Inferring human activities from GPS tracks

Barbara Furletti
KDDLAB - ISTI CNR
Pisa, Italy
barbara.furletti@isti.cnr.it

Paolo Cintia
KDDLAB- ISTI CNR
Pisa, Italy
paolo.cintia@isti.cnr.it

Chiara Renso
KDDLAB - ISTI CNR
Pisa, Italy
chiara.renso@isti.cnr.it

Laura Spinsanti
JRC
Ispra, Italy
laura.spinsanti@jrc.ec.europa.eu

ABSTRACT

The collection of huge amount of tracking data made possible by the widespread use of GPS devices, enabled the analysis of such data for several applications domains, ranging from traffic management to advertisement and social studies. However, the raw positioning data, as it is detected by GPS devices, lacks of semantic information since this data does not natively provide any additional contextual information like the places that people visited or the activities performed. Traditionally, this information is collected by hand filled questionnaire where a limited number of users are asked to annotate their tracks with the activities they have done. With the purpose of getting large amount of semantically rich trajectories, we propose an algorithm for automatically annotating raw trajectories with the activities performed by the users. To do this, we analyse the stops points trying to infer the Point Of Interest (POI) the user has visited. Based on the category of the POI and a probability measure based on the gravity law, we infer the activity performed. We experimented and evaluated the method in a real case study of car trajectories, manually annotated by users with their activities. Experimental results are encouraging and will drive our future works.

Categories and Subject Descriptors

H.2.8 [**Database Applications**]: Data Mining

General Terms

Algorithms

Keywords

GPS Data, Human activities, Semantic enrichment

1. INTRODUCTION

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The last decade has seen mobile communications technologies pervading our society. Mobile wearable tracking devices sense the movement of people and vehicles, generating large volumes of mobility data, which represent the traces of people's activity. Nowadays, several application areas would benefit from an extensive study on people's activities such as traffic management, public transportation, commercials and advertising, security and police, hazard evacuation management, location based services and so on. Despite the fact that data collected from mobile devices is increasing its location accuracy, it is not improving in the same way their quality in terms of semantic richness. This means that there is a semantic gap between raw data collected from mobile devices and the personal activity that generated the traces. As a consequence, techniques to semantically enrich the collected data are necessary to (semi-) automatically infer the person's activity given her/his location traces. The approach presented in this paper aims at enriching people's movements, represented as trajectories, with semantic information about the activities performed during her/his travel. The basic assumption is that people stops, during the movement, to visit a place where to perform an activity. In this context, we want to infer, with a degree of approximation, which is the activity of the moving person, analysing the raw movement. For example, a person stopping at a museum is performing a cultural activity, while when stopping at a restaurant then it can be associated to an eating activity. To do that, we first need to identify the places where people stopped; secondly, we need to associate these places to a list of possible visited POI; thirdly, we want to infer the most probable activity performed by people during this stop mapping each POI category to a specific activity. In the current approach we assume that a tracking device is installed into a vehicle (e.g. a car). Clearly, the identification of the visited POI can be easy to infer when the GPS device is embedded into a smartphone since the person can be tracked (ideally) also inside the place. However, the identification of the visited POI can be much more problematic when the device is installed into a vehicle since a car usually cannot enter directly inside the POI: the user needs to park the car and then walk to the destination, and this last part of the movement is not tracked. Therefore, an important issue we face is, after the identification of the stops of the trajectory, the association to the POIs visited by the person. More in detail, we propose an algorithm to associate each stop in a user's trajectory to a ranked list of possible visited POIs and we associate to each of these place an activity. Eventually we use a probability law based on the gravity model to infer the most probable activity.

The paper is structured as follows. Section 2 reports some related work, Section 3 introduces the basic definitions and assumptions of the approach. Section 4 present the approach and gives the details of the activity inference algorithm. The experimental results are reported and discussed in Section 5, and conclusions are stated in Section 6.

2. RELATED WORKS

The work proposed in this paper is essentially based on an improvement and extension of the work in [11], which in turn is based on the pioneering work of Spaccapietra et al. in [10]. Here authors propose a conceptual model for semantic trajectories. While trajectories are defined as a time-space function that record the changing of the position of an object moving in space during a given time interval, semantic trajectories are defined as sequences of stops (where the moving object stays still during a time interval) and moves (the part of a trajectory where the position of the object changes). The basic assumption behind the notion of stop is that the place where a person stops is of some interest for her/him. Therefore, each stop is somehow associated to a POI. The association between a POI and a trajectory stop is the objective of several approaches, ranging from the simplest (associating the closest like in [7]) to more sophisticated proposals [8]. However, most of the approaches do not explicitly consider the temporal validity of the association (i.e. if the POI exists or it is accessible during the actual stop), neither the probability value associated to each stop-POI pair, nor the concept of activity and the time dimension.

