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Mining Users' Similarity from Moving Trajectories for Mobile E-commerce Recommendation

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Abstract

Users' similarity mining in mobile e-commerce systems is an important field with wide applications, such as personalized recommendation and accurate advertising. Moving trajectories of e-commerce users contain much useful information, providing a very good opportunity for understanding the users' interesting and discovering the similarity between mobile-device-holders. In this paper, we explores the problems in the existing mobile e-commerce recommendation methods, and propose a mobile users' moving trajectories mining based user similarity discovering approach for mobile e-commerce system. We formally defines the moving trajectory and view the areas, where users stay within for a certain time, as interested regions, which reflect the preferences of mobile-device-holders. Based on the number of overlapped interested areas, a user similarity measure method is proposed. Experimental evaluation, conducted based on the publicly available datasets commendably demonstrate the effectiveness of our approach.

Keywords: *Users' similarity mining, Moving trajectories, Mobile e-commerce, Recommendation*

1. Introduction

The integration of Internet and mobile communication technology is making people's lives more and more convenient and efficient. At present, mobile e-commerce is creating a new kind of consumption pattern, becoming one of most fastest-growing and attractive business prospects [1]. With the fast increase of mobile devices, people can access the information "anytime, anywhere, anyhow and through anyone" [2]. The gradually settlement of e-commerce related fundamental challenges, such as online payment security and fast delivery, "information overload" becomes the main bottleneck in mobile e-commerce development. Studies show that every additional click reduces the transaction probability by 50% in mobile e-commerce environment, due to the small screen and limited processing capacity of the mobile devices [3]. Thus, it is very important to establish effective personalized

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recommendation methods for mobile e-commerce, using the advantage of mobile network environment in information recommendation.

Mobile e-commerce recommendation system, which can provide personalized recommendation services for mobile users and effectively ease the "information overload" problem in mobile circumstance, is an extension of the traditional Internet based recommendation system. Although a lot of effort is being spent on traditional Internet based e-commerce recommendation system and have gained an abundant research achievements, the existing methods cannot be directly applied to the mobile recommendation, due to the particularities of mobility e-commerce systems, *e.g.*, strong mobility, closely context related environment and unstable wireless network connection [4, 5]. Scholars from many well-known universities and research institutions have carried out a lot of researches in personalized recommendation for mobile systems. The related studies cover two aspects: (1) Context based recommend for mobile systems (include location based recommendation, time based recommendation and multidimensional context based recommendation), and (2) Socialization based recommendation for mobile systems. However, little investigation have combined users' trajectory mining with mobile e-commerce recommendation.

Mobile users' trajectories contain much important information, such as moving habits and preferences of the mobile device holders. Mining users' preferences from their trajectories provides a new approach for mobile e-commerce recommendation, but research in this area is relatively rare. Authority statistics shows that about 80% of our daily activities are location related [6] and the popularization of positioning functions (GPS, mobile base station based positioning and other technical means to obtain or reasoning to get location information) in mobile devices have greatly satisfy people's demand for location services. This makes trajectory data mining and knowledge discovery a hot research topic [7-9]. We believe that movement characteristics of mobile devices holders can be extracted by mining their movement-and-reside points, and mobile users' interest areas, where mobile users stays within for a certain region, can be discovered by clustering analysis. Overlap interest areas spatially signify some similar features or interests of the users, and times, occur moments and stop times of the users can be treated as similarity indicators of them.

Based on the analysis above, we put forward a mobile users' trajectory mining based approach to discover users' similarity for mobile e-commerce recommendation. The rest of the paper is organized as follows. The literature background and related work are investigated in Section 2. In Section 3, the general idea of mobile e-commerce users' trajectory representation model, the related assumptions and definitions are given. Also, mobile users' interest area detection algorithm and users' preference similarity calculation algorithm are put forward. The experimental evaluation of the algorithms is conducted in Section 4 and Section 5 concludes the paper with directions for future research.

2. Background and Related Work

2.1. Mobile E-commerce Recommendation

Recommendation is generally deemed as a valuable auxiliary in e-commerce systems, for instance Amazon and Taobao, which aims at giving products to the users or help them deciding what to buy, based upon their preferences. During the past decade, the theory of e-commerce recommendation has developed in a variety of directions, but it is universally acknowledged that the process e-commerce recommendation contains three steps [10-13]: (1) Shopping record of the customers in e-commerce systems are collected and classified according to their preference or other indexes; (2) analyzing the characteristics of a certain user and figuring out what kind of customers he (or she) belongs to, based on the result of the first step, and (3) find a collection of users, whose preferences are similar to others in the second step, and establish recommendations for the user, according to what his (or her) mostly similar users have bought. Finding out the similar users is the key process in nearly all e-commerce systems.

