e.g., physical states, may change considerably among different scenarios. For instance, biometrics such as heart rate and blood pressure are relevant in a mobility scenario where a person may perform physical activities related to locomotion and that require physical efforts. The same biometric may not be as relevant in working environment scenario, e.g., an office, where physical exertion is much more limited, if not non-existent.

Notice how we do not model specific categories of personal information, i.e., sexual orientation, religious, ethnicity and political affiliation, which would most likely be considered specific types of demographics. There are two main motivations for this. The first one is that these types of information are among the most difficult to obtain and are within the core type of personal information that is protected under, even if obtained following standard procedure. The second one, as a consequence, is that they would be very simple to represent in the unlikely case of an application scenario.

Notice also how these categories grounded in our distinction allow us to account the two issues from Section 3, i.e., open vs. closed domains and verticality vs. horizontality. For the first issue, the dynamic vs. static distinction allows us to account for both domain types, since the dynamic attributes are those that become relevant everyday life scenarios involving devices such as smartphones. For the second issue, our categories account by design to the possibility of having a change of focus of a specific domain, which can then be modeled according to the entity-centric formalism.

From our modeling approach point of view, i.e., the entity-centric, we model all the personal data as attributes of the eType Person, whose complete specification can be can be found in the Appendix. We now concentrate on providing a general overview of its attributes. Since quantifiability is the main criterion for dividing between dynamic and static categories of attributes, we will dedicate Chapter 6 and Chapter 7 to provide more details concerning the motivation for their relevance, their modeling, and direct comparison with the relevant standards presented in Chapter 2.

5.4 Summary

In this chapter, we presented the general categorization of personal data to be used as a base to model them according to the entity-centric approach.

The categorization relies on two different dimensions of personal data, based on the state of the art in different communities. The first dimension is the quantifiability, which represents whether one type of personal data can be obtained via measures of any technological means, e.g., sensors. Those data that cannot be measured are called static, while those that can be measured are called dynamic. The second dimension is application scenario dependence, which refers to whether changing the domain in which these type of data can be used, e.g., mobility or healthcare, affects the way they can be modeled and recognized.

Based on these distinctions, we obtained a set of categories of personal data that can be used to model personal data in open domains, while also accounting for a generalized view of a person; the result is the Person eType.

Chapter 6

Static Data

In this chapter, we present the static data according to the division from Chapter 5. As we said, these type of data usually refer to those type of data that may change in a considerable amount of time. Notice that the value of these types of data may change instantaneously albeit infrequently. For instance, I can legally change my name and, once the paperwork is done, it is an instantaneous change. An additional element for staticity is that the value of these type of data is that they cannot be tracked via sensors such as smartphones.

The structure of this chapter is as follows. We present names as our identity attribute in Section 6.1, while Section 6.2 illustrate our modelling of a person's goals. Section 6.3 provides the type of information that we categorize under demographics, and Section 6.4 shows our division of a person's contact information. The last category is knowledge, which is addressed in Section 6.5, while Section 6.6 provides a summary of the chapter.

6.1 Name

In this work, the name of a person is treated as the simplest way to establish the identity of a person, although we are aware that in research areas such as sociology and philosophy it has been suggested that the identity of a person may be contextual. In fact, depending on the frame of reference, multiple identities may be actually valid via roles and enable human interaction; this is what it is broadly claimed in identity theories in sociology (Stets and Burke 2000).

We follow a commonsensical approach and model names as the main means of referring to a person. As we will show in our use cases in Chapter 9, Chapter 10, and Chapter 11, it may also be that names, due to their sensitiveness as identifiers (Regulation 2016; Parliament 1995) , may not be usable; in that case, the name may be substituted with an ID or similar type of reference.

In terms of actual name modelling, our definition and usage of names relies on the philosophical tradition of the last century concerning two aspect of names: whether names have a *meaning* and how they *refer* to an individual. In other words, the first problem addresses the possibility of names having a semantic value whereas the second one tries to capture how names are somehow 'attached to' things in the world. There are three main stances with respect to these dimensions:

1. **Millianism:** According to Mill (Mill 1893), nouns are either connotative or denotative, i.e., they either convey some attribute(s) or denote or single out individuals that fall under that description. Names, being a more specific instance of nouns, "are not connotative; they denote the individuals who are called by them; but they do not indicate or imply any attribute as belonging to those individuals" (Mill 1893). For instance, the town lying at the end of the river Dart, aptly named Dartmouth, would still be called the same even if the river were to change its course, for names are "attached to the object themselves, and are not dependent upon the continuance of any attribute of the object" (Mill 1893). Thus, names only refer to objects and have no meaning whatsoever.

2. **Descriptivism:** Broadly speaking, this theory, first proposed by Frege (Frege 1948), claims that names refer in virtue of being associated with a definite description or set of definite descriptions that are uniquely true of the individual to which the name refers; in addition, the name has a meaning which consists of the description associated with it. A major defender of this theory is Searle in (Searle 1969), where he proposes a 'cluster theory' of meaning for proper names. Consider all the possible statements on Aristotle, e.g., "Plato's pupil" or "The Greek philosopher from Stagira" and so. They can all successfully refer Aristotle, but not because there is some single identifying description expressing the sense of the name 'Aristotle'. Rather, it is because the entity Aristotle satisfies most or a (relative and context-dependant) sufficient number of the identifying descriptions amounting as the unique referent of the name. This is why different speakers associate different identifying descriptions with the same name. Thus, names not only refer to objects, but also carry a semantic meaning, which is the set of their descriptions.

3. **Causal Theories:** This theory developed as a counter-theory to descriptivism, with Kripke as the main proponent (Kripke 1972). The basis of this theory is to reject the idea that names carry any semantics because it leads to a series of philosophical issues such as ignoring counterfactuals and multi-worlds or that people may associate inaccurate descriptions with names. The causal theory rather focuses on two aspects of reference: reference *fixing* and reference *borrowing*. Reference fixing is defined as a "dubbing", generally through perception, even though it could happen via description. Reference-fixing is by perception when a speaker actually performs a naming ceremony (or baptism), e.g., "I call/name/baptise/etc. you X", on a perceived object. Then there is a causal chain that links from the first users of the name to all the possible users, making them effectively borrow their reference from speakers earlier in the chain. Notice that borrowers do not need to identify lenders; all that is required is that borrowers are appropriately linked to their lenders through communication. For instance, the name 'Neptune' was fixed by description, stipulated by the astronomer Leverrier to refer to whatever was the planetary cause of observed perturbations in the orbit of Uranus. Thus, similarly to Millianism, this theory reinforces the idea that names

do not have semantics in them, but provides a more detailed account of the reference process.

Our modeling of person names accounts for the issue of reference in that it is a mandatory attribute and multivalue, thus allowing multiple ways to refer to the same entity. As for the issue of semantics, our modeling accounts for it by considering the structure of names in ageneral enough way to accommodate different traditions across cultures. For instance, the naming custom of Spanish speaking countries, with full names (generally used in official occasions) consisting of a given name (simple or composite) followed by two family names (surnames).

TABLE 6.1: Name Attribute

Attribute Name	Description	DataType
Name	name(s) of the person	<Name>[]

TABLE 6.2: Name ComplexType

Attribute Name	Description	DataType
Name	the full name of the person	NLString
Given Name	the given name of the person	NLString[]
Middle Name	the middle name of the person	NLString
Family Name	the family name of the person	NLString[]
Qualifier	the honorific or suffix of the person	Concept[]

Overall, we treat name as an attribute in Table 6.1 whose value is the ComplexType Name, modelled as shown in Table 6.2. As we can see, Given Name, Middle Name, Family Name and Qualifier act as entries for name elements (i.e., tokens), in addition to a single field where the user can input the whole name(s). Moreover, we adopted Given Name and Family Name over First Name and Surname because, while they indicate the first element in a name sequence, Given Name and Family Name account for the (many) cases of people having one or more first names and/or family names. Qualifier accepts two types of function words, i.e., titles (e.g., Mr.) and generational indicators (e.g., Jr.). The main difference is that titles indicate a relation with a condition (e.g., having a job) or a status (e.g., honorifics like Esq. or academic titles like PhD), whereas generational indicators provide a relation with a person, e.g., Jr., Sr., II, and so on. In fact, qualifiers underline a person's role in a certain social context; for instance, a person will not use his or her occupational title in all situations, rather only in a working context.

With respect to schema.org, name is not a unique attribute but it is rather a set of different attribute as shown in Table 6.3. The major differences are the fact that we handle possible additional name, such as nicknames or pseudonyms, by making the name attribute multivalue, and also by collapsing all type of honorifics in a single attribute "Qualifier". On the other hand, we are aligned with FOAF except for the possibility of having multiple

TABLE 6.3: Comparison between Schema.org, FOAF, ISA with our Person Etype

Schema.org	FOAF	vCard	ISA	Person Etype
name	Name	Name		Name
familyName	Surname	Last Name	patronymic name	Family name
givenName	givenName	First Name		Given Name
additionalName	None	Nickname		Meta attribute
honorificSuffix	None	Prefix		Qualifier
honorificPrefix	None	Prefix		Qualifier

names and accounting for qualifiers. vCard accounts for names structure with the N attribute, which distinguishes between Prefix, First Name, and Last Name, furthermore, vCard accounts for nicknames. Finally, ISA adds the notion of patronymics, since they are important in some countries that either do not have a concept of family name, e.g., Iceland, or use this concept frequently, e.g., Bulgaria and Russia.

6.2 Goals

Goals are fundamental for people as they drive and give meaning to their lives. Notice that goals that we consider in this work are those only affecting a single person. Indeed, much research in areas outside of computer science analyze goals from the point of view of collectives and roles.

Our proposal for modelling goals draws from the i* Framework (Yu 2011), which is a widely used organisational modelling technique. Since its definition, many research projects have used it in different application domains, hence many i* variants have been proposed. For instance, Tropos (Bresciani et al. 2004) for agent-oriented development, and many others, with consequent attempts to develop metamodels to handle variants, e.g., (Lucena et al. 2008).

These are the fundamental elements for according to the i* Framework:

Belief Beliefs are used to represent actors' knowledge of the world

Task A way of attaining to a goal.

Goal Represents an intentional desire of an actor. In other words, it is a state of the world that an agent would like to achieve or satisfy. Notice that the specifics of how the goal is to be satisfied is not described by the goal.

Soft-goal Soft-goals are similar to (hard) goals except that the criteria for the goal's satisfaction are not clear-cut, it is judged to be sufficiently satisfied from the point of view of the actor.

Resource A resource represents a physical or an information entity that one actor wants and another can deliver.

We incorporate these elements by following the intuition that a goal is a change of the state of affairs desired by a person, which can be arbitrarily complex, but that has clear cut criteria of achievement. For instance, it could range from wishing to lose some weight to obtain a promotion to volunteering to improve the city. In terms of the Etype framework, this means that some (person) attribute values should change; in the simplest case of losing weight, it means that a certain value of the attribute weight should be reached. In other words, the completion of a goal can be seen as a requirement of one or more factors affecting either the person or his or her surroundings.

We formalize the Goals attribute as shown in Table 6.4.

TABLE 6.4: Goal Attribute

Attribute Name	Description	DataType
Goal	the long-term or short-term objective(s) of the person	<Goal>[]

where the Goals etype is a subtype of Event, and it has the attributes shown in Table 6.5:

TABLE 6.5: Goal Etype

Attribute Name	Description	DataType
Plan	sequence of sub-goals	<Plan>[]
Task	the requirement to satisfy the goal	<Task>
Value	the value(s) that the goal enforces	<Plan>[]

Plan represents the point of the sequence in the structure allowing us to model the compositionality required to obtain a goal, i.e., the steps to be taken via sub-goals. Table 6.6 illustrates its modelling.

TABLE 6.6: Plan ComplexType

Attribute Name	Description	DataType
Previous goal	the previous goal	<Goal>
Next goal	the next goal	<Goal>

Task represents the required state for the goal to be reached to satisfy the goal, shown in Table 6.7. Its value is one (or more) Task ComplexType, which represents set of condition to be obtained: *i)* the entity, which is the subject of the task, *ii)* the attribute is the entity attribute to be changed as a result of the task and *iii)* value is the required attribute value. For instance, for a person to drive a car, I must have a person with a driving license attribute, whose value could either be a boolean, if I just need to know that the person has one, or the driving license ID, depending on the granularity and data availability.

Values in goals are our representation of soft-goals from i*. In fact, soft-goals are elaborated in terms of the methods that are chosen in the course of pursuing the goal. This understanding of softgoals is very much in line with research in the area of values, especially in the functional theory of values

TABLE 6.7: Task ComplexType

Attribute Name	Description	DataType
Entity	the entity involved in the task	<Entity>
Attribute	the attribute involved in the task	<Concept>
Value	the value required by the task	Datatype

(Gouveia, Milfont, and Guerra 2014) and Schwartz's work (Schwartz et al. 2012) in categorizing the basic human values across cultures. According to this research, values can be seen as referring "to desirable goals that motivate action." Furthermore, they "serve as standards or criteria [...] Values guide the selection or evaluation of actions, policies, people, and events."

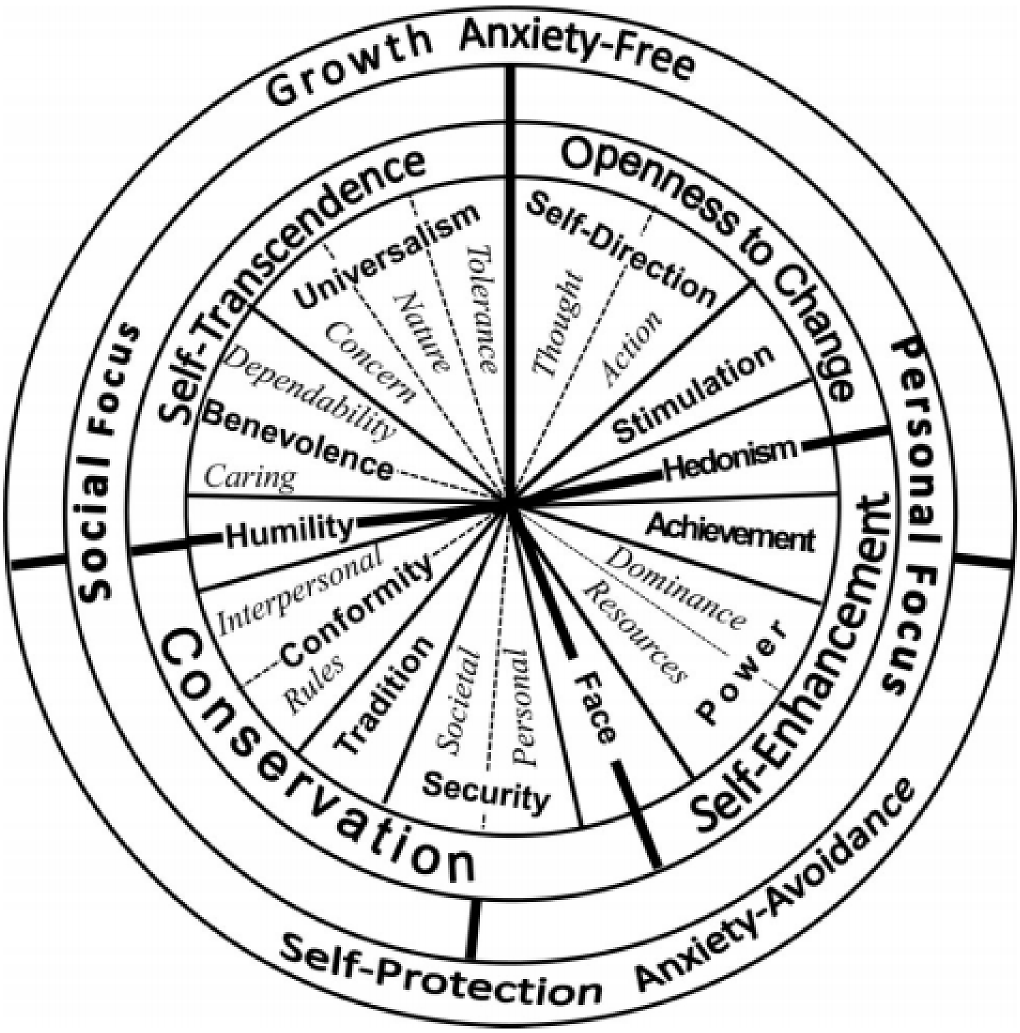


FIGURE 6.1: Proposed circular motivational continuum of 19 values with sources that underlie their order proposed in (Schwartz et al. 2012).

Figure 6.1 shows the circular continuum of 19 values. Values located in adjacent regions (wedges) of the circle have a similar motivational content (e.g., conformity and tradition). Hence, any behavior that promotes, maintains, or defends one value (e.g., following family customs) is likely to serve the adjacent values at the same time. Values located in opposing wedges of the circle express conflicting motivations (e.g., security and stimulation). Hence, any behavior that serves one (e.g., doing risky activities like paragliding) is likely simultaneously to come at the expense of the opposing value (security). The underlying assumption that values form a continuum implies that the circle of values can be partitioned for scientific convenience in many different ways.

In our modelling of goals, each of the 19 values is represented as a concept, and it is multivalue since some of the 19 values can be simultaneously valid to represent the fact that the goal promotes or is promoted by them. Although it is not the focus of this modelling and our work, this modelling of values can also be used in a collective goal scenario, where the existence of values could be used as a way to understand whether the goal can be shared because all the participants share the same or close values.

Unlike name, or other static personal data in general, goals are not represented or modelled in any way from the other personal data standards.

6.3 Demographics

Broadly speaking, demographics as quantifiable characteristics of a given population (Rowland et al. 2003). Notice that here the term quantifiable is not synonymous with our understanding of quantifiable as in the quantified self, i.e., something that is measurable via sensors and that varies rapidly. Demographics refer then to those attributes that concern natality, mortality, occupation, movement (in terms of living or moving permanently somewhere), and so on.

In everyday life, the majority of the information that could be considered as demographics are usually found in any ID card, although slight differences exist around the world, depending also on whether the document is supposed to be national or international, e.g., passport. For instance, in terms of rules, e.g., English speaking countries do not have government-issued compulsory identity cards for their citizens, or in terms of personal data contained, e.g., religion is a mandatory field in countries like Israel or Egypt, unlike Italy or European countries in general. Technology also plays a role in expanding the number and type of data that could be represented on national ID cards. Moving from paper documents designed for single identification applications, eIDs include a microprocessor for stronger document verification but also on-line authentication and signature. As they contain the portrait of the card holder and very often fingerprints, they can be used for biometric identification and biometric authentication when needed. Overall, (inter)national ID cards contain information such as the identity bearer's full name, age, birth date, address, an identification number, card number, gender, citizenship and more.

In terms of modelling, we model the following demographic information: Existence, shown in Section 6.3.1, Residency, shown in Section 6.3.2, Profession, shown in Section 6.3.3, and Education, in Section 6.3.4.

6.3.1 Existence

With Existence, we model the fundamental attributes that contribute to the identity of humans. Firstly, we represent the main dimensions that shape how humans experience, i.e., time and space, and how they circumscribe human life, i.e., when and where one is born when and where one dies. Secondly, we model the gender of a person, as a fundamental biological category where any human falls in. While this last type of attribute can be possibly changed in recent years and it is subject to much discussion in our society, dates, and places of existence are all permanent values that cannot be changed; this factor usually allows them to act as additional parameters to discriminate cases of homonymy.

We distinguish four different types of existence attributes:

Dates of existence: We distinguish between date of birth and date of death of a person.

Locations of existence: We distinguish between the place of birth and the place of death of a person.

Age: We model the age of a person;

Gender: We model the gender of a person.

These attributes are modeled as shown in Table 6.8. Notice that the dates override the corresponding Entity Etype dates, i.e., Start and End.

TABLE 6.8: Existence attributes

Attribute Name	Description	DataType
Date of Birth	the date of birth of the person	Date
Date of Death	the date of death of the person	Date
Place of Birth	the place of birth of the person	Date
Place of Death	the place of death of the person	Date
Age	how many years a person has	Integer
Gender	the gender a person identifies with; the concept restriction is {male,female,non-binary}	Concept

With respect to other personal standards, Table 6.9 shows that there is a perfect alignment, unsurprisingly. In the case of vCard, we considered the vCard specification RFC 6474[1], which adds BIRTHPLACE, DEATHDATE, and DEATHPLACE. Notice that FOAF has no attributes in this sense, mainly because of the fact that it is much more focused on the Web; the only comparable

[1]https://tools.ietf.org/html/rfc6474

attribute is age. Surprisingly, ISA does not account for dates of existence but only for places of existence, differentiating between country and place of birth and death. As for gender, notice that schema.org allows the value of gender to be either male, female, or any type of text in case of nonbinary identification.

TABLE 6.9: Comparison between Schema.org, vCard, ISA and the Person Etype

Schema.org	vCard	ISA	FOAF	Person Etype
birthDate	BDAY			Date of Birth
birthPlace	BIRTHPLACE	place of birth		Place of Birth
deathDate	DEATHDATE			Date of Death
deathPlace	DEATHPLACE	place of death		Place of Death
		country of birth		
		country of death		
			age	Age
gender	GENDER		gender	

6.3.2 Residency

In order to account for the how where people live and migrate in a stable manner, and in general the choices done with respect to one's place in the world. Notice that we do not consider address, which is defined in Section 6.4, since it is treated as a mean of contacting a person. Table 6.10 shows our attributes for of residency:

TABLE 6.10: Residency Attribute

Attribute Name	Description	DataType
City of residence	any city where the person dwells more than temporarily	<Goal>[]
Country of residence	country where the person currently resides	<Administrative unit>

In addition, we also model under this category nationality and citizenship of a person, since they are related to some degree where she lives or has lived. Although nationality and citizenship are often used interchangeably, they are two different and very complex concepts.

Citizenship *is a legal status in a political institution such as a city or a state*. The relationship between a citizen and the institution that confers this status is formal, and in contemporary liberal-democratic models includes both a set of rights that the citizen possesses by virtue of this relationship, and a set of obligations or duties that they owe to that institution and their fellow citizens in return.

On the other hand, nationality denotes *where an individual has been born, or holds citizenship with a state*. An individual's nationality denotes the country where she is born and is the legal citizen. The status is acquired by birth, inheritance or naturalization. On the basis of constitutional provisions, every state sets the criteria which determine who can be the nationals of the country. It provides the country rights over the person.

Overall, citizenship is a narrower concept than nationality and it is factually a specific legal relationship between a state and a person. It gives that person certain rights and responsibilities and does not have to accompany nationality. In some Latin American countries, for example, such as Mexico, a person acquires nationality at birth but receives citizenship only upon turning 18; Mexican children, therefore, are nationals but not citizens.

Given this distinction, we model nationality as a multivalue attribute as in Table 6.11, since it is true that a person has at least one nationality but could have multiple citizenships:

TABLE 6.11: Nationality Attribute

Attribute Name	Description	DataType
Nationality	the nationality of a person	<Nationality>[]

TABLE 6.12: Nationality ComplexType

Attribute Name	Description	DataType
Nation	the nation of the person	<Administrative unit>
Citizenship	the citizenship of the person	<Administrative unit>
National Id	the id used in that country to identify the person	String
Passport	number of the passport for that nationality	String
Tax Id	the Tax / Fiscal ID of the organization or person, e.g. the TIN in the US or the CIF/NIF in Spain	String

With respect to the standards, we actually abstract with respect to schema.org, as Table 6.13 shows. As we already stated for FOAF, given that it is more for representing Web-based attributes, no attributes in this sense exists, whereas the only relatable attribute for vCard, and its extensions, is the ADR (address), although it will be actually considered when discussing address. ISA accounts implicitly for the difference between citizenship and nationality by having the attribute country of birth and nationality, respectively.

TABLE 6.13: Comparison between Schema.org, vCard, ISA, and the Person Etype

Schema.org	ISA	**Person Etype**
homeLocation	Residency	City of Residence
nationality		Nationality
	Citizenship	
Tax ID		Tax ID
VAT ID		

6.3.3 Profession

While profession is a very general term to describe one's occupation, the International Standard Classification of Occupations (ISCO)[2] distinguishes between the concepts of job and occupation. The former refers to "a set of task and duties performed or meant to be performed, by one person," while the latter is "a set of jobs whose main tasks and duties are characterized by a high degree of similarity." Thus, a person job can consist of one or more, possibly related, occupations to be performed.

Therefore, while maintaining profession as the category name, we model it as a sub-type of Event called Job as in Table 6.14. In terms of modeling, notice that the list of possible concepts will be based on the ISCO classification for Job Title, while Job information, Job beginning, and Job end override the respective Entity attributes. Finally, Job location is multivalue to account for possible occupations within the job that require the person to change buildings or event cities.

TABLE 6.14: Job Etype

Attribute Name	Description	DataType
Job Title	the title for which the person is hired and tasked to	Concept
Affiliation	the organization to which the job is obtained	<Organization>
Job description	a description of the main tasks and duties the job entails	NLString
Employer	The person who employs this person. It may also refer to the same person in case of self-employment.	<Person>
Job location	the location where the job is carried out	<Location>
Job beginning	the start of the job	Date
Job end	the end of the job	Date

With respect to other standards, shown in Table 6.15, FOAF and the Person Core do not provide information about the job of a person. However,

[2] http://www.ilo.org/public/english/bureau/stat/isco/

FOAF does represent information about a person's job in terms of contact, i.e., workInfoHomepage and workplaceHomepage.

TABLE 6.15: Comparison between Schema.org, vCard, and the Person Etype

Schema.org	**vCard**	**Person Etype**
hasOccupation		Job
Tax ID	ROLE	Occupation
jobTitle	TITLE	Job Title
worksFor		Employer

6.3.4 Education

Usually, (formal) education involves a certain period of time where a person learns skills and competences which may be mainly theoretical, e.g., higher education such as universities and colleges, or vocational, e.g., institutions teaching courses such as carpentry or agriculture. Nonetheless, there is a wide variety in terms of *i)* time required for each type of education, e.g., in Italy high school lasts five years, unlike France that lasts one year less, *ii)* subjects and topics taught, e.g., in Italy Philosophy is taught in high school, unlike Germany, and *iii)* the name and equivalence of the title awarded upon completion, e.g., Italian "Dottore Magistrale" which can both refer to MSc (Master of Science) or MA (Master of Arts). In fact, there are no real standards that countries follow, except some cases like PhD in the terms of equivalence in title but not necessarily in terms, e.g., of duration (3 years in Italy vs up to 8 years in the US). Nonetheless, there are ways to compare and translate educational titles, e.g., The European Qualifications Framework (EQF)[3] translates all types of education, training and qualifications, from school education to academic, professional and vocational since 2012.

Similarly to Job, we model Education as a sub-type of Event as shown in 6.16:

Among all the standards, none of them explicitly account for personal information on education is. Schema.org only mentions alumniOf to represent the educational organization that the person is an alumnus of. Similarly to Job, FOAF does represent information about a person's education in terms of contact, i.e., schoolHomepage.

6.4 Contact

Contact refers to those technological means of reaching (i.e., contacting) a person, which is a fundamental attribute, especially since our world is based on the exchange of information.

We distinguish between three main different types of contacts: *i)* Phone, i.e., means of contacting via any type of phone, *ii)* Internet, i.e., means of

[3] http://www.isfol.it/eqf

TABLE 6.16: Education Etype

Attribute Name	Description	DataType
Education Title	the title of the subject or topic that were studied during this education event for which the person is hired and tasked to	NLString
Educational Organization	the organization where the education took place	<Organization>
Education description	a description of the main topics and subjects learned during this education	NLString
Education beginning	the start of the education	Date
Education end	the end of the education	Date

contacting via the Web, and *iii)* Facility, i.e., means of contacting via postal services. In addition, we consider a further distinction between *synchronous* and *asynchronous* contacts. The former refers to the fact that the communication, once established, is instantaneous and in real time as in phones and chats, whereas, the latter refers to the fact that the communication because of physical or hardware constraints, is delayed, with various degrees of time span between communication exchanges, e.g., in fax machines and mails.

For the phone contact, we distinguish between three main types of phone-based contact means:

Asynchronous contact

- **Fax:** It refers to the fax machine that allows the telephonic transmission of scanned printed material. As such, it does not allow to establish a synchronous connection with the receiver, and it is therefore treated as asynchronous.

Synchronous contact

- **Landline Phone:** It refers to phones using a solid medium telephone line, e.g., metal wire or fiber optic cable, for transmission. It synchronous because, provided that the receiver picks up, the two persons can seamlessly call each other.
- **Mobile Phone:** a contact referring to phones that can make and receive telephone calls over a radio link by connecting to a cellular network.

For the Internet-based contacts, we distinguish between two main types of contacts:

Asynchronous contact

- **Website:** Websites or are more like a container of contacts, as they lists contacts like phone numbers, email addresses, and so on. Nonetheless, they are commonly used as contacts themselves.

- **Social Network (SNS):** Social networks are online platforms used by people to build social networks or social relations with other people. Given their prominence, we also model them as asynchronous, since the majority of them allows for contacting users with direct messages (DM) which do not allow for direct chat. Nonetheless, some there are some exception, e.g., Facebook with Messenger[4].

Synchronous contact

- **Chat** i.e., a contact referring to programs for real-time direct written or spoken chat, also allowing video communication. Chats are considered synchronous because, although one needs to take some time to type to answer or to start a conversation, the time lapse tends to be rather small, unlike, e.g., e-mails. Still, there are some videoconference systems, e.g., Flash Meeting[5], that force the participants to speak in turns while allowing a normal chat; yet, this is rather the exception when it comes to these systems. Furthermore, at the time of writing, majority of chat systems allow not only written chats but also video conferencing, e.g., Skype[6] and Whatsapp[7]

In terms of facility contact, we consider only one attribute, i.e., the person's address. We define address as a physical location or a mail delivery point. The main issue with this attribute is that its structure varies according to the standard is adopted, as many nations differ both in terms of the nu of minimal elements forming an address, and how these elements are named. Among the many standards available, ISO is currently aiming to develop a standard that, instead of proposing a final conceptual model, provides guidelines for a better structure and coverage of address schemes. According to the ISO 19160[8] illustrating the desiderata from the ISO project, the fundamental elements of an address can be summed up by the following entries:

1. **Address components that represent an identifier for the address, addressable object or delivery point:** e.g., address or road number;
2. **Address components that reference a real world object:** e.g., street name;
3. **Address components that reference a geographical area:** e.g., name of a locality and names or codes for administrative boundaries;
4. **Address components that reference a delivery area:** e.g., postcode or zipcode;

[4] https://www.messenger.com/login.php
[5] http://flashmeeting.e2bn.net/
[6] https://www.skype.com/en/
[7] https://www.whatsapp.com/?l=en
[8] http://www.isotc211.org/Address/iso19160.htm

5. **Address components that specify a kind of mail delivery service:** e.g., 'PO BOX' for Post Office Box in the United States;

6. **Address components that specify a distribution office:** e.g., post office;

7. **Address components that describe proximity:** e.g., kilometre point;

8. **Address components for the person or organization at the address:** e.g., person name or organisation name of the facility;

Overall, we model contact as a multivalue attribute whose value is the Contact ComplexType, as in Table 6.17 to enable persons to have multiple sets of contacts, much like contact card as in (Hume Llamosas 2014). The contact attributes are modelled as in Table 6.18.

