TOWARDS ACTIVITY RECOGNITION IN MOVING OBJECT TRAJECTORIES FROM TWITTER DATA

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Abstract. *The knowledge about people daily activities is of great value for several application domains. On the one hand, the activity recognition in trajectories has not been deeply investigated. On the other hand, social media data such as tweets can be rich in information about where people go and what they do. We strongly believe that the integration of trajectory data and social media can reveal the activities performed by individuals in daily life. In this paper we propose a new method to infer moving object activities from their trajectories, using knowledge extracted from Twitter data. We evaluate the proposed approach with two datasets and show that it outperforms current works.*

1. Introduction

The knowledge about which activities people do at certain Points Of Interest (POIs) can be of great value for several applications. For instance, recommendation systems could infer user activities from visited locations obtained from their Google account [1] and suggest new places based on the inferred activities. Architects and city planners could project better public spaces, such as parks, based on how people perform activities. Augmented reality games, such as Pokemon Go [2], could improve the security of the players by warning them about suspicious activities at POIs to prevent cases of robbery.

We are living the era of big data, where individuals are constantly leaving traces of their movements and their activities. Even though we are not fully aware of it, we are tracked everyday. Our spatiotemporal traces can be delineated as *moving object trajectories*. A raw trajectory is a temporally ordered sequence of geographical coordinates associated with a timestamp, which does not present explicit semantics. A semantic trajectory [Spaccapietra et al. 2008] is represented as a sequence of stops and moves, where stops are the places visited by the object. Bogorny in [Bogorny et al. 2014] extends the concept of semantic trajectory by considering other important aspects such as activities and goals of trajectories. Several recent works address semantic trajectory data analysis [de Aquino et al. 2013, Ying et al. 2014, de Alencar et al. 2015, Furtado et al. 2016], but only a few have focused on activity recognition. While it might be easy to discover visited places in many situations, determining the activities performed at these places is

[1]https://accounts.google.com/
[2]http://www.pokemongo.com

not a trivial task. There is no unique association between each POI (or POI type) and the activities that can be performed at that POI. Several activities may be performed in the same POI (or POI type). There is a wide range of possibilities that vary in number and nature according with the POI type. For instance, at a shopping mall, one could be eating, purchasing, working, socializing, watching a movie, or at a commercial building one could be drinking a coffee, working, visiting, purchasing and at a company one could be working or visiting.

We strongly believe that the main limitation of existing works for activity recognition from GPS trajectory data, such as the works [Weerkamp et al. 2012, Furletti et al. 2013, Njoo et al. 2015] is the assignment of only one activity at a POI, and relying on specialists to manually label POIs (or POI types) with activities that can happen at these POIs (or POI types). Another limitation is the dependence of an annotated trajectory dataset to generate a classification model. In this paper we overcome these problems by proposing a novel solution to recognize activities in moving object trajectories based on tweets sent from the visited POIs. First, we assume that more than one activity can be performed at each POI (e.g. one can study, socialize and eat at a University). Second, we enrich Foursquare POI types with statistics about the activities observed in tweets sent from the respective POI types. Third, we propose a matching process to infer activities based on the similarity between the trajectory and the POI type profiles extracted from Twitter. To the best of our knowledge, our proposal is the first to extract knowledge from Twitter data to infer activities in moving object trajectories. In summary, we make the following contributions: (i) we build a knowledge base with POI type profiles based on activities observed in tweets sent from each POI type; (ii) we propose the algorithm T-Activity to infer activities in trajectory data, by matching the POIs visited by trajectories with POI type profiles in the knowledge base; (iii) we evaluate the proposed approach with real trajectories and census data to evaluate our method in real case scenarios.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 presents the main definitions. Section 4 describes our proposal for activity recognition. Section 5 reports the experimental evaluation, and finally, Section 6 presents our conclusions.

