Mining and Predicting Users M-Commerce Patterns using Collaborative Filtering Algorithm

R.Priyadharshini[1], N.Geethanjali[2], B. Dhivya[3]
PG Scholars
Department of Information Technology SNS College of Technology, Coimbatore, India

Abstract

Mobile Commerce, also known as M-Commerce or mCommerce, is the ability to conduct commerce using a mobile device. Research is done by Mining and Prediction of Mobile Users' Commerce Behaviors such as their movements and purchase transactions. The problem of PMCP-Mine algorithm has been overcome by the Collaborative Filtering Algorithm. The main objective is to analyse the Mobile users' movements to the new locations instead of considering only the frequent moving locations. In the existing approach, a Mobile Commerce Explorer Framework has been implemented to make recommendations for stores and items by analysing the Mobile users'. The drawbacks are the recommendations that made are only for frequently moving locations and stores. The proposed work is to recommend stores and items in new locations by considering the rating of items given by the other users in new locations.

Keywords– Mining, Prediction, Mobile Commerce.

I. INTRODUCTION

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 [1]. 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. At developing pattern mining and prediction techniques that explore the correlation between the moving behaviors and purchasing transactions of mobile users to explore potential M-Commerce features. Owing to the rapid development of the web 2.0 technology, many stores have made their store information, e.g., business hours, location, and features available online.

Collecting and analysing user trajectories from GPS-enabled devices. 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. The mobile transaction sequence generated by the user is {(A,{i_1}), (B,Ø), (C,{i_3}), (D,{i_2}), (E,Ø),(F,{i_3,i_4}), (I,Ø),(K,{i_5})}. 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.

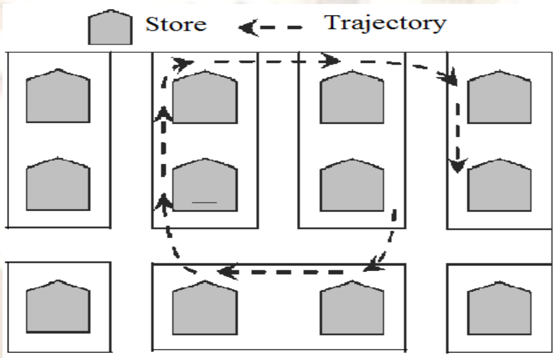

Fig 1 Example of Mobile Transaction Sequence

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.

II. PROBLEM DEFINITION

In the MCE framework, frequently moving locations and frequently purchased items are considered for analysing mobile users' commerce behavior. The Personal Mobile

Commerce Pattern-Mine (PMCP-Mine) algorithm was used to find only frequent datasets, by deleting in-frequent data in the Mobile Commerce Explorer Database. Also, recommendations were done only for the frequent datasets. The similarity values that were found in the Similarity Inference Model (SIM) were not accurate.

III. LITERATURE SURVEY

Chan Lu, Lee and S. Tseng developed the Mobile Commerce Explorer Framework for mining and prediction of mobile users' movements and purchases [1]. Agrawal and Swami presented an efficient algorithm [2] that generates all significant association rules between items in the database.

Han, Pei and Yin proposed a novel frequent-pattern tree (FP-tree) structure, which is an extended prefix-tree [3] structure for storing compressed, crucial information about frequent patterns, and develop an efficient FP-tree based mining method, FP-growth, for mining the complete set of frequent patterns by pattern fragment growth.

Herlocker, Konstan, Brochers and Riedl developed an Automated Collaborative Filtering is quickly becoming a popular technique for reducing information overload, often as a technique to complement content-based information filtering systems [8]. In this paper, present an algorithmic framework for performing Collaborative Filtering and new algorithmic elements that increase the accuracy of Collaborative Prediction algorithms. Then present a set of recommendations on selection of the right Collaborative Filtering algorithmic components.

IV. EXISTING SYSTEM

A novel framework for the mobile users' commerce behaviors has been implemented for mining and prediction of mobile users'. MCE framework has been implemented with three components: 1) Similarity Inference Model (SIM) for measuring the similarities among stores and items, 2) Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs), 3) Mobile Commerce Behavior Predictor (MCBP) for prediction of possible mobile user behaviors. In the MCE framework, only frequently moved locations and frequently purchased items are considered. The modules proposed in framework are:

A. Mobile Network Database

The mobile network database maintains detailed store information which includes locations.

