

Learning Transportation Mode from Raw GPS Data for Geographic Applications on the Web

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ABSTRACT

Geographic information has spawned many novel Web applications where global positioning system (GPS) plays important roles in bridging the applications and end users. Learning knowledge from users' raw GPS data can provide rich context information for both geographic and mobile applications. However, so far, raw GPS data are still used directly without much understanding. In this paper, an approach based on supervised learning is proposed to automatically infer transportation mode from raw GPS data. The transportation mode, such as walking, driving, etc., implied in a user's GPS data can provide us valuable knowledge to understand the user. It also enables context-aware computing based on user's present transportation mode and design of an innovative user interface for Web users. Our approach consists of three parts: a change point-based segmentation method, an inference model and a post-processing algorithm based on conditional probability. The change point-based segmentation method was compared with two baselines including uniform duration based and uniform length based methods. Meanwhile, four different inference models including Decision Tree, Bayesian Net, Support Vector Machine (SVM) and Conditional Random Field (CRF) are studied in the experiments. We evaluated the approach using the GPS data collected by 45 users over six months period. As a result, beyond other two segmentation methods, the change point based method achieved a higher degree of accuracy in predicting transportation modes and detecting transitions between them. Decision Tree outperformed other inference models over the change point based segmentation method.

Categories and Subject Descriptors

H.4.3 [Information System Application]: Communications Applications – *Information browsers*. H.5.2 [Information Interface and Presentation]: User Interface. I.5.2 [Pattern Recognition]: Design Methodology - *Classifier design and evaluation*.

General Terms

Algorithm, Design, Experimentation.

Keywords

Geographic Applications, GPS, Transportation Mode, Machine Learning, Classification.

1. INTRODUCTION

In recent years, on the World Wide Web, geographic information has enabled an explosion of applications in which locality and mobility usually connect to one another closely. Web-based

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mapping applications like Google Maps, Yahoo Maps and Live Maps as well as mobile/local search engines have attracted considerable interest among Web users and developers. Meanwhile, with the increasing prevalence of GPS devices, as never before, many communities that engaged in geographically related activities have been established. For instance, GPS track visualization and sharing over Web maps [1, 2, 3, 4, 5] as well as geo-tagging photos for archiving and browsing [6] have been incubated. In these applications, GPS data have played important roles in bridging them and end users, e.g., ranking the results of mobile/local search, tagging photos with locations, etc. However, to date, most of these applications only use raw GPS data like GPS coordinates and timestamps without much understanding, while other applications needs support from manual efforts. Neither method is optimal for the development of geographic and mobile applications. In this paper, we aim to improve local/mobile applications on the Web and enhance their connections by mining knowledge from raw GPS data with minimal user efforts.

As a kind of knowledge mined from raw GPS data, transportation modes such as walking, driving etc, and the transitions between them are valuable for both users and application systems.

- For users: The information helps individuals effectively reflect on their past events and deeply understand their own life pattern as well. Also, it presents richer knowledge over the plain GPS tracks to other users and facilitates life sharing among people.
- For the application systems: 1) It enables context-aware computing based on a user's present transportation mode and design of innovative web user interface. 2) It empowers the application systems to distinguish GPS tracks by transportation modes so that users can find proper routes to their destinations in a more effective manner. 3) It allows the systems to mine deeper knowledge such as traffic condition, popular routes for different transportation modes, etc., from public GPS data.
- Moreover, in many research [7][8][9][10][11][12] aiming to understand user behavior from raw GPS data, transportation mode is also important knowledge to support their work. It can be used to improve the accuracy of prediction on an individual's outdoor movements. Also, it can contribute to extract a user's life pattern and discover the social pattern. In turn, all the knowledge learned from this work can be leveraged to enhance many innovative local/mobile applications on the Web further.

However, due to the following two reasons, it is not feasible to require every user to manually tag corresponding transportation modes to their GPS tracks. 1) No motivation: Users cannot directly achieve benefits from labeling their trips. 2) Difficulty: A personal trip usually includes different transportation modes. However, it is difficult for people to remember the accurate time when they change their transportation modes.

On the other hand, the identification methods based on simple rule like velocity-based approach, cannot handle this problem with great effect. The features of different transportation modes are usually vulnerable to traffic conditions and weather. Intuitively, in congestion, the mean velocity of driving would be as slow as walking while on a rainy day a bus may move more like a bike from the perspective of velocity. When a user takes more than one kind of transportation modes along a trip, the identification on transportation mode becomes more difficult. Thus, we do need an approach to automatically and accurately infer transportation modes as well as the transitions between them from raw GPS data. Meanwhile, to make the approach more general and universal, we do not expect it relies on the data collected by other sensors like cell-phone, Wi-Fi, RFID, and/or other information extracted from geographic maps, such as road networks etc. In other words, the inference approach should only depend on raw GPS data. To the best of our knowledge, no related work solves this problem.

In this paper, for geographic and mobile applications on the Web, we propose an approach using raw GPS data that is based on supervised learning to automatically learn the transportation modes including walking, taking a bus, riding a bike and driving. The contributions of the work lie in that:

- It is an important step towards improving geographic applications on the Web by using knowledge mined from raw GPS data.
- Such knowledge can enhance the connection between locality and mobility, and enable more novel applications on the Web.
- It helps users deeply understand their own experience and better shares other people's knowledge.
- It enables local/mobile application systems to perform context-aware computing based on transportation mode and create an innovative user interface for Web users.

The advantages of our approach lie in that: 1) our approach can infer compound trips, which contain more than one kind of transportation modes. In addition, it can correctly detect the transition between different transportation modes. 2) The approach is independent of other information from maps and other sensors. 3) The model learned from the dataset of some users can be applied to infer GPS data from others.

The rest parts of the paper are organized as follows. First in Section 2, we briefly introduce the architecture and the prototype of GeoLife where our approach has been deployed to play important roles. The significance of inferring transportation mode is justified by three application scenarios here. Then, the framework of our approach is described in Section 3 while the detail methodologies are given in Section 4. Subsequently, in Section 5, we evaluate our approach based on the GPS data from 45 people over a period of six months. Some experiments results and corresponding discussions are also presented. Finally, after introducing some related work in Section 6, we draw conclusions and offer an outlook for our future work in Section 7.

2. GEOLIFE

The work reported in this paper is a part of research into our project GeoLife, which is a GPS-log-driven application over Web Map. It focuses on lively visualization, effective organization, fast retrieval and deeply understanding of GPS track logs for both personal and public use.