The identification of mobile activities from trajectories of people is not new in the literature [14]. A trend of research is devoted to the identification of transportation means like the work [15]. Using speed, acceleration and speed change rate, the authors first detect the positions where the movement switches between walking and non-walking. In a second step, they refine the non-walking segments into segments characterized by the other transportation modes: bicycle, bus, and driving. They use a combination of techniques, from supervised learning to decision tree inference, and add a post-processing step to improve the accuracy of the segmentation. The post-processing step relies on a graph that contains commonsense constraints about the real world and typical human behaviors.

Another trend is concentrating on the identification of the activity during a stop. A work in the same direction of our approach has been proposed in [12], where authors present a method to automatically extract sequences of activities from large set of trajectory data. The assumption is that activities may be carried out at a POI during a stop in the user trajectory. The association between a stop and a POI - as in our case - is crucial and may depend on several factors. One is the distance between the POI and the trajectory and the other is the duration of the event. They base their approach on the concept of influence and influence duration for associations among trajectories, POIs, and activities. Influence is a distance based measure, such that a trajectory T can only be associated with a POI if there exists at least one point on T that is *influenced* by the POI. They use the Voronoi diagram as a division of the area where each cell represents the influence area of the POI. They test their algorithms using synthetically generated trajectories dataset with the POIs collected in a specific area in California. Naturally, the drawback of this testing is that there is no real validation of the method since there is no proof of the correctness of the inferred POIs.

The work of [4] is again in the direction of inferring activities from users trajectories. This paper presents an approach using spatial temporal attractiveness of POIs to identify activity-locations and durations from raw GPS trajectory. The algorithm they propose finds the intersections of trajectories and spatial-temporal attractiveness prisms to indicate the potential possibilities for activities. The experiments use one months GPS trajectories from 10 volunteers where they show an high accuracy of the method.

Kifer and Stein [5] propose a method for user intention recognition in the mobile case. They propose a framework where movement information through GPS data in used by a system of production rules and classification technique for the intention recognition process. They use a grammatical formalism with spatial knowledge. Despite the final objective is somehow similar to ours, this approach mainly focuses on movement features such as speed, angles etc. to segment a trajectory, whereas our approach relies on the stop where no signal have been detected to infer the visited POIs and consequently infer the user activity.

A different approach is the one of [13], where the focus is not on the single user, indeed users' trajectories and domain data such as POIs and road network topology are used together to define functional regions. The results are region represented by a distribution of topics (functions), where a topic is a POI category. With this work authors aim to help people to easily understand the complexity of a metropolitan area. The results are applied to different fields, such as urban planning, location choosing for business, advertimsement casting and social recommendations.

The novelty of our approach, with respect to these similar proposals, is manifold. First of all we take into account many spatial and temporal aspects to realistically associate a stop to POIs, aspects (like the opening times and the stop duration) which are almost disregarded by the most of the other approaches. Furthermore, we explicitly build a probability ranking list of possible visited places based on the gravity model. Respect to the previous work [11] we extended the method in several respects. First of all our current work is concentrated in annotating single stops with activities while the previous work was mainly focused on annotating each trajectories with a behavior, in turn based on the stops and the sequence of stops. Also in [11] authors did not consider gravity law to select the most appropriate POI category but simply they compute a uniform probability. Also the present paper presents a validation of the method in a ground truth dataset which was missing in previous work.

3. BASIC CONCEPTS

Several works in the literature addresses the analysis of trajectory data. Even the definition of what a trajectory is can have several variants. The most intuitive is that a trajectory represents the spatio-temporal evolution of a moving object. However, since trajectories are usually collected by position-enabled devices, the trajectory has to include the concept of sampling, since the device collects the position of the object at predefined time intervals - can be few seconds to minutes or hours, depending on the application. We call raw trajectory the discrete representation of a trajectory as collected by the device as sequence of spatio-temporal points.

A stop in a trajectory is identified by the absence of movement and this can be detected in several ways. There is a rich literature in finding stops in GPS data [6–8]. The segment of a trajectory between two stops is called *move* and indicates the actual movement. In this paper we use the term *trip* to indicate the move between two stops. Intuitively, a trip represents the travel performed by a user to reach a stop and thus to perform some activity.

The notion of stops and moves allows to define a segmentation of a trajectory based on stops and journeys between stops [10] thus generating what is called a *semantic trajectory*: a sequence of stops and moves representing the parts of movement where the object stopped - called stops - and the parts where the object changed its spatio-temporal position - called moves.

