Towards a Sustainable People-Centric Sensing

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***Abstract*—People-centric sensing is a research topic that aims to obtain and analyze urban data from crowdsourcing, such as participatory and opportunistic sensing. Data provided by these sources increase our knowledge about different aspects of our lives in urban scenarios, which can help us to understand and address issues that cities face. Thus, the sustainable people participation is crucial to the development of this sensing paradigm. In this direction, we focus on a central element for the deployment of people-centric sensing applications: guarantee sustainable participation of users. For this, we discuss the existing challenges at the main components of an architecture to support people-centric sensing. In order to enrich this discussion, we also evaluate the incentive mechanisms used by Foursquare, mechanisms that could be used, with proper adaptation, in several types of sensing systems. Among the results, we found evidence that a specific type of incentive (mayorship-based) could be very effective to increase users' engagement. Moreover, we present a set of policies to be incorporated into an existing or new people-centric sensing architecture to complement traditional incentive mechanisms.**

1. Introduction

A clear tendency in the mobile computing paradigm is the use of a plethora of mobile devices to access social networks. Moreover, all sorts of sensing elements are becoming ubiquitous in these mobile devices, allowing them to offer location-based services, among others. Given this scenario, a clear path is the coalescence of social networks and sensing technology available in mobile devices, leading to *people-centric sensing* [1]. People-centric sensing paradigm, also known as mobile crowdsensing, is being used to enable a broad range of applications, such as environmental monitoring [2], identification of cultural boundaries [3] and public safety [4], all of them aim to reduce problems faced by urban centers and provide sophisticated applications.

People-centric sensing has the potential of sensing vast areas and has less energy constraints than traditional Wireless Sensor Networks (WSNs), because it relies on the participation of people carrying their portable devices (e.g., smart phones), which can be recharged regularly, to collect data and collaborate among themselves [1]. Due to a strong dependence of people's participation on sensing activities, the paradigm can be categorized according to the degree of users' engagement [5]: active involvement of people, acting as social sensors sharing contextual information and/or making available their sensed data (i.e., participatory sensing) [6]; and minimal involvement, where data is collected autonomously, thus, while users use their applications in the foreground, the sensing is performed in the background (i.e., opportunistic sensing) [7].

As people's engagement is the foundation for any people-centric sensing application, keeping them motivated is a central element for sustainability. To achieve this goal, it is common sense that incentive mechanisms must be incorporated into people-centric sensing architectures.

In this work, we discuss some of the challenges and key factors that must be present at the core components of an architecture to offer sustainable people-centric sensing. For that, we present a set of policies to be incorporated into existing or new people-centric sensing architectures to complement traditional incentive mechanisms. To enrich this discussion, we also evaluate the effectiveness of non-monetary incentive mechanisms used by Foursquare, which is a popular platform, to gather social contexts about users (e.g., preferences) [3]. Foursquare uses incentive mechanisms based on mayorships and badges to keep its users motivated. Our evaluation of 901 new users shows evidences that mayorship-based incentive could very effective to increase users' engagement.

The rest of this paper is organized as follows. Section 2 presents the related work. Section 3 discusses the research issues faced by people-centric sensing paradigm, and also some possible solutions to provide sustainability beyond traditional incentive mechanisms. Section 4 investigates the efficiency of Foursquare's incentive mechanisms. Finally, Section 5 summarizes our contributions.

2. Related Work

There are several incentive mechanisms proposals to increase user contribution or participation in people-centric sensing systems. In this direction, Yang et al. [8] proposed two incentive mechanisms, both based on money. In the context of people-centric sensing, other money-based incentive mechanisms are also common, such examples include [9], [10]. Since the total amount of rewards paid by the client can quickly rise in money-based incentive mechanisms, there are also proposals on alternative methods. For example, Ueyama et al. [11] proposed an incentive mechanism based on gamification, exploring a point system and a badge scheme. Typically, the evaluation of an incentive mechanism for people-centric sensing is based on simulation or small scale data of real-world application, especially those created for this purpose. In fact, this is the case of all studies mentioned above.

Since there several proposals of incentive mechanisms for people-centric sensing systems, many studies have focused on categorizing them. For instance, Malone et al. [12] consider that there are three basic incentives to motivate people: *money*, *love* or *glory*. Money is the financial reward for participants who performed some task. Love can be the intrinsic interest of people in some activity, collective incentives of a common good, or opportunities to interact among participants. Glory is the recognition by the community for a certain performed activity. Similarly, Jaimes et al. [13] proposed a classification based on two large branches: monetary and non-monetary.

