MyWay: Predicting Personal Mobility

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Abstract

Forecasting the future positions of mobile users is a valuable task allowing to operate efficiently a myriad of different applications which need this type of information. We propose *MyWay*, a prediction system which exploits the individual systematic behaviors modeled by *mobility profiles* to predict human movements. *MyWay* provides three strategies: the *individual* strategy uses only the user individual mobility profile, the *collective* strategy takes advantage of all users individual systematic behaviors, and the *hierarchical* strategy that is a combination of the previous two. A key point is that *MyWay* only requires the sharing of *individual mobility profiles*, a concise representation of the user's movements, instead of raw trajectory data revealing the detailed movement of the users. We evaluate the prediction performances of our proposal by a deep experimentation on large real-world data. The results highlight that the synergy between the individual and collective knowledge is the key for a better prediction and allow the system to outperform the state-of-art methods.

Keywords: Trajectory Prediction, Spatio-temporal Data Mining

1. Introduction

Predicting the future locations of a mobile user is a flourishing research area that is powered by the increasing diffusion of location-based services. The knowledge of mobile user positions fosters applications which need to know this information to operate efficiently. Examples of such services are traffic management, navigational services, mobile phone control and so on. In a typical scenario, a moving object periodically informs the positioning system of its current location. Due to the unreliable nature of mobile devices and to the limitations of the positioning systems, the location of a mobile object is often unknown for a long period of time. In such cases, a method to predict the possible next position of a moving object is required in order to anticipate or to pre-fetch possible services. The strong interest in this kind of applications led to the study of several approaches in the literature addressing the location

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prediction problem. Some of them base the prediction on single users' movement history, while others extract common behaviors from the movement history of all the users in the system and use this global knowledge.

In this paper we propose a shift of paradigm based on the following idea: to predict the future positions of a user we first use her systematic behaviors and, if they are not sufficient we use the systematic behaviors of the crowd. This idea is based on the conviction that typically any individual systematically visits a small set of locations and regularly moves between them by choosing the best routes learned by the daily experience [1, 2]. The task we are addressing is the prediction of the *exact* position visited by the user without applying any apriori spatial discretization. *MyWay* is a system to forecast the future positions of mobile users by using predictors which exploit the individual systematic behaviors of a single user, the individual systematic behaviors of all users in the system, and a combination of them. At individual level it requires that each individual computes an abstract representation of her systematic behavior: the *individual mobility profiles* that captures the paths that are regularly followed by the user, called *routines* [3]. In particular, it adopts the concept of Personal Mobility Store (PMS) where continuously the raw trajectory data, produced by the user mobile devices, are recorded. From the mobility data in the user PMS it is possible to extract the individual mobility profile. It is worth to notice that this vision assumes the computational capability at individual level to extract such mobility profile by the raw trajectory data in the PMS. This is compatible with a scenario of increasing intelligence of the mobile devices as well as with a scenario of cloud services. At collective level *MyWay* requires that the *individual mobility profiles* are shared.

Our claim is that the prediction strategy which uses only individual mobility profiles is comparable with a prediction strategy based on raw movement data. If confirmed, this approach has two important advantages: *(i)* it dramatically minimizes the quantity of information to be transmitted: a mobility profile is a concise representation of the information in the user PMS; and, *(ii)* it reduces enormously the privacy risks: the mobility profile represents a systematic behavior, i.e., paths that are regularly followed by the user, but does not reveal all the details of her past spatio-temporal positions. *MyWay* is based on two steps: a learning phase, that is simply represented by the acquisition of mobility profiles; and a prediction phase, that given the current trajectory of a user predicts her future positions. We present the following three different prediction strategies. *Individual strategy* predicts the user future positions using only the *routines* in her *individual mobility profile*. *Collective strategy* considers the routines of all users exploiting the possibility that a user could follow a path which is systematic for another user but atypical for her. *Hierarchical strategy* uses the collective strategy when the individual one fails. It exploits the possibility to use two levels of knowledge (individual and collective), obtaining advantages from the previous strategies. The great novelty introduced by *MyWay* for which it differs from the methods in the literature is that it does not apply any apriori spatial discretization and this allows to predict the *exact* position visited by the user. Moreover, most of the state-of-art approaches use the temporal information only as a time-stamp of an ordered sequence of visited locations without exploiting it during the mobility behavior extraction and so, during the prediction.

In conclusion, *MyWay* is a flexible prediction system that empowers the user with the full control on her own data: everyone may decide not to share her profile and still can count on a powerful individual prediction strategy. We evaluate the proposed prediction strategies on large real-world data of about 5,000 users and 326,000 trajectories. Our evaluation highlights that the best prediction strategy is the hierarchical one confirming our initial intuition that the synergy between the individual and collective knowledge is the key for a better prediction. We also compare our best prediction strategy to the case of constructing the predictor on shared raw trajectories instead of shared profiles. The resulting performances of the two predictors are surprisingly very close and the small difference does not compensate the price payed for sharing raw data instead of models. By demonstrating the utility of sharing models concisely representing users behaviors, *MyWay* enables application scenarios where the users are encouraged to contribute with their self-knowledge to improve the quality of the service.

The remaining of the paper is organized as follows. Section 2 discusses some works in the literature addressing problems which are similar to our problem. Section 3 introduces some important notions which we use in our framework. In Section 4 we state the problem addressed in the paper. Section 5 describes our prediction methods. In Section 6 we describe our validation measures while in Section 7 we report a deep evaluation of *MyWay* by comparing it with the state-of-the-art. Lastly, Section 8 concludes the paper.

2. Related Work

The prediction approaches proposed in the literature can be classified on the basis of the prediction strategy used. In the literature, a lot of works addressing the location prediction problem propose methods that base the prediction only on the movement history of the object itself [4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]. We say that these approaches use the *individual strategy* for the prediction of user future positions. Some approaches of this category adopt time series analyses [4, 5] to forecast user behavior in different locations from a spatio-temporal point of view. Time series analyses enable estimations as the time of the future visits and expected residence time in those locations [4]. In this kind of works it is necessary to define the set of interesting locations to be considered in the analysis. In [5] these locations are areas defined statically while [4] provides a method for extracting significant locations among which users move more frequently. Others prediction approaches are based on Markovian processes [6] and on machine learning techniques such as classification techniques [7, 8]. In particular, in these two works the location prediction problem is treated as a *classification problem*: in [7] the location information considered for classification refers to the history of user movements that is represented by a vector of h time-ordered locations crossed by a user; while in [8] the classification tree is built based on simple, intuitive features extracted from the user visit sequence data with associate a semantic meaning. In [13] in order to capture aspects of the individual's mobility behaviors authors a modified Brownian Bridge model that incorporates linear extrapolation. Other works such as [10, 11] provide methods for the prediction of the route ahead of a moving object whose movement is constrained to a road network. Kim et al. [10] assumes that the objects' destinations are known. Finally, some works combine historical spatial and temporal data about the user with contextual in contextual data such as accelerometer, bluetooth and call/sms log [12] or with information about social relationships with friends [14].

The main problem of approaches implementing the individual strategy is that it fails in predicting future locations of non-systematic users. In these cases applying a *collective strategy* could improve the prediction. Prediction approaches belonging to this category first extract mobility behavior for each user considering only the user's movement history, like in the individual strategy, and then they merge all the individual models for the construction of the predictor [15, 16, 17].

