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Prediction of M-Commerce User Behavior by a Weighted Periodical Pattern Mining

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Abstract: The rapid advance of wireless communication technology M-Commerce is not only being widely accepted but also it is being more used as a popular way of business / commerce done by portable devices. It is becoming an interesting to find patterns and prediction of mobile user behaviors such as their location and purchase transactions in mobile commerce effectively to provide the service. In this paper, it provides a more efficient service to the mobile commerce users by applying weighted frequent pattern and periodical pattern for prediction of purchase behavior of mobile users. The Mobile commerce Explorer consists of five major components: 1) Similarity inference model 2) Mobile Commerce Behavior Predictor (MCBP) 3) Weighted Mobile Commerce Behavior Predictor (WMCBP) 4) Weighted Mobile Commerce Behavior Periodical Predictor (WMCBPP) 5) Performance Evaluation. In a weighted frequent pattern method, by applying unique weights for each of the itemset and find the closest pattern along with support value. In addition, temporal periodical pattern method is used to find the frequent user behavior in all time intervals of the transaction including the weight of the each item set and support value of the user for an item. Finally, the percentage of precision and recall is measured by comparing the various methods to prove the efficiency of the proposed pattern mining and prediction.

Keywords: M-Commerce, User behavior, Similarity, Pattern, Prediction.

1. INTRODUCTION

Due to a wide range of potential applications, research on mobile commerce has received many interests from both of the industry and academia. The transactions are rapidly transitioning from fixed locations to anytime, anywhere and anyone. The service provider in M-commerce should provide efficient service during their transactions. In this paper, to improve the better prediction for the mobile users by finding more efficient frequent patterns from the user transaction database by considering the weight value of each item set and evaluating the user movements on all time intervals. Pattern mining is a data mining method that involves finding existing patterns in data. For example, an association rule "bread & jam" states that four out of five customers that bought bread also bought jam. where patterns seen both in the temporal and non temporal domains are imported to classical knowledge. Frequent item sets play an essential role in many data mining tasks that try to find interesting patterns from databases, such as association rules, correlations, sequences, episodes, classifiers, clusters and many more of which the mining of association rules is one of the most popular problems. Temporal data mining is concerned with data mining of large sequential data sets. For example, time series constitute a popular class of sequential data, where records are indexed by time. The main goal of prediction is to predict some fields in a database based on Time domain. The task of time-series prediction has to do with forecasting (typically) future values of the Time series based on its past samples.

The mobile transaction sequence generated by the user is { (A,{i1}), (B,#), (C, {i3}), (D, {i2}), (E,#), (F,{i3,i4}), (I,#) ,(K,{i5}) }. It exhibit a moving pattern ABC and two purchase patterns are (A, $\{i_1\}$) and (C, $\{i_3\}$). This pattern is expressed as {(A, $\{i_1\}$)-→B (C, $\{i_3\}$)}, indicates that the user usually purchases item i_1 in store A and then purchases item i_3 in store C on the specific path ABC. It enhanced for incremental and interactive WFP mining using a single database.

2. LITERATURE SURVEY

In this chapter brief description of different papers about temporal pattern mining, mobile pattern

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mining & mobile behavior predictions is carried out. In recent years, a number of studies have discussed the usage of data mining techniques to discover useful rules/patterns from:

- Transaction databases
- □ Mobility data.

Sequential pattern mining was first introduced in to search for time ordered patterns, known as sequential patterns within transaction databases. SMAP-Mine was proposed by Tseng and Lin [2] for efficiently mining users sequential mobile access patterns, based on the FP-Tree to discover both the user movements and service requests. Yun and Chen [5] proposed the Mobile Sequential Pattern (MSP) to take moving paths into consideration and add the moving path between the left hand and the right hand in the content of rules

Hoyoung Jeung , Qing Liu, Heng Tao Shen, Xiaofang Zhou [15] proposed the Hybrid Prediction Model, which estimates an object's future locations based on its pattern information as well as existing motion functions using the object's recent movements. Shakina S, J. Rosaline Nirmala [14] proposed Mining and Prediction of Mobile User behavior in Location Based Service Environment. The services which are provided to the wireless mobile devices (such as PDA, Cellular Phones, and Laptops) from anywhere, at any time using ISAP (Information Service and Application Provider) are enhanced by mining and prediction of mobile user behaviors .But such discovery may not be precise enough for predictions since the differentiated mobile behaviors among users and temporal periods are not considered simultaneously in the previous works.

