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Analysis of Mobility Prediction Techniques and Association Rule Mining

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***Abstract*— Mobility prediction is one of the most essential issues that need to be explored for mobility management. Mobile Commerce is spread across various domains, which is very vast and many research studies are going on. The main domains are data mining and prediction. In data mining we can divide the research work among Mining of association rules and mining of patterns. Comparison of various data mining algorithms can reveal interesting facts. A prediction technique is a popular and well researched domain and includes prediction of patterns in mobile commerce. The increasing use of mobile devices and popular mobile services has led to massive availability of mobile data. Location prediction is a specific topic in mobile data mining, with its potential application in traffic planning, location-base advertisement, and user oriented coupon dispersion. In this paper we have analyze various data mining techniques for the Mobile Prediction and Association Rule Mining in detail.**

***Index Terms*— Association Rule, Clustering, Data Mining, Mobile Computing, Mobile Prediction, Association Rule**

I. INTRODUCTION

Two functions are essential in mobile networks: location management and resource reservation. The location management locates the cell where a mobile user is in order to make a call to him. The resources reservation is intended to ensure continuity of communication when a mobile moves from one cell to another by reserving bandwidth in the cells he goes through. User mobility causes performance degradation in relation to the two previous functions. For location management, the network use Page and Update messages to locate the cell where a mobile user is located. These messages consume a part of the already scarce bandwidth. In resource reservation, the network is often required to reserve resources in cells that the mobile will not cross. These resources will not be used even if other mobiles need them.

If the network has enough information about the mobile user displacement and if it integrates intelligent strategies to profit from this information, it can anticipate his future movement with high accuracy. Consequently, the network can better manage its resources mobilization and sharing by sending a minimum (or nothing) of location messages and reserving resources for appropriate time in the actual future cells that the mobile will visit.

This paper is divided among the five sections. The first part explains the various work strategies using so for the mobile prediction using data mining. Second section explains approaches use for the mobile prediction. Third section explains the methodology for the mobile prediction. The forth section describes the successful work done so for this subject domain. Last section puts the current updates with the other hybrid approaches and application in this domain.

II. STATE OF ART

All Many studies were carried out on prediction. In [1] Zhuang et al. monitor the signal power in the base station to predict the next cell. When the signal in a new base station increases in power, the system concludes that the mobile moves towards this station. This solution was improved in [2] by adding the time factor to predict the mobile arrival time. In [3] Choi, *et al.*, estimate the users mobility according to displacements history observed in each cell. In [4], Shen et al. Developed a prediction system based on the measurement of a pilot signal, and using fuzzy logic, to take into account pilot signals interferences users random movements. In [5, 6], the authors use mobiles localization information recovered by GPS, which they provide to a Markov model to predict the future location. In [7], Soh, *et al.*, present and describe the use of a prediction technique which incorporates roads topographic information; periodically (every second for example), the mobile provides its position to its base station. An algorithm identifies the segment of the road taken by the mobile and its estimated speed. The system then predicts the future base station and estimates the expected time to reach it.

These solutions are limited because they are based on either a probabilistic model which does not completely reflect the users behavior, or on the users individual history which can be missing or insufficient. New solutions based on heuristic methods were used such as those presented in [8, 9, 10] that use neural networks for prediction. In [8], the authors adopted a structure of a cell divided in 2-tier areas (Avicinity area andan edge area). When the mobile is in a cell edges area, its coordinates are provided as input to the neural network which predicts the next cell to be visited. In [9], the authors present a system which periodically captures the connections traces. Theses traces are progressively recorded giving a history record which will be used as input to the neural network to predict the next cell to be visited.