As shown in Figure 1, given the GPS track log as well as associated multimedia data people created in their daily lives, GeoLife helps users visualize their past events on Web maps and

understand their personal life pattern as well. By publishing some of GPS tracks out, users can share life experience with others and absorb rich knowledge from others' GPS tracks. Based on public data, more knowledge such as popular travel routes, hot places and traffic condition, etc., can be mined. The mined knowledge can be recommended to users via Web or mobile user interface (UI) when they need suggestions. Further, a spatial-temporal search function, which allows users to give a spatial range over maps and/or temporal interval as a query, is offered in GeoLife to help people effectively find out the GPS tracks they are interested in. The search function does not only facilitates allowing people to efficiently get information from other's life experience but also support each person's recall of past events.

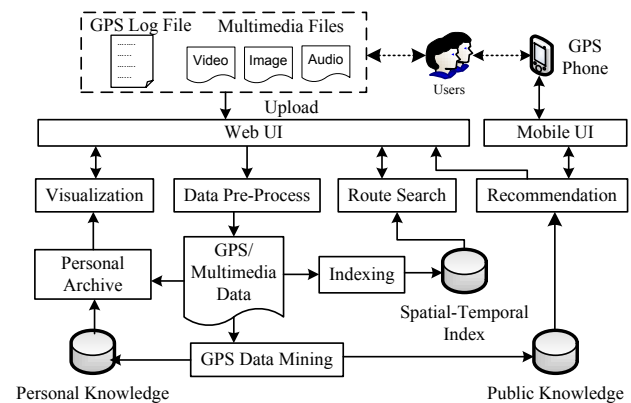


Figure 1. Architecture of GeoLife

Figure 2 depicts the Web user interface of GeoLife prototype. Compared to traditional text-based description, visualizing GPS log over Web maps can provide a more attractive, concise and explicit approach to express people's experience.

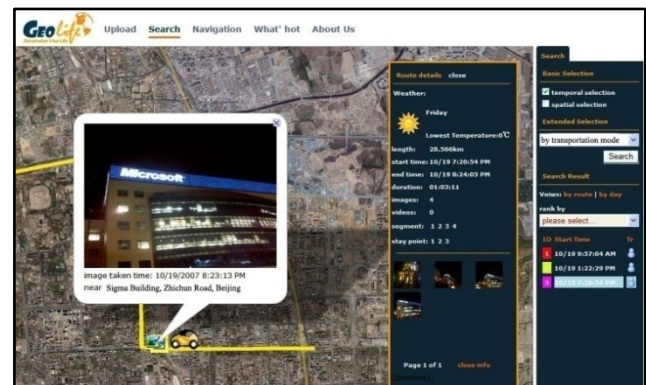
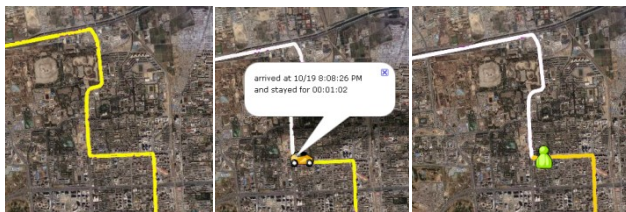


Figure 2. Prototype of GeoLife

Our approach has been deployed in the website to help system automatically tag transportation modes to GPS tracks submitted by users. Also, it can be performed in GPS-phone to infer a person's present transportation mode. Therefore, with the information of transportation mode, 1) users can connect to their personal past better, and obtain more information from others' experience when they browse a GPS track. 2) When searching for a route on desktop machines or mobile devices, users can efficiently retrieve the GPS tracks matching their preference on transportation mode. Intuitively, people do not want to see a riding means when they are trying to find a driving route. 3) For remote users carrying GPS phones, based on their present transportation modes, we can display information with different map scales. 4) The system can model each individual's activity

more accurately and delivery commonsense information, e.g. bus schedules, in advance.

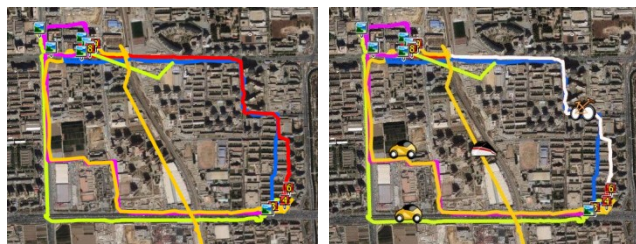
Figure 3 presents an example to distinguish the different Web experience with and without transportation mode. As we can see, without the tag of transportation mode, the track shown in the Figure 3 (a) only provides us some basic location information. However, after we apply our inference model to this track, as illustrated in Figure 3 (b) and (c), richer knowledge has been discovered over the plain track. We can realize that the user first drives a car downtown, and then at the parking lot he/she switches to walking. At least, we know there is a parking lot where we can stop a car, and how long could we might spend on the way if we want to drive. Meanwhile, this track may also suggest walking from the parking lot to downtown to avoid heavy traffic and enjoy shopping. According to the mean velocity of the whole track, the route looks as if it suffers from heavy traffic. Therefore, we will ignore it when searching a way to drive downtown.



(a) Before inference (b) Stop at parking lot (c) Switch to walk

Figure 3. An example of inferring transportation modes from GPS data

Figure 4 give us another example to present the significance of our work on route recommendation based on user preference on transportation mode. In Figure 4 (a), there are many route candidates for selection when people try to find a way from the right-bottom to the left-top. Unfortunately, these routes are less discriminative from one another before we infer their transportation modes.



(a) Raw GPS Tracks (b) Tracks after inference



(c) A track of bike (d) A track of car

Figure 4. Route recommendation based on transportation mode

Actually, as shown in Figure 4 (b), these routes are generated by different users taking different transportation modes. Thus, when a person wants to ride a bike to the destination, we should recommend the route shown in Figure 4 (c). Likewise, when a user intends to drive, we should present the route depicted in

Figure 4 (d). This recommendation makes sense to remote users when they search an efficient route to a location via mobile phone.

Another potential application of our work is related to mobile/local search. As shown in Figure 5, when people search for a restaurant around them, the system can return different search results with different map scales based on their present transportation mode. For instance, in Figure 5 (a), if the person is walking, we can return the top ten restaurants within a distance of 500 meters. However, in Figure 5 (b), if the person is driving, we can return the top ten restaurants within a farther distance like two or three kilometers. Intuitively, people who drive do not care about the distance of two or three kilometers while that distance is relatively far to a person who is walking. Since, in Figure 5 (b), more restaurants will be retrieved from a larger spatial range, the quality of top 10 restaurants may be higher than the results in (a).



(a) Search results for WALK (b) Search results for CAR

Figure 5. Using transportation mode to improve mobile search

3. FRAMEWORK

In this section, we first define several terms used in this paper and then describe procedures of inference from a high level. Our approach is comprised of a segmentation method, an inference model, and post-processing method.

