A Framework for Personal Mobile Commerce Pattern Mining and Prediction

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Abstract-- Due to a wide range of potential applications, research on mobile commerce has received a lot of interests from both of the industry and academia. Among them, one of the active topic areas is the mining and prediction of users' mobile commerce behaviors such as their movements and purchase transactions. In this paper, we propose a novel framework, called Mobile Commerce Explorer (MCE), for mining and prediction of mobile users' movements and purchase transactions under the context of mobile commerce. The MCE framework consists of three major components: 1) Similarity Inference Model (SIM) for measuring the similarities among stores and items, which are two basic mobile commerce entities considered in this paper; 2) Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs); and 3) Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of mobile users' commerce behaviors in order to recommend stores and items previously unknown to a user. We perform an extensive experimental evaluation by simulation and show that our proposals produce excellent results.

Keywords: *Data mining, Mobile commerce.*

I. INTRODUCTION

The rapid advance of wireless communication technology and the increasing popularity of po-werful portable devices, mobile users not only can access worldwide information from anywhere at any time but also use their mobile devices to make business trans-actions easily, e.g., via digital wallet. Meanwhile, the availability of location-acquisition technology, e.g., Global Positioning System (GPS), facilitates easy acquisition of a moving trajectory, which records a user movement histo-ry. Thus, we envisage that, in the coming future of Mobile Commerce (M-Commerce) age, some m-commerce services will be able to capture the moving trajectories and purchase transactions of users. Take the recent an-nounced Shopkick as an example, it gives mobile users rewards and offers when users checkin in stores and on items. Anticipating that some users may be will-ing to exchange their locations and transactions for good rewards and discounts, we expect more mobile commerce applications, whether they will bear a business model similar with Shopkick or not, will appear in the future. In this paper, we aim at developing pattern mining and pre-diction techniques that explore the correlation between the moving behavior and purchasing transactions of mobile users to explore potential M-Commerce features.

Owing to the rapid development of the Web 2.0 tech-nology, many stores have made their store information, e.g., business hours, location, and features available on-line, e.g., via mapping services such as Google Map. Ad-ditionally, user trajectories can be detected by GPS-enabled devices, when users move around.When a user enters a building, the user may lose the satellite sig-nal until returning to the outdoors. By matching user tra-jectories with store location information, a user's moving sequence among stores in some shop areas can be ex-tracted. Fig. 1 shows a scenario, where a user moves among stores while making some purchase transactions (or transactions in short). Fig. 1(a) shows a moving se-quence, where underlined store labels indicate some transactions being made there. Fig. 1(b) shows the trans-action records of a user, where item i1 was purchased when this user is in store A. The mobile transaction se-quence generated by this user is {(A, {i1}), (B,), (C, {i3}),(D, {i2}), (E,), (F, {i3, i4}), (I,), (K, {i5})}.

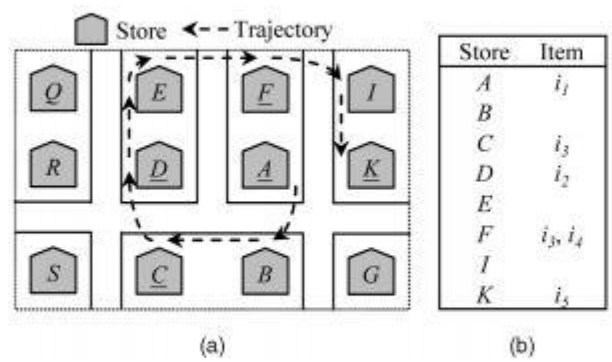


Fig. 1. An example for a mobile transaction sequence

There usually is an entangling relation between mov-ing patterns and purchase patterns since mobile users are moving between stores to shop for desired items . The moving and purchase patterns of a user can be captured together as mobile commerce patterns for mobile users. For example, the user taking the shopping trip shown in Fig. 1 may exhibit a moving pattern ABC and two purchase patterns (A, {i1}) and (C, { i 3}). This pattern, which can be expressed as {(A, {i1}) B (C, {i3})}, indicates that the user usually purchases item i1 in store A and then pur-chases item i3 in store C on the specific path ABC. Armed with knowledge of this pattern, an m -commerce service could push some discount coupons of item i3 to the user to boost the sales of store C when the user purchases item i1 in store A. To provide this mobile ad hoc advertisement, mining mobile commerce patterns of users and accurately predicts their potential mobile commerce behaviors ob-viously are essential operations that require more re-search. They are also presented in this paper.

