Mobile Subscriber Profiling and Personal Service Generation using Location Awareness

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***Abstract*—In the mobile environment, the location and the next move of subscribers are important. In this study, a method to detect the next move of the subscribers is proposed. In addition to the categorization of subscribers by using their Internet usage history, the knowledge of the next move pattern of subscribers will provide the flexibility to guide them to decide the next move. During the tracking of subscribers, the mobile devices of the subscribers are used as sensors to get in-depth knowledge about their preferences in their social life. The method presented here is the first in the literature to estimate the next move without connecting to any social networks. It combines the geographic locations and the Internet usage of the subscribers in order to predict their movement. In addition, most of the IoT studies either concentrate on network topologies or power consumption, while in this study, dynamicity and exact location estimation are utilized to handle the challenges and attain the required results. The results of the experiments show that the proposed system predicts the next move of a subscriber with a precision of more than 90 percent.**

***Index Terms*—social network services, artificial neural networks, data mining, real-time systems, cooperative communication.**

I. Introduction

The rapid change in telecommunication technologies has affected the behavior of Internet users. It has been estimated by Portio Research that the number of mobile subscribers is 92% of the world's population and was predicted that it would be more than 100% between the years 2015 and 2016 [1]. The shift from fixed broadband Internet usage to mobile usage has encouraged service providers to adapt their services to obtain better revenue through the subscribers by employing differentiated services with varying data usage plans and additional subscriber tracking and advertisement systems. The area of programmatic advertisement burst in order to effectively utilize the advertisement sector mainly by subscriber analytic systems.

This growth rate is faster when it comes to the number of devices connected to the Internet, which is increasing exponentially [2]. This growth rate is reached by enabling the connectivity of diverse devices in size, capability, processing power, lifetime and ability to move. In addition, they have the ability to communicate in a Machine-to-Machine (M2M) manner without or with limited human intervention [3]. The Internet-of-Things (IoT) concept is built upon utilizing the M2M communication [4]. Nowadays, most of the companies/organizations delivering traffic information are mainly tracking vehicles through the mobile applications installed on their mobile device. All alternative paths and duration of the selected paths are estimated by using the help of the "things" owned by the people inside the vehicles. These systems are the pioneers of the IoT revolution.

User profiling in computer networks is a very common method for classifying users for various reasons such as fraud detection, usage predictions, marketing etc. From the networking perspective, a user can be classified by using his/her previous page visits. For instance, the access logs of the Internet traffic can be used to identify the interest of a subscriber [5] [6]. On the other hand, from the mobile social user perspective, user is an entity that travels and communicates by means of both data and voice. For instance, Chang,Yi, Lingyun, Purui, and Dengguo [7] proposed a user profiling approach for location based mobile messaging applications by forming a life profile for each user based on network usage, location, daily activities and social bindings.

In mobile networks, Burge and Taylor [8] proposed a behavior profiling approach, which is strengthened by the differential analysis of users on calculating the Hellinger distance from alarming point. Loskot, Hassanian, Farjady, Ruffini and Payne [9] emphasized the change in user tendencies over the next generation networks, which exclusively underline the importance of multimedia streaming. Ghosh, Beal, Ngo and Qiao [10] traced a wireless network on campus for a year and were able to calculate a probability value of each user's current location in a significant time period by looking at the historical mobility of that user. Similarly, Lee, Lim, Park and Kim [11] used the location data obtained from Wi-fi access point fingerprint data to analyze the next movement of a user in a weekly regularity basis. They applied Markov chain methods and spatio-temporal data mining techniques to predict the next movements by considering regularities.

The service providers (e.g. Google, Facebook, Twitter etc.) can easily track the content usage of the visitors to obtain their behaviors and the interests. This helps them to profile subscribers according to their interests and expectations by the adaptive algorithms applied to the traces of the user's content access. This is the way in which the service providers are sponsored through their "free" services. The connection service providers are motivated by the idea to get higher revenue from the subscribers by controlling their Internet access data to i) apply personalized policies; ii) monitor and control the service traffic; iii) gain more revenue.

