Understanding Human Mobility for CrowdSensing Strategies with the ParticipAct Data Set

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Abstract— **The Mobile CrowdSensing (MCS) paradigm has been increasingly adopted in the last years. Its adoption has been proved as beneficial for different scenarios, such as environmental monitoring and mobility analysis. However, one of the major barriers of the MCS initiatives, is the difficulty in recruiting users for the purpose of collecting data. We focus in this work to such limitation, and we analyze the mobility traces collected with a real-world MCS experiment, namely ParticipAct. Our goal is to discuss how to exploit the mobility features of the recruited users, as grounding information to plan and optimize a MCS data collection campaign. In detail, we analyze the quality of the data set, its accuracy and several features of human mobility such as radius of gyration and the real entropy of the locations visited. We discuss the impact of such metrics on the task scheduling, allocation and how to obtain a certain Tcoverage of data from visited locations.**

Keywords—Mobility Analysis, Mobile CrowdSensing..

I. Introduction

The Mobile CrowdSensing (MCS) [1] paradigm is a promising approach designed to involve citizen to actively collect data. Such paradigm consists in exploiting the user's devices in order to gather data useful to understand complex dynamics of urban and rural areas, such as studying the urban mobility, measuring the quality of life of specific regions or monitoring some environmental data. The implementation of the MCS paradigm requires a mobile software platform generally distributed as a mobile app, a set of volunteer users joining the MCS initiative and a back-end server able to submit tasks to the users and to store the collected data.

The number of ongoing MCS experiments increases constantly, since the MCS offers the possibility of measuring, with a fine-grained temporal resolution, phenomena that hardly can be observed with tradition methods. However, the effectiveness of the MCS paradigm is currently limited by several barriers [2]. Users are generally sceptic to be recruited as part of the MCS initiative for at least 3 reasons: privacy issue, adoption of a mobile app, benefits obtained. Concerning the privacy issue, users have to be aware of the data their devices can provide to the back-end. Moreover, the design of the mobile app has to be done so that to reduce the battery consumption and to motivate users in keep using the app. Concerning the expected benefits, the recruited users have to be somehow reworded; under this respect several works already address some possible solution [1, 3]. Such barriers claim for an optimal involvement of the users recruited [4]. In particular, it becomes crucial to optimize the amount of tasks submitted to the users, by maximizing their completion rate and by increasing the data gathered and the quality of the data collected.

This work moves toward the optimization of a MCS experiment. In particular, our goal is to study some of the mobility features of a real-world MCS data set with the goal of discussing how such features can be exploited for planning an effective MCS data collection campaign. We focus on the analysis of ParticipAct [5], a project leaded by the University of Bologna. We analyse mobility traces collected with ParticipAct in 2014, from roughly 170 volunteer users. We analyse the mobility in an aggregate way, and we show how the knowledge extracted can benefit a MCS initiative. In particular, in Section III we introduce the data set and we describe the amount of mobility traces collected and the accuracy of the traces obtained during the observation period. We further analyse some relevant mobility features. In particular, we study the distance travelled by users and the amount of locations visited. We also investigate the existence of preferential location and stop locations, namely locations where users tend to rest. In Section IV, we discuss how the information extracted can be used for 3 relevant aspects of a

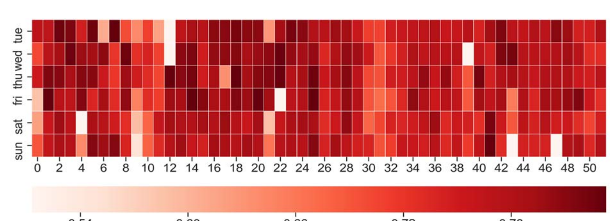

Fig. 1 Ratio between the expected and collected mobility traces.

MCS initiative: scheduling, allocating MCS tasks and how to increase the spatial coverage of the data collected from the regions visited by the users.

