A Survey of Mobile Phone Sensing

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ABSTRACT

Mobile phones or smartphones are rapidly becoming the central computer and communication device in people's lives. Application delivery channels such as the Apple AppStore are transforming mobile phones into App Phones, capable of downloading a myriad of applications in an instant. Importantly, today's smartphones are programmable and come with a growing set of cheap powerful embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and camera, which are enabling the emergence of personal, group, and community-scale sensing applications. We believe that sensor-equipped mobile phones will revolutionize many sectors of our economy, including business, healthcare, social networks, environmental monitoring, and transportation. In this article we survey existing mobile phone sensing algorithms, applications, and systems. We discuss the emerging sensing paradigms, and formulate an architectural framework for discussing a number of the open issues and challenges emerging in the new area of mobile phone sensing research.

INTRODUCTION

Today's smartphone not only serves as the key computing and communication mobile device of choice, but it also comes with a rich set of embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and camera. Collectively, these sensors are enabling new applications across a wide variety of domains, such as healthcare [1], social networks [2], safety, environmental monitoring [3], and transportation [4, 5], and give rise to a new area of research called mobile phone sensing.

Until recently mobile sensing research such as activity recognition, where people's activity (e.g., walking, driving, sitting, talking) is classified and monitored, required specialized mobile devices (e.g., the Mobile Sensing Platform [MSP]) [6] to be fabricated [7]. Mobile sensing applications had to be manually downloaded, installed, and hand tuned for each device. User studies conducted to evaluate new mobile sensing applications and algorithms were small-scale because of the expense and complexity of doing experiments at scale. As a result the research, which was innovative, gained little momentum outside a small group of dedicated researchers. Although the potential of using mobile phones as a platform for sensing research has been discussed for a number of years now, in both industrial [8] and research communities [9, 10], there has been little or no advancement in the field until recently.

All that is changing because of a number of important technological advances. First, the availability of cheap embedded sensors initially included in phones to drive the user experience (e.g., the accelerometer used to change the display orientation) is changing the landscape of possible applications. Now phones can be programmed to support new disruptive sensing applications such as sharing the user's real-time activity with friends on social networks such as Facebook, keeping track of a person's carbon footprint, or monitoring a user's well being. Second, smartphones are open and programmable. In addition to sensing, phones come with computing and communication resources that offer a low barrier of entry for third-party programmers (e.g., undergraduates with little phone programming experience are developing and shipping applications). Third, importantly, each phone vendor now offers an *app store* allowing developers to deliver new applications to large populations of users across the globe, which is transforming the deployment of new applications, and allowing the collection and analysis of data far beyond the scale of what was previously possible. Fourth, the mobile computing cloud enables developers to offload mobile services to back-end servers, providing unprecedented scale and additional resources for computing on collections of large-scale sensor data and supporting advanced features such as persuasive user feedback based on the analysis of big sensor data.

The combination of these advances opens the door for new innovative research and will lead to the development of sensing applications that are likely to revolutionize a large number of existing business sectors and ultimately significantly impact our everyday lives. Many questions remain to make this vision a reality. For example, how much intelligence can we push to the phone without jeopardizing the phone experience? What breakthroughs are needed in order to perform robust and accurate classification of activities and context out *in the wild*? How do we scale a sensing application from an individual to a target community or even the general population? How do we use these new forms of large-scale application delivery systems (e.g., Apple AppStore, Google Market) to best drive data

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collection, analysis and validation? How can we exploit the availability of big data shared by applications but build watertight systems that protect personal privacy? While this new research field can leverage results and insights from wireless sensor networks, pervasive computing, machine learning, and data mining, it presents new challenges not addressed by these communities.

In this article we give an overview of the sensors on the phone and their potential uses. We discuss a number of leading application areas and sensing paradigms that have emerged in the literature recently. We propose a simple architectural framework in order to facilitate the discussion of the important open challenges on the phone and in the cloud. The goal of this article is to bring the novice or practitioner not working in this field quickly up to date with where things stand.

Figure 1. *An off-the-self iPhone 4, representative of the growing class of sensor-enabled phones. This phone includes eight different sensors: accelerometer, GPS, ambient light, dual microphones, proximity sensor, dual cameras, compass, and gyroscope.*

Sensors

As mobile phones have matured as a computing platform and acquired richer functionality, these advancements often have been paired with the introduction of new sensors. For example, accelerometers have become common after being initially introduced to enhance the user interface and use of the camera. They are used to automatically determine the orientation in which the user is holding the phone and use that information to automatically re-orient the display between a landscape and portrait view or correctly orient captured photos during viewing on the phone.

Figure 1 shows the suite of sensors found in the Apple iPhone 4. The phone's sensors include a gyroscope, compass, accelerometer, proximity sensor, and ambient light sensor, as well as other more conventional devices that can be used to sense such as front and back facing cameras, a microphone, GPS and WiFi, and Bluetooth radios. Many of the newer sensors are added to support the user interface (e.g., the accelerometer) or augment location-based services (e.g., the digital compass).

The proximity and light sensors allow the phone to perform simple forms of context recognition associated with the user interface. The proximity sensor detects, for example, when the user holds the phone to her face to speak. In this case the touchscreen and keys are disabled, preventing them from accidentally being pressed as well as saving power because the screen is turned off. Light sensors are used to adjust the brightness of the screen. The GPS, which allows the phone to localize itself, enables new location-based applications such as local search, mobile social networks, and navigation. The compass and gyroscope represent an extension of location, providing the phone with increased awareness of its position in relation to the physical world (e.g., its direction and orientation) enhancing location-based applications.

