PREDICTION OF M-COMMERCE USER BEHAVIOR BY PATTERN MINING

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Abstract

Information plays a major role in any organization .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) which is a new approach for mobile commerce behavior mining and prediction. The MCE framework consists of components like Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs); and Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. The proposed work is to recommend stores and items previously unknown to a user. The framework MCE achieves a very high precision in mobile commerce behavior predictions and the experimental results show that our proposed framework are highly accurate under various conditions. We have conducted experiments that implement our approach on real-life aggregated data and the results support the viability of our integration approach as well as the appropriateness of extended association rules. We also intend to undertake a further performance study with larger data sets, using different hardware platforms and various types of indexes.

Keywords*- *data mining, mobile commerce , MCBP, PMCE,F-transaction.

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1. Introduction

Data mining refers to extracting or mining knowledge from large amounts of data. Data Mining(DM) uses the powerful software tools to separate important or significant qualities that are previously unknown from databases or data warehouses[1]. Data mining uses information from past data to analyze the outcome of a particular problem or situation that may arise. Data mining works to analyze data stored in data warehouses that are used to store that data that is being analyzed. The advantages of data mining are, Marketing/Retailing, Banking/Crediting, Law Enforcement, Researchers. Mobile Commerce, also known as M-Commerce or mCommerce, is the ability to conduct commerce using a mobile device . Mobile Commerce is a new emerging technology with greater scope. Mobile commerce is the buying and selling of goods and services through Wireless handheld devices. Mobile devices mainly smart phones overcome laptops and desktops in many perspectives. Its size, portability, convenience and so on. It is advantage to the customers during purchasing; customers usually carry a mobile device mainly a smart phone than laptops because of its smaller size and portability. Mobile commerce has several applications, in that Localization of products and services plays a major role. It is used to know user locations and the services requested by the user. Information plays a major role in any organization. We suggest a novel way of acquiring more information from corporate data mining without the complications and drawbacks of deploying additional software systems.

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[3].data mining captures many different aspects of the business process such as manufacturing, distribution,sales, mobile commerce and marketing. This data reflects explicitly and implicitly customer patterns and trends, business practices, strategies, know-how and other characteristics. Therefore, this data is of vital importance to the success of the business whose state it captures, which is why companies choose to engage in the relatively expensive undertaking of creating and maintaining the data mining (a recent study reports the median cost of $1.6 million for creating a data mining with additional $0.6 million for annual operating cost). While some information and facts can be gleaned from the data mining directly, much more remains hidden as implicit patterns and trends. The discovery of such information often yields important insights into the business and its customers and may lead to unlocking hidden potentials by devising innovative strategies. The discoveries go beyond the standard on-line analytical processing which mostly serves reporting purposes (albeit in an increasingly complex and sophisticated manner). Information plays a major role in any organization . 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) which is a new approach for mobile commerce behavior mining and prediction. The MCE framework consists of components like Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs); and Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors.

When a user enters a building, the user may lose the satellite signal until returning outdoors. By matching user trajectories with store location information, a users' moving sequence among stores in some shop areas can be extracted[4]. The mobile transaction sequence generated by the user is {(A,{i1}), (B,Ø), (C,{i3}), (D,{i2}), (E,Ø),(F,{i3,i4}), (I,Ø),(K,{i5})}. There is 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. To provide this mobile ad hoc advertisement, mining mobile commerce patterns of users and accurately predicts their potential mobile commerce behaviors obviously are essential operations that require more research. Fig 1 Example of Mobile Transaction Sequence To capture and obtain a better understanding of mobile users' mobile commerce behaviors, data mining has been widely used for discovering valuable information from complex data sets. They do not reflect the personal behaviors of individual users to support M-Commerce services at a personalized level. Mobile Commerce or M-Commerce, is about the explosion of applications and services that are becoming accessible from Internet-enabled mobile devices. It involves new technologies, services and business models. It is quite different from traditional e-Commerce. Mobile phones impose very different constraints than desktop computers.

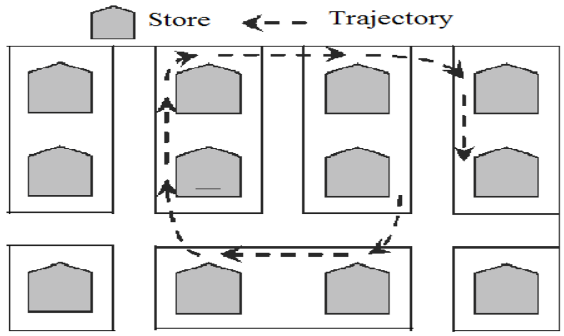

Figure 1. An example for a mobile transaction sequence

2. Existing Work

2.1Association-Rule Data in Data Mining

Association rule mining is a popular and well researched method for discovering interesting relations between variables in large databases . It is used to identify strong rules discovered in databases (e.g. Basket data analysis, clustering, and classification). The association rule mining can be of two types:

1. Frequent item sets: The items that frequently occur in the database and satisfies the minimum support count.

2. Generate strong association rules from the frequent item sets: Satisfy the minimum support and minimum confidence based on the rules.

