

Article

A System of Mining Semantic Trajectory Patterns from GPS Data of Real Users

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Abstract: Positioning devices allow users' movement to be recorded. The GPS (Global Positioning System) trajectory data typically consists of spatiotemporal points, which make up the major part of the big data concerning urban life. Existing knowledge extraction methods about the trajectory share a general limitation—they only investigate data from a spatiotemporal aspect, but fail to take the semantic information of trajectories into consideration. Therefore, extracting the semantic information of trajectories with the context of big data is challenging pattern recognition task that has practical application prospects. In this paper, a system is proposed to extract the semantic trajectory patterns of positioning device users. Firstly, a spatiotemporal threshold and clustering based pre-processing model is proposed to process the raw data. Then, we design a probabilistic generative model to annotate the semantic information of each trajectory after the pre-processing procedure. Finally, we apply the PrefixSpan algorithm to mine the semantic trajectory patterns. We verify our system on a large dataset of users' real trajectories over a period of 5 years in Beijing, China. The results of the experiment indicate that our system produces meaningful patterns.

Keywords: spatiotemporal data application; semantic annotation; data mining; pattern recognition

1. Introduction

The increasing use of private vehicles with positioning services and the rapid advance in wireless mobile communication technology (such as 4G and beyond) enable us to collect large-scale GPS trajectories [1]. Mining trajectory patterns from the GPS data of users have incited wide interest in both academia and industry since they are valuable for a variety of urban applications, i.e., solving transportation problems and developing reasonable urban planning. For example, if a number of users are found to pass from L_a to L_b at a certain time, relevant departments can consider opening a new bus line connecting L_a to L_b . This would be useful to relieve traffic pressure and improve air quality. Lee and Chen [2] proposed an efficient graph-based mining algorithm. Monreale and Pinelli [3] applied the T-pattern Tree approach to mine the trajectory pattern in a certain area. Moreover, in Lee and Han's research [4], the temporal tightness of trajectory patterns was addressed.

However, a general limitation—the failure to take the semantics of a trajectory into consideration—exists in the present research [5–10] on trajectory pattern mining. Thus, the mined trajectory patterns are unable to reflect the semantic information hidden in the trajectory. A user's trajectory not only contains the physical movement track but also embodies the user's purpose for moving. For example, when working out after work is found as a frequent pattern, it is brilliant idea for the employee to offer a gym service in the office building. So, analyzing semantic trajectory patterns can be more valuable than analyzing the patterns without semantic information.

Research on mining semantic information has incited widespread interest. For example, Rawassizadeh et al. [11] proposed a clustering-based algorithm to detect and classify spatiotemporal

events in mobile data. Ghahramani et al. [12] presented an exploratory spatial data analysis to detect hotspots. Furthermore, Tanusri et al. [13] utilized spatiotemporal density estimation and line count inference to predict and rank users' POI(s) (points of interest) and a system [14] was designed to accomplish spatiotemporal online reasoning and management.

However, the application scenarios of the abovementioned methods are based on data collected from users' devices (user-centric) and not from service provider data. User-centric data such as geo-tagged photos and social media footprints are generally associated with some obvious semantic information. Therefore, our work is based on service provider data, the bottom layer of the spatiotemporal data, which is continuous but without any obvious semantic information. The contribution of this paper is as follows:

First, we put forward a spatiotemporal threshold and clustering-based method to extract stopover points in the raw trajectories.

Then, based on the extracted stopover points and the map information, we propose a probabilistic generative model to accomplish the semantic annotation.

Finally, we mine semantic trajectory patterns with the sequence mining algorithm to construct a framework of mining semantic information from spatiotemporal data.

2. Problem Statement and Solution Process

2.1. Problem Statement

We first propose some key definitions and necessary explanations.

The semantic information of users' trajectories is mainly hidden in the stopover points, while the moving parts of trajectories contain little semantic information regarding users. So, it is important to extract the stopover points efficiently and accurately.

Definition 1 (Raw trajectory) Locations generated chronologically by user i on the j th day consist of one raw trajectory $R_j^i = \{l_1, l_2, \dots, l_n\}$. Each location l_k ($k = 1, 2, \dots, n$) is further expressed as spatiotemporal sequence (lan_k, lon_k, t_k) , where lat , lon , and t represent the latitude, the longitude, and the located time of the trajectory location, respectively.

Definition 2 (Initial stopover trajectory) The location set $IS_j^i = \{l_1, l_2, \dots, l_m\}$ ($m \leq n$), wherein time intervals are longer than the threshold t_0 and the distance is shorter than the threshold d_0 , represents the stopover points of the trajectory generated by user i on the j th day.

Definition 3 (Terminal stopover trajectory) A terminal stopover trajectory $TS_j^i = \{l_{t1}, l_{t2}, \dots, l_{ts}\}$ ($s \leq m$) is the sequence of fine-grained extracted initial stopover points.