3.1 Preliminary

Before we start describing the framework of our approach, we have to clearly define the terms, GPS log, track, trip, segment, change point, *Walk Segment* and *non-Walk Segments* mentioned in this paper. Basically, as depicted in the left part of Figure 6, GPS log is a sequence of GPS points $P_i \in \{P_1, P_2, \dots, P_n\}$. Each GPS point P_i contains latitude, longitude and timestamp. We can sequentially connect these GPS points into a track, and divide the track into trips if the time interval of the consecutive points exceeds a certain threshold.

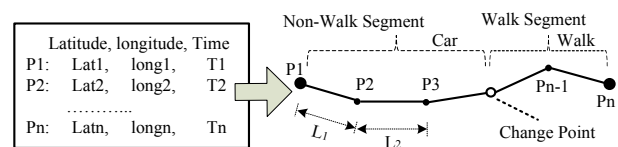


Figure 6. GPS log, segment and change point

A change point stands for a place where people change their transportation modes. Since users usually change their transportation modes along a trip, i.e., a trip may contain more than two kinds of modes, we should first distinguish the segments of different transportation modes. For the description convenience, we name the segment of walk after *Walk Segment* while the segments of other transportation modes are called *non-Walk Segments*. Further, we denominate the GPS point from a *Walk Segment*, such as P_{n-1} , *Walk Point* while the GPS point from *non-*

Walk Segment, e.g., P_2 , is called *non-Walk Point*. For instance, in Figure 6, a trip can be partitioned into a *Walk Segment* and a *non-Walk Segment* by a change points. The duration of a trip is the time interval between its start point and end point while the length of a trip denotes the sum of distance between each two consecutive points. The same definition also goes to the segment.

3.2 Inference Strategy

As shown in Figure 7, when a GPS Log file comes, first, we divide the GPS track into trips and then partition each trip into segments by change points. Then, we extract the features from each segment and send these features to the inference model. Two alternative ways are considered when we attempt to learn a user's transportation mode. In one way, we regard the segments of GPS tracks as independent instances. General classifiers like Decision Tree are employed to perform inference. After the inference, a post-processing, which takes the transition probability between different transportation modes into account, is implemented to improve the prediction accuracy. In the other way, GPS data are deemed as a kind of sequential data. Conditional random field (CRF) [13], a framework for building probabilistic models to segment and label sequence data, is leveraged to perform the inference. Since the conditional probabilities between different transportation modes have been considered in the CRF graphical model, in this way, we do not take the post-processing. In the inference, the mode of transportation can take four different values including Bike, Bus, Car and Walk. At the same time, we do not discriminate driving private car from taking taxi. Both of them are deemed as Car.

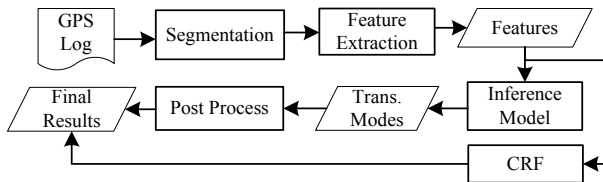


Figure 7. Procedure of inferring transportation mode

3.3 Post-Processing

After taking the former inference process, as depicted in Figure 8, we can get the predicted transportation mode ranked by its probability value for each segment. If we directly select the transportation mode with maximum probability as the final results, the prediction is Car→Bike→Bike while the ground truth is Car→Walk→Bike. I.e., a prediction error is occurred. At this moment, we can improve the prediction accuracy by considering the conditional probability between different transportation modes.

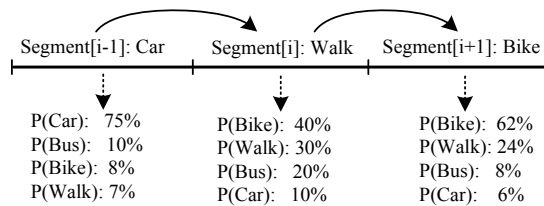


Figure 8. An example of post-processing

If in a segment, e.g., segment $i-1$, the probability of the top transportation mode exceed a threshold (for instance, 70 percent in our experiment), we use this transportation mode as the final prediction result on this segment. Then, we can re-calculate the probability of each kind of transportation mode of its adjacent segment, e.g., segment i , according to the following equations.

$$Segment[i].P(Bike) = Segment[i].P(Bike) \times P(Bike|Car), \quad (1)$$

$$Segment[i].P(Walk) = Segment[i].P(Walk) \times P(Walk|Car), \quad (2)$$

....

where $P(Bike|Car)$ and $P(Walk|Car)$ stands for the transition probability from Car to Bike as well as that from Car to Walk. $Segment[i].P(Bike)$ represents the probability of Bike on the segment i . After the calculation, we use the transportation mode with maximum probability as the final results. In the case depicted in Figure 8, since the transition probability between Car and Bike is very small, the probability of Bike will drops behind Walk after the multiplication shown in equation (1) and (2).

3.4 CRF-Based Inference

In the later inference way we described in Section 3.2, CRF is responsible for the prediction on transportation mode. So, we present the graphic mode we designed for CRF in Figure 9. The top part of Figure 9 depicts a trip where a person transfers his/her transportation modes from Bus to Walk and then to Car. After partitioned by two change points, the trip is divided into three segments. The top line of the graphical model is a sequence of states $\{\dots, M_{i-1}, M_i, M_{i+1}, \dots\}$ represented by black nodes while each white node $\{\dots, X_{i-1}, X_i, X_{i+1}, \dots\}$ on the bottom denotes the observation of corresponding state. Each observation and corresponding state compose an instance $\langle X_i, M_i \rangle$, and these consecutive instances construct a sequence. In our approach, each state stands for the transportation mode of a segment while an observation is the features we extract from the segment. The lines connecting a state M_i to its adjacent observations X_{i-1} and X_{i+1} represent that each state not only depends on current observation but also depends on its previous and next observation. In other words, a person's present transportation mode has close relationship with the modes of both previous and next segment.

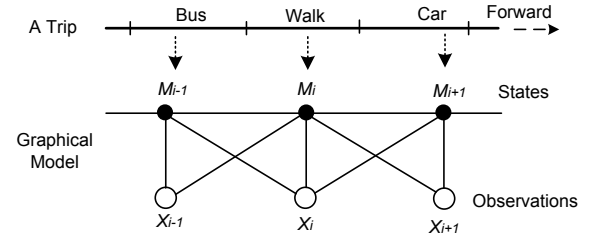


Figure 9. Graphical model of CRF

4. Change Point Based Segmentation

In this section, we will demonstrate how change points can be detected automatically. The detecting approach is derived from the following commonsense knowledge of real world, and justified by Table 1.

- People must stop and then go when changing their transportation modes. I.e., there must be some GPS points whose velocities are close to zero during transition.
- Walk should be a transition between different transportation modes. In other words, the start point and end point of a *Walk Segment* could be a change point in very high probability.

