# Trust Evaluation for Participatory Sensing

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**Abstract.** Participatory sensing, combining the power of crowd and the ubiquitously available smart phones, plays an important role to sense the urban environment and develop many exciting smart city applications to improve the quality of life and enable sustainability. The knowledge of the participatory sensing participants' competence to collect data is vital for any effective urban data collection campaign and the success of these applications. In this paper, we present a methodology to compute the trustworthiness of the participatory sensing participants as the belief on their competence to collect high quality data. In our experiments, we evaluate trust on the sensing participants of BusWatch, a participatory sensing based bus arrival time prediction application. Our results show that our system effectively computes the sensing participants' trustworthiness as the belief on their competence to collect high quality data and detect their dynamically varying sensing behavior.

**Keywords:** Trust evaluation, participatory sensing, mobile and ubiquitous computing.

## 1 Introduction

Participatory sensing, a novel sensing technique that enables citizens to use ubiquitously available smart phones and high speed Internet to share data, is enabling many exciting applications for transportation and planning, environmental monitoring, and health-care [1,8]. The performance and the efficacy of these applications is heavily dependent on the quality of data contributed by the sensing participants [3]. However, the data collection may not be the primary task of the sensing participants and they may also have different capabilities to collect data, depending on their context, familiarity with data collection application and task, and demographics [9,12]. Consequently, they may submit low-quality, misleading, or even malicious data that can threaten the usefulness of the applications [6,12]. Available sensing participants contributing high quality data may opt out of a sensing campaign due to a lack of motivation [10]. A trust evaluation system that associates a trust score to sensing participants as the belief on their competence to collect high quality data enables the applications, using participatory sensing to collect data, to dynamically identify and select sensing participants contributing high quality data [2,10]. However,

K. Zheng, M. Li, and H. Jiang (Eds.): MOBIQUITOUS 2012, LNICST 120, pp. 176–187, 2013.

existing research work lacks a system that evaluates trust on the participatory sensing participants using aforementioned criteria.

In this paper we define and evaluate trust in participatory sensing participants considering their competence to collect high quality data. We use system predictions derived from contributed data and system user feedback about those predictions as input to the trust evaluation system to first estimate the quality of contributed data and later use the data quality score to compute the trustworthiness of sensing participants. Our system bootstraps the trust score of the newly arrived participants, contributing data for the first time and continuously refines the trust score of the existing participants on every new interaction with the application. The trust score presents the evidence of the quality of sensing participants' contribution to the application.

In our experiments, we compute the trust in the sensing participants of BusWatch, an application that uses the bus sighting reports from sensing participants to predict bus arrival times. Our dataset, provided by Dublin Bus, consists of ten days of bus arrival times. We simulate different user behaviors, such as trusted users, malicious users, and users changing their behavior from trusted to malicious and evaluate their trustworthiness. Our results show that the trust evaluation system successfully estimates the data quality of sensing participants' contributions and keeps track of the historical evidence of the trustworthiness of different sensing participants to identify their data contribution behavior pattern to an application. Our paper has the following contributions.

- Definition of trust in participatory sensing participants
- Methodology to evaluate the quality of sensing participants' contributed data
- Novel approach to compute participatory sensing participants' trust score
- Strategy to bootstrap sensing participants trust score
- Methodology to dynamically evolve trust score to depict varying quality of sensing participants' data contributions

The rest of the paper is organized as follows: Section 2 illustrates a motivational scenario. Section 3 discusses our trust evaluation system. Section 4 describes the data set, provided by Dublin Bus that we use in our experiments. Section 5 presents the experiments to evaluate our approach. Section 6 compares existing works and our approach. Section 7 summarizes this work and discusses future directions.