The disadvantage of these methods is that they require a long training phase on mobile user behavior before the prediction succeeds. Moreover, the mobile user can change his behavior during the training phase or can go to a location he has never visited before, thus making the prediction ineffective. In [11], Samaan, *et al.*, present a solution which includes spatial and user contexts. The spatial context consists of a set of abstract maps describing the geographical environment in which the mobile user progresses. Places, buildings and roads which lead to these places are described in theses maps. The user context includes a set of information related to the mobile user making it possible to predict his mobility. This information is then combined using Dempster Shafer algorithm to predict

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the future mobile location. Even if this solution seems to provide suitable results when mobile history is lacking, it is however too constraining because it requires additional information not easy to acquire and likely to frequent change. In [12], the authors suggest a method based on information theory in which each mobile device collects a set of clues such as its position in a particular road and its stay time during its previous displacements. These clues are then processed by the current cell to predict the future cell. The use of information theory and decision trees allows choosing the most relevant clues for prediction. Its disadvantage is the need to store these clues in the mobile itself, which consumes memory, energy and bandwidth when communicating this information to the cell. In [13,14], the authors propose a solution based on an ant system to predict the future cell a mobile will cross, based on past movements of the mobile itself and other mobiles that move in the same way. This solution provides good prediction results in environments where the mobile produce common behaviors such as cities but does not give good results when the displacements are random. [15] applies adaptive resonance theory (ART) to mobility prediction algorithms. Though it can adapt to trajectory of mobile user, it suffers from slow response to fast motion

III. Association Rule Mining

Association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using different measures of interestingness.[1] Based on the concept of strong rules, Rakesh Agrawal et al. introduced association rules for discovering regularities between products in large-scale transaction data recorded by point-of-sale (POS) systems in supermarkets. For example, the rule found in the sales data of a supermarket would indicate that if a customer buys onions and potatoes together, he or she is likely to also buy hamburger meat. Such information can be used as the basis for decisions about marketing activities such as, e.g., promotional pricing or product placements. In addition to the above example from market basket analysis association rules are employed today in many application areas including Web usage mining, intrusion detection, Continuous production, and bioinformatics. In contrast with sequence mining, association rule learning typically does not consider the order of items either within a transaction or across transactions

The useful concepts for the mobile predication are:

- The support of an itemset is defined as the proportion of transactions in the data set which contain the itemset
- The confidence is defined as the support to supply
- The lift is defined as the support to the some only item set

IV. The process of mining using association rule

Association rules are usually required to satisfy a user-specified minimum support and a user-specified minimum confidence at the same time. Association rule generation is usually split up into two separate steps:

1. First, minimum support is applied to find all frequent itemsets in a database.
2. Second, these frequent itemsets and the minimum confidence constraint are used to form rules.

While the second step is straightforward, the first step needs more attention.

Finding all frequent itemsets in a database is difficult since it involves searching all possible itemsets (item combinations). The set of possible itemsets is the power set I over and has size $2^n - 1$ (Excluding the empty set which is not a valid itemset). Although the size of the powerset grows exponentially in the number of items in efficient search is possible using the downward-closure property of support (also called anti-monotonicity) which guarantees that for a frequent itemset, all its subsets are also frequent and thus for an infrequent itemset, all its supersets must also be infrequent. Exploiting this property, efficient algorithms can find all frequent itemsets

V. Apriori Algorithm

Apriori is an algorithm for frequent item set mining and association rule learning over transactional databases. It proceeds by identifying the frequent individual items in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The frequent item sets determined by Apriori can be used to determine association rules which highlight general trends in the database: this has applications in domains such as market basket analysis.

Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time (a step known as candidate generation), and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found.

Apriori uses breadth-first search and a Hash tree structure to count candidate item sets efficiently. It generates candidate item sets of length K from item sets of length k-1.

Then it prunes the candidates which have an infrequent sub pattern. According to the downward closure lemma, the candidate set contains all frequent k-length item sets. After that, it scans the transaction database to determine frequent item sets among the candidates.

