

This is the final peer-reviewed accepted manuscript of:

Veljko Pejovic and Mirco Musolesi. 2015. Anticipatory Mobile Computing: A Survey of the State of the Art and Research Challenges. *ACM Comput. Surv.* 47, 3, Article 47 (April 2015), 29 pages.

The final published version is available online at : <https://doi.org/10.1145/2693843>

Rights / License:

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (<https://cris.unibo.it/>)

When citing, please refer to the published version.

Anticipatory Mobile Computing: A Survey of the State of the Art and Research Challenges

VELJKO PEJOVIC, School of Computer Science, University of Birmingham, UK
MIRCO MUSOLESI, School of Computer Science, University of Birmingham, UK

Today's mobile phones are far from mere communication devices they were ten years ago. Equipped with sophisticated sensors and advanced computing hardware, phones can be used to infer users' location, activity, social setting and more. As devices become increasingly intelligent, their capabilities evolve beyond inferring context to predicting it, and then reasoning and acting upon the predicted context. This article provides an overview of the current state of the art in mobile sensing and context prediction paving the way for full-fledged anticipatory mobile computing. We present a survey of phenomena that mobile phones can infer and predict, and offer a description of machine learning techniques used for such predictions. We then discuss proactive decision making and decision delivery via the user-device feedback loop. Finally, we discuss the challenges and opportunities of anticipatory mobile computing.

Categories and Subject Descriptors: A.1 [Introductory and Survey]; H.3.4 [Systems and Software]: Distributed systems; H.1.2 [User/Machine Systems]; I.2.6 [Learning]; J.4 [Social and Behavioral Sciences]

General Terms: Design, Human Factors, Performance

Additional Key Words and Phrases: Anticipatory Computing, Mobile Sensing, Context-aware Systems

1. INTRODUCTION

The ability to communicate on the move has revolutionised the lifestyle of millions of individuals: it has changed the way we work, organise our daily schedules, develop and maintain social ties, enjoy our free time, and handle emergencies. In the past decade mobile phones have reached every part of the world, and 86% of the world's population had a cellular subscription in year 2012 [International Telecommunication Union 2012]. When smartphones replaced feature phones another mobile revolution happened. Nowadays, phones serve for travel planning, staying in touch with online social network contacts, online shopping and numerous other purposes. Today's smartphones with multi-core CPUs and gigabytes of memory are capable of processing tasks that yesterday's desktop computers struggled with. However, unlike desktop computers, smartphones are small mobile devices. Consequently, phones became a part of everyday life and remain continuously present and used at all times. In addition,

modern-day smartphones host a variety of sophisticated sensors: a phone can sense its orientation, acceleration, location, and can record audio and video. As such, a smartphone is not just a mobile computer – it is a perceptive device capable of extending human senses [Lane et al. 2010]. Finally, these devices are connected to the Internet and, therefore, they can share the collected data and exploit the resources offered by cloud services.

Despite the recent phenomenal progress, the area of mobile personal devices promises further advances as sensing and processing capabilities of mobile phones grow. In this survey we discuss the emergence of *anticipatory mobile computing*, a field that harnesses mobile sensing and machine learning for intelligent reasoning based on the prediction of future events. We build this new paradigm upon the theoretical postulates of anticipatory systems – computing systems that base their actions on a predictive model of themselves and their environment. Smartphones are potentially a revolutionary platform for anticipatory systems as they bridge the gap between the device, the environment and the user. First, they fulfil the necessary prerequisites for successful anticipatory reasoning: they are equipped with numerous sensors and can infer and monitor the context, while powerful processing hardware allows them to run machine learning algorithms and develop sophisticated models of the future. Second, phones are very closely integrated with everyday life of individuals [Katz 1997]. Thus, models developed on mobile phones can be very personal, timely and relevant for the user. In addition, interaction with the environment, which is crucial for the realisation of anticipatory decisions, is naturally supported due to the user’s reliance on smartphone-provided information.

Anticipatory mobile computing is inherently interdisciplinary. Mobile sensing, human-computer interaction (HCI), machine learning, and context prediction are major research fields related to anticipatory mobile computing. Each of these areas is thoroughly covered in the existing survey literature, such as [Butz et al. 2003; Chen and Kotz 2000; Lane et al. 2010; Burbey and Martin 2012; Lanzi 2008], so we concentrate on an orthogonal goal and examine the role of each of the stages in the process of designing anticipatory mobile systems. Still, when necessary we systematically present developments in these subfields in order to provide a practitioner with an overview of possible implementation options. Overall, our goal is not only to give a thorough overview of the state of the art, but also to sketch practical guidelines for building anticipatory mobile systems.

We note that anticipatory computing is an often misused term, especially when it comes to describing the recent wave of context-aware and predictive applications for mobile devices. In the first part of this survey (Section 2) we embrace and examine a well established definition of anticipatory computing [Rosen 1985] stating that only applications that rely on past, present and anticipated future in order to make judicious actionable decisions can be considered anticipatory applications. We then argue that the smartphone is a true enabler of anticipatory computing (Section 3). One of the smartphone’s main affordances is the ability to sense an abundance of information about the environment. Therefore, we dedicate a part of the survey to mobile sensing and context inference (Section 4) from the point of view of anticipatory systems. These processes aim to reconstruct key characteristics of the user behaviour and the environment from sensed signals [Coutaz et al. 2005]. For reliable reconstruction, in each of the domains, whether it is speech analysis, movement tracking, object recognition or any other domain, we need to identify features of raw signals that are useful for inferring higher-level concepts and characteristics. We describe how information flows from the physical environment through phone’s sensors, and gets processed by machine learning algorithms so that high-level information is extracted. The ability to infer the context in which it is operating makes a phone more than a communica-

tion device – it becomes a *sense* [Campbell and Choudhury 2012]. Although the area of mobile sensing remains far from being fully explored, recent research is increasingly focused on providing *cognitive* capabilities to mobile phones. This allows the phone to be trained to *predict* future events from current and past sensor data. The ability to predict users’ location, social encounters or health hazards pushes the smartphone further to an irreplaceable source of personalised information. While inferring usage context on the smartphone remains difficult due to the sheer amount and variable quality of highly user-specific data, predicting the future context is even more difficult. Context prediction is tied with problems such as identifying and gathering data relevant for prediction, and determining prediction reliability, prediction horizon and possible outcomes. The later part of this survey provides an overview of the existing work in context prediction with smartphones (Section 5). Finally, in the true sense of anticipatory computing, predictions made with the help of data gathered through mobile sensing can be used as a basis for intelligent decision making. In Section 6 we investigate anticipatory mobile computing systems, that is, systems that rely on past, present and anticipated future in order to make judicious decisions about their actions. Ideas about computing devices that can autonomously adapt their performance over time is not new [Kephart and Chess 2003]. With smartphones we are for the first time able to realise personalised anticipatory computing on a large scale (Section 7). However, this also means that novel issues arise; these challenges for anticipatory mobile computing are examined in Section 8.

2. OVERVIEW OF ANTICIPATORY SYSTEMS: DEFINITIONS AND APPLICATIONS

In this section we discuss a possible definition of anticipatory systems and the application of this class of systems to three different domains.

2.1. Defining Anticipatory Systems

An anticipatory system is defined by Rosen as:

“A system containing a predictive model of itself and/or its environment, which allows it to change state at an instant in accord with the model’s predictions pertaining to a later instant” [Rosen 1985].

This definition hints that an anticipatory device needs to be capable of obtaining a realistic picture of its state and the surrounding environment, i.e., the context in which the user and the device are. Equipped with an array of sensors and powerful processing hardware that can support sophisticated machine learning algorithms, smartphones can build predictive models of the context. Anticipatory actions that impact the future state are then based on the predictions of the future state of the context. Tightly integrated with users’ lifestyle, a phone can learn personalised patterns of their behaviour, and with the help of rich user interface it can communicate anticipatory actions to the users.

2.2. Anticipatory Mobile Computing Applications

To illustrate the potential of smartphone-based anticipatory mobile computing here we present three example applications.

2.2.1. Personal Assistant Technology. A mobile phone has access to a wealth of personal information, including Web browsing history, calendar events, and online social network contacts. Application developers can tap into this data and design applications that predict users’ intentions and display momentary relevant content. MindMeld is one such application that enhances online video conferencing with information that the users are likely to find relevant in near future [MindMeld 2013]. For this purpose

MindMeld harnesses real-time speech analysis, machine learning and WWW harvesting. Google Now takes a more general approach and aims to provide a mobile phone user with any information or functionality she may need, without the user explicitly asking for it [Google Now 2013]. If augmented with a model that anticipates environment’s reaction to user’s actions these predictive applications could become intelligent anticipatory personal assistants that perform autonomously for user’s benefit. Such an application could, for example, foresee an encounter with one’s business partners and prepare documents for a successful impromptu meeting.

2.2.2. Healthcare. Mobile sensing has been proposed as a means of providing in situ diagnosis [Gruenerbl et al. 2014]. In addition, mobile phones are increasingly being used to deliver personalised therapies [Klasnja et al. 2009; Morris et al. 2010; Yardley et al. 2013]. Currently these therapies tend to be pre-loaded on users phones and react according to the sensed context. Anticipatory computing can be used to build and develop a model of human behaviour and devise therapies automatically, aiming to lead the user towards a certain well-being goal. For example, through a built-in accelerometer the phone can sense user’s level of physical activity and, by means of a Bluetooth sensor and calling behaviour, it can sense user’s sociability. Then, the phone can infer the well-being state and predict if the user is in risk of major depression. Finally, it can adjust the therapy on-the-fly, for example by sending a link to two discounted theatre tickets, incentivising the participant to go out and socialise. Such a self-contained application that anticipates changes in user’s health and behaviour allows scalability and personalisation unimaginable in the traditional physician-patient world.

2.2.3. Smart Cities. The ratio of urban population experiences a steady growth and nowadays more than a half of approximately seven billion people living on Earth reside in urban areas [World Health Organization 2010]. Issues such as traffic, pollution and crime plague modern cities. Participatory mobile sensing, where citizens are actively involved in data collection, as well as opportunistic mobile sensing, where users simply volunteer to host an autonomous application on their devices, are already being employed for tackling urban problems¹. For instance, MIT’s CarTel project uses mobile sensing for traffic mitigation, road surface monitoring and hazard detection [Hull et al. 2006]; ParkNet system collects parking space occupancy information through distributed sensing from passing-by vehicles [Mathur et al. 2010]; Dutta et al. demonstrate a participatory sensing architecture for monitoring air quality [Dutta et al. 2009]. An anticipatory system that makes autonomous decisions and reasons about their consequences can push such projects further. Thus, we envisage a smart navigation system that predicts traffic jams and directs drivers in order to alleviate road congestion and balance pollution levels across the city.

To demonstrate the challenges of bringing the applications such as the above to life, and to show possible solutions, in Figure 1 we sketch a fictional application, inspired by StressSense [Lu et al. 2012]. This proactive stress management application unobtrusively monitors social signals [Vinciarelli et al. 2012], such as the voice of a busy user, infers current stress levels from voice features, predicts future ones based on the user’s calendar and then intelligently reschedules meetings so that the anticipated stress level is within healthy boundaries. We dissect the application with respect to the implementation stages: context sensing and inference, context prediction, and intelligent actioning. In the rest of the paper we will discuss main developments and key challenges in each of the stages.

¹For an overview of urban sensing and human-centric sensing research, we refer the reader to [Campbell et al. 2008], [Srivastava et al. 2012] and [Evans-Cowley 2010].

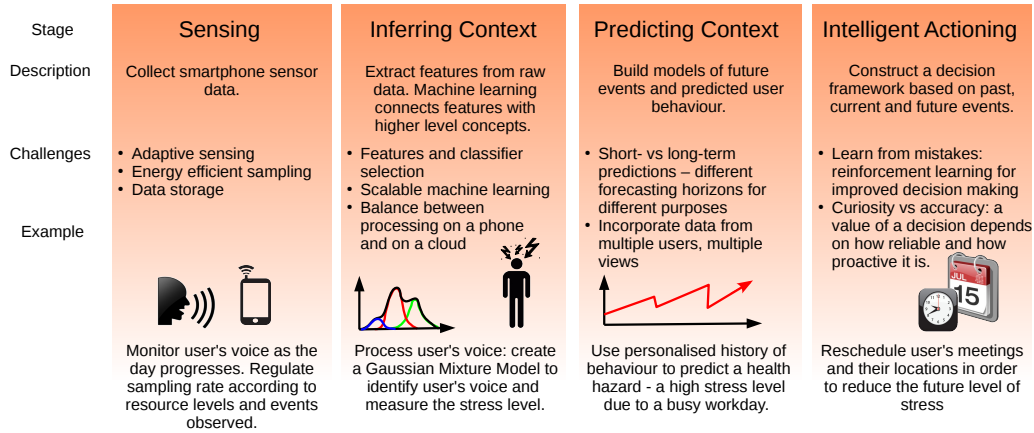


Fig. 1: Key stages in the anticipatory mobile computing depicted on an example stress management application: collecting sensor data, processing it in order to infer context, predicting future events and using past, present and future to make intelligent autonomous decisions.