As shown in Table 1, the above knowledge can be proved by the transition matrix summarized from the GPS data collected by 45 people for six months. Almost in all the cases, Car, Bus and Bike transfer to Walk while the direct transition among them is quite rare. On a few occasions, a person could take a taxi immediately after he/she gets off a bus. The very short *Walk Segment* between these two transportation modes is easy to be neglected when the

person label his/her GPS data. However, Walk essentially exists in this situation. That is the reason causing the direct transition between Car and Bus.

Table 1. Transition matrix of transportation Modes

Transportation modes	Walk	Car	Bus	Bike
Walk	/	53.4%	32.8%	13.8%
Car	95.4%	/	2.8%	1.8%
Bus	95.2%	3.2%	/	1.6%
Bike	98.3%	1.7%	0%	/

On the contrary, over the same dataset, Figure 10, 11 and 12 respectively shows the distribution of average velocity, maximum velocity and maximum acceleration of different transportation modes. The data shown in these figures paint a richer picture about how difficult it is to give some simple rules to directly distinguish the segments of different transportation modes. Without knowing how many modes a trip contains, it is especially difficult to tackle the problem by simple rules.

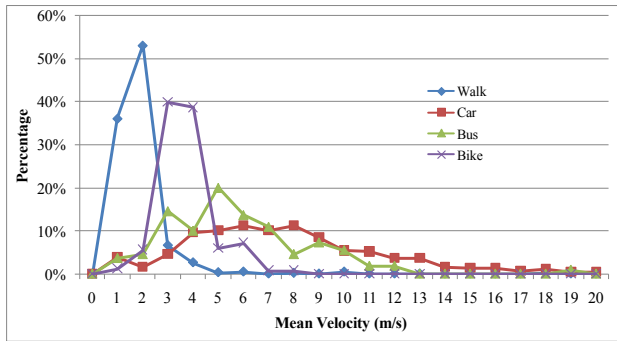


Figure 10. Distribution of average velocity

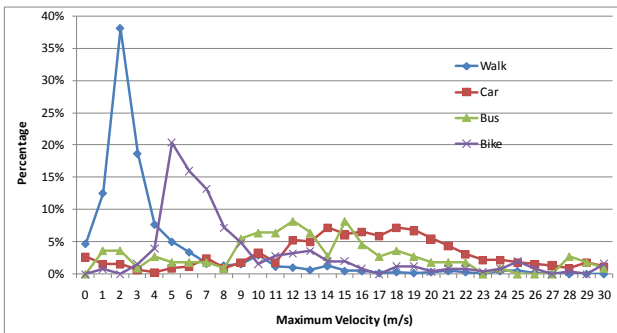


Figure 11. Distribution of maximum velocity

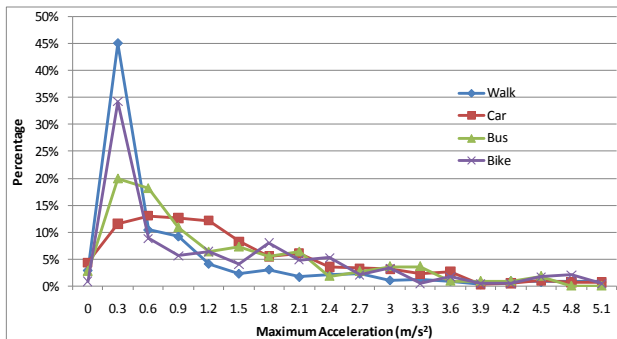


Figure 12. Distribution of maximum acceleration

Enlightened by the above-mentioned commonsense approach as well as the knowledge mined from GPS data, we can first find the change points by detecting *Walk Segments* from a trip. Then by leveraging these change points, the trip are partitioned into alternate *Walk Segments* and non-*Walk Segments*. Since segments from a trip are only categorized directly into two classes rather than four classes {Bike, Bus, Car, Walk}, the complexity of segmentation has been reduced greatly. Subsequently, we can extract the features of each segment and infer its specific transportation mode further. By leveraging Figure 13 as an example where an individual transfers his/her transportation mode from Bus to Car using Walk as a transition, we describe the detecting procedure as follows.

- **Step 1:** Using a loose upper bound of velocity (V_t) and that of acceleration (a_t) to distinguish all possible *Walk Points* from non-*Walk Points*.
- **Step 2:** If the length of a segment composed by consecutive *Walk Points* or non-*Walk Points* less than a threshold, merge the segment into its backward segment.
- **Step 3:** If the length of a segment exceeds a certain threshold, the segment is regarded as a *Certain Segment*. Otherwise it is deemed as an *Uncertain Segment*. If the number of consecutive *Uncertain Segment* exceeds a certain threshold, these *Uncertain Segments* will be merged into one non-*Walk Segment*.
- **Step 4:** The start point and end point of each *Walk Segment* are potential change points, which are leveraged to partition a trip.

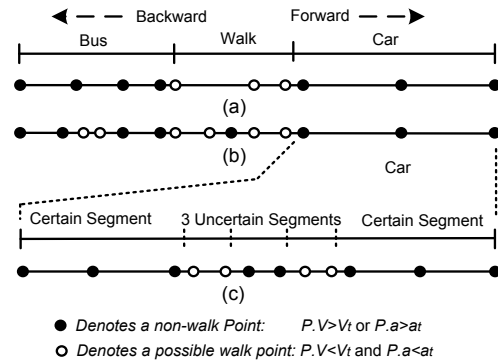


Figure 13. An example of detecting change points

As shown in Figure 13, each possible *Walk Point* (white points in Figure 13) is a GPS point whose velocity ($P.V$) and acceleration ($P.a$) are both smaller than the given bound. As shown in the Figure 13 (a), in an ideal case, only one *Walk Segment* will be detected from this trip.

However, as depicted in Figure 13 (b), when car or bus moves slowly in some transient occasion, a few GPS points from non-*Walk Segments* may be detected as possible *Walk Points*. Also, because of the locative error, a few points from the *Walk Segment* will exceed the bound and become a non-*Walk Points* (black points in Figure 13). To reduce the probability of detecting error, we require that the length of each retrieved segment must exceed a certain distance. Otherwise, it will be merged into its backward segment. For instance, in Figure 13 (b), the two *Walk Points* in the segment of Bus cannot construct a segment due to the short distance between them. The same criterion is also applied to handle the outlier points in *Walk Segment*.

