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

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Today's mobile phones are far from the mere communication devices they were 10 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

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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. Currently, phones serve for travel planning, staying in touch with online social network (OSN) contacts, online shopping, and numerous other purposes. Today's smartphones with multicore CPUs and gigabytes of memory are capable of processing tasks with which yesterday's desktop computers struggled. However, unlike desktop computers, smartphones are small mobile devices. Consequently, phones became a part

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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, and 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, whereas 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 to 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 (e.g., Butz et al. [2003a], Chen and Kotz [2000], Lane et al. [2010], Burbey and Martin [2012], and 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 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 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 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 a phone's sensors and is 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 communication 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. Although 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 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, for the first time, we are 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

Rosen defines an anticipatory system as follows:

> "*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—that is, the context of the user and the device. 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, 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 OSN 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 the 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 the environment's reaction to the user's actions, these predictive applications could become intelligent anticipatory personal assistants that perform autonomously for the 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 preloaded 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 the user's level of physical activity and, by means of a Bluetooth sensor and calling behaviour, can sense the user's sociability. Then, the phone can infer the well-being state and predict if the user is at risk of major depression. Finally, it can adjust the therapy on-the-fly, such as 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 the 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 today more than a half of the 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 problems.[1] 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. [2009] demonstrate a participatory sensing architecture for monitoring air quality. 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 to alleviate road congestion and balance pollution levels across the city.

To demonstrate the challenges of bringing the mentioned applications 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 article, we will discuss main developments and key challenges in each of the stages.

3. DESIGNING AND IMPLEMENTING ANTICIPATORY MOBILE SYSTEMS

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

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[1]For 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].

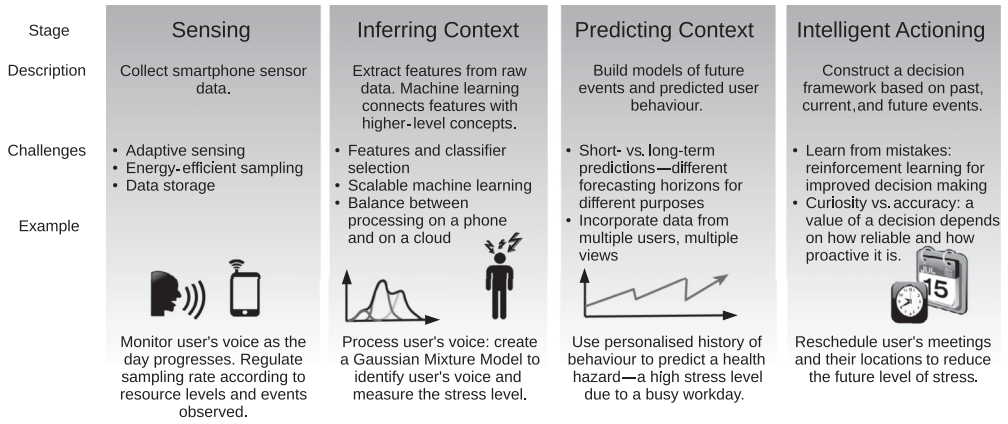| Stage	Sensing	Inferring Context	Predicting Context	Intelligent Actioning
Description	Collect smartphone sensor data.	Extract features from raw data. Machine learning connects features with higher-level concepts.	Build models of future events and predicted user behaviour.	Construct a decision framework based on past, current, and future events.
Challenges	• Adaptive sensing • Energy-efficient sampling • Data storage	• Features and classifier selection • Scalable machine learning • Balance between processing on a phone and on a cloud	• Short- vs. long-term predictions—different forecasting horizons for different purposes • Incorporate data from multiple users, multiple views	• Learn from mistakes: reinforcement learning for improved decision making • Curiosity vs. accuracy: a value of a decision depends on how reliable and how proactive it is.
Example	Monitor user's voice as the day progresses. Regulate sampling rate according to resource levels and events observed.	Process user's voice: create a Gaussian Mixture Model to identify user's voice and measure the stress level.	Use personalised history of behaviour to predict a health hazard—a high stress level due to a busy workday.	Reschedule user's meetings and their locations to reduce the future level of stress.

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

3.1. Anticipatory Behaviour and Anticipatory Computing Systems

Butz, Sigaud, and Gerard define anticipatory behaviour as follows:

> "*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. 2003b]

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], whereas neuropsychology has provided further insights into 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.