Mobile e-commerce recommendation is the extension of traditional Internet based recommendation systems. The emergence of mobile e-commerce leads to an urgent need in precise marketing, comparison shopping and other aspects. The importance of solving the problem of "information overload" in mobile e-commerce is more urgent than that of in traditional Internet based systems. However, due to the limitation of mobile devices, such as low CPU process ability, small display screen and instable wireless network connection, the existing recommendation methods, which is widely used in traditional Internet based network, no longer fit for the new circumstance. The relationship between mobile e-commerce system users and the recommended items can be described in Figure 1. In many mobile e-commerce systems, several applications use the collaborative filtering (CF) technique, which is very commonly used in wired network based e-commerce systems, to provide recommendations. For example, Li *et al.*, improved the traditional CF algorithm and proposed a two-stage CF approach, which takes account mobile users' profiles, preferences and locations factors [14]. Kim *et al.*, studied the particularities of mobile e-commerce systems and put forward a mobile wallpaper recommender system, VISCOR, which combines collaborative and content-based filtering to reduce users' search costs and provide better wallpaper recommendations [15]. Liou and Liu combined mobile phone features and product preference means to provide product recommendations, on the basis of CF techniques, for the mobile Web based e-commerce system [16].

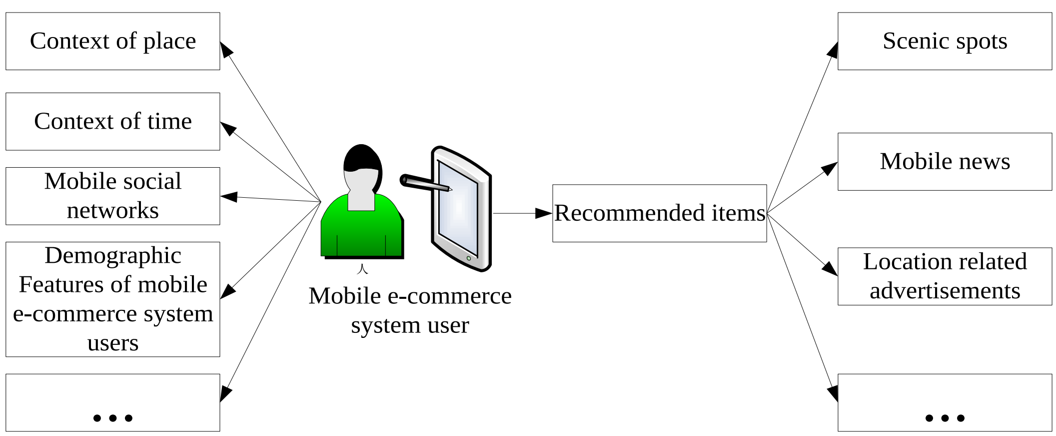


Figure 1. Characteristics of Users and Items in Mobile E-Commerce Systems

In addition, users' location information, obtained from network base station positioning or GPS, has become an important topic in geo-related services for mobile e-commerce systems. For example, R. Simon and P. Frölich established a mobile application framework, which enables a mobile-device-holder to inquire the geo-coded Wikipedia articles related to the place where he (or she stay) [17]. In [18], G. Abowd and *et al.*, designed and developed a Cyberguide system to offer the information for the nearby building and related people's characteristics information. Also, there are many scholars focus on recommending some specific types of locations. Girardello and et al. analyzed the usage of applications used in mobile devices around him (or her), making use of his (or her) location information, to recommend the most frequently used applications for the user [19]. In [20], a CityVoyager system is developed, using the mixture method of collecting the users' shopping histories based on GPS logs, and uses an item-based collaborative filtering method to make recommendations. Jamil, Alhadi and *et al.*, used collaborative filtering techniques to recommend names based on geographical location, in latitude and longitude format, in Twitter environment [21]. In [22], a HITS-based framework is put forward to recommend hot spots, which take into account not only a user's travel experience, but also the interest of a location, for tourism. It has the capability of handling various types of locations and ensure that the really popular locations recommended by experienced users can be recommended. Emrich A, *et al.*, proposed a location based ciudad guide system, which consider only the influence of location context on mobile users' preferences, and recommends hot spot and valuable services (such as restaurants and hotels) around for the user [18]. In [23], a system, using Bayesian learning method to recommend restaurants, is developed, which take into account both users' preferences and location contexts to calculate some potentially recommended services so as to provide a ranking list for recommendation.