To capture and obtain a better understanding of mo-bile users' mobile commerce behaviors, data mining has been widely used for discovering valuable informa-tion from complex data sets. A number of studies have discussed the issue of mobile behavior mining analysis, even though the targeted patterns in these prior works are typically different. For example, Tseng et al. The problem of mining associated service patterns in mobile web environments. They also proposed SMAP-Mine for efficient mining of users' sequential mobile access patterns, based on the FP-Tree [8]. Chen et al. proposed the path traversal patterns for mining mobile web user behaviors. Yun et al. proposed a method for mining mobile sequential pattern (MSP) by taking mov-ing paths of users into consideration. Jeung et al. pro-posed a prediction approach called Hybrid Prediction Model (HPM) for mining the trajectory pattern of a moving object. While the aforementioned studies have been conducted for discovery of mobile patterns, few of them consider the personalization issue. Since patterns mined in these studies are typically from all users, they do not reflect the personal behaviors of individual users, especially when the mobile behaviors may vary a lot amongst different mobile users. In this paper, we aim at mining mobile commerce behavior of individual users to support m-commerce services at a personalized level.

As mentioned earlier, in addition to mining mobile patterns, predicting the next mobile behaviors of a user is a critical research issue. Existing work on mobile behavior prediction can be roughly divided into two categories. The first category is vector based prediction and the second category is pattern based prediction . The idea of vector based prediction is to predict the next location of an object according to its mov-ing direction and velocity. Vector based predictions as-sume that the predictive mobile behaviors of a user can be represented by mathematical models based on his recent movement in form of geographic information. Pattern based prediction models, on the other hand, capture se-mantic patterns that match the user's recent mobile beha-viors well. Pattern based predictions are more precise than vector based predictions.

Hybrid Prediction Model (HPM) represents the state of the art in the field of movement prediction for moving objects. HPM integrates both ideas of the pattern based prediction and vector based prediction. We argue that the vector based prediction models may not be appropriate for mobile user behavior prediction, since an object's movements are more complicated than what the mathematical formulas can represent. Thus, our study follows the paradigm of pattern based prediction. Nevertheless, our work is uniquely different from the existing work because we aim at predicting the mobile commerce behavior in terms of both the movement and purchase transaction, while the existing work mostly focus on predict the movement only.

A crucial issue for pattern based prediction is that the predictions fail if there is no existing pattern to match. In the previous pattern based prediction models, pattern selection is typically based on exact matching, e.g., the similarity between different stores is 0. Take Fig. 1 as an example, the user has never been to store Q, store R, and store S. Since there is no pattern involving these stores, pattern based predictions do not work when a user first moves to these stores. To overcome this problem, our idea is to incorporate the similarities of stores and items into the mobile commerce behavior prediction. Consider the example in Fig. 1 again. Since the user has never been to store Q, the mobile patterns mined by this user do not contain any information about store Q. However, if we know that store A (where the user had visited before) is similar with store Q, we can make recommendation to the user based on the patterns exhibited in store A. In other words, we consider that the mobile behaviors of the user in store A may be similar with those in store Q. Thus, we can employ the inferred behaviors in store A to predict next mobile behaviors in store Q even though the user has never been to store Q. Hence, a fundamental issue is to derive the similarities of stores in this paper.