## 2 Motivational Scenario: BusWatch

Figure 1 shows a participatory sensing based bus arrival time perdition system - *BusWatch*. In this system, the *Data Manager* collects and manages bus sighting reports from *BusWatch* users. The *Bus Time Predictor* uses the bus sighting reports with already trained and tested machine learning algorithms to predict bus arrival time. When a *BusWatch* user makes a bus arrival time query, the *Data Manager* selects and provides bus sighting reports to the *Bus Time Predictor* to predict bus arrival time for that specific user. Before leaving the office

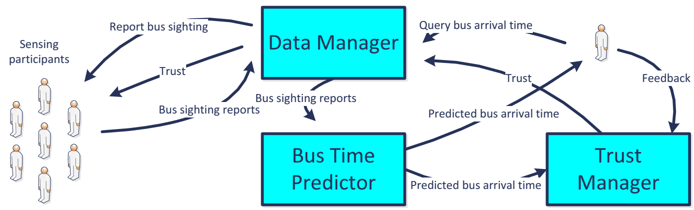



**Fig. 1.** Participatory sensing based bus arrival time prediction system-BusWatch

this evening Bob uses *BusWatch* to check the bus arrival time on his usual bus stop. The *Data Manager* selects the bus sighting reports and the *Bus Time Predictor* uses these reports to predict the bus arrival time and conveys it to Bob. Bob leaves office in time to catch the bus and reaches the bus stop before the expected bus arrival time. However, he waits for the bus longer than expected, considering the BusWatch prediction. Once he boards the bus, the *Trust Manager* requests Bob's feedback about the *BusWatch* prediction. The *Trust Manager* combines the *BusWatch* prediction with Bob's feedback and correlates it with participants' bus sighting reports to find the quality score of each participants' data contribution and transform quality score to trust on corresponding participants as the belief on their competence to contribute high quality data. The *Trust Manager* keeps record of the scores for future transactions. The *Data Manager* uses participants' trust score to select trustworthy bus sighting reports from available bus sighting reports. Evaluating, managing, and using the sensing participants' trust helps *BusWatch* to improve *BusWatch* prediction accuracy.

## 3 System Details

Trust is commonly defined as the belief in the competence of an entity to act reliably to perform her functionality [5]. As the participatory sensing based applications expect from a sensing participant entity to collect high quality data we define trust in a participatory sensing participant entity *as the belief in the competence of an entity to collect high quality data*. The *Trust Manager*, as shown in Figure 2, is a trust evaluation system that takes predictions, based on the sensing participants' data contributions and user feedback as its input and evaluates trust on the sensing participants considering this definition. *Error Analyzer*, *Quality Evaluator*, and *Trust Evaluator* are the main components of the *Trust Manager*. In this section we describe these components.

### 3.1 Error Analyzer

The *Error Analyzer* takes predictions and user feedback as input and outputs error analysis, consisting of prediction residuals and mean value of prediction

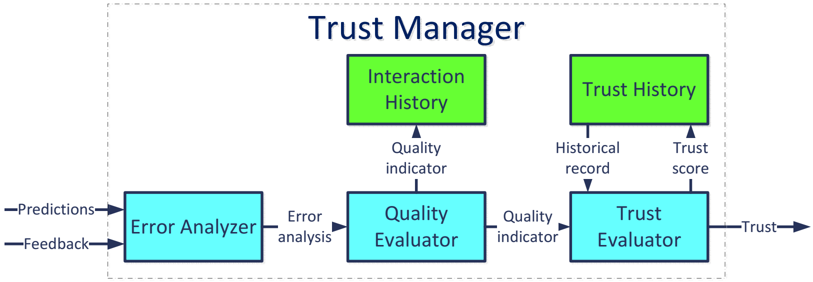



**Fig. 2.** Trust evaluation system for participatory sensing - Trust Manager

residuals. The *Error Analyzer* computes prediction residuals as the difference between the predictions, made on the basis of sensing participants' data contribution and real values, based on the user feedback. For example, if sensing participant $i$ contributes data $x_i$, bus arrival time prediction system predicts bus arrival time $t_{pi}$ on the basis of $x_i$, and user gives his feedback about real bus arrival time as $t$, prediction residual $r_i$ for user $i$ is calculated as the difference between predicted time and real time as follows.

$$r_i = t - t_{pi}$$

We further calculate mean value of error residual $\bar{r}$ for $n$ users as follows

$$\bar{r} = \begin{cases} \frac{\sum_{i=1}^{n} r_i}{n} & \text{if } n > 1 \\ \textit{mean prediction residual during testing phase} & \text{otherwise} \end{cases}$$

The equation shows that if more than one sensing participants contribute data to predict the bus arrival time, we calculate $\bar{r}$ as the mean value of the prediction residuals. Otherwise we take the mean value of the prediction residuals that we calculate during the bus arrival time predictor testing phase as $\bar{r}$. We discuss more about the bus arrival time predictor testing phase in Section 5.1.