2.2. User Similarity Measurement

As a key step in e-commerce recommendation system, user similarity measurement becomes a problem-rich area and a lot of effort is being spent on the issue of how to measure the similarity between users. Li, Zheng, Xie, *et al.*, investigated the importance of discovering users' similarity from individuals' trajectories, and built an hierarchical-graph-based similarity measurement (HGSM) framework to mining the valuable knowledge from large amounts of spatio-temporal data. The framework takes both the sequence property of people's movement behaviors and the hierarchy property of geographic spaces into account, and experimental evaluation proves HGSM can model each individual's location history and effectively measure the similarities among users [24]. Abraham, S. and Lal P. S. think trajectory similarity of moving objects resembles path similarity of user click-streams in web usage mining and put forward a approach to measure users' similarity by analyzing the URL path of each user from historical web access log of dark web [25]. Guy, Jacovi, Perer, et al. investigated nine different sources in social media applications to reveal the similarity between users, and find that the lists of similar people returned by them were found to be highly different from each other as well as from the list of people with which the user is familiar [26].

Some other existing works focused on exploiting user similarity other than trajectory mining. Ying, Lu, Lee, *et al.*, proposed a maximal semantic trajectory pattern similarity approach to measure the semantic similarity between trajectories and then measure the similarity between users [27]. Lee and Chung put forward an approach to calculate user similarity using the semantics of the location and the user's intention and interest [28]. Other scholars investigated users' similarity problem from the point of buying records or web page visiting patterns. Eckhardt established a way of computing the similarity of users for collaborative filtering, based on the idea of a content based user preference model [29], and proved through experimental stimulation that the main advantage of his method is the ability to evaluate the similarities among all users, without the need to have at least some objects rated in common. Bona, Riezler, *et al.*, integrated query similarity metrics as features into a dense model and put forward a framework, which learns rankings of query rewrites from large amount of users' trajectory data [30]. Wei, Shijun, *et al.*, investigated the mess log data recorded in web community system server and explored the relationship between web page visiting conversation degree and users' preference similarity [31]. Wei, Shijun, *et al.*, established a users' similarity model, based on the hypothesis that users sharing similar preferences in history also have the possibility to have similar interest in the future, to remove the adverse influence of popular objects and make personalized recommendation [32].

In this paper, our similarity method is constructed based on the first law of geography, "everything is related to everything else, but near things are more related than distant things" [33], that if two persons share similar geographical overlap areas in history, they will have similar or assemble preferences with each other.

2.3. Trajectory Mining

At present, trajectory mining mainly focus on discovering the potential information and useful knowledge, such as mobile object behavior characteristics, behavior patterns, environmental impact, from moving objects' location log [34]. The pioneer of trajectory mining can be traced to 2007 when the concept of moving object mining is firstly proposed by HAN J. W. [35]. According to the activity environment and motion status, moving objects can be divided into three categories: (1) Environment constrained moving objects [36], which refer to the objects moving along a certain route or greatly restricted by the surrounded circumstance, *e.g.*, elevated rail train, city bus and other moving path fixed equipments [37]; (2) Non-environment constrained moving objects [38], which refers to the no fixed constraint path moving objects, and some relatively small environmentally affected moving objects under specific rules, such as airplanes, cruises, warships and boats [39], and (3) discrete moving objects, which refers to the moving objects without a clear purpose or movement direction, such as mobile users [40].

Motivated by the popularization of mobile devices and the convenience of location data collection, there is a considerable amount of research has performed based on individual GPS trajectory data. These works include discovering the important locations of a mobile users, forecasting mobile-device-holders' movement tendency and preferences, and recognizing user-specific activities at each location [41]. The existing mobile trajectory mining methods include distance-based method, grid partition-based, shape-dependent method and time-dependent method [36]. Cluster, index, pattern detection and anomaly detection are the most commonly used means in moving data mining. How to use these technologies, from the perspective of a more comprehensive and deeper level analysis and study on the behavior of the moving objects, is an important issue at present.

As opposed to the existing works analyzed above, we aim to mine knowledge from multiple users' trajectory histories by discovering move-stop points and movement characteristics rather than recognize user-customized activities. In this paper we use the concepts of stay points, which is proposed by Hariharan and Toyama [42], to define users' trajectory based on GPS points in mobile e-commerce systems. Although our approach of modeling users trajectory are similar, we focus on not only mining users' location information to figure out move-stop-points and interested areas, but also make trajectories comparable. And what is more, we calculate users similarity by mining how many geographically common characteristics (such as how many move-stop-points or interested areas) two users share based on trajectory mining.