Other more complex definitions of semantic trajectories have been proposed recently like in [1, 8]. In these works the notion of semantic trajectory goes beyond the simple stop and moves idea including other contextual aspects like the transportation means, the environment, the purpose of the movement. Semantic trajectory thus includes all the possible aspects that can enrich a simple raw trajectory with more meaning. The process of annotating a raw trajectories with semantic information creating a semantic trajectory is called *Semantic Enrichment*. Our work proposes a contribution in semantically enriching trajectories, focusing on the inference of the activity performed during the stops, which can be seen as the goal of the movement. In other words, the activity explains why the person decided to move (to go to work, to go shopping, leisure etc). It is worth noticing that the understanding of why the object moves, is the last frontier in the mobility analysis. In other words, inferring the activity from the raw mobility data in absence of any metadata about the intention of users for their travels is a high challenging task that can bring highly innovative contribution to the study of human mobility behavior in a urban context.

A stop in a user trajectory is usually associated to a place where the user go to perform some activity. In a urban context such place is denoted as *Point Of Interest* or POI. Each POI has a name, a geographical position, one or more category and additional information like the opening hours or the popularity.

An example of POI is the Eiffel Tour: the representative spatial point s is the center of the tower, the categories can be, for example, "tourist attraction" or "monument" or "tower", depending on the application, and the label "Eiffel Tour" denotes the name. Special case of POIs are the places that are of interest only for a specific user but not to the users community like home, work, house of friends etc. In this paper we refer to POI intending only the places of interest to a communities of people and that can be usually found in many applications like GPS navigators, Google maps, social networks, etc.

A basic assumption of our work is that during the visit to a POI a person may perform an activity, like eating, shopping, studying, playing. The association of an activity to a POI can be intuitive in some cases, but more critical in other cases. For example, a stop at a restaurant can be considered as "eating" but also as "social" when meeting some friends, while a stop to a supermarket can be easily associated to a daily shopping activity. To make this association clear, we defined a list of activities A interesting for a given application, a list of POI categories C extracted from the POIs present in the tracking area, and then we mapped each POI category to an activity, thus defining a POI-to-Activity mapping μ. For example, consider the Louvre POI: the category is Museum. If the list of activities, among others, contains Education we can define a mapping $\mu(Museum) = Education$, thus uniquely associating each museum to a Education activity.

4. METHODOLOGY

The enrichment process aims at annotating a raw trajectory with a list of activities that a user moving by a vehicle could perform when he stops. With the assumption that the GPS is installed into a vehicle we have to consider that a person needs to park the car (the stop place) and then he/she starts walking to reach the destination place. The enrichment process is done by gathering the environmental information around the stop place and in particular by exploiting the POIs nearby.

The semantic enrichment process includes two phases: a start-up and preprocessing phase in which the POIs are collected and integrated, and a second phase where the most probable activities associated to the POIs are identified and used to annotate the stops.

The inputs for the enrichment process are:

- A set of POIs with their categories and other information: $POI = \{$Coordinates: (Lat, Lon); Category: (C), Opening hour: $(H)\}$.
- A set of trajectories with the corresponding stop attributes: $T = \{$Coordinates of the stops: (Lat, Lon), Timestamps: $(ts)\}$.
- A set of characteristics of the Users: $U = \{$Max walking distance: $(Mwd)\}$.
- A list of Activities A.
- The mapping μ of the POI categories to Activities. The type and number of the activities is strongly dependent on the domain and the type of enrichment we are interested in. For example, Restaurant and Pub can be associated to Eating or Food; Library, School and University to Education. In Section 5 we provide a list of activities and the corresponding mappings related to the case we studied.
- A set of spatio-temporal Domain Rules:
  - **Spatial Rule** - Filter out all the POIs outside the range outlined by the Max walking distance.
  - **Temporal Rule** - Check the temporal compatibility of the arrival and departure to the stop with the opening hour of the POIs.
- A probability model that associates to each POI, a probability of being visited:

$$P(POI_i, stop_j) = f(dis(POI_i, stop_j))$$

This model is maily a function of the distance $dis(.,.)$ between the *POI* and the *stop*.

In short, among all the available POIs, some of them are filtered out by using the set of spatio-temporal domain rules provided by the experts. The spatial filter aims at selecting the POIs within a certain spatial range defined by the maximum walking distance a user is willing to travel. The temporal constraints verify instead the temporal compatibility between the stop time and the opening time of the POIs. For the remaining POIs, the probability of "being visited" is computed by using a gravity based function. At the end, for each stop the most probable activity is returned. Example 4.1 shows how the method works.