Another problem is how to define and find the semantic information of trajectories after extracting the stopover points. The semantic information of trajectories reveals the purpose of visits when users pass by a particular place. However, this constitutes a latent variable, which is hard present quantitatively.

In this research, different types of POIs have different functions, so they indirectly reflect the different purposes of people. Taking this into consideration, we used the number of different types of POIs around a location on the digital map to construct a feature vector and obtain the visit purpose.

Definition 4 (Visit purpose) Each location of a terminal stopover trajectory is attached to a visit purpose. So, each terminal stopover trajectory TS_j^i has its sequence of visit purpose $V_j^i = \{v_{t1}, v_{t2}, \dots, v_{ts}\}$.

Definition 5 (Feature vector) A feature vector of a location in a stopover trajectory is defined as $f = \{p_1, p_2, \dots, p_N\}$, where N is the number of POI types on the map and p_i is the ratio of the number of POIs of type i to the total number of POIs in a circular area centered at the location.

The process in which each location in a terminal stopover trajectory is attached to a visit purpose is defined as map matching. The connection between the definitions is shown in Figure 1.

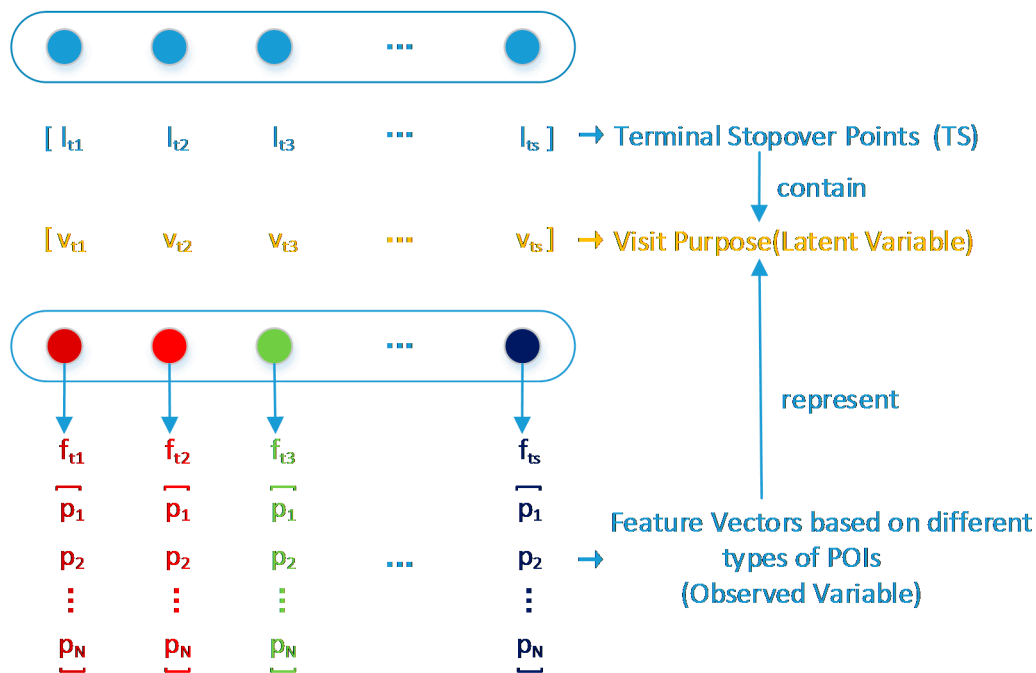


Figure 1. The connection of the definitions.

Definition 6 (Semantic trajectory pattern mining) Given the raw trajectory set R and the visit purpose set P , the concept of semantic trajectory pattern mining is to find the strongest pattern. A semantic trajectory pattern is represented as a sequence of visit purposes arranged in chronological order.

2.2. Solution Process

We designed a system to mine the semantic trajectory patterns, whose framework is illustrated in Figure 2. It includes three parts.