Non-monetary incentives explore social aspects, such as *collective* interest, *intrinsic* motivation or *social-reward*, to allow participants of people-centric sensing motivate each other to participate efficiently.

Our study differs from all other studies because we present a set of policies to be incorporated into existing or new people-centric sensing architectures to complement other incentive mechanisms. Besides that, we also evaluate the effectiveness of game-based incentive mechanisms used by a large-scale application of the real world: Foursquare.

3. Sustainable People-Centric Sensing

In this section, we discuss an important challenge for the deployment of people-centric sensing applications: ensure sustainable participation of people. This task is crucial to achieve the coverage and reliability needed for these applications. For this, we discuss the challenges and key factors that must be present at main components of an architecture to support people-centric sensing (Section 3.1). Moreover, we propose a set of efficient policies to complement existing incentive mechanisms (Section 3.2). Finally, we discuss the difficulty finding the best way to maintain users motivated across different contexts (Section 3.3).

3.1. Architectures for people-centric sensing

Architecture proposals such as MetroSense [1], reference architecture [14] and mobile ecosystem [15] support large-scale people-centric sensing applications. In common, these architectures address the requirements for transforming raw data collected from heterogeneous sources into contextual information that could be used to provide customized services to citizens. To enable that, we identified three main "layers" present in all architectures: *sensing*, *networking* and *processing* layers. We believe that these layers should be present somehow in other architectures with the same purpose. More details about these layers are discussed in the following:

Sensing layer. Explores people's participation (either participatory or opportunistic) to sense events in urban areas through mobile devices [1]. The data collected in a participatory fashion could have several formats, ranging from medias/tags (e.g., audio, tweets and checkins) to hardware sensors (e.g., GPS, gyroscope, compass and accelerometer), and they could be shared on Web applications, including social networks [6]. Data can also be collected opportunistically, where devices collect, process and disseminate data with minimal user participation [1]. Ensuring significant autonomous sampling to achieve the quality of sensing and produce the desired data to people-centric applications is a complex problem in this layer [13]. For instance, Thebault-Spieker et al. [16] show that areas with low socioeconomic status and suburban/rural areas have access to significantly fewer participants, which can affect the sensing performance in these areas.

Networking layer. The collected data of each participant is disseminated/shared through a wireless communication channel using either an infrastructure or an opportunistic communication. In the former case, participants of people-centric sensing leverage pre-existing infrastructure in the city (e.g., 3G/4G mobile networks and WLANs), and can establish a "direct" communication with a server (e.g., Twitter) to share their data in a centralized manner [14]. In the latter case, opportunistic communication is used to forward messages among participants with infrastructure-free techniques to build decentralized networks (e.g., Bluetooth and WiFi Direct) [7]. Opportunistic networks (ONs) [17], which are an evolution of mobile ad hoc networks (MANETs), are suitable for communication in pervasive environments that are saturated by mobile devices, such as urban centers. The combination of these communication paradigms creates the hybrid mobile networks, which might meet the needs for the reliable communication paradigm that is scalable and resilient [14]. However, several challenges arise from this combinations. For instance, a potentially huge growth of data traffic in cellular networks, caused by people-centric sensing applications, will probably overload infrastructure-based networks, requiring new management and communication algorithms [18]. Another important aspect to consider is that significant progress has been made separately for both communication paradigms. However, further efforts are needed to interlink the two forms of communication [14].

Processing layer. Users share their sensed data that are aggregated and processed to extract useful information for representing knowledge of crowds on different aspects of cities (e.g., security, traffic and weather). For this, several techniques, such as stochastic modeling, data mining and machine learning, are used to transform raw data into information that supports decision making [18]. Having this information, users may choose to change their behavior, for instance, to avoid areas with heavy traffic. Performing aggregate analysis of large volumes of heterogeneous data to extract context information and make them available in real/quasi-real time is a major challenge in this layer [19].

All these points give an idea of how dynamic a people-centric sensing platform could be and the challenges that emerge when dealing with this dynamism in terms of data collection, transmission, dissemination and prediction. The existing architectures for people-centric sensing are important frameworks, despite the open challenges mentioned. Additionally, little attention is given to challenges inherent specifically to incentive mechanisms in the people-centric sensing architecture. Thus, it is fundamental to incorporate incentive mechanisms to keep participants motivated to ensure coverage and quality in sensing tasks.