$\mathrm{Apriori}(T, \epsilon)$
  $L_1 \leftarrow \{\text{large } 1 - \text{itemsets}\}$
  $k \leftarrow 2$
    while $L_{k-1} \neq \emptyset$
      $C_k \leftarrow \{a \cup \{b\} \mid a \in L_{k-1} \wedge b \in \bigcup L_{k-1} \wedge b \notin a\}$
      for transactions $t \in T$
        $C_t \leftarrow \{c \mid c \in C_k \wedge c \subseteq t\}$
        for candidates $c \in C_t$
          $count[c] \leftarrow count[c] + 1$
      $L_k \leftarrow \{c \mid c \in C_k \wedge \ count[c] \geq \epsilon\}$
      $k \leftarrow k + 1$
    return $\bigcup_k L_k$

VI. Mobile Prediction and Data Mining

A. Data mining in Mobile Commerce

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In data mining, association rule learning is the basic technique which can explore the fundamentals of all other techniques. In association rule learning the best known constraints are support and confidence. After done the survey of various association rule learning techniques, we studied the mining of patterns. The studies reveal that the previous studies adopt an Apriori like (Candidate set generation) which is costly. As a result scientists explored and discovered frequent pattern mining, thus reduced the costly candidate generation. But still there exists the problem. The final achievement is not to reduce the costly candidate generation, but to eliminate it. As a result researchers found out frequent pattern tree, which has no candidate generation.

B. Prediction of patterns in mobile commerce

Intelligent mobile agents are mandated to communicate with users, at the same time the capturing of users behavior patterns is also done. The patterns are captured according to location information and purchasing patterns. Some prediction models didn't consider individual mining of patterns of each user. However individual mining can provide services to each user, which influences them, there by motivation of mobile commerce can be done easily. In [16], Chen et al., propos e the path traversal patterns for mining web user behaviors. Yunand Chen, propos e the Mobile Sequential Pattern [17]. The, Tseng et al., propos e the TMSP-Mine for determine the temporal mobile sequence pat terns in a location based service environment. Jeung et al., propose a predict ion approach called Hybrid Predict ion Model [18] for calculate approximately an object's future locations based on its pattern information.

C. Movement Prediction and Data Mining

Users' movements are not completely random because they follow professional and social behavior. They are not completely deterministic because they obey the will of the individual. A study, carried out in the USA for better organizing public transport [19], has shown that nearly 80% of users displacements relate to work and nearly 20% relate to social or cultural reasons. During holidays, the percentage is only nearly 2%. It also showed that displacements are influenced by the infrastructures of the places (trades, highways, streets, paths, *etc.*). Displacements for work and social reasons are the most frequent and the most usual. The knowledge of the history (habits) of a user and his current location (on a road for example) could be useful to determine his probable future location. But it is also probable to determine the future location of a user even if his history is not known or if he takes an unusual displacement (holidays for example). In this case, one can use the history of his neighbors who follow the same direction. A user who is in a highway surely goes in the same direction as his neighbors.

Data mining is the process of extracting hidden knowledge or non-trivial from a large database [20]. It is a set of techniques drawn from various fields like data analysis, information theory and artificial intelligence applied to a data set to analyze and draw, either useful new information or hidden relationships between these data. The data mining applications vary widely. We cite for example the risk analysis and Marketing where the discipline is often used.

VII. METHODOLOGIES OF MOBILE PREDICTION

D. Mining of Association rules

Mining association rules [21] are planned to find important items in a transaction database. In [21], Agrawal and Srikant, propose the Apriori algorithm to extract the association rules. The association rules are a technique of data mining that naturally find its utility in movement prediction and location management. The association rules found hidden links between data. These links can be useful and exploited. The relationships found are like; if a customer buys bread, butter and coffee, it is likely that he also buys milk. This technique can be used in our case to find links between cells and have information of a kind; if a mobile has already crossed the cells x, y and z, It is likely that he will cross the cell t (cell covering a portion of highway for example). This information could be used for long-term prediction and making resources reservations at the appropriate time in the predicted cells. Rachida Aoudjit[22] has demonstrated the practical setup for the mobile movement prediction based on Association Rules. It proves the accuracy up to 90%.

