

# Chapter 10

## Epidemic Estimation over Social Networks using Large Scale Biosensors

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### ABSTRACT

*Infectious diseases, such as the recent Ebola outbreak, can be especially dangerous for large communities on today's highly connected world. Countermeasures can be put in place if one is able to predict determine which people are more vulnerable to infections or have been in contact with the disease, and where. Contact location, time and relationship with the subject are relevant metrics that affect the probability of disease propagation. Sensors on personal devices that gather information from people, and social networks analysis, allow the integration of community data, while data analysis and modelling may potentially indicate community-level susceptibility to an epidemic. Indeed, there has been interest on social networks for epidemic prediction. But the integration between large-scale sensor networks and these initiatives, required to achieve epidemic prediction, is yet to be achieved. In this context, an opportunistic system is proposed and evaluated for predicting an epidemic outbreak in a community, while guaranteeing user privacy.*

### INTRODUCTION

Distributed systems have been employed as platforms for allowing the interaction between groups of individuals and set of devices. As technology advances, sensing, computation, storage and communications become widespread, ubiquitous sensing devices will become a part of global distributed sensing systems (Lane et al., 2010) (Campbell et al., 2008).

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Recently, the predominance of mobile phones equipped with sensors, the explosion in social networks and the deployment of sensor networks have created an enormous digital footprint that can be harnessed (Zhang et al., 2010). Furthermore, developments in sensor technology, communications and semantic processing, allow the coordination of a large network of devices and large dataset processing with intelligent data analysis (Lane et al., 2010).

The sensing of people constitutes a new application domain that broadens the traditional sensor network scope of environmental and infrastructure monitoring. People become the carriers of sensing devices and both producers and consumers of events (Miluzzo et al., 2010). As a consequence, the recent interest by the industry in open programming platforms and software distribution channels is accelerating the development of people-centric sensing applications and systems (Miluzzo et al., 2010)(Lane et al., 2010).

To take advantage of these emerging networks of mobile people-centric sensing devices, researchers arrived at the concept of Mobiscopes, i.e. taskable mobile sensing systems that are capable of high coverage. They represent a new type of infrastructure, where mobile sensors have the potential to logically belong to more than one network, while being physically attached to their carriers (Abdelzaher et al., 2007). By taking advantage of these systems, it will be possible to mine and run computations on enormous amounts of data from a very large number of users (Lane et al., 2010).

A people-centric sensing system imbues the individuals it serves in a symbiotic relationship with itself (Kansal et al., 2007) (Campbell et al., 2008). People-centric sensing enables a different approach to sensing, learning, visualizing and data sharing, not only self-centered, but focused on the surrounding world. The traditional view on mesh sensor networks is combined with one where people, carrying sensors turn opportunistic coverage into a reality (Campbell et al., 2008). These sensors can reach into regions static sensors cannot, proving to be especially useful for applications that occasionally require sensing (Abdelzaher et al., 2007). By employing these systems, one can aim to revolutionize the field of context-aware computing (Zhang et al., 2010).

An alternative based on worldwide coverage of static sensors to develop people-centric systems is unfeasible in terms of monetary costs, management and permissions (Kansal et al., 2007)(Campbell et al., 2008). In addition, it is extremely challenging in static sensing models, due to band limits and issues that arise from covering a vast area, to satisfy the required density requirements (Abdelzaher et al., 2007). Thanks to their mobility, mobile sensors overcome spatial coverage limitations (Abdelzaher et al., 2007)(Kansal et al., 2007).

Adoption issues might come up as potential users are usually unaware of the benefits that arise from technological developments. However, with the advent of smartphones, a direct impact in daily life is easier to achieve, making advantages clearer. By using opportunistic sensing, functionality can be offered in a transparent fashion (Lane et al., 2010), leaving the user agnostic of system activity and circumventing adoption obstacles that might be present in participatory sensing.

Behavioral modeling requires large amounts of accurate data (Peebles et al., 2010). These systems constitute an opportunity for intelligent analysis systems, as relevant information can be obtained from large-scale sensory data and employed in statistical models (Peebles et al., 2010)(Lane et al., 2010). Great benefits can be taken from this unconstrained human data, in opposition to the traditional carefully setup experiments (Peebles et al., 2010). With these developments it is now possible to distribute and run experiments in a worldwide population rather than in a small laboratory controlled study (Lane et al., 2010).

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