2. Related Work

There are different works in the literature related to human activity recognition using different types of data, such as social media and GPS trajectories. The works based on social media focus on text classification, and extract features from text and POIs to build classifiers for activity recognition. For instance, Liu in [Liu et al. 2012] builds a classifier over tweets in order to predict the POI type of tweets linked to Foursquare. Although this work does not recognize activities, it recognizes POI types that can be related to different activities. Weerkamp in [Weerkamp et al. 2012] proposed an approach to predict the popular activities that will happen in a future time window, such as tonight, tomorrow, and next week, by using a future time-window and keywords related to activities. Zhu in [Zhu et al. 2016] builds a multi-label classifier using tweets manually annotated with activities in order to predict up to three activities. To build the classifier, it considers the tweet text, the tweet posting time, the POI type from Foursquare and POI name from Foursquare.

On the other hand, only a few works try to recognize activities on GPS trajectories. Moreno in [Moreno et al. 2010] proposed an algorithm that given a set of stops of a trajectory, uses a predefined set of rules that considers the minimum time and maximum speed to infer the goal of movement. However, the set of rules has to be defined by a specialist, and the matching process is based on movement aspects of the goal, such as its minimum time and its maximum speed. Therefore, it ignores important aspects such as the place and the time of the goal. Our work, instead, focuses on recognizing activities, and we do not depend on a specialist, since we extract the knowledge from Twitter in order to build a knowledge base that describes the activities that can be performed at a POI. Furletti in [Furletti et al. 2013] proposed a method for activity recognition where a set of activities is manually defined for POI types, and given a trajectory, it finds the stops and matches the POI type of the stop with the manually defined activities. Our work on the other hand considers that multiple activities can happen at each POI and computes the similarity of the trajectory and the activities in the knowledge base in order to infer activities. Reumers in [Reumers et al. 2013] uses a dataset of semantic trajectories annotated with activities and proposes to infer activities using a decision-tree based model. To build the tree, it uses the start time, duration and activity of each stop, but does not consider the place where the activity happened and depends on the annotated trajectory data to build the model. Kim in [Kim et al. 2014] builds a classification model to recognize groups of activities, as for instance, home, work and transportation. It uses spatial regions annotated with the frequency of time, duration and frequency of the activities. However, it does not infer activities, just groups of activities, and it also depends on the annotated trajectory data to build the model. Njoo in [Njoo et al. 2015] also manually defines an activity for each POI type, and using a dataset of semantic trajectories annotated with activities it builds classifiers with trajectories from the same moving object, to represent the routine of a moving object. However, if the moving object goes to a place that was not previously seen, it matches the POI type with the manually defined activity.

Overall, our work is different from the previous approaches since we do not depend on a specialist to build the knowledge base, instead, we extract the knowledge from Twitter data. We also consider that multiple activities can take place at each POI and we propose an algorithm to match trajectories with our knowledge base to infer activities.

3. Main Definitions

There are several definitions of semantic trajectories in the literature, such as [Bogorny et al. 2014] and [Spaccapietra et al. 2008]. In this work we adapt the definition of semantic trajectory defined by Spaccapietra, considering a semantic trajectory as a set of stops and the POI type of the stops. Definition 1 shows our formal definition of semantic trajectory.

Definition 1 (**Semantic Trajectory**)**.** A semantic trajectory $S = \{s_0, s_1, ..., s_n\}$ is a set of stops, where the ith stop is a tuple $s_i = (x_i, y_i, st_i, et_i, poi_i)$, with x_i and y_i being the spatial coordinates of the stop from the start time st_i to the end time et_i at the POI poi_i.

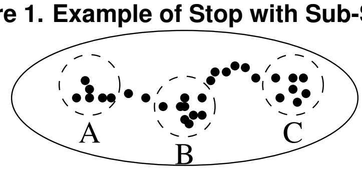
A stop of a trajectory occurs at a place, called POI, given in Definition 2.

Definition 2 (**Point of Interest**)**.** A point of interest is a tuple $poi = (type, x, y, ot, ct)$ where $type$ is the type of the POI (e.g. Restaurant, Gym, University, Shopping Mall), x

and y are its spatial coordinates, and ot and ct are, respectively, the opening and closing times of the point of interest.