3. Users' Preference Similarities Exploration based on Trajectory Mining

In this section, we first clarify some terms used in the paper. Then, we detail the processes of mobile e-commerce users' trajectory presentation, move-stop-points-detection algorithm and the similarity calculation method.

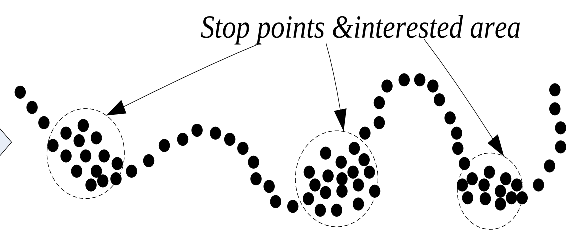
3.1. Preliminary

Definition 1 (Mobile E-commerce User's Trajectory) A mobile e-commerce user's trajectory $MEUTraj$ is consists of a series of GPS points, and every point P can be presented as a triple $<Lat, Lon, T>$ (Lat, Lon and T denote latitude, longitude and time respectively). $MEUTraj$ can be formally represented as:

$$MEUTraj = P_1 \to P_2 \to \cdots \to P_n \; (P_i.T < P_{i+1}.T, \quad 0 < i < n, \quad i \in N) \quad (1)$$

Figure 2 (a) shows a mobile e-commerce user's trajectory consisted of some GPS points.

	Lat	Lon	T
P_1	Lat_1	Lon_1	T_1
P_2	Lat_2	Lon_2	T_2
…	…	…	…
P_n	Lat_n	Lon_n	T_n



(a)*Mobile E-commerce User's Trajectory* *(b)Original trajectory of mobile e-commerce users*

Figure 2. Composition of Users' Trajectory

Definition 2 (Stay point) A stay point S stands for a geographical region where a user stayed over a time threshold θ_t within a distance threshold of θ_d. Stay point S of a user U can be formally represented as:

$$S = \{P_m, P_{m+1}, \ldots, P_{n-1}, P_n\}, \forall m < i \le n, Distance(P_i, P_m) < \theta_d, |P_m.T - P_n.T| \ge \theta_t \quad (2)$$

where P_m stands for a GPS point and $Distance(P_i, P_m)$ denotes the Euclidean distance between P_i and P_m. Stay points of a user is shown Figure 2 (b).

Definition 3 (Interested area) Interested area IA is consisted of a series of points, which can reflect the moving feature and preferences of the user. IA can be defined as a quad, according to the definition of stay point.

$$AI = < \mathrm{Lat}, \mathrm{Lon}, \mathrm{arvT}, \mathrm{levT} > \quad (3)$$

where $arvT$ and $levT$ stands for in interested area time and out interested area time respectively. Also,

$$AI.Lat = \sum_{i=m}^{n} \frac{P_i.Lat}{|P|}, \; AI.Lon = \sum_{i=m}^{n} \frac{P_i.Lon}{|P|}, \; AI.arvT = P_m.T, \; AI.levT = P_n.T \quad (4)$$

Definition 4 (Mobile User's Preference Model) Mobile user's preference can be presented by a series of interested areas in a user's trajectory. Preference model PM of user u can be formally defined as:

$$PM = \{(T_1, A_1, \Delta T_1)(T_2, A_2, \Delta T_2)\ldots(T_i, A_i, \Delta T_i)\ldots(T_n, A_n, \Delta T_n)\} \quad (5)$$

where $T_i = \frac{A_i^u.arvT + A_i^u.levT}{2}$, $\Delta T_i = |A_i^u.arvT - A_i^u.levT|$, $i \in N$, $T_{i-1} > T_i$ and A_i^u stands for the ith interested area of u, ΔT_i denotes the time user u stay within the interested area.

3.2. Interested Area Detection

As defined in Definition 1, interested area is consisted of some points that moving relatively slow and stay within a distance for a long time (See Figure 2 (b)). Typically, interested area may appear while strolling along an amusement park, a nice beach, a super mark or attracted by a landmark of building. In our opinion, interested area discovering is a GPS points clustering process. The basic idea of interested area detection algorithm can be described as follow.

