# On the Use of Participatory Sensing to Better Understand City Dynamics

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## Abstract

In this position paper we argue that certain types of social media systems, such as Instagram and Foursquare, can act as valuable source of sensing, providing access to important characteristics of urban locations and urban social behavior. We discuss some of our previous studies and present our thoughts about the future of this field based insights obtained from them.

# **Author Keywords**

Participatory sensing; city dynamics; mobile social networks; big data; location sharing services

## **ACM Classification Keywords**

J.4 [Computer Applications]: Social and Behavioral Sciences; G.3 [Mathematics of Computing]: Probability and Statistics—Statistical computing; H.4 [Information Systems Applications]: Miscellaneous

# **General Terms**

Measurement

## Introduction

Location-based social networks (LBSNs) [8], such as Foursquare<sup>1</sup> and Instagram<sup>2</sup> build new virtual

<sup>&</sup>lt;sup>1</sup>http://www.foursquare.com.

<sup>&</sup>lt;sup>2</sup>http://www.instagram.com.

environments that integrate user interactions. Recently, such systems are becoming very popular. The ubiquity of smartphones, associated with the adoption of social media websites, enable unprecedented opportunities to study cities, e.g., its dynamics and urban social behavior, by analyzing the data generated by users. In this way, LBSNs systems allow people to share useful data about the area in the city where they are located at any given moment, acting as a source of sensing and thus being called participatory sensing systems [1, 5].

From participatory sensing systems we can derive participatory sensor networks (PSNs), where each node in the network consists of a user and his/her mobile device, sending data to web services. For example, in an Instagram derived PSN, the sensed data is a picture of a specific place. Data from PSNs can be usually collected through the API of the specific system (e.g., Instagram API). Figure 1 illustrates a PSN, and more details about PSNs can be found in [7, 5].

Up to now most of the studies in the literature, including ours, have addressed two dimensions of the shared data in PSNs, namely time and space. In fact, those dimensions are the most important ones, and they can provide useful information about cities.

# Using PSNs to study cities

Recently there have been some efforts to extract new insights on city dynamics as, for instance, their particularities and inhabitant routines from PSNs, such as [3, 2, 4]. Here we will discuss some of our previous studies in this direction.

As the data provided by PSNs may be very complex, a fundamental step in any investigation is to characterize the collected data in order to understand its challenges

and usefulness. So far, we have characterized data collected from two different PSNs, one derived from photo sharing services, particularly Instagram (see detailed results in [7]), and another from location sharing services, such as Foursquare (details in [5]). Among the results, we showed the planetary scale of those networks, as well as the highly unequal frequency of data sharing, both spatially and temporally, which is highly correlated with the typical routine of people.

Such characterization provided us with a deeper understanding of the properties of those PSNs, and revealed their great potential to support studies on city dynamics and urban social behavior, motivating then the proposition of techniques in those directions.

For example, in [6] we proposed a technique called City Image, which provides a visual summary of the city dynamics based on the movements of individuals. This technique exploits urban transition graphs, a directed weighted graph G(V, E), where a node  $v_i \in V$  is the category of a specific location (e.g., nightlife) and a direct edge  $(i, j) \in E$  marks a transition between two categories. In Figure 2 we demonstrate this technique for London / UK and Surabaya / Indonesia. Each cell in the City Image represents the willingness of a transition from a given category at a given place (vertical axis) to another category (horizontal axis). Red colors represent rejection, blue colors represent favoring and white represents indifference. First note the differences between those cities. Observe, for example, that in London people are very favorable to perform the transitions in Nightlife locations, on the other hand this is not common in Surabaya. Cultural differences might help to explain this result. As we can see the City Image is a promising way to



Figure 1: Participatory sensor network illustration.

better understand the city dynamics, helping us to visualize the common routines of their citizens.

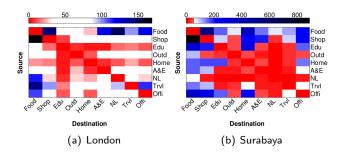


Figure 2: The City Image of London and Surabaya. Abbreviations of categories of places used in the image (extracted from Foursquare): Arts & Entertainment (A&E); College & Education (Edu); Great Outdoors (Outd); Nightlife Spot (NL); Shop & Service (Shop); and Travel Spot (TrvI).

In [7], among other results, we present a technique to identify points of interest (POI) within a city. The technique considers that each pair i of coordinates (longitude, latitude)  $(x,y)_i$  is associated with a point  $p_i$  that represents a shared data, for instance a photo. We compute the geographic distance between each pair of points  $(p_i,p_j)$ , and group the points  $p_i$  that are close to

each other (dependent threshold). To capture the POIs, we exclude groups that may have been generated by random situations (i.e., random people movements), using simple statistical methods (details in [7]). In [7] we demonstrated this technique for the city of Belo Horizonte/Brazil. Here we apply this technique for the city of Rome/Italy. Our initial results are very promising. Figure 3a shows all clusters identified for Rome<sup>3</sup>, and, as we can see, is not very informative. Figure 3b shows the POIs extracted from all clusters. As we can observe it represents most of the sights of the city as well as popular regions in Rome.

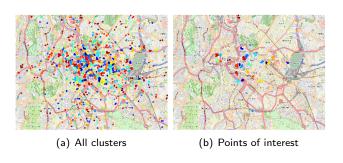


Figure 3: Points of interest of Rome.

<sup>&</sup>lt;sup>3</sup>We used the same dataset present in [7].

## Discussion and future directions

As we could observe in the previous section, data from different PSNs can be represented as sensing layers, each one enabling the access of data related to a certain aspect of the city. Figure 1 displays four different layers, namely: transit monitoring (obtained, e.g., from Waze<sup>4</sup>); location categories (obtained, e.g., from Foursquare); weather condition (obtained, e.g., from Weddar<sup>5</sup>); and pictures of places (obtained, e.g., from Instagram). Common features present in the data in all layers: id of the user who shared the data; the location where the data was shared; and the time when it occurred. The type of data each layer provides, e.g. photos or weather condition, called here specialty data, is what differentiate each layer.

Complementary information about the same given city aspect could be inferred using distinct layers. For instance, the transit condition layer offers structured data about the transit, such as traffic jams. Conditions about the traffic could also be inferred by analyzing the content of the pictures obtained in the pictures of places layer in a given road, despite not being the central goal of this layer.

The use of PSNs can help us to better understand the dynamics of cities, and from this understanding we are able to offer smarter services to meet people's needs. A range of fruitful opportunities may emerge when exploring the specialty data offered by each sensing layer. Since each layer represents a partial view of the city, their aggregation can provide a deeper understanding of it. A future direction we intend to pursue is the investigation of the interplay between different sensing layers.

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<sup>&</sup>lt;sup>4</sup>http://www.waze.com.

<sup>&</sup>lt;sup>5</sup>http://www.weddar.com.