SEMANTIC ANNOTATION OF GPS TRACES: ACTIVITY TYPE INFERENCE

Sofie Reumers[1]*, Feng Liu[1], Davy Janssens[1], Mario Cools[2,1,3], and Geert Wets[1]

[1] Transportation Research Institute (IMOB), Hasselt University
Wetenschapspark 5, bus 6, BE-3590 Diepenbeek, Belgium
Fax.: +32(0)11 26 91 99

[2] Transport, Logistique, Urbanisme et Conception (TLU+C), Université de Liège
Chemin des Chevreuils 1, Bât. 52/3, BE-4000 Liège, Belgium

[3] Centre for Information, Modeling and Simulation (CIMS), Hogeschool-Universiteit Brussel
Warmoesberg 26, BE-1000 Brussels, Belgium

Sofie Reumers
Tel.: +32(0)11 26 91 60
Email: sofie.reumers@uhasselt.be

Feng Liu
Tel.: +32(0)11 26 91 25
Email: feng.liu@uhasselt.be

Davy Janssens
Tel.: +32(0)11 26 91 28
Email: davy.janssens@uhasselt.be

Mario Cools
Tel.: +32(0)485 42 71 55
Email: mario.cools@ulg.ac.be

Geert Wets
Tel.: +32(0)11 26 91 58
Email: geert.wets@uhasselt.be

* Corresponding author

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ABSTRACT

Due to the rapid development of technology, larger data sets concerning activity travel behavior become available. These data sets often lack semantic interpretation. This implies that annotation in terms of activity type and transportation mode is necessary. This paper aims to infer activity types from GPS traces by developing a decision tree-based model. The model only considers activity start times and activity durations. Based on the decision tree classification, a probability distribution and a point prediction model were constructed. The probability matrix describes the probability of each activity type for each class (i.e. combination of activity start time and activity duration). In each class, the point prediction model selects the activity type that has the highest probability. Two types of data were collected in 2006 and 2007 in Flanders, Belgium, i.e. activity travel data and GPS data. The optimal classification tree constructed comprises 18 leaves. Consequently, 18 if-then rules were derived. An accuracy of 74% was achieved when training the tree. The accuracy of the model for the validation set, i.e. 72.5%, shows that overfitting is minimal. When applying the model to the test set, the accuracy was almost 76%. The models indicate the importance of time information in the semantic enrichment process. This study contributes to future data collection in that it enables researchers to directly infer activity types from activity start time and duration information obtained from GPS data. Because no location information is needed, this research can be easily and readily implemented to millions of individual agents.

1 INTRODUCTION

The current research challenges in travel behavior analysis and travel demand modeling, such as obtaining more detailed information and a better behavioral reflection of peoples' choices, often reflect data problems (*1*). Although widely used as data collection methodologies in travel behavior research, travel surveys and activity diaries impose a significant respondent burden. Such surveys are very expensive and some survey methods, e.g. the paper-and-pencil diary, impose a time lag between the data collection process and the data entry. Moreover, the spatial and temporal components of the data collected are subject to biases. Also, traditional travel behavior surveys often incur low response rates. These shortcomings have been well reported in the literature, e.g. (*1-6*).

GPS data collection tools are a possible solution to these problems. A full-fledged activity based model system fully reflects spatial and temporal constraints and opportunities, models interactions among agents, captures time use and allocation behavior, and considers (both in-home and out-of-home) activity participation along the continuous time dimension (*7*). GPS-based data collection tools, especially when combined with activity-travel survey efforts, largely contributed to this by offering rich and detailed data about aspects of behavior (*7*). GPS data provides accurate spatial as well as temporal data on travel patterns, i.e. the exact coordinates and timestamps. The temporal component of diary data, on the other hand, is subject to rounding issues, while there is often no or only limited spatial information collected in a diary survey. Therefore, GPS-based data collection experiments are, nowadays, often combined with activity-travel diary surveys to supplement the information obtained from diary surveys as to obtain richer and more detailed data about travel behavior and the underlying decision processes (*8*).

However, obtaining significant mobility knowledge from raw data of individual trajectories requires detailed processing analysis. Large amounts of data are required to develop the most advanced activity-based models that are sensitive to a multitude of travel demand management strategies. Due to the rapid development of technology, an extensive growth in travel and activity behavior data exists to date while continuously expanding. These technologies offer a solution to the challenges associated with conventional travel surveys. The results are massive amounts of big data sets. However, despite the elimination of the above mentioned data challenges, large data sets lack semantic interpretation, and should thus be augmented to increase its usefulness in supporting the decisions of mobility management. As such, only detailed spatial and temporal resolutions are covered by GPS, which means that an annotation of the activity being pursued or the transportation mode being used is still necessary, explaining why current GPS-based data collection experiments are combined with traditional paper surveys.