Algorithm 1: InterestedAreaDetection
Input: $MEUTraj$ (Trajectory of a mobile e-commerce system user), distance threshold θ_d, time thresh θ_t
Output: A collection of interest areas A
Step 1: $i = 1$, $pointNum = |Point|$;//point number in $MEUTraj$
Step 2: While $i < pointNum$ do
Step 3: $j = i + 1$
Step 4: $d = Distance(P_i, P_j)$ //euclidean distance between P_i and P_j
Step5： if $d \leq \theta_d$ then
Step 6: $t = |P_i.T - P_j.T|$;
Step 7: if $t \geq \theta_t$ then
Step8: cacualte $A.Lat$ //according to formula （4）
Step 9: cacualte $A.Lon$// according to formula （4）
Step 10: $A.arvT = P_i.T$, $A.levT = P_j.T$;// according to formula （4）
Step 11: Add the current interested area to collection A
Step 12: $i = j; break;$
Step 13: $j++;$
Step 14: return A;

Here we wish to detect every stay of the mobile e-commerce system user visit as precisely as possible. However, a proper time threshold have to be adopted to specify an individual's stay for, because a very small time threshold, such as 2 second or even shorter time, would cause the over-detected of interested areas. In addition, there is a GPS sampling time interval, usually 1 to 2 second (depending on the network transmission speed), and also some blind spots caused by building block often leads to great time intervals between two consecutive GPS points. At the same time, too large time interval, which could cause many real interested areas that can reflect user's preference cannot be detected, is not appropriate either.

3.3. Users' Similarity Measurement

It can ascertain from the above sections that the more interested areas two persons share their trajectories, the more likely that they may have similar preferences. However, it does not make sense to measure the similarity of two user just by just by yes or no. We aim to identify how relevant two individuals' are similar, and rank their similarity according to how many interested areas they share.

In this paper, we choose an index, overlapped interested area ratio (OIA), to check the similarity of two users' similarity and set five relevance level to represent their possible relationship, as shown in Table 1. The general process of OIA, which is in calculation can be described as follow.

Table 1. Users' Similarity Classification

OIA value	Relevance level	Possible relationship
0.8-1	Similar	Family members, couples, roommates
0.5-0.8	Generally similar	Good friends, close colleagues
0.3-0.5	Weakly similar	General friends, acquaintances, the same community residents
0.1-0.2	Different	Strangers in the same city
0-0.1	Totally different	Strangers in different cities

Algorithm 2: UserSimilarityCalculation

Input： Preference model PM_{u_1}, PM_{u_2} of $u_1$and u_2, distance threshold θ_d, time threshold θ_t

Output： OIA

Step 1: $i=0$, $j=1$, $\text{OverlapNum}=0$, $\text{InterestArea}Num_{u_1}=|PM_{u_1}|$

$\text{InterestArea}Num_{u_2}=|PM_{u_2}|$;//Interested area number in PM_{u_1} and PM_{u_2}

Step 2: While $i \leq \text{InterestArea}Num_{u_1}$ do

Step 3: While $j \leq \text{InterestArea}Num_{u_2}$

Step 4: $d = Distance(PM_{u_{2i}}, PM_{u_{2j}})$ //euclidean distance between $PM_{u_{1i}}$ and $PM_{u_{2i}}$

Step5： if $d \leq \theta_d$ then

Step 6: $t = |PM_{u_{1i}}.T - PM_{u_{2j}}.T|$;

Step 7: if $t \geq \theta_t$ then

Step 8: OverlapNum++;

Step 9: OIA=$\frac{2*\text{OverlapNum}}{\text{InterestArea}Num_{u_1}+\text{InterestArea}Num_{u_2}}$;

Step 10： return OIA;

4. Experiment Evaluation

To validate the efficiency of the users' similarity measurement approach represented above, we undertook experiments using the GPS trajectory, which is consisted of latitude, longitude, altitude and time in GPS log file format, datasets collected in (Microsoft Research Asia) Geolife project. This dataset was collected by 182 users in a period of over three years (from April 2007 to August 2012), and contains 17,621 trajectories with a total distance of about 1.2 million kilometers and a total duration of 48,000+ hours.

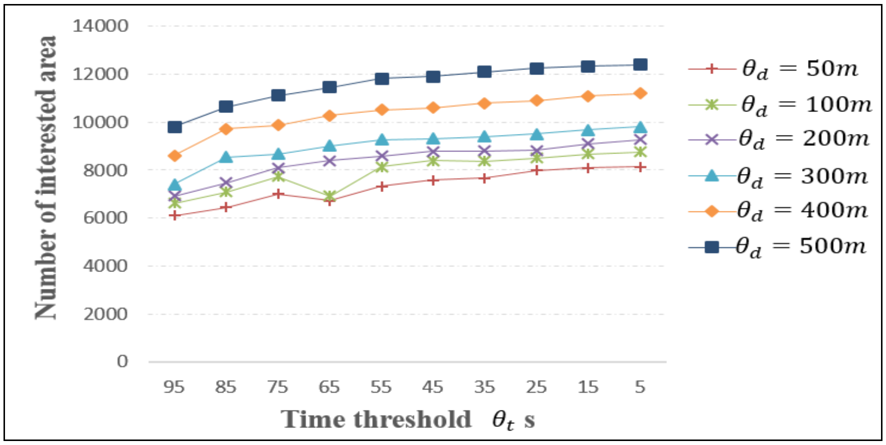


Figure 3. Numbers of Interested Area Detected by Different Time Interval and Distance Threshold