In data mining, association rule learning is a popular and well researched technique for finding relation between variables in large databases. However it has a drawback. It didn't consider the order of items within a transaction. Several research papers are published in this domain. Some papers discover association rules, fast algorithms for mining association rules and so on. R. Agrawal [23] presents an efficient algorithm that generates all significant association rules between items in the databases. The database he considered is a large data base of customer transactions. The algorithm incorporates buffer management, novel estimation and pruning techniques. In this paper the constraint, they considered are min-support and confidence. However they produce candidate generations, it is costly and take some tome. R. Agrawal [24] discovered fast algorithms for mining association rules. They used a hybrid algorithm called Apriori-Hybrid. Scale up experiments showed that Apriori-Hybrid scales linearly with the number of transactions. J.S Park [25] suggested an effective hash based algorithm in which the production of candidate sets generated is in order of Magnitude smaller than by previous methods, thus increasing performance. The previous studies on mining association rules depict rules at single level. A method for mining multiple level association rules is introduced by J. Han R [26][E].This extension of method poses many new issues for further investigation.

The association rules can be used to create location areas. They can also be used for the long-term resource reservation because they provide a chronological order of the crossing cells. The algorithm starts by sorting the displacements history of a mobile by the decreasing order of the date. From this history we generate lists in the form of Table where:

- Cell 1 is the most recent cell in which the mobile is located.
- Cell 2 is the cell which the mobile had crossed before going to cell 1.
- Cell 3 is the cell which the mobile had crossed before going to cell 2.
- ... etc.

We thus obtain a set of lists of K elements indicating the K last cells crossed by a given mobile. We apply then the algorithm Apriori to seek for association rules of order 1, 2, 3… k. An association rule of order 1 is a rule in the form CellA

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– – > CellB. It means that if mobile user is in the cell A it is probable that he will be in the cell B. It is obtained by searching in the lists of Table created, the elements that satisfy a minimum support and confidence calculated as follows:

- Number of app. of Cell A and Cell B in the same list to number of cells
- Number of app. of Cell A and Cell B in the same list to number app. of Cell A in the lists

Confidence indicates if this rule is verified by indicating whether the right side element of the rule appears whenever the left side element appears. The support indicates if this rule is often verified and not only in particular cases by indicating whether the left side of the rule appears sufficiently in the database. From the subset obtained we seek the association rules of order 3 and so on until arrived at the desired ². Subsets obtained, for example {Cell 1, Cell 4, Cell 3, Cell 8}, can constitute a location areas for a mobile and the order in which cells appear can give an indication of the long term crossing cells which can be useful for long-term resource reservation.

E. Mobile Prediction using Clustering

In mobile adhoc network, clustering means a national grouping of mobile nodes into different virtual groups; it can also be defined as the division of whole network into number of virtual groups. During clustering, geographically adjacent nodes are grouped into virtual groups based on node’s behavior or node’s resources with some specified rules. In a cluster, a node may take any one of status as clusterhead (CH), clustermember (CM), clustergateway (CG) or may be on orphan node.

F. Mining of Patterns

In data mining research, mining frequent patterns in transaction databases, time series databases and several other databases have been studied. Frequent pattern tree is a mind blowing invention which eliminates costly candidate generations. The mining of sequential patterns by R. Agrawal [36] showed that Albert’s Apriorisome performs a little better when comparing Apriorisome and AprioriAll. But the generation of candidate sets is still costly. D. Xin [37] has studied the problem of compressing frequent pattern sets in order to reduce the costly candidate generations. He developed two greedy methods, RP Global and RP Local. In his studies he revealed that RP Local mines ever faster than FP Close, a very fast closed frequent pattern mining method. J. Han [38] proposed a novel frequent pattern tree structure for storing compressed, crucial information about frequent patterns. Most of the previous studies considered candidate set generation. But this is the first paper which adopts an efficient FP Tree based mining method for mining frequent patterns without candidate generation. This compact FP Tree saves the costly database scans in the subsequent mining processes.

VIII. CONCLUSION

In this paper Mobile Prediction techniques has been studied across the various domains like location prediction, movement prediction, usability prediction, etc. We found the data mining methodologies is very useful for these problem solving. The association rule mining provides a basic platform for the future location predication of the itemset. In future, we will target the methods the specific application of the mobile prediction. Paper also has studied various data mining approached for the mobile prediction like association rule mining, clustering and specific network domain. We found the hybrid combination of the model can lead to the significant prediction. In future we study the algorithm development on the basis the comparison of the capabilities of the various methods studied here.

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