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A HYBRID WEIGHTED PERIODICAL PATTERN MINING AND PREDICTION FOR PERSONAL MOBILE COMMERCE

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ABSTRACT

In case of large amount of the search engine based applications, mobile e-commerce has established a more interest under both industry and academia. From that mining the user behavior and prediction of the user to analysis the mobile commerce behaviors based on their actions are most important. To perform these steps, previous work proposed a novel structure called Mobile Commerce Explorer (MCE). It can be performed in three ways 1) Similarity Inference Model (SIM) for measuring the similarities amongst stores and items 2) Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for well-organized discovery of mobile users Personal Mobile Commerce Patterns (PMCPs); and 3) Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. Assigning the weight values for each item in the mobile transaction database finds the best frequent pattern mining from the mobile user pattern .Proposed system considering the different weight values for each item and the select the best weight values to frequent pattern mining .Selection of best weight values from the different weight values we use particle swarm optimization algorithm system is initialized with a population of random solution such as different weight values and search for best weight values by updating invention. The particle swarm optimization changing the velocity of each particle toward finds best weight values at both local and global locations. After finding the weight values than derive the frequent pattern mining results from the existing transaction behavior of each mobile users .Weighted frequent pattern mining with PSO achieve an wide-ranging investigational estimation by replication and show that better accuracy outcome.

Key words: PMCP, WMCBP, PSO, Data mining, mobile commerce.

1. INTRODUCTION

Speedy move forward of wireless communication expertise and the ever-increasing reputation of influential moveable devices, mobile users not only can access universal data from wherever at any time ,they also need to access the mobile devices to make business transaction as well as well as similar types of other transaction like e-commerce based applications but also use their data . In the meantime the accessibility of location acquisition technology, e.g., Global Positioning System (GPS), facilitate simple attainment of an affecting trajectory, which proceedings a user group history. Thus, we visualize with the purpose of Mobile Commerce (MCommerce) user details such as age and their some m-commerce services determination is intelligent to confine the moving trajectories and acquire transactions details of users. For example the recent announce Shopkick [1] as an example, it give mobile users plunder and offer when user check-in in supplies and on items. Anticipating that various users may possibly be prepared to exchange their locations and transactions for high-quality rewards and discount, we are expecting additional mobile commerce applications, whether they will determination stand a business model comparable with Shopkick or not, further it motivation appear in future .To capture and attain an improved sympathetic of mobile users' mobile commerce behaviors, data mining [2] has been extensively used for discover precious information from compound data sets. Several methods have been studied the issues of mobile behavior mining examination, but still the targeted patterns in these prior works are characteristically different.

Tseng and Tsui, [3] considered the difficulty of mining connected service pattern in mobile web environment. They also proposed SMAP Mine [4] for well-organized mining of users' sequential mobile access patterns with FP-Tree [5]. Yun and Chen [6] wished-for a technique for mining mobile sequential pattern (MSP) by pleasing moving paths of users into thoughtfulness. As mentioned earlier, in addition to mining mobile patterns, predicting the next mobile behaviors of a user is a critical research issue. 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 among 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.

It is significant to note down to facilitate customers are touching all along an MC surroundings to look for preferred items to purchase, the implication from moving patterns and buying patterns are in fact tangled, and together are of huge significance for studying customer behaviors. Obviously, the characteristic features of information discovery in an MC surroundings increase the complexity of extract information beginning the mobile transaction sequence. Conversely, as these mobile commerce services are attractive more and more well-liked these days it is very important to develop well-organized algorithms for deriving customer buying behavior to get better the quality of these services. As a consequence the plan and development of efficient mining algorithms for information detection in MC surroundings whilst completely explore the intrinsic association among moving and purchase patterns are taken as the purpose of this thesis. Conducting the taking out on the moving and purchase patterns of customers in MC surroundings is called the mining of mobile sequential patterns (i.e., large sequential patterns).In this work main aspire at developing pattern mining and prediction technique that discover the correlation among the moving behavior and purchasing transactions of mobile users to discover possible M-Commerce features. To compute the store and item similarities automatically from the mobile transaction database based on the user mobile commerce features the entire work will be done in the following manners:

1. From the mobile transaction database for each item and store find the similarity that helps to identify the user and their behavior .To perform this task we calculate the Item Store Similarity(ISS) and Store Item Similarity (SIM) ,then derive the two databases that is Store-Item Database (SID) and Item-Store Database (ISD), from the mobile transaction database.
2. After the completion of the task such as SID and ISD then perform PMCP-Mine algorithm to mine the individual mobile commerce patterns proficiently. It is performed in a bottom-up way.
3.PMCP predictor only find the individuals mobile commerce patterns efficiently ,It doesn't consider the mobile commerce behavior prediction in the transaction database ,MCBP provide a high-accuracy mobile commerce behavior predictor, to perform these task first find the best frequent transaction in the ISD and SID tables by focusing the weighted mobile commerce behavior prediction with PSO
4.WMCBP with PSO find the best frequent transaction in the mobile transaction database by values derived from the PSO and then perform the weighted mobile commerce behavior predictor it is named as WMCBP-PSO, it improves the focus on personal mobile pattern mining results than PMCP,WMCBP algorithms .
5. Finally measure the experiment to assess the performance of our scheme. The outcome show higher performance over further mining technique in terms of predictive precision and recall.

2. RELATED WORK

In this section study the various techniques of the similarity measures, mobile pattern mining techniques and mobile behavior predictions. In Han and Fu [7] suggest the multiple-level association rules mining. In this learning, taxonomy is included for in place of the hierarchical relatives of items. SMAP-Mine that can professionally discover mobile users' sequential association patterns related with requested services. It helps the users get needed information effectively in the mobile web systems. Discovery of user behavior can extremely benefit the enhancement on organization performance and superiority of services. Observably the mobile user's behavior patterns, in which the location and the service are inherently coexistent. But we do not know the relations among the items in the dissimilar levels. Existing Han and Fu [7] methods for prediction in Spatio-temporal databases guess that objects move about according to linear functions. This strictly limits their applicability, since in carry out movement is extra composite.

G. Jeh and J. Widom [8] measure the similarity based Structural with various aspects of objects to establish similarity, typically depending on the field and the suitable definition of similarity for that field. In a document corpus, corresponding text may be used, and for collaborative filtering, comparable users may be recognized by widespread preference. G. Jeh and J. Widom [8] a universal approach that exploit the object-to-object relations establish in numerous domain of attention. A comparable approach can be practical to systematic papers and their certification, or to any additional document corpus with cross-reference in order .In the case of recommender systems, a user's favorite for an item constitute a association among the user and the item. Such domains are obviously model as graphs, with nodes on behalf of objects and edges in place of relationships
Mobile Behavior Prediction study on mobile behavior predictions can be approximately separated into two categories. The primary category is a vector-based prediction with the aim of that can be additional divided into two types: 1) J.M. Patel, Y. Chen, and V.P. Chakka [9] and Y. Tao, D. Papadias, and J. Sun [10] proposed a linear models 2) Y. Tao, C. Faloutsos, D. Papadias, and B. Liu [11] presented a nonlinear model.
The nonlinear models confine objects' movements through sophisticate regression functions. Thus, their prediction accuracies are superior to individuals of the linear models. Recursive Motion Function (RMF) [11] is the majority precise prediction method in the copy based on regression functions. The subsequent category is a pattern-based prediction. Y. Ishikawa, Y. Tsukamoto, and H. Kitagawa [12] obtain a Markov Model (MM) that produce Markov transition probabilities from one cell to a dissimilar for predict the consequently cell of the object.