TABLE 6.17: Contact attribute

Attribute Name	Description	DataType
Contact	the fax number of the person	<Contact>[]

TABLE 6.18: Contact ComplexType

Attribute Name	Description	DataType
Fax	the fax number of the person	Digits[]
Phone	the landline phone number	Digits[]
Mobile phone	the mobile phone number	Digits[]
Website	The website(s) of the person	String[]
Social Network	the social network account(s) of the person	String[]
IM	the instant messaging account(s) of the person	String[]
Address	the address of the person	<Address>

Address is in turn a ComplexType, and it is modelled based on abstracting the ISO 19160, excluding number 8. (since it is implicit in our modelling), shown in Table 6.19:

With respect to the person standards, contact as a category is very varied. In terms of phone-based contacts, no standard distinguishes between mobile and landline phone; surprisingly, vCard does not account for fax numbers. In terms of internet-based contact, FOAF is by design the most fine-grained standard, while vCard can reach similar coverage via a dedicated extension. We can match the variety of FOAF thank the IM and Social Network attributes being multivalue. Notice how schema.org does model website, but it does not make them a possible attribute of a person. Finally, in terms of address, we show similar coverage to the other standards. Similarly to us, address is actually an entity in schema.org, i.e., Postal Address [9], which is a child of ContactPoint[10].

[9] http://schema.org/PostalAddress
[10] http://schema.org/ContactPoint

TABLE 6.19: Address ComplexType

Attribute Name	Description	DataType
Address	the whole address as a string	NLString
Address number	any digits specifying the facility, e.g., street number	String
Apartment number	identifier for further sub-dwellings, e.g., door, floor, etc...	String
Street	name of the thoroughfare	NLString
Place	the locality of the facility, be it a city, a town, a village, etc...	<Location>
Administrative area	the most specific region or province of the facility	<Administrative Unit>
Country	the nation of the facility	<Administrative Unit>
Postcode	the numeric code that indicates the postal section of the facility	String

TABLE 6.20: Comparison between Schema.org, vCard, FOAF, and the Person Etype

Schema.org	**vCard**	**FOAF**	**Person Etype**
email	EMAIL		Email
faxNumber			Fax
telephone	TEL		Mobile/Landline
		yahooChatID	IM
		icqChatID	IM
		aimChatID	IM
	X-JABBER	jabberID	IM
	X-SKYPE	skypeID	IM
	X-MSN	msnChatID	IM
	URL	workplaceHomepage	Website
	URL	workInfoHomepage	Website
	URL	schoolHomepage	Website
addressCountry	country-name		Country
addressLocality	locality		Place
addressRegion			Administrative area
postOfficeBoxNumber			
postalCode	postal-code		Postcode
streetAddress	street-address		Street

6.5 Knowledge

In this section, we present our modelling of the notion of knowledge of a person divided in three dimensions. The first dimension is a person's *competences*, i.e., the skills a person possesses in a certain area of knowledge, which may be acquired in different ways. In other words, competences account for *practical* knowledge. The second dimension refer to *interest* and *preferences*: these two terms refer to (implicit) *theoretical* knowledge, since they account for a a predisposition in favor of something that is mainly intellectual. While interests and preferences may also cover areas such as hobbies, they still assumes that a person pursuing them has or will acquire through them knowledge and possibly also competences. Finally, we also model *language*, which represent a sort of middle ground. They may be classified as competences, since there are ways to test one's proficiency, but every person learns (at least) one language by default, so it represents a core element of person. Furthermore, language allows humans to access different mediums of knowledge, e.g., reading a book or listening to a talk on a topic. Notice that a common team that we consider in the modelling of knowledge is that we account both for the type of domain and some level of evaluation of the person involvement with respect to this domain.

The remainder of the section is as follow. We illustrate the modelling of competences in Section 6.5.1, while we detail the modelling of both interest and preferences together in Section 6.5.2. Section 6.5.3 concludes the section by showing our proposed language model.

6.5.1 Competence

Competence is a complex notion, with multiple possible interpretations, depending on the reference standard. According to the HR-XML Consortium work group[11], a competence is a "a specific, identifiable, definable, and measurable knowledge, ability and/or other deployment-related characteristic (e.g. attitude, behavior, physical ability) which a human resource may posses and which is necessary for, or material to, the performance of an activity within a specific business context". More generally, (Cheetham and Chivers 2005) defined competence as "effective performance within a domain/context at different levels of proficiency".

We refer to competencies as any skill in any specific domain of interest distinguishing between the skill name and the level of proficiency shown by the person in that skill. Note that our modelling of competencies makes no explicit assumption of the way of acquiring a competency, i.e., whether it was obtained via formal training, e.g., attending a trade school, or via other means, e.g., autodidacticism. Of course, one can further support a claim of competency via certificates, while self declarations of skills can be incorrect, inaccurate, or insufficient. Indeed, people may not be aware of the level of proficiency they actually possess It is also important to note that competencies are dynamic and an individual's knowledge and experience change over time. Furthermore, the change may not be verified or evaluated consistently. Some competencies may decline because the person does not keep up with them, e.g., switching from a programming language to another may make a programmer "rusty" with respect to the former.

We model competencies as a multivalue attribute in Table 6.21, whose value is the Competency ComplexType, represented in 6.22, to couple the information of the domain of competency and the expertise value together.

[11] `http://hr-xml.org`

TABLE 6.21: Competency attribute

Attribute Name	Description	DataType
Competency	the competency of the person	<Competency>[]

TABLE 6.22: Competency ComplexType

Attribute Name	Description	DataType
Competency area	the competency domain, e.g., programming	Concept
Expertise level	the proficiency; the concept restriction is {basic, intermediate, advanced, expert}	Concept

With respect to the other personal standard, there is no representation of the actual competencies of people.

6.5.2 Interest and Preferences

Interests and preferences are generally treated as synonyms. This can be argued by the fact that often interests supersede preferences, as noted by (Heckmann et al. 2007), and generally refer to domains rather than specific subjects. As (Sosnovsky and Dicheva 2010) notes, interests and preferences are usually considered synonyms and models dealing with preferences and interests only differ in terms of time validity. Intuitively, interests appear to be more static and general, whereas preferences tend to be dynamic and application or domain specific. In addition, "preferences naturally come into different flavor and express different opinions and desires", especially in terms of degree of negativity or positivity. For instance, considering user modelling ontologies from Section 2.1 like GUMO, interests and preferences are treated as synonyms, as no evidence on constraints in terms of predicates or time validity is provided. Furthermore, (Heckmann et al. 2007) notes that "actually everything can be a category for the auxiliary *interest* or *knowledge*", underlining how interest can supersede preferences.

One possible short coming of the previous representation is that, even if we were to group both interests and preferences under the same category, we cannot link explicitly interests in a domain with entities in it, e.g., preference on players or team in the football domain.

The way to connect these two concepts is to aggregate them in two ComplexType. The first is Interest (Table 6.23), which contains the second one, i.e., Preferences in Table 6.24. Notice that this structure allows us to account for interest also without explicit preferences, e.g., somebody just starting getting interested in a domain but yet finding her preferences.

TABLE 6.23: Interest attribute

Attribute Name	Description	DataType
Interest	the interest of the person	<Interest>[]

TABLE 6.24: Interest ComplexType

Attribute Name	Description	DataType
Topic	the topic the user is interested in, e.g., Football	Concept
Value	the weighted value, from 0 to 1, of how much the user is interested in the corresponding topic	Float
Preference	the preference(s) of the person	<Preference>[]

TABLE 6.25: Preference ComplexType

Attribute Name	Description	DataType
Item	the preferred item, e.g., The Silmarillion	<Entity>
Value	the weighted value, from 0 to 1, of how much the user is interested in the corresponding topic	Float

With respect to person standards, as Table 6.26 shows, FOAF and Vcard do account for interest, while schema.org does not. Notice that FOAF also models topic_interest, whose aim is to allow a more detailed vocabularies related to user interests. Overall, no standard supports the characterization of the levels of interest. As for preferences, no standard models preferences either implicitly or explicitly.

6.5.3 Language

We model the languages known by a person as a multivalue attribute, shown in Table 6.27, whose attribute is the ComplexType Language, which distinguishes between the name of the language and the person proficiency in all aspects of knowing one as in Table 6.28:

All The concept restriction on the proficiency attribute allows to refer to these possible values: {low, medium, high}; indeed, there are hardly any standards to define language knowledge, at least worldwide. For instance, the Common European Framework of Reference for Languages: Learning, Teaching, Assessment (CERF)[12] is a guideline used to describe achievements of learners of foreign languages across Europe and divides language knowledge into 3 levels, i.e., Basic user, Independent User, and Proficient User. However,

[12]https://www.coe.int/t/dg4/linguistic/Cadre1_en.asp

TABLE 6.26: Comparison between FOAF, vCard with our Person Etype

FOAF	**vCArd**	**Person Etype**
interest	INTEREST	Interest
topic_interest		

TABLE 6.27: Language attribute

Attribute Name	Description	DataType
Language	the language(s) known by the person	<Language>[]

TABLE 6.28: Language ComplexType

Attribute Name	Description	DataType
Speaking proficiency	the proficiency in speaking in the reference language	Concept
Writing proficiency	the proficiency in writing in the reference language	Concept
Comprehension proficiency	the proficiency in comprehension in the reference language	Concept

this scale requires conversion tables when compared with other standards, for instance, the USA Interagency Language Roundtable (IRL) scale[13], since it consists of 5 different levels, from No proficiency (level 0) to Native or Bilingual proficiency (level 5). Thus, we opted for more general levels without committing to any particular standard for the sake of generality. As for a comparison with standards, neither schema.org nor FOAF represents a person's language knowledge, whereas vCard does with LANG; however, it does not account for the person's proficiency.

6.6 Summary

In this Chapter, we illustrated the static data that we identify and model for representing personal data. We consider static data those data that may never change or may change in a considerable amount of time, in addition to being not possibly recognizable by sensors.

We started by describing names as the main way to represent the identity of a person. We rely and motivate our choice of having name as the main identity attribute on the philosophical tradition behind names as the way to both carry reference and semantics. In doing so, we also align with other personal data representation standards, given the complexity of representing names in different cultures around the world.

We then described the category of demographics, i.e., those human dimension that are studied to quantify and represent the human population. We divide demographics into 4 categories. The first one is existence, i.e., those attributes that refer to human condition such as life and death, where we unsurprisingly align with the standards. The second one is residency, i.e., those attributes that refer to the locations of a person, where we also align with the standards. The third one is about job, i.e., the occupation of a person, where we provide a more comprehensive view of a person's occupation than current standards. The last one is education, which extends current standards.

[13] http://www.govtilr.org/Skills/ILRscale1.htm

We also model a person's goal, which represents one's desire with respect to the state of the world. While we had no representation of these data in the standards, we accounted for a well-known framework such as i* for our modelling, also accounting for human values based on psychological literature.

We then describe contact information, dividing it between the type of means of contact, i.e., phone-, internet-, and facility-based contact. We also distinguished between synchronous and asynchronous contacts. Our modeling allows grouping together different types of contact that are covered with different granularity among standard.

We finally accounted for knowledge. We distinguished between competences, which are not represented in current personal data standards, interest and preferences, by proposing to treat them together to enhance the granularity of our representation, and finally language on its own, given its importance about knowledge acquisition and sharing for humans.

Chapter 7

Dynamic Data

In this chapter, we present the dynamic data according to the division from Chapter 5. As we said, the dynamic element is based of the possibility of "quantifiability" of the attribute values, i.e., that they can be measured to some degree, and that they also can be recognized via sensors such as the ones available to smartphones.

As such, we consider activities and states, which refer to the general "being" of a person. The main differences lie in the intentionality and the reflexiveness of these state. Activities are generally voluntary actions that tend to have a subject and an object, e.g., moving from one place to the other, eating, and so on. Instead, states tend to refer to states that are reflexive and involuntary, e.g., having a certain mood or physiological states. Of course, there is no exhaustive organization of activities, which is also not the main purpose of this work, since we focus on personal data as a whole; rather, we consider these criteria as a general mean of discrimination.

In addition, another dynamic type of personal data is context. While activities and state can be reduced to the sensor data in terms of input, context, although dynamic, relies also on human input, since it must account for the current view of a person's world. Thus it *weaves together*, i.e., it is composed of, dynamic data, which "transfer" their dynamicity, while it is not a type of personal data that can be obtained through sensor data *per se*.

Unlike static data, there are no actual standards to refer to in the state of the art for this type of personal data, although each of them has been investigated in many areas, e.g., linguistics or ubiquitous computing, so we will not compare these attributes with the same standards as in Section 6. Instead, where applicable, we will compare them to Quantified Self applications or other related work.

7.1 Activity

Our choice of naming this type of personal data "activity" is motivated by the needed distinction to another closely related term, i.e., action. Intuitively, action has a smaller scope than activity, as one activity may be composed of actions. In fact, in areas such as ubiquitous computing, actions are usually treated as primitives that fulfill a function or simple purpose, such as walking, jumping, or opening the fridge (Ye Liu et al. 2016).

7.1.1 Exploiting Wordnet

Our general methodology for modeling activities is to exploit the semantic and linguistic relations used in Wordnet. WordNet is a large lexical database of English (Fellbaum 1998). Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. Each of WordNet's 117 000 synsets is linked to other synsets by means of a small number of "conceptual relations". Additionally, a synset contains a brief definition (gloss) and, in most cases, one or more short sentences illustrating the use of the synset members. Word forms with several distinct meanings are represented in as many distinct synsets. Thus, each form-meaning pair in WordNet is unique.

With respect to nouns, the most important relation is the super-subordinate relation (also called hyperonymy, hyponymy or ISA relation), which is transitive. It links more general synsets, e.g., furniture, piece_of_furniture to increasingly specific ones, e.g., {bed} and {bunkbed}. Thus, WordNet states that the category furniture includes bed, which in turn includes bunkbed, so furniture is the hypernym of bed and bed is conversely the hyponym of furniture. On the other hand, the most frequently found relation among verbs is troponymy, i.e., a manner relation where one verbs expresses a specific manner characterizing an event. The specific manner expressed depends on the semantic field. For instance, manner dimensions are speed (move-jog-run) or intensity of emotion (like-love-idolize).

7.1.2 Modeling Activities

Our approach is to represent concepts concerning state by using the hypernym-hyponym hierarchy of nouns to structure the different activities and use the troponymy to specify the quantitative differences as recognizable via sensors. Since verbs do not have hierarchical relations, we only consider those verbs that are derivationally related from nouns, i.e., the terms the same root form and are semantically related although they belong different syntactic categories; for instance, butter as a noun and butter as spreading butter on a surface. In this way, for each activity (noun) we have a set of possible manners to perform it and these manners provide us with suggestion on what it can in turn be required to be addressed at sensor level in everyday life. For instance, the difference between walking and running in terms of body movement sensor point of view can be reduced to the increased speed manner, or changed by the medium manner, i.e., riding a bike or taking the bus. This approach allows us to then inject semantics in the recognition process by modeling concepts that encode their recognition modality.

As an example of this relation, consider the first level of hyponyms of the synset {state}, i.e., "the way something is with respect to its main attributes", having a derivationally related form relation with verbs. Out of the 19 hyponyms of state belonging to their namesake semantic domain, only 4 of the derivationally related verbs are also stative. This indicates that the values determination changes not according to the domain of the noun, but to the verb.

For instance, one of the troponyms of the verb act, whose semantic category is social, is play, whose troponyms include modalities of social recreational activities.

Category	Name	Contents
29	Body	Verbs of grooming, dressing and bodily care
30	Change	Verbs of change of size, temperature, intensity, etc.
31	Cognition	Verbs of thinking, judging, analyzing, doubting, etc.
32	Communication	Verbs of telling, asking, ordering, singing, etc.
33	Competition	Verbs of fighting, athletic activities, etc.
34	Consumption	Verbs of eating and drinking
35	Contact	Verbs of touching, hitting, tying, digging, etc.
36	Creation	Verbs of sewing, baking, painting, performing, etc.
37	Emotion	Verbs of feeling
38	Motion	Verbs of walking, flying, swimming, etc.
39	Perception	Verbs of seeing, hearing, feeling, etc.
40	Possession	Verbs of buying, selling, owning, and transfer
41	Social	Verbs of political and social activities and events
42	Stative	Verbs of being, having, spatial relations
43	Weather	Verbs of raining, snowing, thawing, thundering, etc.

FIGURE 7.1: The 15 semantic categories of verbs in Wordnet, taken from (Fellbaum 1998).

Figure 7.1 shows the division of verb semantic categories into 15 groups following their respective semantic domains, i.e., areas of human knowledge exhibiting specific terminology and lexical coherence. This holds for all categories except number 42, i.e., the stative verbs; in fact, they "do not constitute a semantic domain, and share no semantic properties other than that they refer to states" (Fellbaum 1998).

From the point of view of the Person eType, we represent activities as an attribute whose value is a set of concepts, as shown in Table 7.1.

TABLE 7.1: Activity attribute

Attribute Name	Description	DataType
Activity	the activities of the person	Concept[]

While we do not distinguish further the type of activities since we exploit the structure given by Wordnet, the main type of activity recognized and exploited from the point of view of the Quantified Self covers fitness. In fact, self-tracking wearable devices are increasingly used in the consumer market to track calorie consumption and daily physical activity and to support self-awareness and healthy behaviors. These devices automatically recognize positive behaviors (such as walking) tracking changes over time: the underlaying idea is that having always-available displays could be useful to increase the individual's awareness about individual physical activity level and this could be valuable particularly when people try to change their habits (Consolvo et al. 2008). All self-tracking systems can monitor the entire daily physical activity or can be tailored to the tracking of some specific sports. On the other hand, mental activities are impossible to track with ubiquitous devices, which makes their quantifiability (currently) unlikely.

7.2 State

States can be seen as a heterogeneous category. This feature is mirrored in our modeling since we do not follow the same approach as activities. While we maintain two separate sub-categories, i.e., physical and mental states, they are modeled with different approaches, which we detail in a dedicated section, i.e., Section 7.2.1 and Section 7.2.2.

7.2.1 Physical State

Physical states refer to those state that affects the physical or biological dimension of a person.

Similarly to physical activities, Qquantified Self tool focus on one specific area of states, which is *healthcare*. Tools such as PatientsLikeMe[1] usually detect a single parameter or health-related behavior of the individual, often relying on a device able to measure it, storing it on a website where the user can view changes over time and compare them with those of other users. These services are intended to improve the health condition of the patient and help him to live a more salubrious life by changing its behavior in a positive direction. Often, there are tools dedicated to specific diseases, e.g., diabetes[2].

In terms of personal standards, a valuable resource that can be used to model physical states is SNOMED CT[3]. It is a systematically organized computer processable collection of medical terms providing codes, terms, synonyms, and definitions used in clinical documentation and reporting. SNOMED CT is considered to be the most comprehensive, multilingual clinical healthcare terminology in the world (Tim 2010). The primary purpose of SNOMED CT is to encode the meanings that are used in health information and to support the effective clinical recording of data with the aim of improving patient care. SNOMED CT provides the general core terminology for electronic health records. SNOMED CT comprehensive coverage includes: clinical findings, symptoms, diagnoses, procedures, body structures, organisms and other etiologies, substances, pharmaceuticals, devices, and specimens.

[1] https://www.patientslikeme.com/
[2] https://sugarstats.com/
[3] https://www.snomed.org/snomed-ct

Overall, the major dimension for physical states is healthcare, since, while a person' behavior and lifestyle can directly affect it, its state cannot be voluntarily changed by a person. Furthermore, some physiological attributes cannot be changed in the same voluntary was as a person, e.g., lifts her arm.

From a modeling point of view, we distinguish three possible categories of states that :

Observable features: Following SNOMED, it refers to the physical features that can be observed. We treat physical appearance as the physical characteristics, i.e., defining traits or features about a person's body.

We model physical appearance via the following attributes:

TABLE 7.2: Observable features attributes

Attribute Name	Description	DataType
Eye color	the colour of the person's eyes	Concept
Hair color	the colour of the person's hair	Concept
Distinguishing marks	any distinguishing marks of the person	NLString

Notice that the attributes, in this case, could be argued to be static rather than dynamic, because it may be hard to be recognized and collected via sensors. However, notice one's eye or hair color can be changed multiple time is a short period of applying contacts or dying. The sensor element, in this case, is taken to be the observation from the point of view of the doctor.

Physiological measure: This category represents parameters of the physiological state of a person and corresponds to the measurement term in SNOMED. Measurement of many of these parameters requires invasive monitoring techniques. Usually, a well being of a person relies on these type of parameters being stable, whereas extreme fluctuations are indicative of changes in the person's state. This means that these measures are always asserted against some threshold value.

We model general biometrics that do not require invasive procedures as the following attributes:

Condition: We model conditions that affect a person consisting of a disorder of a structure or function, which may have varying degrees of temporality and severity. For instance, having a flu can be a very short period of time and gravity with respect to suffer from conditions like being diabetic or asthmatic, since they can last years and can seriously affect one's life style.

We model conditions as a type of Event with the following attributes:

7.2.2 Mental State

Mental states refer to those states affecting the psychological sphere of everyday life. Unlike their physical counterpart, mental states, albeit important,

TABLE 7.3: Physiological measure attributes

Attribute Name	Description	DataType
Height	the distance from head to foot	Float
Weight	how much a body weighs	Float
Heart Rate	the rate at which the heart beats, measured in beats per minutes (bpm)	Integer
Blood Pressure	the pressure in large arteries of the systemic circulation, measured in millimeters of mercury (mmHg)	Float
Temperature	the degree of hotness or coldness of a body	Float
Respiratory rate	the rate at which breathing occurs, measured in breaths per minute	Integer
Perspiration	the process of the sweat glands of the skin secreting a salty fluid; the concept restriction is {low, normal, high}	Concept

TABLE 7.4: Condition attributes

Attribute Name	Description	DataType
Condition type	the name of the condition	Concept
History	the description of the history of the condition	SString
Temperature	the degree of hotness or coldness of a body	Float
Symptoms	the symptoms of the condition	Concept[]
Status	the current status of the condition	Concept

is much harder to keep track of and quantify from a Quantified Self point of view. Nonetheless, there is a rise in a specific type of mental state, i.e., mood, via tracking applications and services. They are intended to help users to increase their awareness and understanding of all the factors that influence their "mood states" and their mental health. These applications can track changes in mood over time and identify patterns and correlations with environmental and social factors, to facilitate the identification of variables that can affect the mental states of the person. For instance, there are dedicated mood applications, e.g., "Track Your Happiness"[4] and "Happy Factor"[5] for happiness, or tools that track and allow for the retrieval and analysis of the overall mood of the user.

From a modeling point of view, we distinguish the following categories that can be quantified for mental states:

Feeling: It represents an emotional state in a small window of time and often localized based on the context of the user, e.g., angry. Feelings are

[4]https://www.trackyourhappiness.org/
[5]http://howhappy.dreamhosters.com/

usually the first level of abstraction with respect to external stimuli, and here are "cognitively saturated" as the chemicals related to emotions are processed in our brains and bodies.

Mood: It represents an emotional state in a larger window of time and more connected to the senses; it may be much more independent from context, e.g., happiness and sadness. Moods are typically described as having either a positive or negative valence. Furthermore, moods tend to be heavily influenced by several factors, e.g., the environment (weather and lighting) and physiology (the well-being of a person at a given moment).

Personality It represents the set of habitual behaviors, cognitions and emotional patterns that evolve from biological and environmental factors. There are several scales to represent a person's personality, e.g., The Myers–Briggs Type Indicator (MBTI) (Myers et al. 1998) or The Big Five personality traits (Goldberg 1993), also known as the five-factor model (FFM). Although some personal data standards represent personality, e.g., FOAF with the property Myers-Briggs, the Big Five Traits are widely used in the literature, e.g., computational social sciences (Centellegher et al. 2016; R. Wang, Harari, et al. 2015), so we rely on this framework.

TABLE 7.5: Mental state attributes

Attribute Name	Description	DataType
Feeling	an emotional state in a small window of time and often localized	Concept
Mood	an emotional state in a larger window of time and more connected to the senses	Concept
Personality	one of the five traits of personality; the concept restriction is {neuroticism, extraversion, openness to experience, conscientiousness, agreeableness}	Concept

Table 7.5 shows the three main attribute of mental state. Notice how these attributes also provide the varying degrees in time of psychological states that affect a person, from very quick and localized mood to very long and less dynamic states such as one's personality, which is harder to single out via sensors.

7.3 Context

Humans can only have a limited and partial view of the world at all times in their everyday life. Recalling the definition from (F. Giunchiglia 1993), i.e., "a theory of the world which encodes an individual's subjective perspective about it", this represents the purpose of context.

Imagine a usual state of affairs in a student's everyday life: a classroom with a teacher and students where a lesson is taking place. While these facts can be considered as objective, for each person in the room a different *context* is going on, focusing on certain elements, e.g., the teacher and the subject of the lesson, and ignoring others, e.g., the sound of the projector, the weather outside and so on.

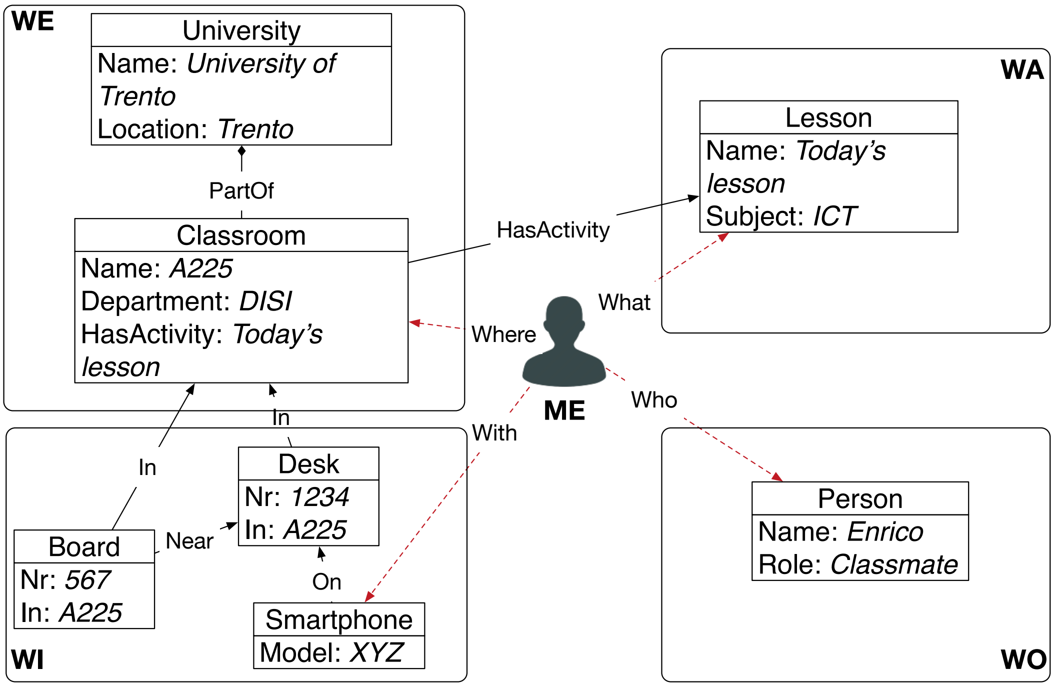


FIGURE 7.2: The four dimensions of context, centered on the user.

Fig. 7.2 shows this scenario as a knowledge graph, representing the personal context of a person in the class. Each node represents an entity, e.g., the person and a friend, with its respective attributes and their attribute values. For instance, attributes of Enrico in Fig. 7.2 are "Class", "Name", and "Role", and their corresponding values are "Person", "Enrico", and "Classmate", respectively. Edges represent relations between entities, e.g., "Classroom" has two relations: 'HasActivity' for "Lesson" and "In" for "Board" and "Desk."

7.3.1 Definition

To account for the structure of context, we model it as a tuple:

$$Cxt =< me, WA, WE, WO, WI > \tag{7.1}$$

where:

- **me** is the person on which the context is centered, with a given role, e.g., student;

- WA is the Temporal dimension, i.e., the dimension that answers the question "**WhA**t are you doing?".

  It covers all the relevant activities for a person in the current context, e.g., attending a lesson;

- WE is the Spatial dimension, i.e., the dimension that answers the question "**WhE**re are you?".

  It covers all the relevant locations for a person in the current context, e.g., a classroom;

- WO is the Social dimension, i.e., the dimension that answers the question "**WhO** are you with?".

  It covers all the relevant people for a person in the current context, e.g., the teacher and classmates

- WI is the Object dimension, i.e., the dimension that answers the question "**W**hat are you w**I**th?".

  It covers all the relevant objects for a person in the current context, e.g., his or her smartphone

Notice that choosing the relevant context and its elements is a non-trivial task which depends on the objective and goals of the subject experiencing it at a particular time (Bouquet and F. Giunchiglia 1995). Also, handling and overcoming unexpected obstacles and changes of the environment on the run (F. Giunchiglia, E. Giunchiglia, et al. 1996) is required. Both these aspects of context are because the surrounding environment of a human can be treated as an open domain, i.e., an environment without *a priori* knowledge and constantly evolving. In fact, in open domains, it is not feasible or possible to predict, and hence model, how the world will present itself (F. Giunchiglia 2006).

From an entity-centric point of view, Context is therefore an attribute of Person, shown in Table 7.6, whose value is Context, which is a sub-type of Event, shown in Table 7.7.

TABLE 7.6: Context Attribute

Attribute Name	Description	DataType
Context	the context of the person	<Context>

Notice that, depending on the granulatiy required, some dimensions can also consist of one single entity. For instance, in the case of Location, this means that the attribute becomes the same as the position of the person, which equals the one of the location where she currently is.

Based on this structure, each dimension is a set of eTypes belonging to the top level eTypes from Section 4.2. While our main contribution is in terms of modeling the context as a framework, we provide further details on how to model context dimensions.