B. Mobile User Data Base

The Mobile User database maintains detailed mobile user information which include network provider.

C. Applying Data Mining Mechanism

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. In the offline data mining mechanism, develop the SIM model and the PMCP Mine algorithm to discover the store/item similarities and the PMCPs, respectively. Similarity Inference Model for measuring the similarities among stores and items. Personal Mobile Commerce Pattern-Mine (PMCP-Mine) algorithm is used for efficient discovery of mobile users' Personal Mobile Commerce Patterns.

D. Behavior prediction engine

In the online prediction engine, implemented a MCBP (Mobile Commerce Behavior Predictor) 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. Mobile Commerce Behavior Predictor for prediction of possible mobile user behaviors.

E. Similarity Inference Model

A parameter-less data mining model, named Similarity Inference Model, to tackle this task of computing store and item similarities. Before computing the SIM, 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. Deriving the SIM to capture the similarity score between stores/items. For every pair of stores or items, SIM assigns them a similarity score. In SIM, used two different inference heuristics for the similarity of stores and items because some stores, such as supermarkets, may provide various types of items.

By applying the same similarity inference heuristics to both of stores and items, various types of items may be seen as similar since different supermarkets are seen as similar. Based on our heuristics, if two stores provide many similar items, the stores are likely to be similar; if two items are sold by many dissimilar stores, the stores are unlikely to be similar. Since the store similarity and item similarity are interdependent, computing those values iteratively. For the store similarity, consider that two stores are more similar if their provided items are more similar. Given two stores sp and sq, compute their similarity SIM (sp; sq) by calculating the average similarity of item sets provided by sp and sq. For every item sold in sp (and, respectively, sq), first find the most similar item sold in sq (and, respectively, sp). Then, the store similarity can be obtained by averaging all similar item pairs. Therefore, SIM (sp; sq) is defined as

$$sim(s_p, s_q) = \frac{\sum_{\varphi \epsilon \Gamma_{sp}} MaxSim(\varphi, \Gamma_{sq}) + \sum_{\Upsilon \epsilon \Gamma_{sq}} MaxSim(\Upsilon, \Gamma_{sp})}{|\Gamma_{sp}| + |\Gamma_{sq}|}$$

Where $MaxSim(e,E) = Max_{e' \epsilon E}\ sim(e,e')$ represents the maximal similarity between e and the element in E. Γ_{sp} and Γ_{sq} are the sets of items sold in sp and sq, respectively. On the other hand, for the item similarity, consider that two items are less similar if the items are sold by many dissimilar stores. Given two items i_x and i_y, compute the similarity $sim(i_x,i_y)$ by calculating the average dissimilarity of store sets that provide i_x and i_y. For every store providing i_x (and, respectively, i_y), first find similarity by averaging all dissimilar store pairs.

F. Personal Mobile Commerce Pattern-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. In this phase, 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. 3) PMCP Mining: This phase is mining all patterns of length k from patterns of length k-1 in a bottom-up fashion.

G. Mobile Commerce Behavior Predictor

MCBP measures the similarity score of every PMCP with a user's recent mobile commerce behavior by taking store and item similarities into account. In MCBP, three ideas are considered: 1) the premises of PMCPs 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) PMCPs with higher support provide greater confidence for predicting users' next mobile commerce behavior. Based on the above ideas, propose a weighted scoring function to evaluate the scores of PMCPs. For all PMCPs, calculate their pattern score by the weighted scoring function. The consequence of PMCP with the highest score is used to predict the next mobile commerce behavior.

H. Performance Comparison

Conduct a series of experiments to evaluate the performance of the proposed framework MCE and its three components, i.e., SIM, PMCP-Mine, and MCBP under various system conditions. The experimental results show that the framework MCE achieves a very high precision in mobile commerce behavior predictions. Besides, the prediction technique MCBP in our MCE framework integrates the mined PMCPs and the similarity information from SIM to achieve superior performs in terms of precision, recall, and F-measure. The experimental results show that the proposed framework and three components are highly accurate under various conditions.

