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An Efficient Framework for Exploring Personal Pattern Mining and Prediction in Mobile Commerce

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Abstract—With the rapid advance of wireless communication technology and the increasing popularity of powerful portable devices, mobile users not only can access worldwide information from anywhere at any time but also use their mobile devices to make business transactions 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 history. We propose a novel framework namely, Mobile Commerce Prediction (MCP) framework consists of three major components: 1) Similarity Model (SM) for measuring the similarities among stores and items, which are two basic mobile commerce entities 2) Mobile Commerce Pattern Mine (MCPM) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns 3) Mobile Commerce User Behavior Predictor (MCUBP) for prediction of possible mobile user behaviors. We perform an extensive experimental evaluation by simulation and show that our proposals to produce excellent results.

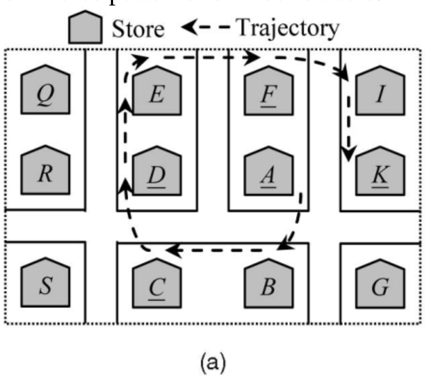
Index Terms—Association rule mining, Data mining, Mobile commerce, Pattern mining and prediction.

I. INTRODUCTION

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. Mobile commerce is a new frontier [1]. It involves the purchase transactions based on a mobile device. The mining and prediction of patterns can suggest stores that are more similar to his/her previous patterns mined and unknown to a customer.

Mobile Commerce is a new emerging technology with greater scope. Mobile devices mainly smart phones overcome laptops and desktops in many perspectives. Its size, portability, availability of internet and so on. Here comes the possibility of mobile commerce. Mobile commerce is the process of business transactions based on a mobile device. When introducing the technology of mining and prediction of mobile commerce patterns with mobile commerce, we can improve the scope of mobile commerce [2]. It is advantageous to customers with the fact that during purchasing, customers usually carry a mobile device mainly a smart phone than laptops because of its smaller size and portability.

By matching user trajectories with store location information, a user's moving sequence among stores in some shop areas can be extracted. Fig.1. shows a scenario, where a user moves among stores while making any purchase transactions (or transactions in short). Fig.1a shows a moving sequence, where underlined store labels indicate some transactions being made there. Fig.1b shows the transaction records of a user, where item i1 was purchased when this user is in store A. The mobile transaction sequence generated by this user is { (A,{ i1}), (B,ø), (C, {i3}), (D, {i2}), (E,ø), (F, {i3, i4}), (I,ø), (K,{i5}) }.There are usually an entangling relation between moving 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.



Store	Item
A	i_1
B	
C	i_3
D	i_2
E	
F	i_3, i_4
I	
K	i_5

(a) (b)

Fig.1. Mobile Transaction Sequence
a) Moving Trajectory b) Transactions

II. RELATED WORK

Multiple-level hierarchical structures can be defined to measure which stores are similar [6], [8]. However, the method requires the users to set up hierarchical structures. It is difficult to determine suitable structures in a mobile commerce environment. In this paper, we develop a similarity inference model (SIM) 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.

To provide a high-precision mobile commerce behavior predictor, we focus on personal mobile pattern mining. Besides, to overcome the predictions failure problem, the similarities of stores and items is incorporated into the mobile commerce behavior prediction.

A. Mining Mobile Sequential Patterns

To better reflect the customer buying behavior in the MC environment [7], an innovative mining model that takes both

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the moving patterns and purchase patterns into consideration is to be developed. In essence, the mining of mobile sequential patterns aggregates the concepts on mining association rules, mining path traversal patterns, and mining sequential patterns, and thus requires a combined use of corresponding techniques. How to strike a compromise among the use of various knowledge to solve the mining on mobile sequential patterns is a challenging issue. As an effort to solve this problem, a procedure, namely *mobile sequential patterns MSPs*),is discovered to conduct the mining of mobile sequential patterns.The procedure MSP splits the problem of mining mobile sequential patterns into four phases, namely: 1) the *large-transaction generation phase*; 2) the *large-transaction transformation phase*; 3) the *sequential-pattern generation phase*; and 4) the *sequential-rule generation phase*.

