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NEW ENHANCED APPROACH PATTERN BEHAVIOR AND PREDICTION OF MINING MOBILE WEB SERVICES

Mr. A.Yoganathan [1], *Mr.C.A.Kanadasmy* [2], *Mr. Dineshkannan Thangavel* [3], *Mr. Elavarasan M* [4], *Ms. Durgadevi M* [5], *Mr. Gnanaprakash P* [6]

[1]Assistant Professor, Department of Computer Applications (MCA), K.S.R. College of Engineering, Tiruchengode,
[2]Research Scholar, Computer Science, KPR College of Arts Science and Research,
[3,4,5,6]PG Students, Department of Computer Applications (MCA), K.S.R. College of Engineering, Tiruchengode,
[1]yoguayn@gmail.com , [2]kandamca86@gmail.com, [3]dineshkannanthangavel25@gmail.com, [4]elavarasanmurugesan03@gmail.com,
[5]durgadevimadheswaran@gmail.com, [6]gnanaprakashmca2002@gmail.com

ABSTRACT

Enhanced Mobile commerce is a young technology that is being studied in both the corporate and academic realms. Analysis and projection of user mobile commerce behaviour is one of their active study topics. In the context of mobile commerce, we provide a method in this paper for mining and predicting the movements and purchase transactions of mobile users. It is common practise to apply location- and time-based data for a variety of mobile service analysis applications. Analysis of user behaviour is done using sequential pattern mining algorithms. The frequency of transactions among mobile users is categorised using clustering algorithms. Most presently used strategies don't concentrate on separating users' and temporal periods' mobile behaviour. The suggested method classifies mobile users. CT Miner is employed (Coincidence Temporal Miner), Temporal intervals are predicted in the algorithm, which was designed to discover recurrent time-interval based patterns.

Index Terms—Temporal mining, mobile sequential patterns, and mobile commerce.

I.Introduction

Rapid advancement of wireless communication technology and the widespread use of powerful mobile phones, mobile users may easily conduct business using their devices and have access to global information from anywhere at any time.In the midst of this, location collection technology is easily accessible and makes it simple to capture a moving trajectory for the purpose of recording a user's movement history. In the midst of this, location collection technology is easily accessible and makes it simple to capture a moving trajectory for the purpose of recording a user's movement history. So, in the future, we expect Mobile Commerce (m-Commerce) to be able to track users' travel patterns and transactional activity. As many mobile transaction logs are generated as a result of mobile users' actions, building a mobile transaction database is challenging. The issue of mobile behaviour mining has been the subject of much investigation. Data mining is a method for locating crucial information in a large collection of data. Data mining is effectively used in numerous applications to get the system to respond quickly. The topic of mining related service patterns in mobile web networks was covered in prior papers. Previous papers also recommended methods for effectively mining FP-Tree-based users' sequential mobile access patterns. For mining user behaviour on the mobile web, path traversal algorithms have been proposed. The moving route was thought to increase forecast accuracy in the aforementioned study. Mobile usage patterns, however, differ based on the user categories and the hours of the day. The forecast of mobile behaviour will be more accurate if the matching mobile patterns can be found in each user cluster and time period. It is clear that extracting time interval-based patterns from such data, sometimes referred to as temporal patterns, is more difficult and calls for a more complex methodology. an alternative approach to mining time-based data points. Sequential pattern mining using time intervals hasn't gotten much attention up to this point. The complex interconnections between event intervals have an impact on this. It is difficult to understand pair-wise interactions between any two time interval-based occurrences. since time intervals differ from time points in a number of important ways. The identification of social groupings that may be used for shared data allocation, targeted advertising, and the customization of content offerings is aided by mobile transaction data clustering. Prior research frequently groups users according to their personal profiles (e.g., age, sex and occupation). With useful mobile apps, obtaining user profiles is usually challenging. Access is thus restricted. to mobile transaction data supplied by the user. Examining how similar mobile transaction sequences are important in order to achieve the aim of user clustering without user profiles. Using the time interval segmentation approach, we may spot a range of user behaviours over time periods. Users might, for instance, make different service requests at the same location at different hours (like day or night). If the time interval element is disregarded, some activities during specific time periods may go unreported. Hence, a time interval table is required to identify all of the mobile behaviour patterns. The grouping of mobile users based on their transactions and the forecasting of time intervals are the main objectives of this work. It is possible to improve the efficiency of mobile business.

The other components of the study are organised as follows: Section II gives a brief overview of pertinent literature; Section III describes the mobile sequential pattern mining model; and Section IV offers findings and ideas for future research.