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—*an anticipatory mobile computing system*. In Figure 2, we adapt
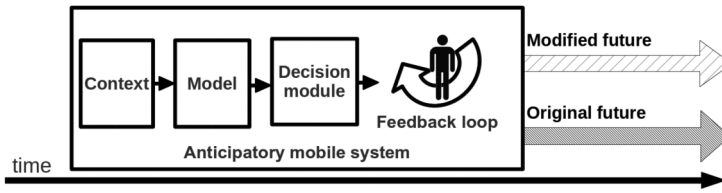
Fig. 2. Anticipatory mobile systems predict context evolution and the impact that system's actions can have on the predicted context. The feedback loop consisting of a mobile and a human enables the system to affect the future.
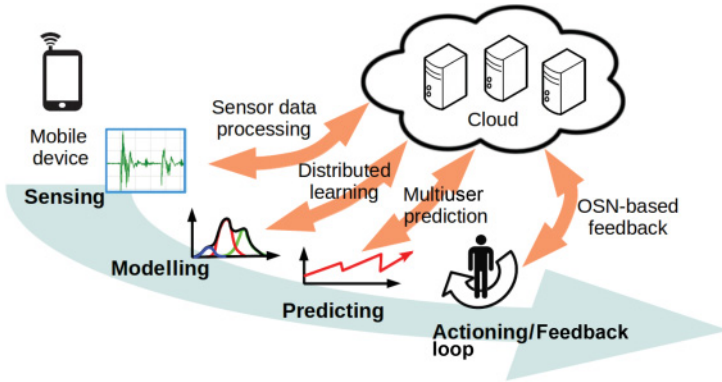

Fig. 3. Anticipatory mobile computing architecture. The mobile device senses, models, and predicts the context, and through interaction with the user, it ensures that anticipatory decisions are implemented. At each step, the computation can be distributed between the mobile device and the cloud.

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 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 a user's meetings according to the learnt model of stress evolution to improve a user's well-being. In Figure 2, the decision module uses the predicted future as a basis for deciding on a 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 generally is 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 to build more accurate models

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

of context evolution, and harness the power of OSNs 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 high-level concepts that describe a context. Smartphones have evolved from communication devices to perceptive devices capable of inferring the surrounding context.

A mobile phone's ability to infer that its user is jogging [Miluzzo et al. 2008], commuting to work, sleeping [Lane et al. 2011a], 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 communication and computation hardware. Today's phone hosts a touchscreen, GPS, accelerometer, gyroscope, proximity and light sensors, and a high-quality microphone and cameras. Multicore processors and gigabytes of memory allow smartphones to locally handle a large amount of data coming from these senses and extract meaningful situation descriptors, whereas 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. Today, 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 also are 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. For example, GPS tracking 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

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] —Harnessing domain structure [Foll et al. 2012; Nath et al. 2012; Paek et al. 2011] —Cloud offloading [Liu et al. 2012]
Computation, storage, and communication	—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 a user's mental load, attitudes, and emotions, is known [Pejovic and Musolesi 2014b].

A single sensor modality is seldom sufficient for inferring the context of a device. 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 a user's location or activity [Puiatti et al. 2011], socioeconomic 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, as 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. [2009] 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. 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, which 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. Although 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, whereas some other modalities, such as a 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, and 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 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, such as a user's physical activity [Tapia et al. 2007]. For the inference to be made, we first need to identify the most informative modalities and features of the raw sensor data, such as 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 a 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 have 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 to 600 Hz, and thus the investigation of DFT coefficient means and variations can help identify speech in an audio trace. Finally, Mel-frequency cepstral coefficients (MFCCs) are another commonly used feature for speech recognition [Lu et al. 2009; Miluzzo et al. 2010; Chon et al. 2012].

The preceding 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 a 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 (e.g., Bishop [2006], Hastie et al. [2009], Rogers and Girolami [2011], and 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 a high audio level is detected in at least 50 out of 1,000 samples taken within a half-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 nonspeech 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, Teager Energy Operator (TEO) and 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 proved to work well in practice. The table 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, GMMs perform well when it comes to speaker identification, as it is possible to extract parameters for a set of

Table II. Context Sensing Domains and Characteristic Features

Domain	Characteristic Features
Speech recognition	—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. 2011a] —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 (PLP) coefficients [Rachuri et al. 2010] —Mean and standard deviation of DFT power [Miluzzo et al. 2008]
Activity classification	—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. 2011a, 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	—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] —Eigenbehaviours: vectors of time–place pairs [Eagle and Pentland 2009] —Hour of day, latitude, longitude, altitude, social ties [De Domenico et al. 2012]
Object recognition	—GIST features [Chon et al. 2012]
Gestures	—Mean, max, min, median, amplitude, andhigh-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	—Galvanic skin response, heat flux, skin thermometer running average and sum of absolute differences [Krause et al. 2006]

Table II. Continued

Domain	Characteristic Features
Thoughts	—Bandpass filtered neural signal from EEG [Campbell et al. 2010]
Call prediction	—Call arrival and interdeparture time, calling reciprocity [Phithakkitnukoon et al. 2011]
Interruptibility	—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]