The moving object can perform multiple activities at each stop, then how could we distinguish, for instance, at a shopping mall, if people are purchasing items at a store, eating at a restaurant or watching a movie? In order to identify multiple activities at the same stop, we split the stop into sub-stops, which are smaller stops happening inside a bigger stop, as proposed by [Moreno et al. 2010]. For example, let us consider Figure 1 as a trajectory of a student that has a stop at a university. Inside this stop, he has a sub-stop at a classroom (A), a sub-stop at the laboratory (B) and a sub-stop at the university cafeteria (C). Therefore, by using the concept of sub-stops we can identify more than one activity at each stop. The formal definition of sub-stop is given in Definition 3.

Figure 1. Example of Stop with Sub-Stops



Definition 3 (**Sub-Stop**). A sub-stop is a tuple $sub = (s, st, et, x, y)$ where sub is the sub-stop from the start time st until the end time et inside the stop s with x and y being the centroid of the sub-stop.

We extend the definition of semantic trajectory to cope with activities. Definition 4 shows our formal definition of activity trajectory.

Definition 4 (**Activity Trajectory**). An activity trajectory $T = \{t_0, t_1, ..., t_n\}$ is a set of stops, where the ith stop is a tuple $t_i = (x_i, y_i, st_i, et_i, poi_i, A_i)$, with x_i and y_i being the spatial coordinates of the stop from the start time st_i to the end time et_i with the set of activities $A_i = \{a_0, a_1, ..., a_n\}$ performed at the POI poi_i, where the jth activity a_j is an activity label.

In this work we extract activities from georeferenced tweets associated with Foursquare, and collect the POI information through the Foursquare API[3]. The definition of georeferenced tweet is given in Definition 5.

Definition 5 (**Georeferenced Tweet**). A georeferenced tweet is a tuple $(text, time, day\_week, POI, act)$, where act is the activity extracted from the tweet text $text$ shared at the time $time$ at the day of the week day_week and at the point of interest POI (as in Definition 2).

We consider that every POI type has a set of activities that can be performed at a given time and with a certain duration. We define this set of activities as the ***POI Type Profile***, given in Definition 6.

Definition 6 (**POI Type Profile**). A POI type profile is a tuple $pro = (POItype, act, meanTime, sdTime, meanDuration, sdDuration, frequency)$, where $meanTime$ is the mean time of the observed ocurrences of the activity act at the POI type $POItype$; $sdTime$ is the standard deviation of this time, $meanDuration$ is

[3]https://developer.foursquare.com

the mean duration time of act at $POItype$, $sdDuration$ is the standard deviation of this duration, and $frequency$ is the frequency of act at $POItype$ relative to the total number of activity occurrences observed at $POItype$.

In the following section we present the proposed approach.

4. Proposed Approach

Our approach to infer activities in moving object trajectories has two steps. The first one is to build a knowledge base in the form of POI type profiles, which are extracted from Twitter, Foursquare and census data. The second step is to infer activities in trajectories by matching the object movement with the POI type profiles in the knowledge base. For that end, we propose an algorithm called *T-Activity*. These steps are described in the following sections.

4.1. Building the Knowledge Base

The knowledge base is a representation of the distribution of activity time and duration that happen at each POI type. It contains the following information: POI type, activity name, average duration, duration standard deviation, average time, time standard deviation and relative frequency. Table 1 shows an example of the knowledge base for the POI Type *Shopping Mall*.

