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Estimate User Meaningful Places through Low-Energy Mobile Sensing

Fulvio Corno*, Luigi De Russis*, and Teodoro Montanaro*
*Politecnico di Torino Corso Duca degli Abruzzi, 24 Torino, Italy 10129
{fulvio.corno, luigi.derussis, teodoro.montanaro}@polito.it

***Abstract*—Due to the increasing spread of location-aware applications, developers interest in user location estimation has grown in recent years. As users spend the majority of their time in few meaningful places (i.e., groups of near locations that can be considered as a unique place, such as home, school or the workplace), this paper presents a new energy efficient method to estimate user presence in a meaningful place. Specifically, instead of using commonly used but energy hungry methods such as GPS and network positioning techniques, the proposed method applies a Machine Learning algorithm based on Decision Trees, to predict the user presence in a meaningful place by collecting and analyzing: a) user activity, b) information from received notifications (receipt time, generating service, sender-receiver relationship), and c) device status (battery level and ringtone mode). The results demonstrate that, using 20 days of training data and testing the system with data coming from 14 persons, the accuracy (percentage of correct predictions) is 89.40% (standard deviation: 8.27%) with a precision of 89.04% and a recall of 89.40%. Furthermore, the paper analyzes the importance of each considered feature, by comparing the prediction accuracy obtained with different combinations of features.**

I. Introduction

As declared by Darbar et al. [1], smartphone usage trend is rapidly increasing. This rapid growth, combined with millions of developed applications (apps) makes smartphones one of the favorite means for spreading innovative services. As very capable sensing platforms, in fact, smartphones support the development of increasing complex apps and the improvement of their services. In addition, thanks to the availability of innovative techniques and knowledge that allow apps to use new complex and/or accurate information about the user, new benefits have been added to apps in the last few years. More precisely, as affirmed by Paek et al. [2], one of the most used information that is used by enhanced services is the user location: they declare that the usage of mobile applications that require and use position information is rapidly increasing in the last few years.

Nonetheless, location information is usually retrieved through energy expensive methods like GPS or network positioning techniques. Consequently, considering that the usefulness of smartphones is limited by their battery life, this paper presents a new method to estimate the most attended user meaningful places through low-energy mobile sensing.

The term "meaningful place" used within this work represents a place in which a user recurrently stays for a certain period of time [3]: it is a group of near locations that can be considered as a unique place, such as home, school or the workplace.

User location estimation is a well explored topic in the literature, and some authors proposed good solutions to avoid or reduce the usage of GPS and/or network positioning techniques to save smartphone battery power. However, to the best of our knowledge, none of them developed a system able to estimate user presence in a meaningful place by collecting and analyzing information that can be acquired with low power consumption such as a) user activity, b) information from received notifications (receipt time, generating service, sender-receiver relationship), and c) device status (battery level and ringtone mode).

This study estimates the accuracy of a Machine Learning classification algorithm based on Decision Trees in predicting user presence in a meaningful place whenever a notification arrives. Results reported in this paper are obtained from the analysis of data acquired through a dedicated Android application installed on 14 user smartphones for 20 days. They demonstrate that the availability of the above mentioned information is sufficient to accurately estimate user presence in a meaningful place. Moreover, the sensitivity of the resulting accuracy from the chosen set of features will be studied.

The remainder of the paper is organized as follows: Section II analyzes existing related works, Section III explains the proposed method, Section IV describes the data selection and collection process, Section V describes the method used to identify the 2 most attended meaningful places, and Section VI show the operations performed on data to obtain useful features for the cross validation phase presented in Section VII. Finally, Section VIII evaluates results obtained by using a Machine Learning classification algorithm based on Decision Trees and Section IX concludes the paper with some considerations and future work.