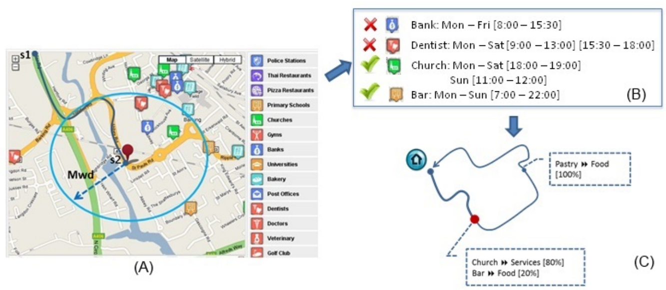

Figure 1: Semantic enrichment: an example

EXAMPLE 4.1. *Let us suppose to have the trip tr from s_1 to s_2 performed on Sunday by the user U. U stops in s_2 from $11:50$ am to $12:05$ am. Let us suppose to have the list of the POIs in the area of interest and the mapping μ of the POI category to the Activities (Figure 1 (A)). From the POIs in the area of interest, we first select the candidate POIs using the spatio-temporal rules. The spatial constraint, derived by the $Mwd = 500$ mt (depicted by the blue circle in the example), excludes the POIs too far from the stop s_2. Then the temporal rules are applied to the remaining POIs (Bank, Dentist, Church and Bar) in order to verify the temporal compatibility. The Bank and the Dentist are excluded because they are closed on Sunday, while the Church and the Bar are selected because the duration of the stop in s_2 is compatible with the Sunday Holy celebration and the Bar is opened almost every days (Figure 1 (B)). For these two candidates, the probabilities $P(Church, s_2)$ and $P(Bar, s_2)$ of being visited are computed. Exploiting the mapping POI category - Activity, the list of the most probable activities associated to s_2 is returned (Figure 1 (C)).*

This process is outlined in Figure 2.

Here we can see that the semantic enrichment process takes as input the raw trajectories, from which we compute the stops. In the literature the problem of stop-detection given a raw trajectory finds many solutions. In this work, we adopt a spatio-temporal constraint-based method: we detect a stop when a subset of the GPS measurements of the trajectory T remains into a spatial buffer δ for a reasonably long time interval τ. The spatial buffer can be defined as a circle with radius r. For the case study presented in the experiments section empirical evaluations suggested to use $r = 50$ *mt* and $\tau = 10$ *min*. Given the stops, the list of POIs and the domain rules, the stops are associated to the most likely POIs based on a probability law. We will see later that we choose the *Gravity model* to compute this probability. Using the mapping function μ that associates each POI category to an activity, we return the ranked list of activities possibly performed by the user during the stops.

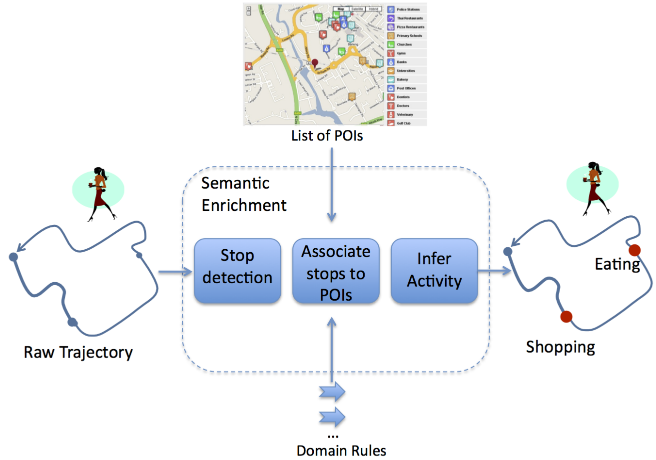

Figure 2: A schema of the semantic enrichment process

The semantic enrichment process has been implemented into the SemanticEnrichment algorithm, described in the next section.

4.1 The SemanticEnrichment algorithm

The algorithm can be described by the different steps anticipated in Figure 2. The pseudocode for the main module is presented below by the main algorithm SemanticEnrichment 1, taking as input a trajectory and returning as output the most probable activity performed for each stop.

The first step for the algorithm is to compute the stops. As already anticipated above, we computed the stop using a spatio-temporal threshold checking if the moving object remains into a spatial buffer δ for a reasonably long time interval τ. Then for each stop we try to find all the reachable POIs considering the maximum walking distance limit. Finally the returned activity is the most probable among the possible detected by the probability law.