II.RELATED WORKS

To propose businesses and goods that the buyer has never heard of before, the Mobile Commerce Explorer Framework enables mining and forecasting of mobile customers' purchase behaviours [1]. The movements and purchases of mobile users may also be predicted and mined. It is suggested to use FP-growth, an efficient FP-tree-based mining approach, to mine the whole collection of common patterns. An enhanced prefix-tree structure called the frequent-pattern tree (FP-tree) was developed to carry shorter, more significant information about frequent patterns. Automated collaborative filtering is quickly gaining acceptance as a means of balancing content-based information filtering systems and reducing information overload. User behaviour is predicted by collaborative filtering, sometimes referred to as user-based and item-based collaborative filtering.In contrast to item-based collaborative filtering, which is based on user behaviour in relation to relevant commodities, user-based collaborative filtering is done based on the behaviours of other comparable users [3]. The Hybrid Prediction Model [4] is a mechanism for forecasting an object's future placements based on its pattern data. After figuring out an item's trajectory patterns for prediction, a cutting-edge access strategy may be utilised to index the object, resulting in rapid query processing. Temporal Mobile Sequential Patterns (TMSPs) of users may be discovered in LBS scenarios using a cutting-edge data mining approach called TMSP-Mine[5].This work presents the first investigation on mining moving sequential patterns related to time intervals and moving paths in LBS settings. Provide an innovative way to predict future behaviour as well. utilising the only just found TMSPs for mobile users. It is possible to find cluster-based temporal mobile sequential patterns by using the Cluster-based Temporal Mobile Sequential Pattern Mining (CTMSP-Mine). Also, a prediction technique is shown to predict the next mobile behaviours. In CTMSP-Mine, user clusters are built using a unique method called the Cluster-Object based Smart Cluster Affinity Search Algorithm. the provided metric, Location-Based Service Alignment, is then used to calculate the degree of similarity between the users (LBS-Alignment). Nowadays, a temporal segmentation technique is used to find time periods with comparable mobility characteristics. [6].

Complex connections between event intervals are handled more effectively using a coincidence representation and the incision technique. Next, a powerful algorithm called CTMiner (Coincidence Temporal Miner) is created to discover frequent time-interval based patterns. [7]. By computing weight values for each item set, the weighted frequent pattern mining approach described in [8] aims to detect the frequent patterns in the transaction database. The recommended strategy unearths a huge weighted frequent item collection in transaction databases with only minimum help. To retrieve the information about time provided by temporal patterns, one can use the time series properties of a database. A temporal pattern or periodic pattern can be found when time series or periodic intervals are allocated between the items specified in transaction databases.Periodic pattern mining is the practise of continuously looking for changes in user data from mobile devices that have made transactions repeatedly. The precise temporal behaviour patterns of mobile users in relation to their locations and the services they have utilised may be determined using the temporal patterns of mobile access [9]. T-MAP may be used to track the temporal mobile access patterns as well as the mobile access patterns of mobile users across a variety of time periods.

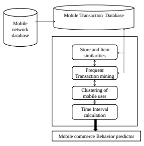
A method known as the credit point system was created in[10] to improve mobile commerce. Even if the Similarity Inference model suggests merchants that are comparable, the result is not particularly precise. We address these issues by incorporating user interests. While logging in or signing up, users have the choice of entering their interests. Users add their interests in accordance with the categories that are established by the administrator. The system will consider the interests in order to react to their forecasts. The user can add a list of interests, which are leaf nodes of the category tree. The user may then see the available categories. When a customer enters a shop, they ought to receive a service tailored to their interests. Users are motivated by this effort, which improves Mobile Commerce apps. Under the credit point system, each retailer is free to choose the minimal number of points needed for a particular item. When users make more purchases and spend more money, their credit points increase. This has raised user interest in mobile commerce.

III.MOBILE SEQUENTIAL PATTERN MINING MODEL

This section describes the procedures involved in architectural design. The procedures include

- Architectural Model
- Measuring store and Item similarities
- Frequent Transaction mining
- Clustering of mobile users
- Time Interval calculation
- Mobile commerce behavior predictor

A. Architectural Model



In Fig.3.1.1, the recommended system design is shown. Specific store information, including locations, is tracked in the mobile network database. Our approach includes a "online" engine for predicting mobile commerce behaviour as well as a "offline" technique for finding metrics of store-item similarity and frequent transaction mining. Mobile customers who move between stores can preserve their user ID, items purchased, and shop information in the mobile transaction database. The business deal Mobile users may be clustered using their time. It is feasible to identify typical time periods using coincidence temporal Miner. This method also makes use of two pruning techniques to efficiently reduce the search space. Probabilistic mobile user behaviour may be predicted using a mobile commerce behaviour predictor.

B.Measuring store and Item similarities

The shop and item similarity may be calculated using the mobile transaction database. We can determine which items are on sale at a specific shop and which stores carry a specific item thanks to the information in our database.