Other approaches address the location prediction problem by using a *global strategy*, i.e., they extract movement behaviors from the movement history of all the users in the database and use this global knowledge to forecast the next location visited by a specific moving object. The basic assumption in this case is that people often follow the crowd, i.e., individuals tend to follow common paths. This strategy was followed in many papers; most of them extract frequent patterns and association rules from data [18, 19, 20, 21, 22, 23, 24, 25, 26, 27] using methods based on *Apriori*, *PrefixSpan* and *FPGrowth* techniques. Some recent works instead use probabilistic models and in particular Markovian models [28, 29, 30, 31]. Some of these approaches are suitable for predicting the next location by using GSM data [20, 23, 26, 27]; while others work well with GPS data [18, 19, 21, 22, 24, 25, 29, 30, 31]. Solutions based on GPS data typically apply a spatial discretization to make easier finding frequent or interesting locations. Two main types of discretization are applied: the first one extracts interesting places applying density based clustering techniques on spatial points [21, 25, 27]; while the second one simply uses a grid on the space, determining for each trajectory the sequence of intersected cells [18, 19, 22, 24, 25, 30]. We highlight the fact that our methods differ from these works because we do not apply apriori spatial discretization allowing us to predict the *exact* positions visited. Moreover, contrary to what most of the above approaches does, we do use the temporal information during the mobility behavior extraction and during the prediction. Some exceptions are [21, 25] which allow to choose the prediction time specifying the temporal information. Others works such as [22] base their location prediction approach on trajectory patterns which are intrinsically equipped with temporal information.

Another interesting way to exploit user mobility information for predicting the next user location, is based on the idea to combine the *global* and *individual* strategies in order to obtain more accurate predictions. In particular, the idea is to have a global predictor constructed using all users' mobility data and for each user also producing a predictive model based only on her individual movements. Therefore, during the prediction the idea is to use one of these two predictors: when using the individual predictor is not possible to provide a valid and accurate prediction then the global predictor is used [32, 33, 34, 35]. Their basic idea is similar to our *hierarchical strategy* where we provide the possibility to combine individual prediction with either the collective one or the global one. However, we differ from works [32, 33, 34] also for the spatial precision of the predictions. Indeed, [33] is based on GPS data but applies a discretization based on clustering; while the others are based on GSM data. Another interesting approach is [36] that uses a global model to improve the personalized model; here, they compute a prediction score that is a combination of the global score and individual one.

All the above works test their proposals on small synthetic or small real dataset both in terms of users and trajectories. We differ from them in testing our methodology in a big data context using a large real-world trajectory dataset.

3. Background

In this section are discussed some important notions useful to understand the prediction method and the powerful of our user-centric approach.

3.1. Mobility Profile

Movements are performed by people in specific areas and time instants. These people are called *users* and each movement is composed by a sequence of spatio-temporal points (x, y, t) where x and y are the coordinates, while t is the time stamp. We call *trajectory* the movements of a user described by a sequence of spatio-temporal points:

Definition 1 (Trajectory). *A* trajectory *m is a sequence of spatio-temporal points $m = \{(x_1, y_1, t_1), \dots, (x_n, y_n,\ t_n)\}$ where the spatial points (x_i, y_i) are sorted by increasing time t_i, i.e., $\forall 1 \leq i \leq k$ we have $t_i < t_{i+1}$*

The set of trajectories traveled by a user u makes her *individual history*:

Definition 2 (Individual History). *Given a user u, we define the* individual history *of the user as the set of trajectories traveled by her and denoted by $M_u = \{m_1, \dots, m_k\}$.*

Using the above definitions and following the profiling procedure proposed in [3], we can retrieve the systematic movements from a certain set of trajectories S. Thus, we group the *trajectories* using a density-based clustering (i.e., Optics [37]) equipped with a *distance function* defining the concept of trajectory similarity:

Definition 3 (Trajectory Similarity). *Given two trajectories m and p, a trajectory distance function* dist *and a distance threshold ε, we say that m is* similar *to p iff $\mathrm{dist}(m, p) \leq \varepsilon$.*

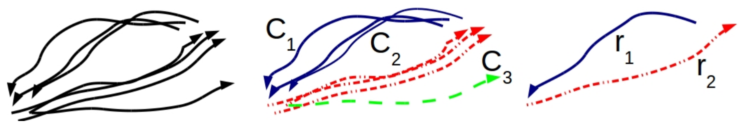

Figure 1: The user *individual history* (black lines), the clusters identified by the grouping function (C_1, C_2, C_3) and the extracted *individual routines* (r_1, r_2) forming her *individual mobility profile*.

The obtained result is a partitioning of the original dataset from which we filter out the *clusters* with few trajectories and the one containing noise. Finally we extract a *representative trajectories* from each remained cluster. These *representative trajectories* are called *routines* and the set of routines is called *mobility profile*. More formally:

Definition 4 (Routine and Mobility Profile). *Let S a set of trajectories, ms a minimum size threshold,* dist *a distance function and ε a distance threshold. Given a grouping function* $\text{Group}(S, ms, \text{dist}, \varepsilon) = \hat{C}$*, such that $\hat{C} = \{C_1 \dots C_k\}$ where $C_i \subset S$, we define a* routine *r_i as the medoid trajectory of a group C_i. The set of routines extracted from $\hat{C}$ is called* mobility profile *and is denoted by $P = \{r_1 \dots r_k\}$.*

The *mobility profile*, which is the key concept of *MyWay*, describes an abstraction in space and time of the systematic movements: the user's real movements are represented by a set of trajectories describing the generic path followed. We must notice that the exceptional movements are completely ignored due to the fact they are not part of the profile (i.e. they are part of the *small clusters* or of the *noise*).

When the routines are computed starting from the set of *individual history* - i.e. S is equal to M_u of a user u - we obtain *individual routines* and an *individual mobility profile* P_u. Fig.1 depicts an example of individual mobility profile extraction. Moreover, given the set of users U, we name *collective mobility profile* P_C the set $P_C = \bigcup_{u \in U} P_u$ containing all the *individual routines* of the considered users.

3.2. Personal Mobility Store

Human mobility data and the knowledge that data mining can extract from it are an invaluable opportunity for organizations and individuals to enable new applications. Unfortunately, today users have a limited capability to control and to exploit their personal data. The need of user data control is leading to a change of perspective towards a *user-centric* model for personal data management. This vision is compatible with the data protection reform of EU and is promoted by World Economic Forum in own last report [38].

The basic idea is to introduce high levels of transparency and full control for the user on the lifecycle of own personal data (e.g., collection, storage, processing, sharing). Therefore, any user should have a *personal data store* that helps her in gathering, storing, managing, using and sharing her own data under her own control. Personal data stores may focus on particular areas such as "health", "education" and so on. In this paper we consider that any user stores all information about her movements on her own personal data store that we call *personal mobility store* (PMS).

The user's PMS may contain both trajectory data generated by her mobility but also more sophisticated knowledge extracted from this data as the individual mobility profiles described above.

4. Problem Definition

The problem we want to face consists in predicting the future positions visited by a user at specific time instants by exploiting the typical mobility behavior of users in the system. The different formulation of the problem and the possible solutions are determined by the type of the object, the area in which it is moving, the kind of prediction returned and how the notion of future is defined. The main challenge of this problem is due to the complexity and fine granularity of GPS data. Often, most of the works in the literature apply a spatial discretization by using clustering techniques on spatial points or simply a grid on the space to reduce the complexity of the problem. Clearly, on one hand, this makes easier finding frequent or interesting locations and patterns to be exploited in the prediction; on the other hand, it impacts on the precision of the prediction that often returns *regions* with a granularity imposed by the apriori discretization.

In this paper we want to study a prediction method that do not use any apriori spatial or temporal discretization and that, given a user u and her current trajectory m, aim at forecasting the future *exact* position visited by the user u at a specific time instant t. This task is composed of two main steps: *(i)* learning a prediction model by observing historical movement data, and *(ii)* applying the prediction model to forecast the future positions. In the following, we propose *MyWay*, a system of prediction strategies capable to solve this challenging task.

5. The prediction system MyWay

In this section we present the details of *MyWay*, a system for predicting the future user's position. It exploits the users systematic mobility stored in their PMS, i.e., the user individual mobility profile, and the knowledge coming from the crowd in the form of collective profile. To build such models we refer to the mobility profiles presented in Section 3, but for our purpose we define a new distance function between trajectories which is more efficient and gives a better result in terms of profile quality (with respect to the distance function used in [3]). Then, we define the prediction method, two basic prediction strategies called *individual* and *collective*, and a third strategy that combines the basic ones, called *hierarchical*.

