A NOVEL APPROACH FOR PREDICTING MOVEMENT OF MOBILE USERS BASED ON DATA MINING TECHNIQUES

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Abstract- Predicting locations of users with transportable devices like informatics phones, smart-phones, iPads and iPods public wireless local area networks (WLANs) plays an important role in location management and network resource allocation. Several techniques in machine learning and data processing, like sequential pattern mining and clustering, are wide used. However, these approaches have 2 deficiencies. Sequential pattern technique might fail to predict new users or users with movement on novel methods. Second, exploitation similar quality behaviours in an exceedingly cluster for predicting the movement of users might cause important degradation in accuracy attributable to indistinguishable regular movement and random movement. In this paper, we tend to propose a unique fusion technique that utilizes quality rules discovered from multiple similar users by combining clustering and sequential pattern mining named as ApproxMAP (Approximate Multiple alignment pattern mining), referred to as agreement patterns, from massive sequence databases. This algorithmic rule will modify the lack of data in an exceedingly personal profile and avoid some noise due to random movements by users and also this method has increased efficiency and prediction accuracy.

Key Words: — Clustering, mobile user, mobility pattern, movement prediction, sequential pattern, ApproxMAP.

1. INTRODUCTION

Public wireless local area networks (WLANs) such as city or campus WLANs enable a large number of mobile users to access Internet applications from where they want and still remain connected to the Internet while on the move. Whenever a mobile user moves from one cell to another, called a handover or handoff, network resources must be reallocated for his device at the new cell to continue the service. If the required network resources are not available or are insufficient, the network will force a termination of service to the user. Dropping a service in progress is considered to have a more negative impact from the user's perspective than blocking a newly requested service. This means that, handoff services must be assigned a higher priority over new services. Location prediction that may accommodate the network with future location information of all mobile users has played a crucial role in the accurate estimation of network resource demands at a future time. Because location prediction may provide useful location information for reserving resources in cells where users are likely to be located, several research works have focused on this subject toward more efficient network resource management. Until now, location prediction has relied on various techniques, including probability models machine learning techniques pattern matching and sequential pattern mining. Among them, sequential pattern mining includes the ability to ignore outdated historical data without retraining and to incorporate contextual information in the model. Therefore, it has been widely used for location prediction based on the past mobility behaviours of mobile users in a WLAN. Because mobility histories hide useful knowledge that describes the typical behaviour of mobile users, most previous approaches made use of such mined knowledge to predict future locations of mobile users in wireless networks.

These approaches may be grouped into two classes. Most approaches based on single users, such as use individual movement history make predictions. A few other works have investigated a group of users with similar movement behaviours. Most of them have some deficiencies. The first group for location prediction is based only on individual mobility behaviours; hence, the lack of information on personal movement profiles may cause false predictions. For example, these approaches may fail to make a prediction for new users or users with movements on novel paths. The second group of location prediction applies similar mobility behaviours of multiple users to facilitate predictions in the case of new users or users with movements on novel paths. However, this group does not distinguish between regular movements and random movements of mobile users, so they may cause significant degradation in the prediction accuracy. In order to make prediction on user with novel path and also to increase the prediction accuracy we have proposed a novel fusion technique that utilizes mobility rules discovered from multiple similar users by combining clustering and sequential pattern mining named as ApproxMAP used to mine approximate sequential patterns, called consensus patterns, from large sequence databases.

We have organized the paper as: section 2 contains the related works that has already been done in network resource allocation using data mining techniques for WLAN. Section 3 contains the proposed work using the ApproxMAP method. The last session 4 concludes the paper.

2. RELATED WORK

2.1 Overview of Location Prediction

Location prediction has driven applications in location management, call admission control, smooth handoffs, and resource reservation for improved quality of service. Therefore, location prediction has attracted a great deal of research interest. This paper does not attempt to describe several algorithms used for location prediction, but instead conducts a comprehensive survey of various prediction approaches. Several approaches [18]–[20] have used contextual knowledge or spatial conceptual maps such as traffic topology, road topology, and received signal strength (RSS), while most approaches have considered utilizing the past mobility behaviours of WLAN users. Approaches based on topology [18]–[20] often require a vast amount of information to be collected and processed. Moreover, these approaches may not perform very well with changes to the surrounding infrastructure. Meanwhile, RSS schemes require no information of the infrastructure and instead rely on the constant tracking of relative distances between the mobile user and the neighbouring access points (APs). Such schemes will likely suffer from the large overhead accrued from the constant monitoring. In summary, the approaches that rely on such contextual knowledge may not be suitable for public WLANs. This is because public WLANs often support a large number of portable devices and may change their surroundings.