### 3.2 Quality Evaluator

*Quality Evaluator* takes error analysis report, consisting of prediction residual for a specific sensing participant's data contribution and mean value of prediction residuals as the input of the function and outputs data quality indicator in the range [0 .. 1]. *Quality Evaluator* uses the Gaussian membership function for that purpose. Gaussian membership function is a real-valued function that depends upon the distance of a point from origin, so that $\phi(x) = \phi(|x|)$. It means that quality indicator will only depend upon the absolute value of prediction residual. Positive and negative prediction residuals having same absolute value will have same quality indicator value. We set the origin of the curve as mean value of the prediction residual. We use the following equation to transform prediction residual to reputation measure.

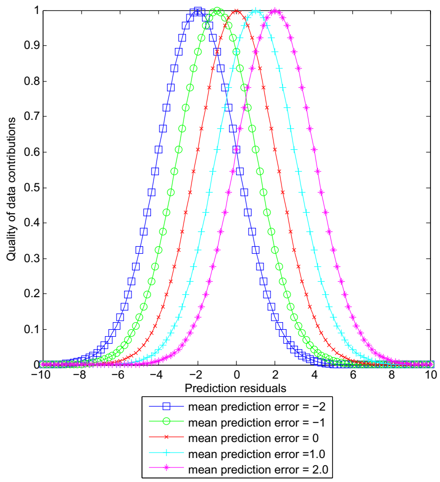



**Fig. 3.** Quality evaluator computing quality of data contributions with different mean prediction error values

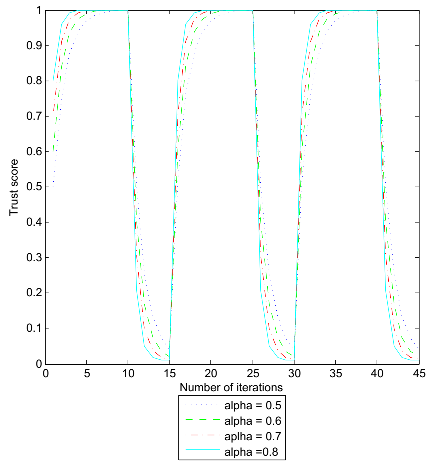



**Fig. 4.** Trust evaluator computing trust score with different values of $\alpha$ and quality indicator score

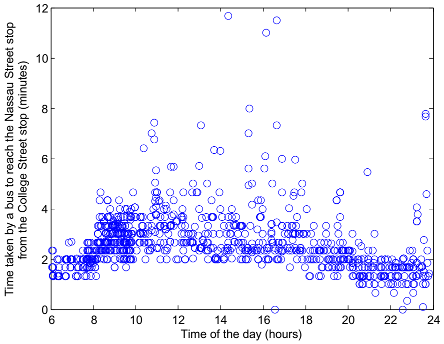
$$Q(r) = \frac{e^{(r-\bar{r})^2}}{2\sigma^2}$$

Where $e$ is $E$uler's number, approximately equal to 2.71828, $r$ is the prediction residual, and $\bar{r}$ is man prediction residual. Mean prediction residual set the center of the Gaussian curve as shown in Figure 3 that shows Gaussian membership function curves mapping prediction error to quality indicator using different mean prediction error values. Quality is maximum at the mean prediction error and then it starts to decrease smoothly in both directions. We can also set the width of curve with change in value of $\sigma$. These attributes of Gaussian membership function make it very suitable to transfer prediction residual to quality indicator value.