In [5], a system was developed to monitor and analyze the Internet access (http access logs) of the subscribers of a service provider in order to classify the subscribers into an

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interest category (or into several interest categories) by using a category database as a categorization engine. In their proposed system, an Internet category database, which was compatible with the IAB [12] category database was used. The aim of the study was to allow the service providers to find differentiating properties between the subscribers in order to get higher revenue to improve the click rate of the advertisements shown to the subscribers by advertising them according to their interests. The study was extended in [6], in order to have the ability to classify multiple subscribers using the same wire-line broadband subscriber system. Moreover, the extension allowed the broadband operators to realize the changing interests of the subscribers over time.

The rise in the ability and services delivered by Content Service Providers (Google, Amazon etc.) allow them to stick together with their users, which weakens the relationship between the Connection Service Providers (CSP) and their subscribers. The loosely coupled connection between CSPs and their subscribers weakens over time, and increases the probability of Churn for the subscriber. The CSPs are looking for a solution to get know more on their subscribers in order to i) get more revenue over their subscribers and ii) reduce the churn rate to have tightly coupled relationship with their subscribers.

The aim of this study is to predict the next movement of a subscriber based on his/her preferences that is what s/he will do next. The proposed system differs from the others by understanding the behavior of the users by combining both movement prediction and preferences while others are concentrating only on one of them at any given time. The system is designed by the guidance of the nature of mobile platforms and additional abilities incurred from using them. The proposed system tracks the movements of the subscribers in order to select more appropriate advertisements to the subscribers to allow the advertiser to move a step ahead of his competitors. It also allows the service provider to promote the visit of several locations by providing free Internet access or similar promotions when they visit those locations. The contribution of the proposed system in the present study in comparison with others are: i) the simultaneous visibility of subscriber interest and the location to the operator, ii) the estimation capability for the next location of the subscribers, iii) the ability of advertising entertainment/shopping place advertisement to enforce the next move to get additional revenue over their subscribers (case i).

The rest of the paper is organized as follows. In section II, a brief summary of related literature is delivered. The proposed system to deliver targeted advertisements is described in section III. In section IV, the experimental results are presented. The conclusions and future directions are given in section V.

II. Subscriber Profiling and Location-Aware Internet Advertisement Systems

The prediction of the next movement of a person is an important research area, which may lead to valuable information for companies to follow the future movements of a user. Vintan, Gellert, Petzold, and Ungerer [13] proposed using multilayer perceptron with back-propagation learning algorithm. The study concentrates on local predictors to predict the movement of a person by training the neural network with the movements of a single person as input parameters. The movement area of the person was limited to a number of rooms, and all rooms were coded by using a binary coding. The binary codes were assigned to each room indicating the current and the next locations. Moreover, by means of the previous movement data, it also predicts the next move of a person through the global predictors. In the global predictors, all individuals in the system are also coded by binary codes. The results of the study show that the prediction accuracy of a movement by using local predictor is between 90% and 92%, whereas it is between 85% and 87% by using global predictors. In a subsequent study, Gellert and Vintan [14] reintroduced the problem and applied Hidden Markov Models to solve the same problem. The results of the study show that the success rates of the movement prediction system are almost identical.

Furthermore, Akoush and Sameh [15] applied Bayesian Neural Network to predict both next location and next service to request. The next call estimation success ratio is 60% for the scenario covering all system users, whereas it is as high as 89% when the number of users is limited to 6 with common interests (such as being the student of a faculty). Moreover, Ghosh, Beal, Ngo and Qiao [10] traced a wireless network on campus for a year and were able to calculate a probability value of each user’s current location in a significant time period by looking at the historical mobility of that user. Pham and Cao [16] also proposed a Markov model to identify an individual by using their "spatio-temporal profiling model".