Table 1. Knowledge Base for POI Type *Shopping Mall*

POI Type	Activity Name	Avg Time (hrs)	Time Std Dev	Avg Duration (hrs)	Duration Std Dev	Relative Frequency (%)
Shopping Mall	Consumer Purchases	13.98	3.57	0.74	0.86	0.17
Shopping Mall	Socializing, Relaxing, and Leisure	14.57	4.00	0.78	0.99	0.45
Shopping Mall	Eating & Drinking	14.17	3.52	0.63	0.48	0.28
Shopping Mall	Movies	16.35	3.12	2.27	0.77	0.10

Each attribute is described as follows: (i) POI Type is extracted from Foursquare, and it is present in the tweet to show where the activity happened; (ii) Activity Name is the activity we want to infer. We can extract this information from any taxonomy of activities; (iii) Average Duration is the average time people spend doing an activity at a POI type. We can extract this information from any set or taxonomy of activities; (iv) Duration Std Dev is the standard deviation of the average duration. This information can be extracted from any set or taxonomy of activities; (v) Average Time is the post time of the activity at the POI type. This information is extracted from the tweets; (vi) Time Std Dev is the standard deviation of the average time. This information is extracted from the tweets; and finally (vii) Relative Frequency is the proportion of tweets of an activity that happened at the POI type.

Having described the attributes that compose the knowledge base, Algorithm 1 describes how we build it from a dataset of georeferenced tweets annotated with activities (see Section 5.1 for details) and using any set or taxonomy of activities to obtain the average time spent with each activity at a POI Type. The input of the algorithm is a corpus of georeferenced tweets and any dataset containing the average time people spend with daily activities. It iterates the corpus (lines 4 to 8), extracting the tweet post time to an auxiliary structure of POI types and activities (line 5). Then it adds one to the frequency for the POI type and activity of the same auxiliary structure (line 6), and adds one to the frequency regardless of the activity (line 7) in order to obtain the relative frequency of the activities at each POI type. After that, it iterates the auxiliary structure A (lines 9 to 18) and obtains the POI type and activity of each instance (lines 10 and 11). After that, it calls the method $C.getDuration$, which has a list of durations for each POI type/activity, and gets the activity duration list filtered by POI type and activity (line 12) and calculates the mean and standard deviation (lines 13 and 14). Then it also calculates the mean and standard deviation of the tweet post time (lines 15 and 16) and the relative frequency of the activity for the POI type (line 17). Finally, it returns the POI Type profiles as the knowledge base K (line 19). As this algorithm iterates the corpus of tweets and the auxiliary dictionary A only once, the complexity is $O(n_d + n_p)$, where n_d is the corpus size and $n_p = n_t * n_a$, with n_t being the number of unique POI types in the corpus of tweets D and n_a being the number of unique activities in the corpus of tweets D.

Algorithm 1 Knowledge-Base Builder

Require:
D // corpus of tweets
C // census dataset / activity taxonomy
1: K = empty dictionary;
2: A = empty dictionary;
3: T = empty dictionary;
4: **for each** $tweet$ in D **do**
5: $A[tweet.poi.type, tweet.act].time.append(tweet.time)$;
6: $A[tweet.poi.type, tweet.act].frequency$ += 1;
7: $T[tweet.poi.type].frequency$ += 1;
8: **end for**
9: **for** i = 0; $i < A.size()$; i = i + 1 **do**
10: $ptype$ = $A.getPOIType(i)$;
11: act = $A.getActivity(i)$;
12: $duration\_list$ = $C.getDuration(ptype, act)$;
13: $K[ptype, act].meanDuration$ = $mean(duration\_list)$;
14: $K[ptype, act].sdDuration$ = $sd(duration\_list)$;
15: $K[ptype, act].meanTime$ = $mean(A[ptype, act].time)$;
16: $K[ptype, act].sdTime$ = $sd(A[ptype, act].time)$;
17: $K[ptype, act].frequency$ = $A[ptype, act].frequency$ / $T[ptype].frequency$;
18: **end for**
19: **return** K;

In the next section we describe the algorithm T-Activity and show how to infer activities using the knowledge base.