Table III. Context Sensing Domains and Relevant Machine Learning Techniques

Domain	Machine Learning Technique
Speech recognition	—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	—Boosted ensemble of weak learners [Consolvo et al. 2008; Abdullah et al. 2012] —Boosting and 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)	—Markov chain [Ashbrook and Starner 2003] —Nonlinear time series [Scellato et al. 2011; De Domenico et al. 2012]
Location (with BT or WiFi)	—Bayesian network [Eagle and Pentland 2006; Eagle et al. 2009]
Location (with ambient sensors)	—Nearest neighbour [Maurer et al. 2006]
Scene classification	—K-means clustering [Chon et al. 2012]
Object recognition	—Support vector machine [Chon et al. 2012] —Boosting and tree stump [Wang et al. 2012]
Place categorization	—Labelled LDA [Chon et al. 2012]
Call prediction	—Naive Bayesian [Phithakkitnukoon et al. 2011]
Interruptibility	—Bayesian network [Horvitz and Apacible 2003; Fogarty et al. 2005] —Tree-based learner [Fogarty et al. 2005] —Naive Bayes [Ter Hofte 2007]

Gaussian components from the FFT of the speech signal and use them as a vectorial representation of human voice. This approach has proved to be extremely effective for user identification [Reynolds et al. 2000]. However, a deeper discussion about why certain approaches work in certain domains is outside the scope of this survey.

4.3.3. Handling Large-Scale Inference. The anticipatory mobile computing applications for healthcare and personal assistance that 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 80-year-old person will yield significantly different

accelerometer readings than when the same activity is performed by a 20 year old. Clearly, classification needs to be less general, but does that imply a personal classifier for each user?

In Lane et al. [2011b], the authors propose community similarity networks (CSNs) that connect users who exhibit similar behaviour. User alikeness 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 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. [2011] continuously gathered more than 25 sensing modalities for more than a year from about 130 participants. 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 semisupervised 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. The 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, which are two other steps of anticipatory computing. Unlike context inference, these two areas are less explored. Their real-world implementations are scarce; 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 the user's context at all times, 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 handoff [Sox and Kim 2003]. Yet as data collected by a phone get 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 that 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. The work of Ashbrook and Starner [2003] and Hightower et al. [2005] aims to recognise and predict places that are of special significance to the user. The interest in such prediction was further raised with proliferation of smartphones and commercial location-based services such as 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 a 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 nonlinear time series analysis. More recently, Horvitz and Krumm [2012] devised a method for predicting a user's destination and suggesting the optimal diversion should the user want to interrupt his current trip to, for example, take a coffee break. Noulas et al. [2012] investigate next check-in prediction in the Foursquare network. 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 the mobility of users [Chon et al. 2013].

Research on mobility prediction was additionally boosted by large sets of multimodal data that have been collected and made publicly available by companies and academic institutions. For example, the MIT Reality Mining project [Eagle and Pentland 2006] accumulated a collection of traces from 100 subjects monitored over a period of 9 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) dataset 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 preceding datasets served as a proving ground for a number of approaches towards mobility prediction. Eagle et al. [2009] 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 dataset. De Domenico et al. [2012] exploit movement correlation and social ties for location prediction. Relying on nonlinear time series analysis of movement traces that do not originate from the user but instead originate from the user's friends or people with correlated

Table IV. Modelling Methods for Mobility Prediction

Method	Example
Markovian	—Markov process (MP) [Ashbrook and Straner 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]

mobility patterns, the authors demonstrate improved accuracy of prediction on the MDC dataset. Interdependence of friendships and mobility in a location-based social network was also analysed in Cho et al. [2011]. McInerney et al. [2013] propose a method based on a novel information-theoretic metric called *instantaneous entropy* for predicting departures from routine in individual's mobility. Such predictions are of extreme importance for personalised anticipatory mobile computing applications, such as 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, whereas nonlinear time series approaches assume that people spend similar staying time at similar times of a day [Chon et al. 2013]. Additionally, 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 present commonly used mobility prediction methods.

5.2. Lifestyle, Health and Opinion Prediction

Multimodal traces also enable prediction of behavioural aspects beyond mobility. For example, human activity prediction has been an active subject of research in past years: various approaches have been presented in the literature, such as those based on 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, Liao et al. [2005, 2007] demonstrate the prediction and correlation of activities using location information. Eagle and Pentland [2009] propose the use of multimodal *eigenbehaviours* 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. [2010] use mobile phone–based

co-location and communication sensing to measure characteristic behaviour changes in symptomatic individuals. 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 and 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. [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 an 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 past 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 a user's momentarily behaviour and state.