III. PROPOSED MOBILE COMMERCE PREDICTION (MCP) FRAMEWORK

The Mobile Commerce prediction framework consists of three major components:
1) Similarity Model for measuring the similarities among stores and items, which are two basic mobile commerce entities 2) Mobile Commerce Pattern Mine (MCPM) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns 3) Mobile Commerce User Behavior Predictor (MCUBP) for prediction of possible mobile user behaviors. The framework is as shown in fig.2.

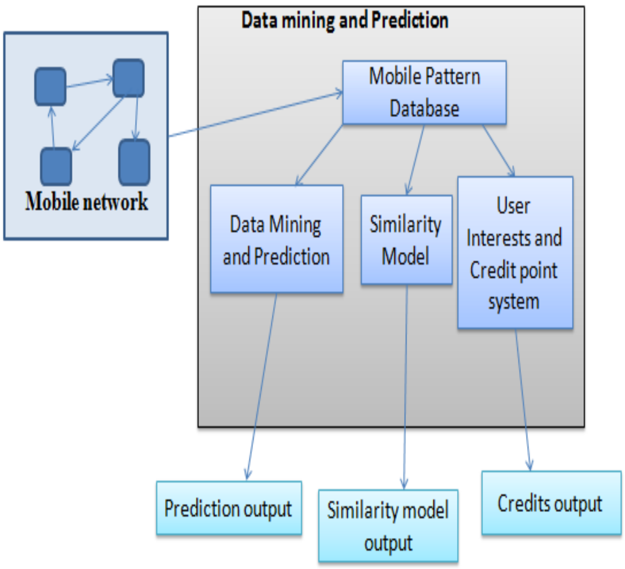


Fig.2. MCP Framework

The mobile network database maintains detailed store information which includes locations. The system has an "offline" mechanism for similarity model and MCPs mining, and an "online" engine for mobile commerce user 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. In the offline data mining mechanism, the SIM model and the MCPM algorithm are used to discover the store/item similarities and the MCPs, respectively. In the online prediction engine, a MCUBP is used based on the store and item similarities as well as the mined MCPs. 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.

Table I shows an example of a mobile transaction database which contains four users and 14 mobile transaction sequences.

Table I
An example Mobile Transaction database

T_{id}	U_{id}	Mobile Transaction Sequence
1	1	$(A,\{i_1\}), (B,\emptyset), (C,\{i_3\}),(D,\{i_2\}), (E,\emptyset), (F,\{i_3,i_4\}), (I,\emptyset), (K,\{i_5\})$
2	1	$(A,\{i_1\}), (B,\emptyset), (C,\emptyset), (D,\{i_2\})$
3	1	$(A,\{i_1\}), (B,\emptyset), (C,\emptyset), (D,\{i_2\}), (E,\emptyset), (F,\{i_3,i_4\}), (I,\emptyset), (K,\{i_5\})$
4	1	$(A,\{i_1\}), (D,\{i_6\}), (C,\{i_5\})$
5	2	$(A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\}), (I,\{i_2\})$
6	2	$(B,\{i_5\}), (A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\})$
7	2	$(A,\{i_1\}), (E,\emptyset), (F,\emptyset), (K,\{i_2\}), (I,\emptyset)$
8	2	$(A,\{i_1\}), (E,\emptyset), (F,\{i_3\}), (K,\{i_2\}), (I,\{i_8\})$
9	3	$(B,\{i_1\}), (A,\emptyset), (E,\{i_3\}), (D,\emptyset), (E,\emptyset)$
10	3	$(B,\emptyset), (A,\emptyset), (E,\emptyset), (D,\emptyset), (B,\{i_1\}), (D,\{i_7\})$
11	3	$(B,\{i_1\}), (A,\emptyset), (E,\{i_3\}), (D,\emptyset)$
12	4	$(D,\{i_4\}), (B,\emptyset), (A,\{i_3\})$
13	4	$(I,\{i_5\}), (F,\emptyset), (E,\emptyset), (D,\{i_4\})$
14	4	$(I,\{i_6\}), (F,\emptyset), (E,\{i_1\}), (D,\{i_4\})$

A. Similarity Model (SM)

An essential task in the 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. The goal is to automatically compute the store and item similarities from the mobile transaction database, which captures mobile users' movements and transactional behaviors (in terms of movement among stores and purchased items). The model makes use of 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 to infer which stores or items are similar. As people usually purchase similar items in certain stores, these stores may be considered as similar.