II. RELATED WORK

The ability to massively collect sensing data from any environment, like Sensors, Vehicular Ad-hoc NETworks (VANETs), and Unmanned Aerial Vehicles (UAVs) [6, 7, 8], made MCS a vital source of information for the management of smart cities. In recent years, studies on MCS focused on aspects like task assignment [9], energy efficiency [10], and user recruitment techniques. However, many issues still afflict large-scale sensing techniques as MCS. Firstly, the devices acting in a real-world massive sensing scenario have heterogeneous computational capacities, as well as different energy resources. The development of techniques that allow to select the appropriate devices for the most resource-consuming sensing operations is a grand challenge [11]. Secondly, the bandwidth wastage is an everlasting problem. Some solutions focus on local data mining to overcome the problem [12], but there is still work to be done to improve. And finally, along with the recruitment issue there is also the problem of how to involve the users' participation in MCS campaigns. In this direction, there have been proposed incentive techniques based on rewards [13].

Concerning mobility datasets, the literature offers some freely accessible mobility data sets that can be used for an in-depth analysis. Focusing on seminal and significant efforts, we mention in particular the Cambridge [14] and the MIT reality [15] data sets, collected respectively in 2005 and 2006, and the Mobile Data Challenge Nokia (MDC Nokia) [16, 17], collected using more powerful smartphones in 2009. These data sets are highly valued for the research community, as they provide a way to test, assess, and compare differentiated solutions for diverse application scenarios ranging from MCS [18, 19] to mobile social computing [20, 21] and opportunistic networking [22]. Moreover, they are based not only on real-world traces of human mobility but also on evidences of their activities and social behaviors.

Among more recent efforts, we cite the GeoLife data set from Microsoft Research Asia. The data set is useful to study human mobility in a crowded region. The data set comprises 182 users moving in the Beijing region for over three years (2007 – 2012) [10 - 12]. Users are tracked both with a smartphone or with a GPS device. Some of the user's trajectories are also labeled with the type of mobility, e.g. pedestrian, car, subway etc. We briefly analyzed GeoLife and we observed that the amount of mobility traces remarkably varies along the time and it is not possible to estimate the accuracy of the device position.

Let us conclude noting that, from our experience, these are issues that often affect real mobility trace data sets. Therefore, in the remainder of this paper we will present a detailed analysis of our ParticipAct data set, that we could fully master, hoping that the introduced features, analysis tools, and methodologies may help other researchers to assess and benchmark similar data sets.

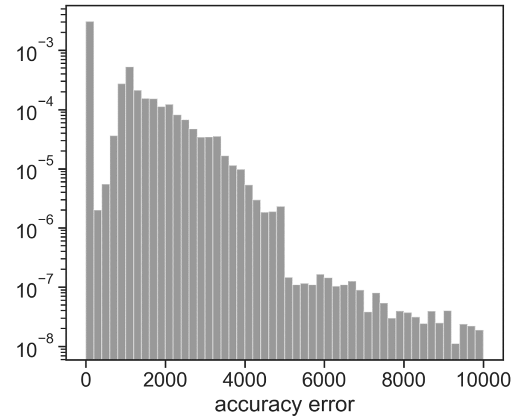

Fig. 2 Distribution of the position accuracy.

III. THE PARTICIPACT LIVING LAB

We now introduce the ParticipAct living lab [5, 23], an MCS project leaded by the University of Bologna. The project aims at organizing several MCS data collection campaigns in Italy, but data collected from other countries will be also considered in the future. We analyse in this work data collected in 2014 in Italy, from roughly 170 users. Users are recruited on a voluntary basis. Moreover, the organizers distributed to the users a smartphone with a SIM card so that to increase the user's participation and involvement to the MCS initiative.

The experiment gathered different kinds of data from the users, through the ParticipAct mobile app. The app interacts with the back-end and it allows to accept/decline a sensing task. Tasks submitted might require to provide personal feedbacks about an event, to upload a picture from a location or to answer to a simple questionnaire. Moreover, the app computes and uploads periodically the position of the device as WGS84 coordinates. The device position is determined by exploiting the Google Location APIs, which localize a mobile device by using the information available from the WiFi Hot Spot coordinates, GPS signal or the cellular base stations. The device position is uploaded at regular intervals. However, several factors affected the amount of traces collected during the experiment, such as: the battery consumption of the device, the absence of connectivity, switch-off of the device.