3. PERSONAL MOBILE COMMERCE PATTERN MINING AND WEIGHTED MCBP-PSO

In PMSE meets the following requirements, First The moving sequence of the mobile transaction for each items and stores first we discuss with the proper example to understand the whole system and what changes made from that to improves the predictor results than the previous work .In this work first we define the moving sequence of the user and the store and item labels are indicated the some transaction made .Figure 1 (1.a) shows the moving sequence and their transaction (1.b)

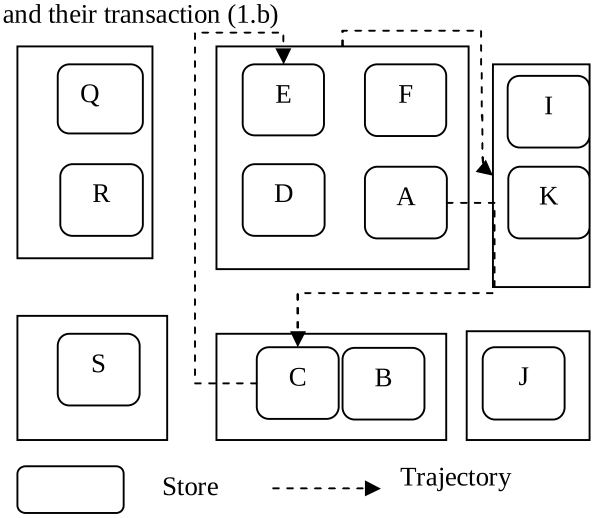

Figure 1.a An example for a mobile transaction sequence with Moving trajectory

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

Figure 1.b Transactions

From this table mobile transaction sequence generated by this user is { (A,{i_1}), (B,#), (C, {i_3}), (D, {i_2}), (E,#), (F,{i_3,i_4}), (I,#),(K,{i_5})}. The mobile system database maintain comprehensive store information which include locations as well as transaction details of mobile users .First the information of mobile users and purchase details are collected in online fashion, then we proceed the offline process thought the steps mentioned in the section 1. Offline method for similarity inference and PMCPs mining and an online steam engine for mobile commerce behavior calculation. While mobile users progress among the stores, the mobile information which include user identification, stores, and item purchase is stored in the mobile transaction database(MTDB).

Table 1 shows an exemplar of mobile transaction database which contain four user and 14 mobile transaction sequences. After that we expand the SIM representation and the PMCPMine algorithm to determine the store/item similarities and the PMCPs correspondingly. MCBP basis on the store and item similarities that are mined from PMCPs. Whilst a mobile user move and purchase the items amongst the stores, the next steps will be the identification of mobile user according to their purchase based on current mobile transactions. The goal of this learning is to extend a structure for mining and prediction of the mobile commerce behaviors together with the movements and transactions of a user, base on the user's present mobile transaction series

Table 1: An example of mobile transaction database

TID	UID	Mobile Transaction series
1	1	(A,i_1)(B,∅)(C,i_3)(D,i_1)(E,∅) (F,i_1, i_3)(I, ∅)(K,i_5)
2	1	(A,i_1)(B,∅)(C, ∅)(D,i_1)
3	1	(A,i_1)(B,∅)(C,, ∅))(D,i_1) (E,∅) (F,i_1, i_3)(I, ∅)(K,i_5)
4	1	(A,i_1)(C,i_5)(D,i_6)
5	2	(A,i_1)(E,∅)(F,∅) (K,i_1) (I,i_1)
6	2	(B,i_5) (A,i_1) (E,∅)(F,∅) (K,i_1)
7	2	(A,i_1)(E,∅)(F,∅) (K,i_1) (I,∅)
8	2	(A,i_1)(E,∅)(F,i_5) (K,i_1) (I,i_8)
9	3	(B,i_1) (A,∅) (E,i_3) (D,∅) (F,∅)
10	3	(B,∅) (A,∅) (D,∅) (E,∅) (B,i_1) (D,i_7)
11	3	(B,i_1) (A,∅) (E,i_3) (D,∅)
12	4	(D,i_4) (B,∅) (A,i_3)
13	4	(I,i_5) (F,∅) (E,∅) (D,i_4)
14	4	(I,i_6) (F,∅) (E,i_1) (D,i_4)

From the Mobile Transaction Database (MTDB) table 2,3 it is automatically compute the store and items similarities which captures mobile users' moving and transactional behaviors. From the database the subsequent information contains the mobile user and their purchase details, it help out us to suppose which stores or items are comparable namely, SID and ISD from MTDB. An entrance SID_{pq} in database SID represent that a user has purchase item q in store p, while an entry ISD_{xy} in database ISD represents that a user has purchased item x in store y. Table 2 show the transformed SID and ISD from MTDB in Table 1. After obtaining the SID and ISD main face we contain to undertake on is to routinely compute the similarities between stores and items.

