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USER MOBILITY PREDICTION BASED ON LOCATION AND SERVICE

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Abstract: The transaction database used in many application areas like supermarket, jeweller's shops, stationary stores, online mobile shops, online ticket booking, etc which may consists of transaction id, behaviour of the purchaser or passenger, purchased items id and soon. This paper mainly focuses on extracting frequent patterns from a Mobile Transaction Database. In this paper, the Mobile Transaction Database is generated at the run time and it consists of transaction id, number of behaviour of the user, location id and service id. Using this database, one can easily and effectively predict the user movement behaviour. For this, Apriori and FP-growth algorithms are used in the proposed system for predicting user movement behaviour patterns and their performances are analyzed. Here, the Activity Mining is introduced for predicting the user and type of service the user can access. With the help of the previous log the upcoming users can easily access the services in the location.

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Keywords: Apriori, FP-Growth, Activity Mining, Mobile Transaction Database

I. INTRODUCTION

In this paper, the main focus is on predicting user movement behaviour patterns in a mobile service environment. Now days, the users do their work with the help of mobile phones. With this, the users can easily locate their location, services available in the location. One user can access more than one service. Based on the services accessed by the users, the new user can predict their services easily. It has been known through various surveys that the mobile user behaviours exhibit various degrees of regularity. Majority of users in a mobile environment do not travel at random. They steer from place to place with specific purposes in mind. In many cases, the patterns of location movement and service invocation of mobile users targeting similar purposes exhibit strong resemblance.

In recent days, mobile communication plays a very vital role among the users. Mobile communication has become a very important and quickly growing technology as it allows users to transmit data from remote field to other fields or fixed fields. Mobile user behaviour pattern consists of detailed information of service requirements and a mobility model that is essential to quality of services and roaming support. Most of the users in a mobile environment do not move at random. They may move from place to place with specific purpose in mind. The most prominent feature of wireless networks is mobility support, which enables mobile users to communicate with others in spite of location. There are numerous factors like user id, location, timestamp, and services. Mobile users are connected to the network through the base station.

The behaviour pattern is a series of user id, location, timestamp, and services. Mobile users can move to various locations and appeal to the services through base stations. Location and services may or may not be same for different users. Some users may move to same location and access same services. Some users may move to same location but access different services. These are illustrated as movement behaviour patterns. When users move within the mobile network, their locations and service requirements are stored in a centralized mobile transaction database. Analyses of user movement behaviour pattern gives benefit to the users by appeal to the services easily. In early days, mobile service systems are inadequate in handling complex user movement behaviour patterns without taking user id, location, timestamp, services.

II. PROBLEM DEFINITIONS & DESCRIPTIONS

The user mobility prediction can be found out by means of joining the four factors like mobile user, location, timestamp and services i.e., U, L, T and S. The match joins of matching mobile access patterns from the user movement database. This database is used to transform raw data into useful knowledge.

Definition 1- [Mobile User]: U= $\{u_1,u_2,u_3,\ldots,u_i\}$ is set of mobile users. Each mobile user represents a physical person who carries a mobile device that has the capability of receiving services from the mobile environment, and is capable of being identified and tracked.

Definition 2- [Location]: Two special locations are used to identify the regularities of the visiting locations are the generic location and the interesting location. The generic location is a collective term of one or more interesting locations, and the interesting location is a subset of the generic location. The generic location can be defined as L= $\{l_1,l_2,l_3,\ldots,l_j\}$ where each element l_j represents generic location. The interesting location can be defined as the user u_i staying at a location l_i longer than the maximum duration.

Definition 3- [Timestamp]: The timestamp Tm is assumed to have an equal period and a even unit.

Definition 4- [Services]: S= $\{s_1,s_2,\ldots,s_n\}$ is the set of services requested by movable users. Each element represents an individual service ID. In addition, an optimum time is set for each service requested. If the mobile users use the acquired service longer than the best time, the service is regarded as an interesting or useful information service.

With the help of the above definitions, we can easily predict the user frequent movement locations in the mobile service environment.