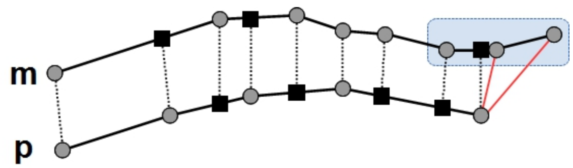

Figure 2: Computation of *Interpolated Route Distance*. The circular gray points are the real points, the black squares are the interpolated ones. The dotted lines are the spatial distances calculated.

5.1. Distance Functions

The mobility profile extraction process uses a distance function during the clustering step to identify *similar* trajectories. The distance function is used in the mobility profile extraction during the clustering process to identify *similar* trajectories, as describe in Section 3. In pratice the distance function defined between two trajectories determines if they are representing similar movements in space and time. There are many possibilities in defining such distance. Some examples are described in [39] (i.e., the one used in [3]) and in [40], and each one analyzes a different perspective and is used for a particular objective. Another important aspect to consider is the complexity of such distance function which greatly affects the performance of the whole process.

In the work presented we define a distance function suitable for our purposes called *Interpolated Route Distance* (IRD): it temporally aligns the two trajectories m and p using the initial time, then for each time in m it interpolates a point in p – if it does not exist – and viceversa. Finally, it computes the spatial distance (spherical) between each pair of aligned points (real or interpolated). When one of the two trajectories has a longer duration the exceeding part is compared with the last point of the other (i.e. we consider as if the user stops at the last point when a trajectory ends). The average of those distances is the result of IRD. Fig.2 and Algorithm 1 show how IRD is computed. We adopted a different distance function from [3] for the following reasons:

Sampling rate: *Route Similarity* is affected by the GPS sampling rate of the trajectories assuming that both of them have the same rate in at the same time. This is not true for our data and the bias introduced by may produce anomalous effects.

Efficency: *Route Similarity* is highly inefficient comparing several time the same point to others.

Moreover, for our purposes we also defined a slight variation of *IRD*- We call this distance function *Constrained IRD* (CIRD) since, besides the two trajectories, it takes as input also two parameters (γ, σ) called respectively *tail percentage* and *prediction threshold*. These parameters are used to verify if in the last $\gamma\%$ of the trajectory m exists a point which is further than σ meters from the trajectory p. If this happens the distance function returns a special value representing an *infinite distance*, i.e., it considers the two trajectories not comparable. An example of the portion of trajectory influenced by the constraint is depicted in Fig.2 as a blue box.

Algorithm IRD (Trajectory t_1, Trajectory t_2)
Result: Distance d
$d \leftarrow 0$;
$i_1 \leftarrow 1$, $i_2 \leftarrow 1$;
$p_1 \leftarrow \text{getPoint}(t_1, i_1)$, $p_2 \leftarrow \text{getPoint}(t_2, i_2)$;
while $\neg(i_1 = \text{getSize}(t_1) \wedge i_2 = \text{getSize}(t_2))$ **do**
  $d \leftarrow d + \text{sphericalDistance}(p_1, p_2)$;
  $len_1 \leftarrow \infty$;
  $len_2 \leftarrow \infty$;
  if *($i_1 < \text{getSize}(t_1)$)* **then**
    $len_1 \leftarrow \text{sphericalDistance}(p_1, \text{getPoint}(t_1, i_1 + 1))$;
  end
  if *($i_2 < \text{getSize}(t_2)$)* **then**
    $len_2 \leftarrow \text{sphericalDistance}(p_2, getPoint(t_2, i_2 + 1))$;
  end
  if *($len_1 < len_2$)* **then**
    $i_1 \leftarrow i_1 + 1$;
    $p_1 \leftarrow \text{getPoint}(t_1, i_1)$;
    $p_2 \leftarrow \text{getNearestPoint}(t_2, p_1)$;
  else
    $i_2 \leftarrow i_2 + 1$;
    $p_2 \leftarrow \text{getPoint}(t_2, i_2)$;
    $p_1 \leftarrow \text{getNearestPoint}(t_1, p_2)$;
  end
end
return d;

Algorithm 1: IRD distance function where getPoint return the i^{th} point in the trajectory (e.g. i=1 indicates the first point), sphericalDistance return the spherical distance between two points, and getNearestPoint given a point and a trajectory find the nearest interpolated point to the segments of the second (i.e. the square points in Fig.2).

5.2. Prediction Method

We define the prediction method as a function over a mobility profile which, given the current trajectory m, returns the *exact* future position s of the user after a time period $\hat{t}$. More in detail, the prediction method is composed of two functions: *Match* which finds in the profile the routine most similar to the current trajectory, and *LookAhead* which predicts the future position having a routine and the current user position.

Definition 5 (Match). *Let γ and σ the CIRD parameters. Given a trajectory*

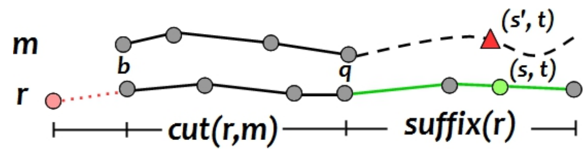

Figure 3: Match example between the current movement m and the routine r.

m, and a mobility profile $P = \{r_1 \dots r_n\}$, the routine r is selected if:

$$r = \text{Match}(m, P, \gamma, \sigma) = \underset{r_i \in P}{\arg\min}\, \text{CIRD}(\text{Cut}(r, m), m, \gamma, \sigma)$$

In the above definition, $\text{Cut}(r, m)$ selects the sub-trajectory of the routine defined between two points: q that is the closest point (real or interpolated) to the last point of the trajectory m, and b that is the temporally antecedent point which makes the length of the sub-trajectory equal to m. If the routine is not long enough b is the first point. The usage of CIRD (and therefore γ and σ parameters) represents our interest in eliminating false positive given by common initial parts of the trip. The routines which make the distance undefined are not considered as *match-able* and are excluded from the computation. If P is empty, undefined or CIRD returns an infinite distance for each $r \in P$, than the process ends without any routine for the match, that is r is *undefined*. The process of matching the trajectory m with a routine r is shown in Fig.3 where in solid black we represent the portions that are compared, while in dotted red and green the parts ignored for the matching.

Once r is obtained, i.e., the most similar routine to the current trajectory m, than we can use it to predict the position within a time period as follows:

Definition 6 (LookAhead). *Let m be the current trajectory, r a routine and $\hat{t}$ a time period. Having $q = (x, y, t)$ as the closest point in r to the user current position, i.e. the last point of m, we define $\text{LookAhead}(r, m, \hat{t}) = s$, where s is the predicted point in r at time $t + \hat{t}$. When the routine is not defined at time $t + \hat{t}$, s is the final point of r.*

The combination of *Match* and *LookAhead* realizes the prediction methods used for all the strategies in *MyWay* system. More formally we can define a predictor as:

$$s = \text{Pred}(m, P, \hat{t}, \gamma, \sigma) = \text{LookAhead}(\text{Match}(m, P, \gamma, \sigma), m, \hat{t})$$

where m is the current trajectory, P a mobility profile, $\hat{t}$ a time period, and s a point which is the resulting prediction. The difference between the three strategies is how the method is used. We must notice that if the result of Match is undefined, than also s will be *undefined*.

The *individual strategy* predicts the future positions of a user by exploiting only the systematic behavior of the user herself. Therefore, it is particularly

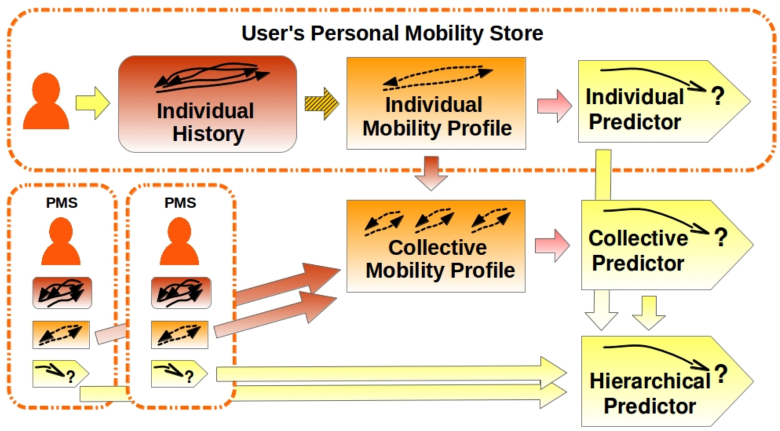

Figure 4: MyWay prediction strategies schema.

suitable for users having an high degree of systematic mobility. More formally, we define the *individual predictor* for a user u as: $s = \text{Pred}(m, P_u, \hat{t}, \gamma, \sigma)$.