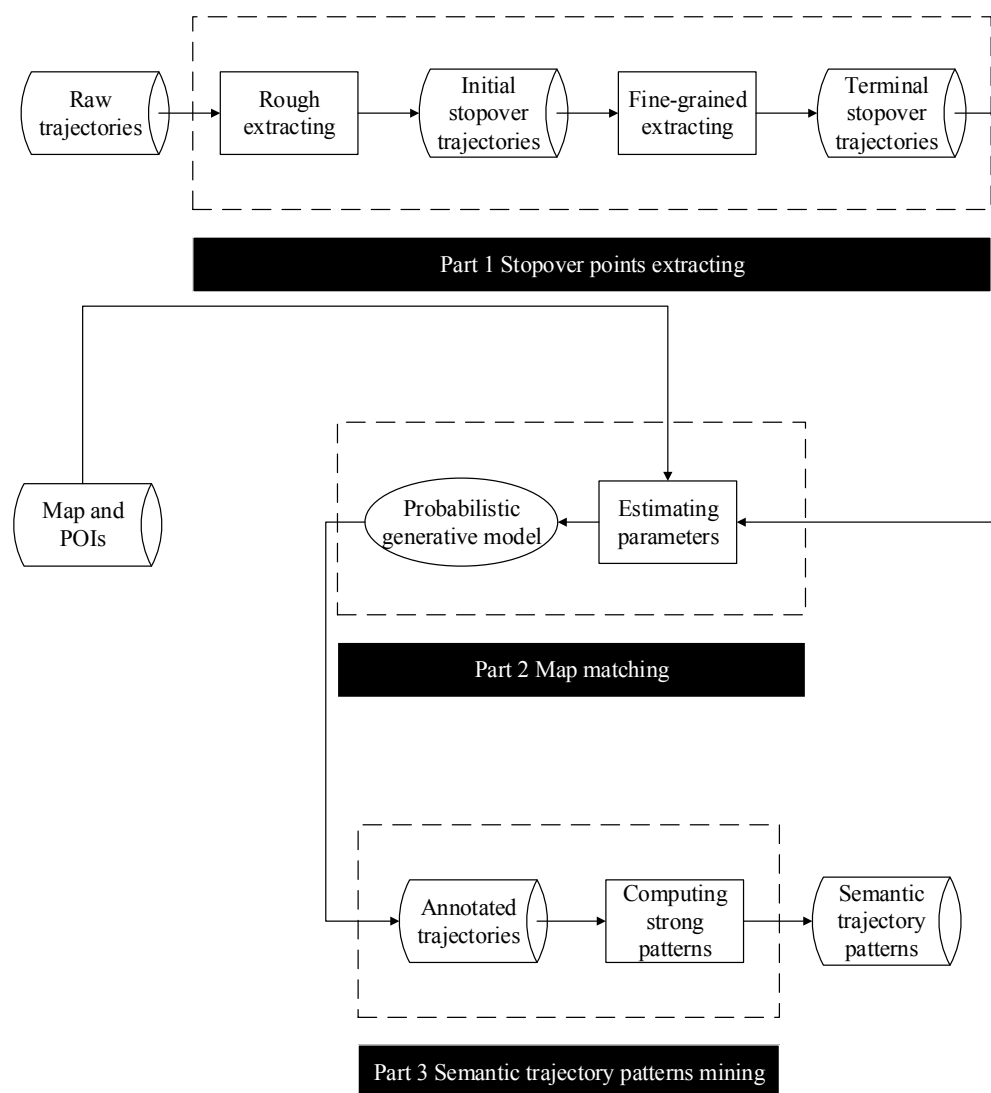


Figure 2. The framework of the mining system.

2.2.1. Stopover Points Extraction

The raw trajectories consist of two parts: the moving paths and the stopover areas. Due to the continuity of the trajectory, the moving part and the stopover areas are difficult to distinguish. So, we designed a spatiotemporal threshold and clustering-based method to extracting the stopover points accurately.

To extract the stopover points, first we set a time threshold t_0 and a distance threshold d_0 and scanned the database of raw trajectories to pick up the points satisfying the standard wherein the time interval is no less than t_0 and the distance is no more than d_0 to complete the a rough extraction and obtain the initial stopover points.

Then we applied the DBSCAN on the following fine-grained extracting to merge spatially adjacent points and collect the center of each cluster to identify the terminal stopover points. In the algorithm, the radius of the circular area Eps and the minimum number of points in the area $MinPts$ have an effect on the result. So, we set $MinPts$ to 4 by experience. Then, we drew the four-distance graph and used the first valley as the value of Eps .

2.2.2. Map Matching

To match the terminal stopover points with the POIs on the map, we proposed a probabilistic generative model to decide the visit purpose of each stopover point. We assume that feature vectors f follow a Gaussian mixture distribution, as described in Equation (1), and the probability that the feature vector f belongs to the visit purpose k is described in Equation (3):

$$p(f) = \sum_{m=1}^N p(m)p(f|m) = \sum_{m=1}^N \pi_m N(f|\mu_m, \Sigma_m) \quad (1)$$

$$N(f|\mu, \Sigma) = \frac{1}{\sqrt{2\pi^p}|\Sigma|} \exp\left(-\frac{1}{2}(f - \mu)^T \Sigma^{-1}(f - \mu)\right) \quad (2)$$

$$\gamma(f_j^i, k) = \frac{\pi_k N(f_j^i|\mu_k, \Sigma_k)}{\sum_{m=1}^N \pi_m N(f_j^i|\mu_m, \Sigma_m)} \quad (3)$$

where μ_k and Σ_k denote the mean and the covariance matrix of the visit purpose k , respectively.