II. Background and Related works

User location estimation has been subject of extensive studies in the literature, nonetheless, location information is usually retrieved through energy expensive methods like GPS or network positioning techniques. Therefore, considering that the utility of smartphones is limited by their battery life (as declared by Metri et al. [4]), there is a growing interest in the problem of reducing power consumption without giving up the benefits of using location information. Most of related works focus on how to reduce the frequency or decrease the duration

of GPS usage: Kjaergaard et al. [5], for example, propose a system that, based on the estimation and prediction of system conditions and mobility, schedules position updates to both minimize energy consumption and optimize robustness. The developed system calculates the optimal plan for power-on and power-off times of device sensors and peripherals, such as the GPS module. Furthermore, Xu et al. [6] proposed a hybrid method for semantic location recognition, which combines k-NN and multiple decision tree models to effectively recognize the location both in outdoor and indoor environments. To reduce battery consumption, they use a decision tree model to check if the user is moving and only when the user stays in a place for a significant time period, the recognition procedure is performed. A similar approach was used by Ryoo et al. [7]: they designed a geo-fencing framework able to determine when users check in or out of a specific area in an energy efficient way, so that appropriate Location Based Services (LBS) can be triggered. In addition, their study is based on the observation that users usually move from one place to another and then stay at that place for a while. This observation is supported by Klepeis et al. [8] and is the basis of several other works related to energy consumption reduction in smartphone location prediction. As demonstrated by Klepeis, in fact, people spend approximately 87% of their daily time in enclosed buildings, so it is possible to identify some user meaningful places in which user spends most of their daily time. This property is also used by Chon et al. [3], that proposed a system able to reduce smartphone battery consumption switching from a high-level to a low-level sensing mode; the two different modes differ in the sensors used to evaluate location. The system assumes that, when a user stays at a place for a certain period of time, she is in a "meaningful place". Consequently, when these places are recognized, the system saves a location signature (i.e., internet connectivity, visiting time, residence-time, and Wi-Fi signature) for future prediction. Therefore, whenever a user enters a place, at first the system tries to identify the location using location signature (this step is called low-level sensing step) and then, only if it is not able to identify the place, it activates the more energy hungry high-level sensing.

The same property is used in this paper, but aiming at using new methods and sources of information to estimate users' meaningful places: we present a technique for applying Machine Learning classification algorithms based on Decision Trees on data available on the smartphone that do not require extra energy to be retrieved.

New methods for obtaining a smartphone location estimation have already been presented in some works found in the literature. Paek et al. [2], for example, propose a system that leverages Cell-ID transitions and a history of GPS readings obtained within a cell to provide an accurate estimation of user current location. The paper demonstrates that the proposed system achieves reasonable accuracy while keeping a low energy overhead. Furthermore, Garbe et al. [9] present a system for mobile devices able to determine user's location when neither GPS nor network positioning information is available. The proposed system uses information coming from 3 different sensors: a gyroscope, a magnetometer that measures the Earth's magnetic field and a barometer that estimates the user's altitude based on air-pressure readings.

Moreover, another useful work is the one presented by Qin et al [10]: the main issue that authors address is how predictable individuals are in their mobility. They use the raw cell ID timestamps combined with the smartphone location (i.e., its coordinates) to calculate and estimate patterns (i.e., the days are classified for each person into regular, personal patterns) and "life" entropy, used then for meaningful places (that they call "persons important locations") estimations.

III. Method

As declared by Chon et al. [11], people usually spend $85 \pm 3\%$ of their time staying in a place, while they spend $13 \pm 3\%$ of their time on the move. Based on this knowledge, in this paper a method that is able to establish user presence in the 2 most attended meaningful places is evaluated. Specifically, it is demonstrated that it is possible to estimate where the user is in a certain moment of the day with high accuracy and without using energy expensive methods. In order to demonstrate such an assumption, a method that uses Machine Learning supervised classification algorithms based on Decision Trees is proposed for predicting user presence in a meaningful place.

The Decision Tree algorithm has been evaluated according to the work-flow shown in Figure 1. After an initial phase in which data are collected through a dedicated Android application, the 2 most attended meaningful places are identified in the "Meaningful places estimation" phase and labels are assigned to collected data. In addition, collected items are filtered in the "Features selection & Pre-processing" phase: it is dedicated to a) remove useless information from the collected data and b) encode data for better performance of the classification algorithm. The dataset resulting from these three phases is used as input for the 10-fold cross validation process that produces accuracy, precision and recall measures as method estimation results.

Due to the different daily routine of each user, the shown steps are replicated for every user involved in the study and, at the end, a mean value is calculated for each computed measure. The following sections describe each phase with more details explaining the contribution of each step to the whole accuracy estimation.