We derive two databases, namely, SID and ISD, from the mobile transaction database. An entry SIDpq in database SID represents that a user has purchased item q in store p, while an entry ISDxy in database ISD represents that a user has purchased item x in store y. Table II shows the transformed SID and ISD from mobile transaction database in Table I. There are eight stores and eight items in this database. After obtaining SID and ISD, we have to automatically compute the similarities between stores and items.

Table II
Store Item and Item Store database

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

B. Mobile Commerce pattern Mine (MCPM)

The MCPM algorithm is divided into three main phases:

Frequent-Transaction Mining.

A Frequent- Transaction is a pair of store and items indicating frequently made purchasing transactions. In this phase, first all Frequent-Transactions(Fr-Trans) for each user is discovered. At first, the support of each (store, item) pair is counted for each user. The patterns of frequent 1-transactions are obtained when their support satisfies the user-specified minimal support threshold T_{SUP}. A candidate 2-transaction, indicating that two items are purchased together in the transaction, is generated by joining two frequent 1-transactions where their user identifications and stores are the same. Next, the candidate 2-transaction is generated. Finally, the same procedures are repeated until no more candidate transaction is generated.

Table III
Frequent transactions

User ID	Store	Item Set	Itemset Mapping	Large Transaction	Path	Sup.
U_1	A	$\{i_1\}$	LI_1	(U_1, A, LI_1)	A	4
U_1	D	$\{i_2\}$	LI_2	(U_1, D, LI_2)	D	3
U_1	F	$\{i_3\}$	LI_3	(U_1, F, LI_3)	F	2
U_1	F	$\{i_4\}$	LI_4	(U_1, F, LI_4)	F	2
U_1	K	$\{i_5\}$	LI_5	(U_1, K, LI_5)	K	2
U_2	A	$\{i_1\}$	LI_1	(U_2, A, LI_1)	A	4
U_2	K	$\{i_2\}$	LI_2	(U_2, K, LI_2)	K	4
U_3	B	$\{i_1\}$	LI_1	(U_3, B, LI_1)	B	3
U_3	E	$\{i_3\}$	LI_3	(U_3, E, LI_3)	E	2
U_4	D	$\{i_4\}$	LI_4	(U_4, D, LI_4)	D	3
U_1	F	$\{i_3, i_4\}$	LI_6	(U_1, F, LI_6)	F	2

The frequent transactions are shown in Table III. In the table, we use an item mapping table to re label item sets in order to present F-Transactions.

Reducing the Mobile Transaction Database.

Based on the all Frequent-Transactions, the original mobile transaction database can be reduced by deleting infrequent items. The main purpose is to increase the database scan efficiency for pattern support counting. In this phase, those F-Transactions are used to transform each mobile transaction sequence S into a frequent mobile transaction sequence S'.

Table IV
Reduced Mobile Transaction database

T_{id}	Frequent Mobile Transaction Sequence
1	$(U_1,A,LI_1) \xrightarrow{BC} (U_1,D,LI_2) \xrightarrow{E} (U_1,F,LI_6) \xrightarrow{I} (U_1,K,LI_5)$
2	$(U_1,A,LI_1) \xrightarrow{BC} (U_1,D,LI_2)$
3	$(U_1,A,LI_1) \xrightarrow{BC} (U_1,D,LI_2) \xrightarrow{E} (U_1,F,LI_6) \xrightarrow{I} (U_1,K,LI_5)$
4	$(U_1,A,LI_1) \xrightarrow{DC}$
5	$(U_2,A,LI_1) \xrightarrow{EF} (U_2,K,LI_2) \xrightarrow{I}$
6	$\xrightarrow{B} (U_2,A,LI_1) \xrightarrow{EF} (U_2,K,LI_2)$
7	$(U_2,A,LI_1) \xrightarrow{EF} (U_2,K,LI_2) \xrightarrow{I}$
8	$(U_2,A,LI_1) \xrightarrow{EF} (U_2,K,LI_2) \xrightarrow{I}$
9	$(U_3,B,LI_1) \xrightarrow{A} (U_3,E,LI_3) \xrightarrow{DE}$
10	$\xrightarrow{BAED} (U_3,B,LI_1) \xrightarrow{D}$
11	$(U_3,B,LI_1) \xrightarrow{A} (U_3,E,LI_3) \xrightarrow{D}$
12	$(U_4,D,LI_4) \xrightarrow{BA}$
13	$\xrightarrow{IFE} (U_4,D,LI_4)$
14	$\xrightarrow{IFE} (U_4,D,LI_4)$