Then we can calculate the log likelihood described in Equation (4) of a terminal stopover trajectory based on the probabilistic generative model, where $f(n)$ indicates the feature vector of the n th point in the terminal stopover trajectory and v_m denotes the m th type of visit purpose.

$$\begin{aligned} L(TS_j^i) &= \sum_{n=1}^{ts} \log\left\{\sum_{m=1}^N \pi_m N(f_j^i(n)|\mu_m, \Sigma_m)\right\} \\ &= \sum_{n=1}^{ts} \log\left\{\sum_{m=1}^N P(f_j^i(n)|v_m, \mu_m, \Sigma_m)\right\} \end{aligned} \quad (4)$$

To estimate the model parameters, we apply the EM algorithm with all trajectories. The EM algorithm iteratively estimates the maximum likelihood parameters of a statistical model. To simplify the computation, we utilize the Jensen's inequality to obtain a lower bound F of the log likelihood function, as shown in Equation (5).

$$L(TS_j^i) \geq F = \sum_{n=1}^{ts} \sum_m Q(v_m) \log\left(\frac{P(f_j^i(n), v_m|\mu_m, \Sigma_m)}{Q(v_m)}\right). \quad (5)$$

Then we maximize F by deriving the following update formula of EM steps for all parameters:

$$\mu_k = \frac{\sum_{n=1}^{ts} \gamma(f_j^i(n)|k) f_j^i(n)}{\sum_{n=1}^{ts} \gamma(f_j^i(n)|k)} \quad (6)$$

$$\Sigma_k = \frac{\sum_{n=1}^{ts} \gamma(f_j^i(n)|k) (f_j^i(n) - \mu_k)(f_j^i(n) - \mu_k)^T}{\sum_{n=1}^{ts} \gamma(f_j^i(n)|k)} \quad (7)$$

$$\pi_k = \frac{\sum_{n=1}^{ts} \gamma(f_j^i(n)|k)}{ts} \quad (8)$$

The parameters can be estimated by substituting the update formula iteratively. Finally, we put the parameters into Equation (3) and select the POI type corresponding to the maximum probability as the visit purpose of the location in the stopover trajectory.

2.2.3. Semantic Trajectory Patterns Mining

After realizing the probabilistic generative model, we can add the certain type of POI to the terminal stopover points, which means annotating terminal stopover trajectories with the visit purpose. Thus, we can achieve the annotated trajectories.

Next, we can find the strong patterns based on the annotated trajectories. To define a strong pattern, a few related definitions are proposed:

Definition 7 (Annotated trajectory) *An annotated trajectory AT_j^i is the sequence where each point has been annotated with a visit purpose and its corresponding time.*

Definition 8 (Support) *Given a terminal stopover trajectory TS and its annotated trajectory AT , a semantic trajectory pattern $((v_1, t_1), (v_2, t_2), \dots, (v_l, t_l))$ is supported by TS if and only if the pattern is a subsequence of AT . A semantic trajectory pattern is a strong pattern if its support is larger than the support threshold.*

Definition 9 (Prefix sequence and suffix sequence) *Given two sequences $t = \{t_1, t_2, \dots, t_m\}$ and $s = \{s_1, s_2, \dots, s_n\}$ ($n \leq m$), if there exists $1 \leq j_1 < j_2 < \dots < j_m \leq n$ that make $t_1 \in s_{j_1}, t_2 \in s_{j_2}, \dots, t_m \in s_{j_m}$, then t is the prefix sequence of s , and (s_{j_m+1}, \dots, s_n) is the corresponding suffix sequence.*

The PrefixSpan algorithm turns suffix sequences into prefix sequences to mine strong patterns. First it finds a 1-length prefix sequence and finds the corresponding suffix sequence by scanning the sequences database. Then, based on those prefix sequences and suffix sequences, it begins to process 2-length prefix sequences. Finally, the algorithm utilizes the depth-first search strategy to traverse all the prefix sequences and mine frequent patterns.

3. Experimental Evaluation

3.1. Research Datasets

The POIs were collected from Amap and consisted of 459,751 POIs with 369 fine-grained categories. In our experiment, based on the POI information we collected, we set the number of dimensions of the feature vector to seven, which will be described in detail later in the article.

Our experiments were based on service provider data, so ground-truth was required to validate our results. However, publicly available GPS datasets generally do not contain ground-truth due to privacy considerations. Hence, we recruited 20 volunteers in Beijing with different ages and occupations to collect their daily trajectories with ground-truth for 3 months from the BDS (BeiDou Navigation Satellite System). Thus, our sample dataset contained 1957 trajectories with a total distance of 151,553 kilometers.

The raw test data [15] of our experiments was collected from real users. It contained 17,621 trajectories with a total distance of 1,292,951 kilometers and a total duration of 50,176 hours of 182 users in Beijing over a period of 5 years. Figure 3 plots the distribution (heat map) of the dataset in Beijing.