Algorithm 1: *SemanticEnrichment*

Input:
A trajectory T;
Output:
The activity done during the stops

$Stops = StopDetection(T)$;
for $stop \in Stops$ **do**
    $PossiblePOIs = SelectedPOIs(stop_{point}, stop_{time}, MaxWalkDistance)$;
    $Activity = Probability(PossiblePOIs)$;
end
return *Activity*

To detect the reachable POIs two conditions are taken into account: (1) the POI is within walking distance from the stop, and (2) the POI is open and accessible during

Algorithm 2: *SelectedPOIs*

Input:
A stop point s; A maximum walking distance MWD
Output:
A set of selected POIs

```
SelectedList = [];
for poi ∈ NearestPOIs(stop) do
    /*NearestPOIs is a function that returns the nearest
    POIs from the POI archive*/
    if (distance(stop_point, poi_point) < MWD) and
    (stop_time ⊆ poi_opening_time) then
        SelectedList.append(poi);
    end
end
return SelectedList;
```

the stop. This means that the POI should not be too far away from the stop place and we need to put a limit to the possible travelled distance by the user from the stop to the POI. Moreover, the distance is assumed to be the walking distance over a road network. In work [2], authors propose an algorithm that maps a GPS point on a road map with an accuracy of 77%, when the measurement error is up to 45 meters. Therefore stops and POIs are mapped over a road map and an algorithm to compute the minimum distance is applied. The opening times of the POIs have to be also taken into account. A stop during the closure of the POI can not be matched with that POI, so for example a stop at 11 pm can be matched with a restaurant or a pub but not with a museum).

Formally, we say that a POI is *selected* for a stop if this can be reached walking and the opening time intersects the stop time duration.

DEFINITION 1 (POIS SELECTION). *A POI p for a stop s is selected if $d(p, s) < MaxWalkDistance$, where d is a function that returns the walking distance between two locations, $MaxWalkDistance$ is a parameter that depends on the maximum walking distance and the duration of the stop and the opening time of p intersects the stop time of s.*

Algorithm 2 shows the detailed procedure of retrieving all the selected POIs for a given stop.

The probability computation step measures for each selected POI, the corresponding probability of being visited starting from the stop. We consider a method based on the Gravity model formalized below.

DEFINITION 2 (GRAVITY MODEL). *The Gravity Model is a model derived from Newton's Law of Gravitation and used to predict the degree of interaction between two places. This degree is proportional to the masses and inversely proportional to the square distance between them, represented by the well known formula $GravLaw = \frac{mass_1 \; * \; mass_2}{distance^2}$.*

We instantiate the original definition of the Gravity model using the principle of bodies attraction where $mass_1$ represents the point of stop - to which we give value 1 by definition, and $mass_2$ represents the "mass" of the POI categories. In other words, we provide a probability for POI categories, not for every single POI. This means that to all the POIs associated to the same activity will be assigned the same probability of being visited. This is in line with our objective of finding activities (thus categories) and we are not interested in identifying the single visited POI.

More in detail, for each stop the algorithm instantiates the original definition of the Gravity Model in such a way that $mass_2$ is the number of reachable POIs of a given category, and the distance is the minimum distance among all the distances of POIs associated to the same activity.

More formally, for every stop s we determine the probability P of an activity as:

$$P(s, act) = \frac{|\{p \in SelectedPOIs(s) | \mu(p.category) = act\}|}{min(d(s,p)^2)}$$

where $SelectedPOIs$ returns the POIs selected using the SelectedPOI algorithm given the stop s, *p.category* indicates the category of POI p and d is a function returning the distance between the stop and the set of POIs p associated to the same activity. As we show in Algorithm 3, the selected POIs are the input for the Probability algorithm. Thus, with this model we associate a probability to each possible activity relative to the stops. To do this we take into account not only the distance of the POIs from the stops, but also the characteristics of the location where the user stopped. For example, a stop in an area with many restaurants and few stores, the Gravity Model gives more mass to restaurants respect to stores, then making a better distinction between the two possible mapped activities (Food or Shopping).

Example 4.2 could clarify the probability computation step.

EXAMPLE 4.2. *Let us suppose to have the stop and the selected POIs shown in Figure 3. The POIs, located at different distances from the stop, belong to categories mapped to activities Food or Services respectively. According to the Gravity Model definition above, the probabilities for the two activities are the following:*

$$P(Stop, Food) = \frac{2}{90^2} * \frac{1}{\varphi} = 0.45$$
$$P(Stop, Services) = \frac{3}{100^2} * \frac{1}{\varphi} = 0.55$$

where $\frac{1}{\varphi}$ is a normalization factor. This result means that we have a higher probability to have a Service activity since the POIs mapped to Service are globally closer compared to the POIs mapped to Food.