The experiment was conducted at the computer with an Intel (R) Core™ i3-2310 CPU @2.10GHz (4 CPUs), 6GB RAM, Windows 7 Ultimate 64-bit, using C# Programming Language (in Microsoft Visual Studio 2010 Professional). We choose only the trajectories generate by walking users. As shown in Figure 3, the number of interested areas increase with the increase of time and distance threshold accordingly. At the same time, interested areas increase with the increase of distance threshold, in case of the same time threshold value.

Trajectories of 75 people are selected to testify the validity the users' similarity calculation algorithm proposed in this paper. There is a variety of the combinations of θ_d and θ_t, it is impossible to stimulate all the combination cases. The typical interested area, such as a shopping mall, is about 150×150 meter georegion, so we select a distance threshold of 150 meter in our similarity calculation algorithm. The experimental result, as shown in Figure 4, indicates an obvious increase of trajectories numbers at the same OIA value.

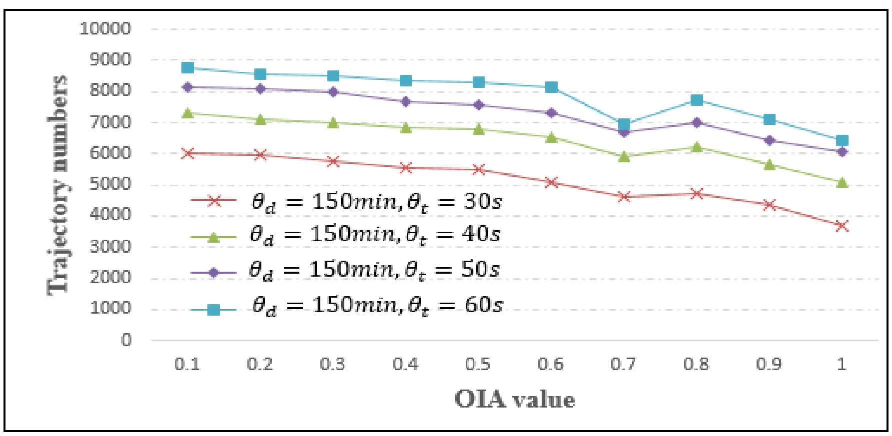


Figure 4. Stimulation of Users' Similarity Calculation Algorithm

5. Conclusion

The paper put forward a new approach to discover users' similarity, which is very important for mobile e-commerce recommendation. From a concept that people have more geospatial overlaps have more possibility to similar, an interested area detection similarity measure approach is put forward to calculate the similarities among mobile users, and an indicator, OIA, is set to measure the possible their relationship. Experimental evaluation, using the GPS trajectory dataset, which is publicly available, proves the effectiveness of our method. Obviously, distance threshold θ_d and time threshold θ_t are the key factors determining the precision of our algorithm.

Mobile e-commerce systems generate great quantities of data every day, but traditional data mining approaches often focus on business information, and ignore the location information. Trajectory mining can be used to understand user interests, which is especially valuable for business organizations to achieve improved customer satisfaction. This article just puts forward a research framework of users' similarity mining from trajectory, many related topic remains to be further investigated. In the future, we plan to take into account more features of mobile e-commerce system users' movements characteristics to improve the efficiency of our algorithm, design and develop a users' trajectories mining based mobile e-commerce system.

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References

[1] G. Wang and X. Gui, "Dynamic Recommendation Trust Evaluation Model Based on Mobile E-Commerce", Proceedings of the High Performance Computing and Communication & 2012 IEEE 9th International Conference on Embedded Software and Systems (HPCC-ICESS), Liverpool, United Kingdom, **(2012)** June 25-27.

[2] J. W. Kim, C. S. Kim, A. Gautam and Y. Lee, "Location-Based Tour Guide System using mobile GIS and Web crawling", Web and Wireless Geographical Information Systems, vol. 34, no. 28, **(2005)**.

[3] Durlacher Research Ltd. Mobile Commerce Report, www.durlacher.com, **(2000)**.

[4] D.-R. Liu and C.-H. Liou, "Mobile commerce product recommendations based on hybrid multiple channels", Electronic Commerce Research and Applications, vol. 10, no. 1, **(2011)**.