3. DESIGNING AND IMPLEMENTING ANTICIPATORY MOBILE SYSTEMS

In this section we discuss the concept of anticipatory behaviour and we present a general architecture of anticipatory computing systems.

3.1. Anticipatory Behaviour and Anticipatory Computing Systems

Anticipatory behaviour is defined by Butz, Sigaud and Gerard as:

“a process or behaviour, that does not only depend on past and present but also on predictions, expectations, or beliefs about future” [Butz et al. 2003].

This behaviour is natural, in the sense that it is deeply integrated with intelligence, and biological systems often base decisions for their actions on predictions [Rosen 1985]. An animal increases its chance of survival by predicting a dangerous situation, a tennis player hits a ball on time by predicting its trajectory, and the prediction of rain helps us carry an umbrella and stay dry. Anticipatory behaviour has been confirmed in experimental psychology [Tolman 1932], while neuropsychology has provided further insights about brain mechanics related to anticipation [Gallese and Goldman 1998].

Are computing devices capable of implementing brain functions and mimicking the mind when it comes to anticipation? A positive answer would lead to the realisation of anticipatory behaviour in a computing system and open up tremendous opportunities for exploiting such capabilities in applications ranging from personal assistants to healthcare and robotics. The past three decades saw substantial efforts in the area of anticipatory computing, with the goal of bringing anticipatory computing systems, as defined by Rosen, to life. During this time milestones such as the formalisation of anticipatory computing system architecture [Nadin 2010], mathematical foundations of anticipatory behaviour [Dubois 1998], and real-world implementations of anticipatory computing in robotics [Stolzmann and Butz 2000] have been achieved. Yet the inability to seamlessly interact with the environment and sense feedback that will guide anticipatory learning is the major obstacle for further proliferation of anticipatory computing applications.

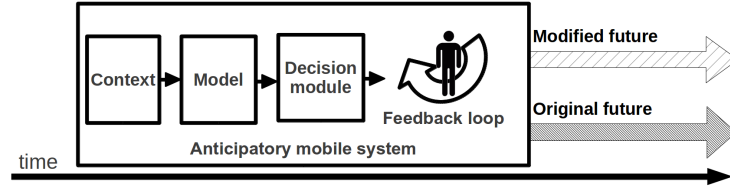


Fig. 2: Anticipatory mobile systems predict context evolution and the impact their actions can have on the predicted context. The feedback loop consisting of a mobile and a human, enables the system to affect the future.

3.2. Architecture of Anticipatory Mobile Systems

With smartphones the restriction on the interaction is lifted. Multimodal sensing and high processing capabilities of modern phones enable momentary awareness of the surrounding environment. At the same time, phones' anytime-anywhere use and a rich interface with the user enable a tight feedback loop ensuring that anticipatory decisions are realised. The symbiosis of the smartphone and the user allows for a new kind of a system – *anticipatory mobile computing system*. In Figure 2 we adapt Nadin's conventional anticipatory computing architecture [Nadin 2010] to mobile system design, sketching the anticipatory mobile system's core functional parts. First, the surrounding context is sensed, then a predictive model of the context is built. At this point it is worthwhile to note the difference between a *predictive* and an *anticipatory* system. A predictive system has a model of what the future state of the context and/or the system itself will be. If the stress app presented in the previous section were merely predictive, it would predict the user's expected stress level and inform the user about it. An anticipatory system makes intelligent decisions in order to impact the future to the benefit of the user. Thus, a fully anticipatory version of our stress relief app would, after predicting dangerous stress levels, reschedule user's meetings according to the learnt model of stress evolution in order to improve user's well-being. In Figure 2 the decision module uses predicted future as a basis for deciding on system's actions. The action is selected so that it results in a favourable change in the future state of the system or the environment. The action is, in general, performed by the user who is influenced by the information provided by the smartphone. The phone remains in a feedback loop with the user: besides informing the user, the phone observes the outcome of its suggestions on the evolving model of the system.

Anticipatory mobile computing requires multiple processing stages, relationships among which are shown in Figure 3. The stages include context sensing and modelling, context prediction and impacting the future through interaction with the user. Unlike previously attempted anticipatory computing realisations, the proposed architecture can benefit from devices' always on connectivity. Thus, the phone can offload computation to the cloud, integrate predictions of multiple users in order to build more accurate models of context evolution, and can harness the power of online social networks for enhanced interaction with users.

4. CONTEXT SENSING AND MODELLING FOR ANTICIPATORY COMPUTING

Mobile sensing has grown from the need for computing devices that are truly integrated with the everyday life of individuals. This can happen only if the devices are cognisant of their environment. Situations and entities that comprise the environment are collectively termed *context*. Context may have numerous aspects: geographical, physical, social, temporal, or organisational, to name a few. Context sensing aims at bridging physical stimuli sensed by the device's sensors, also known as *modalities*, and

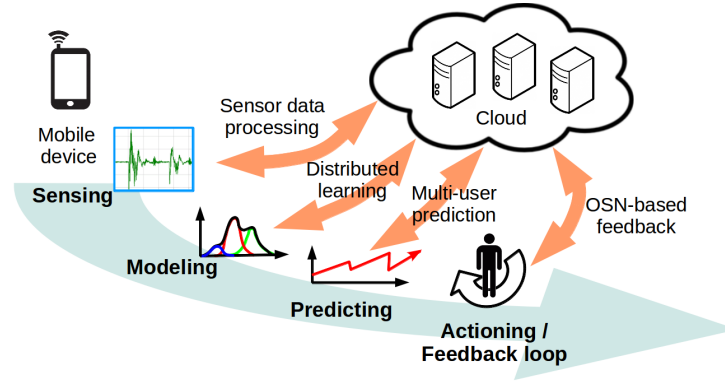


Fig. 3: Anticipatory mobile computing architecture. The mobile senses, models and predicts the context, and through interaction with the user ensures that anticipatory decisions are implemented. At each step, the computation can be distributed between the mobile and the cloud.

high level concepts that describe a context. Smartphones have evolved from communication devices to perceptive devices capable of inferring the surrounding context.

Mobile phone’s ability to infer that its user is jogging [Miluzzo et al. 2008], commuting to work, sleeping [Lane et al. 2011] or even feeling angry [Rachuri et al. 2010] is enabled by two factors. First, modern day smartphones are provisioned with sophisticated sensors, as well as with communication and computation hardware. A today’s phone hosts a touch-screen, GPS, accelerometer, gyroscope, proximity and light sensors, a high quality microphone and cameras. Multi-core processors and gigabytes of memory allow smartphones to locally handle a large amount of data coming from these senses and extract meaningful situation descriptors, while a range of communication interfaces, such as WiFi, Bluetooth, 4G/LTE, and a near-field communication (NFC) interface, allow distributed computation and data storage. The second key factor that enables phones to make high level inferences is the increasingly ubiquitous and personal usage of mobile phones. Nowadays, the majority of the world’s population owns a mobile phone, and these phones are closely integrated with people’s lifestyle. These devices are not only physically present with their owners for most of the day, but are also used for highly personal purposes such as organising meetings, navigation, online social networking and e-commerce.

Context inference is a complex process that lies at the foundation of anticipatory mobile computing. Figure 4 depicts the stages needed to get from environmental data to high-level inferences about the context. The first stage, *sensing*, aims to provide an interface between the physical world and a mobile device. *Feature extraction* is an intermediate step at which raw data are transformed to a form suitable for context inference. *Modelling context* concentrates on the construction of models that connect interesting events or behaviours and extracted data features.

4.1. Multimodal Context Sensing for Anticipatory Mobile Computing

Context sensing plays a major role in anticipatory mobile computing. First, sensed data serve as a basis for building predictive models of the phenomenon of interest. GPS tracking, for example, can be used to predict user whereabouts. Second, mobile sensors can reveal high level information about users’ internal state. In Section 3.2 we note that future-changing actions in anticipatory mobile systems depend on the user to execute them. These actions can be communicated more efficiently, if the state of



Fig. 4: Mobile sensing: from real-world signals to high-level concepts.

Table I: Context sensing challenges and possible solutions.

Challenge	Solution
Adaptation and context-driven operation	– Adaptive sampling [Kim et al. 2011; Rachuri et al. 2011]
	– Hierarchical modality switching [Wang et al. 2009; Lu et al. 2010; Paek et al. 2010; Kang et al. 2008; Kim et al. 2010]
Computation, storage and communication	– Harnessing domain structure [Foll et al. 2012; Nath 2012; Paek et al. 2011]
	– Cloud offloading [Liu et al. 2012]
	– Hierarchical processing [Lu et al. 2010; Lee et al. 2013]
	– Cloud offloading [Miluzzo et al. 2008; Cuervo et al. 2010; Rachuri et al. 2011; Chun et al. 2011]
	– Hardware co-processing [Priyantha et al. 2011; Lin et al. 2012]

the user, such as user’s mental load, attitudes and emotions, is known [Pejovic and Musolesi 2014b].

A single sensor modality is seldom sufficient for inferring the context in which a device is. In addition, multimodal information can offset the ambiguities that arise when single sensor data are used for inference [Maurer et al. 2006]. Today’s smartphones avail highly multimodal sensing, and are unobtrusively carried by their owners at all times. Beyond momentarily context inference, this also allows smartphones to sense multiple aspects of human behaviour, relate them, and uncover relationships previously unknown or difficult to confirm through conventional social science approaches. For example, mood can be correlated with user’s location or activity [Puiatti et al. 2011], socio-economic factors can be uncovered from calling and movement patterns [Lathia et al. 2012; Frias-Martinez and Virsesa 2012], and mental and physical health can be assessed via mobile sensing [Rabbi et al. 2011; Madan et al. 2012]. In this section we pay particular attention to multimodal sensing for supporting anticipatory systems, and we put an accent on the affordances of, and challenges associated with smartphone based sensing.

4.2. Implementation Issues

Applications that use smartphone sensing are subject to constraints coming from the devices’ hardware restrictions. In anticipatory mobile computing frequent sensing of different modalities and collaboration of multiple agents are likely to be necessary for accurate anticipation, emphasising the need for resource-efficient mobile sensing solutions. Energy-efficient operation, processing, storage and communication constrains are the most common practical mobile sensing challenges. In Table I we summarise the state-of-the-art solutions to address these issues.

4.2.1. Sensing Adaptation and Context-driven Operation. Energy shortage issues are exacerbated by the design of smartphone sensors as occasionally used features, rather than constantly sampled sensors. Two popular means of reducing the energy consumption are adaptive sampling, i.e., sampling less often, and, in the case of a device with multiple sensors, powering them on hierarchically, i.e., preferring low-power sensors to

more power hungry ones. In SociableSense, a mobile application that senses socialization among users [Rachuri et al. 2011], a linear reward-inaction function is associated with the sensing cycle, and the sampling rate is reduced during “quiet” times, when no interesting events are observed. The approach is very efficient with human interaction inference, since the target events, such as conversations, are not sudden and short. On another side of the solution spectrum, the Energy Efficient Mobile Sensing System (EEMSS) proposed by Wang et al. hierarchically orders sensors with respect to their energy consumption, and activates high-resolution power-hungry sensors, only when low-consumption ones sense an interesting event [Wang et al. 2009]. Adaptive sampling and hierarchical sensing are not the only means of reducing energy usage. The inherent structure of the context inference problem can also be used to improve sensing efficiency. This is the main idea behind the Acquisitional Context Engine (ACE) proposed in [Nath 2012]. Here, Nath develops a speculation-based sensing engine that learns associative rules among contexts, an example of which would be “when a user state is *driving*, his location is not *at home*”. When a context-sensitive application needs to know if a user is at home or not, it contacts ACE that acts as a middle layer between sensors and the application. ACE initially probes a less energy costly sensor – accelerometer – and only if the sensed data does not imply that a user is driving, it turns the GPS on and infers the actual user’s location. While demonstrated on simple rules, Nath argues that ACE can be complemented with tools that examine the temporal continuity of context, such as SeeMon [Kang et al. 2008] to extract sophisticated rules like “if a user is *at home* now, he cannot be *in the office* in the next ten minutes”.