3.2. Policies for sustainability

Despite the existence of several proposals of incentive mechanisms to increase/sustain user participation, as we discussed in Section 2, we emphasise here the importance of having "efficient policies" as an additional motivator to help the achievement of a sustainable people-centric sensing platform. An efficiency policy makes sure that a certain task in a people-centric sensing architecture is as efficient as possible.

These policies could help to avoid user discouragement in the participation of the sensing process, aiming to minimize waste of essential resources (e.g., battery and bandwidth) with sensing tasks. To better illustrate this idea, we discuss below some efficient policies that could be provided by a people-centric sensing architecture.

Energy-efficiency. A critical challenge to people-centric sensing applications is introducing low energy costs for users' devices. As energy is consumed in all aspects of people-centric sensing, ranging from data collection, processing and transmission, it is important to make use of these aspects in a conservative manner. For instance, request sensing tasks, e.g., make GPS sensor readings, take photos or perform long-range transmissions, exhaustively for the same set of users can affect significantly their portable devices' battery, which could prevent users to perform their usual (private) tasks. Therefore, it is important that people-centric sensing applications are efficient on the management of energy consumption.

Reliable communication. Due to the intermittent nature of networks and highly dynamic topologies of hybrid mobile networks, it is important to provide resilient communication in both ways: user to server and server to user, even in large scale. One possible aid in this issue is to enable data forwarding among mobile users. To handle different scenarios that might emerge in people-centric sensing, new management and communication algorithms for each scenario are needed. For instance, users could share data in an opportunistic fashion to avoid the costs related to infrastructure-based networks, and still continue to receive spatio-temporal information available on infrastructure-based servers through opportunistic networks.

Privacy and security. Ensuring users' privacy in many people-centric sensing applications is an important aspect for several reasons. For instance, GPS sensor readings can be used to infer private information about the user, such as the most common places and routes he/she typically visits during daily routines. This information could be used to improve recommendation systems and better understand the dynamics of the city. On the other hand, it could threaten the security of users, because a malicious user could use this information, for instance, to rob someone. In this way, sensitive data should be encrypted before being shared by users to avoid that a malicious user obtains it. The challenge then is to find the right threshold that enables the use of the sensed data to extract useful information for the application while preserving user's privacy and security. A lack of this factor in a people-centric sensing platform may impact the user's willingness to contribute to the system.

Information quality. The quality of the information (e.g., precision, trustworthiness and up-to-dateness) generated by the application has a direct impact on the user's behavior, being an important motivation for users. If the quality of the information generated is low, users might not see value of the system and stop contributing to it, thus reducing the number of sensed data to work with, and, consequently, may harm the people-centric sensing system. To keep the quality of the information high, one important challenge to be addressed is deal with low-quality sensed data created by users. Since users in the people-centric sensing context can produce sensor readings with relatively little effort, data integrity is not always guaranteed. Some people-centric sensing systems might allow users to post whatever, even incorrect, information in different formats. This demands new mechanisms for data filtering and strategies to select data from certain participants, for instance a reputation system.

3.3. Right incentive mechanisms

It is common sense that incentive mechanisms are fundamental to keep a people-centric sensing system sustainable. However, the first problem is that we do not have guarantees that using the same successful incentive mechanism for one system, it will produce the same performance in a different people-centric sensing system. For instance, it is not possible to predict whether a people-centric sensing application based on intrinsic motivation, like CROWDSAFE [4], could improve contribution using another incentive mechanism, for instance badges, which are incentives widely used in successful systems (e.g., Foursquare and Waze). In the case of CROWDSAFE users could consider badges not attractive, scenario that could actually decrease contribution. To overcome this challenge, a possible direction is to model key aspects of different real-world systems, and user's behavior on those systems to enable simulations about the effect of different strategies of incentive mechanisms. In this way, a developer might test new incentive mechanisms and try to find the most suitable one for a particular system based on people-centric sensing.

In addition to that, a spatio-temporal evaluation of incentive mechanisms is still needed. Typically, the effectiveness of incentive mechanism is not demonstrated using large-scale experiments. Instead, they are designed for particular application and do not scale when many different applications coexist [5]. Thus, some incentive mechanism might work well only for some specific regions. Similarly, if we consider an incentive based on micro-payments, this incentive might have an acceptable performance only in certain periods of the day. This might bring an opportunity to develop a new approach to dynamically select different incentive mechanisms considering specific spatio-temporal information. In this sense, we conduct an evaluation of the effect of Foursquare's incentive mechanisms to increase user engagement.