III. RELATED WORK

The user behaviour mining is interesting enough but it is not the main theme in [13]. The primary goal of [13] is to explore user behaviour for high-quality information services in mobile environments. Activity mining techniques are used to uncover user behaviour patterns. The key point, however, is to develop effective mechanisms for data management based on user activities. Among the previous work on mobility or sequential patterns mining, very few of them have in depth discussion on how to employ the discovered patterns for data management and information services.

The data allocation algorithm was devised based on the classification of user moving patterns to achieve local and global optimization in terms of likelihood of local data access [14]. The use of user schedules for active replica

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management such that local availability of data can also be significantly improved. The MoDA scheme was further proposed by Yamasaki et al. employs the knowledge of user trajectories to determine how replica of data are copied and transferred among mobile nodes. No similar notion of activity, however, has ever been proposed among all these work.

In [6], a user establishes a point-to-point communication with the server so that their queries can be answered on demand.

In [5], the processing load at the server side increases with the number of queries was discussed. In applications involving numerous clients, the server may be overwhelmed by their queries or take prohibitively long time to answer them. To avoid this problem, Imielinski et al. proposed a wireless data broadcast, a promising technique that leverages the computational capabilities of the clients mobile devices and pushes the query processing task entirely to the client side. In this environment, the server only monitors the locations of the data objects, but is unaware of the clients and their queries.

The automatic classification of web user navigation patterns are studied in [9]. A novel approach is proposed to classify user navigation patterns and predict user's future requests. This approach is based on the combined mining of web server logs and the contents of the retrieved web pages.

A novel data mining method is proposed in [7], namely temporal mobile access patterns that can efficiently discover mobile user's temporal behaviour patterns associated with location and requested services. Furthermore, a novel data structure T-Map is presented to store the temporal mobile access patterns. The advantage of this data structure compactly stores the user's behaviour pattern according to location and service information in memory.

In [2], the author has said, the mining of sequential patterns takes a different approach by discovering frequent sequences such as sequential item purchasing behaviour, general sequential data, multidimensional sequential data, sequential patterns for interval-based data, and sequential mobile access patterns [11].

It was only until recently that both spatio and temporal relationships are considered together in mining sequential patterns [8]. X.Li and Q.Li take a step further to combine movement and access pattern analysis for better services in cellular systems [12].

The user movement behaviour patterns and their activities are clearly mentioned in [1 and 2].

In [4], mobile object tracking is explained. Further, a protocol is proposed to track a mobile object in a sensor network dynamically in [10].

A decision support system model with two important characteristic: 1) mobile technologies are applied in the decision process and 2) the set of alternatives is not fixed over time to address dynamic decision situations in which the set of solution alternatives could change throughout the decision-making process in [3].

IV. PROPOSED SYSTEM

The common patterns of location movement may due to geographic relationships between locations or service allotment. The regularity in service invocation may come from the dependencies between services or the proximity of service providers. It is potentially beneficial to find out such mobility and service patterns to facilitate network and data management.

In the previous work, there is a problem while accessing the services in different locations. Because, it was based on location-only or service-only patterns. But in this paper, the three different parameters like user id, location, and services are used in the database and also we incorporate the location-service pair along with the previous work. With the help of this database and activity mining, the behaviour of the user can be easily predicted.

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After predicting the user behaviour, the new user can easily get the services in an effective manner. The user can request services at anytime and in anywhere. Based on the user request, the services are yet to be provided. Some users can access the services in the particular location frequently.

User static profile is analyzed and services can be located accordingly fast access. Also the dynamic behaviour of user movement pattern is logged and mined and appropriate service structure could be updated. The location updating can be done in a proactive manner or in a reactive manner and appropriate services could be located.

The match joins of mobile access patterns from the user movement database. This database is used to transform raw data into useful knowledge.

Mobile User: U= {u1,u2,u3,…,ui} is set of mobile users. Each mobile user represents a physical person who carries a mobile device that has the capability of receiving services from the mobile environment, and is capable of being identified and tracked.