After step 1 and step 2, the trip is divided into a serial of alternate *Walk Segments* and *non-Walk Segments*. Unfortunately, in some occasion shown in the Figure 13 (c), e.g. a user meets congestion or heavy traffic, a segment of car may be comprised of many alternate *Walk Segments* and *non-Walk Segments* after detection. It is not appropriate for the inference model to directly predict their transportation modes over the features extracted from such segments. It is commonsense that the longer a segment is, the richer features of its transportation mode a segment will express. Hence, it is more probable for us to infer its transportation mode correctly. On the contrary, the shorter a segment is, the higher the uncertainty is. To avoid the incorrect partition which will lead to the further inference error, we take the following policy to merge, to some extent, the consecutive *Uncertain Segments*. We define a segment whose length exceeds a threshold (e.g., fifty meters used in the experiments) as a *Certain Segment*. Otherwise, we deem it as an *Uncertain Segment*. I.e., we are not sure about the transportation mode of this segment even if it holds the condition of a *Walk Segment*. If the number of consecutive *Uncertain Segments* exceeds a certain threshold, e.g., three we find out in experiments, we still deem all these *Uncertain Segments* as one *non-Walk Segments*. It is not difficult to understand that common users will not frequently change their transportation modes within such a short distance. For instance, as depicted in Figure 13 (c), within a certain distance, it is impossible for a person to take the following transition, Car → Walk → Car → Walk → Car. So, we believe the middle three segments between the two *Certain Segments* are also *non-Walk Segments*, Car here. Thus, we can merge the three *Uncertain Segments* into one segment and perform the further inference.

5. EXPERIMENTS

In this section, at first, we describe the framework of the experiment. The setup includes GPS data, toolkits and parameters of each algorithm we used in our experiments and are presented respectively. Subsequently, detailed experimental results are given. Finally, corresponding discussions are provided based on the evaluation results.

5.1 Framework of the Experiments

From a hierarchical perspective of view, Figure 14 illustrates the framework of the experiment we performed. It includes four steps: segmentation, feature extraction, inference and evaluation.

Segmentation: Over the GPS log data, change point based segmentation method is leveraged to divide a GPS track into segments. To validate the effectiveness of our segmentation method, two baseline methods are also selected to partition the trips. They are uniform duration based and uniform length based segmentation. In other words, each segment will have same duration after being partitioned by the former method or same length after being partitioned by the later one.

Feature Extraction: We extract features including length, mean velocity, expectation of velocity, covariance of velocity, top three velocities and top three accelerations from each segment. In case the features of a segment are dominated by an abnormal point with positional error, we need to select top three velocities and top three accelerations rather than the maximum velocity and maximum acceleration. Using Figure 6 as an instance, we calculate the features of a segment by following formula.

$$L_i = \text{Dist}(P_i, P_{i+1});$$

$$\Delta T_i = P_{i+1}.T - P_i.T;$$

$$V_i = L_i / \Delta T_i;$$

$$a_i = (V_{i+1} - V_i) / \Delta T_i$$

$$\bar{V} = \frac{\sum_{i=0}^n L_i}{P_n.T - P_0.T}$$

$$E(V) = \frac{\sum_{i=0}^n V_i}{n}$$

Inference: two alternative ways are considered when we select the inference model to learn a user's transportation mode. In one way, the three white boxes on the top level, we regard the segments of GPS tracks as independent instances. Three different classification algorithms including Decision Tree, Support Vector Machine (SVM) and Bayesian Net are selected to learn the transportation mode of each segment. Meanwhile, we respectively use Bootstrap aggregating (bagging) [14] as a meta-algorithm to improve the accuracy of these three models by reducing variance and over-fitting. After the inference, the post-processing is performed. In the other way, the box with gray background, GPS data is deemed as a kind of sequential data. CRF is leveraged to perform the inference. In this way, we do not perform the post-processing.

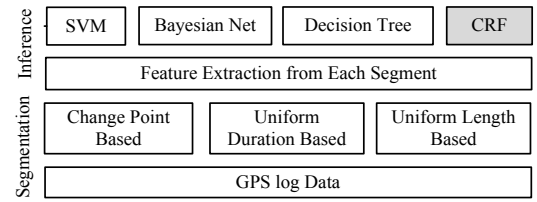


Figure 14. Schema of segmentation and inference model

Evaluation: During the process of the experiment, we are interested in the following two variables: three segmentation methods and four different inferring algorithms. Therefore, over each segmentation method, four different approaches can be employed. To validate the effectiveness of each approach, both the inference accuracy of transportation mode and that of change points, which denotes user makes a transition between different modes, are investigated. With regard to the prediction accuracy of transportation mode, since the number of segments of a trip partitioned by different segmentation methods is quite differential, we focus on the following two evaluation criteria: *Accuracy by Length* (A_L) and *Accuracy by Duration* (A_D).

$$A_L = \frac{\sum_{j=0}^m \text{CorrectSegment } [j].\text{Length } h}{\sum_{i=0}^N \text{Segment } [i].\text{Length } h};$$

$$A_D = \frac{\sum_{j=0}^m \text{CorrectSegment } [j].\text{Duration}}{\sum_{i=0}^N \text{Segment } [i].\text{Duration}};$$

where N stands for the total number of the segments after being partitioned by a segmentation method while m denotes the number of segments our approach correctly predicted over the segmentation method.

About the inference accuracy of change point, we investigate its recall and precision while its recall has higher priority over its precision. For the uniform duration based and uniform length based segmentation method, if the predicted transportation modes of two consecutive segments are different, a change point is detected between the two segments. If the distance between the inferred change point and actual change point extracted from user's label is within a certain distance, we regard the detected change point as a correct inference.

5.2 Settings

GPS Data and Toolkits: As shown in Figure 15, the GPS data we used in the experiments are collected by 45 users over a period of six months. The data cover 15 cities, and its total length has exceeded 20,000 kilometer. About 70 percent of the data are used as a training set while the rest is used as test data. The GPS device we chose to collect data from included handheld GPS receivers (Magellan Explorist 210 or 300) and GPS phones. All the GPS devices receive GPS coordinates every second and record a GPS point once the velocity of a user changes to a certain extent or his/her moving direction varies up to a threshold. After data collection, we segment the track into trips if the interval between two consecutive GPS points exceeds 20 minutes. Further, these trips are partitioned into separate segments by the three segmentation methods mentioned above. With regard to the toolkit we used in the experiments, Weka 3.4 toolkit [14] is selected to implement Decision Tree (REPTree), SVM/SMO (linear) and Bayesian Net while CRF++ [15] are leveraged to perform CRF algorithm over the partitioned segments.