Once the frequent itemsets from transactions in a database D have been found, itis straightforward to generate strong association rules from them, where strong association rules satisfy both minimum support and minimum confidence. This can be done using the following equation:

confidence(A=>B)=P(B|A) = support_count(AUB) / support_count(A)

The conditional probability is expressed in terms of itemset support count, where:support_count(AUB) is the number of transactions containing the itemsets AUB and support_count(A) is the number of transactions containing the itemset A. Based on this equation, association rules can be generated as follows:

For each frequent itemset l, generate all nonempty subsets of l.

For every nonempty subset s of l, output the rule “s => (l-s)” if support_count(l) /support_count(s)>=min_conf, where min_conf is the minimm confidence threshold. ARM may not discover any association rules in situations when there are several meaningful associations that involve multiple dimensions.

2.2 Mobile Pattern based Mining

Sequential pattern mining has been first introduced to search for time-ordered patterns, known

Sequential pattern mining has been first introduced to search for time-ordered patterns, known as sequential patterns within transaction databases. Chen etal., propose the path traversal patterns for mining web user behaviors. Tseng[6] and Tsui, first study the problem of mining associated service patterns in mobile web environments. Tseng et al., propose the TMSP-Mine for discovering the temporal mobile sequence patterns in a location-based service environment. Jeung et al.,[2] propose a prediction approach called Hybrid Prediction Model for estimating object's future locations based on its pattern information.The algorithm involves several different parameters that are database specific. The following example illustrates the general optimization principles without going into system specific issues.

Example 1: Consider mining extended association rules from the data mining based on the following question:

Find products bought frequently together by customers from a particular zip-code in a particular month.

This question involves four tables, namely Product, Customer, Calendar, and Sales. Typically, the size of a fact table (such as Sales) will be several orders of magnitude bigger than the size of any of the dimension tables. In order to make the example concrete, suppose that the sizes and attribute cardinalities for these tables are as follows:

• Table Product has 10 thousand tuples (records)

• Table Customer has 10 thousand tuples within 100
different zip-codes

• Table Calendar has 300 tuples within 12 different
months

• Table Sales has 1 million tuples.

Furthermore, suppose that the support threshold is 100. Ultimately, in order to find pairs of products bought
frequently together we have to join some portion of the Sales table with itself. A naïve approach, writing the
query directly .The cost of this join is likely to dominate the cost of the mining process so the optimization goal is to reduce the size of the portion of Sales before we do the self-join.

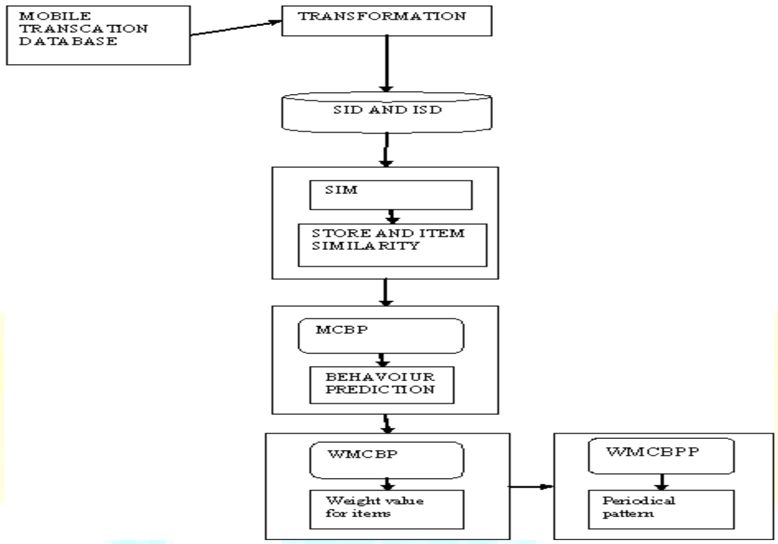

Figure 2. The mobile commerce explorer framework

3. Proposed Method

3.1 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 divided into main phases: 1) Frequent Transaction Mining. A Frequent- Transaction is a pair of store and items indicating frequently made purchasing transactions. In this phase, we first discover all Frequent-Transactions for each user. 2) Mobile Transaction Database Transformation. 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.

TABLE 1
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

3.3.1 Frequent-Transaction Mining

In this phase, we mine the frequent transactions (FTransactions) for each user by applying a modified Apriori algorithm[3] .Several of these variations are summarized as follows:

1. Hash-based technique can be used to reduce the size of the candidate k-itemsets, Ck, for k>1. For example when scanning each transaction in the database to generate the frequent 1-itemsetes, L1, from the candidate 1-itemsets in C1, we can generate all of the 2-itemsets for each transaction, hash them into a different buckets of a hash table structure and increase the corresponding bucket counts:

a. H(x,y)=((order of x)X10+(order of y)) mod 7

b. A 2-itemset whose corresponding bucket count in the hash table is below the threshold cannot be frequent and thus should be removed from the candidate set.