IV. Data collection

As presented in the previous section, the first step in evaluating the proposed method is the "Data collection" phase. An ad-hoc Android application was developed and implemented to support this phase. It implements different background services registered as listeners of operating system messages and/or signals to collect needed data. Furthermore, every time the user enables GPS and/or network positioning services (for example, when she uses mapping services) the application

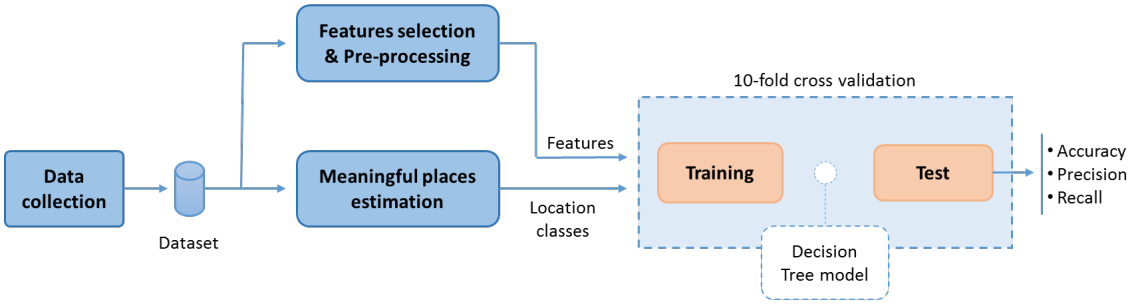

Fig. 1: Model that describes the estimation process performed for each user

Time information	Time
	Date
	Day of the week
Notification information	Type
	Generating service
	Sender-receiver relationship
Device state	Battery level
	Charging state
	Ringtone mode
User information	Current activity
	Absolute location

TABLE I: Collected data

registers available absolute location that will be used as labels in the training phase of the Machine Learning algorithm.

Table I shows the information chosen among all the sources of information available to the smartphone that do not require extra energy to be retrieved and that is collected through the Android application. The table shows 4 main categories of information: the "Time information" represents the moment in which the estimation is performed. It is expressed by three different fields: the time of day, in seconds, the date (that contains the day of the month (1-31), the month and the year), and the day of the week. This values are always available on all smartphones and do not require any extra energy consumption to be retrieved. Moreover, "Notification information" represents the data contained in a notification, such as a) the type of the notification (e.g., message, email, ... etc), b) the generating service (e.g., Telegram, Whatsapp, Snapchat, ...), and c) the relationship between the sender and the receiver of the notification. The sender-receiver relationship is expressed by one of the following values: "family", when the sender and receiver are relatives, "friend", when the sender is a friend of the receiver, and "work", when the sender works with the receiver. This information is asked to the user at the first application installation for only the most important persons present in her contact list. On Android smartphones, every time a notification is received, a broadcast message with all available information related to the just received notification is sent to all registered apps. Consequently, the exposed means of information are acquired without consuming extra energy. Furthermore, "Device state" indicates the values related to battery level, charging status (i.e., charging/non charging) and selected ringtone mode (i.e., silence, vibration, and sound). As declared in the Google documentation [12] these values do not require a lot of energy if they are acquired with the right frequency. In addition, 2 more pieces of information about user are collected: user current activity and user current absolute location. User current activity is retrieved using the Google Activity Recognition service: the activities are detected by periodically waking up the device and reading short bursts of sensor data. The Google documentation [13] reports that the activity recognition process "only makes use of low power sensors in order to keep the power usage to a minimum".

Apart from these features, for meaningful places estimation, user current absolute location is collected. It can be acquired through 2 different methods: using the GPS module or using network positioning techniques. In both cases extra energy is needed, but within this study the absolute location is needed only to establish label (meaningful places) for the training of the Machine Learning algorithm, so, it is acquired only whenever the user enables GPS and/or network positioning services for her purposes (for example, when she uses mapping services).

In order to collect significant real data, 14 users were asked to install the app on their personal smartphone to obtain information about their usual daily mobility within 20 days of usage. Almost all users were aged between 18 and 30, apart from 2 users that were aged between 30 and 45.