Not only are these sensors useful in driving the user interface and providing location-based services; they also represent a significant opportunity to gather data about people and their environments. For example, accelerometer data is capable of characterizing the physical movements of the user carrying the phone [2]. Distinct patterns within the accelerometer data can be exploited to automatically recognize different activities (e.g., running, walking, standing). The camera and microphone are powerful sensors. These are probably the most ubiquitous sensors on the planet. By continuously collecting audio from the phone's microphone, for example, it is possible to classify a diverse set of distinctive sounds associated with a particular context or activity in a person's life, such as using an automatic teller machine (ATM), being in a particular coffee shop, having a conversation, listening to music, making coffee, and driving [11]. The camera on the phone can be used for many things including traditional tasks such as photo blogging to more specialized sensing activities such as tracking the user's eye movement across the phone's display as a means to activate applications using the camera mounted on the front of the phone [12]. The combination of accelerometer data and a stream of location estimates from the GPS can recognize the mode of transportation of a user, such as using a bike or car or taking a bus or the subway [3].

More and more sensors are being incorporated into phones. An interesting question is what new sensors are we likely to see over the next few years? Non-phone-based mobile sensing devices such as the Intel/University of Washington Mobile Sensing Platform (MSP) [6] have shown value from using other sensors not found in phones today (e.g., barometer, temperature, humidity sensors) for activity recognition; for example, the accelerometer and barometer make it easy to identify not only when someone is walking, but when they are climbing stairs and in which direction. Other researchers have studied air quality and pollution [13] using specialized

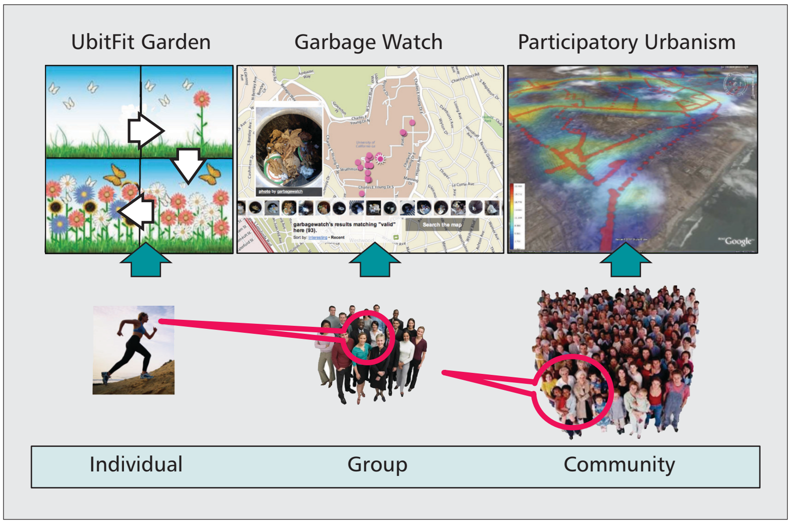

Figure 2. *Mobile phone sensing is effective across multiple scales, including: a single individual (e.g., UbitFit Garden [1]), groups such as social networks or special interest groups (e.g., Garbage Watch [23]), and entire communities/population of a city (e.g., Participatory Urbanism [20]).*

sensors embedded in prototype mobile phones. Still others have embedded sensors in standard mobile phone earphones to read a person's blood pressure [14] or used neural signals from cheap off-the-shelf wireless electroencephalography (EEG) headsets to control mobile phones for hands-free human-mobile phone interaction [36]. At this stage it is too early to say what new sensors will be added to the next generation of smartphones, but as the cost and form factor come down and leading applications emerge, we are likely to see more sensors added.

APPLICATIONS AND APP STORES

New classes of applications, which can take advantage of both the low-level sensor data and high-level events, context, and activities inferred from mobile phone sensor data, are being explored not only in academic and industrial research laboratories [11, 15–22] but also within startup companies and large corporations. One such example is SenseNetworks, a recent U.S.-based startup company, which uses millions of GPS estimates sourced from mobile phones within a city to predict, for instance, which subpopulation or *tribe* might be interested in a specific type of nightclub or bar (e.g., a jazz club). Remarkably, it has only taken a few years for this type of analysis of large-scale location information and mobility patterns to migrate from the research laboratory into commercial usage.

In what follows we discuss a number of the emerging leading application domains and argue that the new application delivery channels (i.e., app stores) offered by all the major vendors are critical for the success of these applications.

TRANSPORTATION

Traffic remains a serious global problem; for example, congestion alone can severely impact both the environment and human productivity (e.g., wasted hours due to congestion). Mobile phone sensing systems such as the MIT VTrack project [4] or the Mobile Millennium project [5] (a joint initiative between Nokia, NAVTEQ, and the University of California at Berkeley) are being used to provide fine-grained traffic information on a large scale using mobile phones that facilitate services such as accurate travel time estimation for improving commute planning.

SOCIAL NETWORKING

Millions of people participate regularly within online social networks. The Dartmouth CenceMe project [2] is investigating the use of sensors in the phone to automatically classify events in people's lives, called *sensing presence*, and selectively share this presence using online social networks such as Twitter, Facebook, and MySpace, replacing manual actions people now perform daily.

ENVIRONMENTAL MONITORING

Conventional ways of measuring and reporting environmental pollution rely on aggregate statistics that apply to a community or an entire city. The University of California at Los Angeles (UCLA) PEIR project [3] uses sensors in phones to build a system that enables personalized environmental impact reports, which track how the actions of individuals affect both their exposure and their contribution to problems such as carbon emissions.

HEALTH AND WELL BEING

The information used for personal health care today largely comes from self-report surveys and infrequent doctor consultations. Sensor-enabled mobile phones have the potential to collect in situ continuous sensor data that can dramatically change the way health and wellness are assessed as well as how care and treatment are delivered. The UbiFit Garden [1], a joint project between Intel and the University of Washington, captures levels of physical activity and relates this information to personal health goals when presenting feedback to the user. These types of systems have proven to be effective in empowering people to curb poor behavior patterns and improve health, such as encouraging more exercise.