[5] F. Ricci, "Mobile recommender systems", Journal of Information Technology and Tourism, vol. 12, no. 3 **(2011)**.

[6] M. Lu, "A Study of Semantic Service of Spatial Information for Navigable Geo-Spatial Database Based on Ontology", East China Normal University, Shanghai, **(2006)**.

[7] Z. X. Yan, "Semantic trajectories: computing and understanding mobility data", Swiss Federal Institute of Technology, Lausanne, Switzerland, **(2011)**.

[8] Z. X. Yan, "Towards semantic trajectory data analysis: a conceptual and computational approach", Proceedings of the 35th ACM SIGMOD Conference on Very Large Databases, Lyon, France, **(2009)** June 29-July 2.

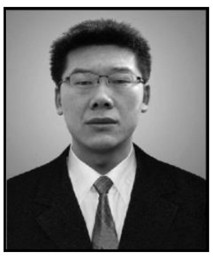
[9] G. Marketos, E. Frentzos and I. Ntousi, "Building real-world trajectory warehouses", Proceedings of the 7th ACM International Workshop on Data Engineering for Wireless and Mobile Access, Vancouver, Canada, **(2008)** June 13-14.

[10] E. Baglioni, L. Becchetti, L. Bergamini, U. Colesanti, L. Filipponi, A. Vitaletti and G. Persiano, "A lightweight privacy preserving SMSbased recommendation system for mobile users", Proceedings of the Recommendation System 2010, New York, US, **(2010)** December 4-6.

[11] D.-N. Chen, P. J.-H. Hu, Y.-R. Kuo and T.-P. Liang, "A Web-based personalized recommendation system for mobile phone selection: Design, implementation, and evaluation. Expert Systems with Applications. 37, 12 **(2010)**.
[12] A.-J. Cheng, Y.-Y. Chen, Y.-T. Huang, W. H. Hsu and H.-Y. M. Liao, "Personalized travel recommendation by mining people attributes from community-contributed photos", Proceedings of the Proceedings of the 19th ACM international conference on Multimedia, Scottsdale, Arizona, USA, **(2011)** November 28.
[13] T. H. Dao, S. R. Jeong and H. Ahn, "A novel recommendation model of location-based advertising: Context-Aware Collaborative Filtering using GA approach", Expert Systems with Applications, vol. 39, no. 3, **(2012)**.
[14] L. Li, F. Lee, Y. Chen and C. Cheng, "A multi-stage collaborative filtering approach for mobile recommendation", Proceedings of the 3rd International Conference on Ubiquitous Information Management and Communication, Suwon, South Korea, **(2009)** September 3-6.
[15] C. Y. Kim, J. K. Lee, Y. H. Cho and D. H. Kim, "Viscors: a visual-content recommender for the mobile web", IEEE Intelligent Systems, vol. 19, no. 6, **(2004)**.
[16] C. H. Liou and D. R. Liu, "MPF-based hybrid recommendations for mobile commerce", Proceedings of the International Conference on Information and Knowledge Engineering, Las Vegas, NV, **(2009)** July 13-16.
[17] R. Simon and P. Frölich, "A mobile application framework for the geospatial web", Proceedings of the 16th International Conference on World Wide Web, Banff, Alberta, Canada, **(2007)** May 8-12.
[18] G. Abowd, C. Atkeson, J. Hong, S. Long, R. Kooper and M. Pinkerton, "Cyberguide: a mobile context-aware tour guide", Wireless Networks, vol. 3, no. 5, **(1997)**.
[19] A. Girardello and F. Michahelles, "AppAware: Which mobile applications are hot?", Proceedings of the Human Computer Interaction with Mobile Devices and Services, New York, US, **(2010)** September 7-10.
[20] Y. Takeuchi and M. Sugimoto, "CityVoyager: An outdoor recommendation system based on user location history", Proceedings of the Ubiquitous Intelligence and Computing, Wuhan, China, **(2006)** September 3-9.
[21] N. Jamil, A. C. Alhadi and S. A. Noah, "A collaborative names recommendation in the Twitter environment based on location", Proceedings of the 2011 International Conference on Semantic Technology and Information Retrieval (STAIR), Shenzhen, China, **(2011)** November 26-27.
[22] Y. Zheng, L. Zhang, X. Xie and W.-Y. Ma, "Mining interesting locations and travel sequences from GPS trajectories", Proceedings of the 18th international conference on World wide web, New York, NY, USA, (**2009**) April 4-May 3.
[23] G. Abowd, C. Atkeson, J. Hong, S. Long, R. Kooper and M. Pinkerton, "Cyberguide: A mobile context-aware tour guide", Wireless Networks, vol. 3, no. 5, **(1997)**.
[24] M.-H. Park, J.-H. Hong and S.-B. Cho, "Location-based recommendation system using Bayesian user's preference model in mobile devices", Proceedings of the Ubiquitous Intelligence and Computing, Hong Kong, China, **(2007)** July 11-13.
[25] Q. Li, Y. Zheng, X. Xie and W.-Y. Ma, "Mining user similarity based on location history", Proceedings of the ACM SIGSPATIAL GIS, Irvine, CA, USA, **(2008)** November 5-7.
[26] S. Abraham and P. S. Lai, "Spatio-temporal Similarity of Web User Session Trajectories and Applications in Dark Web Research", Proceedings of the Pacific Asia Workshop on Intelligence and Security Informatics, Beijing, China, **(2011)** July 24-26.
[27] I. Guy, M. Jacovi, A. Perer, I. Ronen and E. Uziel, "Same places, same things, same people?: mining user similarity on social media", Proceedings of the 2010 ACM conference on Computer supported cooperative work, Savannah, Georgia, USA, **(2010)** February 6-10.
[28] J. J.-C. Ying, E. H.-C. Lu, W.-C. Lee, T.-C. Weng and V. S. Tseng, "Mining user similarity from semantic trajectories", Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks, San Jose, California, **(2010)** November 3-5.
[29] M.-J. Lee and C.-W. Chung, "A user similarity calculation based on the location for social network services", Proceedings of the Database Systems for Advanced Applications, Hong Kong, China, **(2011)** April 22-25.
[30] A. Eckhardt, "Similarity of users' (content-based) preference models for Collaborative filtering in few ratings scenario", Expert Systems with Applications, vol. 39, no. 14, **(2012)**.
[31] F. D. Bona, S. Riezler, K. Hall, M. Ciaramita, A. delen and M. Holmqvist, "Learning dense models of query similarity from user click logs", Proceedings of the Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Los Angeles, California, **(2010)** June 2-4.
[32] Y. Wei, L. Shijun, Z. Yunlu and Z. Zhuo, "Mining Users Similarity of Interests in Web Community", Journal of Computers, vol. 6, no. 11, **(2011)**.
[33] M. Gan and R. Jiang, "Constructing a user similarity network to remove adverse influence of popular objects for personalized recommendation", Expert Systems with Applications, vol. 40, no. 10, **(2013)**.
[34] W. R. Tobler, "A computer movie simulating urban growth in the Detroit region", Economic geography, vol. 46, no. 2, **(1970)**.