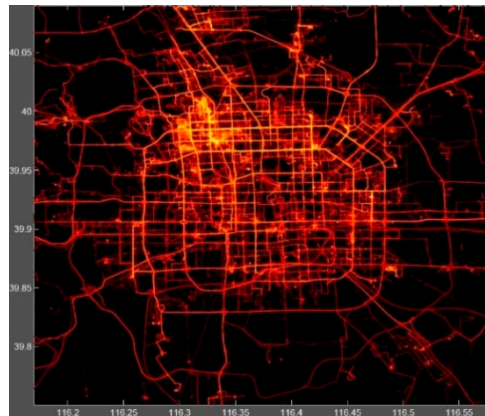


Figure 3. Distribution of the dataset in Beijing.

3.2. Compared Methods and Performance Metrics

Compared methods. To the best of our knowledge, there are few generative models being purposed to determine the semantic visit of a position with a multi-dimensional feature based on the POIs of map information. Therefore, we compared our approach with some representative algorithms that have been used in most existing works on mining trajectory data. Two competing techniques are described as follows.

First, we compared our approach with the K-Means algorithm. This method analyzes all the positions of trajectories separately, and utilizes the standard K-Means algorithm [16] to cluster the corresponding feature vectors into T visit purposes. After that, we applied the PrefixSpan algorithm to find the strong patterns.

Then, we compared our approach with the DBSCAN algorithm. A variation of the DBSCAN algorithm [17] has been proposed for the purposes of extracting the interesting places in trajectories. In this approach we also utilized the PrefixSpan algorithm to mine the strong patterns.

Performance Metrics. In order to evaluate each method, the coherence and anti-diversity [18] were utilized to evaluate the quality of clustering. Furthermore, the coverage was used to measure the quality of the mined patterns.

Anti-diversity is the similarity between the different visit purposes of trajectory stopover points, as described in Equation (9):

$$\frac{1}{T(T-1)} \sum_{m \neq n} Sim(\mu_m, \mu_n) \quad (9)$$

where μ_i is the Gaussian distribution's mean of λ_i , and $Sim(a, b)$ indicates the cosine of the angle between two vectors:

$$Sim(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|} \quad (10)$$

Coherence is the average similarity between each terminal stopover trajectory that supports the same strong pattern, when a pattern and its corresponding supporting terminal stopover trajectory TS_j^i is given.

$$\frac{1}{TS} \frac{2}{M(M-1)} \sum_{k=1}^{TS} \sum_{1 \leq i < j \leq M} Sim(f_k^i, f_k^j) \quad (11)$$

Coverage is described as the percentage of the trajectories supported by patterns in the trajectory collection C .

3.3. Case Study

We here demonstrate the illustrative cases of our approach. Based on the scale and distribution of our dataset, the number of visit purposes T was set to seven and the support threshold τ_0 was set to 200. We defined λ_1 as housing areas including apartments, dormitories, etc., λ_2 as working areas including companies, offices, etc., λ_3 as shopping areas including malls, markets, etc., λ_4 as transportation landmarks including bus stations, subway stations, etc., λ_5 as entertainment areas including gyms, parks, etc., λ_6 as studying areas including schools, libraries, etc., and λ_7 as food areas.

There existed a great difference in quantity between the trajectories of each user. We report the strong semantic trajectory patterns in Table 1. It is obvious that there is a tendency for a trajectory to start with or end with a position of purpose λ_1 . This complies with our expectations.

Table 1. Semantic trajectory patterns and support.

Users (Source)	Semantic Trajectory Patterns	Support
1(GPS)	<i>Apartment</i> \rightarrow <i>Office</i>	1241
2(BDS)	<i>Office</i> \rightarrow <i>Gym</i> \rightarrow <i>Apartment</i>	774
3(GPS)	<i>Office</i> \rightarrow <i>Food</i> \rightarrow <i>Office</i>	658
4(GPS)	<i>Apartment</i> \rightarrow <i>Subway Station</i> \rightarrow <i>Office</i> \rightarrow <i>Mall</i>	519
5(BDS)	<i>Apartment</i> \rightarrow <i>Science Place</i> \rightarrow <i>Food</i> \rightarrow <i>Gym</i> \rightarrow <i>Library</i>	443

These cases demonstrate that our approach can discover interesting semantic mobility patterns. When we obtained the strong patterns of one user, some interesting message could be found next. Take the last record as an example. The semantic trajectory is shown in Figure 4. Some timestamps of each switch in this record are listed in Table 2 (to make the user semantics more intuitive, we replaced part of the seven main classes with the subclass after manual comparison with the location on the map). Thus, we could get some useful knowledge of the user's lifestyle:

1. It usually takes the user 20 min to have dinner at the New Dining Hall at around 17:30.
2. After dinner, the user is fond of going to the gymnasium for about half an hour.
3. At around 20:00, the user likes going to the library for about an hour and a half.