4.2.2. Processing, Storage and Communication Efficiency. Despite ongoing technological advances mobile phones still have limited processing and data storage capabilities. Remote resources available via online cloud computing can be used to help with data processing. However, the transfer of the high-volume data produced by mobile sensors can be costly, especially if done via a cellular network. Balancing local and remote processing was tackled in one of the first smartphone sensing applications, CenceMe [Miluzzo et al. 2008]. This application performs audio and activity classification on the phone, while some other modalities, such as user’s location, are classified on a remote server. The distribution of the computation is not performed solely because of the limited computation resources of a smartphone. Distributed computation also allows for aggregation of data from multiple phones, therefore a larger context can be inferred. In SociableSense [Rachuri et al. 2011], the split between local and remote data processing is done on the basis of energy expenditure, data transmission cost, and the computation delay. Custom-made application execution partitioning, such as the one used in CenceMe and SociableSense, requires significant effort from the developer’s side. More general solutions allow an application developer to delegate the partitioning task to a dedicated middleware. MAUI, for example, supports fine-grained code offloading to a cloud in order to maximise energy savings on a mobile device [Cuervo et al. 2010].

4.3. Context Modelling for Anticipatory Mobile Computing

Raw sensor data, such as those from phone’s accelerometer, are seldom of direct interest and machine learning techniques are usually employed to infer higher level concepts, for example, a user’s physical activity [Tapia et al. 2007]. For the inference to be made, first we need to identify the most informative modalities and features of the raw sensor data, e.g. accelerometer data mean intensity and variance. Then, appropriate machine learning techniques are used to build a model of the phenomenon of interest, i.e. physical activity, and train the model with the data gathered so far.

4.3.1. Selecting Useful Modalities and Features from Sensor Data. The first challenge in context modelling is the identification of those modalities of raw data that are the most

descriptive of the context. Interdisciplinary efforts and domain knowledge are crucial in this step. For example, if we try to infer user’s emotions, the existing work in psychology tells us that emotions are manifested in a person’s speech [Bezooijen et al. 1983]. Consequently, we can discard irrelevant modalities and concentrate our efforts on processing microphone data.

The next step includes the selection of the appropriate representation for the sensor data. Consider EmotionSense, an experimental psychology research application, which infers emotions from microphone data [Rachuri et al. 2010]. Before the classification, however, raw microphone data has to be transformed into a suitable form. Distinctive properties extracted from the data are called *features*. The EmotionSense authors built its speech recognition models on Perceptual Linear Predictive (PLP) coefficients, a well established approach to speech analysis [Hermansky 1990]. An alternative, but less sophisticated means of microphone data manipulation that has proven successful in mobile sensing is the Discrete Fourier Transform (DFT) [Miluzzo et al. 2008]. The majority of speech energy is found in a relatively narrow band from 250 Hz to 600 Hz, thus the investigation of DFT coefficient means and variations can help identify speech in an audio trace. Finally, Mel-Frequency Cepstral Coefficients (MFCC) are another commonly used feature for speech recognition [Lu et al. 2009; Miluzzo et al. 2010; Chon et al. 2012].

The above example shows that numerous features can be extracted from a single modality. In many domains, however, certain feature types have crystallised out as the most informative. Table II lists the most commonly observed features and the domains in which they are used. The table is not meant to be a comprehensive survey of feature extraction, but should point out that even with a small number of sensors there can be hundreds of possible features all of which may or may not contribute to context inference [Choudhury et al. 2008]. Modality and feature selection impact the rest of the context inference; a careful consideration at this stage of the process can help improve classification accuracy or reduce the computational complexity of the learning process. As mobile sensing matures the variety of context types that we strive to infer broadens. In addition, the number of sensors available on the smartphone increases steadily. Therefore, identifying and quantifying the strength of a link between a domain and a modality (or a feature) emerges as an important research direction in mobile sensing.

4.3.2. Classification Methods. A plethora of machine learning techniques can be used to transfer distilled sensor data into mathematical representations of a phone’s environment or user’s behaviour. In this survey we concentrate on a small subset of techniques that have been successfully applied in practice, and we refer an interested reader to machine learning texts such as [Bishop 2006; Hastie et al. 2009; Rogers and Girolami 2011; Barber 2012].

We examine how context inference models are built in the case of StressSense, a mobile phone application that analyses speech data collected via a built-in microphone and identifies if a user is under stress [Lu et al. 2012]. The first step in StressSense is sound and speech detection. The application assumes that sound is present if high audio level is detected in at least 50 out of 1000 samples taken within a half a second period. In such a case, StressSense divides the audio signal into frames and for each of the frames calculates its zero crossing rate (ZCR) and root mean square (RMS) of the sound. These features correspond to sound pitch and energy. A tree-based classifier that decides between speech and non-speech frames is built with ZCR and RMS as attributes. Further, thresholds on ZCR and spectral entropy are used to discern between voiced and unvoiced frames of human speech. Finally, Gaussian Mixture Models (GMMs) are built for the two target classes – stressed speech and neutral speech. Pitch,

Table II: Context sensing domains and characteristic features.

Domain	Characteristic Features
Speech recognition	<ul style="list-style-type: none"> – Sound spectral entropy, RMS, zero crossing rate, low energy frame rate, spectral flux, spectral rolloff, bandwidth, phase deviation [Lu et al. 2009; Lane et al. 2011] – Mel-Frequency Cepstral Coefficients (MFCCs) [Lu et al. 2009; Miluzzo et al. 2010; Chon et al. 2012; Lu et al. 2010; Lu et al. 2012] – Teager Energy Operator (TEO), pitch range, jitter and standard deviation, spectral centroid, speaking rate, high frequency ratio [Lu et al. 2012; Lu et al. 2010] – Running average of amplitude, sum of absolute differences [Krause et al. 2006] – Perceptual linear predictive (PCP) coefficients [Rachuri et al. 2010] – Mean and standard deviation of DFT power [Miluzzo et al. 2008]
Activity classification	<ul style="list-style-type: none"> – Accelerometer FFT principal component analysis (PCA) [Krause et al. 2006] – Accelerometer intensity/energy/mean [Eston et al. 1998; Lu et al. 2010; Rabbi et al. 2011; Abdullah et al. 2012] – Accelerometer variance [Miluzzo et al. 2008; Lu et al. 2010; Rabbi et al. 2011; Aharony et al. 2011] – Accelerometer peaks/mean crossing rate [Miluzzo et al. 2008; Lu et al. 2010] – Accelerometer spectral features [Lu et al. 2009; Lu et al. 2010; Lane et al. 2011; Rabbi et al. 2011] – Accelerometer correlations [Abdullah et al. 2012] – Accelerometer frequency domain entropy [Abdullah et al. 2012] – Barometric pressure [Rabbi et al. 2011]
Location	<ul style="list-style-type: none"> – Days on which any cell tower was contacted, days on which a specific tower is contacted, contact duration, events during work/home hours [Isaacman et al. 2011] – Tanimoto Coefficient of WiFi fingerprints [Chon et al. 2012] – Eigenbehaviors - vectors of time-place pairs [Eagle and Pentland 2009] – Hour of day, latitude, longitude, altitude, social ties [De Domenico et al. 2012]
Object recognition	<ul style="list-style-type: none"> – GIST features [Chon et al. 2012]
Gestures	<ul style="list-style-type: none"> – Mean, max, min, median, amplitude, and high pass filtered values of acc. intensity and jerk; spectral features; screen touch location, slope, speed, strokes number, length, slope and location [Coutrix and Mandran 2012]
Physiological state	<ul style="list-style-type: none"> – Galvanic skin response, heat flux, skin thermometer running average and sum of absolute differences [Krause et al. 2006]
Thoughts	<ul style="list-style-type: none"> – Bandpass filtered neural signal from EEG [Campbell et al. 2010]
Call prediction	<ul style="list-style-type: none"> – Call arrival and inter-departure time, calling reciprocity [Phithakkitnukoon et al. 2011]
Interruptibility	<ul style="list-style-type: none"> – User typing, moving, clicking, application focus, app. activity, gaze, time of day, day of week, calendar, acoustic energy, WiFi environment, [Horvitz and Apacible 2003] – Mean, energy, entropy and correlation of accelerometer data [Ho and Intille 2005]

Teager Energy Operator (TEO) and Mel-Frequency Cepstral Coefficient (MFCC) based features of each voiced frame are used for user stress inference.

The variety of classification methods and data features can be overwhelming for a mobile sensing application designer. To help with the selection of a context inference approach, in Table III we list mobile sensing challenges and the corresponding machine learning techniques that have been proved to work well in practice. The table

Table III: Context sensing domains and relevant machine learning techniques.

Domain	Machine learning technique
Speech recognition	<ul style="list-style-type: none"> – Hidden Markov Model (HMM) [Chon et al. 2012; Choudhury and Pentland 2003] – Threshold based learning [Wang et al. 2009] – Gaussian Mixture Model (GMM) [Rachuri et al. 2010; Lu et al. 2012]
Activity classification	<ul style="list-style-type: none"> – Boosted ensemble of weak learners [Consolvo et al. 2008; Abdullah et al. 2012] – Boosting & HMM for smoothing [Lester et al. 2005] – Tree based learner [Tapia et al. 2007; Abdullah et al. 2012] – Bayesian Networks [Krause et al. 2006]
Location determination (with GPS)	<ul style="list-style-type: none"> – Markov chain [Ashbrook and Starner 2003] – Non-linear time series [Scellato et al. 2011; De Domenico et al. 2012]
Location (with BT or WiFi)	<ul style="list-style-type: none"> – Bayesian network [Eagle and Pentland 2006; Eagle et al. 2009]
Location (with ambient sensors)	<ul style="list-style-type: none"> – Nearest neighbour [Maurer et al. 2006]
Scene classification	<ul style="list-style-type: none"> – K-means clustering [Chon et al. 2012]
Object recognition	<ul style="list-style-type: none"> – Support vector machine [Chon et al. 2012] – Boosting & tree-stump [Wang et al. 2012]
Place categorization	<ul style="list-style-type: none"> – Labelled LDA [Chon et al. 2012]
Call prediction	<ul style="list-style-type: none"> – Naive Bayesian [Phithakkitnukoon et al. 2011]
Interruptibility	<ul style="list-style-type: none"> – Bayesian Network [Horvitz and Apacible 2003; Fogarty et al. 2005] – Tree based learner [Fogarty et al. 2005] – Naive Bayes [Ter Hofte 2007]

is meant to be a starting point for mobile sensing practitioners, and does not imply that alternative techniques would not perform better. The structure of the problem at hand often hints towards an efficient classification approach. For example, Gaussian Mixture Models perform well when it comes to speaker identification, as it is possible to extract parameters for a set of Gaussian components from the FFT of the speech signal and use them as a vectorial representation of human voice. This approach has been proved extremely effective for user identification [Reynolds et al. 2000]. However, a deeper discussion about why certain approaches work in certain domains is outside of the scope of this survey.

4.3.3. Handling Large-Scale Inference. Anticipatory mobile computing applications for healthcare and personal assistance we sketched in Section 2 are of broad interest. We envision a multitude of such applications to be distributed through commercial app stores such as Apple App Store and Google Play. Scaling up the number of users imposes novel challenges with respect to sensing application distribution, data processing and scalable machine learning. Data diversity calls for more complex classification: walking performed by an eighty year old person will yield significantly different accelerometer readings than when the same activity is performed by a twenty year old. Clearly, classification needs to be less general, but does that imply a personal classifier for each user?

In [Lane et al. 2011] the authors propose community similarity networks (CSNs) that connect users who exhibit similar behaviour. User likeness is calculated on the basis of their physical characteristics, their lifestyle and from the similarity between their smartphone-sensed data. For each of these three layers in the CSN, a separate boosting-based classifier is trained for any individual user. However, a single-layer classifier is trained on the data coming from not only the host user, but also from all the other users who show strong similarity on that CSN layer. In this way the CSN approach tackles the shortage of labelled data for the construction of personalised models, a common issue in large-scale mobile sensing.

Besides increased user diversity, mobile sensing applications interested in monitoring user behaviour often have to cope with long-term observations. In their “social fMRI” study Aharony et al. continuously gather over 25 sensing modalities for more than a year from about 130 participants [Aharony et al. 2011]. Machine learning algorithms need explicit labelling of the high level concepts that are extracted from sensor readings. However, with highly multimodal sensing integrated with everyday life, querying users to provide descriptions of their activities becomes an intrusive procedure that may annoy them. Instead, a semi-supervised learning technique called *co-training* is used to establish a bond between those sensor readings for which labels exist, and those for which only sensor data are present [Zhu and Goldberg 2009]. Co-training develops two classifiers that provide complementary information about the training set. After the training on the labelled data, the classifiers are iteratively run to assign labels to the unlabelled portion of the data. In the mobile realm, unlabelled data representing an activity of one user could be similar to labelled data of the same activity performed by another user. In this case, labels can propagate through the similarity network of users [Abdullah et al. 2012].

In addition to a larger user base and an increased amount of gathered data, mobile sensing is further challenged by a growing number of devices used for context-aware applications. We increasingly observe *ecosystems of devices*, where multiple devices work together towards improved context sensing. Fitbit, for example, markets a range of wearable devices that track user metrics such as activity, sleep patterns, and weight [Fitbit 2013]. As the popularity of these devices grows we can expect that a single user will carry a number of context sensing devices. Darwin Phones project tackles distributed context inference where multiple phones collaborate on sensing the same event [Miluzzo et al. 2010]. First, via a cloud infrastructure, phones exchange locally developed models of the target phenomenon. Later, when the same event is sensed by different phones, inference information from each of the phones is pulled together so that the most confident description of the event is selected.