The *collective strategy* considers the routines of all users for the prediction, thus exploits the possibility that a user could follow an atypical path for her but systematic for another user. More formally, we define the *collective predictor* as: $s = \text{Pred}(m, P_C, \hat{t}, \gamma, \sigma)$.

The *collective strategy*, mixing up all the user's routines with the routines of the crowd, loses the added value of knowing the individual mobility profile of a specific user which enables very accurate predictions. For this reason we define the *hierarchical strategy* as a composition of the two basic ones:

$$s = \begin{cases} \text{Pred}(m, P_u, \hat{t}, \gamma, \sigma) & \text{if } defined \\ \text{Pred}(m, P_C, \hat{t}, \gamma, \sigma) & otherwise \end{cases}$$

It first uses the individual predictor, and if it cannot find a prediction, the collective one is used. In other words, the idea behind the hierarchical strategy is to recognize the specificity of the individual profile compared to the collective profile.

The resulting three predictors are shown in Fig.4, depicting how the individual history, the individual profile and the *individual predictor* are inside the user PMS, while the *collective predictor* is outside and therefore handled by a third party that orchestrates the users' information as well as the *hierarchical predictor*. This third party, usually called *coordinator*, has the responsibility for the storage and management of the users' profiles. Our experiments will show how the hierarchical strategy achieves the best performances.

6. Evaluation Measures

In this section we present some measures used to evaluate the prediction results. It is important to note how the proposed method is challenging a very

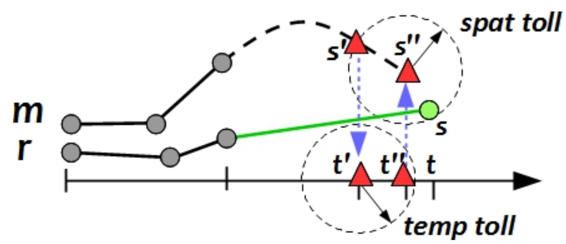

Figure 5: Example of usage of the spatial and temporal tolerances: the red triangles are the real points s' and s'' such that $|t' - t''| \leq temp_{tol}$, the green circle is the predicted point such that $\|s - s''\| \leq spat_{tol}$.

hard prediction problem due the following considerations: *(i)* users do not move every time in the same period of the day (at least not exactly); *(ii)* movement speed is not constant during the travel, even following the same route; *(iii)* possible errors deriving from spatial sampling of the data could influence deeply the predicted position both in time and space. Consequently, it is reasonable to consider a set of tolerances to fairly evaluate the results. In the following, we will use $spat_{tol}$ and $temp_{tol}$ to describe the spatial and temporal tolerances which generate a spatio-temporal area around the real point. This area contains all the values considered correct for the prediction problem. An example of usage of these tolerances is shown in Fig.5.

Definition 7 (spatio-temporal tolerance). *Given the predicted position s at time t, the real position s' at time t', and the position s'' at time t'' that is the closest real position to s such that $|t' - t''| \leq temp_{tol}$, then the prediction is considered correct if and only if $\|s - s''\| \leq spat_{tol}$.*

It is worth to underline that if $temp_{tol} = 0$ then $s' = s''$ and thus we are predicting exactly the point where the user will transit in future without any temporal tolerance. To enhance the importance of $spat_{tol}$ we can consider tow different environments for applying prediction. For example, taking into account an academic campus, it is completely meaningless to adopt $spat_{tol}$ greater than kilometers because nearly every prediction would be classified as correct. On the other hand, if we are considering tool roads then low $spat_{tol}$ would be inadequate.

Furthermore, let $\mathcal{TS}$ be the set of trajectories for which we want a prediction, $\mathcal{TP}$ the set of trajectories for which a prediction is provided, and $\mathcal{TPC}$ the set of trajectories for which the future spatio-temporal position is correctly predicted, then the following validation measures are defined:

- *Prediction rate* $= \frac{|\mathcal{TP}|}{|\mathcal{TS}|}$ allows to estimate the predictive ability and corresponds to the percentage of trajectories for which a prediction is supplied;
- *Accuracy rate* $= \frac{|\mathcal{TPC}|}{|\mathcal{TP}|}$ allows to estimate the prediction goodness and corresponds to the percentage of future spatio-temporal positions correctly predicted;

- *Spatial Error* $= \frac{\sum_{\forall(s,s'')} \|s-s''\|}{|\mathcal{TP}|}$ allows to estimate the error of the predictions (both correct and incorrect).

7. Experiments

In this section we evaluate *MyWay*'s prediction strategies performances.

7.1. Experimental Setting

Dataset. As a proxy of human mobility, we used real GPS traces collected for insurance purposes by *Octo Telematics S.p.A.* This dataset contains 9.8 million car travels performed by about 159,000 vehicles active in a geographical area focused on Tuscany in a period from 1st May to 31st May 2011[1]. From this dataset we selected only the users traveling through Pisa province with at least 20 travels considering only week-days. Considering that in Pisa province there are about 476,260 trajectories, this led to a dataset with 30% of the all users and 80% of the all trajectories, that is about 5,000 users and 326,000 trajectories. We considered as training set the first 3 weeks and as test set the remaining last week. We tested *MyWay* using two different test sets: one got by considering only the first 33% of each trajectory ($test_{33}$), and one by considering the first 66% ($test_{66}$). These two test sets represent two levels of knowledge of the current movements and we will show how they affect accuracy and prediction rate.

User's Profiles. We extracted from the training set three different collections of individual mobility profiles P_{100}, P_{500} and P_{1000} obtained by using the following distance threshold values: 100, 500, 1000 meters. We analyze some statistics of these profiles for selecting the more promising for our prediction strategies. The aspects we consider are: *(i)* the dataset coverage, *(ii)* the profile distribution per user, and *(iii)* the profile distribution in time. In Fig.6(left) the number of routines per users is shown. The first important aspect to notice is the coverage of the dataset, in fact for P_{100} we have only the 57,9% of the users with at least one routine against the 72.7% for P_{500} and the 77.4% for P_{1000}. Moreover, we observe that both P_{100} and P_{500} have two peeks at 0 and 2 representing respectively, the users without regularity and the users with common behavior *home-work and back*. Instead, P_{1000} has a lot of users having only one routine. This happens usually when the behaviors are mixed together by the clustering algorithm due a too permissive threshold. Finally, in Fig.6(right) the temporal distribution of the trajectories and routines is shown. It illustrates how all the three profile sets follow the same trend of the trajectory data, highlighting the three peeks during morning, lunchtime and evening. In this case, we can see how P_{100} is too strict eliminating a lot of mid-frequent behavior while P_{500} and P_{1000} are more similar to the original data allowing a

[1]This dataset can't be shared due the country privacy law, we are working with the data provider in order to find a way to share at least a sample.