In this paper, a semantic annotation of GPS traces will be discussed. This annotation is mainly based on heuristics (i.e. if-then rules) that are derived from the activity time information of an activity-travel diary survey (*9*), and are applied to the GPS traces of an associated GPS survey to infer activity type information. The information from the diary survey is used for model calibration and estimation. The data from the associated GPS survey is used to test the model and to assure the method is applicable when only GPS data is available. The resulting heuristics could mean an important improvement for the travel and activity behavior data collection process and the problems associated with it, since data collection by means of GPS-devices or mobile phone no longer need to be associated with a supplementary diary survey to annotate the activities. When fully annotated, travel diaries can be reconstructed (i.e. estimation of the complete activity-travel schedule of respondents) from GPS traces and can be fed into activity-based models. Therefore, the main purpose of this research is the development of an expert system that links GPS trajectories to the corresponding activity type, by merging the raw and behaviorally poor big data with the smaller but behaviorally richer travel survey data using machine learning algorithms. Two models, i.e. a predicted probability distribution and a point prediction model, were derived from a decision tree classification. The inference of activity information, solely from GPS data, reduces the large data collection efforts associated with conventional diary surveys and even eliminates the use of paper diary surveys for certain research purposes. The heuristics resulting from this research can be applied to large data sets, in which only activity time information is available.

In literature, many studies (e.g. (*10-15*)) can be found in which the relationship between the activity, its start time and its duration is analyzed. In most of these studies, additional information (e.g. land use data) was used as well. In the procedure used by Stopher et al. (*16*), land use data is even the most important data source for deducing the trip purpose (and transportation mode) from GPS traces. McGowen (*17*) also investigated the use of GPS devices in replacing diary surveys. The models predicted in which of 26 different activity types the individual participated. The best model, predicting out-of-home activities, was 63% accurate, while increasing up to 79% when combined with home activities. Even though McGowen uses several methods for model development, he explains that only classification trees are able to show the structure of the model and, in this way, offer an additional validation method (i.e. by determining if the splits of the tree seem logical). However, in his doctoral dissertation, McGowen does not provide simple heuristics (i.e. if-then rules) that can be extracted from the classification tree constructed. Despite the more than modest contribution on the semantic annotation of GPS traces in the literature, more specifically regarding the activity purpose, to the authors' knowledge none of these studies explicitly offer heuristics that can be applied in future research efforts. This research attempts to meet that shortfall by listing the resulting if-then rules.

Furthermore, many studies also address the inference of transportation modes from raw GPS data (e.g. (*16*), (*18*), (*19*), (*20*)). Even in this respect, explicit inference heuristics are rarely presented in the literature, for example in (*19*). The approach presented is oriented towards an inference from raw GPS data without additional information. Even here, the authors point out that detailed land use data will be necessary when extending their approach to determine activity purposes.

In the field of data mining and informatics, a number of prominent machine learning algorithms exist and are being used in modern computing applications. A common application for these algorithms often involves decision-based classification and adaptive learning over a training set. As explained by Drazin and Montag (*21*), a decision tree is a decision-modeling tool that graphically displays the classification process of a given input for given output class labels.

The remainder of the paper is structured as follows. Section 2 describes the data, with respect to data collection, data processing, some descriptive statistics of the data and potential errors in the data used for analysis. In section 3, the research methodology is clarified. Finally, in the last section, the most important results are discussed. This section also elaborates on some potential future research ideas.

2 DATA

2.1 Data Collection and Data Description

The data used for this study stems from a mixed-mode survey design, in which two types of data collection methods were used, namely a paper-and-pencil activity-travel diary survey and a corresponding survey in which GPS-enabled PDA's (Personal Digital Assistants) were used. The data were collected in 2006 and 2007 in Flanders, Belgium, in the context of a large scale survey that was conducted on 2500 households in the study area. A more thorough elaboration on this survey can be found in (*9*).

In the paper-and pencil diary survey, the respondents recorded trip (and activity type) information during the course of one week, such as the transportation mode, the travel party, information on the activity, and so on. The trip time information, i.e. the trip start time and the trip end time, is also recorded. However, since the diary is often filled out at the end of a survey day, this is merely an approximation for which the proximity is determined by the recall skills of the respondent. Half of the households were given a GPS-enabled PDA, called PARROTS (**P**DA system for **A**ctivity **R**egistration and **R**ecording **o**f **T**ravel **S**cheduling). Typically GPS-devices collect data into GPS logs, in which the longitude, latitude, a timestamp, and the velocity of a trip are recorded on a second-to-second basis. Similarly, the device used in this research was able to capture this route information, during the course of one week, but respondents were also asked for further information, like the purpose of the trip, the transportation mode used and the travel party (*22*).