TABLE 7.7: Context eType

Attribute Name	Description	DataType
Me	the role of the person in the context	<Role>
Location	the relevant location(s) of the person	<Location>[]
Event	the the relevant event(s) of the person in the context	<Event>[]
Social relation	the relevant social relation(s) of the person in the context	<Role>[]
Object	the relevant object(s) of the person in the context	<Artifact>[]

Roles are the attribute values for both Me and Social relations, where the only difference is that the role of a person in a context may be different from the role of the people around her. For instance, while working I may share the role of my colleagues, but there are also other roles, e.g., my boss. As stated previously, in our entity-centric approach roles do carry identity, and we account for their time validity with the fact that they inherit start and end from Entity. Defining different social relations can be addressed by considering, for instance, W3C recommendations[6], using the RELATIONSHIP vocabulary[7]

Locations and their specification are based on the work from (Das and F. Giunchiglia 2016). In this work, the authors define GeoeTypes, which is the set of all eTypes concerning geographical entities. A geographical entity is defined as a physical object (i.e., a tangible and visible physical entity), which has an existence in our planet Earth and occupies a certain geometric area which we represent as a point, line, and polygon, and which maintains their identity through time. Geographical regions separated for administrative purposes (e.g., country, province) or classified based on the Earth's vegetation pattern (e.g., Alpine region, Savanna region, Tundra region) as well as man-made objects such as buildings or constructions (having permanent position on the Earth's surface) are considered as a Geo entity. Among the main GeoeTypes, in addition to Location and Administrative Unit (presented in Section 4.2), there are also Building, Body of water, and Transportation Area.

In the case of events, the structure of the children eTypes can be adapted to the type of context and possibly obtained automatically by accessing other available services, e.g., apps for calendar management. At the same time, we must remark the distinction between an activity and an event, where the difference is that the former can become the latter once the temporal information is integrated with the spatial information. For instance, the activity behind moving an arm may become an event once we localize it, e.g., brushing my teeth vs. cooking; however, this passage depends on the required granularity in terms of modeling and the type of data available.

For representing artifacts, while relying on the parent eType Artifact from Section 4.2, a fundamental artifact to be modeled for the scope of this work is

[6]https://www.w3.org/2011/gld/wiki/Terms_for_describing_people
[7]http://vocab.org/relationship/

the smartphone. In fact, it is the main interface from a user point of view to obtain information not only in terms of sensors but also users'. Smartphones also allow for the representation and detection of other (smart) devices thanks to their connectivity, e.g., via Bluetooth or WiFi.

7.3.2 Endurants and perdurants

In addition to dimensions, contexts also account for the fact that they aggregate based on points of view, i.e., that humans fundamentally use two elements to drive their representation: time and space. We account for this with the notions of *endurant* and *perdurant* contexts. According to (Gangemi et al. 2002), endurants are "individuals wholly present whenever they are present, and that persist in time while keeping their identity", e.g., buildings and people, while perdurants are "individuals composed of temporal parts", e.g., events. So the context can provide different representation of the same state of affairs depending on which element is more important. For instance, consider the scenario described in Sec. 7.3. In an endurant context, one could say "I'm in class", thus choosing also a certain level of granularity within the building since it could also be understandable to say "I'm at the university". In a perdurant context, one could say "I'm studying", while other activities may be going on, e.g., somebody leaving or two or more people discussing and so on. The state of the world is the same, but the representation is different.

Fig. 7.3 extends the scenario described at the beginning of Section 7.3. Notice that Fig. 7.3 is at the level of the entity classes shown in Fig. 7.2, and focuses only on WA and WE for clarity's sake.

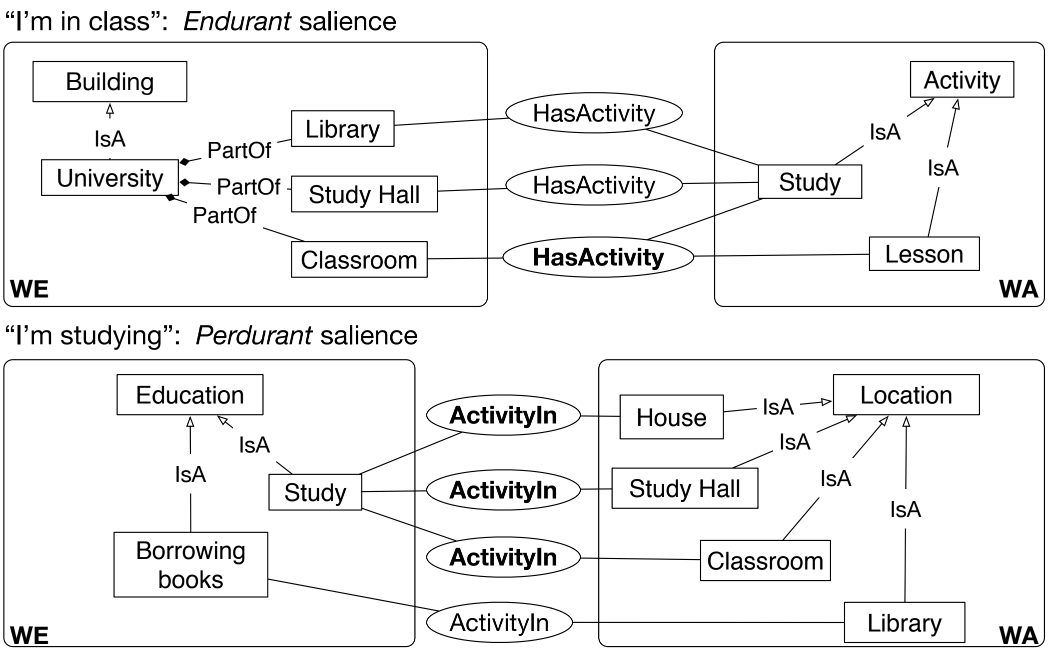


FIGURE 7.3: The difference between the notions of endurant and perdurant when describing the context.

The two possible representations are as follows:

- **Endurant context:** In this case, being in the classroom is more relevant, so the activities to be performed are fixed: the possible activities are either studying or having a meeting.
- **Perdurant context:** In this case, among the events, studying is more relevant, so the possible locations, and their granularity, are less relevant and may be very different types of locations.

Note that the relations (in bold) mapping locations and activities and vice versa, i.e., "HasActivity" and "ActivityIn" respectively, are not simply inverse functions, i.e., $ActivityIn = HasActivity^{-1}$ does not necessarily hold. In fact, in Fig. 7.3 in the case of endurant context "HasActivity" maps classroom to both "Study" and "Lesson", whereas in the perdurant context "ActivityIn" maps "Study" to many more elements, i.e., "House", "Study Hall", "Classroom", and "Library". This shows the structure change depending on the viewpoint, since the relations do not map to the same elements.

These phenomena affect the activity recognition process, since, depending on which context is active, the elements to be recognized and to be expected, along with possible services, change. For instance, in the case of endurant contexts, location-based services, e.g., sharing a location with friends, may be more relevant for a user.

7.4 Summary

In this chapter, we illustrate the dynamic data following the division from Chapter 5. Based on the criterion of "quantifiability" of the attribute values, i.e., that they can be measured to some degree and that they can be recognized via sensors, we can distinguish three types of dynamic data.

The first one is activity, which refers to those actions consciously carried out by a person, e.g., locomotion or cognitive processes like thinking or studying, which are usually described in natural language via transitive verbs of different types of semantic areas, e.g., following Wordnet classifications, communication and consumption (Yang Liu et al. 2004). We cite Wordnet since we rely on its semantic relations structure to build the way we can recognize and model activity data. In fact, we propose to represent concepts concerning activities by using the hypernym-hyponym hierarchy of nouns to structure the different activities, and use the troponymy of verbs, i.e., the manner relation, to specify the quantitative differences as recognizable via sensors. Thus, each class of activities can be associated with the set of possible manners of performing it, which translate in the way they can be recognized. This modeling allows us to enable a more semantic-aware recognition of the concepts.

The second one is state, which represents to those modes of being of a person that natural language describes via adjectives and usually refers to stative verbs, e.g., feelings and physiological conditions; furthermore, it refers to those elements on which a person has little or no control at all, e.g., heart rate. Based on the literature, we identify two types of states: physical and mental. The former is concentrated on healthcare and distinguishes between observable features, e.g., the color of eyes, physiological measures, e.g., blood pressure, and conditions, e.g., diseases. The latter covers three mental states of decreasing dynamicity, i.e., feeling, mood and personality.

The third and final one is context, which is not innately dynamic, unlike the previous two. Its main purpose is to put together different elements which themselves can be dynamic. We present a modeling of context based on four dimensions, centered on the subject, which are locations, events, social relations and objects. To model them, we rely on the top level eTypes from Section 4.2. Also, we account for the fact that users tend to focus on time or space to define their environments by accounting for endurants and perdurants.

Chapter 8

Reference Architecture

Having presented the modelling of the Person eType, we now present how the modelling is contextualized in the general system architecture developed by the members of the Knowdive[1] group, in particular (Fernandez and Ignacio 2012), (Hume Llamosas 2014) and the work of Mattia Zeni from (Zeni, Zaihrayeu, and F. Giunchiglia 2014). Since the actual technical development is outside of the scope of our work, we will only provide a general overview of which element of the architecture is affected by the modelling choices.

A (partial) logical view of the reference architecture is presented in Figure 8.1. This view shows its different components and how they are connected together. The are two main areas: Data Acquisition and Management Subsystem, and Knowledge Generation Subsystem. The main point of this architecture is that, while our modelling address the issue of the semantic gap from the representational point of view, this architecture addresses the same issue but from a technical point of view, allowing users to provide to collect and manage their own data, be they static or dynamic, and also data from other sources. With respect to this architecture, Section 8.1 illustrates how personal data in terms of sensors and knowledge is collected from a person and then stored, while Section 8.2 shows how knowledge can be generated and maintained by updating information about the person.

8.1 User Data Acquisition and Management Subsystem

As we have discussed in this thesis, personal data can be generated from a person either from her knowledge as a direct input or sensor data. In order to collect data from either source, we rely on the i-Log application (Zeni, Zaihrayeu, and F. Giunchiglia 2014), described in Section 8.1.1, which can then be stored in our system in different storage options as detailed in Section 8.1.2.

8.1.1 i-Log

The i-Log application, shown in Fig 8.2, can be installed on a person's smartphone, which, as we showed in Section 2, are being more and more employed

[1] http://disi.unitn.it/~knowdive

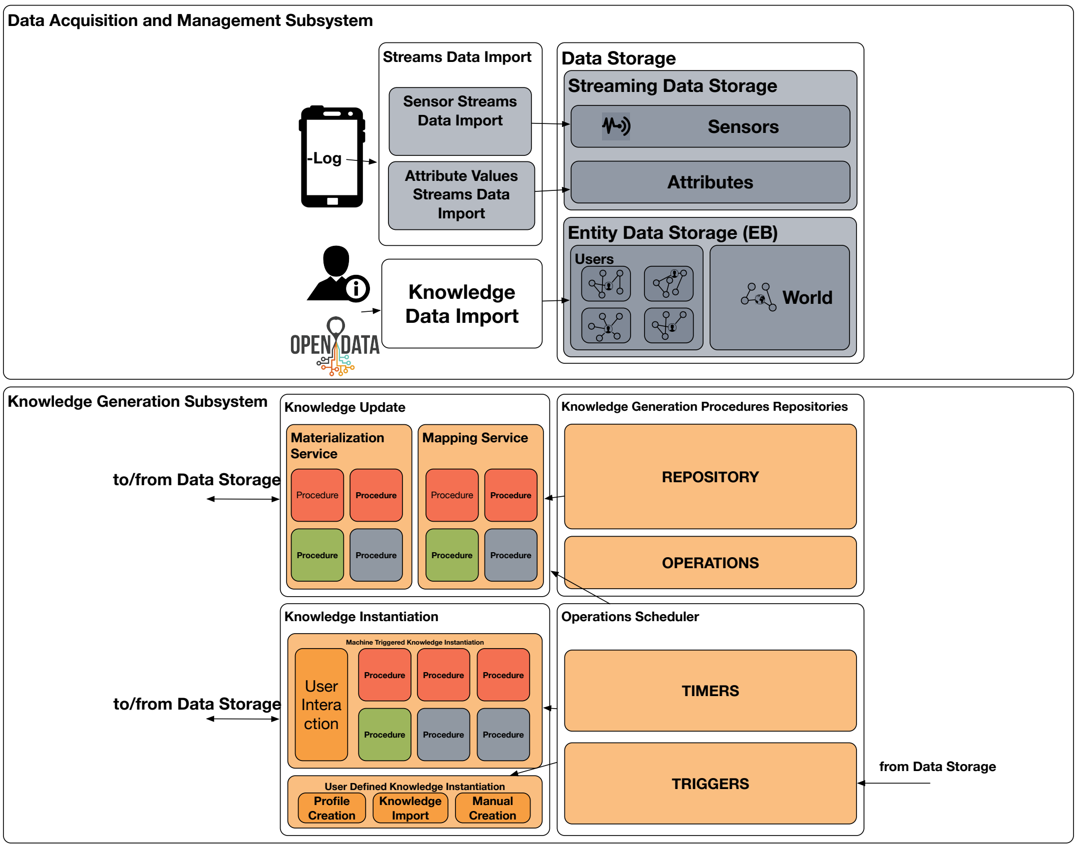


FIGURE 8.1: Schematic of the reference architecture with the two main subsystems: Data Acquisition and Management, and Knowledge Generation.

in different areas of research for their pervasive. i-Log provides us with two functionalities. With respect to sensor data input, i-Log can collect up to 30 different sensors, with the final number depending on the actual sensors availability on the user's smartphone. As for human input, i-Log can administer time diaries, in accordance with the methodology from Section 2.7, to users at configurable time intervals, thus adjusting the context information granularity. i-Log has been designed *i)* to be modular and adapt to each smartphone model, especially in terms of sensing strategies for both smartphones and their internal sensors (which can greatly vary among different models), *ii)* to consume as little battery as possible, by devising sensor-dedicated energy consumption strategies and delegating all computation server-side, and *iii)* to ensure users' privacy from data collection to its analysis.

This app is the front-end to the back-end subsystem that accounts for the data collection component. Also, it allows people to register to the system once she executes it for the first time and thus becomes a user.

8.1.2 The Entity Base (EB)

As shown in Figure 8.1, the Data Collection and Management subsystem is composed of three main parts:

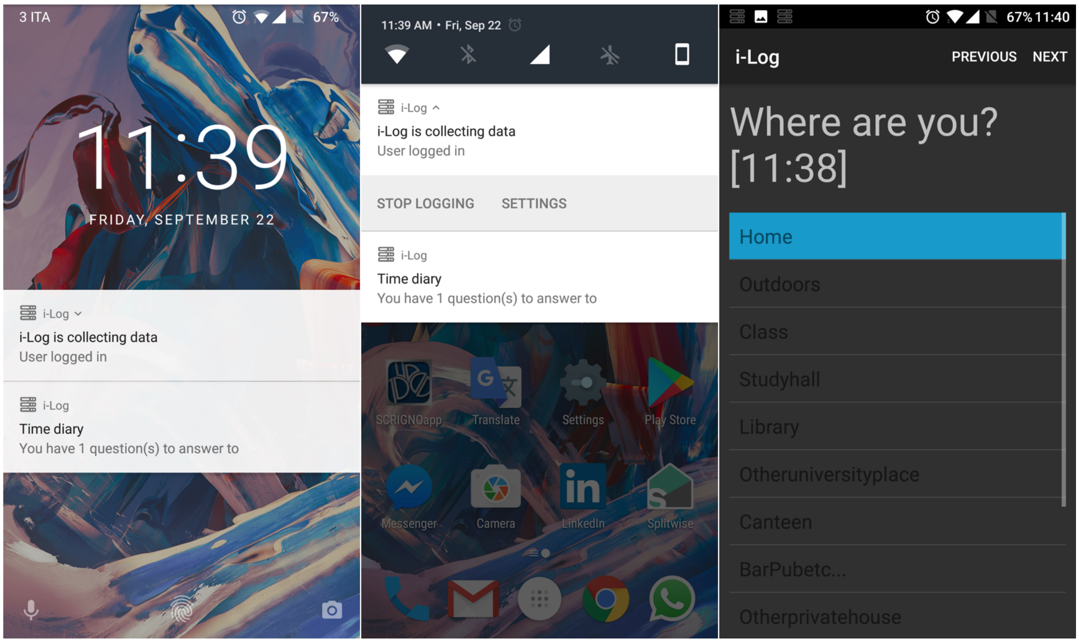


FIGURE 8.2: i-Log is unobtrusive and does not alter the user experience. It only creates a notification to tell the user that the data collection is running and a second notification when a new question is generated.

- **Data Sources.** The system deals with different types of data that are generated from different sources. On the one hand there is the user, where her smartphone can be used to generate stream of sensor data, but also high level knowledge in terms of. The knowledge is generated in terms of answers to specific questions i.e., through feedbacks in terms of answers on time diaries. The other source of information do not concern the user, and regard any other form of data referring to the world, composed by streets, buildings, institutions, etc.

- **Data Import.** The data are generated from different sources, namely a person or external actors. The data import component allows create data pipelines that adapt the incoming data to a format that allows to be stored.

- **Data storage.** For both sensor data and knowledge data, the system allows for a separate storage solution, due to their very different characteristics, requirements and modelling: one are time series data while the other follows the entity-centric approach.

Among these components, we focus on the entity-centric data storage, called Entity Base. In fact, the entity-centric data storage allows to store eTypes and also to *instantiate* them in entities, which describe any real world element. This representation is associated with a set of attributed that characterize the entity. Formally, it is defined as a tuple:

$$E =< SURL, SURI, \{N\}, ET, \{A\} > \tag{8.1}$$

where,

- *Semantic Uniform Resource Locators (SURL)* a SURL is defined as a semantic Uniform Resource Locators (URL) that represents a particular representation (from the user point of view) of a real-world entity. A SURL is created for each entity being represented by the user, it is globally unique and can be dereferenced to obtain the full representation of the entity. In other words, it encodes the location of a particular representation of a real-world entity within the storage.

- *Semantic Universal Resource Identifiers (SURI)* SURI is defined as a semantic Universal Resource Identifiers (URI) that represents a real-world entity without attaching it to a particular representation. The same SURI is shared by different users describing the same real-world entity, it is also globally unique. A SURI cannot be directly used to retrieve an entity representation, because it does not commit to one single representation and it rather includes the different points of view from which an entity is represented.;

- *{N}* is a set of strings representing the names used by the corresponding representation Entity (E) to identify the real-world entity;

- *Entity Type (ET)* is the eTypes among those allowed in the system;

- *{A}* is a non-empty set of attributes, based on their respective attribute definition AD.

The need for SURL and SURI, based on the work (Fernandez and Ignacio 2012), allow us to split the identification of a real-world entity and its representation(s) , unlike other approaches from the Semantic Web that combine URIs and URLs to identify entities in the Web (e.g., OKKAM, semanticweb.org[2], www.w3.org[3]), the separation between local and global identifiers allow . Furthermore, other approaches implicitly impose a representation for the real world entity when reusing the identifier, while we (by adopting the local/global identifiers) embrace diversity with regard to the point of views represented by different users. Furthermore, this element allows us to account for commonsensical ways to use identity, i.e., names as showed in Section 6.1, while at the same time ensuring that they are understandable from the point of view of machines and enabling them to reference them globally and locally.

Thus, for each person within the system, the EB is responsible for storing and maintaining the knowledge. Figure 8.4 and Figure 8.3 show an example of both the Person eType and a Person eType instance, i.e., Fausto Giunchiglia. Notice that this is only a partial representation due to both available data and clarity's sake. In the context of this thesis, the main piece of knowledge refers to personal data of a user, be they static or dynamic like her context, which comprise her representation of the world. In this case, depending on the situations, the entities that are relevant for the user in a specific situation

[2] `http://semanticweb.org/wiki/Uniform_Resource_Identifier`
[3] `http://www.w3.org/TR/cooluris/#semweb`

are enabled to compose the user context. Since the system has to deal with multiple users, everyone with her own knowledge, the EB system follow a specific configuration to allow all the data to be separated for privacy reasons.

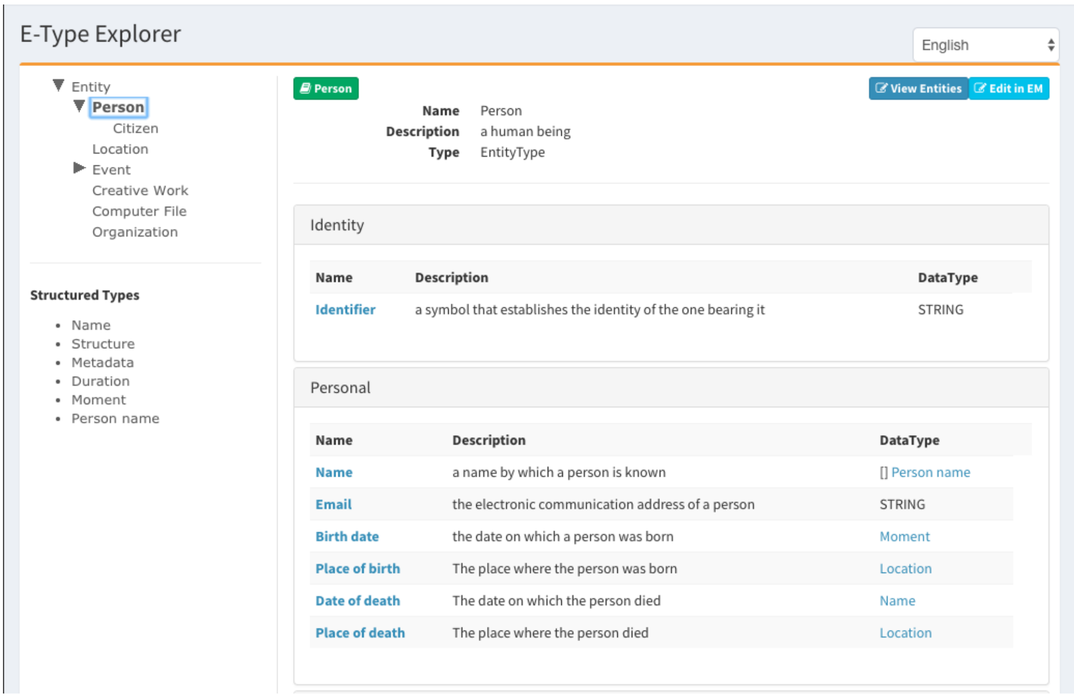


FIGURE 8.3: Implementation of the Person eType within the EB.

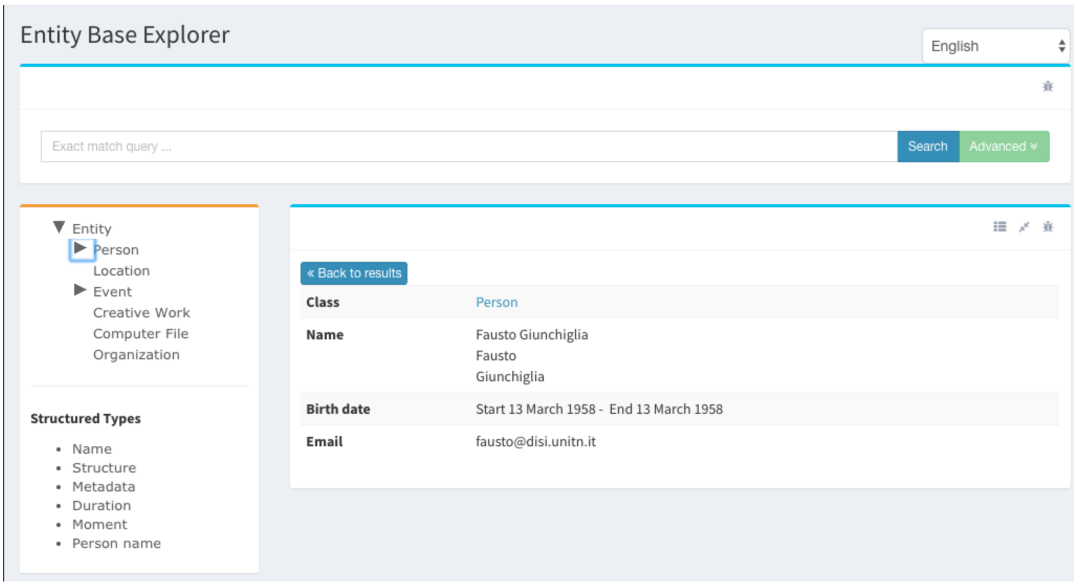


FIGURE 8.4: Snapshot of an Entity, namely Fausto Giunchiglia, within the EB

In addition to the individual knowledge of the user in the system in terms of her own personal data, the entities inside this EB system should refer to a more objective view of the world which is not personalized on the user. They should refer to locations, services, objects, streets that are part of cities, municipalities, states. Having this knowledge, in terms of eTypes, has the main purpose of alleviating the issue of creating etypes or adding or modifying the real world information about entities for each user in their own EB. Thus, the system has a separate EB that represent the world knowledge.

8.2 Knowledge Generation Sub-system

In addition to the storage of the user knowledge, the system allows for two types of operations on it, namely knowledge *instantiation* and knowledge *update*, which account the fact that user's knowledge of the world change constantly either because of new elements, i.e., entities, she encounters or because of changes of varying degree of dynamicity. Section 8.2.1 describes the Knowledge Instantiation subsystem, while Section 8.2.2 illustrates the Knowledge Update subsystem. We also provide a detailed overview of the update procedures, which are stored the Procedure repository. Finally, we give a brief overview of the Operation Scheduler in Section 8.3.

8.2.1 Knowledge Instantiation Subsystem

By knowledge instantiation, we refer to to the ability of adding or removing entity instances from the EB. This database at the beginning is empty and progressively must be filled up with the entities that the user believes are relevant to represent her and her context.

Once the user creates her profile in the system, the knowledge instantiation can be done manually or automatically. In the first case, the instantiation can be done using the dedicated interface in the EB shown in Section 8.1.2 or *importing* the knowledge, e.g., from open data repositories. In the second case, the user can also allow the system to automatically suggest entities based on the streaming data collected by i-Log. For instance, while the system collects and analyzes the GPS data with a clustering algorithm, it can generate clustered locations and suggest them as candidate locations like home or work.

8.2.2 Knowledge Update Sub-system

As we showed in Section 7.3, the user context is dynamic, since it is used to represent the situations in which the user is involved. There is then the need to update the entities in this snapshot of the user knowledge. Doing so corresponds to updating the attributes of these entities depending on the sensor data collected from the user's smartphone.

To update the knowledge, the system has two components: the Knowledge Mapping component and the Knowledge Materialization component. Whenever new information appears from the streaming of data from the phone and the streaming of knowledge, which can also represented as an attribute value, this information is *mapped* into the corresponding stream into the Streaming

Data Storage. Then, when the update needs to be reflected to the Entity Base, so the value is *materialized*.

All these update operations are based on *procedures*. A procedure is a type of abstraction and default method to read and access the input data from both the storage systems, the Streaming and the EB, and allows to push the results to the corresponding attribute. In our case, this means that each attribute of the Person Etype requires a dedicated Procedure to be defined for the update, depending on the needs and the available data within the application scenario. Furthermore, in the case of activities, procedures allow us to implement the modelling exploiting Wordnet relations as described in Section 7.1. In fact, by considering the type of dimension to differentiate and recognize, e.g., change in speed, we can implement it as a *recognition strategy*. As such, these procedures concern only dynamic data within the context.

We distinguish between two types of updates:

- **Numeric:** the update of a numeric attribute value is necessary to quantify the entity that then can be aggregated together to infer higher level contextual elements. These updates have little or no meaning for the user while they are necessary for the machine.

- **Semantic:** by updating a relational attribute the entity is linked with another one. If the newly linked entity was disabled in the current snapshot of the context, it becomes automatically enabled in the new one. An example of this is the attribute Location of the User (that we assume to be always enabled). If this attribute was set to point to the Location entity "Workplace" and the algorithm changes it to the Location entity "Home" I *disable* the Location entity "Workplace" entity from the current snapshot of the context and I consequently *enable* "Home". This update works for the different representations of the same entity too.

The core of both update methodologies consists in the fact that the sensor data collected by the users are exploited, in combination with the contextual information to update the attribute values of the entities.

All procedures are stored in the Repository component. This repository is shared among all the users and when one of them has to use one of the procedures, it can get and instantiate it in his own Knowledge Generation component.

8.2.2.1 Numeric Attribute Update Procedure

Consider this scenario. The system needs to know how fast the user is moving. Of course, the person can use multiple transportation means: walking, using the bus, using the car, among others. Unfortunately we do not have any direct way of inferring the user's speed because we don't have a dedicated sensor on her smartphone. On the other hand we are able to detect the user's car speed because of an IoT device that produces these data. We also have the information about when the user is in the car. By merging these two pieces of information, we are able to infer the required user speed that can then be used to make other analysis.

In our scenario, there are two entities involved, the user (eType Person) and the car, (eType Vehicle, which is-a Artifact). They have different Attributes (A) that characterize the entity themselves. For the sake of simplicity, here we present only the ones required to explain the example. For the **Person** we have:

- **Speed:** this is the Attribute (A) we need to update leveraging on sensor streams and contextual information. Here we assume that we require this attribute to infer a range of possible activities.

$$P_{SPEED} =<< Speed, FLOAT >, 0.0 > \tag{8.2}$$

while for the **Vehicle** we have,

- **Speed:** this is the Attribute (A) collected as a **stream of sensor data** from an external device. It is defined as

$$V_{SPEED} =<< Speed, FLOAT >, 48.0 > \tag{8.3}$$

- **UserPresence:** the car is provided with a sensor that detects the user presence which generates a boolean value

$$V_{USERPRESENCE} =<< Presence, BOOLEAN >, true > \tag{8.4}$$

In this situation the attribute *speed* of the person is the one we want to update using other entities in the context, in this case the *vehicle*. For this, a small computation task must be performed so that the different elements can be merged to produce the result used to update the value.

In order to solve the situation presented in the motivating example above, we present the following procedure that is able to update those attributes that have an Attribute Type (AT) of one of the allowed numeric types (i.e., integer, long, float, boolean).

A **Numeric Update Procedure (NP)** is defined for each Attribute Definition (AD) in the schema. This procedure will be then applied by the machine anytime an update is requested. It is composed by one or more input sensor stream $\{SS\}$, one or more attribute values of other entities $\{A\}$ (optional), a set of features $\{F\}$ to be extracted from the data and an algorithm that processes all such inputs to generate the output of the same format of the Attribute Type (AT) of the specific Attribute Definition (AD). Formally speaking it is defined as a tuple

$$NP =< AT, \{SS\}, \{F\}, \{A\}, O, ALG > \tag{8.5}$$

where,

- *AT* is the data type of the Attribute Definition (AD) the procedure is updating;

- *{SS}* is a non-empty set of sensor streams the attribute value has to be computed from. They can be mandatory and optional. The optional ones, if present, can be used to reinforce the output;
- *{F}* is a set of features that need to be analyzed by the algorithm to generate the output. These features are computed from the input sensor streams {SS} by a dedicated Feature Extraction component in the procedure;
- *{A}* is a non-empty set of attributes belonging to the same or other entities whose values has to be considered in the analysis. They can be mandatory and optional. The optional ones, if present, can be used to reinforce the output;
- *O* is the output Attribute of the entity of type AT the procedure has to update;
- *ALG* is the algorithm that generates the numeric value that updates the entity attribute. It takes into account both the mandatory inputs and the optional ones if present and the reinforcement strategy in the latter case should be defined.