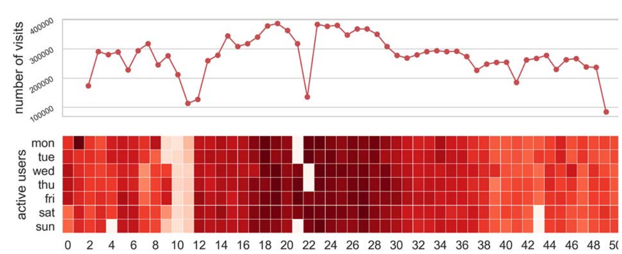

Fig. 3 Number of weekly locations visited and active users in 2014.

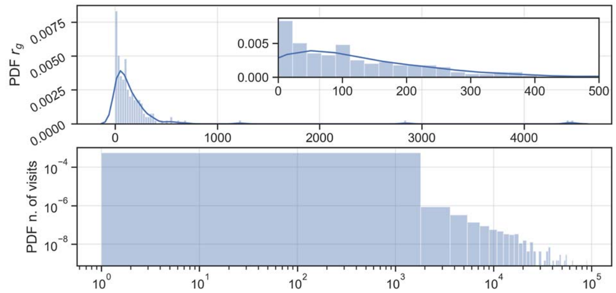

Fig. 4 PDF of the radius of gyration and of the number of visits per location.

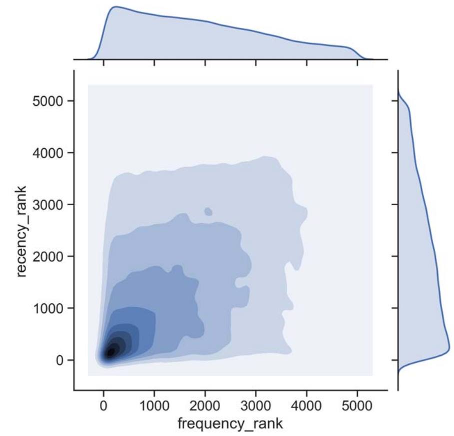

Fig. 5 Frequency and receny of the locations visisted.

In the next sections, we describe the amount of traces collected as well as some mobility features of the ParticipAct data set. In particular, we first provide a general overview of the traces collected (see Section III-A and III-B) and then we analyse several mobility metrics useful to understand dynamics of human mobility for the purpose of defining an effective MCS data collection campaign (see Section IV).

A. Description of the Data set

The mobility data set comprises timestamped WGS84 traces. We analyze the data collected from January 2014 to December 2014. The data set provides 15.615.341 traces from 177 distinct users roaming mostly in Emilia Romagna region, Italy. The device position is computed periodically, approximately every 2.5 minutes. In order to measure the amount of traces actually obtained, we compute the ratio between the traces collected with respect to the expected ones. Figure 1 reports a heatmap showing such ratio. We compute the ratio on a weekly period (0 to 51 weeks of 2014), and we aggregate the results for each of the week's days, as reported by the rows of the heatmap. From Figure 1, we observe that only few weeks' days report a low number of traces, while for the majority of the weeks, the ratio is always acceptable. We measure a mean ratio of 75% of the expected traces, with a minimum of 21% and maximum of 85%.

The device position is computed by using the information available from the smartphone, therefore the resulting accuracy might remarkable vary. The Google Location APIs also provides an indication of the accuracy error. It quantifies the radius of a circle centered on the location computed. Therefore, the lower the radius, the higher the precision of estimated positions.

In Figure 2, we show the distribution of the accuracy error on a semi-log y scale. From the graph, we observe that the highest probability is given with low values of radius, ranging from 1.7 meters to 27 meters. As a general trend, we measure the 25th percentile of 27 meters and the 50th percentile of 43 meters which represent admissible values for the purpose of this work.

In addition, we analyze the number of locations visited during the whole 2014 aggregated per weeks, and the number of active users in 2014, as shown in Figure 3. The figure shows on the top the time series of the number of locations visited week-by-week. Users visited a median of 278.509 locations every week, with a minimum of 84.225 and maximum of 387.164 locations visited respectively. We observe two time intervals during which the number of locations visited drops abnormally (weeks 4, 9 to 11, 21 and 43). Those situations were due a few mobile app updates that were causing problems in the interactions with the back-end system.