TABLE 1 Trip Diary Data

ID Respondent	Date	Trip Start Time	Trip End Time	Main Transportation Mode	Distance travelled	Trip Purpose
HH4123GL10089	08/05/2006	08:30:00	09:00:00	Car – driver	20	Work
HH4123GL10089	08/05/2006	17:00:00	17:30:00	Car – driver	20	Home
HH4123GL10089	09/05/2006	07:45:00	08:00:00	Car – driver	12	Work
HH4123GL10089	09/05/2006	17:00:00	17:15:00	Car – driver	12	Shopping
HH4123GL10089	09/05/2006	17:20:00	17:30:00	Car – driver	3	Home

Table 1 shows a small selection of the trips from the trip diary survey. Only the variables that are relevant for current study are shown here, i.e. the date, the trip start and end time (in Central European Time), the main transportation mode, the distance travelled (in kilometers) and the trip purpose. The GPS data is recorded as

GPRMC-strings that contain a time stamp (in Greenwich Mean Time), the latitude and longitude, the speed (in knots), the current direction (measured as an azimuth) and the date. These sentences had already undergone a trip end identification procedure as to determine the trips from the raw GPS data. Table 2 shows the information that was obtained from the GPS logs. Here, the trip start and end times are expressed in Central European Time, as to reflect the diary data. Furthermore, the trip start and end times were used to calculate trip durations, both for the diary and the GPS data.

TABLE 2 GPS Trip Data

ID respondent	Date	Trip Start Time	Trip End Time	Latitude and Longitude Start Location	Latitude and Longitude End Location
HH4123GL10089	08/05/2006	08:44:23	08:54:18	50.787217 N 5.501612 E	50.739833 N 5.547843 E
HH4123GL10089	08/05/2006	17:18:23	17:36:16	50.774338 N 5.525688 E	50.791950 N 5.623698 E
HH4123GL10089	09/05/2006	07:49:54	08:02:04	50.791530 N 5.602290 E	50.739787 N 5.547468 E
HH4123GL10089	09/05/2006	17:03:27	17:19:01	50.740218 N 5.547355 E	50.812638 N 5.596675 E
HH4123GL10089	09/05/2006	17:24:32	17:28:35	50.812488 N 5.596607 E	50.791993 N 5.623525 E

2.2 Data Processing

The comparison of the two data sources (i.e. the diaries and the GPS logs) shows a certain mismatch in time registration. This mismatch is most likely due to incomplete schedules, the trip end identification process applied during the data processing and cleaning step, but also GPS burn in (i.e. lack of GPS recording due to insufficient satellite signals), battery instability, incorrect diary reporting and incorrect use of GPS devices. For most trips, only a small deviation in time registration was detected, reflecting rounding errors and burn in problems. These deviations could also be depicted when comparing the temporal information in table 1 and the temporal information in table 2. About 5 % of the data, however, show deviations in trip starting times and trip durations that exceed one hour. In case of such discrepancies, the data of that respondents' day were removed from analysis. It is assumed that these large deviations mainly result from an inaccuracy during the process of trip end identification or during the data cleaning.

During the data processing step, both the trip data derived from the activity diaries and the GPS trip data for which matching diary data was available, were converted into activity data sets. The activity before the first and after the last trip of each respondent on each survey day was assumed to be a home activity. Furthermore, the activity start and end times were used to calculate activity durations, both in the diary and in the GPS data.

Three variables were considered in the analysis: the activity duration (AD), the activity start time (AST) and the activity type. The activity duration and activity start time are used as explanatory variables to predict the activity type. Both explanatory variables are recorded in Central European Time (CET) and are expressed in minutes, starting from midnight for the activity start time variable (e.g. 660 minutes at 11:00 AM, 900 minutes at 03:00 PM….). CET is 1 hour ahead of Coordinated Universal Time (UTC) (i.e. UTC+01:00). Consequently, the activity start times are specified in CET. The variable activity type has six possible values: home, work, bring/get, leisure (e.g. sports), shopping and social (e.g. visits).

The resulting, randomly sampled, training data set consists of 8550 observations (75%), while 2898 observations (25%) constitute the validation data set. Both the training and the validation data set concern data that stems from the diary survey. The training set was used to train the model, the validation set to tune the model, e.g. for pruning the decision tree. As indicated by Wets et al. (*23*), using a random sample of 75 percent of the cases for training and a 25 percent subset for validation is frequently used and judged to be sufficiently reliable. Finally, an independent test set was used to obtain the performance of the model on real-world data. This test set concerns the GPS traces for which corresponding diary data is also available, representing 290 activities.