In telecommunication systems, user profiling was mostly used in fraud detection. Cortesao, Martins, Rosa and Carvalho [17] defined the 3M's (Motive, Means, Method) of fraudulent activities and the ways of profiling the fraudulent users. Together with location support, location-based user mobility profiling are also proposed by Lin, Cao, Zheng, Chang, and Krishnaswamy as a user verification method for wireless networks [18]. Furthermore, Hilas and Sahalos [19] made an application for fraud user profiling using a statistical machine learning approach for detecting the fraudulent activities, and a "user group partition algorithm and behavior pattern matching algorithm" was proposed by Ko and Thwin [20] in order to identify anomalous calls. Burge and Taylor [8] proposed a behavior profiling approach for users by using the differential analysis of users by calculating the Hellinger distance from a pre-defined fraudulent point.

Advertisements through networks were another important topic in need for a user profiling approach. The idea behind the user profiling approach in the advertisement sector was the targeted online advertising method by Schuman, Wangenheim, and Groene [21]. If the advertisement is displayed to the correct audience with a correct timing, the advertisement is believed to be more effective. To illustrate this approach, Haddadi, Hui and Brown [22] proposed a mobile advertising system, which uses mobile phones to create user profiles by using the data mining techniques, and Ullah, Boreli, Kaafar, and Kanhere [23] proposed a method to utilize Google user profiles in ad targeting. Oztoprak [5-6] proposed a solution to profile the subscribers according to their Internet access patterns to allow the advertisers to find the appropriate subscriber for their advertisements.

In the networking perspective, user profiling is studied on infrastructure data such as web usage logs or proxy logs. As a networking application, Fujimoto, Etoh, Kinno, and Akinaga [24] proposed a method of profiling web users based on proxy logs. Castellano, Fanelli, Mencar, and Torsello [25] also proposed a fuzzy clustering algorithm to identify the user profiles by using the web usage logs. Moreover, Makvana and Shah [26] used web usage data for users in order to create a personalized web search methodology. Hall and Kanar [27] offered an advertisement delivery system according to the locations of the subscribers through mobile networks. The system keeps an interest database of the mobile subscribers to deliver appropriate advertisements respective to their locations. The proposed model by Wilson, Kachappilly, Mohan, Kapadia, Soman, and Chaudhury [28] was designed to gather subscriber data from a mobile operator network; then to analyze through big data systems, and finally to classify the subscribers into several categories.

In addition to subscriber categorization, predicting the location and next move of mobile users drew the attention of the researchers. Zhang et al. [29] used Foursquare check-in traces to detect the location of the mobile users. They concluded that most of the check-in data is either missing or superfluous (multiple nearby check-in). One step further for the advertisers is to predict the next move of the users. Noulas, Scellato, Lathia, and Mascolo [30] proposed a model to predict the next place location of the users from the current check-in in Foursquare system. They offered supervised learning models to estimate the next move for the users. Similarly, Zheng, Thompson, Lam, Yoon, and Gnanasambandam [31] proposed to use Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to predict the selection of a restaurant by using the users registered in Foursquare. The results demonstrate that the success of ANN is 93%, whereas it is 54% in SVM.

III. History-Aware Next Movement Prediction Engine Architecture – HANMEA

The mobile access to telecommunication services has rapidly evolved over the last two decades. The ability to reach the Internet access and location of the subscribers in mobile networks shifted the expectations of mobile operators from knowing the interest of the subscribers into knowing how to get revenue from them for the specified location. To do the described task, the operators should i) categorize the subscribers according to their interests, ii) get the trace of the subscribers where they spend their time, iii) track the locations of the subscribers to upsell several advertisements. In order to solve the above problems, a History-Aware Next Move Categorization Engine is proposed. The motivation behind this study is to enable Connection Service Providers to build a subscriber analytics platform, which allows them to get more on their subscribers in order to gain more revenue over them by employing targeted advertisements or proposing additional services more appropriate to their situation.

A. *Interest Prediction using Internet Access*

The HANMEA consists of two main components. The first component is the categorization engine to assign subscribers to predefined categories. The categorization task has been performed similar to the one proposed by [6] which has the ability to know sliding interest changes of the subscriber over time. The model proposed in this study is a simplified version of [6] in terms of the number of categories. The number of categories is reduced to four main groups (rather than IAB compatible systems) as depicted in Table I. Although the system was designed to categorize broadband subscribers, it is perfectly suitable to categorize a mobile subscriber's behavior into interest categories. The same approach has been applied to categorize the subscribers in mobile networks. The interested researchers can refer to [5] for further information on how the categorization is employed according to subscriber Internet access trends.