With respect to our initial scenario, the procedure is defined as follows:

- The situation illustrates the need of creating one Procedure (NP) for updating the Value (V) of the Attribute (A) speed of the Entity (E) person.
- The data type AT is a FLOAT
- The input stream is only the vehicle speed, V_{SPEED}
- The feature that needs to be used is the average of the speed values so that to remove unwanted fast changes
- The contextual information input is the presence of the user in the car that maps to the corresponding attribute $V_{USERPRESENCE}$
- The attribute where to update is P_{SPEED}
- The algorithm ALG in this case is straightforward and does not require particular machine learning techniques.

The resulting procedure is represented as follows:

$$P =< FLOAT, V_{SPEED}, AVERAGE, V_{USERPRESENCE}, P_{SPEED}, ALG > \tag{8.6}$$

8.2.2.2 Semantic Attribute Update Procedure

Consider this scenario. A smart home environment needs to know when the user arrives at home in order to perform some task, i.e., turning on the lights of the living room. Instead of having dedicated sensors deployed in the environment the system leverages on the data collected from the user smartphone. The smartphone collects multiple sensor streams and few of them allow to determine the user position: the *GPS coordinates* or the *WiFi network the user is connected to*. For both sensor streams, an additional step is required to translate the raw data to the higher level situation of "being at home". This step uses the raw data in combination with some contextual information to change the Position attribute of the Person, i.e., which in this case represents the person location in the WE context dimension as defined in Section 7.3, to "Home".

In this example there are three entities involved (actually two plus one which was not mentioned in the example). These entities are: the User, the Home and the Office. The first one is of Entity Type (ET) **Person** while the other two are **Location**. They have different Attributes (A) and to keep things simple, with present only the ones directly related with this example.

For the **Person** we have:

- **Position:** this is the most recent known position of the user. It is represented as a relational attribute that links the user with another entity that pertains to his knowledge (view of the world). It is defined as

$$P_{POSITION} =<< Position, ENTITY >, E_{SURI} > \tag{8.7}$$

  where E_{SURI} is the identifier (as explained in Section 8.1.2) of the representation the user has of a certain location represented by entity E.

while for the **Office** we have,

- **Position:** this is the position of the user's office in the real world, expressed with an object defined as **Coordinates**

$$O_{POSITION} =<< Position, OBJECT >, coordinates > \tag{8.8}$$

  where *Coordinates* is composed by three numeric float values: *latitude*, *longitude*, *altitude*

$$Coordinates =< latitude, longitude, altitude > \tag{8.9}$$

and for **Home**:

- **Position:** this is the position of the user's office in the real world, expressed with an object defined as **Coordinates**

$$H_{POSITION} =<< Position, OBJECT >, coordinates > \tag{8.10}$$

where *Coordinates* is composed by three numeric float values: *latitude*, *longitude*, *altitude*

$$Coordinates =< latitude, longitude, altitude > \tag{8.11}$$

- **WifiNetworkAddress:** this is the MAC address of the WiFi router present in the user home. Is is defined as:

$$H_{WIFINETWORKADDRESS} =<< Address, STRING >, "address" > \tag{8.12}$$

A **Semantic Update Procedure (SP)** is defined for each Attribute Definition (AD) in the schema. This procedure will be then applied by the machine anytime an update is requested. With respect to the procedure for the Numeric Attribute Types, this one needs to account for the variability of the attributes of the entities and then is more complex. It is composed by one or more input sensor stream $\{SS\}$, one or more attribute values of other entities $\{A\}$ (optional), a set of features $\{F\}$ to be extracted from the data, an algorithm ALG that processes all such inputs and searches for a match $\{SR\}$ in the user knowledge that will be then provided as output to the attribute O. Formally speaking it is defined as a tuple

$$P =< \{SS\}, \{F\}, \{A\}, \{SR\}, O, ALG > \tag{8.13}$$

where,

- *{SS}* is a non-empty set of sensor streams the attribute value has to be computed from. They can be mandatory and optional. The optional ones, if present, can be used to reinforce the output;

- *{F}* is a set of features that need to be analyzed by the algorithm to generate the output. These features are computed from the input sensor streams {SS} by a dedicated Feature Extraction component in the procedure;

- *{A}* is a set of attributes belonging to the same or other entities whose values has to be considered in the analysis. They can be mandatory and optional. The optional ones, if present, can be used to reinforce the output;

- *{SR}* is a set of entity SURI that match the query performed by the algorithm ALG based on the result of the computation of the input streams {SS} based on the attribute values {A}, if any;

- *O* is the output Attribute of the entity the procedure has to update;

- *ALG* is the algorithm that generates the numeric value that updates the entity attribute. It takes into account both the mandatory inputs and the optional ones if present and the reinforcement strategy in the latter case should be defined.

With respect to our initial scenario, the procedure is defined as follows::

- The situation illustrates the need of creating one Procedure (P) for updating the Value (V) of the Attribute (A) **Position** of the Entity (E) Person.
- There are two input streams, the *GPS coordinates* and the *WiFi network the smartphone is connected to*;
- The feature that needs to be computed for the GPS data is a median point that averages the last X collected points in a short period of time in order to balance the uncertainly. This is done with a clustering algorithm. For the WiFi network name, nothing is done;
- There is no contextual information input $\{A\}$
- The attribute where to update is $P_{POSITION}$
- The algorithm ALG needs to perform different tasks:
  - Take the point generated from the feature extraction component and, if any, perform a query to the knowledge database of the user, the EB system, for entities of type Location which Position attribute matches the point;
  - Or, if the stream of GPS points is empty, use the second stream, the WiFi network address the phone is connected to. In this situation will search for the entities of type Location which WifiNetworkAddress attribute matches the WiFi address;
  - The SURI of the found entity will be then sent to the output O of the Procedure.

The resulting procedure is represented as follows:

$$P =< \{GPS, WiFi\}, \{CLUSTER, -\}, -, U_{POSITION}, ALG > \tag{8.14}$$

8.3 Operations Scheduler

The Operations Scheduler is the component that schedules all the Knowledge Instantiation and Update tasks. There are two ways the knowledge can be generated:

- **Timers.** The timer allows performing operations on a regular basis the user or an external service defined. For example, a service that generates a quantified self-report can be executed during the night, on the data of the previous day, so that in the morning the user can visualize it and see information of the day before. The timer can be arbitrarily complex, allowing to do any possible combination with exceptions.
- **Triggers.** On the other hand, some external inputs can trigger the knowledge generation process, like the user input or a change to any value of the entities in the context.

8.4 Summary

In this Chapter, we proviede an overview of the reference architecture which allows us to implement the Person eTypes. We illustrated a logical view that consists in a schematic showing all the system architecture. They can be grouped into three sub-systems: Data Acquisition and Management Subsystem, Knowledge Generation Subsystem, Knowledge Exploitation Subsystem.

We presented the different sources of the data, both streaming and knowledge, their importing pipelines and the data storage. We focused on this latter element, since it consist in the storage not only of streaming data but also the user knowledge and therefore the modelling of her personal data. This data storage is the Entity Base (EB) System.

We then described how the knowledge can be generated, dividing this phase into two sub-phases: the knowledge instantiation and the knowledge update. The former is used to create entity instances that are not present in the user EB, while the latter allows to update the existing entities so that to adapt to the context changes, according to different procedures defined depending on the data (in our case personal data). Finally, we explained how the knowledge generation can be triggered, using a timer that schedules the operations at fixed time intervals or using external triggers.

Part III

Use cases

Chapter 9

The Mainkofen Hospital

This section introduces the first use case for our approach for modeling personal data. It refers to a scenario within the geriatric ward of the Mainkofen hospital which was at the base of a collaboration with DFKI within the SmartSociety EU project. Our contribution was to model of nurses' behavior. It is our first use case at modeling personal data in terms of eTypes, especially in terms of context dimensions focusing on locations, activities, and objects.

The remainder of the chapter is as follows. Section 9.1 presents the Mainkofen hospital scenario, while Section 9.2 details the eTypes of the scenario. Section 9.3 concludes the chapter illustrating the importing process for the entities in our database.

9.1 The Scenario

The use case took place in the Mental Hospital Mainkofen in Deggendorf, Germany. The initial objective of this experiment was motivated by the request for an application assisting nursing documentation and the need to develop a solution that can be deployed in an average hospital. From this three main constraints resulted:

1. The only sensor placement on which the nurses could agree was to just put it into the coat pocket, as shown in Figure 9.1. Not all had pockets in the trousers, and strapping anything to the body was considered to be too much of a disruption and potential source of injury when patients would hold on to a nurse. Furthermore, all other locations could easily expose the sensor to damage.

2. No videos were allowed, and sound could only be recorded if it was cut into pieces and randomly mixed so that no speech could be retrieved.

3. The nurses could be followed while researchers took notes, but could not interfere with the nurses' routines.

In the hospital ward chosen, four nurses performed a morning hygiene routine for a few (2 to 3) patients each, including activities like washing, showering, drying, dressing, making the bed, measuring pulse and blood pressure and so on. The experiment at the ward lasted for a total duration of 14 days, each with four recorded runs of the morning shift procedure with a total of 18 different nurses. Overall, more than 800 hours of sensor data were

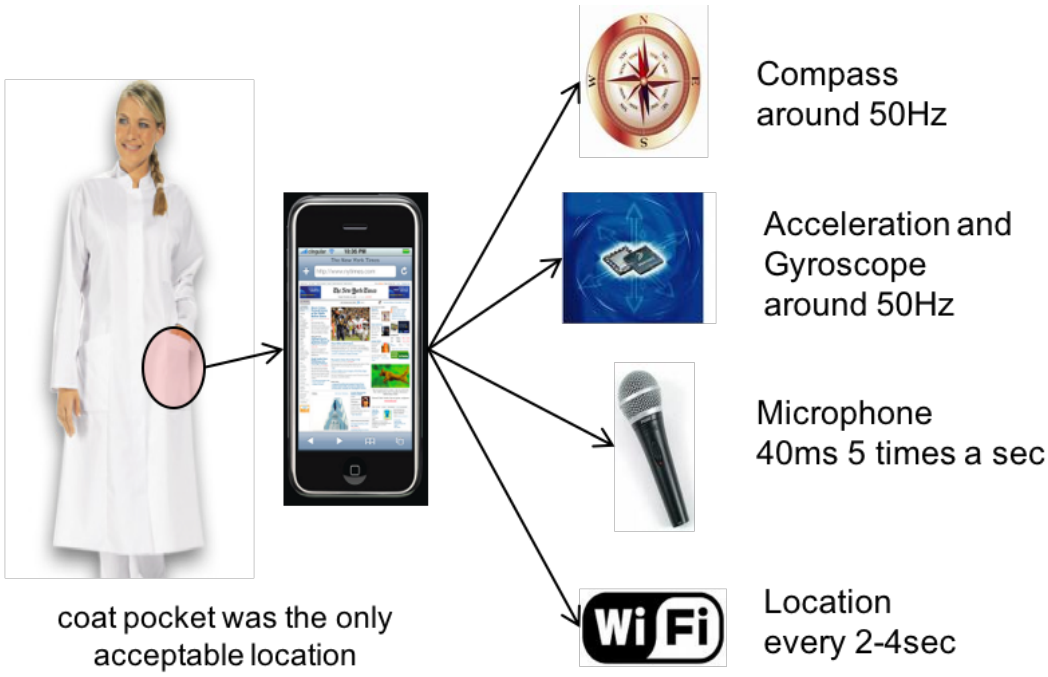


FIGURE 9.1: The position of smartphones and the available sensors.

recorded. Each of these runs was slightly different, both because the nurses were free to choose the order of execution of some activities as well as the need to fit them to a patient's requirements.

The platform used for sensing was a standard smart-phone, placed in the coat pocket of each nurse. Nurses' smartphones were equipped with the following sensors: accelerometer, compass, gyroscope, sound, and Wi-Fi. Major constraints were invisibility towards patients and unobtrusiveness, as it was not permissible to obstruct or hinder the nurses in any way. Notice that patients do not have any sensors attached, so they can be "sensed" only when interacting or being close to nurses. Similarly, there are no sensors attached to objects of the environment, therefore only those directly picked up by one or more sensor, e.g., sound in the case of electric shavers or gloves, can be recognized. The recorded sensor data was annotated by a researcher trailing each nurse, using iPads running a labeling application developed for this study. This allowed annotations at less than 1-minute scale. To maintain the quiet atmosphere on the ward, only two of the four nurses work could be annotated every day. As a result, 30 sets of activity annotations (including approximately 130 patient and 120 nurse flow executions) were collected.

Figure 9.2 shows the floorplan of the ward. Rooms starting with Z are patient rooms, often having a bathroom inside (save for Z5) and have one nurse assigned to them (except fro Z10, which is shared by two nurses), while the rest of the rooms are service room, ranging from other bathrooms to waiting rooms.

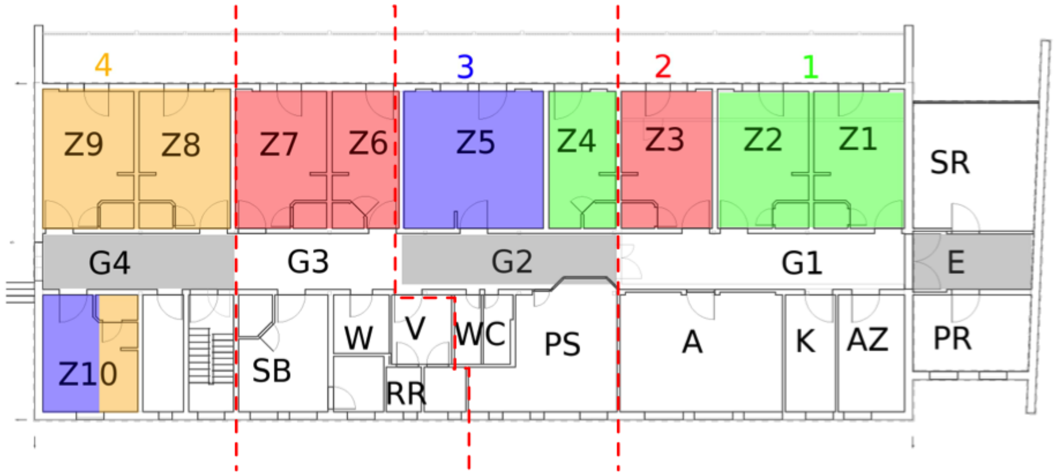


FIGURE 9.2: Mainkofen Hospital ward

9.2 The Mainkofen eTypes

For our model we relied on the nurse logs noting their activities together with the various rooms visited in their daily routine. The notes follow a legend created ad hoc representing:

1. Location: Rooms of the ward, e.g., G1, and SB, and the hotspots in a room: e.g., Z2-closet

2. Patients: Patients were labeled with their room number and the position of their bed

3. Activities, Objects, and Body parts: Activities always start with a number, which specifies the kind of task, and is followed by "-" and one activity that can, in turn, involve either an object or a body part. Objects and body parts always start with a capital letter, activities always start with a lower case letter. For instance, "1Activities - put down" (common activity, i.e., put down (something))

Based on these elements, we modeled the eTypes of the use case as showed in Figure 9.3.

Notice that how the Mainkofen model represents the four dimensions from Section 7.3 and show how our granularity of representation can change depending on the available data, e.g., lack of information. These details will be addressed in the following subsections, where we describe each eType, providing a detailed overview and motivation for its modeling.

9.2.1 Person

Table 9.1 shows our model for the Person eType. There are two possible roles for Person: nurse and patient. The latter, since it does not have a dedicated sensor, can only be recognized indirectly through nurses and thus cannot

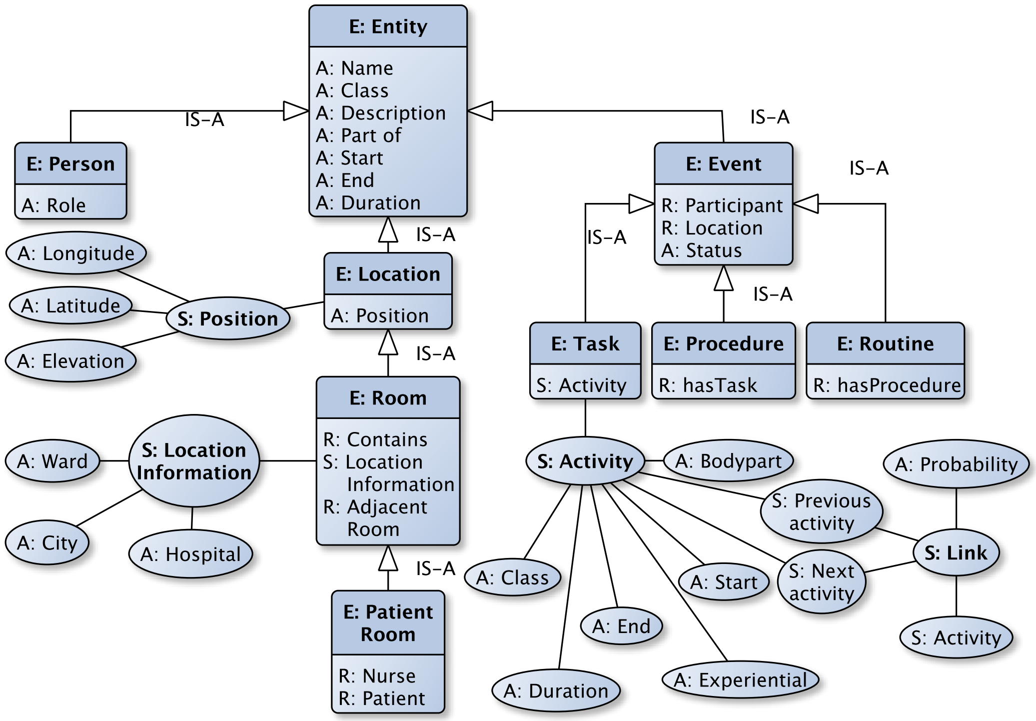


FIGURE 9.3: Final model of the Mainkofen eTypes

TABLE 9.1: Person eType

Attribute Name	Description	DataType
Role	the role of a person; the concept restriction is {nurse,patien}	Concept

justify additional attributes. To avoid complicating the model, we put role as an attribute instead of creating two different eTypes. Furthermore, since patients are only known through IDs based on the position in their room, we cannot understand whether the patient is the same in every routine, whereas the nurses' IDs are unique. The scarcity of attributes is mainly because, for privacy reasons, neither nurses or patients had additional information apart from their name and role.

9.2.2 Location

Since the location eType here is a simplified version of the core eType from Section 4.2, we only detail its subtypes, i.e., Room and Patient Room shown in Table 9.2 and 9.4 respectively.

In the case of Room, the attribute Contains accounts for those rooms included in other rooms (mostly bathrooms). The attribute Furniture represents the furniture that can be found in the room. Finally, the attribute Adjacent Room represents the set of rooms that have at least one shared a wall with the room.

TABLE 9.2: Room eType

Attribute Name	Description	DataType
Contains	other room(s) included in this room	<Room>
Furniture	the furniture in the room	Concept
Adjacent Room	the adjacent room(s)	<Room>
Location Information	information about the room	<Location Information>

The modeling of the ComplexType Location Information, shown in Table 9.3, is in accordance with the entity-centric methodology whenever there is a scarcity of data. In fact, while it would make sense to represent Ward, Hospital, and City as eTypes, since they can be uniquely referred via names, the real word data does not either support nor motivate their presence.

TABLE 9.3: Location Information ComplexType

Attribute Name	Description	DataType
Ward	the ward of the hospital	NLString
Hospital	the hospital of the ward	NLString
City	the city of the hospital	NLString

As for Patient rooms, they are relevant sub-types since that is where the majority of the activities are performed together with bathrooms. The amount of patients depends on the room, while in the majority of the cases only one nurse is assigned per each patient room.

TABLE 9.4: Patient Room eType

Attribute Name	Description	DataType
Nurse	the assigned nurse in the room	<Person>
Patient	the patient(s) in the room	<Person>

9.2.3 Event

We propose three sub-types of the core eType Event:

Tasks: localized activities during the daily routine

Procedures: the set of activities that are part of the daily routine and are usually performed to each patient

Routine: the complete sequence of activities performed in a day by a nurse

LISTING 9.1: Excerpt from a nurse log

```
1304397687.039   4Examin-cuffON
1304397696.604   4Examin-inflate
```

```
1304397704.559  4Examin−MEASURE
1304397713.088  4Examin−cuffOFF
1304397716.696  4Examin−search pulse
1304397719.605  4Examin−MEASURE
1304397750.344  2P−Activities−take P to
1304397754.067  Z10−bathroom
1304397771.246  5Hygiene−undress
1304397780.845  2P−Activities−sit on toilet
```

Listing 9.1 shows an excerpt from a nurse log: Here we can see that the uppercase string beginning with a number, e.g., 4Examin, is a *procedure*, while lowercase string after it, e.g., *cuffON*, is a task, and finally, the whole log file is the routine, for that day, of a nurse.

Tasks are the "semantic" step forward with respect to the previous experiment since it is the coupling of the spatial *and* temporal information, which is an approach already considered in works in the ontology-based activity recognition, e.g., (Riboni and Bettini 2011). The advantage is that it allows for filtering impossible or not likely activities, e.g., showering a patient in a corridor, since the model has the representational power to associate this information and ignore impossible or very unlikely pairs of activities and locations. Indeed, while locations provide spatial information, activities provide the temporal information of a person, and they cannot be represented as entities since they lack identity. For instance, brushing one's teeth is not different *per se* but changes depending on where it is performed and who is performing it thus becoming a discrete part of reality, i.e., an event; hence, we treat activities are treated as ComplexTypes.

To model the activity, we restructured the eight classes of activities and 1 of objects from the nurses' logs. The classes are as follows:

1. **1Activities:** this class contains "general" activities, i.e., not associated with any specific procedure; these activities can often be found in other classes. For instance, "pick up," "put on," and "take off."

2. **2P-Activities:** this class contains activities concerning interactions with the patient. For instance, "wake up," "sit on toilet," and "lie down."

3. **4Examin:** this class contains activities and objects concerning the process of measuring the patient's blood pressure. For instance, "search pulse" and "sphygmomanometer."

4. **5Hygiene:** this class contains activities and the body parts involved in the process of washing the patients, mainly by taking them to the bathroom, in addition to other body care activities, e.g., shaving. For instance, "brush teeth" and "Chest."

5. **6WASHBed:** this class contains activities and the body parts involved in the process of washing bedridden patients; hence, many activities are similar to 5Hygiene.

6. **7Dress:** this class contains activities and clothes involved in the process of dressing or undressing the patient. For instance, "undress" and "socks."

7. **8Clean:** this class contains activities and objects concerning the cleaning of the patients' room. For instance, "make bed" and "lock closet."

8. **9Medics:** this class contains activities concerning the process of handling medical equipment and performing some treatments. For instance, "search vein" and "bandage."

Given that these classes and their membership did not follow any (formal) methodology, we encounter several issues when building the activity tree:

1. Same activity in different classes: general activities are repeated in various classes, e. g., "pick up," increasing the cases of multiple inheritances

2. Different semantics but same activity class: the same term was used to refer to a different concept, e.g., "clean" used to mean both washing and tidying a room.

3. Inconsistent distinction between activity and objects: some activities incorporate objects in their name, e.g., "prep wChair" (i.e., preparing a wheelchair for taking the patient to another room). We consistently divided activities and objects as concepts, e.g., "prepare" and "wheelchair", and explicitly link them through the modeling of activity.

4. Incorrect English words or not translated German words: some words were incorrectly translated from German or not translated at all.

Although there is no explicit hierarchy in the activity list, we established one, shown in Appendix B.2, where we divided between individual activities (i.e., 1Activity) and patient activities (i.e., the other classes); furthermore, we put bed-ridden activities (i.e., 6WASHBed) under Hygiene activities since they are a special case of hygienic procedure, i.e., cleaning a bed-ridden patient, and share some activities.

To structure the object and activity ontology, we relied on Wordnet, following a slightly different approach from the one described in Section 7.1. In fact, we we initially treated Mainkofen activities as verbs since the noun *act* did not cover Mainkofen activities as much as verbs. Nonetheless, there are cases of an actual alignment between the act synset tree and the verbs trees, since in some cases the noun is simply the –ing form of the verb, e.g., cleaning and packing, whereas in other cases it is a noun in its own right, e.g., removal. In fact, only 3 of the Mainkofen activities are actually related to this synset. Generally speaking, out of the Mainkofen activities, only 9 are not represented in Wordnet at all, i.e., "search pulse", "draw blood", "sit on", "sit into", "take to", 'search vein", "check on", "go to", "pack up", "pull up", and "uncuff". Because of the structure of verbs in Wordnet, Mainkofen activities were either *i)* distinct verb trees or *ii)* the root of their own trees. The verbs falling under case *i)* can be found in Appendix B.4, whereas following verbs fall under case *ii)*: **use**;

open; **release**; **close**; **lead**; **uncover**. These synsets have different hyponyms and hypernyms; in other words, while there may be ontological alignment or ontological synonymy at node level, there is not at edges level, since their syntactical category entails different relations.

Overall, Wordnet covers a fair number of Mainkofen activities:

1. The verb had a derivational noun that is either:
   (a) a hyponym of:
      i. Act: 5
      ii. Activity: 18
      iii. Action: 20
   (b) Not a hyponym of a): 7
   (c) The verb had no derivational noun: 15 + 10 new concepts

Similarly to activity, we created a hierarchy of objects and bodyparts in Appendix B.3 and faced the following issues when creating it:

Same object in different classes: some objects are associated with activity classes; however, they can actually be composed with other activity classes, mostly in the case of 1Activities;

Objects and body parts: body parts are treated as objects in both Hygiene Activity and Bed Ridden Activity activity classes.

Table 9.5 shows the Task eType, while Table 9.6 shows the Activity ComplexType. Notice that the start and end of the activity have timestamp as a data type since that is the format adopted in the Mainkofen logs. We characterized activities by adding Patient, Bodypart and Object to account for the additional information about the activity in accordance with the logs, while Experiential is to handle those hints provided in the logs on whether the activity was associated with a specific sound, e.g., water running or hair dryer blowing. These hints also followed a manner-like relation with the activities, in the sense that their sensors could be inferred *a posteriori* with the manner of carrying out the activity

The Link ComplexType, shown in Table 9.7, represents a Finite State Machine-like structure allowing us to navigate through the sequence of activities and hence tasks. The link between two activities has a certain probability value, which is not directly taken from sensors but that can be computed from the notes. Therefore, we can track the sequence of individual events without moving to more abstract entities, e.g., procedures. In fact, procedures can often be interrupted by individual tasks or procedures, e.g., a nurse forgetting a stethoscope while examining a patient and going back to pick it up.

Procedures are therefore modeled as sequences of events and they are important recurring events because they tend not to happen to the same patient and in the same room in the same day, i.e., in the daily routine. Nonetheless, they tend to change according to nurses and the available patients, although some medical procedures tend to follow a more rigid sequence. Finally, routines are in turn acting as a sequence of procedures, thus raising the abstraction further.

TABLE 9.5: Task eType

Attribute Name	Description	DataType
Activity	the localized activity	<Activity>

TABLE 9.6: Activity ComplexType

Attribute Name	Description	DataType
Start	the start of the activity	Timestamp
End	the end of the activity	Timestamp
Duration	the duration of the activity	Float
Class	the class of activity	Concept
Object	the optional object to carry out the activity	Concept
Patient	the patient involved in the activity	<Person>
Body Part	the body part involved in the activity	Concept
Experiential	the hints from the nurses' logs	NLString
Previous activity	the activity before this one	<Link>
Next activity	the activity after this one	<Link>

9.3 Processing nurses logs

Once the model was defined, it had to be imported into our system to extract high-level information needed for the success of this experiment.

9.3.1 Pre-importing phase

As we agreed, the information to build the model was taken from two data sources:

1. Test logs from the tests performed at the Mainkofen Hospital in 2011. The test logs cover the activities performed by the nurses in the four areas of the ward on the 2nd, 3rd, 5th, 9 th, 16 th, 18 th, and 19th May 2011.

2. The .json files, i.e., menues, roomhotspots, and person, providing information about activity and object classes, locations and people, which can be found in Appendix B.5.

9.3.2 Parsing Tool System

Once we imported the structure of the model, we needed to populate it; this required an ad hoc program "translating" testlogs lines into entities. As showed in Figure 9.4, it consist of two components:

TABLE 9.7: Link ComplexType

Attribute Name	Description	DataType
Activity	the activity in the sequence	<Activity>
Probability	the probability of the activity in the sequence	Float

TABLE 9.8: Procedure eType

Attribute Name	Description	DataType
HasTask	the task(s) in the procedure	<Task>[]

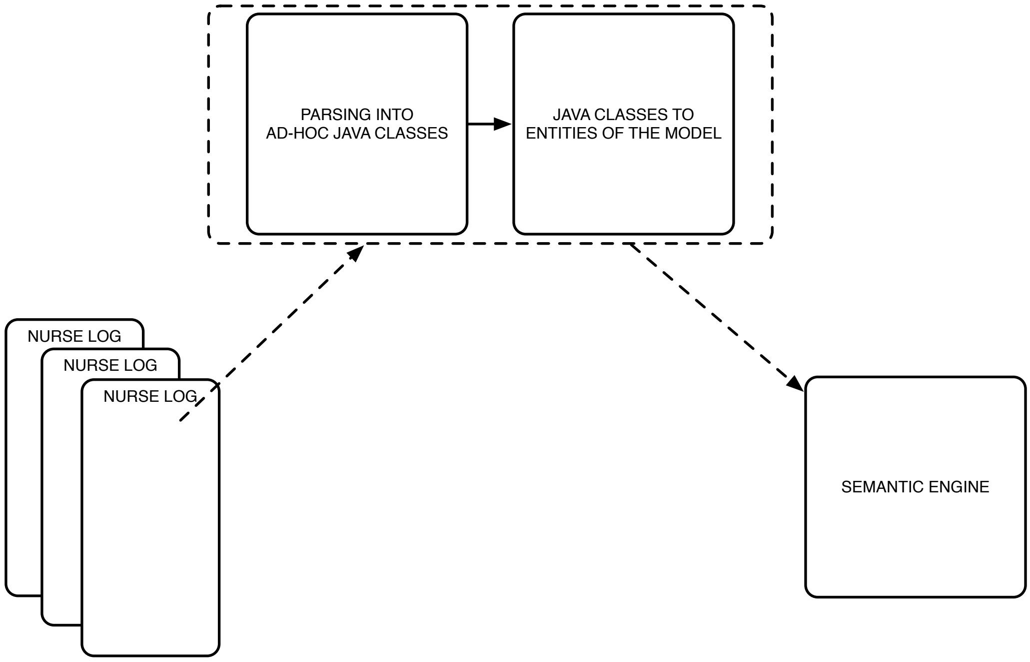


FIGURE 9.4: Translation program architecture

1. The first component interprets test log files line by line and creates ad hoc Java classes, which mirror the classes of the model. In the first phase, the program imports as a cache the hospital locations and their structure. Then it handles rooms, patient rooms, hallways, and bathrooms, specifying for each one the adjacent rooms and those contained, i.e., bathrooms in the case of patient rooms; these objects will be used by other classes. Then, the program captures the logs labels line by line to save it in the corresponding class. To do this step, we created four files called rooms.txt, rooms_ detail.txt, nurses.txt e patients.txt to assist the transition from logs to classes.