In this section we summarised how machine learning can be used for context inference. Machine learning techniques are crucial for context prediction and anticipatory decision making, two other steps of anticipatory computing. Unlike context inference, these two areas are less explored. Their real-world implementations are scarce, and in the following sections we present recent advances in mobile prediction and anticipatory decision-making. Integration of machine learning approaches in context inference, prediction and anticipation, however, remains an interesting research challenge.

5. CONTEXT PREDICTION

Predictions of human behaviour, crucial for many anticipatory computing applications, are for the first time available to application developers. These predictions are enabled by the close integration of the phone and the user, which allows the phone to record user’s context at all time, and the fact that humans remain creatures of habit and patterns of behaviour can be identified in the sensed data.

5.1. Mobility Prediction

Historically, the prediction of mobile phone users’ movement patterns was tied with system optimisations. Anticipation of surges in the density of subscribers in a cellular network was proposed for dynamic resource reservation and prioritised call hand-off [Sox and Kim 2003]. Yet, as data collected by a phone gets more personal, the opportunity for novel user-centric applications increases. User movement can be examined on different scales. For small-scale indoor movement predictions, systems can rely on sensors embedded in the buildings. An example of such systems is MavHome: the authors proposes a smart home which adjusts indoor light and heating according

to predicted movement of house inhabitants [Cook et al. 2003]. A large part of the current research, however, concentrates on the city-scale prediction of users' movement. In addition, predicted location can be considered on a level higher than geographical coordinates. Work of Ashbrook and Starner, as well as of Hightower et al. aims to recognise and predict places that are of special significance to the user [Ashbrook and Starner 2003; Hightower et al. 2005]. The interest in such prediction was further raised with proliferation of smartphones and commercial location-based services such as Foursquare [Foursquare 2013]. In such as setting, targeted ads can be disseminated to phones of users who are expected to devote a certain amount of their time to eating out or entertainment. The NextPlace project aims to predict not only user's future location, but also the time of arrival and the interval of time spent at that location [Scellato et al. 2011]. The authors base the prediction on a non-linear time series analysis. More recently, Horvitz and Krumm devised a method for predicting a user's destination and suggesting the optimal diversion should the user want to interrupt his/her current trip in order to, for example, take a coffee break [Horvitz and Krumm 2012]. Noulas et al. investigate next check-in prediction in the Foursquare network [Noulas et al. 2012]. They show that a supervised learning approach that takes into account multiple features, such as the history of visited venues, their overall popularity, observed transitions between place categories, and other features, is needed for successful prediction. SmartDC merges significant location prediction with energy-efficient sensing, and proposes an adaptive duty cycling scheme to provide contextual information about mobility of users [Chon et al. 2013].

Research on mobility prediction was additionally boosted by large sets of multimodal data that has been collected and made publicly available by companies and academic institutions. For example, the MIT Reality Mining [Eagle and Pentland 2006] project accumulated a collection of traces from one hundred subjects monitored over a period of nine months. Each phone was preloaded with an application that logged incoming and outgoing calls, Bluetooth devices in proximity, cell tower IDs, application usage, and phone charging status. Similarly, the Nokia Mobile Data Challenge (MDC) data set was collected from around 200 individuals over more than a year [Laurila et al. 2012]. The logs contain information related to GPS, WiFi, Bluetooth and accelerometer traces, but also call and SMS logs, multimedia and application usage. The above data sets served as a proving ground for a number of approaches towards mobility prediction. In [Eagle et al. 2009] Eagle et al. demonstrate the potential of existing community detection methodologies to identify significant locations based on the network generated by cell tower transitions. The authors use a dynamic Bayesian network of places, conditioned on towers, and evaluate the prediction on the Reality Mining data set. De Domenico et al. exploit movement correlation and social ties for location prediction [De Domenico et al. 2012]. Relying on nonlinear time series analysis of movement traces that do not originate from the user, but from user's friends or people with correlated mobility patterns, the authors demonstrate improved accuracy of prediction on the MDC data set. Interdependence of friendships and mobility in a location-based social network was also analysed in [Cho et al. 2011]. McInerney et al. propose a method, based on a novel information-theoretic metric called instantaneous entropy, for predicting departures from routine in individual's mobility [McInerney et al. 2013]. Such predictions are of extreme importance for personalised anticipatory mobile computing applications, for example the ones that aim to elicit a positive behaviour change in a human subject [Pejovic and Musolesi 2014a].

Different approaches to mobility prediction make different assumptions about human mobility. Markov predictors often assume that people spend similar residence time at the same places, while non-linear time series approaches assume that people spend similar staying time at similar times of a day [Chon et al. 2013]. Additionally,

Table IV: Modelling Methods for Mobility Prediction.

Method	Example
Markovian	– Markov process (MP) [Ashbrook and Starner 2003; Song et al. 2004]
Nonlinear time series analysis (NTSA)	– NTSA [Scellato et al. 2011] – NTSA with social information [De Domenico et al. 2012]
Bayesian	– Dynamic Bayesian Network [Eagle and Pentland 2006; Eagle et al. 2009] [McInerney et al. 2013; Etter et al. 2013] – Road-topology-aware with Bayes rule [Ziebart et al. 2008]
Other/Hybrid	– MP with NTSA [Chon et al. 2013] – Road-topology-aware MP [Sox and Kim 2003] – Information-theoretic uncertainty minimisation [Bhattacharya and Das 2001; Cook et al. 2003] – Probabilistic road-topology aware [Horvitz and Krumm 2012] – Statistical regularity-based model [McNamara et al. 2008], – Temporal, spatial and social probabilistic model [Cho et al. 2011], – Frequent meaningful pattern extraction [Sadilek and Krumm 2012] – M5 trees and linear regression [Noulas et al. 2012]

certain real-world restrictions, such as the fact that ground movement has to follow the road network, can figure in prediction methods. In Table IV we list, and provide examples of, commonly used mobility prediction methods.

5.2. Lifestyle, Health and Opinion Prediction

Multimodal traces also enable prediction of behavioural aspects beyond mobility. Human activity prediction, for example, has been an active subject of research in the past years: various approaches have been presented in the literature, based for example on accelerometers [Choudhury et al. 2008; Tapia et al. 2007], state-change sensors [Tapia et al. 2004] or a system of RFIDs [Wyatt et al. 2005]. In a series of seminal works such as [Liao et al. 2005; Liao et al. 2007], Liao et al. demonstrate the prediction and correlation of activities using location information. Eagle and Pentland propose the use of multimodal *eigenbehaviours* [Eagle and Pentland 2009] for behaviour prediction. Eigenbehaviours are vectors that describe key characteristics of observed human behaviour over a specified time interval, essentially lifestyle. The vectors are obtained through the principal component analysis (PCA) of a matrix that describes a deviation in sensed features. Besides being a convenient notation for time-variant behaviour, by means of simple Euclidean distance calculation, eigenbehaviours enable direct comparison of behaviour patterns of different individuals. Eagle and Pentland demonstrate the ability of eigenbehaviours to recognise structures in behaviours by identifying different groups of students at MIT.

Certain aspects of the context that are internal to the user can also be predicted. In their work on health status prediction, Madan et al. use mobile phone based co-location and communication sensing to measure characteristic behaviour changes in symptomatic individuals [Madan et al. 2010]. The authors find that health status can be predicted with such modalities as calling behaviour, diversity and entropy of face-to-face interactions and user movement patterns. Interestingly, they demonstrate that both physiological as well as mental states can be predicted by the proposed framework. Our running example of an anticipatory stress relief app could rely on such internal well-being state predictions. Finally, political opinion fluctuation is a topic of another work by Madan et al. [Madan et al. 2011], which shows the potential use of the information collected via mobile sensing for understanding and predicting human behaviour at scale. In this work call and SMS records, Bluetooth and WiFi environment are used to model opinion change during the 2008 presidential elections in the United States. Face-to-face personal encounters, measured through Bluetooth and WiFi collocation, are the key factor in opinion dissemination. The authors also discover patterns

of dynamic homophily related to external political events, such as election debates. Automatically estimated exposure to a political faction can predict individual's opinion on the election day.

6. CLOSING THE LOOP: SHAPING THE FUTURE WITH ANTICIPATORY COMPUTING

Theoretical underpinnings of anticipatory computing have been laid down in the last few decades. Practical applications are lacking due to inability to maintain tight interaction of a computing system, its environment and a user. Smartphones for the first time enable a quick *model – action – effect* feedback loop for anticipatory computing.

6.1. Persuasive Mobile Computing

The existence of the feedback loop can be observed on the example of digital behaviour change intervention (dBCI) applications. These applications harness a unique perspective that a personal device has about its user to catalyse positive behavioural change. Behaviour change can address some of the most prevalent health and well-being problems, including obesity, depression, alcohol and tobacco abuse. Delivered via smartphones dBCIs support those who seek the change with timely and relevant information about the actions that should be taken. With smartphones, interventions scale to a potentially very large number of users, and can be delivered in accordance to user's momentarily behaviour and state.

UbiFit [Consolvo et al. 2008] and BeWell [Lane et al. 2011], although not behavioural interventions in the strict therapeutic sense, represent the first step towards mobile dBCIs. In the former a phone's ambient background displays a garden that grows as user's behaviour gets in accordance with predefined physical activity goals. In BeWell, core aspects of physical, social, and mental well-being – sleep, physical activity, and social interactions – are monitored via phone's built-in sensors. For example, sleep patterns are inferred from phone recharging events and periods when a phone's microphone indicates near-silent environment. The feedback is provided via a mobile phone ambient display which shows an aquatic ecosystem where the number and the activity of animals depend on user's well-being. Among the early dBCI applications we find SociableSense, an app that examines the socialisation network within an enterprise and provides feedback about individual sociability [Rachuri et al. 2011]. Similarly, SocioPhone monitors turn taking in face-to-face interactions and enables dBCI applications to be designed on top of it [Lee et al. 2013]. One of the applications proposed by the authors is SocioTherapist. Designed for autistic children, SocioTherapist presents a game in which a child is rewarded each time it performs a successful turn taking. Social environment is also used as a motivator in the Social fMRI, an application that aims to increase physical activity of its users [Aharony et al. 2011]. In Social fMRI a close circle of friends get automatic updates whenever an individual phone registers that its user is exercising, promoting a competitive and stimulating environment.

It is interesting to note that the mobile phone is the most personal computing device people have. Feelings that the users have towards their phones parallel those that they have towards their fellow humans [Lindstrom 2011]. The above examples show that this relationship can be harnessed for influencing users' behaviour, bringing us to the concept of *persuasive mobile sensing* [Lane et al. 2010]. What remains unclear is the most appropriate modality of mobile-human interaction. Indeed, UbiFit and BeWell exploit innovative user interface techniques to close the loop between mobile sensing and actionable feedback. The ambient display is always present, and each time a phone is used, its owner gets a picture of his or her physical activity and level of sociability. For many other applications that need to deliver an explicit timely advice, interaction with the user is an open problem: if the user has to be notified via SMS, for example,

how often should a message be sent, at what time, in which context? These are typical human-computer interaction questions related to interruptibility.

6.2. Personalised Interaction

Smartphone's ability to sense and predict the user's context can serve as a basis for interaction adaptation and seamless integration with the user's daily routine. In his 1991 manifesto of ubiquitous computing Weiser advocates pervasive technology that coexists unobtrusively with its users [Weiser 1991]. This "calm technology" is not our current reality, and indeed we get an abundance of notifications from an increasing number of devices we own. Thus, we receive irrelevant instant messages while working on an important project, a phone may sound an embarrassing "out of battery" tone in the middle of a meeting, and a software update pop-up may show up while we are just temporarily connected to a hot spot in a coffee shop. From the anticipatory mobile computing point of view, inappropriate interaction moments potentially reduce the ability to impact the future with current actions, as the user, annoyed by the poorly communicated information, may decide to ignore it.