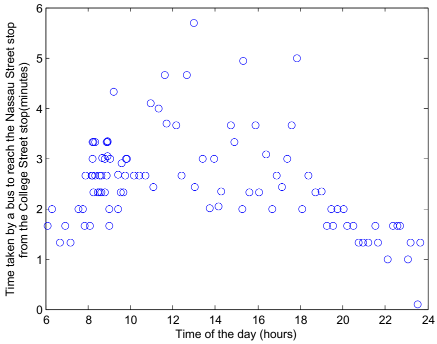
### 3.3 Trust Evaluator

*Trust Evaluator* combines the quality indicator value of the sensing participant's data contribution derived by *Quality Evaluator* for current interaction with sensing participant's historical trust score based on her previous interactions to evaluate sensing participants' trustworthiness. If the sensing participant is contributing data for the first time then her historical trust score will be 0 and *Trust Evaluator* only uses quality score to transform it to trust score. *Trust Evaluator* uses the following equation to combine current quality indicator score and historical trust scores.

$$Trust = \alpha Q + (1 - \alpha)T^h$$




(a) Nine days Dublin Bus data for route 25B used to train prediction algorithm




(b) One day Dublin Bus data for route 25B used to test prediction algorithm

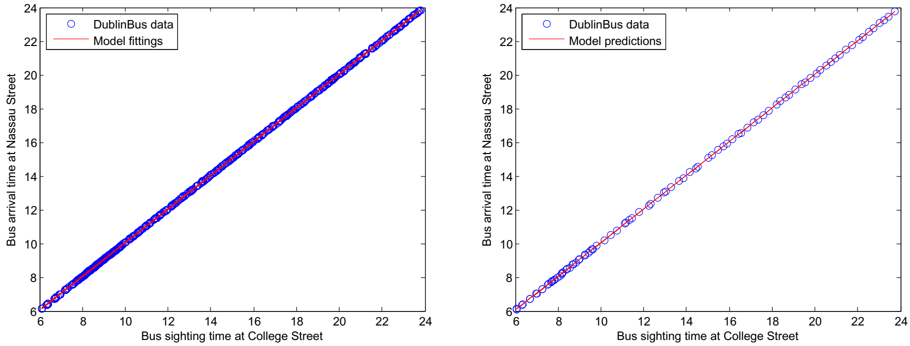
**Fig. 5.** DublinBus data for route 25B used for training and testing predictor

Where $Q$ is the current quality indicator score, $T^h$ is the historical trust score, and $\alpha$ decides the proportion of the current quality score and historical trust scores in the trust value. A higher value of $\alpha$ means that trust depends more upon the value of data quality indicator for last interaction, while a lower value of $\alpha$ means that current value of trust depends more upon historical trust value. Applications using participatory sensing data may choose the value of $\alpha$ depending upon their requirements for trust evaluation system.

Figure 4 shows trust evaluator function combines current quality indicator score and historical trust value of a sensing participant with increase in number of iterations with different values of $\alpha$. Sensing participants current quality indicator score fluctuates as 1 for first ten interactions and 0.5 for next five interactions. This cycle is repeated for three times. Different graphs show that how smoothly trust is shifted with change in data quality indicator with different values of $\alpha$.

## 4 Data Description

We use Dublin Bus bus arrival time data at different bus stops on route 25B. Dublin Bus uses a combination of Global Positioning System (GPS) and an estimation system to track their buses in the city and records their arrival time at different bus stops from the Dublin Bus control center. In our experiments, we use ten days of data for all the bus journeys of route 25B between bus stops College Street and Nassau Street. These bus stops are situated in the Dublin city center and the bus travel time between them varies considerably depending on the time of the day and the volume of traffic, as shown in Figure 5. We divide the data in two parts. We use nine days of data, as shown in Figure 5a, to train the bus arrival time prediction system and one day of data, as shown in Figure 5b, to test the system and simulate sensing participants in our experiments.