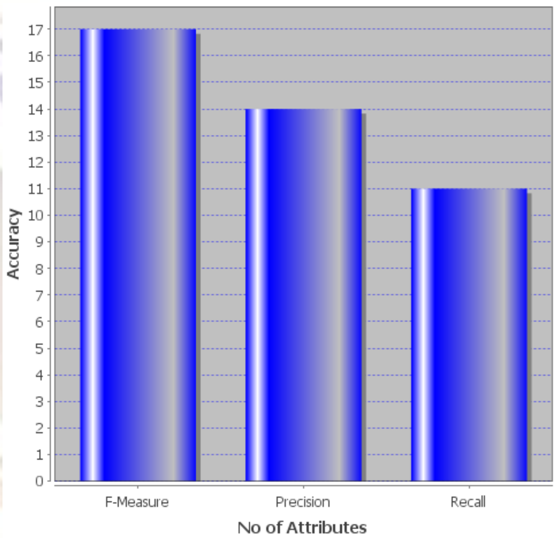

Fig 2 Performance Comparison

V. PROPOSED SYSTEM

A. Similarity Inference Model

Propose a parameter-less data mining model, named Similarity Inference Model, to tackle this task of computing store and item similarities. Before computing the SIM, 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. Deriving the SIM to capture the similarity score between stores/items. For every pair of stores or items, SIM assigns them a similarity score. In SIM, used two different inference heuristics for the similarity of stores and items because some stores, such as supermarkets, may provide various types of items.

By applying the same similarity inference heuristics to both of stores and items, various types of items may be seen as similar since different supermarkets are seen as similar. Based on our heuristics, if two stores provide many similar items, the stores are likely to be similar; if two items are sold by many dissimilar stores, the stores are unlikely to be similar. Since the store similarity and item similarity are interdependent, computing those values iteratively. For the store similarity, consider that two stores are more similar if their provided items are more similar. Given two stores sp and sq, compute their similarity SIM (sp; sq) by calculating the average similarity of item sets provided by sp and sq. For every item sold in sp (and, respectively, sq), first find the most similar item sold in sq (and, respectively, sp). Then, the store similarity can be obtained by averaging all similar item pairs.

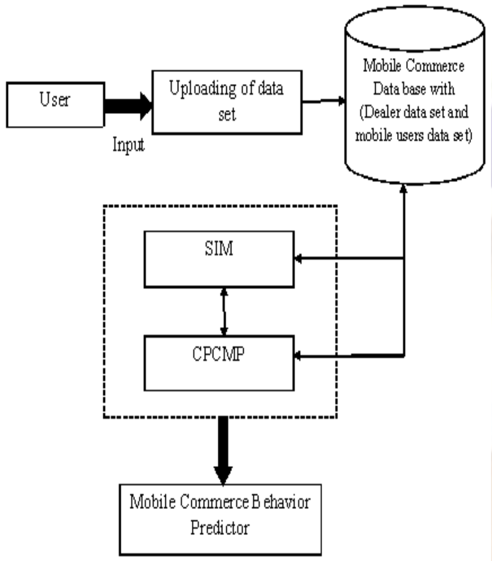

Fig 3 Block Diagram of Mobile Commerce Explorer Framework

B. Collaborative Personal Mobile Commerce Pattern Algorithm

The proposed system is developed by implementing CPCMP - Collaborative PCMP Algorithm which takes into account the newly updated locations and predicts behavior of the user based on the Collaborative Filtering. Although collaborative filtering methods have been extensively studied recently, most of these methods require the user-item rating matrix. However, on MCE Database, in most of the cases, other user preferences and transactions are not always available. Hence, collaborative filtering algorithms cannot be directly applied to most of the recommendation tasks on the database, like query suggestion etc.

Combine the Collaborative filtering aspects of predicting the unknown entities along with the proposed PCMP which mining the patterns of the user transactions behavior. This hybrid algorithm facilitates dynamic predictions and hence recommendation to the users for better customer service and experience. For better similarity inference modelling in cases of users visiting unknown locations, a new hybrid similarity inference model is proposed to take into account the items transacted and stores visited by a similar user in the same location who have similar Personal mobile commerce pattern – i.e the frequent mining patterns of the unknown user matches with respect to the user under consideration. So, the proposed work improves the quality of predictions of the preferred items and stores of the customer or user thereby bring about better sales and customer support experience and feedback.