4.2. T-Activity

Before we describe the algorithm that performs activity inference, we introduce the activity inference model, which is based on time, duration and the relative frequency. The time similarity is computed in Equation 1, where K is the POI type profile, st is the sub-stop start time, $meanTime$ is the average time the activity starts in the POI type profile and $\frac{K_{sdTime}}{K_{meanTime}}$ is the variation coefficient of the time in the POI type profile.

$$T(K, st) = 1 - \left| \frac{K_{avgTime} - st}{K_{avgTime}} \right| * \frac{K_{sdTime}}{K_{meanTime}} \tag{1}$$

The duration similarity between the sub-stop and each activity in the POI type profile is computed using Equation 2, where K is the POI type profile, d is the sub-stop duration, $meanDur$ is the average duration of the activity in the POI type profile and $\frac{K_{sdDur}}{K_{meanDur}}$ is the variation coefficient of the duration in the POI type profile.

$$D(K,d) = 1 - \left| \frac{K_{meanDur} - d}{K_{meanDur}} \right| * \frac{K_{sdDur}}{K_{meanDur}} \tag{2}$$

However, if the score between the activities is too much similar, the time and duration cannot describe which activity happened. Therefore, our model considers the frequency of the activities, according to Equation 3, where K is a POI type profile and $frequency$ is the relative frequency of the activity at the POI type.

$$M(K,d,st) = K_{frequency} * D(K,d) * T(K,st) \tag{3}$$

Considering the matching metrics, Algorithm 2 describes the activity recognition. It receives as input a semantic trajectory S, a knowledge base in the form of POI Type profiles K, a radius that intersects the sub-stop locations $radius$, and the parameters of the algorithm CB-SMoT [Palma et al. 2008]. In order to identify sub-stops, we followed the steps described in [Moreno et al. 2010], which runs the algorithm CB-SMoT over stops to find the sub-stops.

Algorithm 2 T-Activity

Require:
S // semantic trajectory
K // set of POI Type Profiles
$radius$ // radius to intersect sub-stop centroids
$MaxAvgSpeed, MinTime, MaxSpeed$ // CB-SMoT parameters
1: $T = computeSubStops(S, MaxAvgSpeed, MinTime, MaxSpeed)$;
2: **for each** $stop$ in T **do**
3:     **for each** sub in $stop$ **do**
4:         $area = buffer(sub.x, sub.y, radius)$;
5:         $near\_substops = intersect(area, stop)$;
6:         $duration = sum(near\_substops.getDuration())$;
7:         $freq = getFrequency(K, sub.s.poi.type)$;
8:         $score\_time = getSimTime(K, sub.s.poi.type, sub.st)$;
9:         $score\_duration = getSimDuration(K, sub.s.poi.type, duration)$;
10:         $ranked\_activities = getRankedActivities(freq, score\_time, score\_duration)$;
11:         $sub\_act = max(ranked\_activities)$;
12:         $stop.A.append(sub\_act)$;
13:     **end for**
14: **end for**
15: **return** T

The algorithm starts by initializing the activity trajectory T, computing the sub-stops by calling the method *computeSubStops*, which considers the points of the stop as a trajectory and calls algorithm CB-SMoT, and if no sub-stop is found, it considers the whole stop as the sub-stop (line 1). After that, it iterates the stops and sub-stops of the trajectory (lines 2 to 14). Then, for each sub-stop, it creates an area with a radius of size $radius$ from the sub-stop centroid (line 4) and calls the method $intersect$ to find all sub-stops that intersect the area (line 5) in order to group them as they happened at the same location, and sum the sub-stop duration as the whole time spent at the same location (line 6). After that, it computes the similarity between the sub-stop sub and the activities in the knowledge base K. First, it gets the relative frequency of the activities at the POI type of the stop from the knowledge base K (line 7). Then it computes the time similarity score of each activity at the POI type of the stop using Equation 1 (line 8). After that it computes the duration similarity score of each activity at the POI type of the stop using Equation 2 (line 9). Then, it computes the score of each activity by multiplying the activity scores of each set using Equation 3 (line 10), and selects the activity with the highest score (line 11). Finally, it appends the activity with the highest score to the stop (line 12), and returns the activity trajectory (line 15).

The complexity of this algorithm is $O(n_s + n_{sub}^2)$, where n_s is the number of stops and n_{sub} is the number of sub-stops. Also, as the algorithm CB-SMoT is executed outside the loop, it does not increase our complexity. In the next section we describe the performed experiments and compare our results with other work.