Attentive user interfaces manage user attention so that the technology works in symbiosis with, rather than against user's interruptibility. Context sensors proved to be instrumental in identifying opportune moments to interrupt a user. Performed before the smartphone era, early experiments relied on external sensors, such as a camera and a microphone, along with the information about user's desktop computer usage [Horvitz and Apacible 2003]. Horvitz et al. developed a framework for inferring user's workload in an office setting via a Bayesian network in which variables such as the presence of voice, user's head position and gaze, and currently opened applications on a user's PC are connected with the probability distribution of interruptibility. The idea of connecting sensed data with user interruptibility was reconsidered with early mobile computing devices. Ho and Intille investigate the interruption burden in case of mobile notifications [Ho and Intille 2005]. Their study uses on-body accelerometers, and triggers interruptions only when a user switches her activity. The authors find that moments of changing activity, as inferred by the accelerometers, represent times at which an interruption results in minimal annoyance to the recipient. Fischer et al. demonstrate that interruptions coming immediately after the episodes of mobile phone activity, such as a phone call completion or a text message sending event, result in a more responsive user behaviour [Fischer et al. 2011]. Pielot et al. collected a data set of text messages exchanged via smartphones together with the associated phone usage context [Pielot et al. 2014]. Time since the screen was on, time since the last notification, and similar features were used in a classifier that infers if the users is going to attend the message within a short time frame. In [Pejovic and Musolesi 2014b] the authors discuss the design and implementation of InterruptMe, a real-time interruptibility inference framework that maintains a sensor data-based classifier of user interruptibility. The authors show that context, as sensed by a smartphone, can be used to identify moments when a user is likely to react to the delivered piece of information.

6.3. Online Social Networks for Anticipatory Actioning

Although conceived as platforms for fun, leisurely interaction and information dissemination, Online Social Networks (OSNs) are increasingly being recognised for their persuasive power. Given their popularity, they might be used to influence the future behaviour of users. For example, through social reinforcement an individual's health-related behaviour is influenced by the behaviour of her OSN neighbours [Centola 2010]. Moreover, in a controversial study on emotional expression on Facebook,

Kramer et al. showed that emotions expressed by others in our OSN vicinity impact our own emotional expression [Kramer et al. 2014].

Anticipatory computing applications can use OSNs for both information dissemination tool, as well as for indirect persuasion. For example, an anticipatory traffic management application can send proactive driving directions via Twitter to a large number of users. Highly personalised mobile applications that aim to improve users' well-being, on the other hand, can harness social contagion to improve users' state. For example, obese people tend to have obese friends [Christakis and Fowler 2007] and a well-being application could prevent a user from becoming obese by proactively tackling obesity in the user's social circle. Although with a potential for high impact, OSN-based anticipatory behaviour intervention applications pose serious ethical challenges [Pejovic and Musolesi 2014a]. The issues are exacerbated by the latent effect of OSN actions on users who are not even taking a part in the application.

6.4. Anticipatory Decisions

The timing and the means of information delivery are important for anticipatory actions to be picked up and performed by the user. Yet, the delivery becomes irrelevant if the action does not induce the preferred change in the future state. Deciding on the action is the core problem of anticipatory computing and a significant body of research deals with artificial implementations of anticipatory decision logic [Rosen 1985; Butz et al. 2003]. In addition, two types of anticipatory behaviour are examined in the literature: implicit and explicit. Implicit anticipation refers to the case where decisions are embedded in the program of the system beforehand. Instead, explicitly anticipatory systems maintain a model of the environment and learn how to interact with the environment during their lifetime. We are particularly interested in explicit anticipation as we see it suitable for mobile sensing devices. A thorough discussion of anticipatory behaviour in adaptive learning systems, however, is beyond the scope of this survey, and for more details we refer an interested reader to [Butz et al. 2003]. Instead, in the following we discuss some key implementation issues for a practical smartphone-based anticipatory mobile computing system.

6.4.1. Reinforcement Learning. Mobile phones, carried by their owners at all times, are subject to frequent context changes that depend on the individual behaviour of the user. Therefore, pre-programmed implicit anticipation is unlikely to be feasible; for this reason, we concentrate on the explicit modelling of the context evolution. Such a model can be based on the types of predictions discussed in Section 5. The anticipatory decision module has to make a decision based on the predicted future. In case the problem space can be cast to the Markovian framework, i.e., if the current state depends only on the previous state, we can represent the state of the model and the rewards associated with each of the actions as a Markov Decision Process (MDP). Through reinforcement learning the system evaluates the reward it gets for an action performed in a certain state, with the goal of maximising the payoff [Sutton and Barto 1998]. Just as biological systems learn from mistakes, so an artificial system reinforces actions that lead to favourable outcomes, and suppresses the others. To give a practical example, consider the stress relief smartphone application in Figure 1. The application will occasionally reschedule user's meetings. Just like in the biological learning, the consequence will be evaluated, and if the application made a mistake, i.e., if the changes to the schedule turn out to be counterproductive, interfere with user's lifestyle or actually cause more stress for the user, a lesson will be learnt. However, two major issues arise with reinforcement learning in this situation. First, how does the application obtain signals that guide the learning? This can be done by an explicit query to the user, essentially asking the person if he is happy with decisions made by the appli-

cation. Yet, the user may consider frequent querying to be irritating. Another option is to look for implicit signals. For example, monitoring if the user makes changes to the schedule immediately after the application interventions. The second issue comes from the intrinsic need of the reinforcement learning to make mistakes in order to learn from them. If the mistakes are costly (and increasing someone's stress level can surely be costly) the application should be careful about experimenting with decisions made with low confidence. Thus, there is a trade-off, commonly known as *the exploitation versus exploration trade-off*, between improving reinforcement learning models and minimising negative impact on the user [Sutton and Barto 1998].

6.4.2. Learning without Interfering. To solve the problem of intrusive probing, we can employ *latent learning*, a form of learning that takes place when a subject is immersed into an unknown environment without any rewards or punishments associated to the environment [Tolman 1932]. Despite the lack of obvious incentives for learning, experiments with both humans and animals show that subjects form a cognitive map of the environment solely because they experience the world around them. Later, that cognitive map figures in decision making, essentially behaving as a learnt concept. The artificial implementation of latent learning has been demonstrated for example in [Stolzmann and Butz 2000]. In this work the authors designed a robot that, just like in experiments with living rats, relies on latent learning to find its way around a maze. Latent learning relies on the subject's ability to sense the environment. Immersed in the constant sensing of a large number of modalities, mobile phones can bring artificial latent learning to the next level. In the stress relief application example, instead of learning how to reschedule meetings only when a user gives feedback on the proposed schedule, a phone could passively monitor a user's meeting pattern, construct a latent model of events and take it into account even during the first rescheduling instance when the feedback is not yet available. Other approaches that are relevant for learning anticipatory systems are those belonging to the area of so-called probabilistic robotics [Thrun et al. 2005].

Finally, so far we have proposed implementations of learning context evolution and action-reward modelling. The definition of anticipatory systems additionally calls for modelling the effect that actions will have on the context. While predicting the reward from the environment (i.e., its *action value*) represents the key feature of reinforcement learning, a true anticipatory system should be able to predict the consequence of its interaction on the environment (i.e., the *action effect*) [Lanzi 2008]. Recent progress in this area has been made through the development of *anticipatory classifier systems* [Stolzmann 1998]. In these systems the expectation of a future environment state is embedded within classifiers that model the problem. These classifiers are organised in a population that evolves over the course of its interaction with the environment. The evolving collection of classifiers itself is known as the *learning classifier system*, and has been a subject of extensive research, an overview of which can be found in the survey article by Lanzi [Lanzi 2008].

7. TOWARDS LARGE-SCALE ANTICIPATORY MOBILE COMPUTING

Applications that rely on anticipatory computing are posed to be more human-like in their behaviour than legacy ones without predictive reasoning. Whether as personal assistants, doctors or even parents, anticipatory applications can provide domain-expert knowledge and personalised advising. Yet, these applications can go even further since, unlike humans, they are not constrained to a single subjective view of a situation. Rather, multiple phones can collaborate towards common predictions and interactions. Such a large-scale anticipatory system introduces novel challenges (Figure 5), which we summarise in the following subsections.

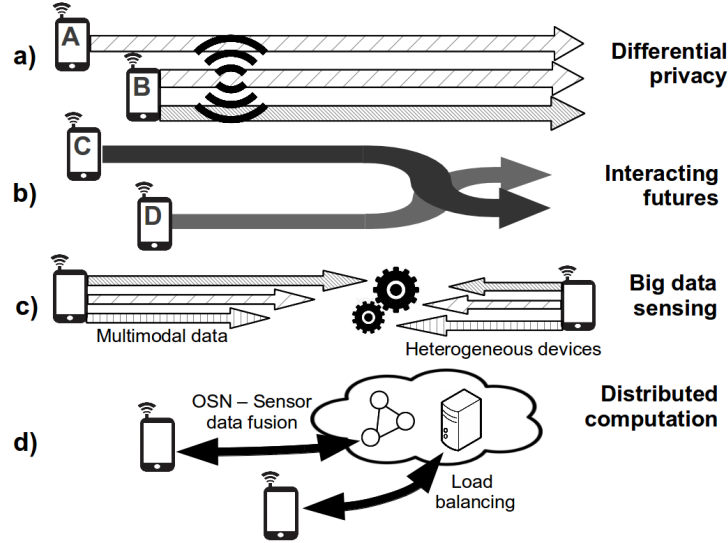


Fig. 5: Large scale anticipatory computing challenges.

7.1. Privacy and Anonymity

Smartphones can provide information about their owner's location, activities, and emotions. In addition, phones are, for most of the time, physically close to their users and connected to the global network. Thus, privacy and anonymity breaches in mobile sensing can result in unprecedented leaks of personal data. This information might be related not only to the current state of an individual, but also about the predictions made about her. For example, sensitive information might include future locations of an individual. Another privacy problem indigenous for mobile sensing stems from mismatched privacy policies over multiple users. We sketch the problem in Figure 5.a). User *A* volunteers his Bluetooth data only. User *B* on the other hand, volunteers her GPS and her Bluetooth data. When users *A* and *B* are collocated, the information about user *A*'s location is inadvertently exposed. Although observable in general mobile sensing area, this privacy problem is exacerbated in anticipatory mobile computing. In fact, latent learning in an anticipatory computing application can include modelling the behaviour of a person who does not use the application himself. This is a classic problem of differential privacy [Dwork 2006]: the new challenge here is to consider not only the current data about a certain individual, but also the information predicted about her. In anticipatory mobile computing, differential privacy is unlikely to be sufficient, since, as shown in the previous example, privacy of non-participating individual can be breached through latent sensing.

7.2. Interacting Futures

High density of sensing devices, including smartphones, wearables and environment sensing networks, calls for joint consideration of all the sensing sources when it comes to anticipatory mobile computing. Frameworks for collaborative sensing include AnonySense [Cornelius et al. 2008], Pogo [Brouwers and Langendoen 2012] and PRISM [Das et al. 2010]. These projects allow application developers to distribute sensing over a large number of mobile devices and process individual devices' sensor data in a centralised way. In Section 7 we already noted that context sensing can harness multiple views of the same event for improved inference. When it comes to

context prediction and intelligent decision making, however, collaboration raises new research questions. Here multiple users do not only observe, but participate in context shaping. As sketched in Figure 5.b), one person's future often depends on anticipated behaviour of another person. This interaction of subjective futures is evident on a simple example of traffic regulation. An intelligent phone might suggest an alternative route when a traffic congestion is anticipated on the usual route. Yet, if everyone involved in the congestion is advised to take the same alternative route, the conditions on which the route calculation is based will change, and the routing suggestions lose their value.

7.3. Big Data Sensing

We are living in a world characterised by enormous amounts of data. We post photos on Facebook, we tweet about our thoughts, and we carry smartphones that sense every second of our lives. Traditional methods of understanding human behaviour are insufficient to cope with the growing influx of personalised digital data [Lazer et al. 2009]. Chon et al. mined opportunistically sensed multimodal data coming from multiple users in order to characterise places that those users visit [Chon et al. 2012]. While such a fusion of sensed data improves inference, a large amount of streaming data represent a challenge when it comes to storage and processing. Stream processing solutions have been proposed for centrally-managed static sensor networks [Madden and Franklin 2002], but processing heterogeneous, opportunistically collected data remains an open problem. Overload with multiple sensing applications on a single phone, heterogeneity of smartphones, and high bandwidth demand resulting from data aggregation are identified as main challenges of large-scale crowdsensing [Xiao et al. 2013]. In addition, a large number of sources makes it hard to monitor the quality of a single source. Sensor malfunctioning, malicious participants or the fact that human behaviour might change when the subjects are aware of the sensors [Davis et al. 2012], can lead to erroneous context inference and prediction.

7.4. Distributed Computation

Distributed processing can be used at any stage of the anticipatory mobile computing pipeline, for improving resource utilisation [Rachuri et al. 2011] or context inference accuracy [Miluzzo et al. 2010]. The cloud also enables online social network and sensor data fusion [Yerva et al. 2012], which can lead to richer context inference and novel context-aware OSN applications. Distributed computation does not come for free: communication cost, unreliable nodes and delay in gathering results are some of the main obstacles. In addition, OSN-data fusion is challenging due to distributed coordination of OSN querying and mobile sensing. Interestingly, anticipatory computing can both benefit and improve distributed processing. The prediction itself of user connectivity, presented in [Nicholson and Noble 2008], can guide decisions on whether to process sensed data locally or in the cloud. Utilisation of cloud resources or other devices in the future vicinity of the users (see *cyber foraging* [Satyanarayanan 2001]) can also be anticipated and exploited in the distribution of the computational load.