2. The second components converts the Java classes created by the first component into dedicated classes to be imported in the semantic engine

However, we could not make the translation process from the raw log form to parsable text file fully automatic. The main reason is that, while they

TABLE 9.9: Routine eType

Attribute Name	Description	DataType
HasProcedure	the procedure(s) in the routine	<Procedure>[]

did have a predefined set of activities, people, and locations, their flow is not always consistent. For instance, patients in the logs are recognized and the all the activities following them assume them until a new patient is recognized. Moreover, this may happen in short time, as in Listing 9.2, or can take several minutes.

LISTING 9.2: Switching from one patient to another

```
1304398904.962  1Activities-talk
1304398904.962  Z8-M
1304398929.120  Z8-M
1304398946.926  note-calm down Patient
1304398996.388  G4
1304399005.475  Z9
1304399016.295  Z9-T
1304399018.390  1Activities-talks
```

Therefore, we manually had to translate a set of nurse logs based on the parsing schema done by the program. For instance, the activity of instructing patient Z7-T while the shower is on in Listing 9.3

LISTING 9.3: Original nurse log example

```
1304397289.762  Z7-T
1304397389.561  5Hygiene-SH +
1304397451.591  5Hygiene-instruct
```

would then be translated as showed in Listing 9.4

LISTING 9.4: Translation of nurse logs example

```
{"timestamp" : 1304397451, "activity" : {"name" :
"instruct", "end" : 1304397460, "patient" : "Z7-T",
"experiential" : "shower"}, "procedure" : "5Hygiene"}
```

This allowed us to inject semantics in the nurse logs to ease the population of the model. Furthermore, it allowed us to better compute the probability of sequences of activities. Unfortunately, this process had to be done manually since the logs are not consistent enough in terms of notation, even across the same nurse, making the automatization of the translation infeasible.

Currently, our model has been populated with 2514 entities, consisting for the majority of individual tasks taken from 6 routines of the first two days of the Mainkofen experiment, two per nurse. The full view of these data can be found in the Appendix B.1. Overall the table represents the whole current model populated, while also tracking the computed probability of next and previous activities.

Chapter 10

SmartUnitn

The second use case is the SmartUnitn project, which is a sub-project of the ƧMAЯTRAMS research program[1]. These projects leverage on technologies, such as smartphones, living in symbiosis with their users and perceiving the world as they do to extract behavioural patterns from users and develop systems that assist them in their everyday life.

SmartUnitn is based on the collaboration between the Department of Information Engineering and Computer Science with the Department of Sociology and Social Research of the University of Trento. The main goal of the project, is to fill the research gap concerning students' time allocation and academic performance by providing a detailed description of how their time management affects their academic achievement. It is be two-year project that is run every 6 months, with every iteration involving more students and hence more data.

The remainder of the chapter is structured as follows. Firstl, we give an overview of the project, its motivation, and our contribution to it in Section 10.1. We provide a detailed account in Section 10.2 in terms of process and requirements of our modelling of students within the project. Then illustrate the two iterations of the SmartUnitn project in Section 10.3 and Section 10.4.

10.1 The SmartUnitn Project Overview

In fact, empirical evidence has shown how students' time management ability and its consequent translation into time allocation between academic and other daily activities may have an impact on students' performance (Fernex, Lima, and De Vries 2015; Grave 2011). Several works found that there is a positive correlation between lesson attendance and academic performance (Roby 2004) and between self-study and academic achievement (Doumen, Broeckmans, and Masui 2014), while (R. Stinebrickner and T. R. Stinebrickner 2003; Pike, Kuh, and Massa-McKinley 2008) analyzed the negative effect of working during university on academic performance.

Currently, there is a lack of data about students' time allocation, especially in Italy, which are only available as aggregate data, e.g., (Mucciardi 2013). The current lack of knowledge between time inputs and students' academic performance is almost certainly a result of the cost and difficulty of collecting appropriate data (R. Stinebrickner and T. R. Stinebrickner 2004). Studies in this

[1] See http://trams.disi.unitn.it for more information

field usually ask students stylized-questions that provide the researchers with aggregated time use information. Stylized questions methods suffer especially from memory bias, since respondents must not only recall their activities in the recent past, but must also provide an accurate form of averaging (J. Robinson and Godbey 2010). This may lead to overestimation or underestimation of time spent in some activities, together with lack of detail in reporting them (Kan and Pudney 2008). However, self reports such as time diaries, presented in Section 2.7, are helpful to overcome this limitation. In fact, they provide more detailed information not only in terms of the total amount of time spent by students in certain activities, but also their order and duration during a specific time window, allowing sociologist to correlate them with data on students' academic performance.

Smartphones can enhance time diaries by administering them to users, which then are able to answer them in (almost) real time, in addition to performing sensor collection, e.g., GPS, accelerometer, Bluetooth, call logs, and running applications, among others (F. Giunchiglia, Zeni, et al. 2017). These two functionalities of smartphones can be exploited to match any given triple of reported activity, location, and social relation with the status of the smartphone as a proxy of the actual user behavior.

Our contribution in this project is twofold:

1. From a technical point of view, based on Mattia Zeni's work, we install the i-Log mobile application on students' smartphones so that we were able to collect data about them. The analysis consisted in extracting useful information from such data related to how students manage their time, and then understand if there was a correlation with their academic performances. In addition, students are administered time diaries to learn about their behaviors, as the answers provide annotations and an additional source of information to smartphone sensor data.

2. From a modelling point of view, we modelled students, resulting in the Student eType.

10.2 Modelling Student

For modelling students' personal information, we had two requirements. Firstly, with respect to currents standards in modelling students, shown in Section 10.2.1, and also with respect to the time diaries methodology, shown in Section 10.2.2.

10.2.1 Student Data Standards

As we shown in Section 6.3.4, there are several ways to represent completed education. In this use case, however, we were dealing with people in the process of obtaining a post-secondary education such as university students. Therefore, we had to consider existing standards dedicated to represent students of this level of education.

Firstly, we considered the way student information is structured in our University, shown in Figure 10.1, since the project involves students from there. A student profile consists mainly of demographic data, such as: student id, the study course level, the profile, the current year of enrollment, the date of enrollment, the course, study system and the type of study plan. Overall, we considered as candidate attributes all those non system specific, which lead us to ignore the student's profile property.

ENRICO BIGNOTTI - [MAT. 149608]

General information regarding your university career.

Student information

Study course level: Master
Student's profile: Standard
Year of enrollment: 2
Date of first enrollment: 19/10/2010
Study course: [0420H] - Philosophy and the Languages of Modernity
Study system: [0420HR09] - Ordinamento 2009
Study plan: [P0004] - standard

Enrollment status

Academic year	Study course	Year of enrollment	Date	Enrollment status	Years of delay	Under condition
2010/2011	0420H Philosophy and the Languages of Modernity	1	19/10/2010	On time	0	NO
2011/2012	0420H Philosophy and the Languages of Modernity	2	15/09/2011	On time	0	NO

FIGURE 10.1: The student profile in the University of Trento, using the thesis author's record as a Master student.

With respect to more general standards, in order to make the eType as general and reusable as possible, we considered the IMS-LIP (Smythe, Tansey, and Robson 2001) specifications from the IMS Global Learning Consortium [2]. It is a data model that describes characteristics of a user needed for the general purpose of recording and managing learning related history, goals and accomplishments, engaging the user in a learning experience, and discovering learning opportunities for user. Among these characteristic, we focused on the *affiliation* module, which is used to store the descriptions of the organization affiliations associated with the learner, here our students. It has 12 main attributes, the most important ones being: *classification*, i.e., the type of affiliation membership, e.g., student, *the dates of affiliation*, and the *affiliation of the organization*, in order to enable arbitrarily complex affiliation structures to be constructed. Since the student profile only lists the course but not the department, we relied on the recursive affiliation to include both pieces of information in the student eType.

Finally we also considered other standards at European and international level. However, the main issue in these standards is they tend to be country specific. For instance, The Common Education Data Standards (CEDS)

[2] https://www.imsglobal.org/

project[3] is a national collaborative effort to develop voluntary, common data standards for a key set of education data elements to streamline the exchange, comparison, and understanding of data in the United States. It is at the version 7 of its vocabulary for representing education data, including post secundary students. While some concepts may be reused for general purposes, e.g., information about enrollment and courses, some are specific to the United States, e.g., CTE courses within a student's area of career interest or K12 transcripts.

10.2.2 Adapting to Time Diaries

In addition to standards, there was the need to adapt the student eType to account for the type of data researched in the time diary methodology.

Consequently, the general requirement was to adapt our modelling of context from Section 7.3 to become a time diary that students could answer to concerning their everyday life. The adaptation proceeded in accordance with these methodological considerations:

1. **Perdurant context:** Since activities are the main focus of research for time diaries, the context to be mapped to the annotations is a perdurant one. This allows us to mirror the relevance of activities, since events are the aggregating elements for perdurant contexts.

2. **From ontology to annotation lists:** Following the sociology experts inputs, to make the ontology usable it has to be adapted to a list of annotations, i.e., answers, without any sort of hierarchy. In fact, a simpler, leaner presentation is more likely to elicit and engage the users' answers, coupled with a controlled vocabulary for reducing possible ambiguities for users. In order to capture the most salient triple of location, activity and social relations (Hellgren 2014), the annotations act as a list of possible answer for the corresponding questions, i.e. "Where are you?" (locations), "What are you doing?" (activities) and "Who is with you?" (social relations).

3. **No *WI* context dimension:** In the case of SmartUnitn, given that objects and artifacts are not usually investigated outside the standard triple of activities, location and social relations, the sociology experts do not deem the *WI* context dimension relevant. Thus, no mapping with the object context is required.

4. **Ordering of the questions:** According to the sociology experts, and in general for time use surveys (Hellgren 2014), activities are more relevant than locations and social relation in the experiment. Thus, the ordering of the three question mirrors this hierarchy: activities first, locations second and then social relations.

5. **No locations and activities constraints:** In activity recognition, locations can often act as as constraints for the activities performed there

[3] https://ceds.ed.gov/

(Riboni and Bettini 2011); for instance, when in bathrooms, people are more likely to be showering than cooking. However, from a sociological point of view, constraining may lead to a loss of valuable sociological data, e.g., students studying in places not explicitly designed for it, such as workplaces, bars or gyms. As a result, no constraints are imposed between the locations and activities annotation lists.

6. **Adding "Other":** In time use surveys, the answer "Other" is a standard option with possible variations, e.g., the "n.e.c." field (i.e., Not Elsewhere Classified) in the ATUS (Shelley 2005) at the end of each activity class. Methodologically speaking, this means that the possible activity, location or social relation is outside the research scope of the sociologist, so it does not matter; "Other" covers such cases (Claessens et al. 2007). Ontologically speaking, "Other" acts as an element of openness, i.e., as a placeholder node in the ontology to accommodate and expand new pieces of information to be added in time to an ontology.

The result of the mapping between our ontology and the sociological methodology for the experiment is three different lists of annotations. Notice that there is a decreasing level of granularity among activities, locations, and social relations in the mapping. In fact, since they are taken from a perdurant context, activities, being more relevant, are both more in terms of number of nodes and granularity than locations and roles

Fig. 10.2 shows the mapping of activities, i.e., the *WA* context dimension, from the perdurant context and the question about activities. Here the annotations are adapted by the first tier of activities, especially for "Relax", which maps to 4 annotations, i.e., "Hobbies", "Cultural Activity", "Other Free Time", and "Social Life". This coarseness in the mapping is due to the fact that, in order to capture high level patterns, the activities are required to be very general. Furthermore, more detailed activities, as underlined by the sociology experts, would cause more cognitive load in terms of memory by users and force them to answer more questions to reach an unnecessary fine grained level of detail.

Fig. 10.3 shows the mapping from the locations, i.e., the *WE* context dimension, of the perdurant context to the question about locations. Here the mapping is almost one to one with the lowest tier, except for "Other University place" and "Other Home", since they group more specific types of buildings.

Notice also that, even though "En route" is an activity, it refers to actual locations. So, if a student chooses it, then, instead of the options in Fig. 10.3, a list of means of transportation is provided and the question is "How are you travelling?". The possible means of transportation are listed as suggested directly by the sociology experts, i.e., "By Foot", "By Bus", "By Train", "By Car", "By Motorbike", and "By Bike".

Fig 10.4 shows that, in the case of social relations, unlike locations and activities, the mapping is one to one, since they are a simple list in our current version of the *WO* context dimension.

The three lists of annotations compose the time diary to be administered to users, shown in Table 10.1. Each list of answers is the mapped set of

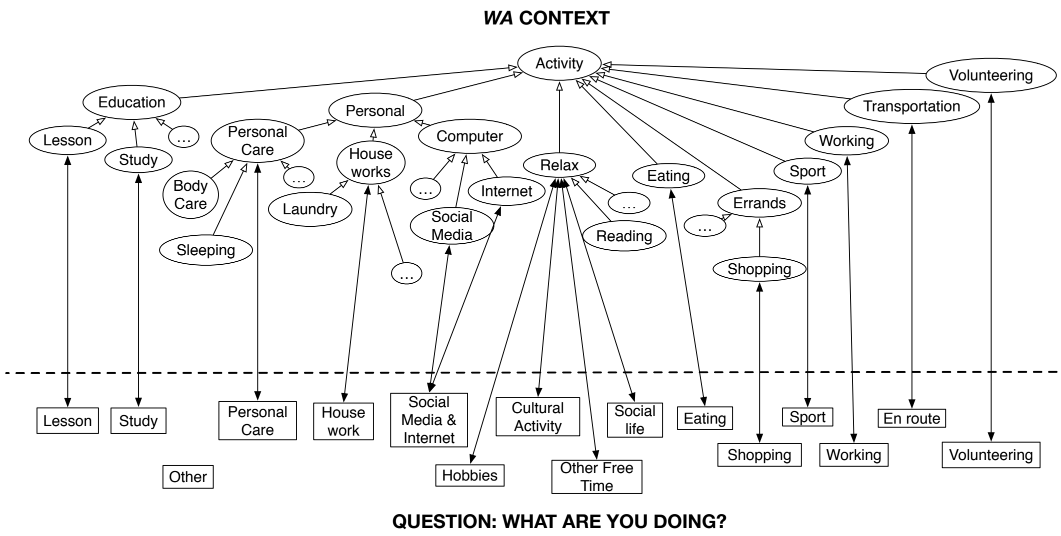


FIGURE 10.2: The mapping from the perdurant context to the activities annotation list.

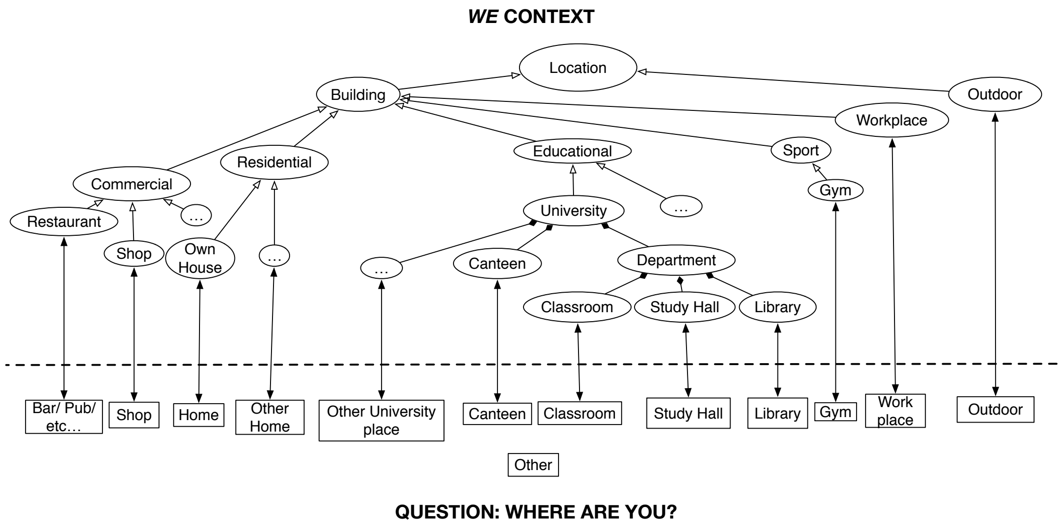


FIGURE 10.3: The mapping from endurant context to the locations annotation list.

annotations from Fig, 10.2, i.e., activities answering the question "What are you doing?", Fig. 10.3, i.e., locations answering the question "Where are you?" and Fig. 10.4, i.e., social relations answering the question "Who is with you?". The link between the fourth question "How are you travelling?" and the "En route" activity is shown via an asterisk at the end of the latter.

10.2.3 The Student eType

Based on the requirements from Section 10.2.1 in terms of static and demographic data, and Section 10.2.2 in terms of context data, this is the mapping between them and our categories of personal data from Chapter 5:

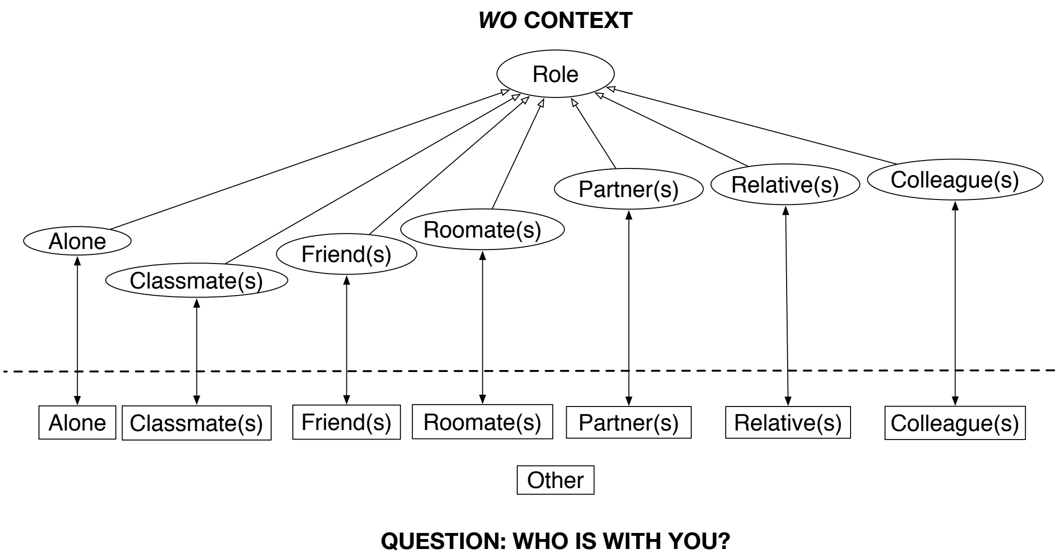


FIGURE 10.4: The mapping from role to the social relations annotation list.

TABLE 10.1: The time diary obtained from the adaptation process.

What are you doing?	Where are you?	Who is with you?
Lesson	Class	Alone
Study	Study Hall	Classmate(s)
Eating	Library	Friend(s)
Personal Care	Other University place	Roomate(s)
En route (*)	Canteen	Partner(s)
Social life	Bar/ Pub/etc	Colleague(s)
Social media & internet	Relative(s)	Other
Cultural Activity	Home	
Sport	Other Home	**(*) How are you travelling?**
Shopping	Workplace	By Foot
Hobbies	Outdoors	By Bus
Other Free Time	Gym	By Train
Work	Shop	By Car
Housework	Other Place	By Bike
Volunteering		Other
Other		

Name: Due to privacy reasons, we could not collect the name of students, thus we identify them through their UUID managed in the Stream Base System (SB). In addition, we also account for the student ID, since it would be needed for the sociologist to be compared with the academic performance data;

Goals: This category exists also in the IMS-LIP package; however, goals were not relevant in our use case, so we did not model them

Demographics: In this category we list the available demographics of students collected in terms of their role within the university. The only "general" demographic collected, i.e., among those from Section 6.4, was gender. With respect to the specific demographics for the use case, we relied on the way data is structured in our University database. Overall, the collected demographics consisted of 7 attributes: 1) gender 2) *dates* of *each* enrollment, 3) department, 4) faculty, 5) study course, 6) study course level, and 7) whether the student was awarded with a scholarship. Notice that we modified this attribute to account for the history of enrollment for student, thus making it explicit from the visualization in Esse3, whereas the other demographics were kept the same.

Contact: In this category we only considered the email as the only available contact to update students during and after the project.

Knowledge: No attribute from this category was required for this eType

Context: Given the adaptation from Section 10.2.2, students activities, locations and social relations were modelled as a single attribute without any further specification.

Academic Performance: This category is specific to this eType, and it represents the measures used to evaluate the progress of students' career:

Credito Formativo Universitario (CFU): Integer. It represents the credits for each exam taken by a student, whose amount varies depending on the length of a course;

Number of exams: Integer. It represents the total amount of exams successfully taken by a student;

GPA: Float. It represents the average grade of the student

These measures allow us to capture both the progress of their university career, i.e., CFU and number of exams since they refer to the progress of students' university career, and the qualitative dimension of academic performance, i.e., GPA, since it refers to the quality of students' performance.

10.3 SmartUnitn One

In the first iteration of the SmartUnitn project, 72 students were selected from the ones enrolled at our university in the academic year 2015-2016 and in particular only those who fulfilled three specific criteria: *i)*, to have filled three university surveys in order to obtain their socio-demographic data, shown in Table 10.3, and other characteristics, e.g., psychological and time use related; *ii)* to attend lessons during the period of our project in order to describe their daily behavior during the university experience, and *iii)* to have an Android smartphone with an Android version 5.0.2 or higher.

The students were asked to attend an introductory presentation where they are presented with the aims of the project and how to use the application. If they wished to participate, after the presentation they signed a consent

TABLE 10.2: Student eType

Attribute Name	Description	DataType
UUID	the identifier of the student	UUID
Student ID	the id of the student assigned by the University	Integer
Gender	the gender of the student; the concept restriction is{male,female}	Concept
Year of enrollment	Number of years the student has been enrolled	Date []
Dates of enrollment	dates of each enrollment	Date []
Department	the department of the student	<Organization>
Faculty	the faculty of the student	<Organization>
Study course	the course being undertaken by the student	NLString
Study course level	the level of study course; concept restriction is {bachelor, master}	Concept
Scholarship	whether the student is awarded with a scolarship	Boolean
Email	the student's email	NLString
Activity	sensed activities and states of the student	Concept
Locations	sensed locations of the student	Concept
Social relations	sensed social relations of the student	Concept
Credito Formativo Universitario (CFU)	the credits for each exam taken by a student, whose amount varies depending on the length of a course	Integer
Number of exams	the total amount of exams successfully taken by a student	Integer
GPA	the average grade of the student	Float

TABLE 10.3: Socio-demographics of students from our project

Gender		**Departments**		**Scholarship**	
Male	Female	Scientific	Humanities	True	False
61.1%	39.9%	56.9%	43.1%	37.5%	62.5%

form, and then installed i-Log on their own smartphones. Users were informed about all aspects of the management of their personal information concerning privacy, from data collection to storage to processing. Furthermore, before starting the data collection, we obtained the approval from the ethical committee of our university.

The project lasted two weeks: during the first one, students were asked to answer a time diary on their smartphone about their time use, while the application was collecting sensor data in the background. During the second week they were only required to have the application running for collecting sensor data.

Students received a fixed money compensation, as an incentive to participate, with additional three final prizes assigned to random users that were considered eligible. Eligibility was based on three parameters: *i)* how much data students' smartphones recorded in via GPS, Bluetooth, and Wi-Fi. We chose these three sensors since they are the only sensors that students could decide to turn off; *ii)* how many questions were answered by students, and *iii)* how long they kept the application running, knowing that they could turn it off at any moment.

We collected a total of 110 Gb of data from the 72 students for the whole duration of the project. The resulting dataset is a behavioural dataset that contains both time diaries answers and sensors data, thus exploiting sociological insights from the very beginning. It is also merged both with pre and post project surveys collecting socio-demographic characteristics of students, their time use habits asked through stylized-questions, some psychological traits measured by validated scales (i.e. pure procrastination scale or goal orientation scale) and academic performance data from the administrative office from our university.

In terms of answers, we collected a total number of 27111 answers triples, 9905 were empty because expired, resulting into a final value of 17207 valid answers triples, i.e., 51621 individual answers. A major reason for expired answers is the students were sleeping while they were generated. Furthermore, if we consider that on average people spend 8 hours sleeping, i.e., roughly 33% of a day, this suggests that students answers roughly every available questions in the rest of the day. Table 10.4 provides a breakdown of all the possible answers' categories divided by their corresponding question, i.e., "What are you doing?" (Table 10.4a), "Where are you?" (Table 10.4b), "Who is with you?" (Table 10.4c), and "How are you travelling" (Table 10.4d), i.e., the optional location question activated when selecting the "en route" activity.

In the case of activities, we can see that, while studying and attending lessons are common activities as expected for students (12% and 10% respectively), eating (17%) and self care (15%) are the most performed activities. This may be due to the fact that eating could cover also cooking and preparing food in general (which takes more time than actual eating), while self care refers to several activities such as cleaning oneself or indicate sleeping. In the case of locations, home is the most common location were students spend their time, since they spend there more than half their day (54.8%) and, among the different areas of the university, students spend most of their time in class (18.0%). The smaller amount of time spent in places specifically for studying such as libraries or study halls (2.5% and 1% respectively) may be due to the fact that the project was carried out a couple of months away from finals. In terms of social relations, it seems that students spent more than half of their days (36.9%) alone or with friends (25.8%), which however might also include classmates outside of the university and it may depend on commuters in our sample, since they would have the chance to meet people outside of the

TABLE 10.4: All answers provided by the students to the time diary questions:

(A) What are you doing?

Answer	Total (%)
Eating	3543 (17,8)
Selfcare	3017 (15.1)
Study	2437 (12.2)
Lesson	2123 (10.6)
Social media & Internet	1957 (9.8)
En route*	1849 (9.3)
Other free time	1679 (8.4)
Social life	1186 (5.9)
Other	419 (2.1)
House-work	379 (1.9)
Work	350 (1.7)
Hobbies	294 (1.4)
Sport	249 (1.2)
Shopping	166 (0.8)
Cultural activity	109 (0.5)
Volunteer-ing	106 (0.5)
Total	19881

(B) Where are you?

Answer	Total (%)
Home	8729 (56.8)
Class	2767 (18.0)
Other private house	1068 (6.9)
Bar/Pub-/etc	469 (3.0)
Outdoors	439 (2.8)
Study hall	397 (2.5)
Other place	313 (2.0)
Other university place	305 (1.9)
Workplace	210 (1.3)
Gym	191 (1.2)
Library	165 (1.0)
Shop	162 (1.0)
Canteen	141 (0.9)
Total	15356

(C) Who are you with?

Answer	Total(%)
Alone	6356 (36.9)
Friends	4447 (25.8)
Roommates	1837 (10.6)
Relatives	1579 (9.1)
Partner	1455 (8.4)
Colleagues	1118 (6.4)
Other	413 (2.4)
Total	17205

(D) *How are you travelling?

Answer	Total(%)
By foot	663 (43.1)
By car	529 (34.4)
By bus	278 ()
By train	271 (18.0)
By bike	77 (5.0)
By motorbike	23 (1.4)
Total	1536

university circle. As for the preferred mean of transportation, considering that the university is located in a small to medium sized Italian city, students can easily move around by walking (43%). The fact that car is the second most common answer (34%) may be due to the fact that some students commute daily from neighbouring towns.

10.4 SmartUnitn Two

The second iteration of the SmartUnitn project is scheduled to begin in April 2018. There are two main limitations of the previous iteration that SmartUnitn Two aims at addressing:

1. **Duration:** Two weeks are a relatively small window of time compared to other studies in computational social sciences, e.g., 10 weeks in SmartGPA (R. Wang, Harari, et al. 2015) and almost one year in the Copenhagen Networks Study (Karpinski et al. 2013). However, notice that one week of time diaries is considerably more than the usual amount of days recorded in sociology, which is usually limited to two days (one weekday and one weekend) (Romano 2008), and thus allowed us a bigger time window to extract patterns from.

2. **Sample size:** The original sample size of 72 students is considerably smaller than other studies in sociology, e.g., 263 students in (Rosen, Carrier, and Cheever 2013) and 1839 students in (Junco 2012). However, our sample is still larger than other works in the area of computational social sciences, e.g., 48 students in SmartGPA (R. Wang, Harari, et al. 2015) and 35 students in (Lee et al. 2017).

At the time of writing, a small sample of 12 students from the Master course in Sociology are testing an updated version of i-Log, consisting in:

- **Updated interface:** Users can navigate between questions to alleviate carelessness and improve the overall quality of their answers.
- **Audio collection:** In terms of sensors, a major addition is the audio sensor. In fact, in the area of activity recognition, audio can provide insights in terms of locations or activities that require sound (Heittola et al. 2013; Heittola et al. 2010; Scott and Dragovic 2005; Betsworth et al. 2013; Lu et al. 2009; Zeng et al. 2008; Eronen et al. 2006), e.g., understanding from the sound of a train approaching that the user is close to a railway. From a sampling point of view, this means collecting audio in chunks of ten seconds every minute, specifically to preserve the privacy of the user.
- **New deployment:** The stability of the application was improved to meet the policies of the Play Store, as shown in Figure 10.5. The main advantage is that now users can download the application remotely, thus without the need of time consuming interactions with the researcher. Furthermore, updating i-Log is now easy and automatic as with any other application.
- **New permission procedure:** The procedure has been streamlined and improved to meet criteria of transparency and allow users to choose which data they feel confident in sharing and which not.

From a study point of view, the major element of novelty is the addition of questions about students' mood, which is an important dimension in the area of computational social sciences as shown in Section 2.6. To capture this dimension of users, the time diaries were extended with a question "How do you judge your mood?" whose possible answers are a Likert-like scale from 0 (negative) to 10 (positive). Furthermore, two questions providing information about the expectations from students on their day and how it went, i.e., "How do you think you day will go?" and "How did your day go?", are administered at 8 AM and 8 PM, respectively.

In terms of modelling students, this means that the attribute "Mood" was added to the eType Student. While in this current iteration the value is encoded as an Integer, since the mood is represented as a range, the final implementation will have a set of Concept in accordance with the modelling of mental states in Section 7.2. These two options allow for two different understanding of the mood: the positive-negative one goes in the direction of understanding arousal, whereas the semantic one provides a different level of depth for the emotional spectrum of a student.