Multiple-level hierarchical structures can be defined to measure which stores are similar . However, the method requires the users to set up hierarchical struc-tures. It is difficult to determine suitable structures in a mobile commerce environment. In this paper, we develop a similarity inference model to automatically measure the similarities between stores and between items. Based on our observations, we identify two basic heuristics as the bases of our inference model: (1) two stores are similar if the items they sell are similar; (2) two items are dissimilar if the stores which sell them are dissimilar. Accordingly, we infer the store similarity and item similarity from each other. Although a number of similarity measures have been studied to measure the similarity of two vectors in the literature, they are not applicable in this work due to the following factors:(1) most of similarity measures can only process numerical data but not the categorical data considered in this paper; (2)consider both store similarity and item similarity at the same time. In [11], Jeh *et al.* propose an iterative similarity computation method named SimRank. Although Si-mRank bears with similar ideas as SIM, SimRank is not applicable to our problem. Particularly, SimRank needs to set a decay factor C and a fixed number of iterations K to perform. In mobile commerce environments, it is difficult to determine which parameters are suitable.

To provide a high-precision mobile commerce beha-vior predictor, we focus on personal mobile pattern min-ing. Besides, to overcome the predictions failure problem, we incorporate the similarities of stores and items into the mobile commerce behavior prediction. Hence, in this pa-per, we propose a novel framework, namely *Mobile Com-merce Explorer* (*MCE*), to mine and predict mobile users' movements and transactions under the context of mobile commerce. The *MCE* framework consists of three major components:

1) *Similarity Inference Model* (*SIM*) for mea-suring the similarities among stores and items, which are two basic mobile commerce entities considered in this paper;

2) *Personal Mobile Commerce Pattern Mine* (*PMCP-Mine*) algorithm for efficient discovery of mobile users'

Personal Mobile Commerce Patterns (*PMCPs*); and
3) *Mobile Commerce Behavior Predictor* (*MCBP*) for prediction of possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of mobile users' commerce behaviors that may recom-mend stores and items previously unknown to a user. Finally, through an extensively experimental evaluation, we show that our proposals deliver an excellent perfor-mance in terms of precision, recall and F-measure.

The advantages and contributions of this paper are five-fold.

We propose the MCE framework, a new approach for mobile commerce behavior mining and predic-tion. The problems and ideas in MCE have not been well explored in the research community.

We propose a novel model SIM for automatically measuring the similarities among stores and items from a mobile transaction database.To understand the personal mobile behaviors, we propose a novel algorithm PMCP-Mine for mining PMCPs from a mobile transaction database.

The remainder of this paper is organized as follows. We briefly review the related work in Section 2. In Section 3, we formulate the problem. In Section 4, we first intro-duce the proposed framework MCE. Then, we describe the proposed approaches SIM, PMCP-Mine, and MCBP. In Section 5, we perform an empirical performance evalu-ation. Finally, in Section 6, we summarize our conclusions and future work.

II. RELATED WORK

In this section, we review and classify relevant previous studies into three categories: 1) similarity measures, 2) mobile pattern mining techniques, and 3) mobile behavior predictions.

Similarity Measure. There have been many studies on measuring the similarity between two objects. The first one is based on multiple-level hierarchical structures. In, Lu first proposes the concept of multiple -level hie-rarchical structure in data mining. In , Han et al. pro-pose the multiple-level association rules mining. In this study, taxonomy is incorporated for representing the hie-rarchical relations of items. In, Tseng et al. first ap-plies the multiple-level hierarchical concept to mine asso-ciated service patterns in mobile web environments. Based on the structure, the items in the same level are regarded as similar items. However, we do not know the relations between the items in the different levels. The second one is sequence alignments. In, Jeh et al. pro-pose the SimRank to iteratively compute the similarities between objects. The idea is that two objects are similar if they are related to similar objects. To improve the effi-ciency of SimRank, in , Yin et al. develop the hierar-chical structure named SimTree to reduce the computa-tion cost and the storage of object similarities but still dis-cover the relationships between objects. In, Xin et al. propose a pattern distance measure based on set similari-ty between two association patterns. The concept of set similarity is to apply Jaccard Measure to calculate the si-milarity of two sets. Let S1 and S2 be two sets, the set simi-larity set_similarity(S1, S2) is defined as (1). However, set similarity is not applicable to store similarity in mobile commerce. For example, there are two stores A and B which only provides milk and coffee, respectively. The similarity of store A and store B should not be 0, since milk and coffee belong to the same drink category.