(a) Training phase data and predicitons (b) Testing phase data and predictions

**Fig. 6.** Ten days Dublin Bus data showing the real bus arrival time and predicted bus arrival time at bus stop Nassau Street against bus sighted times at bus stop College Street for bus route 25B for predictor training and testing phase

## 5 Experiments and Evaluation

We evaluate our trust computation system on the basis of the motivational scenario discussed in Section 2. For that purpose we developed a prototype participatory sensing based bus arrival time prediction system. In our experiments, we evaluate the quality of the sensing participants' data contribution We further compute the trustworthiness of the sensing participants by combining the quality score of the sensing participants' data contribution with their historical trust score. We imitate different sensing behaviors of the sensing participants over their multiple interactions with the bus arrival time prediction system. The subsequent section discusses our experiments in detail.

### 5.1 Experiment 1: Bus Time Prediction and Error Analysis

The bus time predictor takes bus sighting reports at one stop as an input to the system and predicts the bus arrival time at the other stop. We use a data set provided by Dublin Bus. The dataset consists of bus sighting times at College Street bus stop and bus arrival times at Nassau street bus stop. As shown in Figure 5a, we use nine days of dataset to train the bus arrival time predictor. We use a first degree linear regression model to fit the training data. Figure 6a shows the fitting of the prediction model to training data. The prediction model has a mean absolute prediction residual of 37.72 seconds during the training phase.

To test the prediction accuracy of the bus arrival time prediction system on unseen data, we use one day Dublin Bus data, as shown in Figure 5b. Figure 6b shows the predicted bus arrival times the Nassau Street bus stop. We have a mean absolute prediction residual of 35.29 seconds during the testing phase. Figure 7 also shows that most of the instances in the testing phase have a prediction residual of less than half a minute. Considering the variability of bus

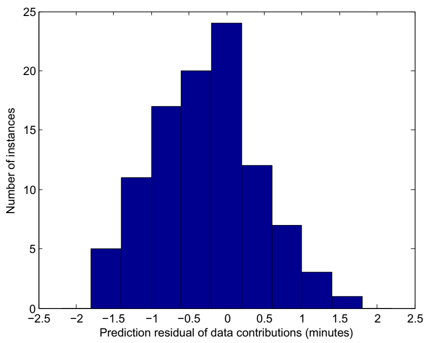



**Fig. 7.** Prediction residual distribution over time for bus sighting reports

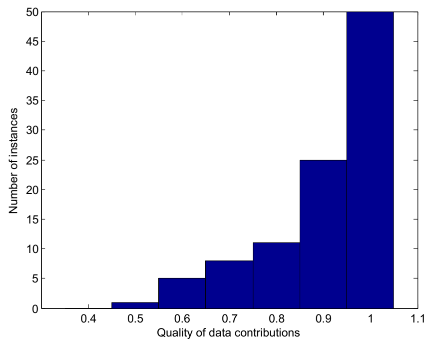



**Fig. 8.** Quality score distribution for bus sighting reports

traveling times during the different hours of the day, as shown in Figure 5, the mean absolute prediction residual of about half minute proves that if we get accurate bus sighting reports at one stop we can predict the bus arrival times at subsequent stops with a high accuracy. We use this prototype implementation of the participatory sensing based bus arrival time prediction system to evaluate the trust evaluation system.

### 5.2 Experiment 2: Quality Evaluation

In this experiment we use the one day data designated for testing purpose, as described in Section 4. We simulate sensing participants' data contributions and user feedback with the data. We use the bus arrival time at the College Street as the sensing participants bus sighting reports and the bus arrival times at Nassau Street as user feedback about the exact bus arrival time. Sensing participants send the bus sighting reports at College Street to the bus arrival time prediction system that predicts the bus arrival time at Nassau Street. User gives feedback in terms of the exact bus arrival time. We calculate the prediction residuals as the difference between bus arrival time predictions and the user feedback as described in Section 3.1. Figure 7 shows the prediction residuals distribution. Figure 9 shows the prediction residuals for each bus sighting report.

We further evaluate the quality score for each instance of a bus sighting report as discussed in Section 3.2. We set the width of the function as 1.5 and its center at 0 to fit the prediction residual distribution. We provide prediction residuals as an input to the quality evaluation function to get a data quality score for each interaction. Figure 8 shows the quality score distribution. Figure 10 shows the quality score for each instance of bus sighting reports.