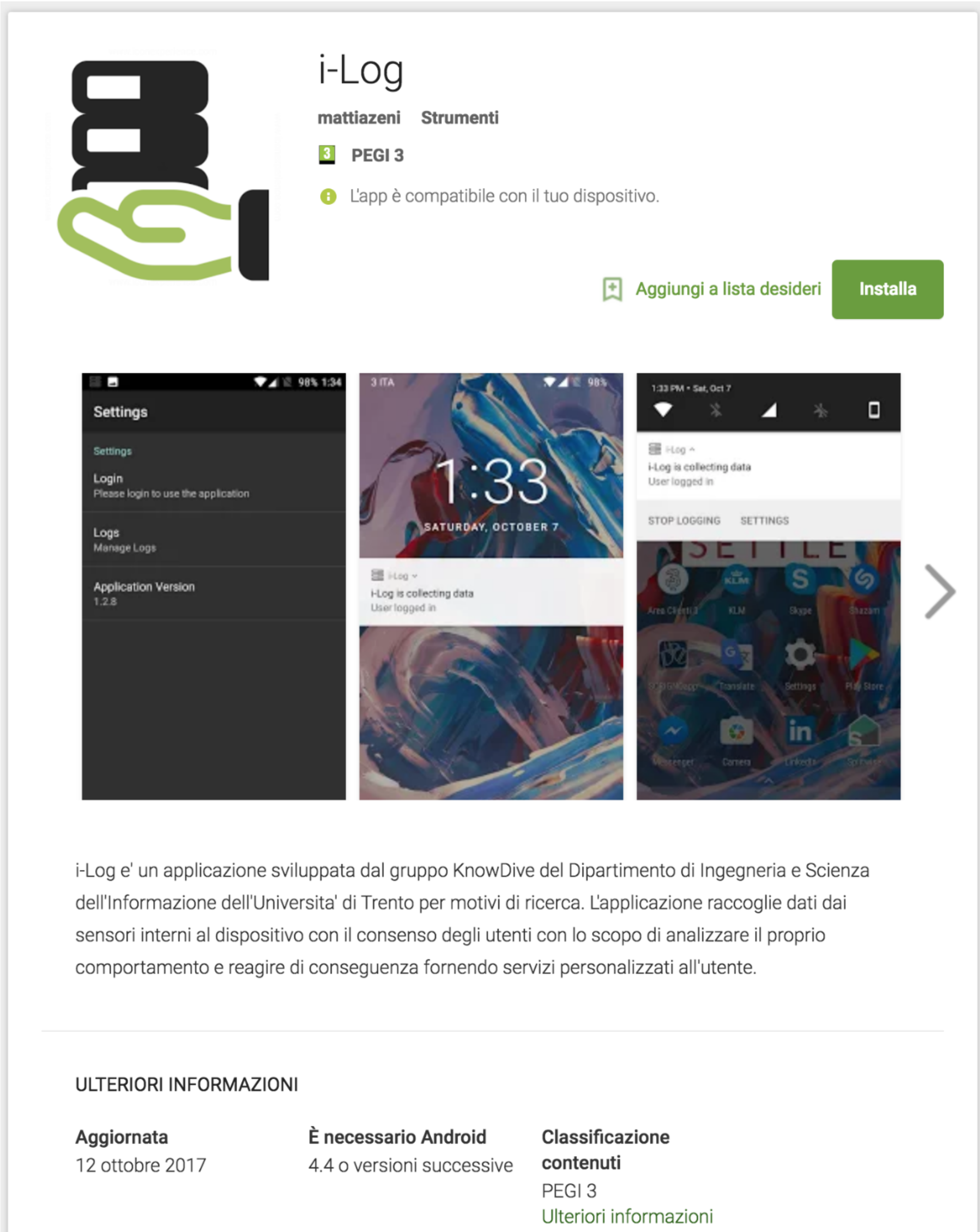


FIGURE 10.5: The i-Log mobile application published on the Google Play Store.

Chapter 11

QROWD

The final use case for our modeling of personal data is within the QROWD project, which is funded by the European Union's Horizon 2020 research and innovation programme. In addition to the University of Trento, the other partners involved in this project are both business and research. The business partners are TomTom[1], ATOS[2], AI4BD[3], and INMARK[4]. The academic institutions are the University of Southampton[5] and the Institut Fur Angewandte Informatik (INFAI)[6]. Finally, there is also an institutional partner, i.e., The Municipality of Trento [7].

The main motivation for this project is that European cities face daily problems with the mobility of their inhabitants and visitors, as well as with the delivery of goods and services along with their streets and connecting roads. QROWD offers local government and transportation businesses innovative solutions to improve mobility, reduce traffic congestion and make navigation safer and more efficient. Better use of urban infrastructures and reduced travel times will improve the environment by curbing CO2 emissions – ultimately enhancing the quality of life in European cities.

To achieve this, the QROWD project will integrate different sources of data – maximizing the value of Big Data in planning and managing urban traffic and mobility. It will exploit the potential of cross-sectoral Big Data integration and analysis to improve transportation and mobility across European cities. Furthermore, the QROWD project aims to integrate geographic, transport, meteorological, cross-domain and news data, to capitalize on hybrid Big Data integration and analytics methods, while efficiently combining algorithms and human computation incorporated in the entire Big Data Value Chain.

Within this project, the role of the University of Trento consists in leading the data storage, using the architecture described in Chapter 8, and contribute to the use case for the Municipality of Trento.

The remainder of the chapter is as follows. We first provide an overview of the use case in collaboration with the Municipality of Trento to provide some context to our work in Section 11.1. Then, we provide more details on

[1] https://www.tomtom.com/ge_ge/
[2] https://atos.net/en-na/north-america
[3]
[4] http://www.grupoinmark.com/
[5] https://www.southampton.ac.uk/
[6] https://infai.org/
[7] http://www.comune.trento.it/

our contribution, i.e., the modeling of the citizen's data involved in the use case, in Section 11.2.

11.1 The Municipality Use Case

For the last decade, the Municipality of Trento has been fighting inner-city traffic. Because of its position within a mountain valley, Trento has limited options of expanding its road infrastructure and hence needs actively to discourage excessive car traffic in its city center, supported by a policy also enforced by regional law. While recent measures, e.g., the creation of a limited traffic zone, the deployment of bike sharing services, or the establishment of paid parking zones with variable fees, have had positive effects on traffic, the municipality has only limited means of quantifying these improvements and of understanding the underlying reasons.

A key standard metric for understanding traffic is the modal split, i.e., a parameter that tells the percentage of the population using a particular type of transportation. However, the current practice of obtaining the modal split through population surveys is costly and, consequently, it is carried out only about once each decade. In the meantime, traffic remains heavy, pointing towards a need for further measures.

At the time of writing, there are no clear and adopted standards for modal split neither in terms of data collected nor in terms of comparability. In the EU, the European Platform on Mobility Management [8] provides tools for mobility management to public administration, with a modal split database of over 450 European cities. However, there is a lack of data quality assessment and standardization since it only acts as a repository rather than a policy enforcer. Among the European countries, only France has a national system of detection of urban mobility, while in other countries like Belgium, UK, and Spain, the individual town or city councils take care of the data collection. As for Italy, mobility information is mainly obtained through ISTAT data [9]. However, when considering Italian municipalities, many of the biggest ones (and hence the ones with the most complex transportation) produce their data, whereas the smaller municipalities rely on external companies, which is detrimental to the representativeness and comparability of the data.

In addition to modal split, another area known for having a profound impact on city traffic and for being a source of pollution is parking. As such, efficient parking policies are crucial when dealing with both these issues. However, the Municipality has little knowledge about usage of parking spots around the city, mainly limited to off-street, underground parking. A comprehensive analysis of parking availability would help the Municipality setting priorities for future policies.

The mobility use case is therefore based on how to obtain information on these two phenomena. To do so, the Municipality will rely on the combination and analysis of big data from the Municipality's database, participatory

[8] http://www.epomm.eu/index.php

[9] http://www.istat.it/it/

sensor data from the mobile devices of citizens, e.g., their travelling habits, lightweight electronic surveys on mobile devices, e.g., asking the type of travel or requiring them to take pictures of their surroundings, and data provided by the TomTom company.

In addition to the involvement, the Municipality will not only collect data through citizens sensing but also provide citizens with valuable services in exchange for their contribution. An assessment of the needs of the citizens of Trento has been carried out mainly by getting input through an ideas competition; results not only show an increased awareness of citizens in terms of traffic reduction and alternative mobility but also a need to be informed about mobility in Trento.

The modal split can, therefore, be computed yearly or even monthly as opposed to every ten years, at a fraction of the cost, with higher precision due to a continuous, comparable computation, and with finer granularity, in terms of geographic coverage as it involves commuters other than resident citizens. Parking availability will be analyzed based on alternative data sources with a specific focus on on-street parking for cars, motorcycles, and bicycles as well as on special parking areas such as parking for people with disabilities and freight load/unload.

Finally, citizens of Trento will directly benefit through an improved mobility experience in their daily life. Citizens are also motivated to partake sustainably in the endeavor by getting free access to a set of personalized services:

1. A personal modal split service offered to users providing them with a general report about how they move around the city of Trento.

2. Citizens should be able to visualize useful aggregated data concerning mobility on a web-based citizen dashboard. The citizen dashboard is intended as a one-stop-shop where citizens can access different useful information concerning mobility.

3. A personalized service of traffic information based on the inferred citizen traveling habits in terms of routes, to help them avoid wasting time in traffic. The service will result in a simple visualization/notification system from traffic data.

11.2 Modelling Citizen

In this use case, our contribution is providing a model of the citizen data to be stored in our knowledge repository to structure both dynamic data collected via i-Log and static data as provided by the Municipality. However, before explaining our modeling of citizens, we also need to provide a general modeling of all the entities involved in the Municipality use case, which we also contributed to in terms of modeling.

11.2.1 QROWD Data Model

In terms of requirements for the data model, shown in Figure 11.1, the major one, because QROWD is an EU innovation project concerning smart cities, is that it should be compliant with the FIWARE data models[10]. FIWARE[11] is a community that makes and shares open source technology for smart solutions to build an open sustainable ecosystem around public, royalty-free and implementation-driven software platform standards that ease the development of new smart applications in multiple sectors including, but not limited, to smart cities. Notice that FIWARE does not have any modeling of person, using it only as a value for attributes, e.g., owner of a vehicle. A further requirement was that the data model could accommodate the static data provided by the Municipality, and available via the Open Data Trentino platform[12]. This is still a work in progress because some new dataset will be available in March 2018, e.g., real-time navigation of buses, camera feed from lampposts, and bike sharing dock stations.

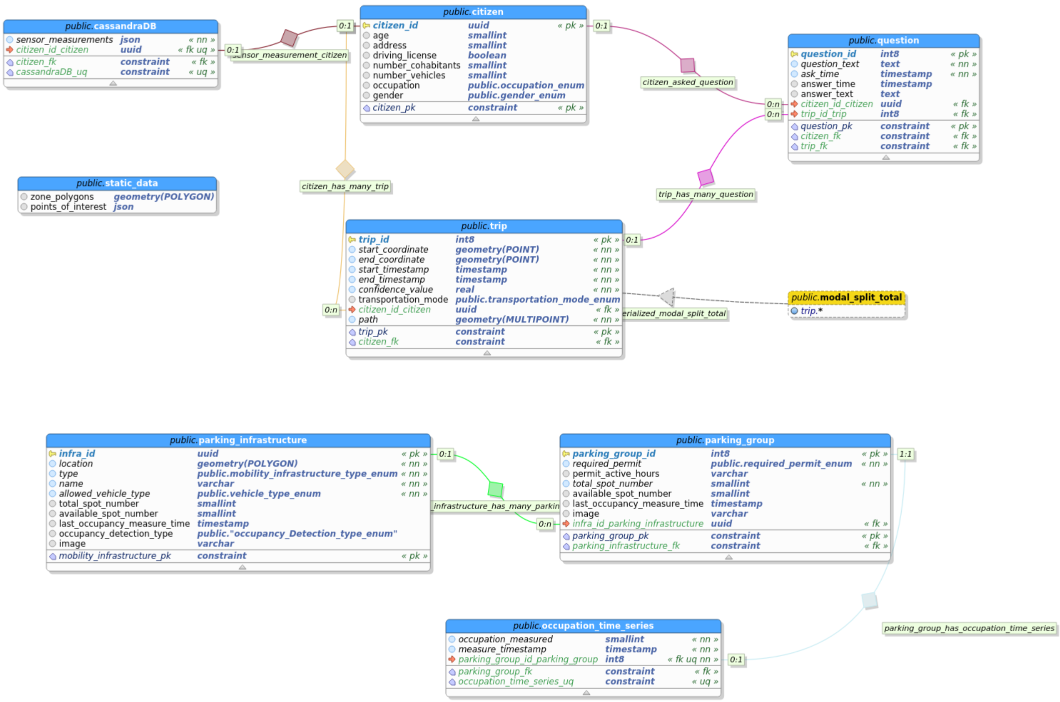


FIGURE 11.1: The QROWD data model. Some slight differences may arise in terms of actual eType attribute names due to different standards with respect to the methods to obtain the data.

Although our focus is on the Citizen eType, we also collaborated in producing the following eTypes: Trip, Parking Infrastructure, and Parking Group. We now provide the current specifications for each of these eTypes, without

[10] https://www.fiware.org/data-models/
[11] https://www.fiware.org/about-us/
[12] http://dati.trentino.it/

going into many details as they are not the main part of our contribution but still provide a general overview of the entity-centric approach.

The Trip eType, shown in Table 11.1, represents a trip, which is defined as a movement from a stationary point A to a stationary point B. It is bounded either by the citizen reaching the destination or by changing his mode of transport.

TABLE 11.1: Trip eType

Attribute Name	Description	DataType
IDtrip	the identifier of the trip	UUID
Citizen	the citizen for which this trip was sensed	<Citizen>
Origin	the starting point of the trip	Geometry
Destination	the place designated as the end	Geometry
Path	an established line of travel or access	Geometry []
Transportation mode	the inferred transportation mode; the concept restriction is {car, bus, train, motorcycle, cable car, bicycle, foot}	Concept
Confidence value	the confidence value of the transportation mode classification, ranging from 0 to 100	Double
Purpose	the purpose of the trip; the concept restriction is {work, home, other}	Concept
Start Date	the start of the trip	DATE
End Date	the end of the trip	DATE

The Parking Infrastructure eType, shown in Table 11.2, represent all the types of parking spots available in the city of Trento, i.e., off-street parking sites with explicit entries and exits, on street, free entry (but might be metered) parking zone which contains at least one ore more adjacent parking spots, and bike-sharing docking station.

The Parking Group eType, shown in Table 11.3, represents a group of parking spots, whose granularity level can vary. It can be a storey on a parking garage, a specific area belonging to a big parking lot, etc. or just a group of spots, differentiated for a specific purpose (usage, restrictions, etc.).

11.2.2 The Citizen eType

The main, and only, type of person in this use case is represented by the citizens involved, whose main focus in terms of data are those that concern their modal split habits.

Figure 11.2, taken from (Pornbacher and Niederkofler 2004), shows the main demographics that are of interest to the Municipality of Trento. There are two types of data: family (in Italian, "livello familiare") and individual (in Italian, "singolo componente"). For the family, what is collected are the number of the following means of transportation owned: *i)* cars, *ii)* motor bikes, and *iii)* bikes; additionally also the distance between a family's home and the

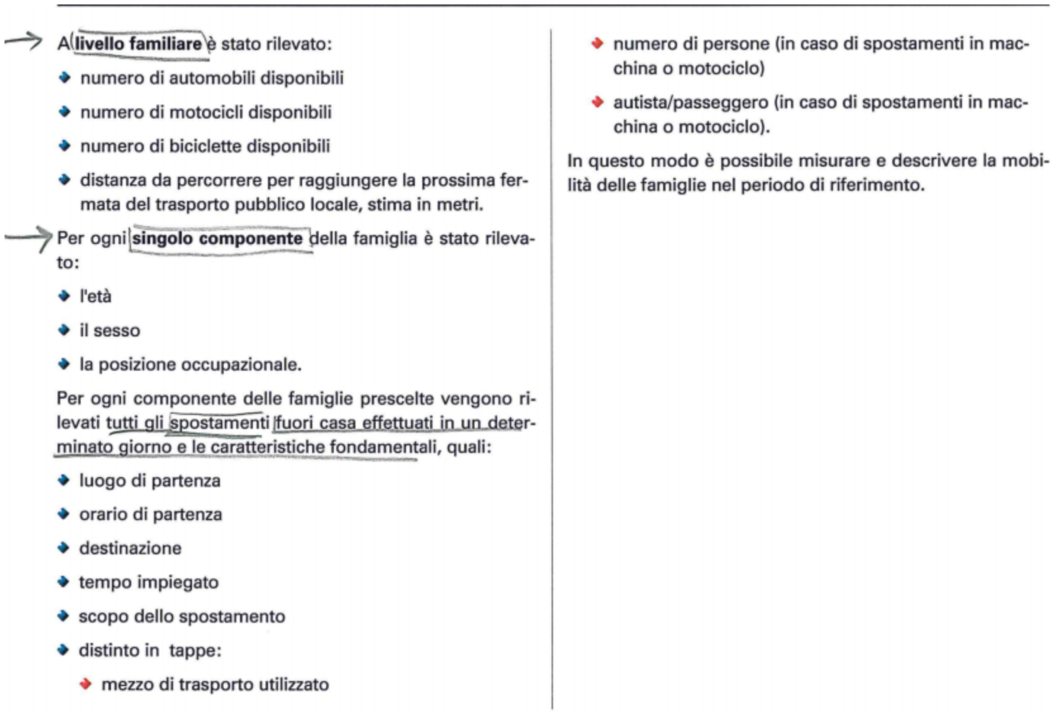
TABLE 11.2: Parking Infrastructure eType

Attribute Name	Description	DataType
ID	the infrastructure identifier	URI
Location	where the parking infrastructure is located	Geometry[]
Name	the name, where available, of the parking infrastructure.	NLString
Total Spot Number	he total number of parking spots in the parking infrastructure	Integer
Available Spot Number	the currently available number of parking spots in the parking infrastructure	Integer
Last Occupancy Measure Time	the timestamp of the last time the occupancy was measured	Date
Image	an image of the parking infrastructure, which is to be collected by citizens	varchar

TABLE 11.3: Parking Group eType

Attribute Name	Description	DataType
ID	the parking group identifier	URI
Required permit	the type of required permit to access; the concept restriction is {residentPermit,noPermitNeeded,disabledPermit}	Concept
Permit Active Hours	the time slots during which the permit is required to access the parking group	Date
Total Spot Number	he total number of parking spots in the parking infrastructure	Integer
Available Spot Number	the currently available number of parking spots in the parking infrastructure	Integer
Last Occupancy Measure Time	the timestamp of the last time the occupancy was measured	Date
Image	an image of the parking infrastructure, which is to be collected by citizens	varchar

closest public transportation stop, e.g., bus stop. For the individual, there are only three types of demographics: *i)* age, *ii)* gender, and *iii)* occupation.


A **livello familiare** è stato rilevato:

- numero di automobili disponibili
- numero di motocicli disponibili
- numero di biciclette disponibili
- distanza da percorrere per raggiungere la prossima fermata del trasporto pubblico locale, stima in metri.

Per ogni **singolo componente** della famiglia è stato rilevato:

- l'età
- il sesso
- la posizione occupazionale.

Per ogni componente delle famiglie prescelte vengono rilevati tutti gli spostamenti fuori casa effettuati in un determinato giorno e le caratteristiche fondamentali, quali:

- luogo di partenza
- orario di partenza
- destinazione
- tempo impiegato
- scopo dello spostamento
- distinto in tappe:
  - mezzo di trasporto utilizzato
  - numero di persone (in caso di spostamenti in macchina o motociclo)
  - autista/passeggero (in caso di spostamenti in macchina o motociclo).

In questo modo è possibile misurare e descrivere la mobilità delle famiglie nel periodo di riferimento.

FIGURE 11.2: The demographics necessary for representing and calculating citizen's modal split.

In this use case, the same demographics are to be collected, with some important differences. Firstly, the focus is much more on individuals rather than families, which means that there is no need for a dedicated eType. Secondly, additional data that are needed for the use case are as follows: *i)* domicile and residence, *ii)* number of people living in the same house, and *iii)* whether the citizen has a driving license. Thirdly, to compute the official modal split for the whole city a sample size must be identified taking into account two parameters: *i)* whether the citizen is a resident or a commuter, since Trento is the capital of the Province and many people from neighbouring cities commute daily, and *ii)* the type of occupation for each individual, i.e., worker, student, unemployed, retired, or stay-at-home.

In addition to these domain-based requirements, we also considered the following categories from Chapter 5:

Name: Because of privacy reasons, we cannot store a person's name, which required us to create an anonymized id, similarly to SmartUnitn.

Demographics: We consider the domain based requirements to fall under gender, age and occupation. Residency is implicitly within the Trento province, while the nationality is not collected. As for education, it was not considered relevant.

Contact: We consider the domain based requirement of the citizen's address, both home and work, to fall under this type of attribute.

Knowledge: We consider the domain based requirement of having a license as a type of competence since it requires a person to know how to drive. The preference of the type of transportation mode can be modeled following our schema, where the interest can be referred as the general domain of transportation, and the preference as the specific mode. Since there is no need of detailing which individual vehicle the person prefers, only concepts are used; furthermore, in this use case no need for a degree is required, so no values are collected.

Context dimension: We consider the domain based requirements concerning the number of cohabitants and number of vehicles to be static information that can be ascribed to the context dimensions of social relations and artifacts, respectively. Furthermore, we do not model them as entities but only as numerical values, since the level of granularity required is coarse enough to allow this level of abstraction.

Overall, we modeled the Citizen eType as shown in Table 11.4.

TABLE 11.4: Citizen eType

Attribute Name	Description	DataType
ID	the anonymized id of the citizen	UUID
Age	the age of the citizen	Integer
Gender	the gender of the citizen; the concept restriction is {male, female}	Concept
Profession	the address of the citizen	Concept
Address	the currently available number of parking spots in the parking infrastructure	<Address>
Work address	the address of the citizen's workplace	<Address>
Driving license	whether the citizen has a driving license	Boolean
Number cohabitants	the total number of people living in the same house	Integer
Number vehicles	the total number of vehicles available to all cohabitants	Integer
Preferred mode	the type of preferred transportation mode of the citizen; the concept restriction is {car, bus, motorbike, taxi, bike}	Concept

In terms of future work, although this eType is quite stable, we can still foresee some modifications soon since we expect real-life experiments to provide insights to unforeseeable issues. In fact, the QROWD data model, and thus also the citizen eType as well, has not been tested yet. The timeline for the use case is as follows:

Non-official Trial (February 2018): The non-official trial will involve users from Viaggia Trento Play&Go[13]. It is an app that tracks the users' movements and allows the to earn point, where the more the user chooses smart and green options, e.g., choosing public transportation over cars, the more points are earned. Every week, users can participate in thematic and customized challenges to get bonuses and win top places in the standings.

First Trial (April 2018): The first official trial will involve up to 1000 citizens, and will collect data on a specific day where citizens can annotate their traveling habits for modal split. Also, citizens will also participate in specific competitions about mobility, e.g., helping the municipality obtain information about bike racks.

Second Trial (October 2018): The second official trial will involve even more citizens and, in addition to the same tasks from the previous one, it will also involve providing the citizens with dedicated services, e.g., personalized traffic management.

Finally, in terms of modeling, the final Citizen eType will be proposed to FIWARE as part of its data model by the end of May 2018, after the end of the first citizen trial. Thus, it would be a stronger candidate, having been used successfully in real life scenarios.

[13] http://www.smartcommunitylab.it/apps/viaggia-trento-playgo/

Part IV

Conclusions

Chapter 12

Conclusions

12.1 The Context

This Ph. D. Thesis deals with the semantic gap problem in the context of personal data. The problem consists in the lack of coincidence between low-level sensor streaming data collected by sensors in a machine-readable format and high-level semantic knowledge that can be generated from these data and that only humans can understand thanks to their intelligence, habits, and routines. The reason for this problem lies in the fact that the same sensor data can be analyzed and produce very different results from the human perspective. Being inside a building, or one meter away outside the window is very different for a human being while for the machine this can make little difference. Furthermore, from a representational point of view, the semantic gap affects several communities that are forced to address either only a specific portion of personal data or to limit the generality of their modeling and recognizing strategies. We need to represent the personal data, be it static or dynamic such as his context and allow the machine to use them to analyze the data in a context-aware way.

12.2 The Contributions

Within this context, the contributions developed in this thesis can be summarized as follows: The contributions of this Ph. D. Thesis are:

- *The definition of a methodology* based on an interdisciplinary approach combining philosophy, sociology and computer science to **categorize and recognize personal data**. The methodology is based on the entity-centric approach and based on two fundamental criteria to define and structure personal data to address the issues of open domains and verticality of application scenarios.
- *The definition of an ontology of personal data* to represent human in a general way while also accounting their different dimensions of their everyday life;
- *The instantiation of the personal data representation* above in a reference architecture that allows implementing the model and that can exploit the methodology to account for how to recognize personal data.

- *The adoption of the methodology for defining personal data and its instantiation* in three real-life use cases with different goals in mind, proving that our modeling works in open domains and can account for several dimensions of the user.

12.3 The Use Cases

We evaluated all the dimensions of the methodology and system developed in this thesis in three different use cases. For each of them, we analyzed the requirements and standards, then modeled personal data to enable different purposes depending on the use case aims.

The Mainkofen hospital: This was the first test for modeling personal data, especially in terms of context dimensions. The use case was done in collaboration with DFKI with the SmartSociety project, and it took place in the Mental Hospital Mainkofen in Deggendorf, Germany. The initial objective of this experiment was motivated by the request for an application assisting nursing documentation and the need to develop a solution that can be deployed in an average hospital. Our contribution was to build a model based on the data collected and the logs of nurses' routines to add semantics and improve the context recognition. We focused on modeling people (nurses and patients), events, and locations. Especially in the case of events, we devised a finite state like structure to allow us to traverse with different granularity in the routine of nurses. We moved to the importing of the logs and showed that we can represent the routines any required level of granularity.

SmartUnitn: This was the very first large-scale use case executed on people in the wild, outside of a controlled environment. It was managed by the Department of Information Engineering and Computer Science and the Department of Sociology and Social Research of the University of Trento on the students of the same institution. The final goal was to study how the students' allocation of time affects their academic achievements both in terms of grades but also on the number of credits, i.e., number of exams. We modeled the students with a dedicated Etype, adapting standards and the time diary methodology from social sciences to learn students' habits. The first iteration, called SmartnUnitn One, involved 72 students that generated data for two weeks. We obtained an impressive amount of labels, which allowed us to obtain a very detailed picture of students' life. The second iteration is to be started later in 2018, and will involve modeling mood as an additional dimension to investigate.

QROWD: The last use case we designed, but that still has to take place, is again within the QRWOD project. It involves a mobility use case, in collaboration with the Municipality of Trento, to be carried out in April 2018 related to the analysis of the modal split, in other words, how the citizens split their journey to reach their final destinations and parking spaces. This will improve how the citizens live their city but will also help the municipality in defining new laws and strategies to reduce traffic and pollution. In fact, a law imposes the Municipality of Trento to reduce by 1% on yearly bases the number of cars used by citizens. Our contribution is a modeling of citizens' data in accordance with modal split standards, the data provided by the Municipality and data that we will collect via i-Log. Also, we also model other relevant entities like trips taken by citizens.

Chapter 13

Future Work

Some opportunities to extend the scope of this thesis were left for future work. In this (short) chapter, we will provide some possible new research directions.

First of all, one relevant direction is to apply our methodology in other, different use cases. For example, a possible new use case will be replicating the SmartUnitn project in the Jilin[1] University in Changchung, China. This possibility is relevant because of several reasons. Firstly, it will allow us to experiment with a huge amount of students, possibly more than 1000. Secondly, it will involve studying a very different environment from the cultural point of view. Thirdly, it will require adaptation in terms of personal data collection from the local laws, e.g., privacy. In addition to these new possibilities, new iterations will be carried out in SmartUnitn, and we will see how our modeling fares in the context of the Municipality of Trento use case and its acceptance as a FIWARE standard.

Regarding personal data, another area that would be interesting to pursue is to add interdisciplinarity in our research by extending the modelling of roles and context. In this sense, a preliminary direction is studying oriental philosophy and the concept of the mandala. Mandala is "a Hindu or Buddhist graphic symbol of the universe, a circle enclosing a square with a deity on each side that is used chiefly as an aid to meditation"[2]. Mandala is generally a cosmic diagram that depicts the integrated organizational structure of life. It describes material as well as non-material realities and appears in every aspect of life, including the celestial circles such as the sun, moon and earth; and the conceptual circles of family, friends, and community. We believe that mandala can act not only as a visualization framework for modeling, but also as a way to organize different roles and their interactions in context.

Another area to explore in terms of personal data is modelling collectives, thus expanding some of the dimension of personal data we already analyzed for individuals and extend them to groups of people, e.g., roles and goals. For instance, the issue of identity in collectives is extremely important as it could be argued that their goals *provide* their identity since the act as a way to attract intentions and objectives. Furthermore, the status of machines within their collectives and how they interact with individual members and the collective as a whole is also a relevant research area.