C. Frequent Transaction mining

Such a purchase might be categorised as a frequent buy if a mobile user makes purchases from a certain shop on a regular basis. An individual mobile commerce pattern mining algorithm will make this possible. The Personal Mobile Commerce Pattern Mining method took inspiration from the TJPF algorithm, which is related to Apriori. We see, however, that user ID, which is essential for distinguishing unique mobile operations, is not taken into consideration by the TJPF algorithm. Moreover, the TJPF technique ignores the user cluster and time interval components, both of which are essential for gathering all of the information on individual mobile behaviour. Our approach makes reliable forecasts of mobile behaviour by taking into consideration all of these variables.

D.Clustering of mobile users

Based on the kind of transactions that they often do, mobile users can be categorised. A mobile transaction database contains users who display a variety of mobile transaction behaviours in each cluster. This clustering may be achieved by exceeding the minimal threshold of frequent transactions, which is where frequent and infrequent users are discriminated.

E.Time Interval calculation

Different behaviours are found in various time intervals using time intervals. Using the same place as an example, users can request various services at various times. Using CTMiner to compute this Time Interval can help you avoid spending time creating and testing candidates for temporal pattern mining. It converts each database interval sequence to coincidence format. CTMiner divides the temporal database into a number of smaller projected databases, and then extends each projected database's temporal patterns by include locally frequent slices.Also, in order to narrow the search space and prevent making unreliable projections, CTMiner uses the suggested optimization procedures. Both simulated and actual datasets demonstrate that CTMiner performs better than earlier methods.

F.Mobile commerce behavior predictor

Based on frequent and infrequent mobile user clusters and location-based services, it is possible to predict potential mobile user behaviours. In order to benefit the devoted consumers, mobile commerce is a form of location-based service that may include localised promotions or advertising that targets customers depending on their current location.

IV.CONCLUSIONS AND FUTURE WORK

Applications for mobile service analysis that leverage location- and time-based data are numerous. User behaviour is analysed using sequential pattern mining algorithms. Mobile sequential patterns are recognised using location and temporal data. Based on comparable local transactions, mobile device users are categorised. Time Interval may be forecasted using the CTMiner approach. This is an effective approach to condense the search space.
More efficient mobile commerce pattern mining algorithms should be the subject of future study. Object tracking, sensor networks, and the aim of achieving high precision in object behaviour prediction are additional applications for this technology.

REFERENCES

[1] Eric HsuehChan Lu,Chien Lee, and Vincent Tseng“ AFramework for Personal Mobile Commerce Pattern MiningAn Prediction” IEEE Trans. on Knowledge and data EngineeringYear 2012.

[2] J. Han, J. Pei, and Y. Yin, “Mining Frequent Patterns without Candidate Generation,” Proc. ACM SIGMODConf. Management of Data, pp. 1-12, May 2000.

[3] J.L. Herlocker, J.A. Konstan, A. Brochers, and J.Riedl, “An Algorithm Framework for Performing CollaborativeFiltering,”Proc. Int’l ACM SIGIR Conf. Research and Development in Information Retrieval,pp. 230-237, Aug 1999.

[4] H. Jeung, Q. Liu, H.T. Shen, and X. Zhou, “A HybridPrediction Model for Moving Objects,” Proc. Int’l Conf. Data Eng., pp. 70-79,Apr. 2008.

[5] V.S. Tseng, H.C. Lu, and C.H. Huang, “Mining Temporal Mobile Sequential Patternsin Location Based ServiceEnvironments,” Proc. Int’l Conf. Parallel and DistributedSystems, pp. 1-8, Dec. 2007.

[6] Eric Hsueh-Chan Lu, Vincent S. Tseng, and Philip S. Yu “Mining Cluster-Based Temporal Mobile Sequential Patterns in Location-Based Service Environments” IEEE transactions on knowledge and data engineering year 2011.

[7] Yi-Cheng Chen, Ji-Chiang Jiang, Wen-Chih Peng and Suh-YinLee ”An Efficient Algorithm for Mining Time Interval based Patterns in Large Databases” CIKM '10 Proceedings of the 19th ACM internationalconference on Information and knowledge management.

[8] S.Krithika M.Moorthi“Prediction of M-CommerceUser Behavior by a Weighted Periodical Pattern Mining”Int’l J. of Advanced Research in Computer and Communication Engineering. Vol. 2, Issue 6, June 2013

[9] S.C. Lee, J. Paik, J. Ok, I. Song, and U.M. Kim, “Efficient Mining of User Behaviors by Temporal Mobile AccessPatterns,” Int’l J. Computer Science Security, vol. 7, no.2, pp. 285-291, Feb. 2007

[10] Reshma Cherian and Bright gee Varghese.R “ Individual Mining and Prediction of Patterns for Improving MobileCommerce”Int’l J.of Computer Applications (0975 – 8887) Vol66– No.3, Mar 2013