8. CHALLENGES AND OPPORTUNITIES

It is possible to identify several research challenges that need to be addressed in order to realise the vision of anticipatory mobile computing. We now discuss some key topics, which in our opinion represent both challenges and opportunities for the research and industrial communities in the years to come.

8.1. Implementing Anticipatory Mobile Computing Systems

8.1.1. Non-deterministic behaviour in computing systems. Anticipation is unlikely to be deterministic. Predictions are done with a certain level of confidence, and biological systems often consider multiple possible futures in parallel. Nadin augments Rosen’s definition of anticipatory system with the idea of unpredictability of the future, i.e., many possible futures might be possible given a current situation, and argues that a non-deterministic computer has to be at the core of an anticipatory system [Nadin 2010]. Implementation of such a system with a smartphone, a deterministic machine with a limited ability to fully mimic biological systems, seems challenging. We argue, however, that its tight bond with the user makes the smartphone an ideal platform for anticipatory computing. While a device has a capability of bringing autonomous decisions based on its internal models of context evolution, actions are for most part taken in accordance with the user, possibly step by step. The user is guided by the phone, yet she considers the whole spectrum of possibilities before performing the action. Anticipatory applications might need a varying level of autonomy, and not all of them benefit from user’s direct involvement in actioning. How, and whether at all, can we implement non-deterministic behaviour in a completely autonomous anticipatory mobile computing system remains an interesting research question.

8.1.2. Filtering context sensed data for practical anticipatory computing. With an ever-increasing number of sensing modalities available on a phone, an anticipatory mobile system faces the problem of selecting useful features from a myriad of extracted sensor data. Psychological experiments show that the human mind is well versed in filtering out signals that are irrelevant for the task at hand [Simons and Chabris 1999]. Machine learning tools often implicitly filter out unimportant signals, for example, a regression model weights factors according to their influence on the target variable. Sensing and processing sensor data, as well as machine learning modelling, require substantial resources, and explicit filtering, such as the one performed by human intuition, could improve the performance of artificial anticipatory systems.

8.1.3. Defining the scope of anticipation. The amount of sensory input is not the only limitation that anticipatory systems should impose onto themselves. Anticipatory systems should be aware of the scope in which they operate and limit their liability to a specific time horizon and events within that scope. The time horizon of anticipation determines how far into future the anticipation goes. Setting the appropriate horizon is of great practical importance. A decision on whether to bring an umbrella or not is useless if made once we are already on the way to work. A decision to bring an umbrella on a day which is a year from now is likely to be inaccurate. Obviously, there is an inherent tradeoff between *accuracy* and *curiosity* that anticipatory systems have to deal with. Highly proactive behaviour is useful only if the underlying predictions are correct. A sweet spot that determines how far in the future a decision should be made depends on the accuracy of the model, but also on the application for which predictions are made.

8.2. Designing Advanced Applications

As the area matures, and the predictions that mobile devices afford become more reliable, we expect closer integration with fields that can directly benefit from anticipatory mobile applications. The most likely synergies can be envisioned in the areas of psychology and healthcare. Predictions of future context can help with psychological therapy design and delivery [Lathia et al. 2013; Pejovic and Musolesi 2014a]. On the other hand, behavioural theory can potentially be integrated with machine learning algorithms for more robust and reliable predictions. Information and communication technologies are key enablers of *smart cities* – efficient, sustainable urban environ-

ments. Rich computing and sensing capabilities together with smartphones’ geographically limitless inter-connectivity allow both broad, society-wide, as well as individual context inference. In future smart cities, anticipatory mobile computing could manage crowds and traffic, help with environmental monitoring and protection, and be used as a basis for public safety applications.

Anticipatory mobile computing enables paradigm-changing opportunities for adaptive systems, as introduced in Section 5.1. It is possible to envision a network that adapts its connectivity to accommodate predicted usage surges. But even beyond adaptation to predicted physical context, systems can adapt to predicted inner state of the user. Psychological computing was proposed by Bao et al. as a class of computing systems that sense user’s inner context and utilise it on the core system level [Bao et al. 2013]. Anticipatory computing systems based on predictions of users’ internal state fulfil this definition of psychological computing. For example, we can also envision flexible content delivery systems that cache digital content according to predicted users’ interests and emotional states.

9. SUMMARY

In this article we discussed the nascent field of anticipatory mobile computing, and surveyed the key concepts on which it is founded. Context inferences made through mobile sensing serve as a basis for predictive models on which anticipatory computing is based. In addition, anticipatory decisions are often delivered by the phone and executed by the user. Context-sensitive delivery, enabled by mobile sensing, is crucial for efficient actioning. In this survey we paid special attention to sensing, modelling and prediction of high-level context concepts. On the anticipatory computing side, our aim was to present reinforcement learning and latent learning as suitable solutions for the least intrusive, and efficient anticipatory mobile computing implementation.

We note that the foundations of anticipatory mobile computing – mobile sensing and anticipatory computing – are continuously changing. Indeed, merely seven years have passed since Apple released its iPhone. In each subsequent generation smartphones have been equipped with a larger number of sensors and more powerful computational resources that allow to execute more powerful sensor data processing algorithms. Similarly, anticipatory computing is an active ever-changing research area driven by recent advances in diverse fields from robotics to psychology. Therefore, in this survey we concentrated on identifying state-of-the-art practical endeavours and promising research trends. In addition, our goal was to extract best implementation practices and consolidate disjoint efforts from mobile sensing and anticipatory computing research communities.

Surge of related research activity together with a number of recently released predictive applications, such as Google Now, Microsoft Cortana, Apple Siri, Yahoo Aviate and MindMeld, stand as evidence of the rising importance of anticipatory mobile computing. The smartphone is already capable of both society-wide and individual context inference and prediction. Once we merge phone’s predictions with advance intelligence capable of steering the future through interaction with the user, a whole new set of ground-breaking applications might be possible. It is our hope that the path laid out in this article represents a valuable guideline for further efforts in this fascinating emerging area.

Acknowledgements

The authors thank Mihai Nadin from UT Dallas for a thoughtful discussion about anticipatory computing.

REFERENCES

- Saeed Abdullah, Nicholas D. Lane, and Tanzeem Choudhury. 2012. Towards Population Scale Activity Recognition: A Scalable Framework for Handling Data Diversity. In *AAAI'12*. Toronto, Canada.
- Nadav Aharony, Wei Pan, Cory Ip, Inas Khayal, and Alex Pentland. 2011. The Social fMRI: Measuring, Understanding, and Designing Social Mechanisms in the Real World. In *UbiComp'11*. Beijing, China.
- Daniel Ashbrook and Thad Starner. 2003. Using GPS to Learn Significant Locations and Predict Movement Across Multiple Users. *Personal and Ubiquitous Computing* 7, 5 (October 2003), 275–286.
- Xuan Bao, Mahanth Gowda, Ratul Mahajan, and Romit Roy Choudhury. 2013. The Case for Psychological Computing. In *HotMobile'13*. Jekyll Island, GA, USA.
- David Barber. 2012. *Bayesian Reasoning and Machine Learning*. Cambridge University Press, Cambridge, UK.
- Rene Van Bezooijen, Stanley A. Otto, and Thomas A. Heenan. 1983. Recognition of Vocal Expressions of Emotion A Three-Nation Study to Identify Universal Characteristics. *Journal of Cross-Cultural Psychology* 14, 4 (1983), 387–406.
- Amiya Bhattacharya and Sajal K. Das. 2001. Lezi-Update: An Information-Theoretic Framework for Personal Mobility Tracking in PCS Networks. *Wireless Networks* 8 (2001), 121–135.
- Christopher M. Bishop. 2006. *Pattern Recognition and Machine Learning*. Springer, New York, NY, USA.
- Niels Brouwers and Koen Langendoen. 2012. Pogo, a Middleware for Mobile Phone Sensing. In *Middle-ware'12*. Montreal, Canada.
- Ingrid Burbey and Thomas L. Martin. 2012. A Survey on Predicting Personal Mobility. *International Journal of Pervasive Computing and Communications* 8, 1 (2012), 5–22.
- Martin V. Butz, Olivier Sigaud, and Pierre Gerard (Eds.). 2003. *Anticipatory Behavior in Adaptive Learning Systems: Foundations, Theories, and Systems*. Springer.
- Martin V Butz, Olivier Sigaud, and Pierre Gerard. 2003. Internal models and anticipations in adaptive learning systems. In *Anticipatory behavior in adaptive learning systems*. Springer, 86–109.
- Andrew Campbell and Tanzeem Choudhury. 2012. From Smart to Cognitive Phones. *IEEE Pervasive Computing* 11 (2012), 7–11.
- Andrew T. Campbell, Tanzeem Choudhury, Shaohan Hu, Hong Lu, Matthew K. Mukerjee, Mashfiqui Rabbi, and Rajeev D. S. Raizada. 2010. NeuroPhone: Brain-Mobile Phone Interface using a Wireless EEG Headset. In *MobiHeld'10*. New Delhi, India.
- Andrew T. Campbell, Nicholas D. Lane, Emiliano Miluzzo, Ronald A. Peterson, Hong Lu, Xiao Zheng, Mirco Musolesi, Kristf Fodor, Shane B. Eisenman, and Gahng-Seop Ahn. 2008. The Rise of People-Centric Sensing. *IEEE Internet Computing: Mesh Networking* 12, 4 (July 2008), 30–39.
- Damon Centola. 2010. The spread of behavior in an online social network experiment. *Science* 329 (2010), 1194–1197.
- Guanling Chen and David Kotz. 2000. *A Survey of Context-Aware Mobile Computing Research*. Technical Report TR2000-381. Dartmouth Computer Science Department.
- Eunjoon Cho, Seth A. Myers, and Jure Leskovec. 2011. Friendship and Mobility: User Movement in Location-Based Social Networks. In *KDD'11*. San Diego, CA, USA.
- Yohan Chon, Nicholas D. Lane, Fan Li, Hojung Cha, and Feng Zhao. 2012. Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones. In *UbiComp'12*. Pittsburgh, PA, USA.
- Yohan Chon, Elmurod Talipov, Hyojeong Shin, and Hojung Cha. 2013. SmartDC: Mobility Prediction-based Adaptive Duty Cycling for Everyday Location Monitoring. *IEEE Transactions on Mobile Computing* 13 (2013), 3.
- Tanzeem Choudhury, Sunny Consolvo, Beverly Harrison, Jeffrey Hightower, Anthony LaMarca, Louis LeGrand, Ali Rahimi, Adam Rea, Gaetano Borriello, Bruce Hemingway, Predrag Klasnja, Karl Koscher, James A. Landay, Jonathan Lester, Danny Wyatt, and Dirk Haehnel. 2008. The Mobile Sensing Platform: An Embedded Activity Recognition System. *IEEE Pervasive Computing* 7, 2 (April-June 2008), 32–41.
- Tanzeem Choudhury and Alex Pentland. 2003. Sensing and Modeling Human Networks using the Sociometer. In *ISWC'03*. White Plains, NY, USA.
- Nicholas A. Christakis and James H. Fowler. 2007. The Spread of Obesity in a Large Social Network over 32 Years. *New England Journal of Medicine* 357, 4 (2007), 370–379. DOI: <http://dx.doi.org/10.1056/NEJMSa066082>
- Byung-Gon Chun, Sunghwan Ihm, Petros Maniatis, Mayur Naik, and Ashwin Patti. 2011. Clonecloud: elastic execution between mobile device and cloud. In *EuroSys'11*. Salzburg, Austria.