3 METHODOLOGY AND RESULTS

Using the activity data sets, a classification of the activity start times and activity durations was obtained from a decision tree induction. The J48 decision tree-inducing algorithm of the Waikato Environment for Knowledge Analysis (Weka) interface, which is the Weka implementation of C4.5 published by Ross Quinlan in 1993, was applied. Weka is an open-source Java application which consists of a collection of machine learning algorithms for data mining tasks (*24*). C4.5 was chosen because it is one of the most commonly used algorithms in the machine learning and data mining communities (*25*). For many domains, the trees produced by C4.5 are both small and accurate, resulting in fast reliable classifiers, and making decision trees a valuable and popular tool for classification (*25*). In decision trees, each internal node contains a test that decides what branch to follow from that node. C4.5 and its predecessor, ID3, both use formulas based on information theory to evaluate whether a test extracts the maximum amount of information from a set of cases, given the constraint that only one attribute will be tested. The method that is used here for pruning the decision tree estimates the error rate of every subtree and replaces the subtree with a leaf node if the estimated error of the leaf is lower (*26*).

Several decision trees were built on the training set, and evaluated using the validation data set and the test set. The classification was optimized by pruning the tree, i.e. by considering minimum class frequencies and by creating balance between the number of leaf nodes and the degree of impurity. The classification error was used to measure this degree of impurity. By lowering the confidence in the training data not only the tree size was reduced, but statistically irrelevant nodes that would otherwise lead to classification errors were also filtered out. For this, several values for the confidence factor were tested when generating the decision tree to find the most appropriate value for the training set.

TABLE 3 If-then Rules from Optimal Decision Tree

If…	Then activity type = …
AD < = 10min and AST < = 11:15 PM	Bring/get activity
AD < = 10min and AST > 11:15 PM	Home activity
10min < AD < = 35min and AST < = 7:45 AM	Home activity
10min < AD < = 35min and 7:45 AM < AST < = 6:45 PM	Shopping activity
10min < AD < = 35min and 6:45 PM < AST < = 7:15 PM	Social activity
10min < AD < = 35min and 7:15 PM < AST < = 8:55 PM	Home activity
10min < AD < = 35min and 8:55 PM < AST < = 11:20 PM	Leisure activity
10min < AD < = 35min and AST > 11:20 PM	Home activity
35min < AD < = 50min and AST < = 5:45 PM	Shopping activity
35min < AD < = 3h30min and 5:45 PM < AST < = 8:30 PM	Social activity
35min < AD < = 2h5min and 8:30 PM < AST < = 9:50 PM	Leisure activity
35min < AD < = 3h30min and AST > 9:50 PM	Home activity
50min < AD < = 3h30min and AST < = 5:45 PM	Home activity
2h5min < AD < = 3h30min and 8:30 PM < AST < = 9:50 PM	Home activity
3h30min < AD < 14h25min and 2:30 AM < AST < = 9:30 AM	Work activity
AD > 3h30min and AST < = 2:30 AM	Home activity
AD > 3h30min and AST > 9:30 AM	Home activity
AD > 14h25min and 2:30 AM < AST < = 9:30 AM	Home activity