[1] http://global.jlu.edu.cn/User/Index/index
[2] https://www.merriam-webster.com/dictionary/mandala

Appendix A

Person eType

The full specification of the person eType can be found at this link
`https://goo.gl/QBwHzS`

Appendix B

Mainkofen Hospital use case

B.1 Parser Implementation Details

Tasks			Prev Activity			Next Activity		
Activity	**Object**	**Location**	**Activity**	**Object**	**%**	**Activity**	**Object**	**%**
pick up	record	G2				store	record	100.0%
store	record	PS	pick up	record	100.0%	pick up	sphygmo.	100.0%
pick up	sphygmo.	PS	store	record	25.0%	talk		25.0%
			pick up	steto	25.0%	pick up	steto	25.0%
			read	record	25.0%	put down	sphygmo.	25.0%
			write		25.0%	pick up	gloves	25.0%
pick up	steto	PS	put down	hyg. b.	33.3%	wake up		33.3%
			disinfect		33.3%	talk		33.3%
			pick up	sphygmo.	33.3%	pick up	sphygmo.	33.3%
wake up		Z1	pick up	steto	33.3%	talk		33.3%
			talk		33.3%	cuffon		33.3%
			pick up	gloves	33.3%	raise bed		33.3%
talk		Z1	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
cuffon		Z1	wake up		20.0%	search pulse		20.0%
			measure		20.0%	inflate		80.0%
			talk		40.0%			
			raise bed		20.0%			
inflate		Z1	cuffon		80.0%	measure		100.0%
			search pulse		20.0%			
measure		Z1	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
search pulse		Z1	measure		50.0%	measure		83.3%

			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
measure		Z1	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
write		Z1	measure		50.0%	talk		50.0%
			put down	sphygmo.	50.0%	pick up	sphygmo.	50.0%
talk		Z1	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
wake up		Z1	pick up	steto	33.3%	talk		33.3%
			talk		33.3%	cuffon		33.3%
			pick up	gloves	33.3%	raise bed		33.3%
cuffon		Z1	wake up		20.0%	search pulse		20.0%
			measure		20.0%	inflate		80.0%
			talk		40.0%			
			raise bed		20.0%			
inflate		Z1	cuffon		80.0%	measure		100.0%
			search pulse		20.0%			
measure		Z1	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
cuffoff		Z1	measure		100.0%	search pulse		100.0%
search pulse		Z1	measure		50.0%	measure		83.3%
			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
measure		Z1	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
put down	sphygmo.	Z1	measure		66.6%	open		33.3%
			pick up	sphygmo.	33.3%	write		33.3%
						put down	steto	33.3%
write		Z1	measure		50.0%	talk		50.0%
			put down	sphygmo.	50.0%	pick up	sphygmo.	50.0%
pick up	sphygmo.	Z1	store	record	25.0%	talk		25.0%
			pick up	steto	25.0%	pick up	steto	25.0%
			read	record	25.0%	put down	sphygmo.	25.0%

			write		25.0%	pick up	gloves	25.0%
put down	sphygmo.	Z1	measure		66.6%	open		33.3%
			pick up	sphygmo.	33.3%	write		33.3%
						put down	steto	33.3%
open		Z1	talk		33.3%	take out	towel	33.3%
			put down	sphygmo.	33.3%	take out	clothes	33.3%
			take out	washcloth	33.3%	take out	washcloth	33.3%
take out	washcloth	Z1	open		20.0%	open		20.0%
			talk		20.0%	put down	socks	20.0%
			brush teeth		20.0%	put down	washcloth	20.0%
			take out	towel	20.0%	stand up		20.0%
			sit on toilet	toilet	20.0%	help		20.0%
put down	washcloth	Z1-bath.	stand up		50.0%	wear	gloves	50.0%
			take out	washcloth	50.0%	sit down		50.0%
wear	gloves	Z1-bath.	fetch		25.0%	talk		25.0%
			put down	socks	25.0%	take out	diaper	25.0%
			write	steto	25.0%	take out	towel	25.0%
			put down	washcloth	25.0%	take out	clothes	25.0%
take out	diaper	Z1-bath.	wear	gloves	50.0%	put down	diaper	50.0%
			take out	clothes	50.0%	take out	clothes	50.0%
take out	clothes	Z1-bath.	take p to		20.0%	take p to		20.0%
			open		20.0%	pick up	hyg. b.	20.0%
			take out	diaper	20.0%	take out	diaper	20.0%
			wear	gloves	20.0%	fetch	shirt	20.0%
			take out	towel	20.0%	put in	clothes	20.0%
take p to		Z1-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
take out	clothes	Z1-bath.	take p to		20.0%	take p to		20.0%
			open		20.0%	pick up	hyg. b.	20.0%
			take out	diaper	20.0%	take out	diaper	20.0%
			wear	gloves	20.0%	fetch	shirt	20.0%
			take out	towel	20.0%	put in	clothes	20.0%
fetch	shirt	Z1-bath.	take out	clothes	100.0%	talk		100.0%
talk		Z1-bath.	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
sit on toilet	toilet	Z1-bath.	talk		100.0%	take out	washcloth	100.0%
take out	washcloth	Z1-bath.	open		20.0%	open		20.0%
			talk		20.0%	put down	socks	20.0%
			brush teeth		20.0%	put down	washcloth	20.0%
			take out	towel	20.0%	stand up		20.0%
			sit on toilet	toilet	20.0%	help		20.0%
stand up		Z1-bath.	sit up		8.3%	pull up		16.6%

			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
put down	washcloth	Z1-bath.	stand up		50.0%	wear	gloves	50.0%
			take out	washcloth	50.0%	sit down		50.0%
sit down		Z1-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
instruct		Z1-bath.	sit down		100.0%	wash		100.0%
wash		Z1-bath.	instruct		100.0%	instruct		100.0%
instruct		Z1-bath.	undress		25.0%	wash	face	50.0%
			wash		25.0%	brush teeth		25.0%
			stand up		25.0%	wash	pubic area	25.0%
			comb		25.0%			
wash	face	Z1-bath.	instruct		100.0%	undress	nightgown	50.0%
						wash	back	50.0%
undress	nightgown	Z1-bath.	wash	face	100.0%	pick up	washcloth	100.0%
pick up	washcloth	Z1-bath.	undress	nightgown	50.0%	hand to p	washcloth	50.0%
			put down	towel	50.0%	stand up		50.0%
hand to p	washcloth	Z1-bath.	pick up	washcloth	100.0%	dry	face	100.0%
dry	face	Z1-bath.	hand to p	washcloth	100.0%	help		100.0%
help		Z1-bath.	dry	face	20.0%	pick up	laundry	20.0%
			put in	trashbag	20.0%	brush	tooth	20.0%
			wash	pubic area	20.0%	wear	clothes	20.0%
			pick up	socks	20.0%	wash		20.0%
			take out	washcloth	20.0%	wear	socks	20.0%
wash		Z1-bath.	help		100.0%	stand up		100.0%
stand up		Z1-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
wash	back	Z1-bath.	wash	face	33.3%	dry	back	66.6%
			stand up		33.3%	pick up	socks	33.3%
			put in	clothes	33.3%			
dry	back	Z1-bath.	wash	back	100.0%	sit down		50.0%
						wash	thorax	50.0%

			pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
sit down		Z1-bath.	talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
wear	pullover	Z1-bath.	sit down		100.0%	wear	diaper	50.0%
						comb		50.0%
wear	diaper	Z1-bath.	wear	patch	50.0%	sit down		50.0%
			wear	pullover	50.0%	stand up		50.0%
			pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
sit down		Z1-bath.	talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
wear	pants	Z1-bath.	sit down		100.0%	pull up	pants	50.0%
						stand up		50.0%
pull up	pants	Z1-bath.	wear	pants	100.0%	pick up	shoes	100.0%
pick up	shoes	Z1-bath.	wear	clothes	50.0%	wear	shoes	100.0%
			pull up	pants	50.0%			
wear	shoes	Z1-bath.	sit up		33.3%	sit down		33.3%
			pick up	shoes	66.6%	stand up		66.6%
			pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
sit down		Z1-bath.	talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
			talk		33.3%	instruct		33.3%
comb		Z1-bath.	sit down		33.3%	put in	trash	33.3%
			wear	pullover	33.3%	take off	gloves	33.3%
			talk		33.3%	take off	gloves	33.3%
put in	trash	G1	comb		33.3%	put in	laundry	66.6%
			wear	socks	33.3%			
			put in	trash	50.0%	talk		25.0%
put in	laundry	G1	put in	laundry	25.0%	take off	gloves	25.0%
			put in	clothes	25.0%	put in	laundry	25.0%
						put in	clothes	25.0%
			put in	trash	50.0%	talk		25.0%
put in	laundry	G3	put in	laundry	25.0%	take off	gloves	25.0%
			put in	clothes	25.0%	put in	laundry	25.0%
						put in	clothes	25.0%
			wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
talk		G2						

			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
comb		Z1-bath.	talk		33.3%	instruct		33.3%
			sit down		33.3%	put in	trash	33.3%
			wear	pullover	33.3%	take off	gloves	33.3%
instruct		Z1-bath.	undress		25.0%	wash	face	50.0%
			wash		25.0%	brush teeth		25.0%
			stand up		25.0%	wash	pubic area	25.0%
			comb		25.0%			
brush teeth		Z1-bath.	instruct		100.0%	take out	washcloth	100.0%
take out	washcloth	Z1-bath.	open		20.0%	open		20.0%
			talk		20.0%	put down	socks	20.0%
			brush teeth		20.0%	put down	washcloth	20.0%
			take out	towel	20.0%	stand up		20.0%
			sit on toilet	toilet	20.0%	help		20.0%
help		Z1-bath.	dry	face	20.0%	pick up	laundry	20.0%
			put in	trashbag	20.0%	brush	tooth	20.0%
			wash	pubic area	20.0%	wear	clothes	20.0%
			pick up	socks	20.0%	wash		20.0%
			take out	washcloth	20.0%	wear	socks	20.0%
brush	tooth	Z1-bath.	help		100.0%	pick up	unknown	100.0%
pick up	unknown	Z1-bath.	brush	tooth	100.0%	take p to		100.0%
take p to		Z1-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
take off	gloves	G1	take p to		25.0%	put in	trashbag	75.0%
			put in	trash	25.0%	disinfect		25.0%
			put in	laundry	25.0%			
			comb		25.0%			
put in	trashbag	G1	take off	gloves	100.0%	talk		33.3%
						stand up		33.3%
						help		33.3%
talk		G1	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
			wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%

talk		A						

			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
sit down		A	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
talk		A	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
fetch		SB	talk		50.0%	wear	gloves	50.0%
			take out	towel	50.0%	put down	clothes	50.0%
wear	gloves	Z1	fetch		25.0%	talk		25.0%
			put down	socks	25.0%	take out	diaper	25.0%
			write	steto	25.0%	take out	towel	25.0%
			put down	washcloth	25.0%	take out	clothes	25.0%
take out	towel	Z1	open		33.3%	fetch		33.3%
			wear	gloves	33.3%	take out	clothes	33.3%
			pick up	clothes	33.3%	take out	washcloth	33.3%
take out	clothes	Z1	take p to		20.0%	take p to		20.0%
			open		20.0%	pick up	hyg. b.	20.0%
			take out	diaper	20.0%	take out	diaper	20.0%
			wear	gloves	20.0%	fetch	shirt	20.0%
			take out	towel	20.0%	put in	clothes	20.0%
take out	diaper	Z1	wear	gloves	50.0%	put down	diaper	50.0%
			take out	clothes	50.0%	take out	clothes	50.0%
put down	diaper	Z1-bath.	take out	diaper	100.0%	put down	clothes	100.0%
put down	clothes	Z1-bath.	fetch		25.0%	pick up	prot pad	25.0%
			pick up	hyg. b.	25.0%	put down	hyg. b.	25.0%
			put down	diaper	25.0%	put down	towel	25.0%
			pick up	clothes	25.0%	removesrail		25.0%
put down	hyg. b.	Z1-bath.	pick up	hyg. b.	66.6%	sit up		33.3%
			put down	clothes	33.3%	pick up	steto	33.3%

						pick up	hyg. b.	33.3%
pick up	hyg. b.	Z1-bath.	put down	hyg. b.	33.3%	put down	hyg. b.	66.6%
			disinfect		33.3%	put down	clothes	33.3%
			take out	clothes	33.3%			
put down	hyg. b.	Z1-bath.	pick up	hyg. b.	66.6%	sit up		33.3%
			put down	clothes	33.3%	pick up	steto	33.3%
						pick up	hyg. b.	33.3%
sit up		Z1-bath.	put down	hyg. b.	50.0%	wear	shoes	50.0%
			removesbelt		50.0%	stand up		50.0%
stand up		Z1-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
take p to		Z1-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
sit down		Z1-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
flush	toilet	Z1-bath.	sit down		100.0%	undress		100.0%
undress		Z1-bath.	flush	toilet	50.0%	instruct		50.0%
			take p to		50.0%	collect	trash	50.0%
instruct		Z1-bath.	undress		25.0%	wash	face	50.0%
			wash		25.0%	brush teeth		25.0%
			stand up		25.0%	wash	pubic area	25.0%
			comb		25.0%			
wash	face	Z1-bath.	instruct		100.0%	undress	nightgown	50.0%
						wash	back	50.0%
wash	back	Z1-bath.	wash	face	33.3%	dry	back	66.6%
			stand up		33.3%	pick up	socks	33.3%
			put in	clothes	33.3%			
dry	back	Z1-bath.	wash	back	100.0%	sit down		50.0%
						wash	thorax	50.0%
wash	thorax	Z1-bath.	dry	back	100.0%	dry	thorax	100.0%
dry	thorax	Z1-bath.	wash	thorax	100.0%	stand up		100.0%
stand up		Z1-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%

			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
instruct		Z1-bath.	undress		25.0%	wash	face	50.0%
			wash		25.0%	brush teeth		25.0%
			stand up		25.0%	wash	pubic area	25.0%
			comb		25.0%			
wash	pubic area	Z1-bath.	instruct		100.0%	help		100.0%
help		Z1-bath.	dry	face	20.0%	pick up	laundry	20.0%
			put in	trashbag	20.0%	brush	tooth	20.0%
			wash	pubic area	20.0%	wear	clothes	20.0%
			pick up	socks	20.0%	wash		20.0%
			take out	washcloth	20.0%	wear	socks	20.0%
wear	clothes	Z1-bath.	help		100.0%	pick up	shoes	100.0%
pick up	shoes	Z1-bath.	wear	clothes	50.0%	wear	shoes	100.0%
			pull up	pants	50.0%			
wear	shoes	Z1-bath.	sit up		33.3%	sit down		33.3%
			pick up	shoes	66.6%	stand up		66.6%
stand up		Z1-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
talk		Z5	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
put in	trash	G4	talk		33.3%	take off	gloves	33.3%
			comb		33.3%	put in	laundry	66.6%
			wear	socks	33.3%			
take off	gloves	G3	take p to		25.0%	put in	trashbag	75.0%
			put in	trash	25.0%	disinfect		25.0%
			put in	laundry	25.0%			
			comb		25.0%			
put in	trashbag	G1	take off	gloves	100.0%	talk		33.3%
						stand up		33.3%
						help		33.3%
help		Z1-bath.	dry	face	20.0%	pick up	laundry	20.0%
			put in	trashbag	20.0%	brush	tooth	20.0%
			wash	pubic area	20.0%	wear	clothes	20.0%

			pick up	socks	20.0%	wash		20.0%
			take out	washcloth	20.0%	wear	socks	20.0%
pick up	laundry	Z1-bath.	talk		50.0%	put in	laundrybag	50.0%
			help		50.0%	pick up	trash	50.0%
pick up	trash	Z1-bath.	pick up	laundry	100.0%	put down	laundry	100.0%
put down	laundry	Z1-bath.	pick up	trash	100.0%	put down	trash	100.0%
put down	trash	Z1-bath.	put down	laundry	100.0%	disinfect		100.0%
disinfect		Z1-bath.	put down	trash	25.0%	prep wchair		25.0%
			sit down		25.0%	take p to		25.0%
			take off	gloves	25.0%	pick up	steto	25.0%
			put in	clothes	25.0%	pick up	hyg. b.	25.0%
take p to		Z1-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
talk		G1	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
sit down		A	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
disinfect		Z1	put down	trash	25.0%	prep wchair		25.0%
			sit down		25.0%	take p to		25.0%
			take off	gloves	25.0%	pick up	steto	25.0%
			put in	clothes	25.0%	pick up	hyg. b.	25.0%
pick up	hyg. b.	Z1-bath.	put down	hyg. b.	33.3%	put down	hyg. b.	66.6%
			disinfect		33.3%	put down	clothes	33.3%
			take out	clothes	33.3%			
put down	hyg. b.	Z1-bath.	pick up	hyg. b.	66.6%	sit up		33.3%
			put down	clothes	33.3%	pick up	steto	33.3%
						pick up	hyg. b.	33.3%
pick up	steto	Z1-bath.	put down	hyg. b.	33.3%	wake up		33.3%
			disinfect		33.3%	talk		33.3%
			pick up	sphygmo.	33.3%	pick up	sphygmo.	33.3%
pick up	sphygmo.	Z1-bath.	store	record	25.0%	talk		25.0%
			pick up	steto	25.0%	pick up	steto	25.0%
			read	record	25.0%	put down	sphygmo.	25.0%
			write		25.0%	pick up	gloves	25.0%
talk		Z2	wake up		7.1%	fetch		7.1%

			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
cuffon		Z2	wake up		20.0%	search pulse		20.0%
			measure		20.0%	inflate		80.0%
			talk		40.0%			
			raise bed		20.0%			
search pulse		Z2	measure		50.0%	measure		83.3%
			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
inflate		Z2	cuffon		80.0%	measure		100.0%
			search pulse		20.0%			
measure		Z2	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
search pulse		Z2	measure		50.0%	measure		83.3%
			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
measure		Z2	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
cuffon		Z2	wake up		20.0%	search pulse		20.0%
			measure		20.0%	inflate		80.0%
			talk		40.0%			
			raise bed		20.0%			
inflate		Z2	cuffon		80.0%	measure		100.0%
			search pulse		20.0%			
measure		Z2	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
search pulse		Z2	measure		50.0%	measure		83.3%
			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
measure		Z2	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%

						cuffoff		20.0%
put down	sphygmo.	Z2	measure		66.6%	open		33.3%
			pick up	sphygmo.	33.3%	write		33.3%
						put down	steto	33.3%
put down	steto	Z2	put down	sphygmo.	100.0%	write	steto	100.0%
write	steto	Z2	put down	steto	100.0%	wear	gloves	100.0%
wear	gloves	Z2	fetch		25.0%	talk		25.0%
			put down	socks	25.0%	take out	diaper	25.0%
			write	steto	25.0%	take out	towel	25.0%
			put down	washcloth	25.0%	take out	clothes	25.0%
talk		Z2	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
open		Z2	talk		33.3%	take out	towel	33.3%
			put down	sphygmo.	33.3%	take out	clothes	33.3%
			take out	washcloth	33.3%	take out	washcloth	33.3%
take out	towel	Z2	open		33.3%	fetch		33.3%
			wear	gloves	33.3%	take out	clothes	33.3%
			pick up	clothes	33.3%	take out	washcloth	33.3%
take out	washcloth	Z2	open		20.0%	open		20.0%
			talk		20.0%	put down	socks	20.0%
			brush teeth		20.0%	put down	washcloth	20.0%
			take out	towel	20.0%	stand up		20.0%
			sit on toilet	toilet	20.0%	help		20.0%
open		Z2	talk		33.3%	take out	towel	33.3%
			put down	sphygmo.	33.3%	take out	clothes	33.3%
			take out	washcloth	33.3%	take out	washcloth	33.3%
take out	clothes	Z2	take p to		20.0%	take p to		20.0%
			open		20.0%	pick up	hyg. b.	20.0%
			take out	diaper	20.0%	take out	diaper	20.0%
			wear	gloves	20.0%	fetch	shirt	20.0%
			take out	towel	20.0%	put in	clothes	20.0%
pick up	hyg. b.	Z2	put down	hyg. b.	33.3%	put down	hyg. b.	66.6%
			disinfect		33.3%	put down	clothes	33.3%
			take out	clothes	33.3%			
put down	clothes	Z2-bath.	fetch		25.0%	pick up	prot pad	25.0%
			pick up	hyg. b.	25.0%	put down	hyg. b.	25.0%
			put down	diaper	25.0%	put down	towel	25.0%
			pick up	clothes	25.0%	removesrail		25.0%
put down	towel	Z2-bath.	put down	clothes	100.0%	pick up	washcloth	100.0%
pick up	washcloth	Z2-bath.	undress	nightgown	50.0%	hand to p	washcloth	50.0%
			put down	towel	50.0%	stand up		50.0%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%

			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
put in	clothes	Z2-bath.	pick up	bag	25.0%	wash	back	25.0%
			take out	clothes	25.0%	disinfect		25.0%
			stand up		25.0%	put in	laundry	25.0%
			put in	laundry	25.0%	pick up	clothes	25.0%
wash	back	Z2-bath.	wash	face	33.3%	dry	back	66.6%
			stand up		33.3%	pick up	socks	33.3%
			put in	clothes	33.3%			
pick up	socks	Z2-bath.	wash	back	100.0%	help		100.0%
help		Z2-bath.	dry	face	20.0%	pick up	laundry	20.0%
			put in	trashbag	20.0%	brush	tooth	20.0%
			wash	pubic area	20.0%	wear	clothes	20.0%
			pick up	socks	20.0%	wash		20.0%
			take out	washcloth	20.0%	wear	socks	20.0%
wear	socks	Z2-bath.	help		100.0%	put in	trash	100.0%
put in	trash	G1	talk		33.3%	take off	gloves	33.3%
			comb		33.3%	put in	laundry	66.6%
			wear	socks	33.3%			
put in	laundry	G1	put in	trash	50.0%	talk		25.0%
			put in	laundry	25.0%	take off	gloves	25.0%
			put in	clothes	25.0%	put in	laundry	25.0%
						put in	clothes	25.0%
take off	gloves	G1	take p to		25.0%	put in	trashbag	75.0%
			put in	trash	25.0%	disinfect		25.0%
			put in	laundry	25.0%			
			comb		25.0%			
disinfect		Z2	put down	trash	25.0%	prep wchair		25.0%
			sit down		25.0%	take p to		25.0%
			take off	gloves	25.0%	pick up	steto	25.0%
			put in	clothes	25.0%	pick up	hyg. b.	25.0%
prep wchair		Z2-bath.	disinfect		100.0%	talk		100.0%
talk		A	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
take out	washcloth	Z2	open		20.0%	open		20.0%
			talk		20.0%	put down	socks	20.0%
			brush teeth		20.0%	put down	washcloth	20.0%
			take out	towel	20.0%	stand up		20.0%
			sit on toilet	toilet	20.0%	help		20.0%
put down	socks	Z2-bath.	take out	washcloth	100.0%	wear	gloves	100.0%

wear	gloves	Z2-bath.	fetch		25.0%	talk		25.0%
			put down	socks	25.0%	take out	diaper	25.0%
			write	steto	25.0%	take out	towel	25.0%
			put down	washcloth	25.0%	take out	clothes	25.0%
take out	clothes	Z2-bath.	take p to		20.0%	take p to		20.0%
			open		20.0%	pick up	hyg. b.	20.0%
			take out	diaper	20.0%	take out	diaper	20.0%
			wear	gloves	20.0%	fetch	shirt	20.0%
			take out	towel	20.0%	put in	clothes	20.0%
put in	clothes	Z2-bath.	pick up	bag	25.0%	wash	back	25.0%
			take out	clothes	25.0%	disinfect		25.0%
			stand up		25.0%	put in	laundry	25.0%
			put in	laundry	25.0%	pick up	clothes	25.0%
pick up	clothes	Z2-bath.	pick up	prot pad	50.0%	take out	towel	50.0%
			put in	clothes	50.0%	put down	clothes	50.0%
take out	towel	Z3	open		33.3%	fetch		33.3%
			wear	gloves	33.3%	take out	clothes	33.3%
			pick up	clothes	33.3%	take out	washcloth	33.3%
fetch		Z2-bath.	talk		50.0%	wear	gloves	50.0%
			take out	towel	50.0%	put down	clothes	50.0%
put down	clothes	Z2-bath.	fetch		25.0%	pick up	prot pad	25.0%
			pick up	hyg. b.	25.0%	put down	hyg. b.	25.0%
			put down	diaper	25.0%	put down	towel	25.0%
			pick up	clothes	25.0%	removesrail		25.0%
pick up	prot pad	Z2-bath.	put down	clothes	100.0%	pick up	clothes	100.0%
pick up	clothes	Z2-bath.	pick up	prot pad	50.0%	take out	towel	50.0%
			put in	clothes	50.0%	put down	clothes	50.0%
put down	clothes	Z2-bath.	fetch		25.0%	pick up	prot pad	25.0%
			pick up	hyg. b.	25.0%	put down	hyg. b.	25.0%
			put down	diaper	25.0%	put down	towel	25.0%
			pick up	clothes	25.0%	removesrail		25.0%
removesrail		Z2-bath.	put down	clothes	100.0%	removesbelt		100.0%
removesbelt		Z2-bath.	removesrail		100.0%	sit up		100.0%
sit up		Z2-bath.	put down	hyg. b.	50.0%	wear	shoes	50.0%
			removesbelt		50.0%	stand up		50.0%
wear	shoes	Z2-bath.	sit up		33.3%	sit down		33.3%
			pick up	shoes	66.6%	stand up		66.6%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
take p to		Z2-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
undress		Z2-bath.	flush	toilet	50.0%	instruct		50.0%
			take p to		50.0%	collect	trash	50.0%
collect	trash	Z2-bath.	removed		50.0%	undress	shoes	50.0%

			undress		50.0%	removed		50.0%
removed		Z2-bath.	collect	trash	100.0%	collect	trash	100.0%
collect	trash	Z2-bath.	removed		50.0%	undress	shoes	50.0%
			undress		50.0%	removed		50.0%
undress	shoes	Z2-bath.	collect	trash	100.0%	shower		100.0%
shower		Z2-bath.	undress	shoes	100.0%	stand up		100.0%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
sit down		Z2-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
dry		Z2-bath.	stand up		100.0%	sit down		100.0%
sit down		Z2-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
wear	patch	Z2-bath.	sit down		100.0%	wear	diaper	100.0%
wear	diaper	Z2-bath.	wear	patch	50.0%	sit down		50.0%
			wear	pullover	50.0%	stand up		50.0%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%

			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
pull up		Z2-bath.	stand up		100.0%	sit down		100.0%
sit down		Z2-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
wear	pants	Z2-bath.	sit down		100.0%	pull up	pants	50.0%
						stand up		50.0%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%
			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
pull up		Z2-bath.	stand up		100.0%	sit down		100.0%
sit down		Z2-bath.	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
wear	pullover	Z2-bath.	sit down		100.0%	wear	diaper	50.0%
						comb		50.0%
comb		Z2-bath.	talk		33.3%	instruct		33.3%
			sit down		33.3%	put in	trash	33.3%
			wear	pullover	33.3%	take off	gloves	33.3%
take off	gloves	Z2-bath.	take p to		25.0%	put in	trashbag	75.0%
			put in	trash	25.0%	disinfect		25.0%
			put in	laundry	25.0%			
			comb		25.0%			
put in	trashbag	Z2-bath.	take off	gloves	100.0%	talk		33.3%
						stand up		33.3%
						help		33.3%
stand up		Z2-bath.	sit up		8.3%	pull up		16.6%
			wear	diaper	8.3%	instruct		8.3%
			pick up	washcloth	8.3%	take p to		25.0%
			put in	trashbag	8.3%	wash	back	8.3%
			sit down		8.3%	dry		8.3%
			wear	pants	8.3%	talk		8.3%
			wear	shoes	16.6%	sit down		8.3%

			shower		8.3%	put down	washcloth	8.3%
			wash		8.3%	put in	clothes	8.3%
			take out	washcloth	8.3%			
			dry	thorax	8.3%			
take p to		Z2-bath.	disinfect		16.6%	talk		16.6%
			pick up	unknown	16.6%	sit down		33.3%
			take out	clothes	16.6%	undress		16.6%
			stand up		50.0%	take off	gloves	16.6%
						take out	clothes	16.6%
sit down		A	pull up		16.6%	flush	toilet	8.3%
			take p to		16.6%	talk		16.6%
			wear	diaper	8.3%	wear	patch	8.3%
			dry		8.3%	disinfect		8.3%
			talk		16.6%	wear	pants	16.6%
			put down	washcloth	8.3%	wear	pullover	16.6%
			dry	back	8.3%	instruct		8.3%
			wear	shoes	8.3%	stand up		8.3%
			stand up		8.3%	comb		8.3%
talk		PS	wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%
			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
pick up	laundry	Z2-bath.	talk		50.0%	put in	laundrybag	50.0%
			help		50.0%	pick up	trash	50.0%
put in	laundrybag	Z2-bath.	pick up	laundry	100.0%	pick up	bag	100.0%
pick up	bag	Z2-bath.	put in	laundrybag	100.0%	put in	clothes	100.0%
put in	clothes	Z2-bath.	pick up	bag	25.0%	wash	back	25.0%
			take out	clothes	25.0%	disinfect		25.0%
			stand up		25.0%	put in	laundry	25.0%
			put in	laundry	25.0%	pick up	clothes	25.0%
put in	laundry	Z2-bath.	put in	trash	50.0%	talk		25.0%
			put in	laundry	25.0%	take off	gloves	25.0%
			put in	clothes	25.0%	put in	laundry	25.0%
						put in	clothes	25.0%
put in	clothes	Z2-bath.	pick up	bag	25.0%	wash	back	25.0%
			take out	clothes	25.0%	disinfect		25.0%
			stand up		25.0%	put in	laundry	25.0%
			put in	laundry	25.0%	pick up	clothes	25.0%
disinfect		Z2-bath.	put down	trash	25.0%	prep wchair		25.0%
			sit down		25.0%	take p to		25.0%
			take off	gloves	25.0%	pick up	steto	25.0%
			put in	clothes	25.0%	pick up	hyg. b.	25.0%
pick up	steto	Z2-bath.	put down	hyg. b.	33.3%	wake up		33.3%
			disinfect		33.3%	talk		33.3%
			pick up	sphygmo.	33.3%	pick up	sphygmo.	33.3%
			wake up		7.1%	fetch		7.1%
			talk		7.1%	wake up		7.1%

talk Z2-bath.

			wear	gloves	7.1%	pick up	laundry	7.1%
			pick up	sphygmo.	7.1%	open		7.1%
			stand up		7.1%	read	record	7.1%
			prep wchair		7.1%	talk		7.1%
			take p to		7.1%	cuffon		14.3%
			pick up	steto	7.1%	sit down		14.3%
			put in	trashbag	7.1%	put in	trash	7.1%
			sit down		14.3%	comb		7.1%
			fetch	shirt	7.1%	sit on toilet	toilet	7.1%
			write		7.1%	take out	washcloth	7.1%
			put in	laundry	7.1%			
read	record	PS	talk		100.0%	pick up	sphygmo.	100.0%
pick up	sphygmo.	Z2	store	record	25.0%	talk		25.0%
			pick up	steto	25.0%	pick up	steto	25.0%
			read	record	25.0%	put down	sphygmo.	25.0%
			write		25.0%	pick up	gloves	25.0%
pick up	gloves	PS	pick up	sphygmo.	100.0%	wake up		100.0%
wake up		Z4	pick up	steto	33.3%	talk		33.3%
			talk		33.3%	cuffon		33.3%
			pick up	gloves	33.3%	raise bed		33.3%
raise bed		Z4	wake up		100.0%	cuffon		100.0%
cuffon		Z4	wake up		20.0%	search pulse		20.0%
			measure		20.0%	inflate		80.0%
			talk		40.0%			
			raise bed		20.0%			
inflate		Z4	cuffon		80.0%	measure		100.0%
			search pulse		20.0%			
measure		Z4	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%
cuffoff		Z4	measure		100.0%	search pulse		100.0%
search pulse		Z4	measure		50.0%	measure		83.3%
			cuffon		16.6%	inflate		16.6%
			cuffoff		33.3%			
measure		Z4	search pulse		50.0%	dummy		10.0%
			inflate		50.0%	cuffon		10.0%
						search pulse		30.0%
						put down	sphygmo.	20.0%
						write		10.0%
						cuffoff		20.0%

B.2 Activity hierarchy

B.3 Object hierarchy

B.4 List of verbs being distinct verb trees

1. Children of **Move**

   turn; arrange; rearrange; make; put down; set; put in; fetch; cut; pick up; clean; instruct; lower; raise