Table 2: SID

STORE	ITEM
A	(i_1, i_3)
B	(i_1, i_5)
C	(i_3, i_5)
D	(i_2, i_4, i_6, i_8)
E	(i_1, i_3)
F	(i_3, i_4)
I	(i_2, i_5, i_6, i_8)
K	(i_2, i_5)

Table 3: ISD

STORE	ITEM
A	(i_1, i_3)
B	(i_1, i_5)
C	(i_3, i_5)
D	(i_2, i_4, i_6, i_8)
E	(i_1, i_3)
F	(i_3, i_4)
I	(i_2, i_5, i_6, i_8)
K	(i_2, i_5)

For calculation of store and item similarity the two stores are most similar if and only the items are most similar. Specified two stores s_p and s_q, calculate their correspondence sim (s_p; s_q) by scheming the regular similarity of item sets provide by s_p and s_q. For each item sell in s_p and correspondingly s_q, we primary find the majority of comparable item sold in s_q and correspondingly s_p. After that the store similarity can be obtained by averaging all comparable item pairs. Consequently sim (s_p; s_q) is definite as,

$$sim(s_p, s_q) = \frac{\sum_{\varphi \epsilon \Gamma_{s_p}} MaxSim\left(\varphi, \Gamma_{s_q}\right) + \sum_{\gamma \epsilon \Gamma_{s_q}} MaxSim\left(\gamma, \Gamma_{s_p}\right)}{\left|\Gamma_{s_p}\right| + \left|\Gamma_{s_q}\right|}$$

Where Maxsim (e, E) =$Max_{e' \in E}$ sim (e, e') represents the maximal similarity between E and the element in E. Γ_{s_p} and Γ_{s_q} are the sets of items sold in s_p and s_q, respectively. The item similarity consider with the purpose of two items are fewer similar if they are sold by numerous different stores. Given two items i_x and i_y, we calculate their relationship sim (i_x; i_y) by scheming the standard dissimilarity of store sets that provide i_x and i_y. Consequently sim (i_x; i_y) is definite as,

$$sim(i_x, i_y) = 1 - \frac{\sum_{\omega \epsilon \Omega_{i_x}} MaxSim\left(\omega, \Omega_{i_y}\right) + \sum_{\psi \epsilon \Omega_{i_y}} MaxSim\left(\psi, \Omega_{i_x}\right)}{\left|\Omega_{i_x}\right| + \left|\Omega_{i_y}\right|}$$

Table 4: Frequent transaction database

UID	Store	Itemset and mapping	Support
U1	A	i_1, I_1	4
U1	D	i_2, I_2	3
U1	F	i_3, I_3	2
U1	F	i_4, I_4	2
U1	K	i_5, I_5	2
U2	A	i_1, I_1	4
U2	K	i_2, I_2	4
U3	B	i_1, I_1	3
U3	E	i_3, I_3	2
U4	D	i_4, I_4	3
U1	F	i_3, i_4, I_6	2

MCBP which actions the similarity score of each personal mobile pattern mining by way of a user's current mobile commerce behavior by taking store and item similarities into explanation. In MCBP, the property of personal mobile pattern mining with elevated similarity to the user's current mobile commerce behavior are measured as prediction knowledge; additional current mobile commerce behaviors potentially have a superior effect on next mobile commerce behavior predictions; personal mobile pattern mining with superior support provide better confidence for predicting users' next mobile commerce behavior. MCBP provide a high-accuracy mobile commerce behavior predictor, to perform these task first find the best frequent transaction in the ISD and SID tables. But all of the mobile commerce patterns with high support don't provide the best result, so we proposed a weighted mobile commerce behaviour predictor with PSO.