UbiFit [Consolvo et al. 2008] and BeWell [Lane et al. 2011a], 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 becomes 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 a 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 that shows an aquatic ecosystem where the number and the activity of animals depend on a 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 she 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 gets 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 that people have. Feelings that the users have towards their phones parallel those that they have towards their fellow humans [Lindstrom 2011]. The preceding 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 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, and in which context? These are typical HCI questions related to interruptibility.

6.2. Personalised Interaction

A 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 [1991] advocates pervasive technology that coexists unobtrusively with its users. This "calm technology" is not our current reality, and indeed we get an abundance of notifications from an increasing number of devices that 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, a user's interruptibility. Context sensors have 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 a user's desktop computer usage [Horvitz and Apacible 2003]. Horvitz et al. [2003] developed a framework for inferring a user's workload in an office setting via a Bayesian network in which variables such as the presence of voice, a 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 [2005] investigate the interruption burden in case of mobile notifications. 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. [2011] 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. Pielot et al. [2014] collected a dataset of text messages exchanged via smartphones together with the associated phone usage context. 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, 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. [2014] showed that emotions expressed by others in our OSN vicinity impact our own emotional expression.

Anticipatory computing applications can use OSNs as an 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. 2003a]. 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. Explicit 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. [2003b]. 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, preprogrammed 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—that is, 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 that 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, 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 a user's meetings. Just like in 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 a 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 application. Yet the user may consider frequent querying to be irritating. Another option is to look for implicit signals, such as monitoring if the user makes changes to the schedule immediately after the application interventions. The second issue comes from the intrinsic need of reinforcement learning to make mistakes 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 a 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 with 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. For example, the artificial implementation of latent learning has been demonstrated 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 finds 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 to learning anticipatory systems are those belonging to the area of so-called probabilistic robotics [Thrun et al. 2005].

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. Although 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 [2008].
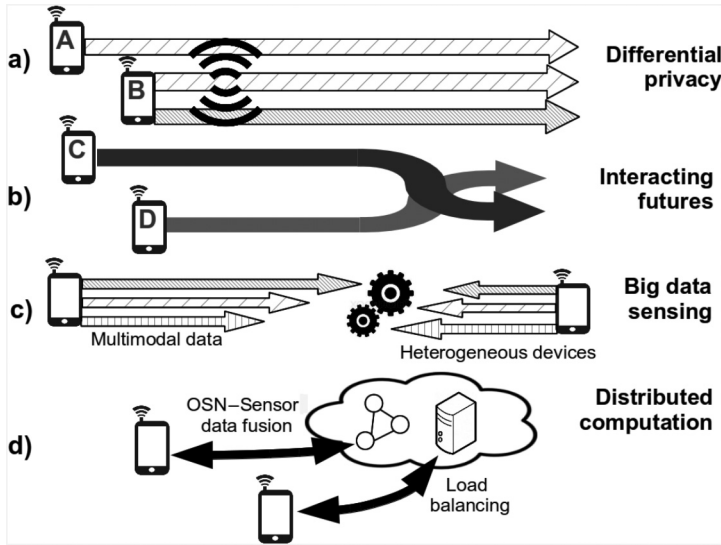
Fig. 5. Large scale anticipatory computing challenges.

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, as, 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 sections.

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 to 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, because as shown in the previous example, the privacy of a nonparticipating 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 sensing sources when it comes to anticipatory mobile computing. Frameworks for collaborative sensing include Anony-Sense [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. We have 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 also 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 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. [2012] mined opportunistically sensed multimodal data coming from multiple users to characterise places that those users visit. Although such a fusion of sensed data improves inference, a large amount of streaming data represents 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 OSN 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* in 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 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. Nondeterministic 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 [2010] augments Rosen's definition of an 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 nondeterministic computer has to be at the core of an anticipatory system. 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. Although a device has the 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 a user's direct involvement in actioning. How and whether at all we can implement nondeterministic 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 myriad extracted sensor data. Psychological experiments show that the human mind is well versed in filtering out signals that are irrelevant to 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 on 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 the 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 it is made once we are already on the way to work. A decision to bring an umbrella on a day that is a year from now is likely to be inaccurate. Obviously, there is an inherent trade-off between *accuracy* and *curiosity* with which anticipatory systems have to deal. 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 not only 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 environments. Rich computing and sensing capabilities together with smartphones' geographically limitless interconnectivity allow both broad, society-wide, and 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 the predicted inner state of the user. Psychological computing was proposed by Bao et al. [2013] as a class of computing systems that sense a user's inner context and utilise it on the core system level. 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 7 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 execution of 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 the best implementation practices and consolidate disjoint efforts from mobile sensing and anticipatory computing research communities.

A 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 a phone's predictions with advance intelligence capable of steering the future through interaction with the user, a whole new set of groundbreaking 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.

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