Eric Hsueh-Chan Lu, Wang-Chien Lee, Vicent S.Tseng [13] proposed a mining mobile commerce behavior of individual users to support m-commerce services at personalized level. To predict the store and items by considering the support value it was unknown to the user. In this paper, mining mobile commerce user behavior by finding the weighted value and evaluating periodical pattern of movements and then prediction is made according to the weighted periodical support value. Efficiency of the service is improved to the mobile users for prediction of unknown store and items.

2.1 Related Work

User behavior patterns are one of the most essential issues that need to be explored in mobile commerce. In this paper, a new algorithm is used efficiently to discover mobile users' sequential movement patterns associated in a Personal Communication Systems network. In the first phase of weighted frequent pattern algorithm, user mobility patterns are mined from the history of mobile user trajectories with weight function are calculated for each item in the store. In the second temporal pattern, mobility rules are extracted from these patterns at time series are calculated but the item, mobility predictions are accomplished by using these rules. The performance results obtained in terms of Precision and Recall indicate that our method can make more accurate predictions than the other methods. Figure 1.Shows the Transaction Database.

TID	UID	TRANSACTIONS	TIME
1	1	(A,{i1})-(B,pi)-(C,{i3})-(D,{i2}) -(E,pi)-(F,{i3,i4})-(I,pi)-(K,{i5}))	1
2	1	(A,{i1})-(B,pi)-(C,pi)-(D,{i2})	1
3	1	(A,{i1})-(B,pi)-(C,pi)-(D,{i2}) -(E,pi)-(F,{i3,i4})-(I,pi)-(K,{i5})	2
4	1	(A,{i1})-(D,{i6})-(C,{i5})	3
5	2	(A,{i1})-(E,pi)-(F,pi)-(K,{i2})-(I,{i2})	1
6	2	(B,{i5})-(A,{i1})-(E,pi)-(F,pi)-(K,{i2})	2
7	2	(A,{i1})-(E,pi)-(F,pi)-(K,{i2})-(I,pi)	2
8	2	(A,{i1})-(E,pi)-(F,{i3})-(K,{i2})-(I,{i8})	3
9	3	(B,{i1})-(A,pi)-(E,{i3})-(D,pi)-(E,pi)	2
10	3	(B,pi)-(A,pi)-(E,pi)-(D,pi)-(B,{i1})-(D,{i7})	3
11	3	(B,{i1})-(A,pi)-(E,{i3})-(D,pi)	1
12	4	(D,{i4})-(B,pi)-(A,{i3})	2
13	4	(I,{i5})-(F,pi)-(E,pi)-(D,{i4})	3
14	4	(I,{i6})-(F,pi)-(E,{i1})-(D,{i4})	1

Figure 1: Mobile Transaction Database

3. PROBLEM FORMULATION

In mobile commerce pattern mining method, prediction is made by considering the support value. To improve the effective prediction for the mobile users the weighted frequent pattern (WFP) mining becomes an important research issue in data mining and knowledge discovery.

In this paper it mainly aims to

- ➢ Finding the accurate similarity in store-wise and item-wise by using SIM.
- ➢ More effectively it predicts stores and items which was previously unknown to the user.

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- Implement weighted Frequent Pattern mining algorithm to find out most frequent itemset according the weight.

- A Temporal or periodical prediction is used to reduce the number of itemset and finds accurate result for prediction at each mobile commerce user at transactions database.