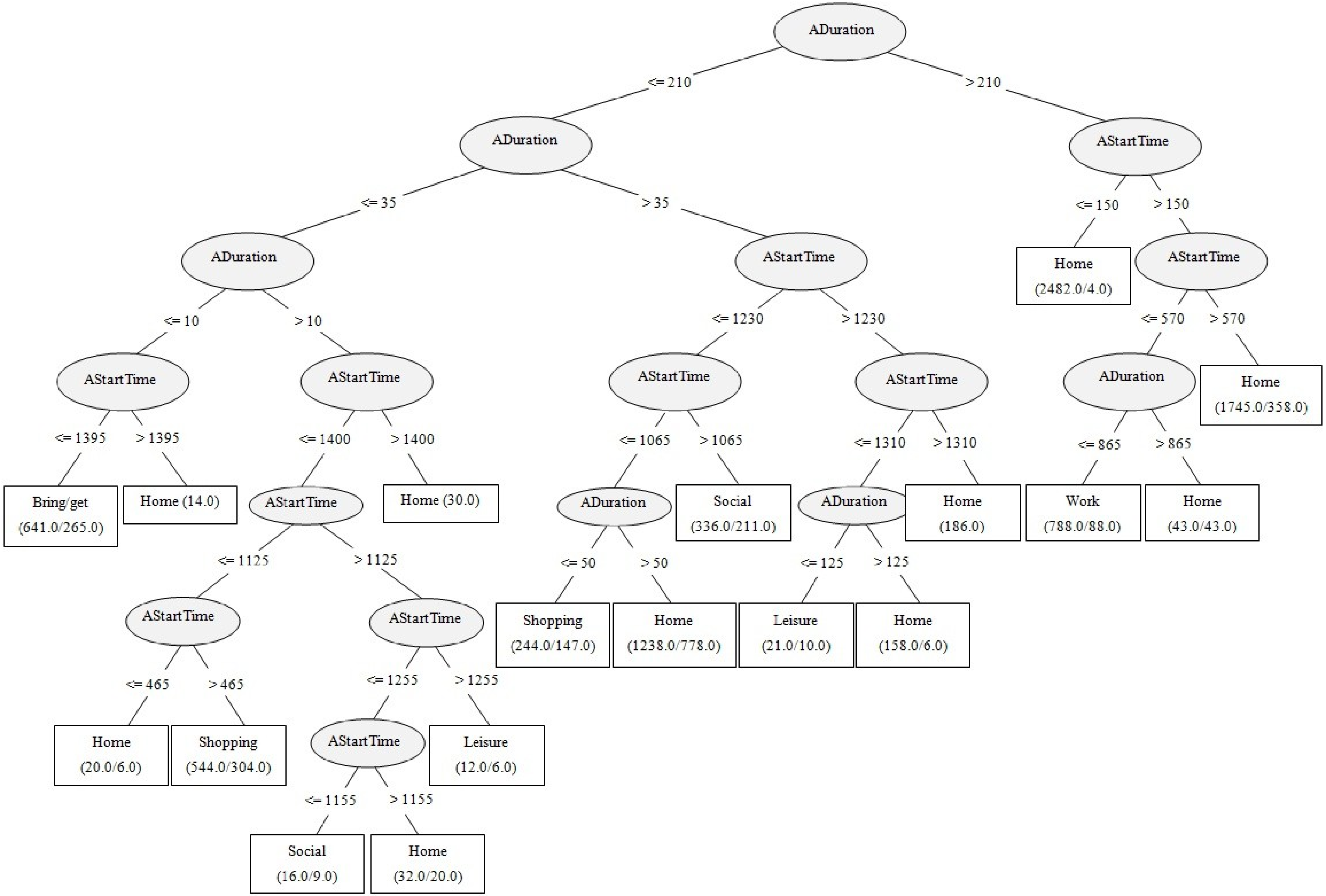

FIGURE 1 Optimal decision tree (DT) for activity type inference.

The most optimal classification tree constructed (when considering both in-home and out-of-home activities) comprises 18 leaves, as shown in figure 1. Here, a minimum of 10 activities per leaf and a confidence factor of 0.001 were used as pruning conditions. Consequently, 18 if-then rules were derived (see table 3). An accuracy of 74% was achieved when training the tree. The accuracy of the model for the validation set, i.e. 72.5%, shows that overfitting is minimal. When applying the model to the (unseen) GPS data, i.e. the test set, the performance was almost 76% accurate. The decision tree classified the activity durations into 7 classes, while the activity start times were categorized into 12 classes. Applying both categorizations to the data set gives a maximum of 84 possible categories. However, in several categories no observations are available, and thus for these categories no predictions will be modeled.

Some conclusions can be drawn from the if-then rules (table 3) that apply to the most optimal decision tree (figure 1). These results also emerge later on in this paper, in table 5 and table 6. It appears that bring/get activities typically have a short duration and that these activities are performed throughout the entire day. On the other hand, the duration of work activities is much longer. The if-then rules indicate that these activities start mostly in the morning. As expected, the rules that apply to shopping activities are consistent with the opening hours of shopping facilities. Accordingly, activities performed in the (late) evening that last longer than 10 minutes are social and leisure activities.

Table 4 shows the true positive rate, false positive rate, precision, and F-measure for each activity type, and for all three data sets. The true positive rate for a specific activity type, e.g. activity x, gives the proportion of examples which were classified as activity x among all examples which truly are activity x. The false positive rate of activity x gives the proportion of examples which were classified as activity x but belong to a different class, among all examples which are not of class x. Furthermore, the precision of class x is the proportion of examples which truly are activity x among all those which were classified as activity x. And finally, the F-measure is a combined measure for the precision and true positive rate.

TABLE 4 Accuracy by Class

Activity	Data set	True Positive Rate	False Positive Rate	Precision	F-Measure
Bring/get	Training data	0.641	0.033	0.587	0.612
	Validation data	0.658	0.033	0.573	0.613
	Test data	0.765	0.066	0.419	0.542
Home	Training data	0.934	0.341	0.802	0.863
	Validation data	0.917	0.364	0.791	0.849
	Test data	0.965	0.275	0.832	0.894
Leisure	Training data	0.039	0.002	0.515	0.072
	Validation data	0.007	0.003	0.125	0.013
	Test data	0.071	0	1	0.133
Shopping	Training data	0.46	0.058	0.428	0.443
	Validation data	0.423	0.06	0.389	0.406
	Test data	0.269	0.042	0.389	0.318
Social	Training data	0.242	0.027	0.375	0.294
	Validation data	0.225	0.03	0.347	0.273
	Test data	0.2	0.03	0.333	0.25
Work	Training data	0.616	0.012	0.888	0.727
	Validation data	0.599	0.016	0.855	0.704
	Test data	0.721	0	1	0.838
Weighted average	Training data	0.741	0.215	0.725	0.715
	Validation data	0.724	0.23	0.69	0.697
	Test data	0.759	0.171	0.767	0.732