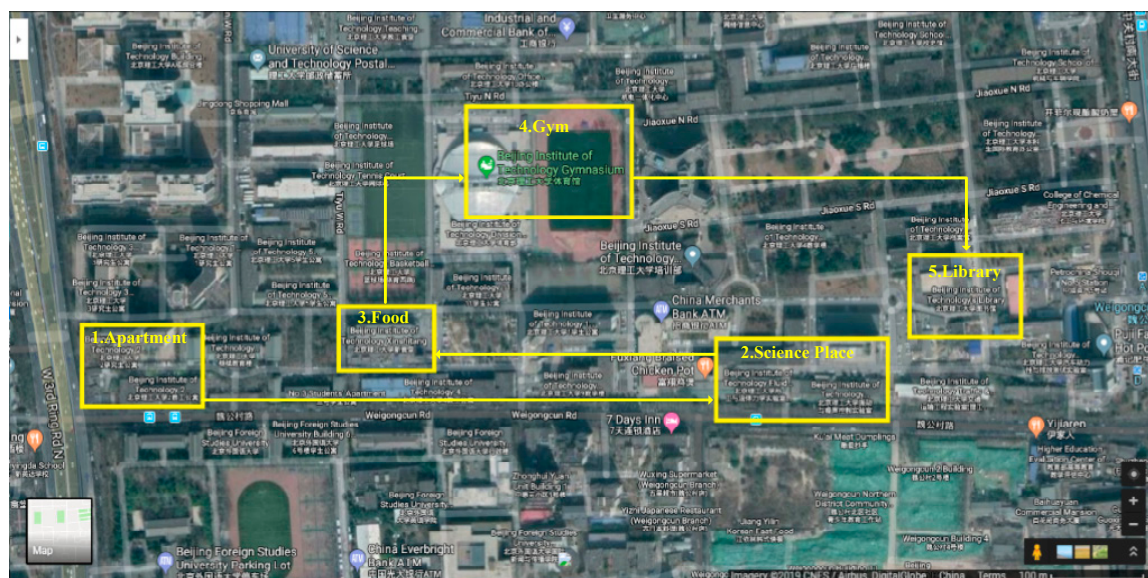


Figure 4. Semantic trajectories of the last record.

Table 2. Some examples of the last records.

<i>Apartment</i> → <i>Science Place</i> (No.2 Graduate Students' Apartment to Laboratory)	<i>Science Place</i> → <i>Food</i> (Laboratory to New Dining Hall)	<i>Food</i> → <i>Gym</i> (New Dining Hall to Gymnasium)	<i>Gym</i> → <i>Library</i> (Gymnasium to Library)
14:06→14:30	17:21→17:40	18:30→19:03	20:03→21:30
13:57→14:25	17:35→17:50	18:50→19:17	19:53→21:25
13:56→14:40	17:30→17:47	18:45→19:13	20:01→21:32
14:10→14:32	17:41→17:57	19:01→19:28	20:10→21:29

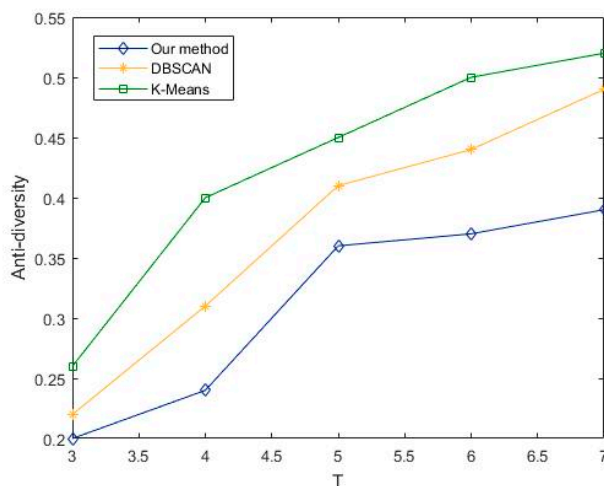
Note. These timestamps represent the time when the user showed up at the location.

We can also infer some latent information of the user from the semantic trajectory patterns:

1. The user is probably a graduate student of the university.
2. The user may have the habit of breaking for lunch for around 25 min at their apartment.

3.4. Comparative Study

We now compare our approach with K-Means and DBSCAN against the three metrics, i.e., anti-diversity, coherence, and coverage. First, we tested the impact of the number of visit purposes T on the performance of the three approaches. As described in Figures 5 and 6, the anti-diversity and the coherence of the three methods rise with T . Thus, it is indicated that when T increases, the feature vectors are divided into more clusters, which enhances the similarity within the cluster. Our method outperforms the other two methods with reference to the anti-diversity and coherence.