APP STORES

Getting a critical mass of users is a common problem faced by people who build systems, developers and researchers alike. Fortunately, modern phones have an effective application distribution channel, first made available by Apple's App Store for the iPhone, that is revolutionizing this new field. Each major smartphone vendor has an app store (e.g., Apple AppStore, Android Market, Microsoft Mobile Marketplace, Nokia Ovi). The success of the app stores with the public has made it possible for not only startups but small research laboratories and even individual developers to quickly attract a very large number of users. For example, an early use of app store distribution by researchers in academia is the CenceMe application for iPhone [2], which was made available on the App Store when it opened in 2008. It is now feasible to distribute and run experiments with a large number of participants from all around the world rather than in laboratory controlled conditions using a small user study. For example, researchers interested in statistical models that interpret human behavior from sensor data have long dreamed of ways to collect such large-scale real-world data. These app stores represent a game changer for these types of research. However, many challenges remain with this new approach to experimentation via app stores. For example, what is the best way to collect ground-truth data to assess the accuracy of algorithms that interpret sensor data? How do we validate experiments? How do we select a good study group? How do we deal with the potentially massive amount of data made available? How do we protect the privacy of users? What is the impact on getting approval for human subject studies from university institutional review boards (IRBs)? How do researchers scale to run such large-scale studies? For example, researchers used to supporting small numbers of users (e.g., 50 users with mobile phones) now have to construct cloud services to potentially deal with 10,000 needy users. This is fine if you are a startup, but are academic research laboratories geared to deal with this?

Sensing Scale and Paradigms

Future mobile phone sensing systems will operate at multiple scales, enabling everything from personal sensing to global sensing as illustrated in Fig. 2 where we see personal, group, and community sensing — three distinct scales at which mobile phone sensing is currently being studied by the research community. At the same time researchers are discussing how much the user (i.e., the person carrying the phone) should be actively involved during the sensing activity (e.g., taking the phone out of the pocket to collect a sound sample or take a picture); that is, should the user actively participate, known as *participatory sensing* [15], or, alternatively, passively participate, known as *opportunistic sensing* [17]? Each of these sensing paradigms presents important trade-offs. In what follows we discuss different sensing scales and paradigms.

Sensing Scale

Personal sensing applications are designed for a single individual, and are often focused on data collection and analysis. Typical scenarios include tracking the user's exercise routines or automating diary collection. Typically, personal sensing applications generate data for the sole consumption of the user and are not shared with others. An exception is healthcare applications where limited sharing with medical professionals is common (e.g., primary care giver or specialist). Figure 2 shows the UbitFit Garden [1] as an example of a personal wellness application. This personal sensing application adopts persuasive technology ideas to encourage the user to reach her personal fitness goals using the metaphor of a garden blooming as the user progresses toward their goals.

Individuals who participate in sensing applications that share a common goal, concern, or interest collectively represent a group. These *group sensing* applications are likely to be popular and reflect the growing interest in social networks or connected groups (e.g., at work, in the neighborhood, friends) who may want to share sensing information freely or with privacy protection. There is an element of trust in group sensing applications that simplify otherwise difficult problems, such as attesting that the collected sensor data is correct or reducing the degree to which aggregated data must protect the individual. Common use cases include assessing neighborhood safety, sensor-driven mobile social networks, and forms of citizen science. Figure 2 shows GarbageWatch [23] as an example of a group sensing application where people participate in a collective effort to improve recycling by capturing relevant information needed to improve the recycling program. For example, students use the phone's camera to log the content of recycling bins used across a campus.

Most examples of *community sensing* only become useful once they have a large number of people participating; for example, tracking the spread of disease across a city, the migration patterns of birds, congestion patterns across city roads [5], or a noise map of a city [24]. These applications represent large-scale data collection, analysis, and sharing for the good of the commu-