We also measure the number of *active* users as a heatmap as reported in Figure 3. A user is active if its device uploads the position at least once during the week. It is worth to notice that the amount of mobility traces uploaded by a device is affected by several factors, such as the battery consumption of the ParticipAct app, crashes of app or network / GPS coverage of the smartphone. From the heatmap in Figure 3, we observe that the most active period corresponds to the mid weeks of the year, specifically from week 18 (May 2014) to week 30 (July 2014).

B. Mobility Features of the ParticpAct Data Set

We now focus on the analysis of the mobility features of ParticipAct. The mobility analysis we present in this section is realized with the scikit-mob python library [24], and it aims at quantitatively measure some patterns of the user mobility.

We analyze the PDF (Probability Density Function) of the radius of gyration and the number of visits per location. The radius of gyration quantifies the "typical distance travelled by an individual" [25]. Given a user, its radius of gyration is computed as follows:

$$r_g = \sqrt{\frac{1}{N}\sum_{i\in L} n_i (r_i - r_{cm})^2}$$

where L represents the set of locations visited the user, r_i provides the coordinates of the i^{th} location, n_i is the visitation frequency of the i^{th} location, r_{cm} is the center of mass of the trajectory of the user and N is the total number of visits of the

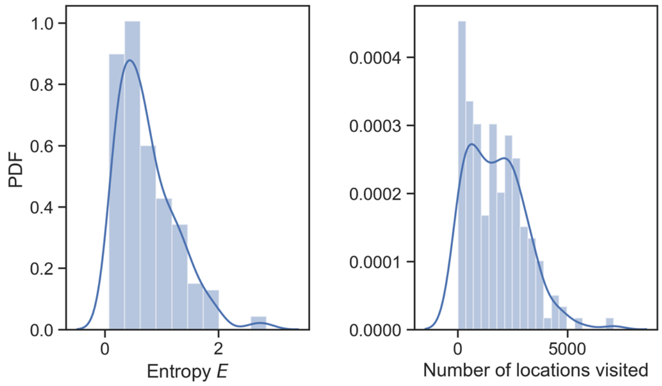

Fig. 6 PDF of the nuber of location visisted and real entropy.

user. The higher the radius, the higher the distance travelled by the users.

Figure 4 shows the PDF of the radius for all the users. The radius varies remarkably, we measure the 25th percentile of 35 km and the 75th percentile of 198 km. The inset in Figure 4 shows the PDF of the radius cut to values lower than 500 km. We observe that the most probable values of the radius range between 0 and 20 km (35% of the users), an admissible distance for short-range commuters. Figure 4 also shows the PDF of the number of visits per location. We observe an equal density for those locations visited in the range $10^0 – 10^3$ giving rise to the existence of a pool of recurrent locations frequently visited by the users.

We then analyze the user's trajectories, namely the ordered sequence of locations visited by the users. We plot the frequency rank of locations visited with respect to the recency rank of the locations visited. The frequency rank for a location determines if the location is highly visited, while the recency rank for a location determines if the location if recently visited. Figure 5 shows the joint plot of the frequency and recency of the locations with iso-centric contours showing the KDE estimator (ranks cut to 5000). From the figure it is clear that the locations highly visited are also the most recently visited. The marginal distributions on the top and left side of Figure 5, further confirm such observation.