4. Foursquare's Incentive Mechanism: A Case Study

In this section, we use the layers presented in Section 3.1 to analyze the functioning of Foursquare. We also study the efficient policies that are met by such system. Finally, we assess the performance of incentive mechanisms used by Foursquare to motivate new users (called newbies).

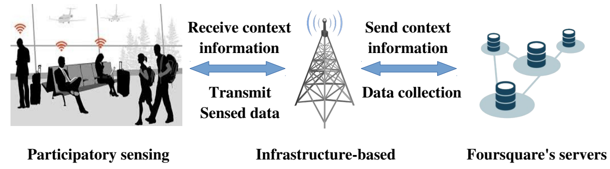


Figure 1. Illustration of Foursquare's framework.

To understand the dynamism of Foursquare, we built the framework with the main steps described above as shown in Figure 1. Foursquare allows users to share their current location (checkins) and knows where their friends are. Besides, users can register information about a place they visited (e.g., tips about meals in some restaurant) and they also can label a place with a category (e.g., airport). All these activities require active participation of users and therefore the data are collected in a participatory fashion. The sensed data are transmitted/received directly to/from Foursquare's servers via infrastructure-based networks. Foursquare's servers can aggregate and process large amounts of data sensed by users to extract context information that makes it useful, for example, guide about the city.

To analyze the efficient policies of Foursquare, we consider *energy-efficiency*, *reliable communication*, *privacy and security*, and *information quality*, as defined in Section 3.2. Regarding energy-efficiency, Foursquare users perform the sensing occasionally and each sensing task demands little computing resource, which implies low energy cost for users. In terms of communication, merely infrastructure-based networks are employed to allow data forwarding among users and servers, which might be not enough to ensure resilience and scalability of the network. However, since Foursquare does not have strict real-time restrictions, users tend to benefit from the service most times. Due to the Foursquare is a location-based social network (LBSN), that results in the lack of privacy and security of users. Nevertheless, the users' desire on sharing more about their daily context is greater than the concern to preserve their privacy to prevent potential threats to security, and, therefore, this factor is not critical to the system. Maintaining high quality information is a critical aspect in Foursquare, because malicious users may mistakenly label the categories of places or assigning checkin intentionally to a wrong activity, which causes the degradation of system quality. To overcome this problem, Foursquare provides a set of rules to avoid bad behavior. In addition, Foursquare has mechanisms to avoid multiple checkins at the same place on a day, to delete spam and inappropriate content, and detect false checkins (e.g., checkins on places which are far away from their actual physical location).

Turning our attention to incentive mechanisms in Foursquare, we now study the efficiency of them. In the following we present a brief description of the Foursquare incentive mechanisms.

- **Mayorships:** users become mayor of a place by checking in more than anyone else during the last 30 days. Mayorships allow users to compete among them to get reputation at all of their local hangouts.
- **Badges:** users earn badges according to their location, their frequency of checkins, some specific events, or commemorative dates.

Foursquare allows users to share their activities in Twitter. When a user gives the first checkin on Foursquare he/she receives a badge named Newbie. Given that, we built a dataset with data collected from users who received a badge Newbie and announced it in Twitter at the same day. Following this process, we discovered 901 newbies and monitored them for 13 weeks. Our dataset contains information, collected once per week, from each user's profile on the Foursquare system: city, number of checkins, number and location of mayorships, number and type of badges. This dataset allows us to measure the level of user participation according to the number of checkins given by users, and also evaluates the efficiency of incentives users receive.

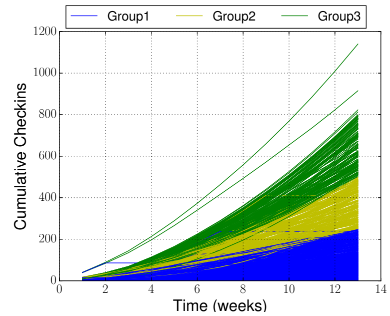
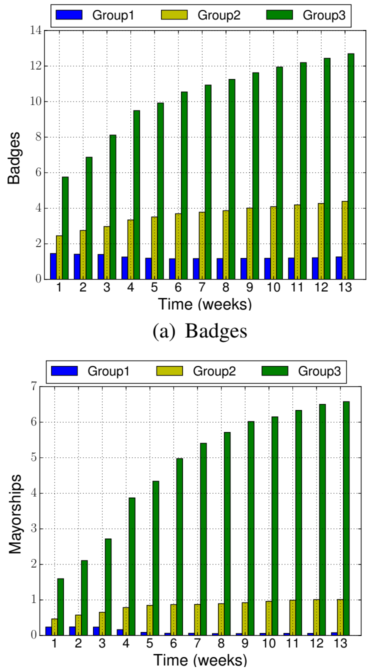


Figure 2. Number of checkins performed by users along the observation period.