B. *Movement Prediction using Past History and Interest Classes*

The second part of the system is to know about where the subscribers are spending their time. The technological evolution in smart phones has allowed us to track the position of a subscriber with a deviation of couple of meters. The perfect design of a location-aware categorization system shall contain the whole digital map of the locations with the ability to distinguish the category of the location. Geo-location data from several Internet applications such as Foursquare, Gowalla, and Brightkite are very helpful for collecting data about the subscribers. However, since they track the people through social media, and track the registered locations, the nature of the data does not reflect the real world. The movements of the subscribers are categorized by reducing the complexity of the designated prototype. The number of location categories was limited into very clear and distinguishing categories: i) food and beverages, ii) entertainment, iii) shopping, iv) transportation. During the selection of the locations/moves, the literature in the marketing domain is considered. Most of the marketing-based studies consider the study of Bahn [32] to simplify the proposed system.

For every user, the day between 08.00 and 20.00 is divided into time slices of one hour. The visiting frequency of an individual is categorized for every hour, and then the next movement for the individual is estimated using the historical data of that timeframe. The prediction data is generated by using a supervised learning environment, which is called Multilayer Perceptron (MLP) since the success ratio of MLP was higher than the other methods in the literature for location tracking. The MLP system is designed using the Neural Network Library of MATLAB Software. It is used to train a neural network using the previous data for predicting the future behavior of the users. The proposed movement prediction system consists of two components: i) subscriber-based prediction system, and ii) system-wise prediction system.

1) *Subscriber Based Movement Prediction*

Subscriber-based movement prediction algorithm is designed to get the movements and the interest of a subscriber as an input. Then the algorithm returns a prediction about the next move of the subscriber. The algorithm initially assigns ID's for potential actions/locations. In this study, the alternatives were limited to four as depicted in Table I. Table I presents the code assigned to the actions as well.

TABLE I. ACTION/MOVE MAPPING

Action Type	Assigned Code
Food and Beverages	00
Entertainment	01
Shopping	10
Transportation	11

For each subscriber, the action performed was recorded by indicating the starting time, duration, day of the week, and the action code. The Multi Layer Neural Network Model using Back-Propagation algorithm was utilized to predict the next action of the subscribers. The input layer consists of eight neurons indicating the current action and the following action, the hidden layer consists of ten neurons and the output layer consists of two neurons indicating the target action as depicted in Fig. 1. The number of neurons in the input layer describes four consecutive moves of a subscriber since any action was coded by using two bits. The number of hidden layers was taken as advised in the literature. Vintan, Gellert, Petzold, and Ungerer [13] advice to use N, N+1 or N+2 neurons in the hidden layer as N indicates the number of neurons in the input layer. Finally, the number of neurons in the output layer is two in order to define the next move of the subscriber.

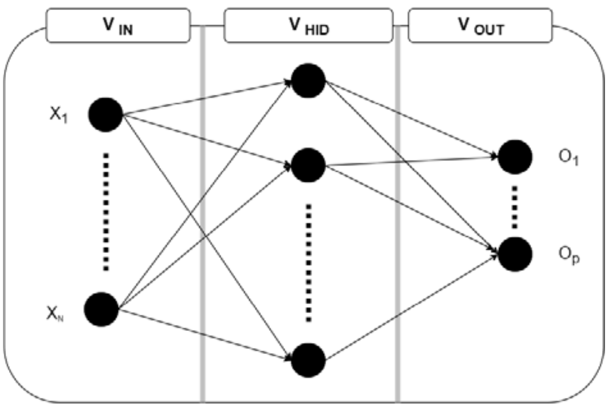

Figure 1. The Neural Network Model for Subscriber Based Predictor

Interestingly, the above neural model concentrates only on the actions (moves) of the subscriber being examined. In order to get more accurate prediction on the movement, the hour of the day, the location, and dominant interests of a subscriber should be provided to the neural network. In order to use the effect of interests in the predictions, the interests should be coded. Since there are only four actions in the prototype system, it is better to reduce the number of interests into four. This enhancement increases the precision of the predictions when there is a need for a decision to select between one of the two values, which are very close to each other in the output layer. Utilizing this method increases the number of input and hidden neurons by the number of bits in the interest categories (two). Similarly, the hour of the day increases each input action by four bits (or more in case of more precise timing constraints), and by three bits for day of the week as well.