Therefore, we consider the existence of a set of *preferential* locations for the users, such locations are both highly and recently visited. We focus on two metrics that characterize the way users visit the locations. In particular, we compute the distribution of the number of locations visited by the users and the predictability of the locations visited by the users, both of the metrics are reported in Figure 6. The number of locations visited, measures the distribution of the number of locations the users visit, while the predictability of the locations measures the capability of predicting the next location visited by a user. To this purpose, we compute the real entry E_i for a given user i. The real entropy considers the frequency and the order of the visits for a location, thus capturing the full spatio-temporal order of the mobility pattern of user i, as described in [26]. From Figure 6 we observe that, on average, users visit 1744 locations, with a 25th and 75th percentile of 645 and 2556 locations respectively. Concerning the real entropy, we measure an average E≈0.73, meaning that the next location, of a randomly chosen user, can be one among 20.73≈1.65 locations. We finally extract from the user's trajectories the stop places, namely, those locations where users stop/rest for a while. To this purpose, we first restrict the analysis to the city of Bologna, the major city of Emilia Romagna region Then, for every user, we find the places where he/she stops for at least 60 minutes in a circular region of radius 200 meters. Then, we cluster such places, by using the DBSCAN clustering algorithm. The resulting heatmap shown in Figure 7, offers an aggregated perspective of the resting locations. From the map, we observe several stop locations in the city of Bologna, such as the train station (inset of Figure 7), several departments of the University of Bologna whose students were involved in the ParticipAct project, and some popular locations in the city center.

IV. Impact of Human Mobility Metrics for MCS

The mobility metrics we measured in Section III can be used to plan several key-aspects for a MCS data collection campaign. In this section, we discuss such aspects with the goal of offering some hints and suggestions for the realization of large-scale MCS initiatives. We focus on three main aspects, namely task scheduling, task allocation and spatial coverage.

For the purpose of this work, we refer to a simple MCS architecture composed by: a back-end server and a number of

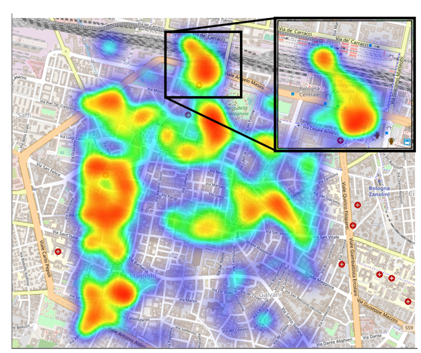

Fig. 7 Stop places of locations cropped in the Bologna city.

devices acting as sensing units and assigned to volunteer users. The back-end server interacts with the devices by submitting MCS *tasks*. Tasks, essentially, allow the back-end to gather data from the devices. In particular, a task is an action that can be completed with or without the explicit user intervention. As for example, a MCS task might require to a set of devices to sample some environmental data or, differently, it might ask to users to take a picture of point of interest. Tasks can be accepted or rejected by users. In the last case, a user deliberately avoids to complete the task, an option that must be considered during the design of a MCS initiative.

A. *Task scheduling*

The submission of tasks to the users requires a prior scheduling, so that to increase the acceptance rate. Indeed, let us remark that in ParticipAct we do not assume to have a real-time MCS data collection, but rather we proactively upload the sensing task request to those smartphones that most probably, according to some historical data and profiling, will be able to complete it. Accordingly, specific knowledge about user mobility can indeed boost during the selection of the best time-period for submitting a task. In this context, the information about the weekly number of locations visited reported in Figure 4 are particularly relevant. In fact, they provide a useful trend in order to better understand the *rhythm* of the crowd on a temporal scale. That, in its turn, could be used to more precisely and timely schedule the task, for specific sensing campaigns (e.g., a sensing task to get feedbacks from as most locations at a certain period of the day), only to those nodes that are very active and mobile at that time span, without bothering and overloading a higher number of users/nodes.

B. *Task allocation to specific areas and induviduals*

MCS tasks can also be further split in two categories: *geo-fence* and *individual* tasks. The first category refers to tasks that can be completed only when a user enters inside a region of interest for the task. As for example, a task that requires to take a picture of a square, should be submitted to the user only when he/she enters inside such region. Differently, individual tasks are submitted to users with specific features, such as their profiles, their mobility patterns or their social habits.