Figure 2 shows the number of checkins performed for each user along the observation period. Note that the number is cumulative, i.e., the number of checkins either increases or stays the same from one week to the next one. We divided the users into three groups: Group1 (blue curves); Group2 (yellow curves); and Group3 (green curves). To make this division, we considered the total number of checkins observed in the last week of our dataset. Group1 is composed of users who performed up to 250 checkins in the period of 13 weeks, i.e., it represents a group of users who were conservative in sharing data, most of them might be unmotivated. Similarly, Group2 is composed of users who performed at least 250 and up to 500 checkins in the 13 weeks, i.e., it represents a group of users more motivated than the first one. Finally, Group3 represents users with more than 500 checkins at the end of our observation, representing users who use the system more intensively.

We consider this division into groups an essential step to perform the evaluation. Without this procedure, the effects of incentives could be smoothed and harder to be studied. Although we have adopted this grouping procedure, other approaches could be applied to this task, and the evaluation methodology would remain the same. In fact, we also experimented calculating the slope of the curve of each user, and using this slope to calculate three ranges representing the three groups and the results are similar. Furthermore, the ranges considered in this work captures sets of curves with few intersections, thus, slight variations in the choice of the cutoffs do not significantly affect the result.

After separating the three groups of users, we can study their characteristics individually. Firstly, we study the average number of badges and mayorship throughout the observation period. Figures 3(a) and 3(b) show these results for badges and mayorships, respectively. For both badges and mayorships we can see a strong correlation between the number of checkins of group of users with the average number of badges and mayorships obtained by them. Note that the average number of badges and mayorships received by users from Group1 decreases along the time, different from



(a) Badges

(b) Mayorship

Figure 3. Average number of badges and mayorships at each group of users considered.

Group2 and, specially, Group3, which presents a growth strictly increasing along the time. This suggests that the incentive mechanisms used by Foursquare might be working to motivate some users. In order to further investigate this question, we studied more details about the badges received by users of each group.

Figures 4(a), 4(b) and 4(c) show word clouds for all badges received by users of Group1, Group2 and Group3, respectively. In these figures, the size of the word represents the frequency of its occurrence, i.e., the higher frequency of the word, the bigger it is drawn in the word cloud. As we can observe, some badges, such as "Newbie" and "4sqDay2012", are very common in all user's groups because they were given to the newbies, and, therefore, these badges are negligible to motivate users. Some specific badges, such as "Adventurer", "SuperUser", "Local", and "Explorer", begin to be significantly frequent among users of Group2 and are the most common ones among users of Group3, indicating that they might be associated in keeping users motivated. Additionally, the types of badges vary more according to the level of user's involvement, i.e., users from Group3, apparently are more motivated and have a wider variety of badges, whereas users from Group1, the most unmotivated ones in our classification, have fewer types of badges.

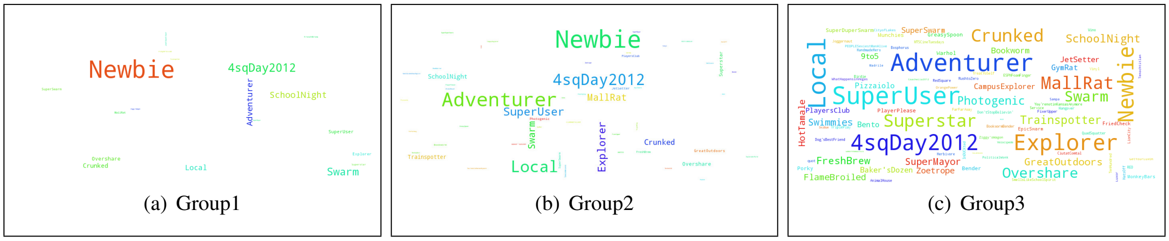
Some specific types of badges seem to be more associated with the more intense use of the system, while others badges do not seem to have the same efficiency. We also studied the efficiency of the mechanism of incentive based on mayorship. Mayorship has a direct effect on checkin, because after some checkins a user becomes a mayor of a place, he/she should continue doing checkins more often than anyone else to keep his/her reputation as mayor of this place. This type of incentive seems to make sense because, as we can see in Figure 3b, the difference between the average number of mayorships of users from Group1 and Group2 is more significant than for badges. Among users from Group1 only 2.86% became mayor. This number is 37.35% and 88.83% for Group2 and Group3, respectively. Only users who won mayorships along the observation are considered.