2) Global Movement Prediction

Global movement prediction algorithm uses the movements and the interests of all subscribers and gives a prediction for the next move of the targeted subscriber. The method assigns binary codes for every subscriber in the system in order to relate the actions performed to a subscriber. Applying this change to the Neural Network offered in Fig. 1 results in additional bits in the input and hidden layers, as more bits are needed for identifying the individuals. For example, if there are 100 individuals in the system, the number of bits to identify the subscribers is seven. This increases the number of input layer neurons from eight to fifteen and increases the number of hidden layer neurons from ten to seventeen.

The same constraints are valid while increasing the precision of the system in subscriber-based prediction system for Global Movement Prediction System.

C. Data Collection and Analyze

One of the most challenging issues in next move prediction systems is the data collection. The data collection issue becomes more prominent during the cold start (beginning without past movement history).

Algorithm 1 History Aware Next Movement Prediction Algorithm (HANMEA)

$M \longleftarrow$ Set all subscribers
while M is not empty **do**
  For each subscriber u, If a user stays more than 6 minutes in a location, mark it as a check into a location – as offered by Zhang et al. [29]. The same approach is applied in our study.–
  If a user checks in a location (staying more than 6 minutes) within a Wi-Fi scanner in the area the location/move of the subscriber is assigned to be the type of the move.
  If a user checks in a location (staying more than 6 minutes) without a Wi-Fi scanner in the area the location/move of the subscriber is assigned with the following moves to overcome the cold start problems. After the training process is completed, the following timings will not be used often.
  - If a user checks in for more than 20 minutes, then the location of the subscriber is checked and marked as "food and beverages".
  - If a user checks in for more than 60 minutes, then the location of the subscriber is checked and marked as "entertainment" accordingly.
  - If a user spends between 6 and 20 minutes in any one location, it is assumed that the user is "shopping".
  - If a user does not check in, the subscriber is classified as being in a "transportation" either walking or by a vehicle. This option is also selected by the GPS data obtained through smart phones.
  - If the user stays in a location longer than three hours "do not categorize" it.

end while

Figure 2. HANMEA Algorithm in detail

In the described method, there are several alternatives depending on whether a subscriber is checked in or not. In addition, the system should describe the rules in order to differentiate the category of the action. Since the subscribers usually worry about the quota and the service quality of the service taken from the cellular networks, they look for a Wi-Fi base station to connect. By using this idea, a Wi-Fi scanner (which is a typical wireless access point with simply modified firmware) collected and recorded all Wi-Fi connection requests. Since the location of the base station was known, it improved the accuracy of the location categorization of the mobile users.

The offered history-aware next movement estimation categorization system works as described in Fig. 2 on the trace data.

Although the numbers change from a person to another person, the timing selected are taken by averaging the earlier samples taken from the Wi-Fi scanners for the installed locations. By employing prescribed algorithms in order, the interest, location and next move of the subscribers are known by the mobile operator, which would allow them to send respective advertisements to the users.

IV. Experimental Results

In this section, the experiments and the results of the designed system are presented. An android application was developed for volunteers who also accepted to access the Internet through our proxy. The volunteers were selected among the students studying Electronics and Computer Engineering Departments at the Faculty of Engineering. By employing the solution, the locations and Internet access of the subscribers were monitored. The experiments were performed for duration of 15 weekdays (The weekends are not included in this study).