5. Experiments

In this section we describe the experiments performed in two trajectory datasets and how we extracted activities from tweets in order to build the knowledge base.

5.1. Building the Knowledge Base from Twitter

We use the Twitter Public Streaming API [4] to gather tweets for the knowledge base. We selected 137,509 instances of georeferenced tweets generated from Foursquare from 14/09/2010 to 11/05/2015. The collection was filtered by Portuguese written tweets inside Brazil's bounding box and with at least 3 words.

To build and evaluate the knowledge base, the first step is to extract the POI information from Foursquare, using the Venue Search API [5]. We do that by looking the Venue ID present in the tweet text. As a result we have the tweet text, the tweet time, the POI type and the POI name. Then, for this experiment we filtered the tweets by the following POI types: Restaurant, Gym, Supermarket, University and Shopping Mall, which are types we assumed to have more than one activity. The result was a corpus with 45,209 tweets.

To identify the activities from tweets, we follow the method proposed by Zhu in [Zhu et al. 2016], which consists of using the activities defined in the American Time-Use Survey (ATUS) [Shelley 2005] to build a classification model to assign each tweet to an activity. We randomly selected a sample of tweets stratified by POI type, with the size determined by a confidence level of 95% and a confidence interval of 5%, and manually classify each one to an activity present in the ATUS taxonomy accordingly to the text of the tweet. Having the annotated tweets, we build a classification model considering the following features: (i) POI Type: as each tweet is georeferenced to a Foursquare POI, we extract the POI type and construct a matrix containing 887 binary features, each one representing a POI type; (ii) Tweet Text: by extracting the most relevant unigrams and bigrams weighted by TF-IDF, we obtain 9394 features from the text; (iii) POI Name: the same way we extract features from the tweet text we extract the POI name, as some POI names can be indicative of activities (e.g. Japanese Restaurant, Fourth Street Market); Posting Time: we chunk the tweet posting time by hour of the day to construct a matrix of 24 features. We combine the previous features in a matrix and apply

[4] https://stream.twitter.com/1.1/statuses/sample.json
[5] https://developer.foursquare.com/docs/venues/search

the Linear SVM package from Scikit-Learn library [Pedregosa et al. 2011] to build the classification model. We select L1-regularization with squared hinge loss and keep the default parameters. We evaluate the tweet classification model using a 10-fold cross-validation, obtaining an average accuracy of 76%.

After building and evaluating the classification model, we classify the remaining tweets. In addition, we run Algorithm 1 to extract the mean and standard deviation of time and duration and also the relative frequency of the activities to store in the knowledge base. Table 2 shows the knowledge base generated for this experiment.

Table 2. Entire Knowledge Base

POI Type	Activity Name	Avg Time (hrs)	Time Std Dev	Avg Duration (hrs)	Duration Std Dev	Relative Frequency (%)
Shopping Mall	Consumer Purchases	13.98	3.57	0.74	0.86	0.17
Shopping Mall	Socializing, Relaxing, and Leisure	14.57	4.00	0.78	0.99	0.45
Shopping Mall	Eating & Drinking	14.17	3.52	0.63	0.48	0.28
Shopping Mall	Movies	16.35	3.12	2.27	0.77	0.10
Supermarket	Consumer Purchases	15.12	4.52	0.69	0.52	0.73
Supermarket	Eating & Drinking	14.50	5.17	0.54	0.47	0.27
Restaurant	Eating & Drinking	12.24	6.83	1.00	0.62	0.78
Restaurant	Socializing, Relaxing, and Leisure	14.60	6.59	1.47	1.34	0.18
Restaurant	Consumer Purchases	14.51	5.28	0.16	0.19	0.04
University	Socializing, Relaxing, and Leisure	14.52	5.69	0.73	0.88	0.02
University	Education	13.38	5.37	3.16	1.90	0.96
University	Eating & Drinking	13.96	4.51	0.51	0.30	0.02
Gym	Sports, Exercise, and Recreation	13.25	5.98	0.99	0.67	1.00

As we can see in Table 2, the majority of the POI types have multiple activities. For instance, *Shopping Mall* has four different activities, where the most common activity is *Socializing, Relaxing, and Leisure*. The relative frequency is a reflex of what people do and tweet about. It is important to notice that the average time is an approximation of multiple distributions, which explains the high standard deviations of time.