Weighted mobile commerce behaviour predictor with Particle Swarm Optimization (WMCBP-PSO)

In this weight mobile commerce behaviour predictor the weight values of each item are calculated using PSO optimization algorithm. The Populations are organized according to some weight values are taken as input for each item, after assigning the many weight values each particles move towards j^{is} in i's neighborhood, i is also in j 's. Each particle communicates with a number of other particles and is precious by the best weight found by its current particle position pi. The vector p_i for that best neighbor, which we will denote with p_g. Initialize the particle's location best known position to its initial position: $p_i \leftarrow x_i$., then likewise update the particles or location of the best transaction frequent item set with weight and their velocity to know the best global position of the weight value to find the best frequent transaction .In PSO algorithm repeat the steps Until a termination criterion is met .Finally after finding the global best position only considers as complete set of weighted frequent item sets. WMCBP system we calculation of the weight value of the item by using PSO. The resulting transaction database with weighted frequent pattern designed for purchase behaviour of mobile user.

Algorithm

Input: Mobile transaction database (MTDB), weight values
Output: Weighted mobile commerce behaviour predictor frequent transaction

1. Get the input mobile transaction database (MTDB).
2. Calculate the calculate the weight value for each item set using PSO
   - Initialize a population array of particles with random positions of each item set and velocities on D dimensions in the search space.
   - Loop
   - For each item set evaluate the desired optimization fitness function in D variables.
   - Compare current frequent item set fitness evaluation with its $pbest_i$. If current value is better than $pbest_i$, then set $pbest_i$ equal to the current value, and Initialize the each frequent item set weight with best known position to its initial position: $p_i \leftarrow x_i$
   - Identify the current frequent item set in the neighborhood with the best success and assign its index to the variable g.
   - If $(f(p_i) < f(g))$ update the swarm's best known position: $g \leftarrow p_i$
   - Initialize the frequent item set velocity: $v_i \sim U(-|b_{upv}-b_{lov}|, |b_{upv}-b_{lov}|)$
   - Change the velocity and position of the frequent item set according to the following equation
   - Until a termination criterion is met, repeat:
   - For each frequent item set of weight values (i = 1, ..., S)
   - Do
   - For each dimension d = 1, ..., n
   - Do
   - Pick random numbers $r_p, r_g \sim U(0,1)$
   - Update the frequent item set weight values velocity $v_{i,d} \leftarrow \omega\, v_{i,d} + \varphi_p r_p (p_{i,d}-x_{i,d}) + \varphi_g r_g (g_d-x_{i,d})$
   - Update the frequent item set weight values position: $x_i \leftarrow x_i + v_i$
   - If $(f(x_i) < f(p_i))$ do:
   - Update the frequent item set weight values of best known position: $p_i \leftarrow x_i$
   - If $(f(p_i) < f(g))$ update the swarm's best known position: $g \leftarrow p_i$
   - Now g holds the best found solution.
   - end loop

3. Accept the best weight values of the frequent item set from the mobile user and calculate the support value of the each item.

Support value= Minimum Support *weight value of item from PSO

4. Weighted mobile commerce behaviour predictor frequent transaction Database

Table 5: Frequent transaction database with PSO

UID	Store	Itemset and mapping	Support
U1	A	i_1, I_1	0.8311
U1	D	i_2, I_2	0.5813
U1	F	i_3, I_3	0.4531
U1	F	i_4, I_4	0.7984
U1	K	i_5, I_5	0.2567
U2	A	i_1, I_1	0.3545
U2	K	i_2, I_2	0.5874
U3	B	i_1, I_1	0.4351
U3	E	i_3, I_3	0.3510
U4	D	i_4, I_4	0.1389
U1	F	i_3, i_4, I_6	0.1899