In order to see the effect of the Wi-Fi scanning support, eight Wi-Fi scanners were placed in the major locations visited by the students. For the rest of the locations there were no location classifications before the experiments. After the experiments were performed, the locations were classified into categories to reduce the overhead of categorization of all possible locations.

A. Subscriber Interest Classification

In our experiments, the total number of users was 50. The total page visits for the users was 86,724 giving an average of 115.63 page visits per user. In the experiments, although the number of accessed domains was 1,338, it has been realized that, 72.8% of the requests were to the top 10 domains. The ratio for the top 100 domains was 93.1%. In order to investigate the behavior of the subscribers with different interest categories, the common domains and interests like search engines, similar news pages, etc. were excluded. At the end of the categorization, interest vectors for 50 users were created. As indicated in the previous studies [5-6], it is important to differentiate the subscribers to attract the advertisers. Concentrating on rarely accessed websites and blogs can only capture the difference. This reality has been observed during the calculations performed. Top 25 (most common) domains such as google.com, mail.ru, apple.com, instagram.com were excluded from the interest classifications in order to differentiate subscribers. In addition to the famous sites, search engines and uncategorized domains were also excluded from the database. After performing the purification steps, the number of total page visits during the experiments decreased to 41,312, the number of accessed domains decreased to 978 where the access ratio for top 10 and top 100 domains decreased to 42.83%, and 79.25% respectively.

TABLE II. TOP 5 INTEREST CATEGORIES ACCORDING TO THE NUMBER OF CONNECTIONS AFTER PURIFICATION

Interest Categories	#of visits	Connection Ratio
Technology and Computer	4.273	10.34%
Social Networks	3.164	7.66%
Content Delivery Networks	1.839	4.45%
Online Video/Audio	1.364	3.30%
Games	1.083	2.62%

TABLE III. TOP 5 INTEREST CATEGORIES ACCORDING TO THE PREFERENCES OF THE USERS AFTER PURIFICATION

Interest categories	Assigned Number of Users
Food and Beverages	8
Entertainment	24
Shopping	12

As it is shown in Table II and Table III, the connection ratio and user profile evaluation are clearly visible and easily understood if there will be a chance to perform the experiments. Obviously, the users are focusing on technology-oriented categories as expected when compared with their background. The interest categories in this study are reduced into three categories (plus a transportation case) in order to map them to a move in the proposed system. The interest categories then became almost the same as the moves: i) food and beverages, ii) entertainment, iii) shopping. The volunteers were categorized in one of the above categories as follows:

- *A vector with three entries was created for each user, which are initialized to zero.*
- *For each access by a user the accessed Web page was checked against the category of the vector and the appropriate entry in the interest vector is increased*
- *At the end the ratio of every interest was calculated for every user.*

Table III gives the number of users having the interest threshold values higher than 0.40. During the experiments only the first interests were evaluated. It indicates a category for a subscriber having more interest into it.

TABLE IV. THE NUMBER OF THE STATES FOR THE USERS DURING THE EVALUATIONS OF THE TRANSITIONS

Location Categories	10 days transition #	5 days transition #
Transportation	2.516	1.373
Food and Beverages	1.169	514
Shopping	596	287
Entertainment	535	234

B. Location-Aware Move Prediction

In the next step, the newly offered model has been evaluated. Totally 12 x 15 = 180 hours of actions are evaluated for each individual during the experiments. The total movement estimation assignment seemed to be 7,224. The movement data is split into two. Using the transitions of the first 10 days formed the first part, which was used to train the subscriber movement’s network based on proposed Artificial Neural Network (ANN) system. The remaining data was used to evaluate the correctness of the systems predictions. The summary of the movement data is figured in Table IV.

The proposed Neural Network applied to subscriber data without any day and timing information. There were 8 input-layer, 10 hidden-layer and 2 output-layer neurons in the network. The system converged after 187 iterations. The results of the simple network are listed in Table V.