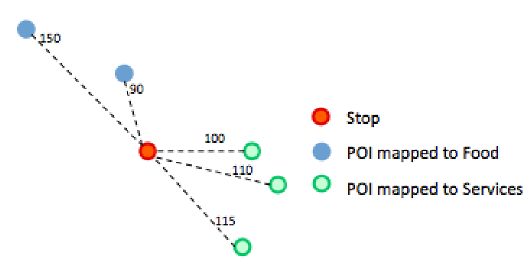

Figure 3: A stop and the activities of the selected POIs with relative distances.

Algorithm 3: *Probability*

Input:
A set of POIs $POIs$; The stop s; The list of activities $ActivityList$
Output:
The activity performed $Activity$

$Probability = []$;
for $act \in ActivityList$ **do**
  // for each group of POIs mapped to the same activity act
  $POIs_{act} = \{p \in POIs : \mu(p) = act\}$;
  // takes as distance the minimum among the stop and all the POIs mapped to the same activity
  $dist = min(distance(s, p)\ for\ p \in POIs])$;
  // compute the mass of these POIs as the number of POIs of the same category
  $mass = len(POIs_{act})$;
  // compute the gravity value for this category / activity and add to the probability list
  $Probability.append(act, mass/dist^2)$;
end
return $activity = max(Probability.act)$;

5. EXPERIMENTS

We tested our activity inference method on a case study in Flanders (Belgium) for which we have both a set of daily trajectories and diaries describing the activities of people during the tracked movements. The trajectories are sets of GPS tracks with timestamps detected by GPS-equipped cars, while the diaries contain, for each user, the list of activities he/she performed during the various stops, with timestamp and duration associated. These data have been gathered from one year of observation of 28 volunteers moving by car, for a around 30000 annotated trips. Trajectories collected by vehicles makes the problem even more challenging since the matching between the parking stop point and the POI actually visited is far to be trivial.

From the diaries we retrieved the following activities: **Working**, **Activity at Home**, **Services** (hairdresser, doctor, bank, ...), **Food** (restaurant, snack bar, snack bar, ...), **Daily shopping** (baker, butcher, supermarket, ...), **Shopping** (clothing, furniture, shopping, ...), **Education and training** (courses or classes, internships, ...), **Social activities** (visiting, bar, party, ...), **Leisure** (sports, fishing, excursions, culture, ...), **Something or someone pick up or drop off**, **Spin** (ride made no specific purpose), **Refueling**, **Other**.

A box plot showing the distribution of the activities based on the duration is shown in Figure 4. In general, the typical duration for each category is reasonable: for example a working activity lasts around 6 hours, the time spent for eating range from 15 to 110 minutes, and the time for refuelling is very short (few minutes). Nevertheless, there are some outliers and anomalies concerning activities that last only few seconds. These cases can be considered both errors made by the users filling the diary and GPS sampling errors.

We downloaded the POIs from both Google Place[1] and OpenStreetMap[2] by using the APIs available in their web sites. For each POI we retrieved *name*, *location*, and *type* (i.e. the commercial category), and we built the mapping activity-to-POI category resulting in Table 1.

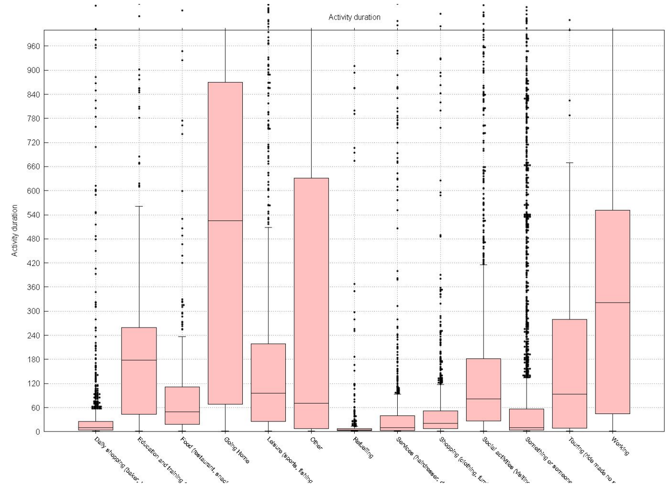

Figure 4: Box plot of the activity duration (in minutes).

Activity	POI Categories
Services	{ATM, Bank, Car rental, Dentist, Doctor, Hospital, Pharmacy, Finance, Insurance, Gas station, Travel agency, Post office, ... }
Food	{Bakery, Bar, Cafe, Food, Meal takeaway, Restaurant}
Daily Shopping	{Grocery or supermarket, Shopping mall}
Shopping	{Book store, Clothing store, Electronics store, Florist, Furniture store, Home goods store, Jewelry store, Library, Pet store, ... }
Education	{School, University}
Leisure	{Airport, Amusement park, Church, Gym, Museum, Night club, Park, Spa, Stadium, Zoo, ... }

Table 1: Mapping POI-to-Activity.