2.2 Location Prediction Based on Individual Movement History

Predictions of this kind are done on individual users, not the entire body of users. Previous works relied on various methods to predict future location, including probability models, machine learning techniques, pattern matching, and sequential pattern mining. These methods have their advantages and disadvantages. Probability models such as the Markov chain [10] and Hidden Markov model [11] use transition matrices; they do not need to store users' past movements since the probabilities denote these statistics. However, it is difficult to include further context because each type of additional context introduces a new set of states in these models [17]. Therefore, these models are best suited to work only under steady–state conditions. Machine learning techniques such as neural networks [13], [14], Bayesian networks [15], and the decision tree [12] may support the exploitation of valuable contextual information of users' movement histories. However, these techniques need to be trained on known data before they are used to predict unknown data [17].

The most significant disadvantages of both probability models and machine learning techniques are that they need to be retrained to add new data or discard old data [17]. If the model is retrained often, it may incorporate recent data but it also uses more computational resources. Conversely, it may miss some predictions because it is not up-to-date. Therefore, these approaches may not adapt to possible changes in user movement habits, such as vacations, new jobs, or new semesters. Meanwhile, pattern matching techniques compile mobility histories and perform approximate similarity matching between the current and stored trajectories in order to derive predictions. However, these techniques do not provide a method to discover mobility patterns in the first place [16]. Finally, most of the research works have used sequential pattern mining to predict future locations. Why is sequential pattern mining more appropriate for location prediction in a public WLAN? Two significant advantages of this model include its ability to ignore outdated historical data without retraining and to incorporate contextual information in the model [17]. The former advantage means that the model can dynamically decide which movements to use for prediction and which to ignore. For example, if a user suddenly changes his movement behaviours, the model may decide to use only the last few days' worth of movements to predict the next day. The latter advantage is the ability to add valuable contextual information to the model and to filter patterns by this further context. For example, the model can filter the daily patterns by day-of-the week or season of the year.

2.3 Location Prediction based on Multiple Users' Movement Histories These approaches apply a group of similar mobility behaviours to predict the future movement of a mobile user. The basis of these approaches is that even though human movement and mobility patterns have a high degree of freedom and variation, they also exhibit mobility behaviours in groups because of geographic, social and friendship constraints. For instance, mobile users in a university campus network can be categorized as students, graduate students, departmental staffers, lecturers, and so on. Students often move to classrooms, laboratories, libraries,
etc., whereas departmental staffers spend most of the day near the administrative offices. In order to exploit similar movement characteristics, it is crucial to determine movement groups where the mobile users belonging to the same group have the same mobility behaviours. In other words, the group mobility behaviour reflects the fact that mobile users often behave as groups. Discovering such groups of similar mobility behaviours is a key issue for predicting the future movement of a new mobile user based on the mobility behaviours of members in the same group.

This approach for predicting future movements based on a user's group of similar movement behaviours they first utilize probabilistic suffix trees (PST) to capture the moving patterns of multiple mobile users. Second, they define a distance function to determine the similarity between two PSTs, and then propose a clustering algorithm to partition mobile users with similar moving behaviours into groups using a distance function. Third, for each group, they select one representative PST to predict future movements of users in the same group. The advantage of this approach is that the storage cost is decreased.