Table 4 shows that the true positive rate is highest for home activities, in all three data sets, and lowest for leisure activities. When considering the false positive rates, the same conclusions can be drawn. About 80% of the activities that were classified as home activities by the model are truly a home activity. A precision of 1, as is the case for leisure and working activities when applying the model to the test data, indicates that all examples that were classified as leisure and work activities in the test data set were truly leisure and work activities, respectively. However, the low true positive rate of leisure activities indicates that among all the examples that truly are leisure activities, only 7.1% was classified as a leisure activity. The remaining 92.9% of leisure activities in the test data were wrongly classified as a different activity. On the other hand, among all examples which are not leisure activities, there were no examples classified as a leisure activity. The model performed better for work activities, since 72.1% of the work activities in the test set were classified as a work activity, and only 27.9% of work activities were classified as another activity.

Based on the decision tree, probability matrices were constructed. For each class of activity start time and activity duration, the probability of conducting the six different activities is predicted. The resulting probabilities, when considering the most optimal classification tree, are shown in table 5. From this probability matrix, a point prediction (majority) matrix was extracted using the highest probabilities per class (see table 6).

TABLE 5 Probability Matrix

	Activity Duration						
Activity Start Time	**<= 10 min**	**<= 35 min**	**<= 50 min**	**<= 125 min**	**<= 210 min**	**<= 865 min**	**> 865 min**
<= 2:30 AM							
- Home	0.7000	0.9167	1.0	0.9706	0.9	0.9986	0.9971
- Work	0.0	0.0	0.0	0.0	0.0	0.0	0.0
- Bring/get	0.3000	0.0	0.0	0.0	0.0	0.0	0.0
- Leisure	0.0	0.0833	0.0	0.0	0.0	0.0009	0.0
- Shopping	0.0	0.0	0.0	0.0	0.0	0.0	0.0
- Social	0.0	0.0	0.0	0.0294	0.1	0.0005	0.0029
<= 7:45 AM							
- Home	0.0286	0.3750	0.5000	0.3125	0.4000	0.0849	0.8571
- Work	0.0	0.2500	0.2500	0.5000	0.4000	0.8962	0.1429
- Bring/get	0.7143	0.0	0.0	0.0	0.0667	0.0	0.0
- Leisure	0.0	0.1250	0.0	0.0	0.0667	0.0189	0.0
- Shopping	0.2571	0.0	0.0	0.0625	0.0	0.0	0.0
- Social	0.0	0.2500	0.2500	0.1250	0.0667	0.0	0.0
<= 9:30 AM							
- Home	0.0240	0.1392	0.3667	0.2738	0.2899	0.0660	0.9655
- Work	0.0180	0.1139	0.0333	0.2976	0.4889	0.8854	0.0345
- Bring/get	0.7485	0.2532	0.1000	0.0238	0.0111	0.0104	0.0
- Leisure	0.006	0.0127	0.0667	0.1548	0.1111	0.2260	0.0
- Shopping	0.2036	0.4684	0.3000	0.1905	0.0556	0.0017	0.0
- Social	0.0	0.0127	0.1333	0.0595	0.0444	0.0139	0.0
<= 5:45 PM							
- Home	0.0854	0.1616	0.1872	0.3220	0.4211	0.7306	n.a.
- Work	0.0122	0.0585	0.0296	0.1119	0.1704	0.1145	n.a.
- Bring/get	0.4695	0.2061	0.0640	0.0424	0.0175	0.0016	n.a.
- Leisure	0.0213	0.0539	0.0936	0.1271	0.1378	0.0685	n.a.
- Shopping	0.3689	0.4496	0.4335	0.1831	0.0927	0.0234	n.a.
- Social	0.0427	0.0703	0.1921	0.2136	0.1604	0.0613	n.a.
<= 6:45 PM							
- Home	0.1190	0.2632	0.4783	0.4058	0.1765	0.9563	n.a.
- Work	0.0238	0.0789	0.0	0.0290	0.0294	0.0040	n.a.
- Bring/get	0.6429	0.2895	0.1739	0.0580	0.0	0.0	n.a.
- Leisure	0.0	0.0526	0.0435	0.1159	0.3824	0.0159	n.a.
- Shopping	0.1905	0.2895	0.0870	0.0435	0.0294	0.0	n.a.
- Social	0.0238	0.0263	0.2174	0.3478	0.3824	0.0238	n.a.
<= 7:15 PM							
- Home	0.1250	0.0625	0.4615	0.1143	0.1000	0.9341	n.a.
- Work	0.0625	0.0625	0.0769	0.0	0.0	0.0	n.a.
- Bring/get	0.5625	0.1875	0.0	0.0857	0.0	0.0	n.a.
- Leisure	0.0	0.0625	0.0769	0.2857	0.4000	0.0220	n.a.
- Shopping	0.1875	0.1875	0.0	0.1714	0.0	0.0	n.a.