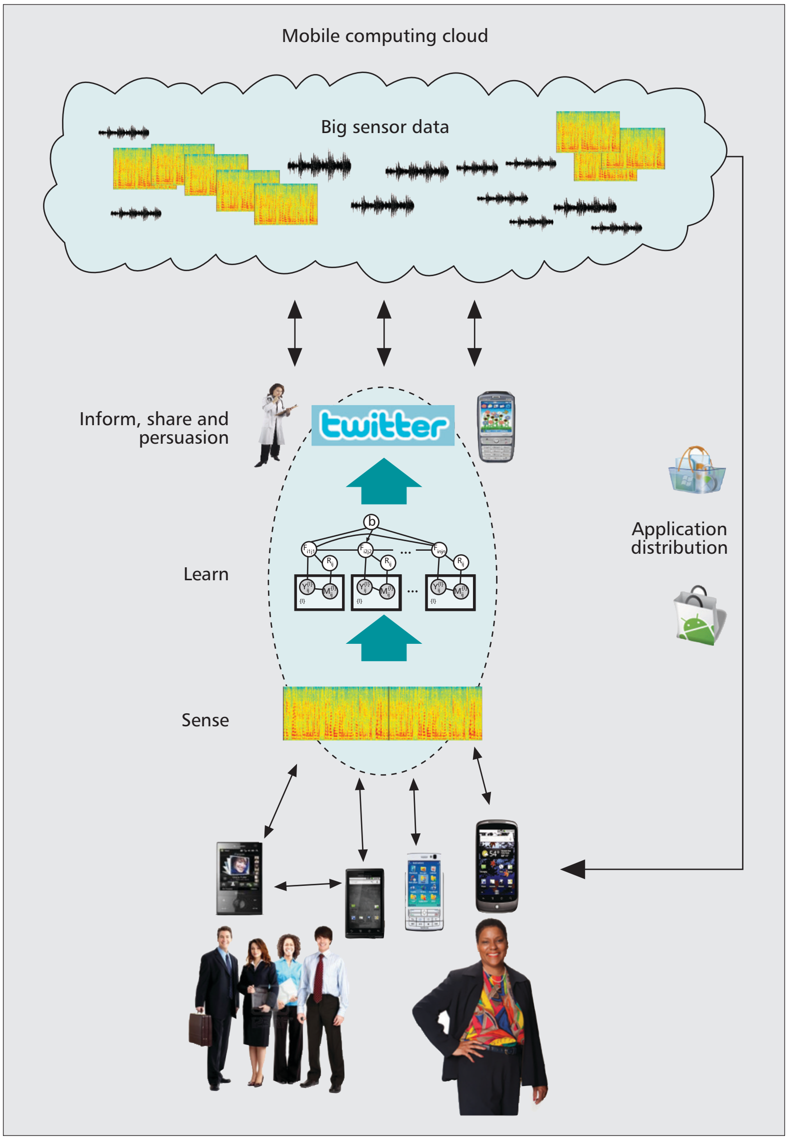

Figure 3. *Mobile phone sensing architecture.*

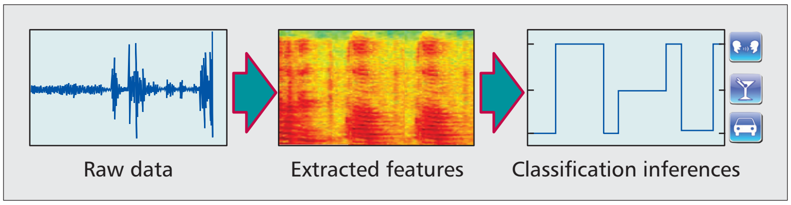

Figure 4. *Raw audio data captured from mobile phones is transformed into features allowing learning algorithms to identify classes of behavior (e.g., driving, in conservation, making coffee) occurring in a stream of sensor data, for example, by SoundSense [11].*

nity. To achieve scale implicitly requires the cooperation of strangers who will not trust each other. This increases the need for community sensing systems with strong privacy protection and low commitment levels from users. Figure 2 shows carbon monoxide readings captured in Ghana using mobile sensors attached to taxicabs as part of the Participatory Urbanism project [20] as an example of a community sensing application. This project, in conjunction with the N-SMARTs project [13] at the University of California at Berkeley, is developing prototypes that allow similar sensor data to be collected with phone embedded sensors.

The impact of scaling sensing applications from personal to population scale is unknown. Many issues related to information sharing, privacy, data mining, and closing the loop by providing useful feedback to an individual, group, community, and population remain open. Today, we only have limited experience in building scalable sensing systems.

Sensing Paradigms

One issue common to the different types of sensing scale is to what extent the user is actively involved in the sensing system [12]. We discuss two points in the design space: participatory sensing, where the user actively engages in the data collection activity (i.e., the user manually determines how, when, what, and where to sample) and opportunistic sensing, where the data collection stage is fully automated with no user involvement.

The benefit of opportunistic sensing is that it lowers the burden placed on the user, allowing overall participation by a population of users to remain high even if the application is not that personally appealing. This is particularly useful for community sensing, where per user benefit may be hard to quantify and only accrue over a long time. However, often these systems are technically difficult to build [25], and a major resource, people, are underutilized. One of the main challenges of using opportunistic sensing is the phone context problem; for example, the application wants to only take a sound sample for a city-wide noise map when the phone is out of the pocket or bag. These types of context issues can be solved by using the phone sensors; for example, the accelerometer or light sensors can determine if the phone is out of the pocket.

Participatory sensing, which is gaining interest in the mobile phone sensing community, places a higher burden or cost on the user; for example, manually selecting data to collect (e.g., lowest petrol prices) and then sampling it (e.g., taking a picture). An advantage is that complex operations can be supported by leveraging the intelligence of the person in the loop who can solve the context problem in an efficient manner; that is, a person who wants to participate in collecting a noise or air quality map of their neighborhood simply takes the phone out of their bag to solve the context problem. One drawback of participatory sensing is that the quality of data is dependent on participant enthusiasm to reliably collect sensing data and the compatibility of a person's mobility patterns to the intended goals of the application (e.g., collect pollution samples around schools). Many of these challenges are actively being studied. For example, the PICK project [23] is studying models for systematically recruiting participants.

Clearly, opportunistic and participatory represent extreme points in the design space. Each approach has pros and cons. To date there is little experience in building large-scale participatory or opportunistic sensing applications to fully understand the trade-offs. There is a need to develop models to best understand the usability and performance issues of these schemes. In addition, it is likely that many applications will emerge that represent a hybrid of both these sensing paradigms.

Mobile Phone Sensing Architecture

Mobile phone sensing is still in its infancy. There is little or no consensus on the sensing architecture for the phone and the cloud. For example, new tools and phone software will be needed to facilitate quick development and deployment of robust context classifiers for the leading phones on the market. Common methods for collecting and sharing data need to be developed. Mobile phones cannot be overloaded with continuous sensing commitments that undermine the performance of the phone (e.g., by depleting battery power). It is not clear what architectural components should run on the phone and what should run in the cloud. For example, some researchers propose that raw sensor data should not be pushed to the cloud because of privacy issues. In the following sections we propose a simple architectural viewpoint for the mobile phone and the computing cloud as a means to discuss the major architectural issues that need to be addressed. We do not argue that this is the best system architecture. Rather, it presents a starting point for discussions we hope will eventually lead to a converging view and move the field forward.

Figure 3 shows a mobile phone sensing architecture that comprises the following building blocks.