2. Transaction reduction – a transaction that does not contain any frequent kitemsets cannot contain any frequent k+1 itemsets. Therefore, such a transaction can be marked or removed from further consideration because subsequent scans of the database for j-itemsets, where j>k, will not require it.

3. Partitioning (partitioning the data to find candidate itemsets): A partitioning technique can be used that requires just two database scans to mine the frequent itemsets.Table 2 shows the mobile transaction database. 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 sati sfies the user-specified minimal support threshold TSUP. 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. For example, the candidate 2-transaction (F,{ i3; i4}) is generated by joining (F, {i3}) and (F, {fi4}), 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 generated. The frequent transactions are shown in

Table 1. In the table, we use an item mapping table to relabel item sets in order to present F-Transactions in Table 1. For each unique item set, we use a symbol LIi (Large Item set 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 in Table 2.

3.3.2 Mobile Transaction Database Transformation

In this phase, we use F-Transactions to transform each mobile transaction sequence S into a frequent mobiletransaction sequence S'[5]. According to Table 1, if a transactionT in S is frequent, T would be kept as an F-Transaction.Otherwise, the store of T is taken as part of a path. The main objectives and advantages of the transformation are: 1) item sets are represented as symbols for efficiently processing, and 2) transactions with insufficient support are eliminated to reduce the database size.

TABLE 2

Frequent-1 PMCPs

Frequent-1 PMCP	Path	Support
(U_1, A, LI_1)	A	4
(U_1, D, LI_2)	D	3
(U_1, F, LI_3)	F	2
(U_1, F, LI_4)	F	2
(U_1, K, LI_5)	K	2
(U_2, A, LI_1)	A	4
(U_2, K, LI_2)	K	4
(U_3, B, LI_1)	B	3
(U_3, E, LI_3)	E	2
(U_4, D, LI_4)	D	3
(U_1, F, LI_6)	F	2

3.2 Mobile Commerce Behavior Predictor

In this section, we describe how to use the discovered PMCPs to predict the users' future mobile commercebehaviors which include movements and transactions[5]. In existing pattern-based prediction models, the pattern selection strategy is based on exact matching, i.e., the similarity between different locations is treated as 0. To provide a high-precision mobile commerce behavior predictor (MCBP), it mainly focus on personal mobile pattern mining. Besides, to overcome the predictions failure problem and incorporate the similarities of stores and items into the mobile commerce behavior prediction. MCBP, which measures the similarity score of every personal mobile pattern mining with a user's recent mobile commerce behavior by taking store and item similarities into account. In MCBP, the premises of personal mobile pattern mining with high similarity to the user's recent mobile commerce behavior are considered as prediction knowledge; more recent mobile commerce behaviors potentially have a greater effect on next mobile commerce behavior predictions; personal mobile pattern mining with higher support provide greater confidence for predicting users' next mobile commerce behavior. In a proposed system a weighted scoring functions evaluate the scores of Personal mobile pattern mining.

Weighted Mobile Commerce Behaviour (WMCBP)

In this module weight values are assigned for each item because all items are not equally treated in

many transactional databases. A support of each itemset is usually decreased as the length of an itemset is increased, but the weight has a different characteristic. A support value is taken by only

considering the similar item and stores frequently the user made a purchase. In WMCBP system calculate the weight value of the item before calculating the support value. A weighted support of a pattern is

defined as the resultant value of multiplying the pattern's support with the weight of the pattern. A

pattern is called a weighted frequent pattern if the weighted support of the pattern is greater than or

equal to the minimum threshold it should be equal to one in the itemset.

4. Conclusion

In this paper, we have proposed a novel framework, namely MCE, for mining and prediction of mobile users' movements and transactions in mobile commerce environments. In the MCE framework, we have proposed Techniques such as PMCP-Mine algorithm for efficiently discovering mobile users' PMCPs; and MCBP for predicting possible mobile user behaviors. To evaluate the performance of the proposed framework and proposed techniques, we conducted a series of experiments.

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. Besides, the prediction technique MCBP in our MCE framework integrates the mined

PMCPs . The experimental results show that our proposed framework are highly accurate under various conditions. The weighted frequent pattern assigns weight values for each item; transaction table result was changed in terms of the performance than the existing system. The experimental results show that the proposed system framework achieves a very high precision in mobile commerce behavior predictions. The system achieve superior performs in terms of precision, recall, and Fmeasure.

5. Future Enhancement

Many advanced tools for data mining are available either as open-source or commercial software. They cover a wide range of software products, from comfortable problem-independent data mining suites, to business centereddata warehouses with integrated data mining capabilities, to early research prototypes for newly developed methods. For the future work, we plan to explore more efficient mobile commerce pattern mining algorithm and develop profound 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.

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