C. Mobile Commerce Behavior Predictor

Propose MCBP, which measures the similarity score of every PMCP with a user's recent mobile commerce behavior by taking store and item similarities into account. In MCBP, three ideas are considered: 1) the premises of PMCPs 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) PMCPs with higher support provide greater confidence for predicting users' next mobile commerce behavior. Based on the above ideas, propose a weighted scoring function to evaluate the scores of PMCPs.

VI. CONCLUSION

A novel framework namely MCE was proposed for mining and prediction of mobile users' movements and transactions in mobile commerce environments. In the MCE framework were designed with three major techniques: 1) SIM for measuring the similarities among stores and items; 2) PMCP-Mine algorithm for efficiently discovering mobile users' PMCPs; and 3) MCBP for predicting possible mobile user behaviors. To best knowledge, it 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. To evaluate the performance of the proposed framework and three proposed techniques, 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 prediction technique MCBP in MCE framework integrates the mined PMCPs and the similarity information from SIM to achieve superior performs in terms of precision, recall, and F-measure. The experimental results show that the proposed framework and three components are highly accurate under various conditions.

To overcome the problems of user moving to new locality, Collaborative Filtering algorithm was implemented to recommend the users about the stores and items instead of considering only frequent data.

VII.FUTURE ENHANCEMENT

For the future work, we plan to explore more efficient mobile commerce pattern mining algorithm, design more efficient similarity inference models, 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.

REFERENCES

[1] Eric Hsueh-Chan Lu, Wang-Chien Lee, and Vincent S. Tseng, "A Framework for Personal Mobile Commerce Pattern Mining and Prediction" IEEE transactions on knowledge and data engineering year 2012.

[2] R. Agrawal, T. Imielinski, and A. Swami, "Mining Association Rule between Sets of Items in Large Databases," Proc. *ACM SIGMOD Conf. Management of Data*, pp. 207–216, May 1993.

[3] J. Han, J. Pei, and Y. Yin, "Mining Frequent Patterns without Candidate Generation," Proc. *ACM SIGMOD Conf. Management of Data*, pp. 1-12, May 2000.

[4] S.C. Lee, J. Paik, J. Ok, I. Song, and U.M. Kim, "Efficient Mining of User Behaviors by Temporal Mobile Access Patterns," *Int'l J. Computer Science Security,* vol. 7, no. 2, pp. 285-291, Feb. 2007.

[5] V.S. Tseng and K.W. Lin, "Efficient Mining and Prediction of User Behavior Patterns in Mobile Web Systems", *Information and Software Technology*, vol. 48, no. 6, pp. 357-369, June 2006.

[6] X. Yin, J. Han, P.S. Yu, "LinkClus: Efficient Clustering via Heterogeneous Semantic Links," Proc. *Int'l Conf. Very Large Data Bases*, pp. 427-438, Aug. 2006.

[7] C.H. Yun and M.S. Chen, "Mining Mobile Sequential Patterns in a Mobile Commerce Environment," *IEEE Trans. Systems, Man, and Cybernetics, Part C*, vol. 37, no. 2, pp. 278-295, Mar. 2007.

[8] J.L. Herlocker, J.A. Konstan, A. Brochers, and J. Riedl, "An Algorithm Framework for Performing Collaborative Filtering," *Proc. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval*, pp. 230-237, Aug 1999.

[9] 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.

[10] Y. Zheng, L. Zhang, X. Xie, and W.Y. Ma, "Mining Interesting Location and Travel Sequences from GPS Trajectories," *Proc. Int'l World Wide Web Conf.*, pp. 791-800, Apr. 2009.

[11] Y. Tao, C. Faloutsos, D. Papadias, and B. Liu, "Prediction and Indexing of Moving Objects with Unknown Motion Patterns," *Proc. ACM SIGMOD Conf. Management of Data*, pp. 611-622, June 2004.