TABLE V. ACTUAL TRANSITIONS AND THE PREDICTED TRANSITIONS WITH ERROR RATES WITHOUT WI-FI SCANNERS AND SIMPLE NEURAL NETWORK

Location Categories	Actual #	Predicted #	Error Rate
Transportation	1.377	1.247	9.44%
Food and Beverages	514	451	12.26%
Shopping	287	386	25.65%
Entertainment	234	324	27.78%

TABLE VI. ACTUAL TRANSITIONS AND THE PREDICTED TRANSITIONS WITH ERROR RATES WITHOUT WI-FI SCANNERS

Location Categories	Actual #	Predicted #	Error Rate
Transportation	1.377	1.314	4.58%
Food and Beverages	514	472	8.18%
Shopping	287	339	15.34%
Entertainment	234	283	17.32%

After applying the simple Neural Network depicted above, the enhanced model is used from now on. In the advanced model, the day of the week and the time of the event are used for each move. Three bits are used for days, and five bits are used for time of the event. It increases the number of input neurons from eight to forty (40 = 4 x (2 + 3 + 5)), which increases the complexity of the system while it increases the precision of the movement prediction.

The results of the estimations and the real movements without Wi-Fi support are presented in Table VI. The results indicate that the prediction system performs better than 82% for all items accuracy. The main problem in the system is the confusion between "shopping and entertainment" resulting in the increase in the error rate. The results of the same experiments with Wi-Fi support are presented in Table VII. The results indicate that the prediction system performs at a rate of 93% or higher for all accuracy items. Even it can reach up to 99% in prediction of Transportation.

TABLE VII. ACTUAL TRANSITIONS AND THE PREDICTED TRANSITIONS WITH ERROR RATES WITH WI-FI SCANNERS

Location Categories	Actual #	Predicted #	Error Rate
Transportation	1.377	1.362	1.09%
Food and Beverages	514	496	3.51%
Shopping	287	299	4.02%
Entertainment	234	251	6.77%

TABLE VIII. ACTUAL TRANSITIONS AND THE PREDICTED TRANSITIONS WITH ERROR RATES WITH WI-FI SCANNERS BY USING GLOBAL PREDICTION

Location Categories	Actual #	Predicted #	Error Rate
Transportation	1.377	1.343	2.47%
Food and Beverages	514	489	4.86%
Shopping	287	314	8.60%
Entertainment	234	262	10.69%

The experiments are performed for global prediction capability of the system. Global system performance is for anyone just entering to the system. By this way, the effect of cold start problem can be eliminated. The results of the global prediction by the support of Wi-Fi scanners are summarized in Table VIII. The results indicate that the performance is worse than subscriber-based prediction, however it is still promising since it gives an understanding about the whole system and allows the system owners to classify a new subscriber easily.

After predicting the next location with the interest knowledge, more precise advertisements would easily attract the users. Increasing click-rate will directly increase the revenue of the connection service provider.

C. Comparison with the State of The Art

While the proposed model in this study is unique among the state of the art, there are several studies addressing similar problems partially. The study proposed by [11] uses wifi access points to identify the location of the subscribers. They used regularity of the patterns and applied a Markov model to estimate the future actions. In comparison to our proposed model, their estimation success ratio is much lower than what is achieved in this study. In addition, the proposed model in [11] cannot generalize the system and does not propose a solution for new users as well. Besides, no class is defined for the users without any specific interest.

The studies performed in [13] and [14] used the notion of local and global predictors similar to the studies performed in this study. Their approach was to estimate the movement of the people across the rooms within a building. They applied Neural Networks and Markov model in their different studies in order to estimate the next movement. The experiments conducted in [13] and [14] were limited to a small area, and did not consider any feature of the people as well as low success ratio compared with the study proposed in this paper.

The experiments conducted in this study indicated that the awareness of the subscriber profiles and the service taken in the past build a synergy among the next move prediction system and the services to be taken.

D. Scalability of the System

Although the proposed location-aware subscriber movement prediction system gives promising results, we would like to elaborate on the complexity and scalability of the system. As indicated in the experimental results there are 40 input-layer, 42 hidden-layer and 2 output-layer neurons in a subscriber-based prediction system. For the global movement prediction, there are additional subscriber bits (6 in the experiments) adding up to 46 input-layer neurons and so.