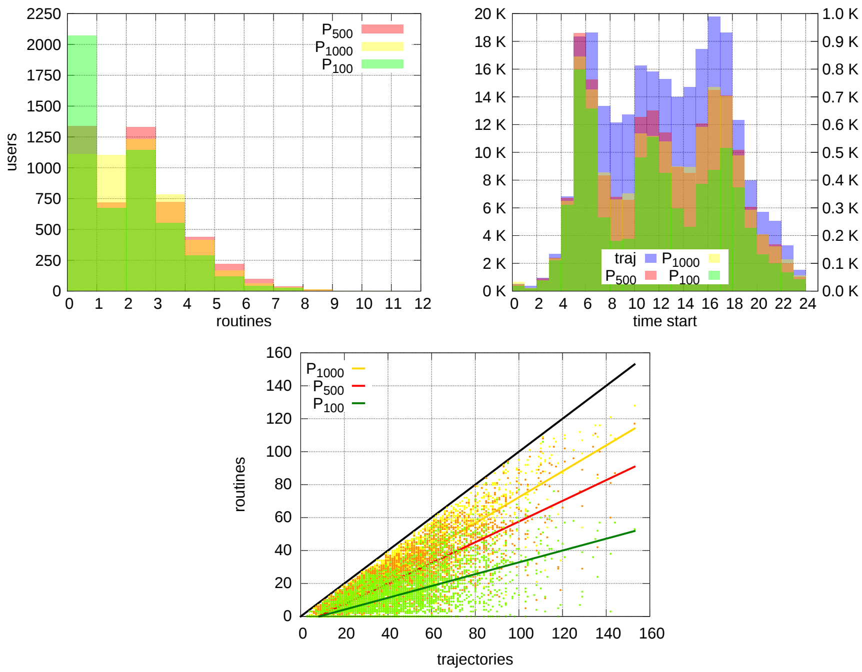

Figure 6: Routines per user distribution (left), trajectories and routines time start distribution (right) and the dataset coverage (bottom).

better representation of the reality. From this empirical study we decided to use P_{500} because the used threshold is not so strict to eliminate all the secondary behaviors, but also not so permissive to mix the home-work/work-home behaviors. Moreover, in Fig.6(bottom) the dataset coverage is studied. We considered *covered* a trajectory which is represented by a profile in the resulting set. Here the difference between the P_{100} and P_{500} compared with the difference between P_{500} and P_{1000} shows how the increasing of the threshold does not correspond to the same increasing of coverage. In other word the set P_{500} represents a good trade-off considering the coverage and the quality of the profile extracted.

7.2. Prediction Evaluation

Individual Strategy. The individual prediction consists in using the mobility profile of a single user to predict her future positions. In Fig.7 the accuracy obtained over the two test sets $test_{33}$(left) and $test_{66}$(right) is shown. Here, different levels of spatial tolerance $spat_{tol}$ are used (from 50 m to 1 km) with a temporal tolerance $temp_{tol}$ of 30 seconds. The first aspect to notice is how varies the accuracy for different time periods $\hat{t}$ used for the look ahead: the prediction for very short-term (1-5 minutes) is lower than the mid-term (5-20 minutes). This is due to the fact that in the short-term predictions the speed of the current movement may be very different from that in the routine, e.g., an

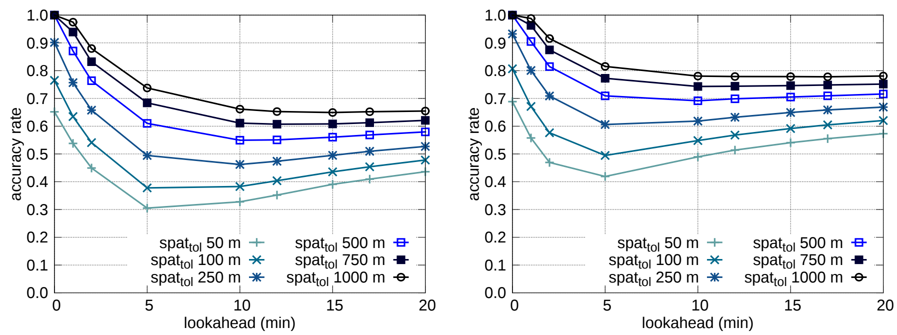

Figure 7: (Individual) Accuracy rate on $test_{33}$(left) and $test_{66}$ (right) using a $temp_{tol}$ of 30 sec, different $spat_{tol}$ values and varying the look ahead.

extemporary acceleration, deceleration or a traffic light may affect the prediction accuracy. On the other hand, for the mid-term prediction the speed tends to be similar to the average speed and the prediction becomes more precise. For example, considering a variation of speed of $30km/h$ in one minute we have a spatial difference of 500 meters. Clearly, using an higher temporal tolerance this effect disappears, but this strongly depends on the application in which the prediction is used. The second aspect to notice is the higher accuracy rate in $test_{66}$ w.r.t. $test_{33}$. This happens because in $test_{66}$ the knowledge on the current movement is higher and therefore our method is able to better understand which is the best routine to use. The third aspect, shown in Fig.8(left), is the prediction rate that is higher in $test_{33}$ than in $test_{66}$. The limited knowledge on the current movement allows the predictor to match more routines even though they are not the exact future trajectory. In details, passing from $test_{33}$ to $test_{66}$, we have an increasing of $10-15\%$ for the accuracy rate and a decrease of $5-8\%$ for the prediction rate. This behavior is really interesting because highlights how $MyWay$ reacts to the information gained from the query or, in other words, how it can tune the prediction in a real scenario as the user proceed along her travel.

In Fig.8 the prediction rate (left) and the accuracy rate (right) are studied varying the prediction threshold. We observe that relaxing this threshold the two measures respectively increase and decrease. Allowing a more loose matching in the end part of the current trajectory more predictions are produced (due to the constraint in CIRD); on the other hand, the accuracy rate decreases but it is important to note how this is not proportional. In other words, the prediction method shows another feature: it is possible to tune the system according to the application needs in order to be more *conservative* - i.e. if the errors in prediction are considered critic fails - or *speculative* -i.e. having a prediction is better even if we introduce errors. Note that the *prediction tale* γ parameter is not shown due to the lack of space but extensive tests revealed that it enhances the prediction threshold effect.

To better understand the quality of the prediction, we study the relation

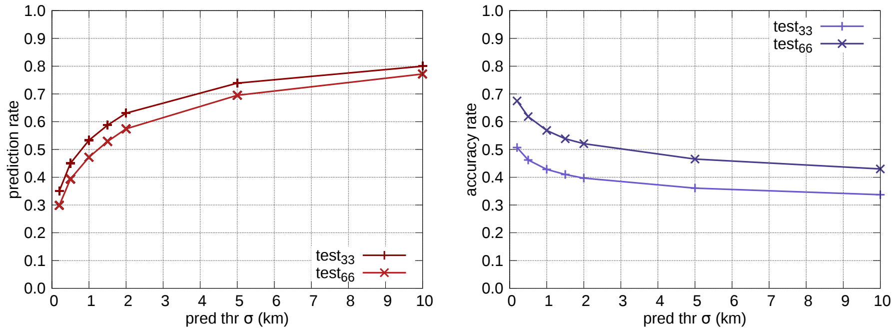

Figure 8: (Individual) How the prediction threshold affects the prediction and accuracy rate using a $spat_{tol}$ of 250 m and a $temp_{tol}$ of 30 seconds.

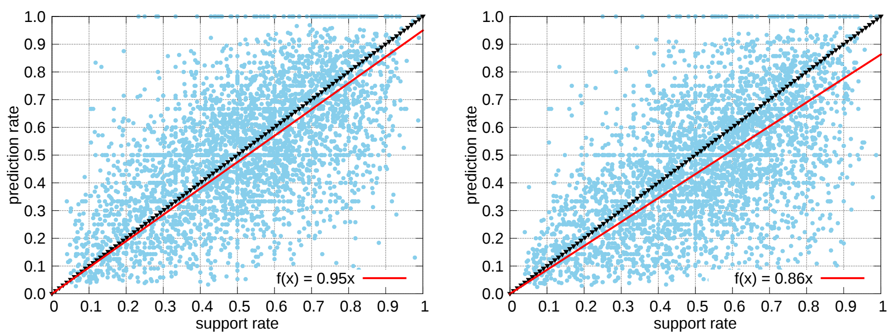

Figure 9: (Individual) Predictability of users vs. prediction rate.

between the *users' predictability* and the prediction rate obtained with this strategy. For this analysis we consider: the prediction rate and the *support rate*, defined as the ratio between the number of trajectories represented by the routines and the number of trajectories in the individual history. The result is shown in Fig.9 where each point refers to a user and in red we represent the linear regression of those points. The dotted black line represents the performance of a theoretical perfect system which matches exactly all the movements to the proper routine. If the user's routines cover $k\%$ of her movements, the theoretical system is able to predict a maximum of $k\%$ of the trajectories because the rest is composed by not systematic movements that are unpredictable using the user's mobility profile. Comparing the two lines we can notice how our system is close to the theoretical one.