- Sunny Consolvo, David W. McDonald, Tammy Toscos, Mike Y. Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony Lamacra, Louis Legr, Ryan Libby, Ian Smith, and James A. Landay. 2008. Activity Sensing in the Wild: a Field Trial of UbiFit Garden. In *CHI'08*. Florence, Italy.
- Diane J. Cook, Michael Youngblood, Edwin O. Heierman III, Karthik Gopalratnam, Sira Rao, Andrey Litvin, and Farhan Khawaja. 2003. MavHome: An Agent-Based Smart Home. In *PerCom'03*. Dallas-Fort Worth, TX, USA.
- Cory Cornelius, Apu Kapadia, David Kotz, Dan Peebles, Minh Shin, and Nikos Triandopoulos. 2008. Anonymize: Privacy-Aware People-Centric Sensing. In *MobiSys'08*. Breckenridge, CO.
- Joëlle Coutaz, James L. Crowley, Simon Dobson, and David Garlan. 2005. Context is Key. *Commun. ACM* 48, 3 (March 2005), 49–53.
- Celine Coutrix and Nadine Mandran. 2012. Identifying Emotions Expressed by Mobile Users through 2D Surface and 3D Motion Gestures. In *UbiComp'12*. Pittsburgh, PA, USA.
- Eduardo Cuervo, Aruna Balasubramanian, Dae-Ki Cho, Alec Wolman, Stefan Saroiu, Ranveer Chandra, and Paramvir Bahl. 2010. MAUI: Making Smartphones Last Longer with Code Offload. In *MobiSys'10*. San Francisco, CA, USA.
- Tathagata Das, Prashanth Mohan, Venkata N. Padmanabhan, Ramachandran Ramjee, and Asankhaya Sharma. 2010. PRISM: Platform for Remote Sensing Using Smartphones. In *MobiSys'10*. San Francisco, CA, USA.
- James Davis, Ben Crow, and Julio Miles. 2012. Measuring Water Collection Times in Kenyan Informal Settlements. In *ICTD'12*. Atlanta, GA, USA.
- Manlio De Domenico, Antonio Lima, and Mirco Musolesi. 2012. Interdependence and Predictability of Human Mobility and Social Interactions. In *Proceedings of the Nokia Mobile Data Challenge Workshop*. Newcastle, UK.
- Daniel M. Dubois. 1998. Introduction to Computing Anticipatory Systems. *International Journal of Computing Anticipatory Systems* 2 (1998), 3–14.
- Prabal Dutta, Paul M. Aoki, Neil Kumar, Alan Mainwaring, Chris Myers, Wesley Willett, and Allison Woodruff. 2009. Demo Abstract: Common Sense - Participatory Urban Sensing Using a Network of Handheld Air Quality Monitors. In *SenSys'09*. Berkeley, CA, USA.
- Cynthia Dwork. 2006. Differential Privacy. In *ICALP'06*. Venice, Italy.
- Nathan Eagle, Aaron Clauset, and John A. Quinn. 2009. Location Segmentation, Inference and Prediction for Anticipatory Computing. In *AAAI'09*. Stanford, CA, USA.
- Nathan Eagle and Alex Pentland. 2006. Reality Mining: Sensing Complex Social Systems. *Personal and Ubiquitous Computing* 10, 4 (March 2006), 255–268.
- Nathan Eagle and Alex Pentland. 2009. Eigenbehaviors: Identifying Structure in Routine. *Behavioral Ecology and Sociobiology* 63, 7 (May 2009), 1057–1066.
- Roger G. Eston, Ann V. Rowlands, and David K. Ingledew. 1998. Validity of Heart Rate, Pedometer, and Accelerometry for Predicting the Energy Cost of Children's Activities. *Journal of Applied Physiology* 84, 1 (January 1998), 362–371.
- Vincent Etter, Mohamed Kafsi, Ehsan Kazemi, Matthias Grossglauser, and Patrick Thiran. 2013. Where to Go From Here? Mobility Prediction from Instantaneous Information. *Pervasive and Mobile Computing* 9 (2013), 784–797.
- Jennifer Evans-Cowley. 2010. Planning in the Real-Time City: The Future of Mobile Technology. *Journal of Planning Literature* 25, 2 (November 2010), 136–149.
- Joel E. Fischer, Chris Greenhalgh, and Steve Benford. 2011. Investigating Episodes of Mobile Phone Activity as Indicators of Opportune Moments to Deliver Notifications. In *MobileHCT'11*. Stockholm, Sweden.
- Fitbit. 2013. <http://www.fitbit.com/uk>. (2013). Accessed: 2013-05-23.
- James Fogarty, Scott E. Hudson, Christopher G. Atkeson, Daniel Avrahami, Jodi Forlizzi, Sara Kiesler, Johnny C. Lee, and Jie Yang. 2005. Predicting Human Interruptibility with Sensors. *ACM Transactions on Computer-Human Interaction* 12, 1 (March 2005), 119–146.
- Stefan Foll, Florian Berg, Klaus Herrmann, and Kurt Rothermel. 2012. A Predictive Protocol for Mobile Context Updates with Hard Energy Constraints. In *MDM'12*. Bengaluru, India.
- Foursquare. 2013. <https://foursquare.com>. (2013). Accessed: 2013-05-23.
- Vanessa Frias-Martinez and Jesus Virsesa. 2012. On The Relationship Between Socio-Economic Factors and Cell Phone Usage. In *ICTD'12*. Atlanta, GA, USA.
- Vittorio Gallese and Alvin Goldman. 1998. Mirror neurons and the simulation theory of mind-reading. *Trends in cognitive sciences* 2 (1998), 493–501.
- Google Now. 2013. <http://www.google.com/landing/now/>. (2013). Accessed: 2013-05-23.

- Agnes Gruenerbl, Venet Osmani, Gernot Bahle, Jose C Carrasco, Stefan Oehler, Oscar Mayora, Christian Haring, and Paul Lukowicz. 2014. Using Smart Phone Mobility Traces for the Diagnosis of Depressive and Manic Episodes in Bipolar Patients. In *Proceedings of the 5th Augmented Human International Conference*. Kobe, Japan.
- Trevor Hastie, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning*. Springer, New York, NY, USA.
- Hynek Hermansky. 1990. Perceptual Linear Predictive (PLP) Analysis of Speech. *Journal of the Acoustical Society of America* 87, 4 (1990), 1738–1752.
- Jeffrey Hightower, Sunny Consolvo, Anthony LaMarca, Ian Smith, and Jeff Hughes. 2005. Learning and Recognizing the Places We Go. In *UbiComp'05*. Tokyo, Japan.
- Joyce Ho and Stephen S. Intille. 2005. Using Context-Aware Computing to Reduce the Perceived Burden of Interruptions from Mobile Devices. In *CHI'05*. Portland, OR, USA.
- Eric Horvitz and Johnson Apacible. 2003. Learning and Reasoning about Interruption. In *ICMI'03*. Vancouver, Canada.
- Eric Horvitz and John Krumm. 2012. Some Help on the Way: Opportunistic Routing under Uncertainty. In *UbiComp'12*. Pittsburgh, PA, USA.
- Bret Hull, Vladimir Bychkovsky, Kevin Chen, Michel Goraczko, Allen Miu, Eugene Shih, Yang Zhang, Hari Balakrishnan, and Samuel Madden. 2006. CarTel: A Distributed Mobile Sensor Computing System. In *SenSys'06*. Boulder, CO, USA.
- International Telecommunication Union. 2012. *Measuring the Information Society*. Technical Report.
- Sibren Isaacman, Richard Becker, Ramon Caceres, Stephen Kobourov, Margaret Martonosi, James Rowland, and Alexander Varshavsky. 2011. Identifying Important Places in People's Lives from Cellular Network Data. In *Pervasive'11*. San Francisco, CA.
- Seungwoo Kang, Jinwon Lee, Hyukjae Jang, Hyonik Lee, Youngki Lee, Souneil Park, Taiwoo Park, and June-hwa Song. 2008. SeeMon: Scalable and Energy-Efficient Context Monitoring Framework for Sensor-Rich Mobile Environments. In *MobiSys'08*. Breckenridge, CO, USA.
- James E. Katz. 1997. The Social Side of Information Networking. *Society* 34, 3 (March-April 1997), 9–12.
- Jeffrey O. Kephart and David M. Chess. 2003. The Vision of Autonomic Computing. *Computer* 36, 1 (January 2003), 41–50.
- Donnie H. Kim, Younghun Kim, Deborah Estrin, and Mani B. Srivastava. 2010. SensLoc: Sensing Everyday Places and Paths Using Less Energy. In *SenSys'10*. Zurich, Switzerland.
- Kyu-Han Kim, Alexander W Min, Dhruv Gupta, Prasant Mohapatra, and Jatinder Pal Singh. 2011. Improving Energy Efficiency of Wi-Fi Sensing on Smartphones. In *INFOCOM'11*.
- Predrag Klasnja, Sunny Consolvo, David W. McDonald, James A. Landay, and Wanda Pratt. 2009. Using Mobile & Personal Sensing Technologies to Support Health Behavior Change in Everyday Life: Lessons Learned. In *AMIA'09*. San Francisco, CA, USA.
- Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock. 2014. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences* 111, 24 (2014).
- Andreas Krause, Asim Smailagic, and Daniel P. Siewiorek. 2006. Context-Aware Mobile Computing: Learning Context-Dependent Personal Preferences from a Wearable Sensor Array. *IEEE Transactions on Mobile Computing* 5, 2 (February 2006), 113–127.
- Nicholas D. Lane, Tanzeem Choudhury, Andrew Campbell, Mashfiqui Mohammad, Mu Lin, Xiaochao Yang, Afsaneh Doryab, Hong Lu, Shahid Ali, and Ethan Berke. 2011. BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing. In *Pervasive Health'11*. Dublin, Ireland.
- Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T. Campbell. 2010. A Survey of Mobile Phone Sensing. *IEEE Communications Magazine* 48 (2010), 140–150.
- Nicholas D. Lane, Ye Xu, Hong Lu, Shaohan Hu, Tanzeem Choudhury, Andrew T. Campbell, and Feng Zhao. 2011. Enabling Large-scale Human Activity Inference on Smartphones using Community Similarity Networks (CSN). In *UbiComp'11*. Beijing, China.
- Pier Luca Lanzi. 2008. Learning Classifier Systems: Then and Now. *Evolutionary Intelligence* 1 (2008), 63–82.
- Neal Lathia, Veljko Pejovic, Kiran Rachuri, Cecilia Mascolo, Mirco Musolesi, and Peter J. Rentfrow. 2013. Smartphones for Large-Scale Behaviour Change Intervention. *IEEE Pervasive Computing* 12, 3 (2013).
- Neal Lathia, Daniele Quercia, and Jon Crowcroft. 2012. The Hidden Image of the City: Sensing Community Well-Being from Urban Mobility. In *Pervasive'12*. Newcastle, UK.
- Juha K. Laurila, Daniel Gatica-Perez, Imad Aad, Jan Blom, Olivier Bornet, Trinh-Minh-Tri Do, Olivier Dousse, Julien Eberle, and Markus Miettinen. 2012. The Mobile Data Challenge: Big Data for Mobile