Sense

Individual mobile phones collect raw sensor data from sensors embedded in the phone.

Learn

Information is extracted from the sensor data by applying machine learning and data mining techniques. These operations occur either directly on the phone, in the mobile cloud, or with some partitioning between the phone and cloud. Where these components run could be governed by various architectural considerations, such as privacy, providing user real-time feedback, reducing communication cost between the phone and cloud, available computing resources, and sensor fusion requirements. We therefore consider where these components run to be an open issue that requires research.

Inform, Share, and Persuasion

We bundle a number of important architectural components together because of commonality or coupling of the components. For example, a personal sensing application will only inform the user, whereas a group or community sensing application may share an aggregate version of information with the broader population and obfuscate the identity of the users. Other considerations are how to best visualize sensor data for consumption of individuals, groups, and communities. Privacy is a very important consideration as well.

While phones will naturally leverage the distributed resources of the mobile cloud (e.g., computation and services offered in the cloud), the computing, communications, and sensing resources on the phones are ever increasing. We believe that as resources of the phone rapidly expand, one of the main benefits of using the mobile computing cloud will be the ability to compute and mine big data from very large numbers of users. The availability of large-scale data benefits mobile phone sensing in a variety of ways; for example, more accurate interpretation algorithms that are updated based on sensor data sourced from an entire user community. This data enables personalizing of sensing systems based on the behavior of both the individual user and cliques of people with similar behavior.

In the remainder of the article we present a detailed discussion of the three main architectural components introduced in this section:

- Sense
- Learn
- Inform, share, and persuasion

Sense: The Mobile Phone as a Sensor

As we discussed, the integration of an ever expanding suite of embedded sensors is one of the key drivers of mobile phone applications. However, the programmability of the phones and the limitation of the operating systems that run on them, the dynamic environment presented by user mobility, and the need to support continuous sensing on mobile phones present a diverse set of challenges the research community needs to address.

Programmability

Until very recently only a handful of mobile phones could be programmed. Popular platforms such as Symbian-based phones presented researchers with sizable obstacles to building mobile sensing applications [2]. These platforms lacked well defined reliable interfaces to access low-level sensors and were not well suited to writing common data processing components, such as signal processing routines, or performing computationally costly inference due to the resource constraints of the phone. Early sensor-enabled phones (i.e., prior to the iPhone in 2007) such as the Symbian-based Nokia N80 included an accelerometer, but there were no open application programming interfaces (APIs) to access the sensor signals. This has changed significantly over the last few years. Note that phone vendors initially included accelerometers to help improve the user interface experience.

Most of the smartphones on the market are open and programmable by third-party developers, and offer software development kits (SDKs), APIs, and software tools. It is easy to cross-compile code and leverage existing software such as established machine learning libraries (e.g., Weka).

Most of the smartphones on the market are open and programmable by third party developers and offer SDKs, APIs, and software tools. It is easy to cross-compile code and leverage existing software such as established machine learning libraries.

However, a number of challenges remain in the development of sensor-based applications. Most vendors did not anticipate that third parties would use continuous sensing to develop new applications. As a result, there is mixed API and operating system (OS) support to access the low-level sensors, fine-grained sensor control, and watchdog timers that are required to develop real-time applications. For example, on Nokia Symbian and Maemo phones the accelerometer returns samples to an application unpredictably between 25–38 Hz, depending on the CPU load. While this might not be an issue when using the accelerometer to drive the display, using statistical models to interpret activity or context typically requires high and at least consistent sampling rates.

Lack of sensor control limits the management of energy consumption on the phone. For instance, the GPS uses a varying amount of power depending on factors such as the number of satellites available and atmospheric conditions. Currently, phones only offer a black box interface to the GPS to request location estimates. Finer-grained control is likely to help in preserving battery power and maintaining accuracy; for example, location estimation could be aborted when accuracy is likely to be low, or if the estimate takes too long and is no longer useful.

As third parties demand better support for sensing applications, the API and OS support will improve. However, programmability of the phone remains a challenge moving forward. As more individual, group, and community-scale applications are developed there will be an increasing demand placed on phones, both individually and collectively. It is likely that abstractions that can cope with persistent spatial queries and secure the use of resources from neighboring phones will be needed. Phones may want to interact with other collocated phones to build new sensing paradigms based on collaborative sensing [12].

Different vendors offer different APIs, making porting the same sensing application to multivendor platforms challenging. It is useful for the research community to think about and propose sensing abstractions and APIs that could be standardized and adopted by different mobile phone vendors.

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Continuous Sensing

Continuous sensing will enable new applications across a number of sectors but particularly in personal healthcare. One important OS requirement for continuous sensing is that the phone supports multitasking and background processing. Today, only Android and Nokia Maemo phones support this capability. The iPhone 4 OS, while supporting the notion of multitasking, is inadequate for continuous sensing. Applications must conform to predefined profiles with strict constraints on access to resources. None of these profiles provide the ability to have continuous access to all the sensors (e.g., continuous accelerometer sampling is not possible).

While smartphones continue to provide more computation, memory, storage, sensing, and communication bandwidth, the phone is still a resource-limited device if complex signal processing and inference are required. Signal processing and machine learning algorithms can stress the resources of the phones in different ways: some require the CPU to process large volumes of sensor data (e.g., interpreting audio data [12]), some need frequent sampling of energy expensive sensors (e.g., GPS [3]), while others require real-time inference (e.g., Darwin [12]). Different applications place different requirements on the execution of these algorithms. For example, for applications that are user initiated the latency of the operation is important. Applications (e.g., healthcare) that require continuous sensing will often require real-time processing and classification of the incoming stream of sensor data. We believe continuous sensing can enable a new class of real-time applications in the future, but these applications may be more resource demanding. Phones in the future should offer support for continuous sensing without jeopardizing the phone experience; that is, not disrupt existing applications (e.g., to make calls, text, and surf the web) or drain batteries. Experiences from actual deployments of mobile phone sensing systems show that phones which run these applications can have standby times reduced from 20 hours or more to just six hours [2]. For continuous sensing to be viable there need to be breakthroughs in low-energy algorithms that duty cycle the device while maintaining the necessary application fidelity.