Figure 15. GPS data and GPS devices

Parameter Selection: With regard to the change point based segmentation method, to recall all the *Walk Segments* from each trip, we need to determine a proper threshold for velocity and acceleration respectively. With the guidance of Figure 9, 10 and 11, using 0.2 as step size, we have tested all the possible values of velocity within [1, 3] m/s and values of acceleration within [0.2, 1.0] m/s². Figure 16 and Figure 17 depict the results of the first step towards detecting the change points over the dataset. As a result, when $v=1.8$ m/s and $a=0.6$ m/s², we can get an acceptable recall with the best precision. Ideally, when we chose a loose bound, all the *Walk Points* along a trip would be retrieved after the first step, i.e. 100 percent recall. However, the unintentional mistakes from users' incorrect labels scarify a few performances. Since it is only the results of the first step, the selected upper bound $\langle v, a \rangle$ should provide high recall first. Meanwhile, it should ensure high precision and make the number of segments as small as possible. The precision of inferred change point will be improved in the following steps.

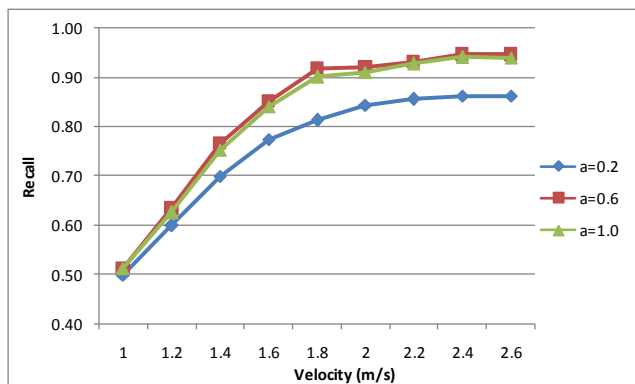


Figure 16 Recall of change points after step 1 towards detecting change points

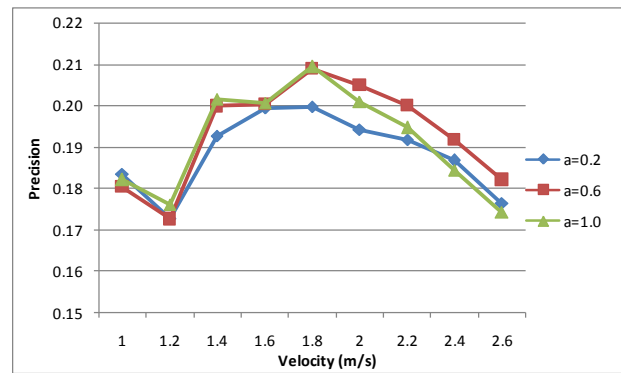


Figure 17. Precision of change points after step 1 towards detecting change points

5.3 Results

As shown in Figure 18, over the change point based segmentation method, the inference accuracy of transportation mode using different four inference models are separately evaluated by two criteria, the *Accuracy by Length* and the *Accuracy by Duration*. If we take both criteria into account, we can see the Decision Tree outperforms other models when we partition trips by change point based segmentation method. Figure 19 and Figure 20 show the recall and precision of retrieved change points respectively. As depicted in Figure 20, when the Decision Tree is selected to perform the inference, almost 90 percent of the actual change points can be retrieved from the corresponding GPS data within a distance of 150 meters to the actual change point.

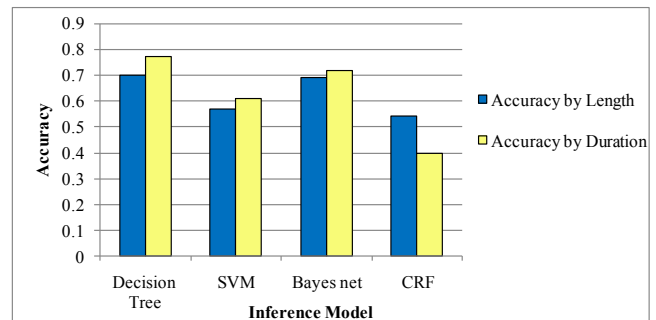


Figure 18. Inferring accuracy of transportation mode

As shown in Table 2, given uniform duration based segmentation, the prediction results of Decision Tree (DT), SVM, Bayesian Net (BYS) and CRF are reported respectively. Although many duration candidates are tested, we just present the results of 60s, 90s and 120s due to the similarity between these results. With regard to the change point, we give its precision and recall within 150 meters of actual transition. Overall, Decision Tree outperforms other inference model. Meanwhile, when we partition trips by 120 seconds, Decision Tree get better performance over other two duration candidates.

In Table 3, we present the inference results given the uniform based segmentation methods. The results of three length candidates including 100 meter, 150 meter and 200 meters are selected to present. The same four inference models are also tested respectively. With regard to the change point, we also give its precision and recall within 150 meters of actual transition. Overall, Decision Tree outperforms other inference model while 100 meter is better beyond other two length candidate for Decision Tree.

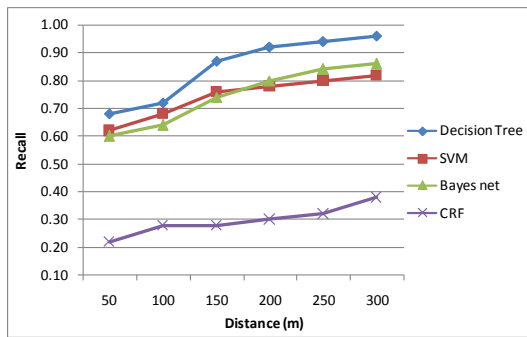


Figure 19. Recall of change point using change point based segmentation method

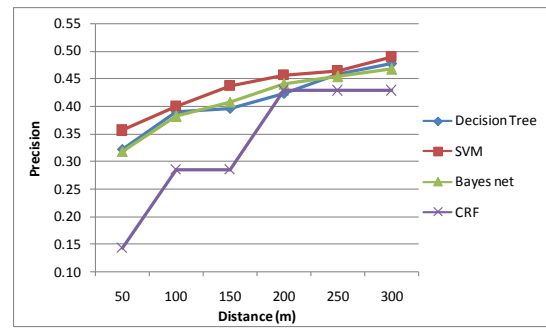


Figure 20. Precision of change point using change point based segmentation method

Table 2 Inference results of uniform duration based segmentation method

	60 second				90 second				120 seconds			
	DT	SVM	BYS	CRF	DT	SVM	BYS	CRF	DT	SVM	BYS	CRF
Accuracy by Length	0.664	0.446	0.119	0.505	0.673	0.197	0.512	0.524	0.687	0.462	0.523	0.544
Accuracy by Duration	0.695	0.505	0.431	0.404	0.699	0.444	0.577	0.413	0.721	0.517	0.574	0.422
Recall/change point	0.867	0.511	0.141	0.090	0.889	0.822	0.889	0.121	0.867	0.578	0.867	0.115
Precision/change point	0.139	0.084	0.167	0.060	0.184	0.194	0.197	0.070	0.197	0.095	0.206	0.072

Table 3 Inference results of uniform length based segmentation method

	100 m				150 m				200 m			
	DT	SVM	BYS	CRF	DT	SVM	BYS	CRF	DT	SVM	BYS	CRF
Accuracy by Length	0.399	0.172	0.500	0.585	0.405	0.174	0.470	0.617	0.429	0.184	0.463	0.616
Accuracy by Duration	0.674	0.504	0.172	0.566	0.647	0.473	0.173	0.525	0.651	0.464	0.182	0.514
Recall/change point	0.867	0.601	0.111	0.641	0.889	0.533	0.111	0.656	0.867	0.511	0.111	0.64
Precision/change point	0.148	0.124	0.167	0.155	0.152	0.132	0.167	0.159	0.127	0.184	0.167	0.152

5.4 Discussions

Over the experiment results, we compare the prediction results of the two inference ways based on the three segmentation methods mentioned above.