**Figure 5.** Comparison of anti-diversity.

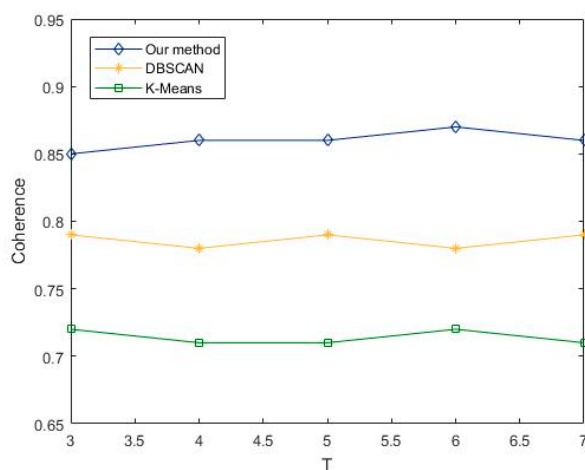


Figure 6. Comparison of coherence.

The comparison of coverage with I and the threshold of support τ_0 is shown in Figures 7 and 8, respectively. The coverage grows when T grows. However, DBSCAN and K-Means are not sensitive to the change of T . The coverage decreases gradually with τ_0 , as a trajectory may support several patterns. It was found that our method outperforms the other two methods in all cases.

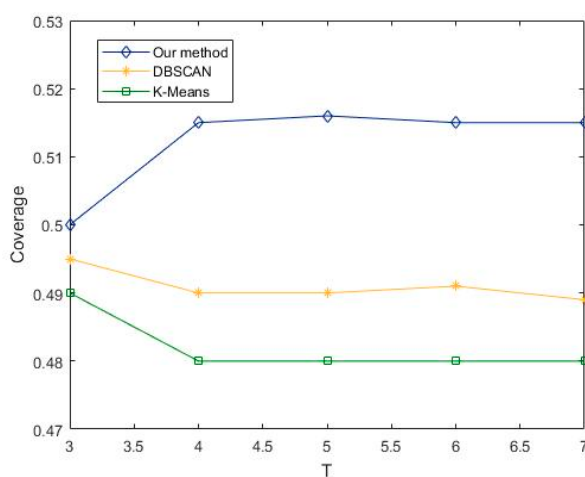


Figure 7. Comparison of coherence with T .

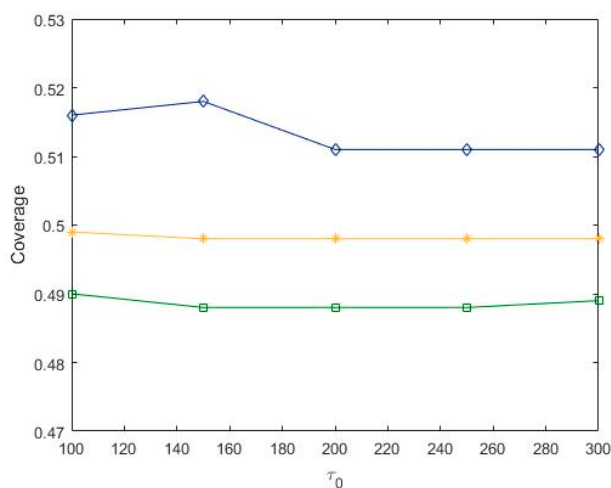


Figure 8. Comparison of coherence with τ_0 .

4. Further Work

There still remain several problems to be addressed in further study:

1. The patterns that occurred with special events, such as the Spring Festival, should be taken into consideration even if their supports are less than the threshold.
2. Some other factors such as the weather or the traffic can be added to enrich the semantic information hidden in the trajectories.
3. With the accumulation of data, effective search and information retrieval mechanisms have become an urgent need in order to filter data, considering the memory limits of small mobile devices. Therefore, analyzing data on a remote host such as the cloud or cloudlet will be a trend in future research. However, the network response time will increase and privacy-related issues should also be taken into account [19]. In recent years, cloud-dew architecture was proposed to solve the problem of all resources existing far from users' premises and far from users' control [20]. The dew servers are analyzed from architectural and organizational aspects as devices that collect, process, and offload streaming data from devices, in addition to facilitating communication with higher-level servers in the cloud [21]. With the support of hardware including NPU and other artificial intelligence (AI) hardware that have excellent packet processing capabilities [22], real-time processing for semantic trajectory patterns mining is a promising possibility.