Early deployments of phone sensing systems tended to trade off accuracy for lower resource usage by implementing algorithms that require less computation or a reduced amount of sensor data. Another strategy to reduce resource usage is to leverage cloud infrastructure where different sensor data processing stages are offloaded to back-end servers [12, 26] when possible. Typically, raw data produced by the phone is not sent over the air due to the energy cost of transmission, but rather compressed summaries (i.e., extracted features from the raw sensor data) are sent. The drawback to these approaches is that they are seldom sufficiently energy-efficient to be applied to continuous sensing scenarios. Other techniques rely on adopting a variety of duty cycling techniques that manage the sleep cycle of sensing components on the phone in order to trade off the amount of battery consumed against sensing fidelity and latency [27].

Continuous sensing raises considerable challenges in comparison to sensing applications that require a short time window of data or a single snapshot (e.g., a single image or short sound clip). There is an energy tax associated with continuously sensing and potentially uploading in real time to the cloud for further processing. Solutions that limit the cost of continuous sensing and reduce the communication overheard are necessary. If the interpretation of the data can withstand delays of an entire day, it might be acceptable if the phone can collect and store the sensor data until the end of the day and upload when the phone is being charged. However, this delay-tolerant model of sensor sampling and processing severely limits the ability of the phone to react and be aware of its context. Sensing applications that will be successful in the real world will have to be smart enough to adapt to situations. There is a need to study the trade-off of continuous sensing with the goal of minimizing the energy cost while offering sufficient accuracy and real-time responsiveness to make the application useful.

As continuous sensing becomes more common, it is likely that additional processing support will emerge. For example, the Little Rock project [28] underway at Microsoft Research is developing hardware support for continuous sensing where the primary CPU frequently sleeps, and digital signal processors (DSPs) support the duty cycle management, sensor sampling, and signal processing.

Phone Context

Mobile phones are often used on the go and in ways that are difficult to anticipate in advance. This complicates the use of statistical models that may fail to generalize under unexpected environments. The background environment or actions of the user (e.g., the phone could be in the pocket) will also affect the quality of the sensor data that is captured. Phones may be exposed to events for too short a period of time, if the user is traveling quickly (e.g., in a car), if the event is localized (e.g., a sound) or the sensor requires more time than is possible to gather a sample (e.g., air quality sensor). Other forms of interfering context include a person using their phone for a call, which interferes with the ability of the accelerometer to infer the physical actions of the person. We collectively describe these issues as the *context problem*. Many issues remain open in this area.

Some researchers propose to leverage co-located mobile phones to deal with some of these issues; for example, sharing sensors temporarily if they are better able to capture the data [12]. To counter context challenges researchers proposed super-sampling [13] where data from nearby phones are collectively used to lower the aggregate noise in the reading. Alternatively, an effective approach for some systems have been sensor sampling routines with admission control stages that do not process data that is low-quality, saving resources, and reducing errors (e.g., SoundSense [11]).

While machine learning techniques are being used to interpret mobile phone data, the reliability of these algorithms suffer under the dynamic and unexpected conditions presented by everyday phone use. For example, a speaker identification algorithm maybe effective in a quiet office environment but not a noisy cafe. Such problems can be overcome by collecting sufficient examples of the different usage scenarios (i.e., training data). However, acquiring examples is costly and anticipating the different scenarios the phone might encounter is almost impossible. Some solutions to this problem straddle the boundary of mobile systems and machine learning and include borrowing model inputs (i.e., features) from nearby phones, performing collaborative multi-phone inference with models that evolve based on different scenarios encountered, or discovering new events that are not encountered during application design [12].

LEARN: INTERPRETING SENSOR DATA

The raw sensor data able to be acquired by phones, irrespective of the scale or modality (e.g., accelerometer, camera) are worthless without interpretation (e.g., human behavior recognition). A variety of data mining and statistical tools can be used to distill information from the data collected by mobile phones and calculate summary statistics to present to the users, such as, the average emissions level of different locations or the total distance run by a user and their ranking within a group of friends (e.g., Nike+).

Recently, crowd-sourcing techniques have been applied to the analysis of sensor data which is typically problematic; for example, image processing when used in-the-wild is notoriously difficult to maintain high accuracy. In the CrowdSearch [21] project, crowd sourcing and micro-payments are adopted to incentivize people to improve automated image search. In [21] human-in-the-loop stages are added to the process of image search with tasks distributed to the user population.

We discuss the key challenges in interpreting sensor data, focusing on a primary area of interest: human behavior and context modeling.

HUMAN BEHAVIOR AND CONTEXT MODELING

Many emerging applications are people-centric, and modeling the behavior and surrounding context of the people carrying the phones is of particular interest. A natural question is how well can mobile phones interpret human behavior (e.g., sitting in conversation) from low-level multimodal sensor data? Or, similarly, how accurately can they infer the surrounding context (e.g., pollution, weather, noise environment)?