Table IV shows the result of reduced frequent mobile transaction database .

MCPM.

This phase is mining all patterns of length k from patterns of length k - 1 in a bottom-up fashion. In this phase, we mine all the MCPs from the frequent mobile transaction database. Frequent 1-MCPs are obtained in the frequent-transaction mining phase, as described earlier. In the mining algorithm, a two-level tree is utilized, named Mobile Commerce Pattern Tree (MCP-Tree) to maintain the obtained MCPs.The upper level of the MCP-Tree keeps track of the frequent mobile transactions. On the other hand, the lower level of the MCP-Tree maintains the users and paths where MCPs occurs. Thus, all the MCPs are captured in the MCP Tree.

C. Mobile Commerce User Behavior Predictor

The discovered MCPs is used to predict the users' future mobile commerce behaviors which include movements and transactions. The similarities of stores and items which are obtained from SIM are integrated into the mobile commerce behavior prediction. MCUBP, which measures the similarity score of every MCP with a user's recent mobile commerce behavior, is done by taking store and item similarities into account. In MCUBP, three ideas are considered:1) the premises of MCPs with high similarity to the user's recent mobile commerce behavior are considered as prediction knowledge;2) more recent mobile commerce behaviors potentially have a greater effect on next mobile commerce behavior predictions; and 3) MCPs with higher support provide greater confidence for predicting users' next mobile commerce behavior. Based on the above discussion, we propose the second prediction strategy named Combination of Support and Matching length (CSM). The idea of CSM is to incorporate both the pattern support and matching length into the mobile commerce behavior prediction. In CSM, we design a scoring function sf(P, P') to compute the matching score between the premise of a MCP and user's recent mobile commerce behavior. The consequence of MCP with the highest score is used to predict the next mobile commerce behavior.

IV. EXPERIMENTAL RESULTS

To assess the performance of the

proposed framework and its components, we conducted several experiments under various system conditions. These experiments are performed on a computer with a 1-GHz Intel CPU and 1GBof memory under Windows XP.

A. Synthetic Mobile Transaction Sequence Generation

In the base experiment model, we use a |W| x |W| mesh network [6] to model the stores. The atomic temporal observation unit of life is "day." In each store, the number of items is randomly generated based on a uniform distribution within a given range N_I . The advancing probability Pa of each neighbor for each store is the probability to move to a given neighboring store from the store and purchase some items sold there. In other words, each directed edge between two neighbor stores is assigned with an advancing probability. In the model, the advancing probability is defined as the ratio of the number of items in each neighbor to those numbers of other neighbors. The backward moving represents that a user will move from the current store back to the store from which he came. The followings are the main measurements for the experimental evaluation.

For comparison, we evaluate the proposed framework MCP as a whole against the prediction frameworks: MSP (Mining Sequential Pattern) [3] under various parameters, including the minimal support threshold, the event probability, and the network size, in terms of precision, recall, and F-measure. In this series of experiments, the main goal is to measure the precisions of mobile commerce behavior predictions by the examined methods.

B. Comparison of Various Similarity Measures

The goal of this experiment is to compare SM with SET as the similarity measure component of MCP in terms of precision, recall, and F-measure. Fig. 3 shows that SM outperforms SET in all metrics. The main reason is that the similarity inference among stores and items for SM is more accurate than that for SET. The similarity between two stores can be accurately measured by SM, even if there is no common item sold in these two stores.