To preserve user privacy, all collected information were anonymous: all sensible pieces of information present in the shown list were anonymized using an hash function.

V. Meaningful places estimation

The second phase in evaluating the proposed method is related to "Meaningful places estimation" step: the 2 most attended meaningful places for each user were identified using the unsupervised machine learning algorithm known as K-means algorithm: as declared by Zhou et al. [14] it is one of the most known and used partitioning clustering algorithm for detecting user meaningful places.

As samples of collected data, Figure 2 and Figure 3 show the absolute locations stored for 2 different users. The round

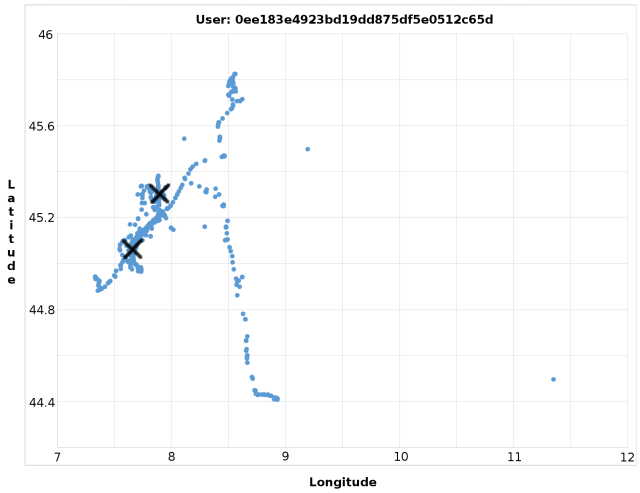

Fig. 2: Absolute locations recorded for user 5

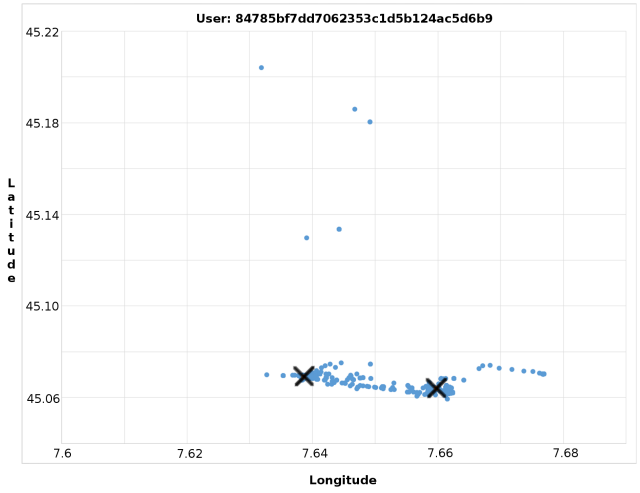

Fig. 3: Absolute locations recorded for user 11

points represent all the unique absolute locations stored for the single user, instead the cross points are the centers of the 2 meaningful places identified by the K-means algorithm. As can be seen, in both cases the 2 meaningful places identified by the algorithm are actually representative of most of the recorded absolute locations. The user location was within 1 km from either cluster centers in 64.26% of the samples.

VI. Features selection and Pre-processing

Another phase in evaluating the proposed method is related to the "Features selection & Pre-processing" step. It refers to every operation performed on the data in order to remove useless information from the collected items and encode data for better performance of the classification algorithm. In this work, three main operations were performed during this phase:

- date and time information were further splitted in 4 main items: time (seconds since midnight), day (number of days since the 1st day of the month), month, year;
- time, day, month, and day of the week fields were splitted in aggregated features; in order to consider the periodicity of time (i.e., 23.59 is near 00.01), in fact, we exctracted 2 different values for time instead of only one: $sin(\frac{2 \cdot \pi \cdot time}{24 \cdot 60 \cdot 60})$ and $cos(\frac{2 \cdot \pi \cdot time}{24 \cdot 60 \cdot 60})$, where the denominator represents the seconds contained in a day and "time" represents the number of seconds since midnight. The same split was performed for the month, the day and the day of the week but substituting the components of the formula with the right values.
- considering that experiments were performed in the same year, the "year" information was removed from the selected features.

VII. Cross validation

After collecting specified data and filtering them (with Features selection, Pre-processing and Meaningful places estimation), an off-line evaluation of our method was performed through a 10-fold cross validation process over the collected dataset.