We relaxed the typical Maximum Walking Distance Mwd of 500 mt as proposed in [9] up to 1 km in order to consider a sufficient number of POIs near each stop. Indeed, we found that in Flanders the POIs with an "informative" category (i.e. with a category different from the generic "establishment") are in the average only around 7, in a buffer of 1 km from a stop in small towns. Thus reducing to 500 mt would have reduced a lot the possibilities of matching POIs to stops.
As you can see, the activities Working and Activity at Home are not in Table 1. This is due mainly to two reasons. One is that they cannot be a-priori associated to any specific POI. The second is that the inference of home and work place can be found using the two most frequent locations [3]. For these reasons our method focuses essentially on the identification of all the activities performed by the users excluding home and work places. Other minor activities like refueling have not been considered in this experiment.

Since the opening hours are not currently included in the POIs metadata we downloaded, we manually compiled a time table basing on the typical openings of commercial activities and recreational places, aggregating the days in [Monday-Saturday] and [Sunday]. Table 2 shows the time table for a subset of POI categories.

[1]Google Place: http://www.google.com/business/ places-forbusiness/

[2]OpenStreetMap: http://www.openstreetmap.org/

POI Category	Mon-Sat Opening Hours	Sun Opening Hours
Bar	[7:00 - 23:00]	[7:00 - 23:00]
Restaurant	[11:30 - 15:00] [18:30 - 22:00]	[11:30 - 15:00] [18:30 - 22:00]
Bank	[08:30 - 13:30] [14:45 - 16:15]	closed
Gym	[09:00 - 23:00]	closed
Hospital	[00:00 - 24:00]	[00:00 - 24:00]
Museum	[10:00 - 18:00]	[10:00 - 18:00]
Night club	[22:00 - 05:00]	[22:00 - 05:00]
Post office	[08:15 - 13:30]	closed
Shopping mall	[08:00 - 21:00]	[08:00 - 21:00]
...		

Table 2: POI categories and opening hours.

The experiment takes into account raw trajectories and diaries separately: on the one hand the raw trajectories are been used as input to the SemanticEnrichment algorithm, on the other hand the diaries are used for both collecting the activities and validation purposes. In short, for each user's trajectory we identify the stops locations. Then for each stop we select the nearby POIs and we apply the spatio-temporal rules according to the $Mwd = 1\ km$ to infer the Selected POIs in term of distance, time and opening times. For these ones we compute the probability of being visited according to the Gravity Model and we obtain a set of annotated trajectories as the following:

User_id	Timestamp	Latitude	Longitude	Activity
13159	2007-11-28 8:45:12	51.280	3.413	null
13159	2007-11-28 12:05:20	51.2309	3.493	Food
13159	2007-11-28 14:28:40	51.0302	3.4212	Shopping
13159	2007-11-28 14:50:01	51.280	3.413	null
13159	2007-11-28 19:00:19	51.170	3.119	null

Table 3: Example of enriched trajectory with annotated stops.

The example above represents a simplified version of the annotation in which we return only the most probable activity among the candidates. This trajectory seems the typical working day of user 13159, who get to work in the morning, than go out for lunch and shopping, subsequently he goes back to work, and then home. As stated before the method does not identify Home and Work activity so it returns the null value.

For the validation phase, we compare, for each user's trajectory, the stops annotated with the most probable activity by the SemanticEnrichment algorithm to the corresponding stops and activity declared by the user in the diary. We obtain a global accuracy of 43% calculated as the percentage of activities correctly identified w.r.t. the ones the users declare in the diary. At a first glance this accuracy may seem not entirely satisfactory. Nevertheless, we believe it is a promising result considering that our method is strongly dependent on the quality of the input data, and in Flanders we found few and incomplete POIs (few POIs of the pursued category, and real opening hours not available). Also we have to consider that the average number of categories of the POIs reachable from a stop is 7, thus we have to compare this 43% with a random probability which is $1/7 = 14\%$. Table 4 (Column A) shows the accuracies per activities i.e. the percentage of activities correctly identified w.r.t. the number of declared activities (of the same type). For example we obtain good results for activities of type "Food" (the method recognizes the 83% of them), while we are unable to identify Daily shopping. We observe that these results are related to the availability of the POIs around the stops. In fact, as shown in Table 4 (Column B), the number of the POIs near all the stops and associated to the activity Daily shopping is only 17 in all the Flanders territory.