Mobile Pattern Mining. In recent years, a number of stu-dies have discussed the usage of data mining techniques to discover useful rules/patterns from WWW, trans-action databases and mobility data named WAP-Mine to efficiently discover web access pat-terns in web logs, using a tree-based data structure with-out candidate generation. Sequential pattern mining has been first introduced in to search for time-ordered patterns, known as sequential patterns within transaction databases. For the studies considering the relation be-tween location and service, in, Chen et al. propose the path traversal patterns for mining web user behaviors. Tseng et al. first study the problem of mining asso-ciated service patterns in mobile web environments. SMAP-Mine has been proposed by Tseng et al. for Tseng et al. propose the TMSP-Mine for discovering the efficiently mining users' sequential mobile access patterns, temporal mobile sequence patterns in a location-based based on the FP-Tree. Lee et al. propose T-MAP to service environment. Jeung et al. propose a prediction efficiently find the mobile users' mobile access patterns in approach called Hybrid Prediction Model (HPM) for distinct time intervals. Yun et al. propose the Mobile Se-estimating an object's future locations based on its pattern quential Pattern (MSP)to take moving paths into information. This paper considers that an object's move-consideration and add the moving path between the left ments are more complicated than what the mathematical hand and the right hand in the content of rules. In formulas can represent. However, there is no work con- sider user relations in the mobile pattern mining

Mobile Behavior Prediction. The studies on mobile be-havior predictions can be roughly divided into two cate-gories. The first category is vector based prediction that can be further divided into two types: (1) linear models and (2) non-linear models. The non-linear models capture objects' movements with sophisticate re-gression functions. Thus, their prediction accuracies are higher than those of the linear models. Recursive Motion Function (RMF) is the most accurate prediction me-thod in the literature based on regression functions.

The second category is pattern based prediction. In Ishi-kawa et al. derive a Markov Model (MM) that generates Markov transition probabilities from one cell to another for predicting the next cell of the object. In HPM the form of a trajectory pattern is Rt1j1 ^ Rt2j2 ^ ... ^ Rtmjm Rtnjn with a confidence c, where Rtiji indicates a user inlocation Rti ji at time ti, i.e., when the premise of the pattern occurs, the consequence will also occur with probability c. However, these methods can only predict the next spatial locations of objects. SMAP-Mine has been proposed to discover sequential mobile access rules and predict the user's next locations and services. The form of the rule is {ri, si} {rj, sj} with a confidence c, where ri and rj are loca-tions, and si and sj are services. It implies that a user re-questing si in ri will have next location and service as rj and sj with c probability. In [30], Yun et al. propose the Mobile Sequential Pattern (MSP) to predict the next mo-bile behaviors. The form of the pattern is {(ri, si), (r1), (r2), (r3), (rj , sj)}, where item (ri, si) indicates a user request ser-vice si at location ri. The pattern above means that a user requests service si in location ri and then requests service sj in location rj via a specific path r1r2r3.

The idea of Collaborative Filtering (CF) may be ap-plied to the prediction of user's behavior. Collaborative filtering can be divided into two types: 1) user-based col-laborative filtering and 2) item-based collaborative filter-ing. The user - based collaborative filtering is based on the behaviors of other similar users. For example, suppose that John and Bob are similar based on their profiles or preferences. We may refer to the behaviors of Bob to pre-dict the next behavior of John. However, the behaviors of two users are not always similar even if the two users are very similar. For the item-based collaborative filtering,