4. PROPOSED METHOD

The Mobile commerce consists of five major components: 1) Similarity inference model 2) Mobile Commerce Behavior Predictor (MCBP) 3) Weighted Mobile Commerce Behavior Predictor (WCMBP) 4) Weighted Mobile Commerce Behavior Periodical Predictor (WMCBPP) 5) Performance Evaluation. So we propose a weighted frequent pattern mining is to find the frequent pattern with calculation of weight values for each itemset in the transaction database. The proposed work finds important weighted frequent itemset in transaction databases, with low minimum support. Temporal patterns reveal time-related information that can be extracted from database with time series properties. Temporal pattern or periodical pattern found by assigns the time series or periodical intervals between the itemset in transaction database. The periodic pattern is the process of continuously mining the changes in the purchase mobile user information at periodic intervals.

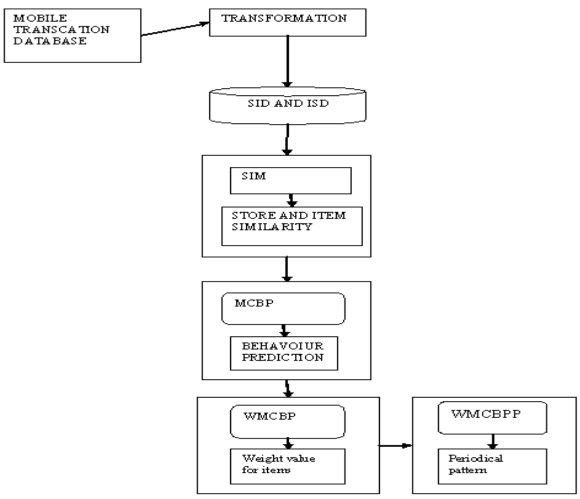

Figure: 2 Block diagram of M-Commerce

Similarity Inference Model (SIM)

In this paper, two basic mobile commerce entities are derived they are stores and items. Similarity Inference Model (SIM) automatically measures the similarities between stores and between items from the mobile transaction database, which captures mobile users moving and purchase behaviors. Based on our observations, we identify two basic derivations as the bases of our inference model: 1) if the items they sell are similar in two stores then both stores are similar; 2) if the stores which sell them are dissimilar then that stores also dissimilar. Before apply this model store similarity and item similarity from each other in the database. 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. Before computing the SIM in Table: 1 two databases are used namely Store to Item and Item to Store from the mobile transaction database. Along with it for every item in the store by allocating a weighted value regarding the basis of some important factors of the item (Eg: Cost, quality, Brand etc.,). The weighted value can be vary from the item to item and as well as store to store.

ISD		SID	
i1	A,B,E	A	i1,i3
i3	C,F,E,A	C	i3,i5
i2	D,K,I	D	i2,i6,i7,i4
i4	F,D	F	i3,i4
i5	K,C,B,I	K	i5,i2
i6	D,I	I	i2,i8,i5,i6
i8	I	B	i5,i1
i7	D	E	i3,i1

Table :1 Item Store Database (ISD), Store Item Database (SID)

Mobile Commerce Behavior Predictor (MCBP)

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

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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 Behavior Predictor (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.

The resultant transaction database with weighted frequent pattern for purchase behavior of mobile user is shown in the Table 2.

UID	STORE	ITEM	MAP	PMCP	PATH	SUPPORT
U1	A	i1	Li1	U1,A,Li1	A	0.3978
U1	D	i2	Li2	U1,D,Li2	D	0.3971
U1	F	i3	Li3	U1,F,Li3	F	0.1992
U1	F	Ii4	Li4	U1,F,Li4	F	0.2195
U1	K	i5	Li5	U1,K,Li5	K	0.1993
U2	A	i1	Li1	U1,A,Li1	A	0.4223
U2	K	i2	Li2	U1,K,Li2	K	0.3920
U3	B	i1	Li1	U1,B,Li1	B	0.3068

Table 2: Weighted Frequent Pattern List

Algorithm or steps to calculate the WMCBP

In the WMCBP, need to balance between the two measures of weight and support. Therefore, by defining a minimum weight constraint like a minimum support in order to prune items which have lower weights. Itemset is defined as a useless itemset if the support of itemset is less than a minimum support and its weight is also less than a minimum support. The weight value of the item will be changed by considering some of the factors of the product (quality, rate, brand etc.,)

Input:

(1) A transaction database: TDB,

(2) Minimum support threshold: min_sup,

(3) Weights of the items within weight range: wi,

(4) Minimum weight threshold: min_weight

Method:

1. Scan TDB once to find the weighted frequent items

2. Calculate the weight value for each itemset before calculating the support value of the item

$$\text{Weight (P)} = \Sigma \text{ length (P)} * \text{Weight } (x_q) / \text{length (p), where } q=1.$$

3. The support values satisfies the following condition, support < min_sup && weight sum value =1.0

Support value= min_sup *weight value of the item

3. The resultant transactional database

A weight of an item is a non-negative real number which is assigned to reflect the importance of each item in the transaction database. For a set of items I = {i1, i2 ...in}, weight of a pattern P{x1, x2 ...xm} is given as follows:

$$\text{Weight (P)} = \Sigma \text{ length (P)} * \text{Weight } (x_q) / \text{length (P), where } q=1.$$

Output: The complete set of weighted frequent itemset.

Weighted Frequent Pattern

U1,D,i1=B=C=U1,D,Li2=E=U1,F,Li4=I=U1,K,Li5

U1,D,i1=B=C=U1,D,Li2

U1,D,i1=B=C=U1,D,Li2=E=U1,F,Li4=I=U1,K,Li5

U1,D,i1=D=C

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U2,D,i1=E=F=U2,K,Li2=I

B=U2,D,i1=E=F=U2,K,Li2

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.

Weighted Mobile Commerce Behavior Periodical Predictor (WMCBPP)

After predicting the weighted pattern for each itemset, the support value is changed to accurate result. But the previous module not contain about the time series based item for purchase behavior of mobile user. In this module we divide the transaction database into n number of periodic intervals, calculate the weight support value for periodic intervals W_i. If the weighted support value W_i is greater than the min_support value the itemset is added to frequent pattern. A pattern is called a periodic pattern, the frequent itemset is greater than the min_support value, and otherwise itemset is non periodic pattern. Support value of the periodic pattern is calculating by combining min_support value, weight value of the item, and time period of periodical pattern got the resultant transaction database.

TEMPORAL PATTERN OR PERIODICAL PATTERN ALGORITHM

In this proposed system, temporal pattern mining algorithm or periodical prediction for mining periodic patterns in itemset sequence path and calculate the support value for store item. The inputs to TDB include a transaction table format database and the interesting period interval specified by minimum support interval. The time list in TDB is maintained for each itemset is maintained by periodical itemset. Essentially, TDB checks the time lists of each itemset for each possible period p. It starts by checking possible valid Patterns form frequent item with the possible time intervals of each itemsets .If there exists a valid segment for an item, such items are enumerated in periodical interval.

Algorithm to calculate the periodical pattern

Input: A transaction database: TDB,

Minimum support threshold: min_sup,

Minimum support interval: Ms

Periodical interval: P

Method:

1. Initialize the TDB database, min_sup, M_s , P

2. Split the database into n number of the periodical interval, the periodical interval is

defined by same as the threshold value.

3. Calculate the weighted support value of itemset in each time interval,

Weight (P) = Σ length (p)* Weight (x_q) / length (P) where q=1.

4. If the (weighted support value >min_sup) then

Itemset is frequent itemset

Else

Itemset is not frequent item set

5. If the (frequent itemset >min_sup value)

Itemset is periodical pattern

Else

Itemset is not periodical pattern

6. Calculating the support value for periodical pattern prediction

Support value= min_sup * weight value of the item * time period of periodical pattern

7. The resultant transactional database with changes supports value in periodical pattern

Output: The complete set of time period based on itemsets in TDB.

Temporal pattern or periodical pattern

U1,A,Li1=B=C=U1,D,Li2=E=U1,F,Li4=I=U1,K,Li5

U1,A,Li1=B=C=U1,D,Li2

U1,A,Li1=B=C=U1,D,Li2=E=U1,F,Li4=I=U1,K,Li5

U1,A,Li1=D=C

U2,A,Li1=E=F=U2,K,Li2=I

B=U2,A,Li1=E=F=U2,K,Li2

U2,A,Li1=E=F=U2,K,Li2=I

Performance Evaluation

In this module the performance is evaluated the proposed system finds and detect the frequent pattern at periodical pattern. The performance of the system is measured in terms of the precision, recall, F-measure value at three methods MCBP, WMCBP,

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WMCBPP. So the proposed system increase the performance compare to the existing method.