- Social	0.0625	0.4375	0.3846	0.3429	0.5000	0.0440	n.a.
<= 8:30 PM							
- Home	0.2174	0.3571	0.3125	0.0741	0.1389	0.9568	n.a.
- Work	0.0	0.1429	0.1250	0.0741	0.0278	0.0	n.a.
- Bring/get	0.6957	0.2143	0.0625	0.0556	0.0	0.0	n.a.
- Leisure	0.0	0.0357	0.0625	0.3519	0.4444	0.0247	n.a.
- Shopping	0.0435	0.0714	0.1875	0.0	0.0	0.0	n.a.
- Social	0.0435	0.1786	0.2500	0.4444	0.3889	0.0185	n.a.
<= 8:55 PM							
- Home	0.0	0.5000	0.5000	0.1429	0.8913	n.a.	n.a.
- Work	0.2000	0.0	0.0	0.0	0.0	n.a.	n.a.
- Bring/get	0.6000	0.5000	0.0	0.0	0.0	n.a.	n.a.
- Leisure	0.0	0.0	0.0	0.5714	0.0217	n.a.	n.a.
- Shopping	0.2000	0.0	0.5000	0.0	0.0	n.a.	n.a.
- Social	0.0	0.0	0.0	0.2857	0.0870	n.a.	n.a.
<= 9:50 PM							
- Home	0.0	0.0	0.0	0.0	0.9911	n.a.	n.a.
- Work	0.0	0.0	0.0	0.0	0.0	n.a.	n.a.
- Bring/get	0.8571	0.3333	0.5000	0.1000	0.0	n.a.	n.a.
- Leisure	0.0	0.6667	0.5000	0.6000	0.0089	n.a.	n.a.
- Shopping	0.1429	0.0	0.0	0.0	0.0	n.a.	n.a.
- Social	0.0	0.0	0.0	0.3000	0.0	n.a.	n.a.
<= 11:15 PM							
- Home	0.0	0.0	1.0	1.0	n.a.	n.a.	n.a.
- Work	0.0	0.0	0.0	0.0	n.a.	n.a.	n.a.
- Bring/get	1.0	0.3333	0.0	0.0	n.a.	n.a.	n.a.
- Leisure	0.0	0.4444	0.0	0.0	n.a.	n.a.	n.a.
- Shopping	0.0	0.0	0.0	0.0	n.a.	n.a.	n.a.
- Social	0.0	0.2222	0.0	0.0	n.a.	n.a.	n.a.
<= 11:20 PM							
- Home	n.a.	n.a.	1.0	n.a.	n.a.	n.a.	n.a.
- Work	n.a.	n.a.	0.0	n.a.	n.a.	n.a.	n.a.
- Bring/get	n.a.	n.a.	0.0	n.a.	n.a.	n.a.	n.a.
- Leisure	n.a.	n.a.	0.0	n.a.	n.a.	n.a.	n.a.
- Shopping	n.a.	n.a.	0.0	n.a.	n.a.	n.a.	n.a.
- Social	n.a.	n.a.	0.0	n.a.	n.a.	n.a.	n.a.
> 11:20 PM							
- Home	1.0	1.0	n.a.	n.a.	n.a.	n.a.	n.a.
- Work	0.0	0.0	n.a.	n.a.	n.a.	n.a.	n.a.
- Bring/get	0.0	0.0	n.a.	n.a.	n.a.	n.a.	n.a.
- Leisure	0.0	0.0	n.a.	n.a.	n.a.	n.a.	n.a.
- Shopping	0.0	0.0	n.a.	n.a.	n.a.	n.a.	n.a.
- Social	0.0	0.0	n.a.	n.a.	n.a.	n.a.	n.a.

n.a. not available because there is no input data for these classes

Table 6 should be interpreted as follows: e.g. if an activity is started at 2:30 AM or earlier and that activity has a duration of 10 minutes or less, than there's a 70% chance that this is a home activity and a 30% chance that it reflects a bring/get activity.

Finally, table 7 shows the majority rules. Here it is clearly shown that activities performed around midnight (i.e. after 11:16 PM but before 2:31 AM) are typically home activities. The same can be said for activity durations of more than 865 minutes. The asterisks in table 7 show for which predictions only weak probabilities were obtained, indicating the significance of the predictions.