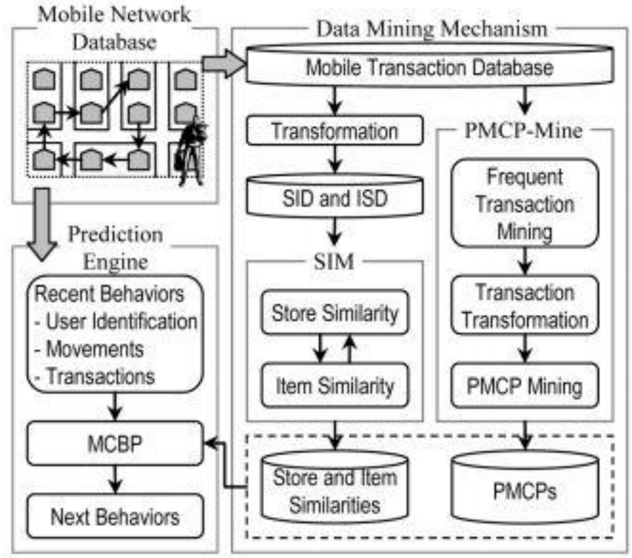
Table:1

Notation	Description
MTD	Mobile transaction database.
D_u	Mobile transaction database for user u, $D_u \in MTD$.
MTS	Mobile transaction sequence, $MTS \in D_u$.
P	Moving path.
$PMCP$	Personal mobile commerce pattern.
s	A store.
S	A set of stores.
Ω_i	The set of stores where the item i is sold.
i	An item.
I	A set of items.
Γ_s	The set of items sold in the store s.
SID	Store-Item Database.
ISD	Item-Store Database.

When we know that a user has purchased Coffee and we try to predict the next behavior of this user, we may refer to the next behavior after this user purchases Milk. However, it is difficult to define the similarity between items. Generally speaking, collaborative filtering techniques rely on user ratings on items to predict user purchase behavior and are not applicable to our study.

III. PROPOSED METHOD

In this section, we describe our design of a personal mobile commerce mining and prediction framework, called MCE, which incorporates three innovative techniques, including 1) Similarity Inference Model for measuring the imilarities among stores and items, which are two basic mobile commerce entities considered in this paper; 2) Personal Mobile Commerce Pattern Mine algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns; and 3) Mobile Commerce Behavior Predictor for prediction of possible mobile user behaviors.



System Framework The proposed MCE framework consists of three modules, 1) a mobile network database, 2) a data mining mechanism, and 3) a behavior prediction engine (See Fig. 2). The mobile network database maintains detailed store information which includes locations. Our system has an "offline" mechanism for similarity inference and PMCPs mining, and an "online" engine for mobile commerce behavior prediction. When mobile users move between the stores, the mobile information which includes user identification, stores, and item purchased are stored in the mobile transaction database. Table 2 shows an example of mobile transaction database which contains four users and 14 mobile transaction sequences. In the offline data mining mechanism, we develop the SIM model and the PMCPMine algorithm to discover the store/item similarities and the PMCPs, respectively. In the online prediction engine, we propose a MCBP based on the store and item similarities as well as the mined PMCPs. When a mobile user moves and purchases items among the stores, the next steps will be predicted according to the mobile user's identification and recent mobile transactions. The framework is to support the prediction of next movement and transaction.

Store	Items
A	i_1, i_3
B	i_1, i_5
C	i_3, i_5
D	i_2, i_4, i_6, i_7
E	i_1, i_3
F	i_3, i_4
I	i_2, i_5, i_6, i_8
K	i_2, i_5

Item	Stores
i_1	A, B, E
i_2	D, I, K
i_3	A, C, E, F
i_4	D, F
i_5	B, C, I, K
i_6	D, I
i_7	D
i_8	I

Similarity Inference Model An essential task in our framework is to determine the similarities of stores and items. The problem may be solved by using store and item category ontology. However, the store or item ontology may not match with the mobile transaction database. Our goal is to automatically compute the store and item similarities from the mobile transaction database, which captures mobile users' moving and transactional behaviors (in terms of movement among stores and purchased items). From the database, we have the following information available: 1) for a given store, we know which items are available for sale; 2) for a given item, we know which stores sell this item. The information can help us to infer which stores or items are similar. As we observe that people usually purchase similar items in certain stores, these stores may be considered as similar. For example, people may purchase hamburgers, French fries, or Cokes in McDonalds and Burger King, we consider them as similar stores. We propose a parameter-less data mining model, named Similarity Inference Model, to tackle this task of computing store and item similarities.