Currently, supervised learning techniques are the algorithms of choice in building mobile inference systems. In supervised-learning, as illustrated in Fig. 4, examples of high-level behavioral classes (e.g., cooking, driving) are hand annotated (i.e., labeled). These examples, referred to as training data, are then provided to a learning algorithm, which fits a model to the classes (i.e., behaviors) based on the sensor data. Sensor data is usually presented to the learning algorithm in the form of extracted features, which are calculations on the raw data that emphasize characteristics that more clearly differentiate classes (e.g., the variance of the accelerometer magnitude over a small time window could be useful for separating standing and walking classes). Supervised learning is feasible for small-scale sensing applications, but unlikely to scale to handle the wide range of behaviors and contexts exhibited by a large community of users. Other forms of learning algorithms, such as semi-supervised (where only some of the data is labeled) and unsupervised (where no labels are provided by the user) ones, reduce the need for labeled examples, but can lead to classes that do not correspond to the activities that are useful to the application or require that the unlabeled data only come from the already labeled class categories (e.g., an activity that was never encountered before can throw off a semi-supervised learning algorithm).

Researchers show that a variety of everyday human activities can be inferred most successfully from multimodal sensor streams For example, [29] describes a system which is capable of recognizing eight different everyday activities (e.g., brushing teeth, riding in an elevator) using the Mobile Sensing Platform (MSP) [6] — an important mobile sensing device that is a predecessor of sensing on the mobile phone. Similar results are demonstrated using mobile phones that infer everyday activities [2, 3, 30], albeit less accurately and with a smaller set of activities than the MSP.

The microphone, accelerometer, and GPS found on many smartphones on the market have proven to be effective at inferring more complex human behavior. Early work on mobility pattern modeling succeeds with surprisingly simple approaches to identify significant places in people's lives (e.g., work, home, coffee shop). More recently researchers [31] have used statistical techniques to not only infer significant places but also connect these to activities (e.g., gym, waiting for the bus) using just GPS traces. The microphone is one of the most ubiquitous sensors and is capable of inferring what a person is doing (e.g., in conversation), where they are (e.g., audio signature of a particular coffee shop) — in essence, it can capture a great deal both about a person and their surrounding ambient environment. In SoundSense [11] a general-purpose sound classification system for mobile phones is developed using a combination of supervised and unsupervised learning. The recognition of a static set of common sounds (e.g., music) uses supervised learning but augmented with an unsupervised approach that learns the novel frequently recurring classes of sound encountered by different users. Finally, the user is brought into the loop to confirm and provide a textual description (i.e., label) of the discovered sounds. As a result, SoundSense extends the ability of the phone to recognize new activities.

SCALING MODELS

Existing statistical models are unable to cope with everyday occurrences such as a person using a new type of exercise machine, and struggle when two activities overlap each other or different individuals carry out the same activity differently (e.g., the sensor data for walking will look very different for a 10-year-old vs. a 90-year-old person). A key to scalability is to design techniques for generalization that will be effective for entire communities containing millions of people.

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To address these concerns current research directions point toward models that are adaptive and incorporate people in the process. Automatically increasing the classes recognized by a model using active learning (where the learning algorithm selectively queries the user for labels) is investigated in the context of heath care [23]. Approaches have been developed in which training data sourced directly from users is grouped based on their social network [12]. This work demonstrates that exploiting the social network of users improves the classification of locations such as significant places. Community-guided learning [30] combines data similarity and crowd-sourced labels to improve the classification accuracy of the learning system. In [30] hand annotated labels are no longer treated as absolute ground truth during the training process but are treated as soft hints as to class boundaries in combination with the observed data similarity. This approach learns classes (i.e., activities) based on the actual behavior of the community and adjusts transparently to the changes in how the community performs these activities — making it more suitable for large-scale sensing applications. However, if the models need to be adapted on the fly, this may force the learning of models to happen on the phone, potentially causing a significant increase in computational needs [12].

Many questions remain regarding how learning will progress as the field grows. There is a lack of shared technology that could help accelerate the work. For example, each research group develops their own classifiers that are hand coded and tuned. This is time consuming and mostly based on small-scale experimentation and studies. There is a need for a common machine learning toolkit for mobile phone sensing that allows researchers to build and share models. Similarly, there is a need for large-scale public data sets to study more advanced learning techniques and rigorously evaluate the performance of different algorithms. Finally, there is also a need for a repository for sharing datasets, code, and tools to support the researchers.

Inform, Share, and Persuasion: Closing the Sensing Loop

How you use inferred sensor data to inform the user is application-specific. But a natural question is, once you infer a class or collect together a set of large-scale inferences, how do you close the loop with people and provide useful information back to users? Clearly, personal sensing applications would just inform the individual, while social networking sensing applications may share activities or inferences with friends. We discuss these forms of interaction with users as well as the important area of privacy. Another topic we touch on is using large-scale sensor data as a persuasive technology — in essence using big data to help users attain goals using targeted feedback.

Sharing

To harness the potential of mobile phone sensing requires effective methods of allowing people to connect with and benefit from the data. The standard approach to sharing is visualization using a web portal where sensor data and inferences are easily displayed. This offers a familiar and intuitive interface. For the same reasons, a number of phone sensing systems connect with existing web applications to either enrich existing applications or make the data more widely accessible [12, 23]. Researchers recognize the strength of leveraging social media outlets such as Facebook, Twitter, and Flickr as ways to not only disseminate information but build community awareness (e.g., citizen science [20]). A popular application domain is fitness, such as Nike+. Such systems combine individual statistics and visualizations of sensed data and promote competition between users. The result is the formation of communities around a sensing application. Even though, as in the case of Nike+, the sensor information is rather simple (i.e., just the time and distance of a run), people still become very engaged. Other applications have emerged that are considerably more sophisticated in the type of inference made, but have had limited up take. It is still too early to predict which sensing applications will become the most compelling for user communities. But social networking provides many attractive ways to share information.

Personalized Sensing

Mobile phones are not limited to simply collecting sensor data. For example, both the Google and Microsoft search clients that run on the iPhone allow users to search using voice recognition. Eye tracking and gesture recognition are also emerging as natural interfaces to the phone.