Concerning the geo-fence tasks, several mobility metrics can be used to plan their allocation. In particular, the accuracy error, the stop places and the existence of preferential locations. The accuracy error reported in Figure 3 is a first indicator of the quality of the geo-fence areas. In fact, knowing that devices are localized with a certain accuracy, supports the decision of adopting the geo-fencing or not. Moreover, the accuracy also provided an indication of the expected error of the data collected from the regions of interests. More precisely, devices that generally provide an accurate position (low accuracy error) are ideal for receiving geo-fence tasks, since they will accept the task only inside the boundary of the region of interest. Conversely, devices with very low position accuracy will accept the geo-fence task also outside from the region of interest. Furthermore, the knowledge of locations where users, generally, stop for a while enables to better draw the boundaries of the regions of interests. From the heatmap in Figure 8, it is easy to draw such boundaries, as shown with the Bologna train station. Such knowledge reduces the possibility of defining off-width regions, or empty regions in which only few devices will activate the task. Finally, the relationship between frequency and recency of the locations visited is a valuable metric when the goal is to gather fresh data from the users. Figure 6 shows an example of frequency and recency for the locations of the ParticipAct data set. The figure clearly shows the existence of preferential locations highly and recently visited, that can be selected when it is required to gather from the users updated information.

Concerning the individual tasks, they are submitted only to a specific set of users. The selection of the target users can be also achieved by observing their adherence to the use of the MCS app. In Figure 4, we report a heatmap with the active users, defined as users whose devices report the position periodically. The heatmap can be used to infer if users tend to use the app during the day and, in turn, to predict if such users are also good candidates for receiving an individual task. Intuitively, the more users tend to use the app (and hence to report their position), the more they likely will accept an individual task. Of course, the selection of the target users is not only restricted to the usage of the MCS app, rather the profile of the users can also be taken into account.

C. *Spatial coverage*

The last aspect we consider is the spatial coverage of the data collected from the users. The coverage of the data refers to the diversity of the regions from which data are gathered.

Such diversity is a desirable feature within MCS initiatives whose goal is to monitor environmental data in an urban area. To this purpose, the study of user's radius of gyration allows to measure quantitatively the distance travelled by users. In Figure 5, we plot the distribution of the radius of gyration for all the users. As described, the higher the radius the more distance users travel. Therefore, the radius is a first metric useful to define the mobility attitude of a set of users. In case the MCS tasks are designed to collect data from a wide region, the target users might be those exhibiting high values of the radius of gyration.

Moreover, the study of the distribution of the number of locations visited further refines the selection of the target users. In particular, we plot in Figure 7 the number of locations the users of ParticipAct visit. This information, combined with the radius of gyration, allows to select those users travelling for long distances and visiting different locations. The resulting users are the ones ideal for allocating environmental monitoring tasks.

V. CONCLUSIONS AND FUTURE WORK

The sensing technologies available on commercial smartphones, enable their adoption for massive sensing data collection campaigns. The Mobile CrowdSensing paradigm exploits such advanced hardware and software features in order to enable an effective solution for gathering data from the crowd. We consider that the effectiveness of a MCS campaign strictly relies on the way volunteer users are involved. To this purpose, we propose in this paper a data-driven approach to show the potentialities of knowledge extracted from the data, to design an effective MCS collection campaign.

More specifically, in the paper we focused our attention on the mobility features of users joining the ParticipAct experiment. We analyzed the quality of the data set, the active users and several pattern of human mobility, such as the distribution of the radius of gyration, the real entropy, and the stop places. We finally discussed how such metrics can be, in turn, analyzed for planning the task allocation to specific users, the task scheduling during specific time periods and how to increase the spatial coverage of the data collected from the users. We remark that considerations reported in Section IV can be further supported with the upcoming sensing technologies such as ultra-wide band (UWB) and 5G.

Propelled by these new technological possibilities, we are now working to further extend the MCS platform along two main directions. On the one hand, the recent UWB U1 chipset available on iPhone 11 can potentially enable high-accurate indoor localization of the devices so that to further decrease the localization error analyzed in Section III. That higher location accuracy would affect the possibility of triggering sensing tasks more accurately to those devices that are actually roaming in a region of interest. On the other hand, the 5G New Radio (NR) technology also pushes forward the accuracy of localization both indoor and outdoor. In fact, the adoption of new frequency bands at mm-wave and of massive MIMO for accurate angle of arrival estimation might increase the localization of devices at very different conditions.

We truly believe that the combination of the above two key-technologies will give rise to a new era for location-based services enabling a wider diffusion of the MCS initiatives.

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