A. Discovery of PMCPs

In this section, we describe the PMCP-Mine algorithm to mine the personal mobile commerce patterns efficiently. The PMCP-Mine algorithm is inspired by the TJPF algo-rithm [30] which is an Apriori-like algorithm. However, we observe that the TJPF algorithm does not consider user identification, which is essential for discovering personal mobile behaviors. In other words, the TJPF algorithm can-not be employed in our framework. The PMCP -Mine al-gorithm is performed in a bottom-up manner. We first discover frequent transaction behaviors in a single store, e.g., {Starbucks, Latte}. Then, these single patterns can be joined to form compound patterns, e.g., {Hang Ten, clothes} Giordano {Starbucks, Latte}. Eventually, the complete mobile commerce patterns can be obtained by the PMCP-Mine algorithm. The PMCP-Mine algorithm is divided into three main phases: 1) Frequent-Transaction Mining. A Frequent-Transaction is a pair of store and items indicating frequently made purchasing transactions.

1) Frequent-Transaction Mining.

A candi-date 2-transaction, indicating that two items are pur-chased together in the transaction, is generated by joining two frequent 1-transactions where their user identifica-tions and stores are the same. For example, the candidate 2-transaction (F, {i3, i4}) is generated by joining (F, {i3}) and (F, {i4}), because the user identifications and purchased stores of them both are U1 and F, respectively. Thus, we keep the patterns as frequent 2-transactions, when their support is larger than TSUP. Finally, the same procedures are repeated until no more candidate transaction is gen-erated. The frequent transactions are shown in Table 5. In the table, we use an item mapping table to re -label item sets in order to present F-Transactions in Table 5. For each unique item set, we use a symbol LIi (Large Itemset i) to represent it, where i indicates a running number. The mapping procedure can reduce the time required to check if a mobile commerce pattern is contained in a mobile transaction sequence. Finally, the frequent 1-PMCPs (same as the F-Transaction) are obtained.

2) Mobile Transaction Database Transformation

In This phase, we use F-Transactions to transform each mo-bile transaction sequence S into a frequent mobile transac-tion sequence S'. According to Table 5, if a transaction T in S is frequent, T would be kept as an F-Transaction. Oth-erwise, the store of T is taken as part of a path. Table 7 shows the result of frequent mobile transaction database transformed from Table 2. Take the partial sequence (U1, A, LI1) BC (U1, D, LI2) in the first mobile transaction.

3) PMCP Mining.

In this phase, we mine all the PMCPs from the frequent mobile transaction database. Frequent 1-PMCPs are obtained in the frequent-transaction mining phase, as described earlier. In the min-ing algorithm, we utilize a two-level tree, named Personal Mobile CommercePattern Tree (PMCP -Tree) to maintain the obtained PMCPs. Fig. 4 illustrates the PMCP-Tree. As shown, the upper level of the PMCP-Tree keeps track of the frequent mobile.

B. Summary of experimental results

The above experiments can be divided into two parts: 1) internal evaluations for store/item similarity measure-ment and mobile commerce behavior prediction in MCE; and 2) external evaluations for MCE and three other pre-diction frameworks. For the first part, the experimental results show the following two conclusions: 1) using SIM to inference the store and item similarities is more precise than using SET. The obtained similarity knowledge can improve the recall of behavior prediction when a user moves to stores or buys items previously unknown to the user. 2) Using MCBP prediction technique can achieve higher precision than using SO or ISM, because MCBP considers not only the pattern supports but also the weighted matching score between pattern premises and users' recent mobile commerce behaviors in behavior prediction. Hence, MCBP can capture a user's recent mo-bile commerce behavior and select the best PMCP to pre-diction the user's next behavior precisely. 3) The perfor-mance of the MCE framework is efficient.