Location: The generic location is a collective term of one or more interesting locations, and the interesting location is a subset of the generic location. The generic location can be defined as L= {l1,l2,l3,…,lj} where each element lj represents generic location. The interesting location can be defined as the user ui staying at a location li longer than the maximum duration.

Services: S= {s1,s2,…,sn} is the set of services requested by movable users. Each element represents an individual service ID. In addition, an optimum time is set for each service requested. If the mobile users use the acquired service longer than the best time, the service is regarded as an interesting or useful information service.

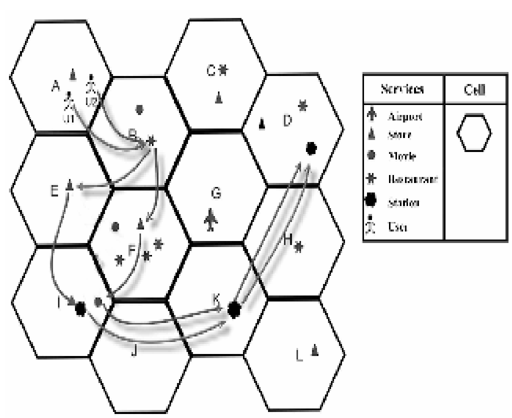

Figure 1: Mobility of User Behavior Patterns and theirActivities

By using the values of mobile user, location and services in the database, one can easily predict the next movement of the user.

V. ACTIVITY MINING AND PREDICTION

For predicting the user movement, the activity mining is carried out in this paper. Here, theAlgorithm1 extends the Apriori algorithm with special emphasis on activity mining. The most important thing is on the generation of the large activity set from the database. By using the large activity set, we can derive candidate set with the help of minimum support value. The function works by enumerating the user id, location, timestamp, and services.
Negotiate the transactions which have the support value which is less than the minimum support value. Use the previous candidate set as the input to the next level of large activity set. Finally, all activities with enough support are joined with user id, location, timestamp, and services activities to form the large movement set. The rest of the activity predicting is essentially a direct adaptation of the Apriori algorithm to the predicting of complex activities.

Algorithm 1.Apriori(Database D)

C_k: Candidate itemset of size k
L_k: frequent itemset of size k
To find minimum support a, a= sum of all frequency of the behavior items/ total number of
behavior items in the transaction
L_1= {frequent items};
for(k= 1; L_k!=∅; k++) **do begin**
    C_{k+1}= candidates generated from L_k;
    for each transaction t in database do
    increase the count of all candidates in C_{k+1}
    that are contained in t
    L_{k+1}= candidates in $C_{k+1}$with min_support
    end
return$\cup_k L_k$;

FP-Growth is extended in Algorithm 2 with the special emphasis on activity mining. While comparing with Apriori algorithm, there is no candidate activity set in FP-Growth algorithm. This is the main advantage of this algorithm. It has less time efficiency to generate the tree construction with this activity set.

Algorithm 2. FP-Growth Algorithm

This algorithm allows frequent itemset discovery without candidate set generation.

To find minimum support a, a= sum of all frequency of the behaviour items/ total number of behaviour items in the transaction.

Step 1: Tree construction
a) To construct the tree, scan the data from the database and find support for each item.
b) Discard the infrequent items and sort the frequent items in decreasing order based on their support.

Step 2: Extracts frequent item sets from the tree
a) Bottom-up algorithm – from the leaves towards the root.
b) Divide and conquer method is used for first look for frequent items.

VI. EXPERIMENTAL RESULTS

The Experimental results for the performance analysis of Apriori and FP-growth algorithms are represented in Figure 2 and Table 1. FP-Growth is an Efficient Mining Method of Frequent Patterns in Large Mobile User Database using a highly compact FP-tree, divide-and-conquer method in nature. The FP-tree is a novel data structure storing compressed, crucial information about frequent patterns. Both Apriori and FP-growth are aiming to find out complete set of patterns. But, FP-growth is more efficient than Apriori in respect to long patterns.