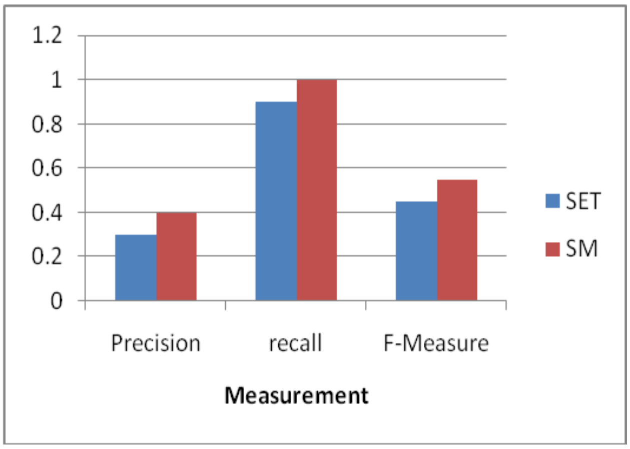


Fig.3. Comparison of Similarity Measure

As the figures show, SM outperforms SET by 41.03 percent in terms of precision, 7.19 percent in terms of recall, and 31.39 percent in terms of F-measure.

C. Comparison of Various Prediction Techniques

This experiment analyzes the precision, recall, and F-measure of examined prediction techniques, including JSO, CSM, and MCUBP. Fig. 4 shows that MCUBP is slightly better than JSO and CSM in terms of precision, but significantly outperforms them in terms of recall and F-measure. This is because that MCUBP considers not only the pattern supports but also the weighted matching score between pattern premises and users' recent mobile commerce behaviors in the behavior prediction.

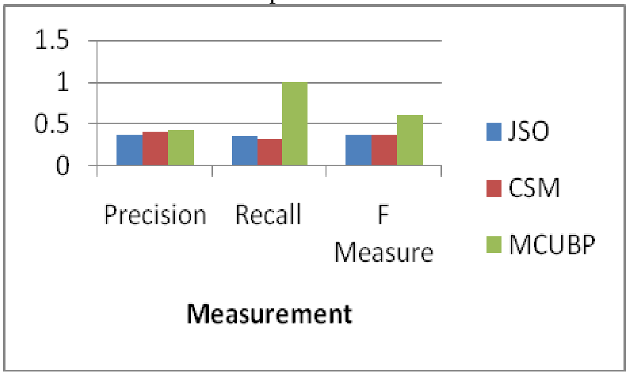
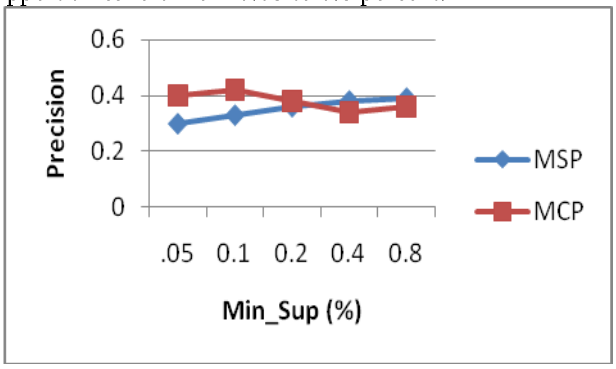


Fig.4. Comparison of various Prediction techniques

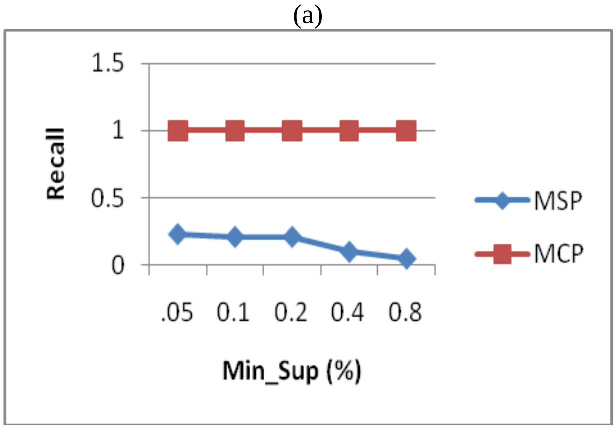
Since the evaluation of weighted matching score is based on store and item similarities, the recall of MCUBP can achieve near 100 percent. The average improvement rates of MCUBP over JSO and CSM are 10.18 and 3.57 percent for the precision, 215.36 and 240.34 percent for the recall, and 69.76 and 72.4 percent for the F-measure, respectively.