2. Children of **Change**

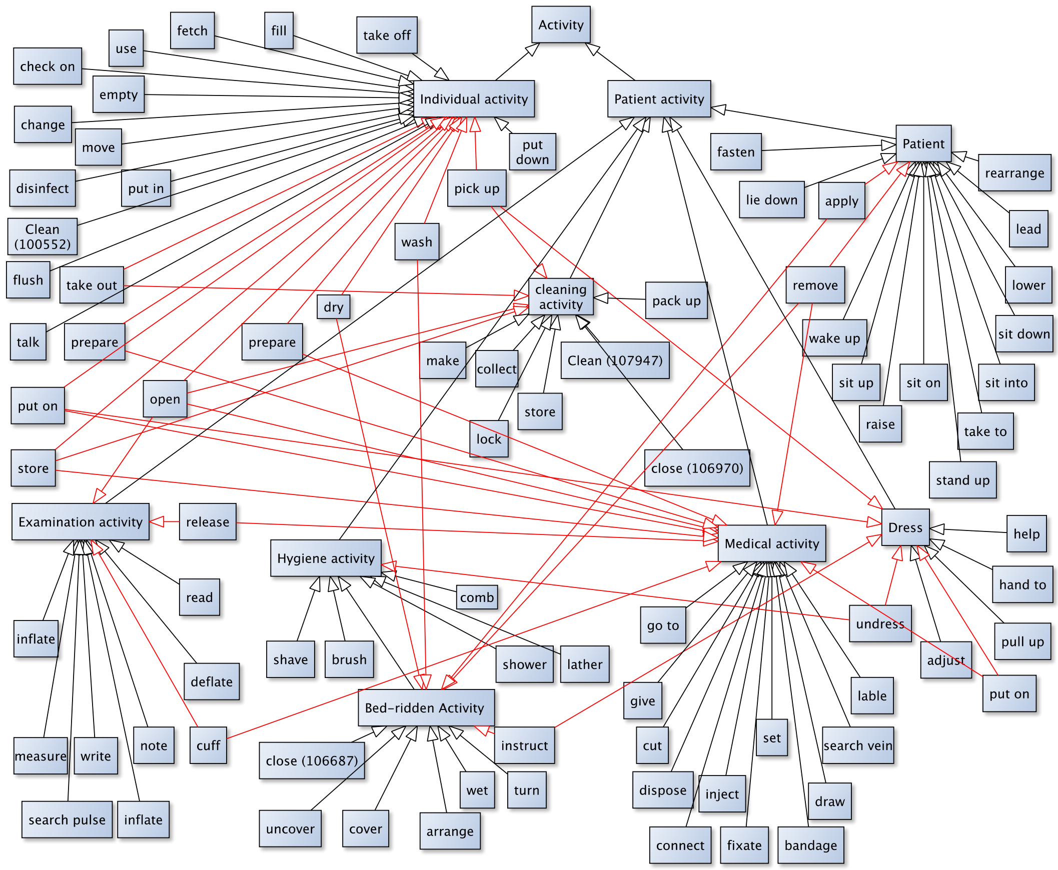


FIGURE B.1: The hierarchy of activities obtained from the logs. Red arrows represent multiple inheritance

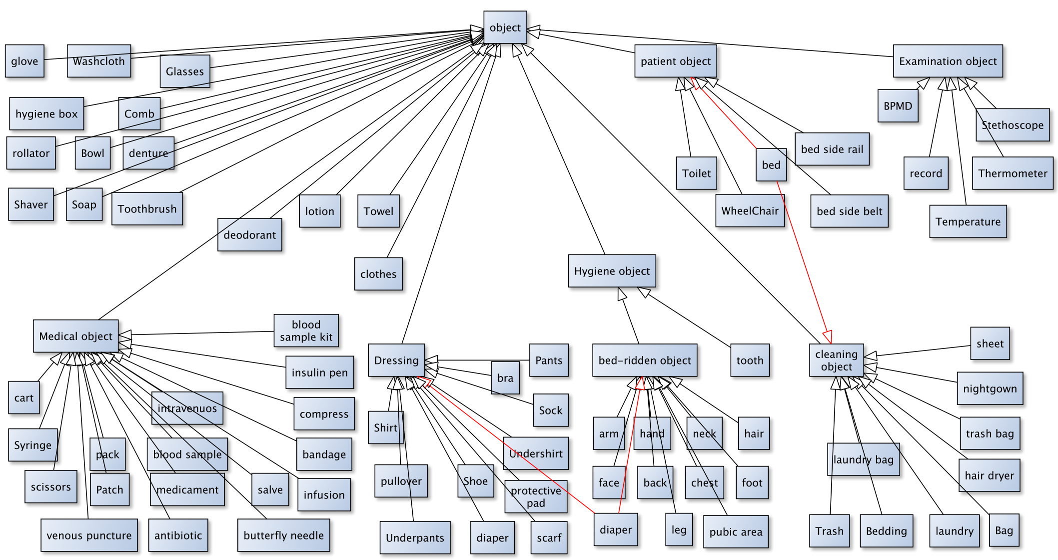


FIGURE B.2: The hierarchy of object and bodyparts obtained from the logs. Red arrows represent multiple inheritance

adjust; wash; clean; disinfect; dry; prepare; empty; fill; flush; deflate; put on; cuff; wet; shower; shave; comb; inflate; wake up; stand up; sit down; lie down; sit up

3. Children of **Connect**

   fixate; bandage; fasten; label; lock; close

4. Children of **Remove**

   take out; take off; dispose; undress

5. Children of **Act**

   talk; write; note

6. Children of **Cover**

   lather

7. Children of **Treat**

   inject; apply

8. Children of **Have**

   store; collect

9. Children of **Transfer**

   give; hand

10. Children of **Support**

    help

11. Children of **Understand**

    read

12. Children of **Decide**

    measure

13. Children of **Guide**

    brush

B.5 Files for Mainkofen

Here are the three .json files used to populate the model.

B.5.1 Menues.json

This file contains all the activities, body parts and objects with their corresponding classes, which we called procedures in the case of activities.

LISTING B.1: Menues.json file

```
"1Activities":["change","check on","clean","disinfect","empty",
"fetch/search","fill","flush","open","pick up","prepare", "put down",
"put in", "put on", "store","take off", "take out","use", "W+","W-",
"wash H","dry H", "talk","furniture"],

"2P-Activities":["wake up", "sit up", "stand up", "lead", "sit down",
"sit on toilet", "sit into wCh", "lie down","take P to", "prep
wChair", "rearrange" "","removeSrail", "applySrail", "removeSbelt",
"fastenSbelt","raise bed", "lower bed", ""],
```

```
"3Things":["BSampleKit","BPMD","Steto", "Record","Clothes","Diaper",
"Towel","Toilet","WashCloth","", "Bowl", "Comb", "Deo","Dentures",
"Hygiene Box", "Lotion/Salve","Toothbrush", "Shaver","Soap",
"Gloves", "Glasses","WheelCh","Rollator"],

"4Examin":["cuffOPEN","cuffON","inflate","cuffOFF","MEASURE",
"deflate","search pulse", "note","read", "write", "BPMD", "Steto",
"Record", "Thermometer", "Temperature"],

"5Hygiene":["apply","brush teeth","comb","dry","dry hair +",
"dry hair -", "instruct", "lather","SH +", "SH -", "shave +",
"shave -","undress","wash","wet", "Arms","Back", "Chest","Face",
"Feet","Hair", "Legs", "Neck","Pubic Area"],

"6WASHBed": ["apply","cover","dry","instruct","turnP","wet", "wash",
"uncover","removeD", "arrangeD", "closeD","Arms","Back", "Chest",
"Face","Feet","Hair", "Legs", "Neck","Pubic Area"],

"7Dress":["re/arrange","undress","pick up", "hand to P", "instruct",
"help", "put on","pull up","Diaper","Underpants","Pants","ProtecPa",
"Undershirt","Bra","Shirt","Pull/Jack", "Socks", "Shoes","Scarf",
"Nightgown"],

"8Clean":["clean","close","collect","lock Clos","make Bed","open",
"pick up","store", "take out","pack up","Bag","Bedding","Laundry",
"LaundryBag","Sheets","Trash","TrashBag"],

"9Medics":["BLOODSAM:","cuffON", "search vein","open","setButterfly",
"witdhraw Bl","cuffOFF","removeButt","lable","store","BloodSample","
Pack","Syringe", "","BANDAGE:","bandage","cut","fixate","open","put
on","remove","Bandage","B-trolley","Compress",
"Pack", "Patch", "Salve" "Sissors","INSULINE:","prepare", "go to
Patient", "inject", "dispose", "InsulinePen","MEDICATION","connect",
"give","prepare", "set", "Antbiotika", "Infusion","Intravenous",
"Medicaments", "Venous puncture"]
```


B.5.2 Person.json

This file contains all the information about the people and locations in the Mainkofen hospital.

LISTING B.2: Person.json file


```
"patients":["Z1-T","Z1-F","Z2-T","Z2-F","Z3-T","Z3-F","Z4-F","Z5-RT"
,"Z5-RM","Z5-RF","Z5-LT","Z5-LF","Z6-F","Z7-T","Z7-F","Z8-T","Z8-M",
"Z8-F","Z9-T","Z9-F","Z10-R","Z10-L","other1", "other2"],
"sisters":["B1-1","B4-1","B2-1","B3-1","StvO","ScUe1","ScUe2"],
"roomindex1":["Z1","Z2","Z3","Z4","Z5","Z6","Z7","Z8","Z9","Z10",
"SB","WC","W","V"],
"roomindex2":["G4","G3","G2","G1","E","SR","A","K","AZ","PS","PR",
"RR"]
```


B.5.3 Roomhotspots.json

This file contains all the information about rooms and their furniture.

LISTING B.3: Person.json file

```
"Z1":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z2":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z3":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z4":["Bed", "bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z5":["Bed TR","Bed FR","Bed TL","Bed FL","trash container",
"bathroom","sink","shower","toilet","closet",
"table","chair","window","door", "room"],
"Z6":["Bed", "bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z7":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z8":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z9":["Bed T","Bed F","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"Z10":["Bed R","Bed L","bathroom","sink","shower","toilet","closet",
"table","chair", "room","trash container","window","door"],
"G1":["trash container","bench"],
"G2":["trash container"],
"G3":["trash container"],
"G4":["trash container","bench"],
"E":[""],
"SR":["FR","rf","rm","lf","lm","lt"],
"SB":["chair","closet","shower"],
"WC":[""],
"W":[""],
"V":[""],
"PS":["cabinet","PC","record trolley","phone","sink", "fridge"],
"A":["big table","small table","couch","TV","armchair"],
"K":[""],
"AZ":[""],
"RR":[""],
"PR":["table","sink","closet"]
```

Bibliography

Abowd, Gregory et al. (1999). "Towards a better understanding of context and context-awareness". In: *Handheld and ubiquitous computing*. Springer, pp. 304–307.

Aharony, Nadav et al. (2011). "Social fMRI: Investigating and shaping social mechanisms in the real world". In: *Pervasive and Mobile Computing* 7.6, pp. 643–659.

Almeida, Aitor and Diego López-de-Ipiña (2012). "Assessing ambiguity of context data in intelligent environments: Towards a more reliable context managing system". In: *Sensors* 12.4, pp. 4934–4951.

Betsworth, Liam et al. (2013). "Audvert: Using spatial audio to gain a sense of place". In: *IFIP Conference on Human-Computer Interaction*. Springer, pp. 455–462.

Bouquet, Paolo and Fausto Giunchiglia (1995). "Reasoning about theory adequacy. a new solution to the qualification problem". In: *Fundamenta Informaticae* 23.2, 3, 4, pp. 247–262.

Bresciani, Paolo et al. (2004). "Tropos: An agent-oriented software development methodology". In: *Autonomous Agents and Multi-Agent Systems* 8.3, pp. 203–236.

Centellegher, Simone et al. (2016). "The Mobile Territorial Lab: a multilayered and dynamic view on parents' daily lives". In: *EPJ Data Science* 5.1, p. 3.

Cheetham, Graham and Geoffrey E Chivers (2005). *Professions, competence and informal learning*. Edward Elgar Publishing.

Chen, Guanling, David Kotz, et al. (2000). *A survey of context-aware mobile computing research*. Tech. rep. Technical Report TR2000-381, Dept. of Computer Science, Dartmouth College.

Chen, Harry, T Finin, and A Joshi (2003). "An intelligent broker architecture for context-aware systems". In: *PhD proposal in computer science, University of Maryland, Baltimore, USA*.

Chen, Liming and Chris Nugent (2009). "Ontology-based activity recognition in intelligent pervasive environments". In: *International Journal of Web Information Systems* 5.4, pp. 410–430.

Chen, Liming, Chris D Nugent, and Hui Wang (2012). "A knowledge-driven approach to activity recognition in smart homes". In: *IEEE Transactions on Knowledge and Data Engineering* 24.6, pp. 961–974.

Chen, Liming, Chris Nugent, and George Okeyo (2014). "An ontology-based hybrid approach to activity modeling for smart homes". In: *IEEE Transactions on human-machine systems* 44.1, pp. 92–105.

Cheng, Heng-Tze (2013). "Learning and Recognizing The Hierarchical and Sequential Structure of Human Activities". In:

Claessens, Brigitte JC et al. (2007). "A review of the time management literature". In: *Personnel review* 36.2, pp. 255–276.

Committee, Federal Geographic Data (2015). *Entity and Attribute Information*. URL: https://www.fgdc.gov/metadata/csdgm-new/05.html.

Consolvo, Sunny et al. (2008). "Flowers or a robot army?: encouraging awareness & activity with personal, mobile displays". In: *Proceedings of the 10th international conference on Ubiquitous computing*. ACM, pp. 54–63.

Das, Subhashis and Fausto Giunchiglia (2016). "Geoetypes: Harmonizing diversity in geospatial data (short paper)". In: *OTM Confederated International Conferences" On the Move to Meaningful Internet Systems"*. Springer, pp. 643–653.

Dey, Anind K, Gregory D Abowd, and Andrew Wood (1998). "CyberDesk: A framework for providing self-integrating context-aware services". In: *Knowledge-Based Systems* 11.1, pp. 3–13.

Dodge, Martin and Rob Kitchin (2007). "'Outlines of a world coming into existence': pervasive computing and the ethics of forgetting". In: *Environment and planning B: planning and design* 34.3, pp. 431–445.

Doumen, Sarah, Jan Broeckmans, and Chris Masui (2014). "The role of self-study time in freshmen's achievement". In: *Educational Psychology* 34.3, pp. 385–402.

Eagle, Nathan and Alex Sandy Pentland (2006). "Reality mining: sensing complex social systems". In: *Personal and ubiquitous computing* 10.4, pp. 255–268.

Eronen, Antti J et al. (2006). "Audio-based context recognition". In: *IEEE Transactions on Audio, Speech, and Language Processing* 14.1, pp. 321–329.

EUROSTAT (2009). *Harmonised European Time Use Surveys (2008 Guidelines)*. https://www.h2.scb.se/tus/tus/AreaGraphCID.html.

Fellbaum, Christiane (1998). *WordNet*. Wiley Online Library.

Fernandez, Pane and Juan Ignacio (2012). "Distributed Identity Management". PhD thesis. University of Trento.

Fernex, Alain, Laurent Lima, and Erica De Vries (2015). "Exploring time allocation for academic activities by university students in France". In: *Higher Education* 69.3, pp. 399–420.

Fox, Brent I and Bill G Felkey (2016). "The Quantified Self". In: *Hospital Pharmacy* 51.2, pp. 189–190.

Frege, Gottlob (1948). "Sense and reference". In: *The philosophical review* 57.3, pp. 209–230.

Gangemi, Aldo et al. (2002). "Sweetening ontologies with DOLCE". In: *International Conference on Knowledge Engineering and Knowledge Management*. Springer, pp. 166–181.

Giunchiglia, Fausto (1993). "Contextual reasoning". In: *Epistemologia, special issue on I Linguaggi e le Macchine* 16, pp. 345–364.

— (2006). "Managing diversity in knowledge". In: *IEA/AIE*, p. 1.

Giunchiglia, Fausto, Enrico Giunchiglia, et al. (1996). "Dealing with expected and unexpected obstacles". In: *Journal of Experimental & Theoretical Artificial Intelligence* 8.2, pp. 173–190.

Giunchiglia, Fausto, Mattia Zeni, et al. (2017). "Mobile Social Media and Academic Performance". In: *International Conference on Social Informatics*. Springer, pp. 3–13.

Goldberg, Lewis R (1993). "The structure of phenotypic personality traits." In: *American psychologist* 48.1, p. 26.

Golemati, Maria et al. (2007). "Creating an ontology for the user profile: Method and applications". In: *Proceedings of the first RCIS conference*. 2007, pp. 407–412.

Gouveia, Valdiney V, Taciano L Milfont, and Valeschka M Guerra (2014). "Functional theory of human values: Testing its content and structure hypotheses". In: *Personality and Individual Differences* 60, pp. 41–47.

Grave, Barbara S (2011). "The effect of student time allocation on academic achievement". In: *Education Economics* 19.3, pp. 291–310.

Gu, Tao, Hung Keng Pung, and Da Qing Zhang (2004). "A middleware for building context-aware mobile services". In: *Vehicular Technology Conference, 2004. VTC 2004-Spring. 2004 IEEE 59th*. Vol. 5. IEEE, pp. 2656–2660.

Guarino, Nicola (1998). *Formal ontology in information systems: Proceedings of the first international conference (FOIS'98), June 6-8, Trento, Italy*. Vol. 46. IOS press.

Haddadi, Hamed et al. (2015). "360-degree quantified self". In: *Healthcare Informatics (ICHI), 2015 International Conference on*. IEEE, pp. 587–592.

Heckmann, Dominikus et al. (2007). "The user model and context ontology gumo revisited for future web 2.0 extensions". In: *Contexts and Ontologies: Representation and Reasoning (2007)*, pp. 37–46.

Heittola, Toni et al. (2010). "Audio context recognition using audio event histograms". In: *Signal Processing Conference, 2010 18th European*. IEEE, pp. 1272–1276.

— (2013). "Context-dependent sound event detection". In: *EURASIP Journal on Audio, Speech, and Music Processing* 2013.1, p. 1. ISSN: 1687-4722. DOI: 10.1186/1687-4722-2013-1. URL: https://doi.org/10.1186/1687-4722-2013-1.

Hellgren, Mattias (2014). "Extracting More Knowledge from Time Diaries?" In: *Social Indicators Research* 119.3, pp. 1517–1534.

Henricksen, Karen, Jadwiga Indulska, and Andry Rakotonirainy (2002). "Modeling context information in pervasive computing systems". In: *Pervasive Computing*, pp. 79–117.

Hervás, Ramón, José Bravo, and Jesús Fontecha (2010). "A Context Model based on Ontological Languages: a Proposal for Information Visualization." In: *J. UCS* 16.12, pp. 1539–1555.

Hume Llamosas, Alethia Graciela (2014). "Distributed Contact and Identity Management". PhD thesis. University of Trento.

Junco, Reynol (2012). "Too much face and not enough books: The relationship between multiple indices of Facebook use and academic performance". In: *Computers in human behavior* 28.1, pp. 187–198.

Juster, F Thomas and Frank P Stafford (1991). "The allocation of time: Empirical findings, behavioral models, and problems of measurement". In: *Journal of Economic literature* 29.2, pp. 471–522.

Kan, Man Yee and Stephen Pudney (2008). "Measurement error in stylized and diary data on time use". In: *Sociological Methodology* 38.1, pp. 101–132.

Kang, Jerry (1998). "Information privacy in cyberspace transactions". In: *Stanford Law Review*, pp. 1193–1294.

Karpinski, Aryn C et al. (2013). "An exploration of social networking site use, multitasking, and academic performance among United States and European university students". In: *Computers in Human Behavior* 29.3, pp. 1182–1192.

Kharbat, Faten and Haya El-Ghalayini (2008). *Building Ontology from Knowledge Base Systems*. INTECH Open Access Publisher.

Knappmeyer, Michael et al. (2013). "Survey of context provisioning middleware". In: *IEEE Communications Surveys & Tutorials* 15.3, pp. 1492–1519.

Kobsa, Alfred (2001). "Generic user modeling systems". In: *User modeling and user-adapted interaction* 11.1, pp. 49–63.

Kripke, Saul A (1972). "Naming and necessity". In: *Semantics of natural language*. Springer, pp. 253–355.

Ladd, A.M. et al. (2004). "On the feasibility of using wireless ethernet for indoor localization". In: *Robotics and Automation, IEEE Transactions on* 20.3, pp. 555–559.

Lee, Heyoung et al. (2017). "Comparing the Self-Report and Measured Smartphone Usage of College Students: A Pilot Study". In: *Psychiatry investigation* 14.2, pp. 198–204.

Liu, Wei, Xue Li, and Daoli Huang (2011). "A survey on context awareness". In: *Computer Science and Service System (CSSS), 2011 International Conference on*. IEEE, pp. 144–147.

Liu, Yang et al. (2004). "Two kinds of hypernymy faults in WordNet: the cases of ring and isolator". In: *Proceedings of the Second Global WordNet Conference*, pp. 347–351.

Liu, Ye et al. (2016). "From action to activity: Sensor-based activity recognition". In: *Neurocomputing* 181, pp. 108–115.

Lu, Hong et al. (2009). "SoundSense: scalable sound sensing for people-centric applications on mobile phones". In: *Proceedings of the 7th international conference on Mobile systems, applications, and services*. ACM, pp. 165–178.

Lucena, Marcia et al. (2008). "Towards a unified metamodel for i". In: *Research Challenges in Information Science, 2008. RCIS 2008. Second International Conference on*. IEEE, pp. 237–246.

Lupton, Deborah (2016). *The quantified self*. John Wiley & Sons.

Madan, Anmol, Manuel Cebrian, David Lazer, et al. (2010). "Social sensing for epidemiological behavior change". In: *Proceedings of the 12th ACM international conference on Ubiquitous computing*. ACM, pp. 291–300.

Madan, Anmol, Manuel Cebrian, Sai Moturu, et al. (2012). "Sensing the "health state" of a community". In: *IEEE Pervasive Computing* 11.4, pp. 36–45.

Marcengo, Alessandro and Amon Rapp (2014). "Visualization of human behavior data: the quantified self". In: *Innovative approaches of data visualization and visual analytics* 1, pp. 236–265.

Mill, John Stuart (1893). *A system of logic, ratiocinative and inductive: Being a connected view of the principles of evidence and the methods of scientific investigation*. Harper & brothers.

Mucciardi, Massimo (2013). "Student time allocation and self-rated performance–Evidence from a sample survey in Sicily (Italy)". In: *Electronic International Journal of Time Use Research*.

Myers, Isabel Briggs et al. (1998). *MBTI manual: A guide to the development and use of the Myers-Briggs Type Indicator*. Vol. 3. Consulting Psychologists Press Palo Alto, CA.

Pan, Jianguo et al. (2007). "Ontology based user profiling in personalized information service agent". In: *Computer and Information Technology, 2007. CIT 2007. 7th IEEE International Conference on*. IEEE, pp. 1089–1093.

Parliament, E (1995). "Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data". In: *Official Journal of the European Communities, number L* 281, pp. 31–50.

Pentland, A. (2000). “Looking at people: sensing for ubiquitous and wearable computing”. In: *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 22.1, pp. 107–119. ISSN: 0162-8828. DOI: 10.1109/34.824823.

Pentland, Wendy E et al. (1999). *Time use research in the social sciences*. Springer.

Pike, Gary R, George D Kuh, and Ryan C Massa-McKinley (2008). “First-year students’ employment, engagement, and academic achievement: Untangling the relationship between work and grades”. In: *NASPA journal* 45.4, pp. 560–582.

Pornbacher, Helmut and Hans Friedel Niederkofler (2004). *La mobilità delle famiglie nel Comune di Trento*. Final Report 225. Version Final. Bolzano, Italy: Apollis.

Rawassizadeh, Reza et al. (2013). “UbiqLog: a generic mobile phone-based life-log framework”. In: *Personal and ubiquitous computing* 17.4, pp. 621–637.

Razmerita, Liana, Albert Angehrn, and Alexander Maedche (2003). “Ontology-based user modeling for knowledge management systems”. In: *User modeling 2003*, pp. 148–148.

Regulation, General Data Protection (2016). “Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46”. In: *Official Journal of the European Union (OJ)* 59, pp. 1–88.

Riboni, Daniele and Claudio Bettini (2011). “COSAR: hybrid reasoning for context-aware activity recognition”. In: *Personal and Ubiquitous Computing* 15.3, pp. 271–289.

Riboni, Daniele, Linda Pareschi, et al. (2011). “Is ontology-based activity recognition really effective?” In: *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference on*. IEEE, pp. 427–431.

Robinson, John P (1985). “The validity and reliability of diaries versus alternative time use measures”. In: *Time, goods, and well-being* 3.

Robinson, John and Geoffrey Godbey (2010). *Time for life: The surprising ways Americans use their time*. Penn State Press.

Roby, Douglas E (2004). “Research on school attendance and student achievement: A study of Ohio schools”. In: *Educational Research Quarterly* 28.1, p. 3.

Rodríguez, Natalia Díaz et al. (2014). "A survey on ontologies for human behavior recognition". In: *ACM Computing Surveys (CSUR)* 46.4, p. 43.

Romano, MC (2008). "Time use in daily life. A multidisciplinary approach to the Time use's analysis". In: *Tech. Rep. ISTAT No 35*.

Rosen, Larry D, L Mark Carrier, and Nancy A Cheever (2013). "Facebook and texting made me do it: Media-induced task-switching while studying". In: *Computers in Human Behavior* 29.3, pp. 948–958.

Rowland, Donald T et al. (2003). "Demographic methods and concepts". In: *OUP Catalogue*.

Schilit, Bill N and Marvin M Theimer (1994). "Disseminating active map information to mobile hosts". In: *Network, IEEE* 8.5, pp. 22–32.

Schmidt, Albrecht, Michael Beigl, and Hans-W Gellersen (1999). "There is more to context than location". In: *Computers & Graphics* 23.6, pp. 893–901.

Schwartz, Shalom H et al. (2012). "Refining the theory of basic individual values." In: *Journal of personality and social psychology* 103.4, p. 663.

Scott, James and Boris Dragovic (2005). "Audio location: Accurate low-cost location sensing". In: *Pervasive Computing*, pp. 307–311.

Searle, John R (1969). *Speech acts: An essay in the philosophy of language*. Vol. 626. Cambridge university press.

Shelley, Kristina J (2005). "Developing the American time use survey activity classification system". In: *Monthly Lab. Rev.* 128, p. 3.

Skillen, Kerry-Louise et al. (2012). "Ontological user profile modeling for context-aware application personalization". In: *Ubiquitous Computing and Ambient Intelligence*, pp. 261–268.

Smeulders, Arnold WM et al. (2000). "Content-based image retrieval at the end of the early years". In: *IEEE Transactions on pattern analysis and machine intelligence* 22.12, pp. 1349–1380.

Smythe, Colin, Frank Tansey, and Robby Robson (2001). "IMS learner information package information model specification". In: *Final Specification Version* 1.

Sonck, Nathalie and Henk Fernee (2013). "Using smartphones in survey research: a multifunctional tool". In: *Sociaal en Cultureel Planbureau*.

Sorokin, Pitirim Aleksandrovich and Clarence Quinn Berger (1939). *Time-budgets of human behavior*. Vol. 2. Harvard University Press.

Sosnovsky, Sergey and Darina Dicheva (2010). "Ontological technologies for user modelling". In: *International Journal of Metadata, Semantics and Ontologies* 5.1, pp. 32–71.

Stets, Jan E and Peter J Burke (2000). "Identity theory and social identity theory". In: *Social psychology quarterly*, pp. 224–237.

Stinebrickner, Ralph and Todd R Stinebrickner (2003). "Working during school and academic performance". In: *Journal of labor Economics* 21.2, pp. 473–491.

— (2004). "Time-use and college outcomes". In: *Journal of Econometrics* 121.1, pp. 243–269.

Stopczynski, Arkadiusz et al. (2014). "Measuring large-scale social networks with high resolution". In: *PloS one* 9.4, e95978.

Sutterer, Michael, Olaf Droegehorn, and Klaus David (2008). "Upos: User profile ontology with situation-dependent preferences support". In: *Advances in Computer-Human Interaction, 2008 First International Conference On*. IEEE, pp. 230–235.

Swan, Melanie (2012a). "Health 2050: the realization of personalized medicine through crowdsourcing, the quantified self, and the participatory biocitizen". In: *Journal of personalized medicine* 2.3, pp. 93–118.

— (2012b). "Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0". In: *Journal of Sensor and Actuator Networks* 1.3, pp. 217–253.

— (2013). "The quantified self: Fundamental disruption in big data science and biological discovery". In: *Big Data* 1.2, pp. 85–99.

Tim, Benson (2010). "Principles of Health Interoperability HL7 and SNOMED". In: *Health Informatics*.

Villalonga, Claudia et al. (2015). "High-Level Context Inference for Human Behavior Identification". In: *International Workshop on Ambient Assisted Living*. Springer, pp. 164–175.

Viviani, Marco, Nadia Bennani, and Elod Egyed-Zsigmond (2010). "A survey on user modeling in multi-application environments". In: *Advances in Human-Oriented and Personalized Mechanisms, Technologies and Services (CENTRIC), 2010 Third International Conference On*. IEEE, pp. 111–116.

Wang, Rui, Fanglin Chen, et al. (2014). "StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones". In: *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, pp. 3–14.

Wang, Rui, Gabriella Harari, et al. (2015). "SmartGPA: how smartphones can assess and predict academic performance of college students". In: *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, pp. 295–306.

Wang, Xiao Hang et al. (2004). "Ontology based context modeling and reasoning using OWL". In: *Pervasive Computing and Communications Workshops, 2004. Proceedings of the Second IEEE Annual Conference on*. Ieee, pp. 18–22.

Xu, Nan et al. (2013). "CACOnt: a ontology-based model for context modeling and reasoning". In: *Applied Mechanics and Materials*. Vol. 347. Trans Tech Publ, pp. 2304–2310.

Yamabe, Tetsuo, Ayako Takagi, and Tatsuo Nakajima (2005). "Citron: A context information acquisition framework for personal devices". In: *Embedded and Real-Time Computing Systems and Applications, 2005. Proceedings. 11th IEEE International Conference on*. IEEE, pp. 489–495.

Yu, Eric (2011). "Modelling strategic relationships for process reengineering". In: *Social Modeling for Requirements Engineering* 11, p. 2011.

Zeng, Zhi et al. (2008). "Adaptive context recognition based on audio signal". In: *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*. IEEE, pp. 1–4.

Zeni, Mattia, Ilya Zaihrayeu, and Fausto Giunchiglia (2014). "Multi-device activity logging". In: *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*. ACM, pp. 299–302.