We observe that bus sighting reports number 5, 55, and 92 have prediction residual of about $-1.48$ , 1.66, and $-1.52$ minutes respectively and corresponding quality scores of about 0.61, 0.54, and 0.59, as evident from their values enclosed in circles in Figure 9 and Figure 10 respectively. We find out that we almost have

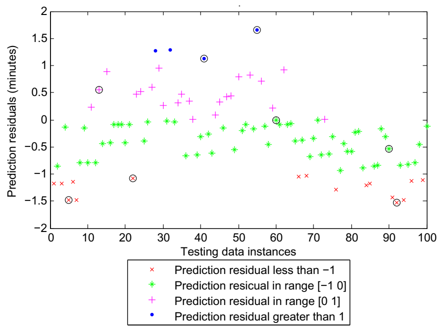



**Fig. 9.** Prediction residuals for each bus sighting report instance

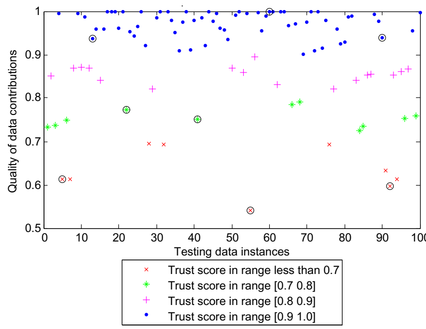



**Fig. 10.** Quality score for each bus sighting report instance

the same quality score independent of the sign of prediction residual. It means that the quality evaluation function is independent of whether the predicted time is before or after the real bus arrival time.

We further observe that the bus sighting reports number 22, 41, 13, 90, and 60 have prediction residuals of −1.08, 1.13, 0.54, −0.53, 0 and corresponding quality scores of 0.77, 0.75, 0.93, 0.93, and 1, as evident from their values enclosed in circles in Figure 9 and Figure 10 respectively. Looking at these values we validate that the quality score for a single interaction is dependent on the absolute score of the prediction residual. We also observe that the quality score increases with decrease in the absolute value of the prediction residual and hence increase in the quality of contribution. These facts establish that our quality evaluation function evaluates quality score for a single interaction as the significance of contribution from the sensing participants.

### 5.3 Experiment 3: Trust Evaluation

In this experiment we imitate different sensing behaviors of the sensing participants over multiple interactions by adding or subtracting an offset value to the Dublin Bus data. For the first interaction, the system does not have any historical value of the trust score and hence bootstraps the trust score using the data quality score as described in Section 3.3. For every subsequent interaction, we combine its data quality score with the historical trust score of that participant. Figure 11 shows data quality scores for every single interaction and evolved trust scores with every subsequent interaction for six users.

Figure 11(a) shows a user that is very trustworthy and always contributes high quality data as evident from the data quality score of each interaction close to 1. We find that their trust score also evolves close to single interaction score and stays there for subsequent interactions. Conversely, our second user is a malecious user and always contributes low quality data as depicted by Figure 11(b). Consequently, the trust score also always stays at its minimum value. Figure 11(c) shows a user that starts with contributing good quality and hence

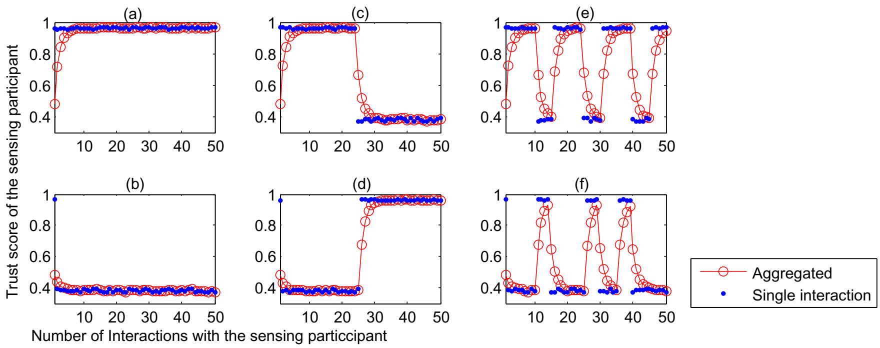



**Fig. 11.** Evolution of sensing participants trust score over multiple interactions

earned high trust score. However, afterwards the user started to contribute low quality data. The evolution of the trust value also shows the same behavior.