Finally, we analyze the spatial error of the predictions shown in Fig.10. We observe on the left how the spatial error increases considering higher look-ahead values, and it slightly decreases with higher value of $temp_{tol}$, while on the right we can see the effect of a higher prediction threshold which makes *CIRD* more *permissive* and therefore the spatial error increases.

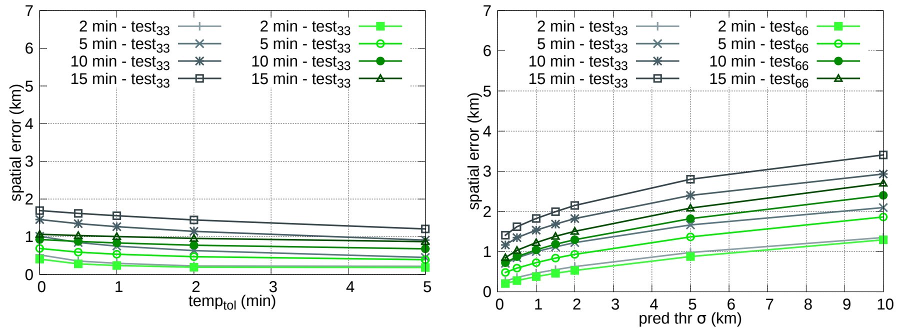

Figure 10: (Individual) The spatial error using $test_{33}$ and $test_{66}$ varying the $temp_{tol}$(left) and the prediction threshold (right).

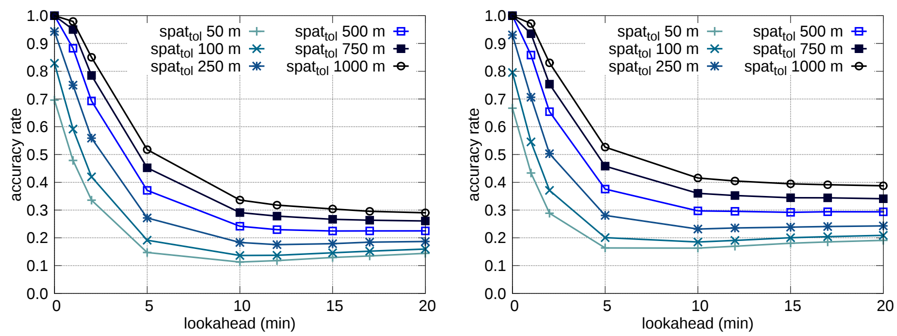

Figure 11: (Collective) Accuracy rate on $test_{33}$(left) and $test_{66}$ (right) using a $temp_{tol}$ of 30 sec, different $spat_{tol}$ values and varying the look ahead.

Collective Strategy. The collective strategy uses the collective mobility profile composed by the union of all the individual profiles (Sec.3). In Fig.11 the accuracy and the prediction rate over the two test sets are reported. We notice how the collective strategy presents a decrease of $15-20\%$ in accuracy, while the prediction rate is increased by a $30-45\%$ obtaining values greater than 85% as shown in Fig.12. The effect of the collective knowledge strongly increases the performances, indeed almost all the queries have a prediction even if their quality decreases. This is due to the fact that we are using strangers behaviors to predict the user's movements.

Moreover, Fig.13(left) shows how this strategy overcomes the predictability limitation: the red line is over the black dotted one representing the fact that the prediction rate for most of the users is over the support of their profiles. Looking at the spatial error, Fig.13(right), and comparing it to the individual strategy we note that it increases following the lower accuracy rate provided by this strategy.

Hierarchical Strategy. The idea behind the hierarchical strategies is to recognize the specificity of the individual profile compared to the collective pro-

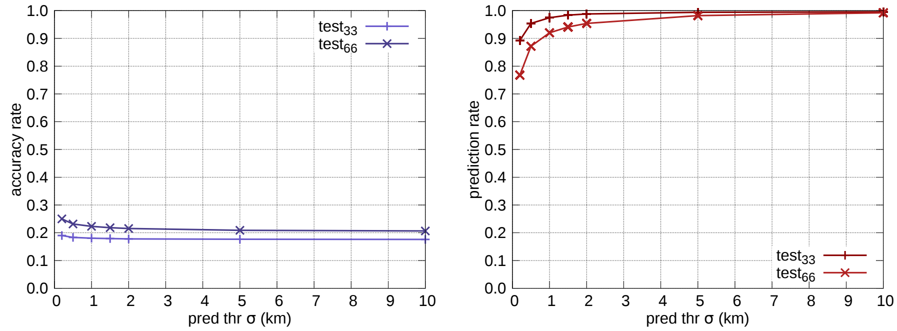

Figure 12: (Collective) How the prediction threshold affects the prediction and accuracy rate using a $spat_{tol}$ of 250 m and a $temp_{tol}$ of 30 seconds.

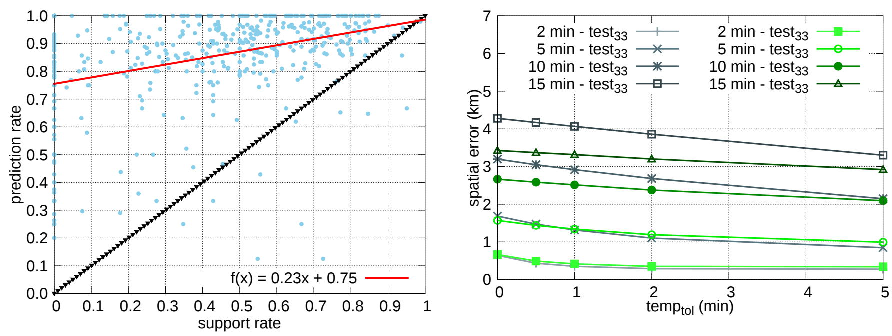

Figure 13: (Collective) Predictability of users vs. prediction rate (left) and the spatial error varying the $temp_{tol}$ (right).

file, in other word it consists in using the user's individual profile and, in the case it fails, in using the collective profile. Obviously this strategy achieves the same prediction rate of the collective one because in the worst case this last strategy is used while, as expected, the evaluation results show an increasing of accuracy equal to 10% as shown in Fig.14. Therefore the hierarchical strategy outperform the basic versions realizing the best trade-off between accuracy and prediction rate. Analyzing Fig.15 we can notice that the spatial error, as well as the accuracy rate, is mitigated by the two levels of prediction showing a decreasing in every combination of the parameter values.

7.3. Data Sharing vs Profile Sharing

Now, we want to compare *MyWay* with a *global predictor* extracting the routines directly from raw data. In other words, we performed the profiling process considering the set S of trajectories in Def. 4 equal to all the trajectory data. In this way we obtain *global routines* and a *global mobility profile*. Note that, a global routine, instead of representing the systematic movement of an individual, represents a *common behavior* of the crowd. In Fig.16 and 17(left)

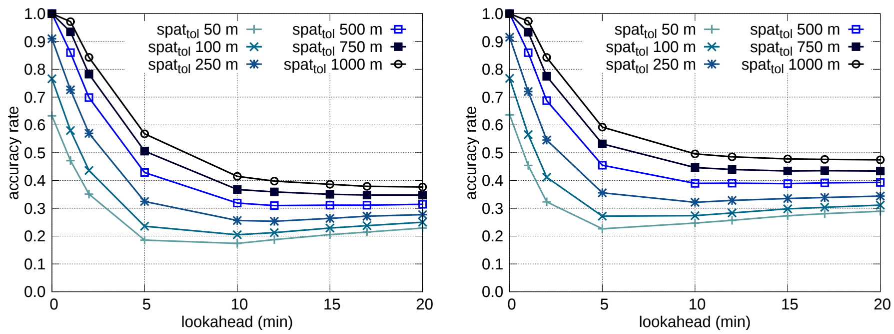

Figure 14: (Hierarchical) Accuracy rate on $test_{33}$(left) and $test_{66}$(right) using a $temp_{tol}$ of 30 sec.