Table 1: Performance Comparison of Apriori and FP-Growth Algorithms

Parameters	Apriori Algorithm	FP-Growth Algorithm
Time	While producing more candidates, its takes more time to execute	Execution time is smaller than Apriori Algorithm
Technique	It uses the Join &Prune properties	It constructs conditional frequent pattern tree and conditional pattern base
Number of Database Scans	Multiple number of scans for generating candidate sets	Scan the Database only twice
Memory Utilization	More number of candidate generation leads to rapidly increasing memory requirements.	Due to Compact Structure and less number of database scan, it requires less memory.

With this, we can clearly see that FP-Growth algorithm has less processing time while comparing with Apriori algorithm.

Table 2: Result of Apriori Algorithm with Activity Mining

User Id	Behavior Items	
	Location Id	Service Id
1	A	1
	B	2
	C	3
	E	7
2	A	1
	B	2
	E	3
	E	5
3	A	1
	B	2
	G	3
4	A	1
	E	8

Database D

Behavior Items		Count
Location Id	Service Id	
B	2	3
A	1	4
E	-	4
-	3	3

Large Frequent Itemset 1

Behavior Items	Count
(B2,A1)	0
(B2,E)	2
(B2,3)	3
(A1,B2)	3
(A1,E)	3
(A1,3)	3
(E,A1)	0
(E,3)	0
(3,B2)	0
(3,A1)	0
(3,E)	2
(E,B2)	0

Candidate Set 2

Behavior Items	Count
(B2,E)	2
(B2,3)	3
(A1,B2)	3
(A1,E)	3
(A1,3)	3
(3,E)	2

Large Frequent Itemset 2

Candidate Set 3

Behavior Items	Count
(B2,3,E)	2
(A1,B2,E)	2
(A1,B2,3)	3
(A1,3,E)	2

Behavior Items	Count
(B2,3,E)	2
(A1,B2,E)	2
(A1,B2,3)	3
(A1,3,E)	2

Large Frequent Itemset 3

Behavior Items	Count
(A1,B2,3,E)	2

Candidate Set 4

Behavior Items	Count
(A1,B2,3,E)	2

Large Frequent Itemset 3

After performing the experiment, the result appears as from the previous Table 2.

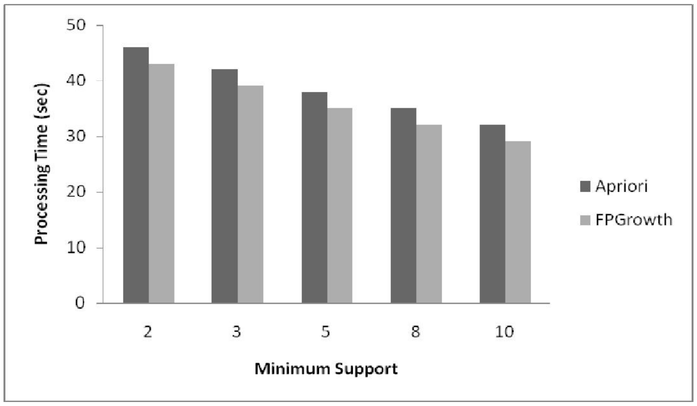

Figure 2: Experimental Results Apriori and FP-Growth Algorithms in terms of Processing Time and Minimum Support

VII. CONCLUSION

In this paper, the activity mining is implemented to predict the future movement of the user. By predicting the next activity of the user, the service providers can improve the quality of service in providing required service to the users. From the Experimental Results, it is known that the FP-Growth algorithm works faster than the Apriori algorithm. With the help of the predicted patterns, the next upcoming mobile users can get their requested services in less time.

VIII. FUTURE ENHANCEMENT

In future, how the required service can be provided to the user effectively in proactive manner. It is intend to extend this analysis to extract the frequent patterns and find the distances of the users in a location based environment. Based on the request of the user, the location distance and available service at the particular location will be announced. In the further research, pattern mining is extending to group pattern mining for dynamic user movement databases.

For the mobility of nodes is variable in the practical networks, the future work may focus on the change of the zone radius aroused by the mobility change of nodes. This will be more accordant with the reality.

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