4. EXPERIMENTAL RESULTS

The experiments results shows that the performance of the system is high or low ,when comparing the results with previous work using the parameters like Precision, Recall, and Fmeasure. Measure the precision, recall, Fmeasure values with existing similarity measures based methods and prediction based measure for both the measures proposed WMCBP-PSO performs than the MCBP, PMCP. The Precision, Recall and Fmeasure values are defined as below and p^+ indicate the numeral of right predictions and p^- wrong predictions correspondingly and |R| indicates the total numeral of item transactions.

$$Precision = \frac{p^{+}}{p^{+} + p^{-}}$$

$$Recall = \frac{p^{+} + p^{-}}{|R|}$$

$$Fmeasure = \frac{2 * Precision * Recall}{Precision + Recall}$$

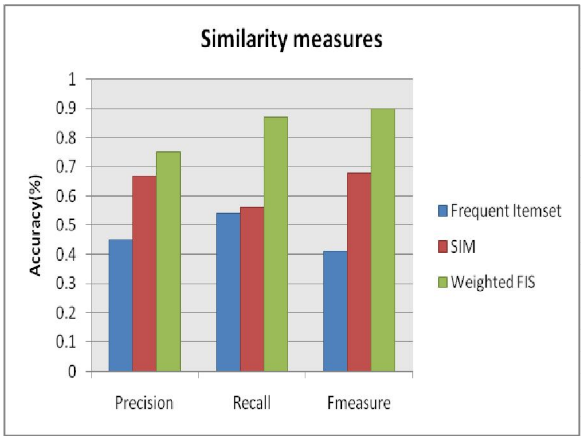

Figure 2: Similarity measures of Mobile transaction database

In this graph we measure the similarity measures of the mobile transaction database with frequent itemset of the general, similarity interference model and weighted frequent items set value of Precision, Recall and Fmeasure results .Proposed Weighted Frequent itemset shows the best Precision, Recall and Fmeasure results.

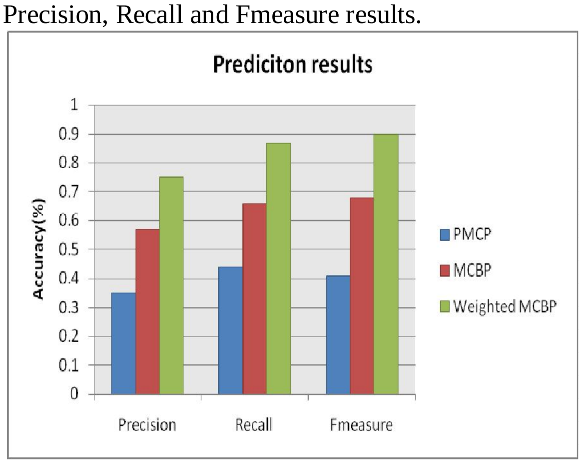

Figure 3: Prediction results of Mobile transaction database

In this graph we measure the Prediction results of Mobile transaction database with mobile commerce mining .The system measures the Precision, Recall and Fmeasure results Personal Mobile Commerce Pattern (PMCP), Mobile Commerce Behavior Predictor (MCBP) and Weighted Mobile Commerce Behavior Predictor (MCBP) PSO for prediction of possible mobile user behaviors .Proposed Weighted Frequent itemset shows the best Precision, Recall and Fmeasure results.

5. CONCLUSION AND FUTURE WORK

In this paper proposed a WMCBP –PSO make easy of mining and prediction of mobile users' commerce behaviors based on frequent item set transaction and Behaviour Predictor (BP) by providing PMCP, MCBP and proposed algorithm. WMCBP –PSO concerning the weight values in calculation strategies, wished-for mining mobile used behaviour and prediction of the mobile user in transactions table using weighted frequent pattern. The experimental results show that our proposed structure and mechanism are extremely precise under various conditions. The experimental consequences show that the structure WMCBP achieves an extremely precision in mobile commerce behavior predictions. It attain superior performs in terms of precision, recall, and F-measure.

In future work we plan to expand the proposed framework with security based mobile transaction and develop reflective prediction strategies to supplementary enhance the WMCBP framework. The system can be also extended to other application such as object tracking Sensor networks and location based services, aim to attain high precision in predicting object behaviors.

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