Activity category	(A) Accuracy	(B) Total nr of POIs
Services	34%	2057
Food	83%	832
Daily Shopping	0%	17
Shopping	23%	939
Education	3%	173
Leisure	49%	727

Table 4: Column (A): Classification accuracy by activity; Column (B): Total number of POIs around the stops grouped by category mapped to the relative activity.

To this aim we are currently working towards several directions for refining and improving the accuracy of the method: on the one hand we are extending the system so that further constraints can be added to exclude less probable POIs. For example, we could add a new constraint to relate the duration of the stop to the typical duration of the visits (a duration of 10 minutes is not compatible with a museum POI). Also we have to consider that the amount of time a person could spent in a place is not the complete stop duration, but the time needed to cover the distance between the POI and the stop must be taken into account. It is worth observing that, in general, the longer is the duration of the stop, the higher is the number of POIs associated to that stop. On the other hand, we are searching for new POI providers in order to improve the quality of the data. Sources like the Yellow Page seems very good because they contain almost all the POIs (both commercial and not) of a town, accurately classified in a hierarchical structure and accompanied by many other details like opening hours. Unfortunately, these web sites do not supply APIs to fast download the data and ad-hoc crawlers have to be developed. The mapping between POIs categories and activities is another important issue. There are in fact some critical cases where the activities performed at a certain place may not be uniquely identified. Consider for example a dinner in a restaurant with some friends: is this activity "Food" or "Social"? We believe that there is not a clear answer to this question and cases like this motivate us to design new rules for building the knowledge base and to better filter the POIs. For example, we can extend the set of activities with "Social eating" defining some temporal constraints to better identify it compared to general Food or Social. In this case a possible rule could be: *Label as "Social eating" an activity performed in a restaurant for dinner and that lasts more than a dinner alone* .

We have to point out that a number of assumptions are at the basis of our approach. For example, there is a general assumption that during a stop a person performs one activity while usually more than one activity can be done (stopping at a bar to take a coffee then buy some food at the supermarket). In this case we consider one activity as the "primary" activity or the main reason of the movement. In the example, the activity is Daily shopping at the supermarket and taking a coffee is considered as a secondary activity. Naturally, it would be interesting to enhance the problem formulation considering the possibility of inferring two or more activities. Another assumption we have is that a person stopping a car proceed walking to the destination.

This may be not always true since, depending on the location, a person could take a tram or bus or metro to reach his/her destination. An improvement of the current method should consider the presence of bus/tram/metro stop in the buffer around the car stop and perform inferences on the duration of the stop to include the possibilities of using public transportation to reach a further place. A special case, difficult to handle, is the case of very short stops. This can be due to GPS or annotation errors - as we have underlined above - but also to very special activities like refueling or bring/get other people. These last activities are the most difficult to grasp since they are not related to any specific POI, but rather to the fact that the stop may be very short. We are studying this problem trying to match to this activities either very short stops like one/two minutes or matching with POIs like schools (bring/get children) airport and train station (bring/get friends or relatives).

6. CONCLUSIONS AND FUTURE WORKS

We propose a method for automatically infer the activities of users during their movement when tracked by a GPS device. This problem is particularly important since we aim at semantically enriching raw GPS trajectories with more meaningful information that can be useful in several application domain, from transportation science, to advertising and sociology. The basic idea of our approach is to detect the stops as the parts of a trajectory where the user stopped to perform an activity and match these stops to the possible visited POIs. Since each POI category is mapped to an activity (like food, shopping, studying ...) finding the most probably POI category corresponds to finding the most likely activity performed. The identification of the visited POI is computed by an algorithm based on several criteria like the stop duration, the time of the stop and computed with a probability law based on the Gravity Model. We have evaluated the algorithm for semantic enrichment in a real case study where the trajectories were already annotated by the users, showing interesting results. Several remaining issues are object of current and future works. First of all, as we already discussed, the lack of rich POI datasets is a major problem when the tracking does not include large cities. Therefore we are investigating the possibility of integrating more detailed POIs datasets like Yellow Pages or TomTom. Secondly, we want to better define the mapping between POI categories and activities. Other issues mainly depend on the quality of the data we can get from the internet like the opening times of POIs. Some social network like Foursquare provide the opening time for each POI. This would greatly improve the accuracy in our algorithm since the opening time set for categories is a coarse approximation of the reality.

We also want to improve the activity inference step considering all the sequence of activities in the trajectory: having two Food in a sequence with no other activities in the middle would give lower probability to the second one. Studying the distributions of the typical sequence of activities on the ground truth dataset would improve this aspect.

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