Having the knowledge base, we run the algorithm *T-Activity* using two different datasets, a semantic trajectory dataset built from census data (Section 5.2), and a semantic trajectory dataset collected in Florianópolis, Brazil (Section 5.3).

5.2. Census Trajectory Dataset

Considering the difficulty for obtaining a semantic trajectory dataset with ground truth, we evaluate our algorithm with a dataset generated from the ATUS dataset. This dataset consists of activity diaries, where each diary corresponds to the semantic trajectory of an individual, resident of the United States of America. The diary contains the activity, the place where the activity was performed (POI), and the start and end times of the activity. From this dataset we selected all households that have activity entries with more than 5 days, resulting in 41 households with 5246 stops. Every POI where an activity was performed is considered as a stop, and as we have multiple entries at the same POI, we consider them as sub-stops. However, and as we do not have the POI coordinates in this dataset, we consider the parameter $radius$ as 0 meters, as we cannot match the location of sub-stops.

We compare the algorithm *T-Activity* with the works [Furletti et al. 2013], [Reumers et al. 2013] and [Njoo et al. 2015]. In order to compare the works, we consider only the activity with the highest score at each sub-stop to calculate f1-score and accuracy. On the other hand, as the POIs can have several activities, the metrics of the related work are calculated based on the activity that consumed more time at the POI. Figure 2 shows the f1-score for the methods of Furletti [Furletti et al. 2013] and Reumers [Reumers et al. 2013]. From the f1-score we can see that our method outperforms the existing works. The work of Furletti has a lower or equal score for all classes. This happens because each POI type is matched to an exclusive activity, and our method considers the similarity of the activities along the relative frequency of the activities. However, considering the relative frequency is problematic for activities that are too similar and have a low frequency, such as *Socializing, Relaxing and Leisure*. On the other hand, as Reumers does not consider the POI type, the f1-score has the lowest result.

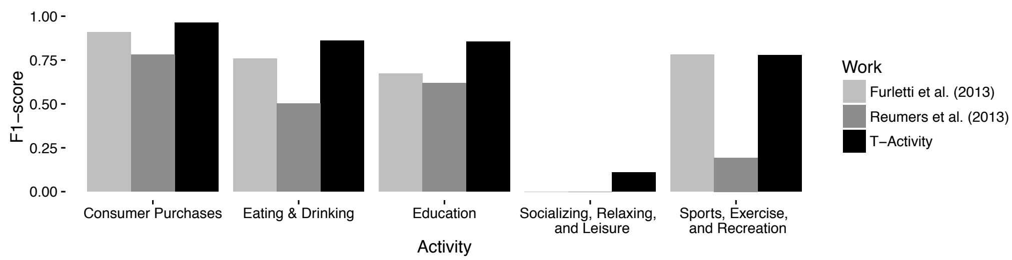


Figure 2. Comparison of F1-Score

In order to demonstrate the multi-activities, we analyze the accuracy at the POI type *University* in Figure 3. It shows that our method outperforms the works of Njoo and Reumers for the activities *Eating & Drinking* and *Socializing, Relaxing, and Leisure*, and that our work is the only one that recognizes the activity *Socializing, Relaxing, and Leisure*. On the other hand, as Furletti and Njoo consider one activity, they have an accuracy of 1.00 for *Education*.