To evaluate the effect of mayorship, we calculate a *score* that measures the influence of the number of checkins performed by users at each group. Let T_i be the number of checkins in a certain week i. If during two consecutive weeks a user does not earn a new mayorship, then the score calculated is: $score_{\text{noMayor}} = (T_j - T_i) / T_j$, where j represents a week after i. When a user receives a mayorship, the score is: $score_{\text{mayor}} = ((T_y - T_k) / T_k + (T_z - T_y) / T_y) / 2$, where T_k represents the number of checkins observed in the week right before receiving a mayorship, T_y represents the number of checkins observed in the week the user received a mayorship, and T_z represents the number of checkins observed in the week subsequently after the user received a mayorship. The gap between both scores reflects the effect on growth of checkins when users get some mayorships between consecutive weeks.

Figure 5 shows a cumulative distribution function of the average $score_{\text{noMayor}}$ and $score_{\text{mayor}}$ values for each user. Figures 5(a), 5(b) and 5(c) show the results obtained for users of Group1, Group2 and Group3, respectively. As we can see, in all categories the scores increased after users won some mayorships. Looking at results for Group1, 50% of the observed $score_{\text{noMayor}}$ is 0, while for $score_{\text{mayor}}$ this value is up to 0.25. For Group2, we can see that 50% of the observed $score_{\text{noMayor}}$ is up to 0.1 and 0.25 for $score_{\text{mayor}}$. Considering the same results for Group3, 50% of the observed $score_{\text{noMayor}}$ is up to 0.1 and 0.22 for $score_{\text{mayor}}$.

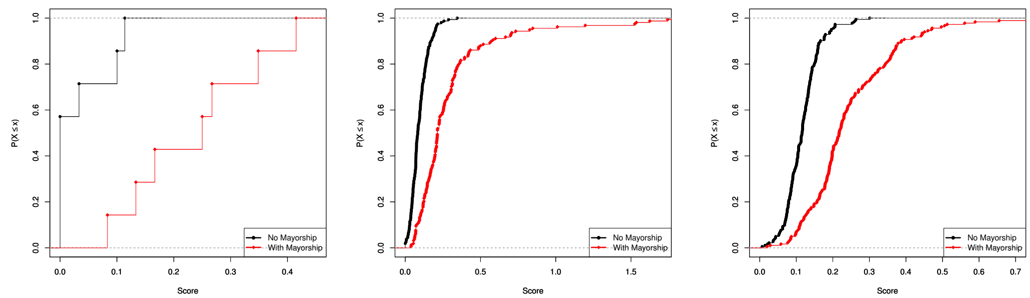
5. Conclusion

In this work, we discussed the existing challenges at the main components of an architecture to support people-centric sensing. From this, we emphasized the attention we need to have regarding incentive mechanisms, fundamental to keep participants motivated to support sustainable people-centric sensing. To overcome this limitation, we presented a set of policies to be incorporated to existing or new people-centric sensing architectures to complement traditional incentive mechanisms. We also analyzed the dynamism of Foursquare, verified the efficient policies that are met by them, and evaluated the effectiveness of game-based incentive mechanisms to motivate new users. Among the results, we found evidence that incentives based on mayorship, which motivates competition among users to become mayor of some place, seems to be efficient to keep users motivated, while incentives based on badges do not seem to have the same efficiency, except for some specific types of badges. Moreover, we noted that Foursquare is energy-efficient and makes efforts to provide quality information. However, Foursquare does not guarantee the privacy and security of its users, despite their wish to share daily activities. We believe that the use of a reliable communication paradigm would make Foursquare even more popular.



(a) Group1 (b) Group2 (c) Group3

Figure 4. Word clouds for all badges received by users.



(a) Group1 (b) Group2 (c) Group3

Figure 5. Cumulative distribution functions of scores. Notice that the users' scores increased after gaining some mayorship.

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