[35] Z. Yu and X. Xing, "Learning Location Correlation from GPS Trajectories", Proceedings of the Eleventh International Conference on Mobile Data Management (MDM), Kansas City, MO, USA, **(2010)** May 23-26.
[36] J. W. Han and M. Kamber, "Data Mining: Concepts and techniques", Beijing: mechanical industry press, **(2006)**.
[37] G. Kellaris, N. Pelekis and Y. Theodoridis, "Trajectory compression under network constraints", Proceedings of the 11th International Symposium on Advances in Spatial and Temporal Databases, Aalborg, Denmark, **(2009)** July 8-10.
[38] I. Ntoutsi, N. Mitsou and G. Marketos, "Traffic mining in a road-network: How does the traffic flow?", International Journal of Business Intelligence and Data Mining, vol. 3, no. 1, **(2008)**.
[39] L. X. Liu, J. B. Fan, S. J. Qiao, J. T. Song and R. Guo, "Efficiently mining outliers from trajectories of unrestraint movement", Proceedings of the 3rd International Conference on Advanced Computer Theory and Engineering, Chengdu, China, **(2010)** August 20-22.
[40] F. X. Zhu, "Mining ship spatial trajectory patterns from AIS database for maritime surveillance", Proceedings of the 2nd International Conference on Emergency Management and Management Sciences, Beijing, China, **(2011)** August 8-10.
[41] Y. Hyoseok, Y. Zheng, X. Xie and W. Woo, "Social itinerary recommendation from user-generated digital trails", Journal on Personal and Ubiquitous Computing, vol. 6, **(2011)**.
[42] J. Krumm and E. Horvitz, "Predestination: Where do you want to go today?", IEEE Comput Mag., vol. 40, no. 4, **(2007)**.
[43] Y. Zheng, L. Zhang, Z. Ma, X. Xie and W.-Y. Ma, "Recommending Friends and Locations Based on Individual Location History", ACM Transactions on the Web., vol. 5, no. 1, **(2011)**.

Authors



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