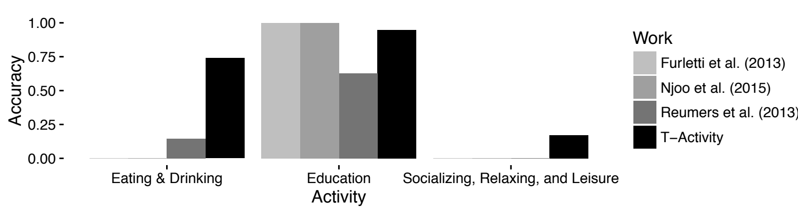


Figure 3. Accuracy Comparison at POI Type University

5.3. GPS Trajectory Dataset

The GPS trajectory dataset is a ground-truth dataset of semantic trajectories annotated with activities collected from 14/04/2016 to 08/06/2016 by 8 participants in the city of Florianopolis, Brazil. The dataset has 59 trajectories, 100 stops and 128 sub-stops. For this experiment we use a $radius$ of 10 meters to group sub-stops at the same location, and consider the activity with the highest score at the sub-stop to calculate f1-score and accuracy. However, as the stops can have several activities, the metrics of the related work are calculated based on the activity that consumed more time at the stop. Figure 4 shows the f1-score in comparison to [Furletti et al. 2013, Reumers et al. 2013]. Analyzing the f1-score we can see that our work has the best result. In addition, Furletti has a score of 1.00 where the main activity is the only activity in the GPS trajectory dataset, such as *Consumer Purchases* for *Supermarket* and *Sports, Exercise and Recreation* for *Gym*, otherwise it has a lower score. Reumers on the other hand, considers the duration and start time of the activities, and as some activities have a similar start time and duration the f1-score is affected.

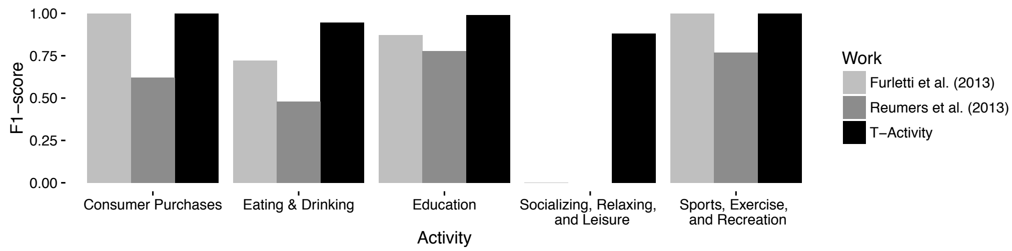


Figure 4. Comparison of F1-Score

We also analyze the accuracy of the works at the POI type *Restaurant* for the activities *Eating & Drinking* and *Socializing, Relaxing and Leisure* in Figure 5. It shows that our work is the only one to recognize the activity *Socializing, Relaxing and Leisure*, as we consider sub-stops to identify multiple activities and the other works can only identify one activity at each stop. Nevertheless, our work also has the highest accuracy.

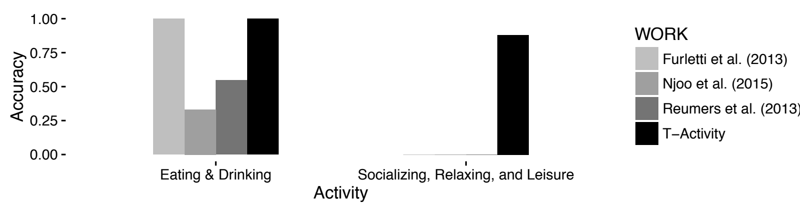


Figure 5. Accuracy Comparison at POI Type Restaurant

6. Conclusion

In this paper we proposed a new method for activity recognition in moving object trajectories, extracting the possible activities from tweets posted at POI types visited by the trajectories. Even though activity recognition is broadly performed with different types of data, infer activities in moving object trajectories is not a trivial task. In this paper we proposed a POI Type profile, in the form of a knowledge base, extracted from georreferenced tweets, to represent the activities that can happen at a POI Type. We proposed the algorithm T-Activity that matches the trajectory and the POI Type profiles for detecting the trajectory activity. As future work, we will go deeper in the activity analysis, defining and recognizing unusual activities, and using Gaussian Mixture Models to calculate the statistics for time and duration in the knowledge base.

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