2.4 Cluster model of location prediction

This model aims to exploit the similar movement characteristics of mobile users to deal with the lack of mobility behaviours of individuals. By using such similar mobility behaviours, the model may facilitate the prediction of future movement of a new user or users with movements that are novel. This model utilizes the proposed clustering algorithm to partition mobile users into groups of similar moving behaviours. Because possible noise in the movement data may negatively impact the prediction accuracy, this model tries to eliminate all random movements from each movement group by means of sequential pattern mining. To predict the future location of the current trajectory, the model selects the movement group to which the current trajectory belongs. After that, all mobility rules that are generated from the corresponding movement group are utilized to predict the future movement of the current trajectory. Each generated rule has a confidence value, and only rules that have confidence values higher than the predefined confidence threshold named frequent rules, are selected for predicting future locations of the current trajectory. The process of generating mobility rules extracts all frequent rules and assigns a weighted value for each generated rule based on a temporal attribute. The details of the process were presented in our previous work. Finally, the current trajectory is matched to the head of rule to find the best matching rule for predicting future locations. By using mobility rules in the same group, this model may not return a no-prediction owing to lack of information on a personal movement profile.

3 PROPOSED WORK

Location prediction is major role in allocating resource in wireless local area network. To perform this first we have to collect user history from the dataset and then with the use of approximate multiple alignment pattern mining, we can predict the future movement of user who are connected in the network. Mainly, our approach for predicting objects' future locations is divided into two sub-problems: (i) mining frequent trajectory patterns and (ii) location prediction based on the extracted patterns.

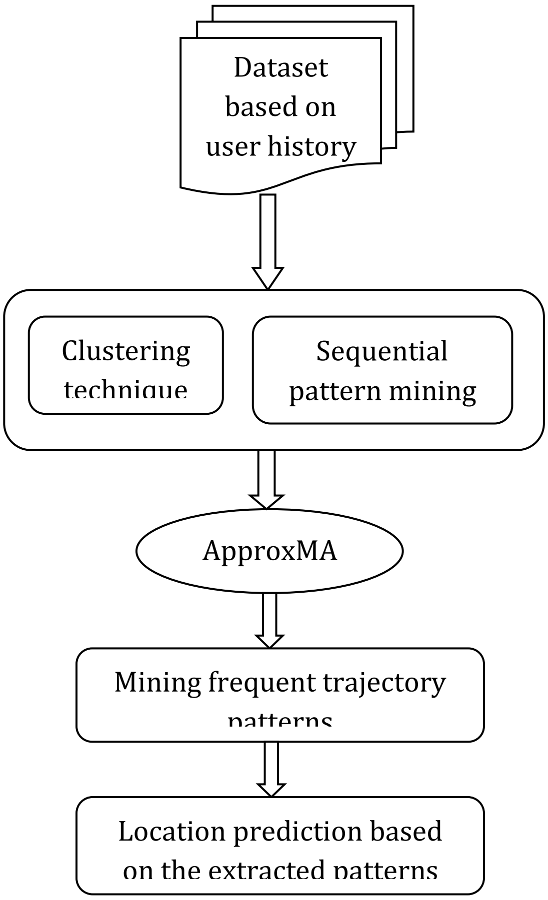

Fig: 1 Design of proposed work

3.1 MODULES DESCRIPTION

Find IP address connected in the network

This module is used to get all the IP address and host name which are connected to the network. When the find option is selected it starts to search and provide the list of IP address that is already connected to the network. This data is already stored in the wifi history dataset, using the dataset they can cluster and find the IP address and host name of the devices.

Get access point of each IP address

This module has number of access point that is provided by the network and also it shows all the IP address which are connected to the router with the respective access point. It has an option called get details which is to provide the details of connected devices in the particular access point.

View Details of Connected Devices

This module is used to view the details of the device such as name of the device, host name, IP address, and duration. These details are updated to the database whenever the access point is changed or moved from one access point to another by the user.

Predict Future Location Using ApproxMAP

This module is used to predict the future movement of user who are connected in the network by using the two steps, first it group the information according to time and date of the user and second mine frequent trajectory patterns in order to predict the next access point the user wants to move in case the connection of current access point is lost.

4. CONCLUSION

In this paper, we have presented a novel approach for predicting the future movement of mobile users in public WLANs.

This approach is based on both clustering and sequential pattern mining. The clustering technique partitions mobile users into groups of similar mobility behaviors to deal with the lack of information in personal profiles. Meanwhile, approxMAP is used to discover frequent mobility patterns to deal with the noise of random movements in the entire body of mobile users' histories.

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