Sensors are used to monitor the daily activities of a person and profile their preferences and behavior, making personalized recommendations for services, products, or points of interest possible [32]. The behavior of an individual along with an understanding of how behavior and preferences relate to other segments of the population with similar behavioral profiles can radically change not only online experiences but real world ones too. Imagine walking into a pharmacy and your phone suggesting vitamins and supplements with the effectiveness of a doctor. At a clothing store your phone could identify which items are manufactured without sweatshop labor. The behavior of the person, as captured by sensors embedded in their phone, become an interface that can be fed to many services (e.g., targeted advertising). Sensor technology personalized to a user's profile empowers her to make more informed decisions across a spectrum of services.

Persuasion

Sensor data gathered from communities (e.g., fitness, healthcare) can be used not only to inform users but to persuade them to make positive behavioral changes (e.g., nudge users to exercise more or smoke less). Systems that provide tailored feedback with the goal of changing users' behavior are referred to as persuasive technology [33]. Mobile sensing applications open the door to building novel persuasive systems that are still largely unexplored.

For many application domains, such as healthcare or environmental awareness, users commonly have desired objectives (e.g., to lose weight or lower carbon emissions). Simply providing a user with her own information is often not enough to motivate a change of behavior or habit. Mobile phones are an ideal platform capable of using low-level individual-scale sensor data and aggregated community-scale information to drive long-term change (e.g., contrasting the carbon footprint of a user with her friends can persuade the user to reduce her own footprint). The UbiFit Garden [1] project is an early example of integrating persuasion and sensing on the phone. UbiFit uses an ambient background display on the phone to offer the user continuous updates on her behavior in response to desired goals. The display uses the metaphor of a garden with different flowers blooming in response to physical exercise of the user during the day. It does not use comparison data but simply targets the individual user. A natural extension of UbiFit is to present community data. Ongoing research is exploring methods of identifying and using people in a community of users as *influencers* for different individuals in the user population. A variety of techniques are used in existing persuasive system research, such as the use of games, competitions among groups of people, sharing information within a social network, or goal setting accompanied by feedback. Understanding which types of metaphors and feedback are most effective for various persuasion goals is still an open research problem. Building mobile phone sensing systems that integrate persuasion requires interdisciplinary research that combines behavioral and social psychology theories with computer science.

The use of large volumes of sensor data provided by mobile phones presents an exciting opportunity and is likely to enable new applications that have promise in enacting positive social changes in health and the environment over the next several years. The combination of large-scale sensor data combined with accurate models of persuasion could revolutionize how we deal with persistent problems in our lives such as chronic disease management, depression, obesity, or even voter participation.

PRIVACY

Respecting the privacy of the user is perhaps the most fundamental responsibly of a phone sensing system. People are understandably sensitive about how sensor data is captured and used, especially if the data reveals a user's location, speech, or potentially sensitive images. Although there are existing approaches that can help with these problems (e.g., cryptography, privacy-preserving data mining), they are often insufficient [34]. For instance, how can the user temporarily pause the collection of sensor data without causing a suspicious gap in the data stream that would be noticeable to anyone (e.g., family or friends) with whom they regularly share data?

In personal sensing applications processing data locally may provide privacy advantages compared to using remote more powerful servers. SoundSense [11] adopts this strategy: all the audio data is processed on the phone, and raw audio is never stored. Similarly, the UbiFit Garden [1] application processes all data locally on the device.

Privacy for group sensing applications is based on user group membership. For instance, although social networking applications like Loopt and CenceMe [2] share sensitive information (e.g., location and activity), they do so within groups in which users have an existing trust relationship based on friendship or a shared common interest such as reducing their carbon footprint.

Community sensing applications that can collect and combine data from millions of people run the risk of unintended leakage of personal information. The risks from location-based attacks are fairly well understood given years of previous research. However, our understanding of the dangers of other modalities (e.g., activity inferences, social network data) are less developed. There are growing examples of reconstruction type attacks where data that may look safe and innocuous to an individual user may allow invasive information to be reverse-engineered. For example, the UIUC Poolview project shows that even careful sharing of personal weight data within a community can expose information on whether a user's weight is trending upward or downward [35]. The PEIR project evaluates different countermeasures to this type of scenario, such as adding noise to the data or replacing chunks of the data with synthetic but realistic samples that have limited impact on the quality of the aggregate analysis [3].

Privacy and anonymity will remain a significant problem in mobile-phone-based sensing for the foreseeable future. In particular, the *second-hand smoke* problem of mobile sensing creates new privacy challenges, such as:

- How can the privacy of third parties be effectively protected when other people wearing sensors are nearby?
- How can mismatched privacy policies be managed when two different people are close enough to each other for their sensors to collect information from the other party?

Furthermore, this type of sensing presents even larger societal questions, such as who is responsible when collected sensor data from these mobile devices cause financial harm? Stronger techniques for protecting the rights of people as sensing becomes more commonplace will be necessary.

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CONCLUSION

This article discusses the current state of the art and open challenges in the emerging field of mobile phone sensing. The primary obstacle to this new field is not a lack of infrastructure; millions of people already carry phones with rich sensing capabilities. Rather, the technical barriers are related to performing privacy-sensitive and resource-sensitive reasoning with noisy data and noisy labels, and providing useful and effective feedback to users. Once these technical barriers are overcome, this nascent field will advance quickly, acting as a disruptive technology across many domains including social networking, health, and energy. Mobile phone sensing systems will ultimately provide both micro- and macroscopic views of cities, communities, and individuals, and help improve how society functions as a whole.

The primary obstacle to this new field is not a lack of infrastructure. Rather, the technical barriers are related to performing privacy-sensitive and resource-sensitive reasoning with noisy data and noisy labels and providing useful and effective feedback to users.

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