For the second part, the experiments consist of three measurements: 1) the studies on precision, 2) the studies on recall, and 3) the studies on F-measure. For the studies on precision, it is observed that MCE outperforms the other three frameworks under various system conditions. For the studies on recall, MM, HPM, and MCE, are close to 100%. MM is a Markov model method, the transition probabilities decide the prediction result. A location can-not be predicted if this location has never been visited by any user. With sufficient training data, the recall can be close to 100%. HPM is a hybrid method. When the pattern based prediction fails, the regression based prediction would be started to predict the next behavior of the mov-ing object. The prediction technique of MCE, i.e., MCBP, is to choose the pattern with the highest weighted match-ing score for predicting the next behavior of mobile commerce applications, low precision in predictions may lead to high penalty in business cost. Hence, the pre-cision is more important than the recall for behavior pre-diction.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a novel framework, namely Mobile Commerce Explorer (MCE), for mining and prediction of mobile users' movements and transactions in mobile commerce environments. In the MCE frame-work, we have proposed three major techniques: 1) Simi-larity Inference Model (SIM) for measuring the similarities among stores and items; 2) Personal Mobile Commerce Pat-tern Mine (PMCP-Mine) algorithm for efficiently discover-ing mobile users' Personal Mobile Commerce Patterns (PMCPs); and 3) Mobile Commerce Behavior Predictor(MCBP) for predicting possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of personal mobile commerce be-haviors that may recommend stores and items previously unknown to a user.

To evaluate the performance of the proposed frame-work and three proposed techniques, we conducted a series of experiments. The experimental results show that the framework MCE achieves a very high precision in mobile commerce behavior predictions. Besides, the pre-diction technique MCBP in our MCE framework inte-grates the mined PMCPs and the similarity information from SIM to achieve superior performs in terms of preci-sion, recall, and F-measure. The experimental results show that our proposed framework and three compo-nents are highly accurate under various conditions.

For the future work, we plan to explore more efficient mobile commerce pattern mining algorithm, design more efficient similarity inference models, and develop pro-found prediction strategies to further enhance the MCE framework. In addition, we plan to apply the MCE framework to other applications, such as object tracking sensor networks and location based services, aiming to achieve high precision in predicting object behaviors.

REFERENCES

[1]. R. Agrawal, T. Imielinski, and A. Swami, “Mining Association Rule between Sets of Items in Large Databases,” Proc. ACM SIGMOD Conf. on Management of Data, pp. 207-216, May 1993.

[2]. R. Agrawal and R. Srikant, “Fast Algorithm for Mining Associa-tion Rules,” Proc. Int'l. Conf. on Very Large Databases, pp. 478-499, Sept. 1994.

[3]. R. Agrawal and R. Srikant, “Mining Sequential Patterns,” Proc. Int'l. Conf. on Data Engineering, 3-14, Mar. 1995.

[4]. S. F. Altschul, W. Gish, W. Miller, E. W. Myers, and D. J. Lip-man, “Basic Local Alignment Search Tool,” J. of Molecular Biolo-gy, vol. 215, no. 3, pp. 403-410, Oct. 1990.

[5]. M.-S. Chen, J.-S. Park, and P. S. Yu, “Efficient Data Mining for Path Traversal Patterns,” IEEE Trans. on Knowledge and Data En-gineering, vol. 10, no. 2,209-221, Apr. 1998.

[6]. J. Han and Y. Fu, “Discovery of Multiple-Level Association Rules in Large Database,” Proc. Int'l Conf. Very Large Data Bases, pp. 420-431, Sept. 1995.

[7]. J. Han and M. Kamber, “Data Mining: Concepts and Tech-niques, 2nd Edition,” Morgan Kaufmann, Sept. 2000.

[8]. J. Han, J. Pei, and Y. Yin, “Mining Frequent Patterns without Candidate Generation,” Proc. ACM SIGMOD Conf. on Manage-ment of Data, pp. 1-12, May 2000.

[9]. J. L. Herlocker, J. A. Konstan, A. Brochers, and J. Riedl, “An Algorithm Framework for Performing Collaborative Filtering,”

[10]. Y. Ishikawa, Y. Tsukamoto, and H. Kitagawa, “Extracting Mo-bility formation Retrieval, pp. 230-237, Aug. 1999.