The former way with post-processing: Overall, Decision Tree outperforms other inference models no matter what kinds of segmentation methods are selected. The reason that Bayesian Net falls behind Decision Tree is in that the probabilistic independencies among selected features do not hold. E.g., average velocity and maximum velocity has some implicit relationship. With regard to the SVM, basically, it is hard for linear SVM to handle multiclass classification problem. What's more, SVM does not offer probabilities of each class in its inference results. Therefore, we cannot improve the prediction accuracy by performing the post-processing algorithm designed in Section 3.3.

As shown in Table 4, we evaluate each segmentation methods using the inference results of Decision Tree as a representation. Suggested by Table 2 and Table 3, the results of 120 seconds are selected to represent the performance of uniform duration based segmentation method while the results of 100 meters are picked out for uniform length based methods. As a result, change point based segmentation method outperforms others in accurately inferring transportation mode and change points. Particularly, the prediction precision of change point is much higher than that of other two methods, though the recall of change point of different segmentation methods looks approximate. In other words, most inferred change points are false predictions caused by the

improper segmentation methods. Intuitively, if we partition a trip by uniform length, two kinds of transportation modes may be assigned to a segment with high probability, especially when user makes a transition. This kind of segment brings lots of trouble to the inference model and leads some actual change points missed.

Table 4. Comparison of different segmentation methods

	change point	uniform duration (120 s)	uniform length (100 m)
Accuracy by Length	0.685	0.687	0.399
Accuracy by Duration	0.773	0.721	0.674
Recall/change point	0.887	0.867	0.867
Precision/change point	0.406	0.197	0.148

CRF-based inference way: Although, in most cases, CRF drops behind Decision Tree, we cannot say that CRF is worse than other prediction model in handling this problem. To investigate the truth behind the evidences, we evaluate the results of CRF model based on different segmentation methods in Table 5. As a result, uniform length based segmentation method outperforms other methods. With regard to the change point based segmentation method, the reason that CRF falls behind other models lies in that the granularity of segments partitioned by change points is too coarse. It causes the number of instances (segments) within a sequence (a trip) to be very small. In the worst case that people only take one kind of transportation mode during a trip, the sole

segment cannot compose a sequence. Intuitively, people will not frequently change their transportation modes within a trip in real world. Consequently, in most cases, a trip will only be partitioned into two or three segments. That is not appropriate to develop the advantages of CRF in labeling sequence data.

Table 5. Comparison of inference results of CRF over different segmentation methods

	change point	uniform duration (90 s)	uniform length (150 m)
Accuracy by Length	0.528	0.524	0.617
Accuracy by Duration	0.358	0.413	0.525
Recall/ change point	0.281	0.121	0.656
Precision /change point	0.286	0.070	0.159

Using uniform duration based or uniform length based segmentation methods, we can get enough instances in a sequence. However, we are facing new challenges. About the uniform duration based segmentation, when users stay in a place for a while without movement, the features extracted from segments of different transportation modes becomes indiscriminative. I.e., under this kind of situations, all the features except duration of a segment are zero. However, the transportation mode can be walk, car, bike and bus. The inference model is unable to handle this problem. Moreover, in the graphic model we designed for CRF, the state is not only depends on its present observation but also depends on its prior and post observations. Therefore, the trouble may infect the inference on more segments as compared to using other models such as decision tree.

By employing uniform length based segmentation method, we get a better performance over other two segmentation methods. The reasons lie in that the weaknesses of the previous two methods are reduced to some extent. However, it is still vulnerable to the unbalance of the training instances. With commonsense of real life, people usually move farther when driving than taking other transportation modes, e.g., walking. Thus, in a trip, the number of segments of car will be much more than that of walk segment, which leads the inference model dominated by Car.

Summary: According the experimental results, we get the following summary:

- Overall, when Decision Tree is performed over change point based segmentation method, we get the best inference accuracy on both transportation mode and change point.
- Among the three segmentation methods, change point based method outperforms others when we take the former way of inference while uniform length based method is slightly better than other two segmentation methods in the CRF-based inference way.
- The three segmentation methods proposed in this paper are not appropriate to apply CRF directly. Based on these methods, CRF do not meet our expectation on predicting transportation mode and transition. In most cases, it even drops behind Decision Tree and SVM although CRF is designed to segment and label sequence data.

6. RELATED WORKS

Single Location Based Applications. Over recent years, geographic information has boomed a lot of application on the Web. For instance, in a more effective manner, Google local and Live local have enabled Web users to find more information over

maps. Meanwhile, for better archiving and browsing photos, in many communities like Flickr and WWMX [6], users are allowed to tag the photos with the location where they are taken. Also, by geo-tagging web pages [16], personal blog [17] and RSS feeds [18], users are essentially assign a location to these Web content. However, these techniques only use the basic geographic coordination about a location. The main difference between our work and above mentioned works is that we focus on the geographic information extracted from a GPS track which is a sequence of location.

Improve Mobile User Interface using geo-Context. By leveraging some location- and orientation-aware devices, some research aimed to enable innovative types of user interfaces on mobile devices. Wasinger et al [19] equipped a mobile device with a digital compass to realize *Geo-Wand*-like pointing functionality. Mitchell et al [20] and Strachan et al [21] applied similar concepts in the context of a mobile multiplayer game and a handheld audio navigation tool respectively. Meanwhile, Rainer et al [22] presented an application framework that allows developers to create innovative geospatial user interfaces on high end devices with advanced navigation features. The essential difference between our work and these research is in that we leverage the knowledge learned from GPS track to improve mobile user interface while they directly employ original stand-alone location as context.

GPS Track Sharing. In the application scenarios [1][2][3][4][5] leveraging users' GPS tracks, some communities have been established to help users share their historical GPS data. These systems tell the users about the basic information, such as distance and duration, of a particular route. Tags and photos are also shown for the route. However, they either provided users raw GPS track [1][2] or required users manually label their tracks [3][4][5]. For instance, the transportation modes of each track are manually tagged by the user who uploads the GPS log. Due to the user efforts for manually tagging, many users are frustrated to give up uploading their GPS data. The essential difference between our work and the work mentioned above is that we understand knowledge from user's GPS track automatically and leverage the knowledge to improve the geographic applications and related mobile applications on the Web.