TABLE 6 Majority Matrix

	Activity Duration						
Activity Start Time	**<= 10 min**	**<= 35 min**	**<= 50 min**	**<= 125 min**	**<= 210 min**	**<= 865 min**	**> 865 min**
<= 2:30 AM	Home	Home	Home	Home	Home	Home	Home
<= 7:45 AM	Bring/get	Home*	Home	Work	Home or Work*	Work	Home
<= 9:30 AM	Bring/get	Shopping*	Home*	Work**	Work*	Work	Home
<= 5:45 PM	Bring/get*	Shopping*	Shopping*	Home*	Home*	Home	n.a.
<= 6:45 PM	Bring/get	Shopping or Bring/get**	Home*	Home*	Leisure or Social*	Home	n.a.
<= 7:15 PM	Bring/get	Social*	Home*	Social*	Social	Home	n.a.
<= 8:30 PM	Bring/get	Home*	Home*	Social*	Leisure*	Home	n.a.
<= 8:55 PM	Bring/get	Home or Bring/get	Home or Shopping	Leisure	Home	n.a.	n.a.
<= 9:50 PM	Bring/get	Leisure	Bring/get or Leisure	Leisure	Home	n.a.	n.a.
<= 11:15 PM	Bring/get	Leisure*	Home	Home	n.a.	n.a.	n.a.
<= 11:20 PM	n.a.	n.a.	Home	n.a.	n.a.	n.a.	n.a.
> 11:20 PM	Home	Home	n.a.	n.a.	n.a.	n.a.	n.a.

n.a. not available because there is no input data for these classes
* weak prediction probability (less than 50%)
** weakest prediction probability (i.e. a majority probability of 29,2%)

4 DISCUSSION AND CONCLUSION

In this paper, a simple and efficient method to annotate (large amounts of) GPS data is presented. The models constructed in this paper indicate the importance of time information in the semantic enrichment process. This paper shows that even when only the temporal dimension of travel diary data is used, reliable and meaningful heuristics can be derived from these diary data. 18 binary if-then rules are presented. Moreover, the high accuracy obtained, by applying the heuristics on independent real-world data (i.e. almost 76%), underlines that the presented heuristics are not data dependent and can be applied to annotate a broad range of GPS data.

This study presents a straightforward and readily implemented algorithm. Consequently, the results are relevant for the ongoing development of the next generation of activity-based travel demand models in a cost-efficient manner. The contribution of this study towards future data collection is promising in that it enables researchers to directly and automatically infer activities from activity start time and activity duration information obtained from GPS data, without any other additional information. After all, the increasing pervasiveness of location-acquisition technologies, such as GPS, is leading to large collections of spatio-temporal data sets. In addition to the substantial reduction of future data collection efforts for researchers, the results of this study also reduce the associated respondents' burden of large and demanding diary surveys. Furthermore, the use of the if-then rules, combined with technological improvements in the field of GPS devices, can have the potential of increased data accuracy. The results of this research are able to enhance activity-based models, thus resulting in a cost-efficient implementation of sustainable policy measures in traffic and transportation policy and effectively predicting future mobility policy. This research may also contribute in understanding the mental processes individuals go through when making certain traffic related decisions, mainly with respect to activity start times and activity durations. In fact, mobility management requires a thorough knowledge and understanding of individual decision processes.

Even though an accuracy of 76% was achieved, this method seems to neglect some of the diversity of the activity type, their time of day and duration. After all, the method depends on identifying typical daily activity patterns based on time of day patterns. The sample is disproportionally made up of the different activity types, therefore possibly inflating the overall accuracy number and masking some inaccurate classifications of social and leisure trips. This implies that the model predicts a more homogeneous set of patterns than a diary-based survey would. Hence, more work is needed to address this issue and to achieve the level of accuracy that is required for this approach to become mainstream.

Using these models (and further improvements from future research) will enrich GPS logs with diary variables, which enables researches to exclusively use GPS data collection devices. This research contributes to the current scientific state-of-the-art in activity and travel behavior analysis and modeling research, with the goal to apply the results of this study to tens of millions of individual agents. Since the conclusions are solely based on a pure time annotation, future research efforts should extend this concept e.g. by using location information from land use databases, sequential information, or socio-economic data that was obtained in the diary survey, to decide whether a pure time annotation is sufficient to derive meaningful decision rules or to improve the weak predictions from this study. Furthermore, future research efforts should compare these results with the results from several different classifiers and other machine learning techniques.

Because of the large deviation in time registration between both data sources, the research methodology should also be applied to other, unrelated data sets, to eliminate additional data biases and overfitting. However, finding more consistent data will be a challenge, since this is a typical travel data problem.

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