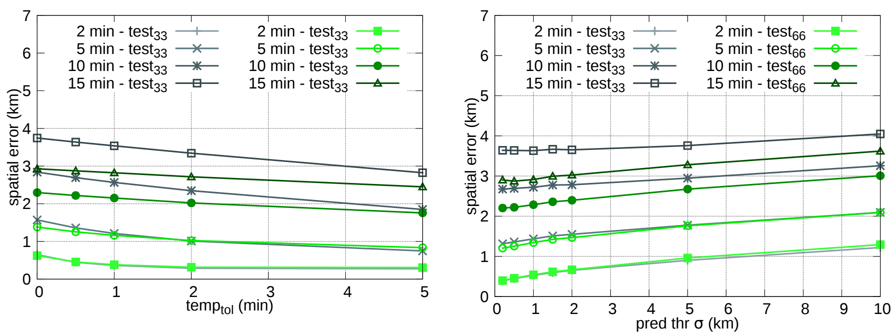

Figure 15: (Hierarchical) The spatial error using $test_{33}$ and $test_{66}$ varying the $temp_{tol}$(left) and the prediction threshold (right).

we report the prediction performances of the *global predictor*. We observe that its prediction rate is substantially the same of our collective strategy, and its accuracy rate increases of less than 3%. This means that for the prediction task the global profile does not increase significantly the level of knowledge. In other words, compared with the collective profile some routines are missing due to the higher level of abstraction. Moreover, some new routines, composed by a *common not systematic behavior*, are created but the overall prediction power remains similar. This is also confirmed in Fig.17(right) showing that the collective profile covers the global profile and viceversa. The containment between them highlights that they substantially represent the same set of behaviors. Fig. 18 shows as the hierarchical approach applied in the global context (individual/global combination) improves the accuracy rate leading to similar performances of our hierarchical strategy.

Furthermore, we observe that *MyWay* presents some other advantages w.r.t. the global predictor.

Data disclosure. A *global predictor* requires that the user shares with the coordinator her individual history that describes in detail all her movements;

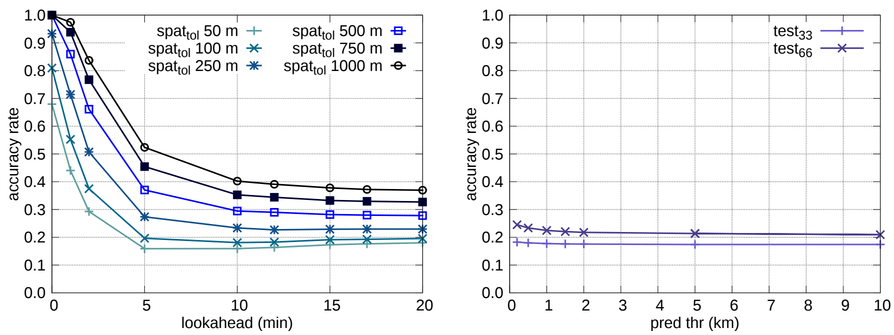

Figure 16: (Global predictor) Accuracy rate on $test_{66}$ using a $temp_{tol}$ of 30 seconds (left) and comparison between $test_{33}$ and $test_{66}$ varying the prediction threshold σ (right).

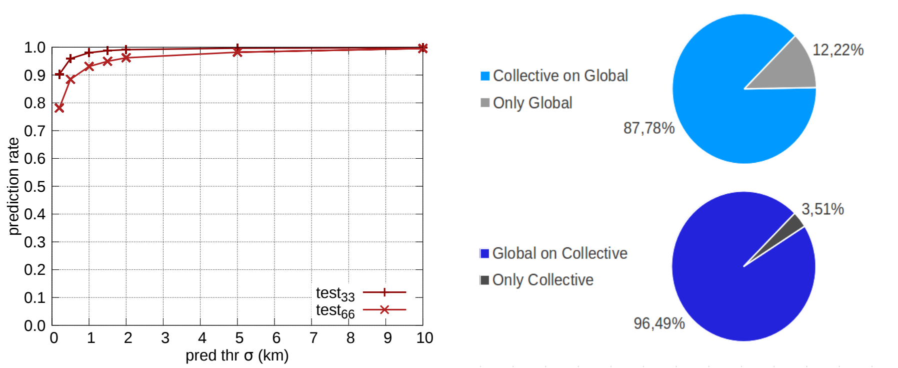

Figure 17: (Global predictor) Prediction rate (left), collective and global coverage (right).

on the contrary, *MyWay*, in the worst case, requires to disclose only the *individual mobility profile*, a model that surely reveals the user mobility behavior with less details. This aspect is very important because today, people are often reluctant to share personal information because in the current systems users have a limited capability to control and exploit it. Therefore, in order to enable applications that require the active participation of people, it is necessary to encourage individuals in contributing with their self-knowledge to improve the quality of services offered by those applications. The opportunity of sharing models instead of detailed trajectories without causing deterioration of the performances is a good advantage of our system.

Communications. The need of sharing all raw data also raises a problem in the communications cost needed to transfer all the data from all the users to the coordinator. With *MyWay* we can transmit only the information which is really needed for the prediction (routines) leading to a reduction of more than 97% of the data (i.e., spatio-temporal points). This is essential for a realistic application which wants to gather information from a wide number of users.

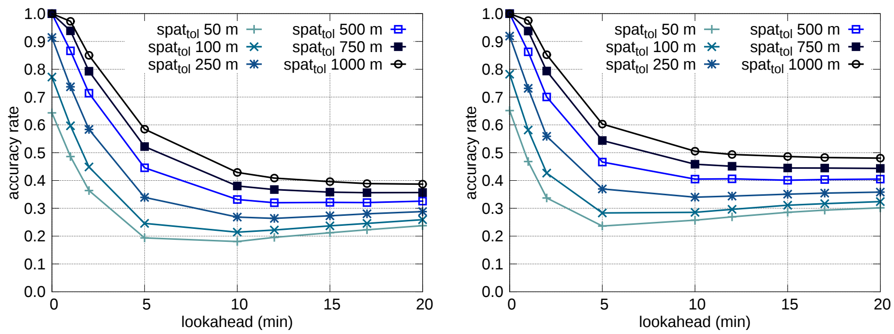

Figure 18: (Hierarchical approach with global predictor) Accuracy rate on $test_{33}$(left) and $test_{66}(right)$ using a $temp_{tol}$ of 30 seconds.

Computational cost. The main difference between the profile extraction in the collective and global predictor is the fact that the first is composed of the union of the individual profiles computed locally by the users, while the second is the profile extracted from the whole data computed by a coordinator. This means that we have $O(\sum_{u \in U} |M_u|)$ for the collective predictor and $O(|\bigcup_{u \in U} M_u|)$ for the global one. Considering that the number of trajectories per user is significantly lower (of orders of magnitude) than the entire dataset, we can appreciate the great advantage of our system in terms of computational cost. For our experiments we obtained an average runtime of 10 seconds for the individual profile (which are computed at individual level), and more than 8 hours for the construction of a global profile (computed on a centralized server).

Profile update. Profiles extracted cannot last forever: the mobility of the users may change significantly during different periods, thus it is reasonable to consider a method to update the profiles in a running system. In the collective strategy we can suppose to have at individual level a method to check if the last profile is still valid or not - e.g., considering the profile coverage over the most recent user's trajectories. In the case of a variation, the user recomputes a new model, sends it to the coordinator updating the collective profile by substituting the old user's profile with the new one. In the global scenario this is not possible, in fact the user must send continuously her data to the coordinator which periodically recomputes the overall profile to remain up-to-date.