In the presented work, the Weka [15] workbench for Machine Learning was used for all the experiments and all the evaluations were done using the k-fold cross validation method with k set to 10.

The dataset used for experiments performed in this study is composed of 27142 samples (a mean of 1507 ± 970 samples per user) labeled with user meaningful places; user presence in a meaningful place was estimated every time a new notification is received, consequently each dataset sample represents data stored at the moment of a notification reception.

For each experiment 3 measures are reported:

- Accuracy, that represents the percentage of correct estimations.
- Precision, that is a measure of result relevancy.
- Recall, that is a measure of how many truly relevant results are returned.

The precision and recall values reported in this paper are calculated as weighted values of repeated single class classification. In our work, in fact, we have 2 classes (location 1 and location 2) data label, so Weka repeats the prediction 2 times: the first time it estimates precision and recall predicting class 1, instead at the second one it estimates precision and recall predicting class 2. Then, it calculates a weighted value considering the class size.

14 users were involved in the study and, considering that each user has her own habits and attends different meaningful places, the model was evaluated separately for each user. Then, a mean value is calculated for each measure over all 14 users.

VIII. Results evaluation

Collected data (Table I) is converted into features suitable for the classification algorithm, as shown in Table II, that contains further details on feature representation.

The first considered feature category (A) is related to time information. As already discussed, all the data were collected at each notification reception, consequently, this data

Feature ID	Feature	Type
A	Time	INTEGER
	Month	INTEGER (1-12)
	Day	INTEGER (1-31)
	Day of the week	Class(Monday, ...)
B	Type	Class(msg, email, ...)
	Generating service	STRING (e.g., Telegram)
	Sender-receiver relationship	Class(family, friend, work)
C	Battery level	INTEGER
	Charging state	Class(charging/ not charging)
D	Ringtone mode	Class(silence, vibration, sound)
E	Current activity	Class(in vehicle, on bicycle, on foot, running, still, tilting, unknown, and walking)

TABLE II: Legend of considered features

represents the time, date and day of the week at which the notification was received.

The second feature category (B) is related to notification information: it represents the type of the notification, the service that generated it and the relationship among the owner of the smartphone and the sender of the message.

Furthermore, features related to device status (battery information (C) and selected ringtone mode (D)) were considered in addition to the revealed user activity. The activity (E) is acquired through the Google Activity Recognition API and can assume one of the following values: a) in vehicle, b) on bicycle, c) on foot, d) running, e) still, f) tilting, g) unknown, and h) walking.

Finally, the target class used as label for the Machine Learning algorithm training is the "Meaningful Place" that can assume one of the 2 values "locationClass1" and "locationClass2".

Aiming at studying the importance of each selected features 31 different experiments were performed: the Decision Tree model was cross-validated on the collected dataset with different combinations of the presented features.

Table III shows the list of performed experiments: in every row we report the features selected for each experiment and the obtained accuracy, prediction, and recall mean values with corresponding standard deviation. The legend of feature IDs is contained in Table II.

The first 16 experiments reported in Table III show the importance of timing information in predicting presence in meaningful places, especially when coupled with other device or user-related features. The importance of this feature was expected to be strictly related to user habits and results demonstrate an obtained accuracy between 88% and 91%.

Moreover, results show that the "Current activity" (E), the only feature that consumes extra energy, is not necessary: when it is considered, the accuracy changes only of less than 1%. Consequently, it can be removed from the used features bringing the proposed method to a zero-energy method.

IX. Conclusions and future work

This paper proposed a new energy efficient method to estimate user presence in a meaningful place. In this study we presented results obtained from the analysis of data acquired through a dedicated Android application installed on 14 user smartphones for 20 days. We demonstrated that it is possible to use a method that applies a Machine Learning algorithm based on Decision Trees, to predict the user presence in a meaningful place by collecting and analyzing: a) user activity, b) information from received notifications (receipt time, generating service, sender-receiver relationship), and c) device status (battery level and ringtone mode). A 10-fold cross-validation process was used to evaluate the method estimating user presence in a meaningful place every time a notification is received.