- Computing Research. In *Proceedings of the Workshop on the Nokia Mobile Data Challenge*. Newcastle, UK.
- David Lazer, Alex Pentland, Lada Adamic, Sinan Aral, Albert-László Barabási, Devon Brewer, Nicholas Christakis, Noshir Contractor, James Fowler, Myron Gutmann, Tony Jebara, Gary King, Michael Macy, Deb Roy, and Marshall Van Alstyne. 2009. Life in the Network: the Coming Age of Computational Social Science. *Science* 323, 5915 (2009), 721–723.
- Youngki Lee, Chulhong Min, Chanyou Hwang, Jaeung Lee, Inseok Hwang, Younghyun Ju, Chungkuk Yoo, Miri Moon, Uichin Lee, and June-hwa Song. 2013. SocioPhone: Everyday Face-to-Face Interaction Monitoring Platform Using Multi-Phone Sensor Fusion. In *MobiSys'13*. Taipei, Taiwan.
- Jonathan Lester, Tanzeem Choudhury, Nicky Kern, Gaetano Borriello, and Blake Hannaford. 2005. A Hybrid Discriminative/Generative Approach for Modeling Human Activities. In *IJCAI'05*. Edinburgh, UK.
- Lin Liao, Dieter Fox, and Henry Kautz. 2005. Location-Based Activity Recognition. In *NIPS'05*. Vancouver, Canada.
- Lin Liao, Dieter Fox, and Henry Kautz. 2007. Extracting Places and Activities from GPS Traces Using Hierarchical Conditional Random Fields. *International Journal of Robotics Research* 26, 1 (January 2007), 119–134.
- Felix Xiaozhu Lin, Zhen Wang, Robert LiKamWa, and Lin Zhong. 2012. Reflex: Using Low-Power Processors in Smartphones without Knowing Them. In *ASPLoS'12*. London, UK.
- Martin Lindstrom. 2011. You love your iPhone. Literally. *New York Times* 1 (2011), 21A.
- Jie Liu, Bodhi Priyantha, Ted Hart, Heitor S. Ramos, Antonio AF Loureiro, and Qiang Wang. 2012. Energy Efficient GPS Sensing with Cloud Offloading. In *SenSys'12*. Toronto, ON, Canada.
- Hong Lu, Gokul T. Chittaranjan Mashfiqui Rabbi, Denise Frauendorfer, Marianne Schmid Mast, Andrew T. Campbell, Daniel Gatica-Perez, and Tanzeem Choudhury. 2012. StressSense: Detecting Stress in Unconstrained Acoustic Environments using Smartphones. In *UbiComp'12*. Pittsburgh, PA, USA.
- Hong Lu, Wei Pan, Nicholas D. Lane, Tanzeem Choudhury, and Andrew T. Campbell. 2009. SoundSense: Scalable Sound Sensing for People-centric Applications on Mobile Phones. In *MobiSys'09*. Krakow, Poland.
- Hong Lu, Jun Yang, Zhigang Liu, Nicholas D. Lane, Tanzeem Choudhury, and Andrew T. Campbell. 2010. The Jigsaw Continuous Sensing Engine for Mobile Phone Applications. In *SenSys'10*. Zurich, Switzerland.
- Anmol Madan, Manuel Cebrian, David Lazer, and Alex Pentland. 2010. Social Sensing for Epidemiological Behavior Change. In *UbiComp'10*. Copenhagen, Denmark.
- Anmol Madan, Manuel Cebrian, Sai Moturu, Katayoun Farrahi, and Alex Pentland. 2012. Sensing the Health State of a Community. *IEEE Pervasive Computing* 11, 4 (2012), 36–45.
- Anmol Madan, Katayoun Farrahi, Daniel Gatica-Perez, and Alex Pentland. 2011. Pervasive Sensing to Model Political Opinions in Face-to-Face Networks. In *Pervasive'11*. San Francisco, CA, USA.
- Samuel Madden and Michael J. Franklin. 2002. Fjording the Stream: An Architecture for Queries over Streaming Sensor Data. In *ICDE'02*. San Jose, CA, USA.
- Suhas Mathur, Tong Jin, Nikhil Kasturirangan, Janani Chandrasekaran, Wenzhi Xue, Marco Gruteser, and Wade Trappe. 2010. Parknet: Drive-By Sensing of Road-Side Parking Statistics. In *MobiSys'10*. San Francisco, CA, USA.
- Uwe Maurer, Anthony Rowe, Asim Smailagic, and Daniel P. Siewiorek. 2006. eWatch: A Wearable Sensor and Notification Platform. In *BSN'06*. Cambridge, MA, USA.
- James McInerney, Sebastian Stein, Alex Rogers, and Nicholas R. Jennings. 2013. Breaking the Habit: Measuring and Predicting Departures from Routine in Individual Human Mobility. *Pervasive and Mobile Computing* 9 (2013), 808–822.
- Liam McNamara, Cecilia Mascolo, and Licia Capra. 2008. Media Sharing Based on Colocation Prediction in Urban Transport. In *MobiCom'08*. San Francisco, CA, USA.
- Emiliano Miluzzo, Cory T. Cornelius, Ashwin Ramaswamy, Tanzeem Choudhury, Zhigang Liu, and Andrew T. Campbell. 2010. Darwin Phones: the Evolution of Sensing and Inference on Mobile Phones. In *MobiSys'10*. San Francisco, CA, USA.
- Emiliano Miluzzo, Nicholas D. Lane, Kristf Fodor, Ronald Peterson, Hong Lu, Mirco Musolesi, Shane B. Eisenman, Xiao Zheng, and Andrew T. Campbell. 2008. Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application. In *SenSys'08*. Raleigh, NC, USA.
- MindMeld. 2013. <http://www.expectlabs.com/mindmeld/>. (2013). Accessed: 2013-05-23.
- Margaret E Morris, Qusai Kathawala, Todd K Leen, Ethan E Gorenstein, Farzin Guilak, Michael Labhard, and William Deleeuw. 2010. Mobile Therapy: Case Study Evaluations of a Cell Phone Application for Emotional Self-Awareness. *Journal of Medical Internet Research* 12, 2 (2010).

- Mihai Nadin. 2010. Anticipatory computing: from a high-level theory to hybrid computing implementations. *International Journal of Applied Research on Information Technology and Computing (IJARITAC)* 1 (2010), 1–27.
- Suman Nath. 2012. ACE: Exploring Correlation for Energy-Efficient and Continuous Context Sensing. In *MobiSys'12*. Lake District, UK.
- Anthony J Nicholson and Brian D Noble. 2008. Breadcrumbs: Forecasting Mobile Connectivity. In *Mobi-com'08*. San Francisco, CA, USA.
- Anastasios Noulas, Salvatore Scellato, Neal Lathia, and Cecilia Mascolo. 2012. Mining User Mobility Features for Next Place Prediction in Location-based Services. In *ICDM'12*. Brussels, Belgium.
- Jeongyeup Paek, Joongheon Kim, and Ramesh Govindan. 2010. Energy-Efficient Rate-Adaptive GPS-Based Positioning for Smartphones. In *MobiSys'10*. San Francisco, CA, USA.
- Jeongyeup Paek, Kyu-Han Kim, Jatinder P. Singh, and Ramesh Govindan. 2011. Energy-efficient Positioning for Smartphones using Cell-ID Sequence Matching. In *MobiSys'11*. Washington DC, USA.
- Veljko Pejovic and Mirco Musolesi. 2014a. Anticipatory Mobile Computing for Behaviour Change Interventions. In *3rd ACM Workshop on Mobile Systems for Computational Social Science (ACM MCSS'14)*. Seattle, WA, USA.
- Veljko Pejovic and Mirco Musolesi. 2014b. InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications. In *UbiComp'14*. Seattle, WA, USA.
- Santi Phithakkitnukoon, Ram Dantu, Rob Claxton, and Nathan Eagle. 2011. Behavior-Based Adaptive Call Predictor. *ACM Transactions on Autonomous and Adaptive Systems* 6, 3 (2011), 21.
- Martin Pielot, Rodrigo de Oliveira, Haewoon Kwak, and Nuria Oliver. 2014. Didn't You See My Message? Predicting Attentiveness to Mobile Instant Messages. In *CHI'14*. Toronto, ON, Canada.
- Bodhi Priyantha, Dimitrios Lymberopoulos, and Jie Liu. 2011. Little Rock: Enabling Energy Efficient Continuous Sensing on Mobile Phones. *IEEE Pervasive Computing* 10 (2011), 12–15.
- Alessandro Puiatti, Steven Mudda, Silvia Giordano, and Oscar Mayora. 2011. Smartphone-Centred Wearable Sensors Network for Monitoring Patients with Bipolar Disorder. In *International Conference of the Engineering in Medicine and Biology Society (EMBC'11)*. Boston, MA, USA.
- Mashfiqui Rabbi, Shahid Ali, Tanzeem Choudhury, and Ethan Berke. 2011. Passive and In-situ Assessment of Mental and Physical Well-being using Mobile Sensors. In *UbiComp'11*. Beijing, China.
- Kiran K. Rachuri, Cecilia Mascolo, Mirco Musolesi, and Peter J. Rentfrow. 2011. SociableSense: Exploring the Trade-offs of Adaptive Sampling and Computation Offloading for Social Sensing. In *MobiCom'11*. Las Vegas, NV, USA.
- Kiran K. Rachuri, Mirco Musolesi, Cecilia Mascolo, Peter J. Rentfrow, Crhis Longworth, and Andrius Aucinas. 2010. EmotionSense: A Mobile Phones based Adaptive Platform for Experimental Social Psychology Research. In *UbiComp'10*. Copenhagen, Denmark.
- Douglas A Reynolds, Thomas F Quatieri, and Robert B Dunn. 2000. Speaker verification using adapted Gaussian Mixture Models. *Digital Signal processing* 10, 1 (2000), 19–41.
- Simon Rogers and Mark Girolami. 2011. *A First Course in Machine Learning*. CRC Press, Boca Raton, FL, USA.
- Robert Rosen. 1985. *Anticipatory Systems*. Pergamon Press, Oxford, UK.
- Adam Sadilek and John Krumm. 2012. Far Out: Predicting Long-Term Human Mobility. In *AAAI'12*. Toronto, Canada.
- Mahadev Satyanarayanan. 2001. Pervasive computing: Vision and challenges. *IEEE Personal Communications* 8, 4 (2001), 10–17.
- Salvatore Scellato, Mirco Musolesi, Cecilia Mascolo, Vito Latora, and Andrew T. Campbell. 2011. Nextplace: A spatio-temporal prediction framework for pervasive systems. In *Pervasive'11*. San Francisco, CA, USA.
- Daniel J. Simons and Christopher F. Chabris. 1999. Gorillas in our midst: Sustained inattention blindness for dynamic events. *Perception* 28, 9 (1999), 1059–1074.
- Libo Song, David Kotz, Ravi Jain, and Xiaoning He. 2004. Evaluating Location Predictors with Extensive Wi-Fi Mobility Data. In *INFOCOM'04*. Hong Kong.
- Wee-Seng Sox and Hyong S. Kim. 2003. QoS Provisioning in Cellular Networks Based on Mobility Prediction Techniques. *IEEE Communications Magazine* 41, 1 (2003), 86–92.
- Mani Srivastava, Tarek Abdelzaher, and Boleslaw Szymanski. 2012. Human-Centric Sensing. *Phil. Trans. R. Soc. A* 370, 1958 (2012), 176–197.
- Wolfgang Stolzmann. 1998. Anticipatory Classifier Systems. *Genetic Programming* 98 (1998), 658–664.

- Wolfgang Stolzmann and Martin Butz. 2000. *Learning Classifier Systems, From Foundations to Applications*. Springer-Verlag, Berlin, Germany, Chapter Latent Learning and Action Planning in Robots with Anticipatory Classifier System, 301–321.
- Richard S. Sutton and Andrew G. Barto. 1998. *Reinforcement Learning: An Introduction*. MIT Press, Cambridge, MA, USA.
- Emmanuel Tapia, Stephen Intille, and Kent Larson. 2004. Activity Recognition in the Home Using Simple and Ubiquitous Sensors Pervasive Computing. *Pervasive Computing* 3001 (2004), 158–175.
- Emmanuel Munguia Tapia, Stephen S. Intille, William Haskell, Kent Larson, Julie Wright, Abby King, and Robert Friedman. 2007. Real-time Recognition of Physical Activities and Their Intensities using Wireless Accelerometers and a Heart Rate Monitor. In *ISWC'07*. Boston, MA, USA.
- G. Henri Ter Hofte. 2007. Xensible interruptions from your mobile phone. In *Mobile HCI'07*. Singapore.
- Sebastian Thrun, Wolfram Burgard, and Dieter Fox. 2005. *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*. MIT Press, Cambridge, MA, USA.
- Edward C. Tolman. 1932. *Purposive Behavior in Animals and Men*. Appleton, New York.
- Alessandro Vinciarelli, Maja Pantic, Dirk Heylen, Catherine Pelachaud, Isabella Poggi, Francesca D'Errico, and Marc Schrder. 2012. Bridging the gap between social animal and unsocial machine: A survey of social signal processing. *IEEE Transactions on Affective Computing* 3, 1 (2012), 69–87.
- Tianyu Wang, Giuseppe Cardone, Antonio Corradi, Lorenzo Torresani, and Andrew T. Campbell. 2012. Walk-Safe: A Pedestrian Safety App for Mobile Phone Users Who Walk and Talk While Crossing Roads. In *HotMobile'12*. San Diego, CA, USA.
- Yi Wang, Jialiu Lin, Murali Annamaram, Quinn A. Jacobson, Jason Hong, and Bhaskar Krishnamachari. 2009. A Framework of Energy Efficient Mobile Sensing for Automatic User State Recognition. In *MobiSys'09*. Krakow, Poland.
- Mark Weiser. 1991. The Computer for the 21st Century. *Scientific American* 265, 3 (1991), 94–104.
- World Health Organization. 2010. *Hidden cities: unmasking and overcoming health inequities in urban settings*. Technical Report. Centre for Health Development, and United Nations Human Settlements Programme Un-habitat.
- Danny Wyatt, Matthai Philipose, and Tanzeem Choudhury. 2005. Unsupervised Activity Recognition Using Automatically Mined Common Sense. In *AAAI'05*. Pittsburgh, PA.
- Yu Xiao, Pieter Simoens, Padmanabhan Pillai, Kiryong Ha, and Mahadev Satyanarayanan. 2013. Lowering the Barriers to Large-Scale Mobile Crowdsensing. In *HotMobile'13*. Jekyll Island, GA, USA.
- Lucy Yardley, Leanne Morrison, Laura Dennison, Sharon Lin, Charlie Hargood, Scott Lloyd, Derek Johnston, Marie Johnston, Paul Roderick, Elizabeth Murray, Susan Michie, Paul Little, Peter Smith, and Mark Weal. 2013. Uptake And Usage Of Digital Self-Management Interventions: Triangulating Mixed Methods Studies Of A Weight Management Intervention. In *Medicine 2.0 '13 World Congress on Social Media and Mobile Apps*. London, UK.
- Surender Reddy Yerva, Jonnahtan Saltarin, Hoyoung Jeung, and Karl Aberer. 2012. Social and Sensor Data Fusion in the Cloud. In *International Conference on Mobile Data Management (MDM)*. Bengaluru, India.
- Xiaojin Zhu and Andrew B. Goldberg. 2009. *Introduction to Semi-Supervised Learning*. Morgan & Claypool.
- Brian D. Ziebart, Andrew L. Maas, Anind K. Dey, and J. Andrew Bagnell. 2008. Navigate Like a Cabbie: Probabilistic Reasoning from Observed Context-Aware Behavior. In *UbiComp'08*. Seoul, South Korea.