For all these reasons we believe that *MyWay* represents the *best way* to build a realistic predictive system able to deal with a real big data context.

7.4. Comparing with State-of-Art

In this section we compare the prediction performances of *MyWay* with individual and global competitors.

Individual Competitor. First, we compare our prediction system with the machine learning based individual predictor presented in [7]. Since this method uses an apriori spatial discretization, for a fair comparison we decided to use a grid that strongly affects our results. In particular, we perform the

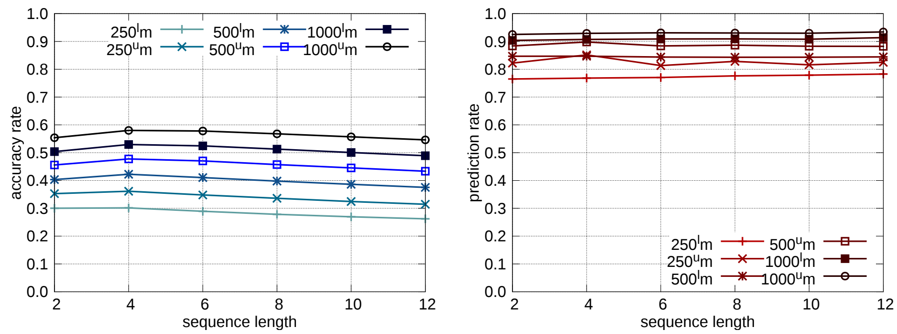

Figure 19: Individual competitor performances using different values of sequence length and grid side.

comparison constructing for each spatial tolerance (250, 500 and 1000 meters) two different kinds of grid. The first one has a cell side equal to the square inscribed in a circle with radius equal to our spatial tolerance (lower bound x^l); while the second one has a cell side equal to the square inscribing this circle (upper bound x^u). Note that, this approach does not use any notion of lookahead, i.e., it cannot predict the future position after a specified time interval from the current time, but it can just predict the next cell. It deals with trajectories represented as sequences of cells in a grid. We reimplement and test this method on our individual routines showing the performances in Fig.19. As in [7], we discretize the trajectories in sequences of length h and we studied the goodness of a prediction varying this value. Note that, we use our individual routines instead of the starting dataset of trajectories because in [7] the authors state that they use systematic movements. Comparing the performances of our *individual strategy* (Fig. 7 & Fig. 8) with this competitor, we can see that our method provides more accurate predictions. This is true even if we consider for the competitor the sequence length that gets the best results. However, the machine learning predictor gets an higher prediction rate w.r.t. our individual strategy. Nevertheless, as shown above, we can overtake this lack by using our hierarchical strategy. Moreover we also test our individual predictor using an infinite $temp_{tol}$ in order to exclude the time dimension (not considered by the competitor) and using $spat_{tol} = 500$ we obtain a prediction rate of 87% and an accuracy over 70% which are clearly higher than the competitor performances for any value of h.

Global Competitors We also compared our proposal with method presented in [22], called WhereNext, that uses a pattern based methodology to predict the next cell of a movement. This is a global approach and considers all the trajectories to generate *trajectory patterns* that contain the information on the travel time between two consecutive cells. The global method differs completely from the collective one, which combines the set of individual profiles, because only the behavior followed by the crowd will survive to the process of extraction. WhereNext is just able to predict the next cell and the time spent

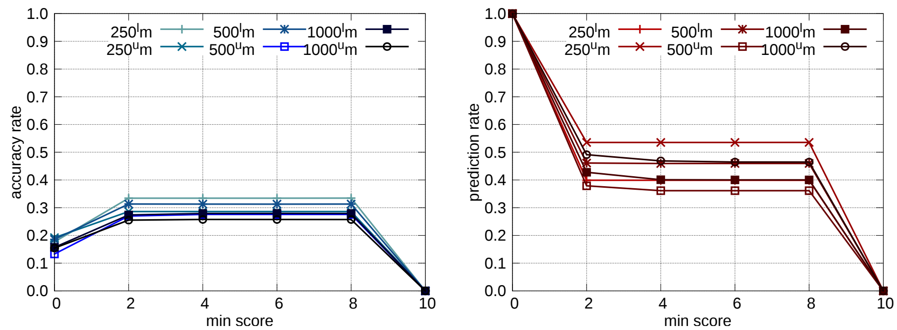

Figure 20: WhereNext performances using different value of minimum score and gride size.

on average for moving from the current cell to the next one. Since even this method applies a spatial discretization, we use the same grid defined above. The goodness of predictions got by WhereNext depends on the quality of trajectory patterns and on the *minimum score* used to consider admissible a prediction. In Fig.20 the results of this competitor are shown for the different grids. Comparing them with *MyWay*, we can see that our *individual strategy*, in general, performs better than WhereNext in terms of both accuracy and prediction rate. While considering the *collective strategy* we pay the increasing of the prediction rate - 40% greater than WhereNext - with decreasing of accuracy which let the competitor win using the 250 grid with an advantage of 5%. This disadvantage disappear if we compare WhereNext with the *hierarchical strategy*.

7.5. Participation Analysis

In the experiments we shown before we considered a complete participation of the users, but in reality *MyWay* users may choose: *(i)* to contribute to the collective knowledge sharing their profiles obtaining a better service using the hierarchical strategy or *(ii)* to maintain their profile private using only the individual strategy. Therefore we studied how the participation of the user effects the overall performances by analyzing the prediction rate and the accuracy varying the percentage of users sharing their profiles. Fig.21 shows the two measures and the overall performances in the two test cases. This result fills the gap between the individual strategy and the hierarchical one which are represented by 0% and 100%. We observe how a greater sharing of routines enables better performances. In particular, the prediction rate dramatically increases at each step, while the accuracy slightly decreases. This happens because a larger number of trajectories become predictable allowing more possible error thanks to the rapid increase of the predictive power, but the overall performances clearly improve.

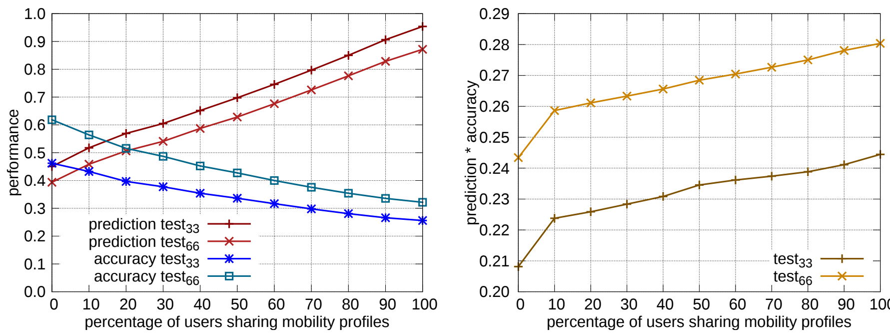

Figure 21: Increasing the participation of the users the prediction rate increase loosing some accuracy (left), but the overall performance rises (right)

8. Conclusion and Future Work

In this paper, we have proposed *MyWay*, a system for predicting future positions of mobile users at specific time instants. It is based on three strategies that exploit in different ways the individual systematic behaviors of users in the daily mobility, described by their *individual mobility profiles*. The *individual strategy* takes advantage of the single user's regularity; the *collective strategy* exploits individual systematic behaviors of all users, and the *hierarchical strategy* combines both of them using two levels of knowledge (individual and collective). We have evaluated our prediction strategies on large real-world trajectory data. Our experiments show that the best prediction strategy is the hierarchical one. Our finding is that individuals can avoid to share the raw data and disclose only their (less detailed) mobility profile without deteriorating the prediction performances. Future investigations will be focused on the study of a well-defined methodology for an apriori evaluation of the predictive powerful of mobility profiles.Finally, it would be interesting to study how much the performances improve if we take into account for the prediction not only the best matching routine, but also the first k best matching routines.

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