D. Impact of Support Threshold

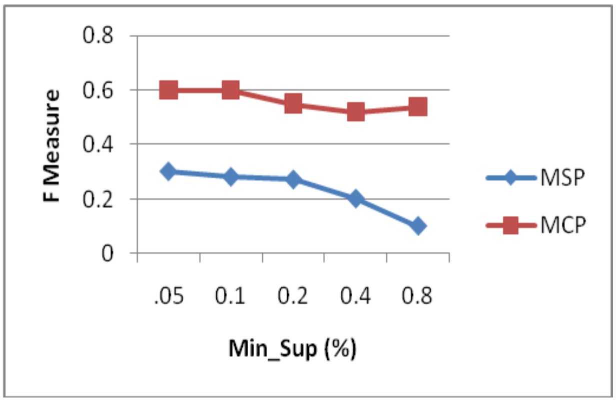
*T*he external comparison of the proposed MCP framework with MSP is discussed here. This experiment analyzes their precision, recall, and F-measure by varying the minimal support threshold from 0.05 to 0.8 percent.



(a)



(b)



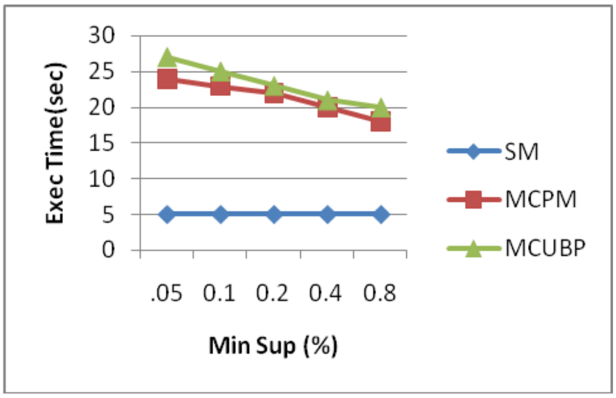
(c)

Fig.5. Comparison of various minimal Support Threshold a) Precision b) Recall c) F- Measure

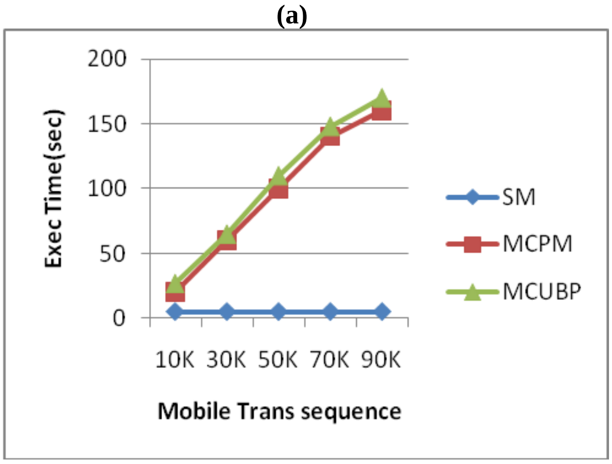
Figs. 5a, 5b, and 5c show that MCP outperforms MSP in terms of precision, recall, and F-measure, respectively. We observe that the recall keeps 100 percent for MCP, while that for MSP decreases as the support threshold increases.

E. Execution Time of proposed Algorithms

This experiment evaluates the performance of the proposed algorithms in the MCP framework in terms of execution time. Figure. 6 a shows the execution time when minimum support varies and for which SM remains constant while the execution time for both MCPM and MCUBP increases as the support threshold decreases. Figure. 6 b shows the execution time when mobile transaction sequence varies and for which also SM remains constant. For the behavior prediction, we observe that MCUBP is efficient even when a lower support threshold is used.



(a)



(b)

Fig.6. Execution time of proposed algorithms a) when minimum support varies b) when Mobile Trans sequence varies

V. CONCLUSION

In this paper, we have proposed a novel framework, namely MCP, for mining and prediction of mobile users' movements and transactions in mobile commerce environments. In the MCP framework, we have proposed three major techniques: 1) SM for measuring the similarities among stores and items; 2) MCPM algorithm for efficiently discovering mobile users' MCPs; and 3) MCUBP for predicting possible mobile user behaviors. To our best knowledge, this is the first work that facilitates mining and prediction of personal mobile commerce behaviors that may recommend stores and items previously unknown to a user.

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