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Data Availability: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

1. Yuan, J.; Zheng, Y.; Xie, X. Discovering regions of different functions in a city using human mobility and pois. In Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Beijing, China, 12–16 August 2012.
2. Lee, A.J.T.; Chen, Y.-A.; Ip, W.-C. Mining frequent trajectory patterns in spatial-temporal databases. *Inf. Sci.* **2009**, *179*, 2218–2231. [\[CrossRef\]](#)
3. Monreale, A.; Pinelli, F.; Trasarti, R.; Giannotti, F. Wherenext: A location predictor on trajectory pattern mining. In Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Paris, France, 28 June–1 July 2009.
4. Lee, J.-G.; Han, J.; Li, X. A unifying framework of mining trajectory patterns of various temporal tightness. *IEEE Trans. Knowl. Data Eng.* **2015**, *27*, 1478–1490. [\[CrossRef\]](#)
5. Frentzos, E. Trajectory Data Management in Moving Object Databases. Ph.D. Thesis, University of Piraeus, Piraeus, Greece, 2008.
6. Güting, R.H.; Schneider, M. *Moving Objects Databases*, 1st ed.; Morgan Kaufmann: Orlando, FL, USA, 2005.
7. Han, J.; Lee, J.-G.; Gonzalez, H.; Li, X. Mining Massive RFID, Trajectory, and Traffic Data Sets (Tutorial). In Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Las Vegas, NV, USA, 24–27 August 2008.
8. Jeung, H.; Yiu, M.L.; Zhou, X. Discovery of Convoys in Trajectory Databases. In Proceedings of the 34th International Conference on Very Large Data Bases (VLDB), Auckland, New Zealand, 24–30 August 2008; pp. 1068–1080.
9. Li, Z.; Ji, M.; Lee, J.-G. MoveMine: Mining Moving Object Databases. In Proceedings of the ACM SIGMO Conference, Indianapolis, IN, USA, 6–11 June 2010; pp. 1203–1206.
10. González, M.C.; Hidalgo, C.A.; Barabási, A.L. Understanding Individual Human Mobility Patterns. *Nature* **2008**, *453*, 779–782. [\[CrossRef\]](#) [\[PubMed\]](#)

11. Rawassizadeh, R.; Dobbins, C.; Akbari, M.; Pazzani, M. Indexing Multivariate Mobile Data through Spatio-Temporal Event Detection and Clustering. *Sensors* **2019**, *19*, 448. [CrossRef] [PubMed]
12. Ghahramani, M.; Zhou, M.C.; Hon, C.T. Mobile Phone Data Analysis: A Spatial Exploration Toward Hotspot Detection. *IEEE Trans. Autom. Sci. Eng.* **2019**, *16*, 351–362. [CrossRef]
13. Bhattacharya, T.; Kulik, L.; Bailey, J. Automatically Recognizing Places of Interest from Unreliable GPS Data Using Spatio-temporal Density Estimation and Line Intersections. *Pervasive Mob. Comput.* **2015**, *19*, 86–107. [CrossRef]
14. Christensen, R.; Wang, L.; Li, F.; Yi, K.; Tang, J.; Villa, N. STORM: Spatio-Temporal Online Reasoning and Management of Large Spatio-Temporal Data. In Proceedings of the ACM SIGMOD Conference, Melbourne, Australia, 31 May–4 June 2015; pp. 1111–1116.
15. Geolife GPS Trajectories. Available online: <https://www.microsoft.com/en-us/download/confirmation.aspx?id=52367> (accessed on 10 March 2019).
16. Kanungo, T.; Mount, D.M.; Netanyahu, N.S.; Piatko, C.D.; Silverman, R.; Wu, A.Y. An efficient k-means clustering algorithm: Analysis and implementation. *IEEE Trans. Pattern Anal. Mach. Intell.* **2002**, *24*, 881–892. [CrossRef]
17. Palma, A.T.; Bogorny, V.; Kuijpers, B.; Alvares, L.O. A cluster-based approach for discovering interesting places in trajectories. In Proceedings of the 2008 ACM Symposium on Applied Computing, Fortaleza, Brazil, 16–20 March 2008; pp. 863–868.
18. Kim, Y.; Han, J.; Yuan, C. Toptrac: Topical trajectory pattern mining. In Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, London, UK, 19–23 August 2015; pp. 587–596.
19. Rawassizadeh, R.; Pierson, T.; Peterson, R.; Kotz, D. NoCloud: Experimenting with Network Disconnection by Design. *IEEE Pervasive Comput.* **2018**, *17*, 64–75. [CrossRef]
20. Wang, Y. Definition and Categorization of Dew Computing. *Open J. Cloud Comput.* **2016**, *3*, 1–7.
21. Gusev, M. A dew computing solution for IoT streaming devices. In Proceedings of the MIPRO, Opatija, Croatia, 22–26 May 2017; pp. 387–392.
22. Jie, L.; Shuhui, C.; Jinshu, S. Implementation of TCP large receive offload on multi-core NPU platform. In Proceedings of the ICTC, Jeju, Korea, 15 July 2016; pp. 258–263.



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