GPS Track Understanding. Several research projects aiming to understand a particular user's behavior from his/her GPS data. These work include extracting significant place of an individual [7][8], predicting a user's movement [9][10] and modeling a user's transportation routine [11][12]. In paper [7], authors aimed to detect the stay point, a place where user stays for a while. In addition, by clustering these stay points, the personally significant locations, such as home and working place, are extracted. However, the stay point is different from change point proposed in this paper. On one hand, sometimes, people may change their transportation modes without staying in a place for a while. E.g., a person gets on a taxi immediately after taking off a bus. On the other hand, people may not change their transportation modes in a stay point. For instance, people usually wait traffic light at a crossroad when driving car.

In paper [11], authors attempted to infer an individual's transportation routine given his/her raw GPS data. Their system first detects a user's set of significant places, and then recognizes the activities in those places using a Rational Markov Network. By leveraging a dynamic Bayesian network, the system learns and infers the person's transportation routines between the significant places. As compared to our approach, this work has three

constraints: 1) It needs the information of road networks, bus stops and parking lots. 2) It also needs the location of a user's car, which implies two GPS receivers are needed. 3) Given above supplementary information, the model learned from a particular user's historical GPS data are customized for the user. I.e., each user needs a personal model learned from his/her historical GPS data respectively. Thus, it is not universal and general to be implemented on the website for public geographic applications.

The main difference between our work and the research mentioned above is that we mine the knowledge from the GPS data collected by multi-users while the knowledge can also contribute to both personal use and public use.

7. CONCLUSIONS

In this paper, by using knowledge mined from raw GPS data, we aim to improve geographic applications on the Web and build closer connections between locality and mobility. The knowledge we gained as well as the connections enable more novel applications and improve user experience in a variety of tasks. An approach has been proposed to automatically learn transportation mode from raw GPS data. The inferred transportation mode can help Web users more deeply understand their own experience while better sharing other users' knowledge. It also enables context-aware computing based on a user's present transportation mode and creation of innovative user interface for Web users. The proposed approach is independent of other information and devices. Therefore, it is universal to be performed in both mobile devices and servers.

Our approach consists of three parts: a change point based segmentation method, an inference model and a post-processing algorithm based on conditional probability. We evaluated our approach using the GPS data collected by 45 people over a period of six months. As compared to uniform duration based and uniform length based segmentation methods, change point based method achieved a higher degree of accuracy in predicting transportation modes. It also obtained better precision in detecting transitions between different transportation modes. Over the change point based segmentation method, Decision Tree outperformed other inference models. However, based on the three segmentation methods mentioned above, CRF did not present its advantages in labeling sequence data.

In the future, we will strive for improving the prediction performance of CRF by designing more reasonable segmentation methods and more sophisticated graphical model for CRF. Combing different segmentation methods is also potential work to do. Meanwhile, we are moving forward to learning more knowledge from raw GPS and hope to leverage them to improve geographic applications on the Web.

8. REFERENCES

- [1] Walk Jog Run. <http://www.walkjogrun.net/>
- [2] Mountain Bike. <http://www.mtb-routes.co.uk/northyorkmoors/default.aspx>
- [3] SportsDo. <http://sportsdo.net/Activity/ActivityBlog.aspx>
- [4] SlamXR. <http://www.msslam.com/slamxr/slamxr.htm>
- [5] Wikiwalki. <http://www.wikiwalki.com>
- [6] Toyama K., Ron L. and Roseway A.. Geographic location tags on digital images. In Proceedings of ACM Multimedia '03 (New York, 2003), ACM Press: 156-166.
- [7] Project Iachesis: Parsing and modeling location histories, In Proceedings of GIScienc'04 (Hariharan Toyama, 2004). Springer Press.
- [8] Ashbrook, D., and Starner, T. Using GPS to learn significant locations and predict movement across multiple users. *Personal and Ubiquitous Computing* 7(5), 275-286.
- [9] Krumm J. and Horvitz E. Predestination: Inferring Destinations from Partial Trajectories. In Proceedings of UBIComp'06 (California USA, September 2006), Springer-Verlag Press: 243-260
- [10] Patterson, D. J., Liao and L., Fox, D. Inferring High-Level Behavior from Low-Level Sensors. In Proceedings of UBIComp '03 (Seattle WA, September 2003), Springer-Verlag Press: 73-89
- [11] Liao L., Patterson D.J., Fox D., and Kautz H. Building Personal Maps from GPS Data. *IJCAI MOO05*, 2005
- [12] Liao L., Patterson D.J., Fox D., and Kautz H.. Learning and Inferring Transportation Routines. In Proceedings of the National Conference on Artificial Intelligence (2004), AAAI Press: 348-353.
- [13] Lafferty, J., McCallum, A., Pereira, F. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the 18th International Conf. on Machine Learning (San Francisco CA, 2001). ACM Press: 282-289
- [14] Weka. <http://www.cs.waikato.ac.nz/ml/weka/>
- [15] CRF++. <http://crfpp.sourceforge.net/#training>
- [16] Tezuka, T., Kurashima, T., and Tanaka, K. Toward tighter integration of web search with a geographic information system. In Proceedings of WWW '06 (Edinburgh Scotland, May 2006). ACM Press: 277-286
- [17] twittervision. <http://twittervision.com/>
- [18] Chen Y. F., Fabbrizio G. D., Gibbon D., Jana R., Jora S., Renger B., Wei B. GeoTracker: Geospatial and Temporal RSS Navigation. In Proceedings of WWW '06 (New Brunswick Scotland, May 2007). ACM Press: 41-50.
- [19] Wasinger, R., Stahl, C., Krüger, A. M3I in a Pedestrian Navigation & Exploration System. In Proceedings of MobileHCI '03, (Udine Italy, September 2003). Springer-Verlag Press: 481-485
- [20] Mitchell, K., McCaffery, D., Metaxas, G., Finney, J., Schmid, S., Scott, A. Six in the City: Introducing Real Tournament – A Mobile Context-Aware Multiplayer Game. In Proceedings of the 2nd Workshop on Network and System Support for Games (California USA, May 2003). ACM Press: 91-100.
- [21] Strachan, S., Eslambolchilar, P., Murray-Smith, R. gpsTunes -Controlling Navigation via Audio Feedback. In Proceedings of MobileHCI '05, (Salzburg Austria, September 2005). ACM Press: 275-278.
- [22] Simon R., Fröhlich P.. A Mobile Application Framework for the Geospatial Web. In Proceedings of WWW '07 (Banff Canada, May 2007). ACM Press: 381-390.