Conversely, Figure 11(d) shows a user that starts by contributing low quality data while ending up contributing high quality data. Figure 11(e) and Figure 11(f) show careless users that alternatively contribute high and low quality data for a few interactions and then change their behavior. In these illustrations, we can observe that sensing participants' trust scores evolve with respect to a change in their sensing behavior. We can also observe that sensing participants trust score successfully depict the quality of sensing participants data contributions.

## 6 Related Work

Trust evaluation is the subject of research efforts in different computer science domains, such as commercial and on-line applications [7], mobile adhoc networks [4], and wireless communications [13]. In those domains, systems compute the trust on an entity as the belief that the entity will act cooperatively and reliably to accomplish a collective objective [5]. However, different domains may have different objectives and hence different criteria to measure the cooperativeness and reliability of an entity. In participatory sensing, we define cooperativeness and reliability of an entity as the belief on the competence of the entity to collect and contribute high quality data. In this section, we discuss existing approaches that compute trust on the participants of sensing campaigns and compare them with our approach.

Saroiu, et al. present their approach at preventing untrusted software and malicious users interfering with sensor readings on a mobile phone[11]. In their approach they sign each sensor reading with a private key specific to a mobile device. They proposed using a trusted platform module for this purpose. However, participatory sensing participants may contribute their observations, such as bus sighting reports, to collectively perform a task. Huang, et al. quantify the reputation of mobile phone sensors, such as a noise sensor, based on their cooperativeness to collect data [6]. They use a consensus-based technique to combine different sensor readings, such as taking the average of all the sensor readings, to find the cooperativeness of a specific sensor and map it to a reputation score. Census-based technique may not be suitable in the case of sensors contributing text data or a single available sensor. Their approach that concentrates only on mobile phone sensors and does not consider human contributed data is not suitable to participatory sensing scenarios.

Reddy, et al. presented a directed sensing campaign model to gather data [10]. Although they emphasized that data timeliness, relevance, and quality are significant for a participant's trust computation, they only used sensing participants likelihood to capture a sample to compute their reputation. Yang, et al. discussed the potential of participatory sensing to realize different applications and proposed to use the sensing participants' demographic information to evaluate the trust on their contributed data [12]. As compared to these work we evaluate trust on sensing participants as the belief on their competence to collect and contribute high quality data.

Mashhadi, et al. propose to calculate trust on sensing participants using their mobility pattern and the quality of their contribution history [9]. They proposed to rate the contribution of a sensing participants by comparing it to the contribution of a trusted sensing participants or explicitly asking the sensing participants to rate each others' contributions. As compared to their proposed system, our approach involves system user feedback to evaluate trust on sensing participants and does not require a trusted sensing participants contributing data from the same vicinity. Our system also keeps historical evidence the participants' contribution to imitate their behavior over large number of transactions.

## 7 Summary

Participatory sensing is an important tool to sense the cities and enable many useful urban applications. Trust computed as the belief on the capabilities of the sensing participants to collect and contribute high quality data may help to dynamically identify and connect to the competent sensing participants and collect high quality data. In this paper, we present trust computation system to compute trust on the participatory sensing participants as the belief on their competence to collect high quality data. Our experiments show that the trust score computed by our system successfully depicts sensing participants' capabilities to collect and contribute high-quality data during their interaction with the participatory sensing based application.

For future work we plan to investigate if the sensing participants' context, such as their location or current activity, demographics, such as age and education, and experience of using data collection applications and smart phone devices affect their capabilities to collect data. We plan to devise a model to correlate different users' data contributions to find their plausibility. We also plan to evaluate our strategies with publicly available data sets.

**Acknowledgment.** This work was supported by Science Foundation Ireland under the Principal Investigator research program 10/IN.1/I2980 "Self-organizing Architectures for Autonomic Management of Smart Cities" The authors also would like to thank Dublin Bus for sharing bus arrival times data with us.

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