5. EXPERIMENTAL EVALUATION

In the paper, store similarity and item similarity is more accurately find by calculating the weight value of each itemset and also applied a periodical pattern for mining the mobile user behavior in time intervals to predict the frequent items. Prediction is more accurately founded by combining support value, weight value of each itemset and purchase behavior in different time intervals. The factors conclude the efficient frequent patterns and prediction is made to the mobile commerce users which are unknown to them.

UID	STORE	ITEM	MAP9999	PMCP	PATH	MCBP	WMCBP	WMCBPP
U1	A	i1	Li1	U1,A,Li1	A	4	0.397	8.393
U1	D	i2	Li2	U1,D,Li2	D	3	0.397	3.307
U1	F	i3	Li3	U1,F,Li3	F	2	0.199	1.198
U1	F	Ii	Li4	U1,F,Li4	F	2	0.219	2.207
U1	K	i5	Li5	U1,K,Li5	K	2	0.199	2.219
U2	A	i1	Li1	U1,A,Li1	A	4	0.422	8.416
U2	K	i2	Li2	U1,K,Li2	K	4	0.392	4.393
U3	B	i1	Li1	U1,B,Li1	B	3	0.306	3.301

Table: 3 Comparison Values of Three Methods.

In this graph we measure the precision, recall and F-Measure value at three different methods, MCBP, WMCBP, and WMCBPP. Comparing the precision value, the proposed system WMCBP is higher than the MCBP, WMCBPP precision value higher than the MCBP, WMCBP for periodical pattern itemset. Finally the precision value of WMCBP periodical pattern achieves the high. In the recall value the WMCBPP is less recall value than the MCBP, WMCBPP recall values is less for periodical itemset. Finally the recall value of the periodical pattern achieves the less degree of recall value other than two methods. Comparing the F-measure value the WMCBP is higher than the MCBP and WMCBPP F-measure value higher than the MCBP, WMCBP for periodical pattern itemset. Finally the F-measure value of WMCBPP periodical pattern is high.

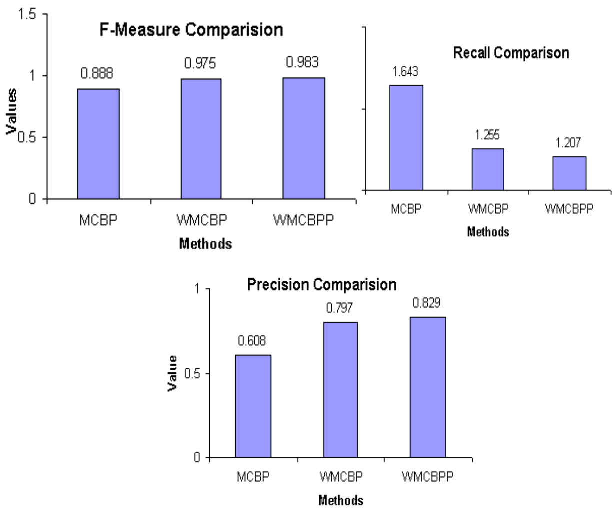

Figure: 3 Comparisons of Precision, Recall and F-Measure.

Precision is used to find the retrieved relevant document in the search and also recall is used to whether the document is retrieved successfully for the relevant query. F-Measure combines the precision and Recall.

6. CONCLUSION AND FUTURE WORK

In this paper, more efficient mobile commerce pattern mining algorithm is designed for similarity inference models and develops profound prediction strategies to further enhance the MCE framework. The proposed periodical pattern or temporal pattern finds more accurate for calculation of the time intervals for each itemset. 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 F-measure. We present a concept-lattice based kernel method for mining the hidden user knowledge. In future, the main idea is to employ concept lattice for constructing item proximity matrix, and then embed it into a kernel function, which transforms the original user feature space into a user concept space, and at last, perform personalized services in the user concept space.

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BIOGRAPHY

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