In order to identify the best combination of features for our purposes 31 experiments were performed. Results demonstrate that the most important features among the considered ones are related to time information. In fact, when timing features are considered, the best obtained accuracy value (percentage of correct predictions) is 89.40% (standard deviation: 8.27%) with a precision of 89.04% and a recall of 89.40%.

In the future we plan to repeat experiments with a larger dataset: more users will be involved in the study for a larger observation period. Moreover, more Machine Learning algorithms will be tested for estimation in order to determine if it is possible to obtain better results with different algorithms.

X. Acknowledgment

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Exp. num.	A	B	C	D	E	Accuracy	Accuracy St. Dev.	Precision	Precision St. Dev.	Recall	Recall St. Dev.
1	Y	Y	Y	Y	Y	89.40%	8.27%	89.04%	8.63%	89.40%	8.27%
2	Y	Y	Y	Y	-	89.31%	8.50%	88.83%	9.13%	89.31%	8.50%
3	Y	Y	Y	-	Y	89.01%	8.46%	88.59%	8.95%	89.01%	8.46%
4	Y	Y	Y	-	-	89.12%	8.51%	88.64%	9.13%	89.12%	8.51%
5	Y	Y	-	Y	Y	89.17%	8.41%	88.66%	8.85%	89.17%	8.41%
6	Y	Y	-	Y	-	89.27%	8.23%	88.66%	8.91%	89.27%	8.23%
7	Y	Y	-	-	Y	88.73%	8.39%	88.15%	8.85%	88.73%	8.39%
8	Y	Y	-	-	-	88.96%	8.39%	88.35%	9.03%	88.96%	8.39%
9	Y	-	Y	Y	Y	**90.19%**	7.81%	**89.96%**	7.90%	**90.19%**	7.81%
10	Y	-	Y	Y	-	90.11%	7.94%	89.83%	8.13%	90.11%	7.94%
11	Y	-	Y	-	Y	89.52%	8.11%	89.18%	8.38%	89.52%	8.11%
12	Y	-	Y	-	-	89.61%	8.01%	89.23%	8.40%	89.61%	8.02%
13	Y	-	-	Y	Y	89.82%	8.39%	89.34%	8.76%	89.82%	8.39%
14	Y	-	-	Y	-	90.08%	7.83%	89.72%	8.05%	90.09%	7.83%
15	Y	-	-	-	Y	89.38%	8.37%	88.67%	9.06%	89.38%	8.37%
16	Y	-	-	-	-	89.90%	7.78%	89.51%	8.01%	89.90%	7.78%
17	-	Y	Y	Y	Y	86.92%	8.56%	86.65%	8.76%	86.92%	8.56%
18	-	Y	Y	Y	-	86.94%	8.02%	86.71%	8.20%	86.94%	8.02%
19	-	Y	Y	-	Y	86.03%	8.69%	85.80%	8.85%	86.03%	8.69%
20	-	Y	Y	-	-	86.01%	8.29%	85.81%	8.45%	86.01%	8.29%
21	-	Y	-	Y	Y	78.89%	10.91%	78.76%	10.98%	78.89%	10.91%
22	-	Y	-	Y	-	77.89%	11.10%	77.75%	11.12%	77.89%	11.10%
23	-	Y	-	-	Y	76.67%	11.89%	76.56%	11.99%	76.67%	11.89%
24	-	Y	-	-	-	75.50%	12.36%	75.59%	12.20%	75.50%	12.36%
25	-	-	Y	Y	Y	87.57%	8.01%	87.31%	8.22%	87.57%	8.01%
26	-	-	Y	Y	-	**87.68%**	7.48%	**87.49%**	7.64%	**87.68%**	7.48%
27	-	-	Y	-	Y	87.26%	8.23%	86.98%	8.51%	87.26%	8.23%
28	-	-	Y	-	-	86.98%	8.08%	86.74%	8.36%	86.98%	8.08%
29	-	-	-	Y	Y	75.59%	11.69%	75.56%	11.62%	75.59%	11.69%
30	-	-	-	Y	-	73.44%	11.88%	73.10%	12.29%	73.44%	11.88%
31	-	-	-	-	Y	72.92%	12.49%	72.24%	12.95%	72.93%	12.49%

TABLE III: Experimental results (Accuracy, Precision and Recall)

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