For a global mobile operator with 100 million subscribers, thousands (4096) of movements, and more accurate timings, the number of neurons increases to (3 bits for days, 8 bits for timing, 12 bits for movement) 23 x 4 = 92 input layer neurons and so. For the global movement prediction system, there should be 27 more input layer neurons to differentiate the subscribers as well as the number of categories for classification, which will typically increase the number of neurons in the output layer to 6-8.

The event triggering time is dependent on the movement type; however, it is in the order of minutes or more. This timing requirement is achievable when compared with the telecommunication systems intensive to seconds. For running the subscriber prediction system, there is no dependency for different subscriber data. Thus, increasing the number of subscribers improves the number of subscribers served by the mobile operator. On the other hand, for the global movement prediction system, it is a challenging problem to synchronize the output of the system.

The complexity of running such a system is dependent on a couple of parameters. The first parameter is the complexity incurred through the neural network. The second one is the complexity incurred through processing the interest-relativeness/movement update of the subscribers. In the worst-case scenario by design (the precision of the system is taken as a minute), an action is triggered by all subscribers. The complexity of the classification is in the order of O(n) where n is the number of updates. Similarly, the complexity incurred from the neural network is $O(kn^2)$ where n is the number of neurons in input and hidden layers (accepting them almost same) and k is the number of neurons in the output layer.

Since search system and update systems are independent from each other, it enables balancing the load among different systems. In the most contented system the number of operations per minute would be 100 million in interest/movement update while 120x120x8 x 100 million for the prediction system. Although, the computing resources mentioned above seems a bit scary, all computing problems mentioned above can be solved by using Big Data systems in real-time. The computing power and storage requirements of such systems is less than 20 ordinary 1U X86 based servers with 2 Xeon Processors having 14 or more cores each with a storage capacity of less than a TB.

V. CONCLUSION

In this study, the effect of categorizing the subscribers for ad networks was investigated with the knowledge of the location of the subscribers. In addition, a method for predicting the next move of the subscriber without any social media connection is proposed. Categorization of the subscribers brings the ability to advertise to the subscribers according to their locations and interest. For instance, when a subscriber enters a shopping mall, the advertisements would easily be directed to guide him/her to places according to his/her interests. This ability would also allow the service providers to attract the attention of the subscribers to specific places when they are in the vicinity to visit them.

The second and more challenging problem attacked in this study is predicting the next move of a mobile subscriber. Predicting the next move would easily bring guidance to the users for their next shopping, restaurant or entertainment visits. By knowing the interests and the next move preferences, the subscriber would also be directed to a preferred location by the advertiser through promoting the preferred location. As another application area, if a service provider makes an agreement with a brand-new restaurant, it would promote it to the individuals by providing them free Internet access in that place, or could add additional free Internet access to the subscriber's quota, or it would broadcast one of the most famous soccer games, movies or anything popular in the promoted location at no charge.

The results of the study build a framework for mobile operators to start with the monetization efforts to use with advertisement networks. It allows the operators to deliver more precise targeted advertisements and location-aware promotions. It plays in an area where IoT revolution, Big Data and subscriber tracking are effectively used together in order to demonstrate how the applications and services in the future will be.

In the future, the information from social media and exact location information from base station would be aggregated to predict next moves. In addition, the next move of the social media users (subscribers of the mobile service provider) would easily be guided. Bringing the Internet users to real places by manipulating the next move would also increase the indirect revenue of the service providers.

Energy consumption of the devices is another main challenging area in IoT and sensor networks which is directly related with the topic of this study. The energy usage optimization methodologies shall also be considered in future studies.

REFERENCES

[1] P. R. Ltd, "Portio Research Mobile Factbook 2013," Portio Research Mobile Factbook 2013 Report accessed online on August 1, 2015, 2015. [Online]. Available: http://www.portioresearch.com/en/free-mobile-factbook.aspx

[2] R. van der Meulen, "Analysts to explore the value and impact of iot on business at gartner symposium/itxpo 2015, november 8-12 in barcelona, spain."

[3] B. C. Villaverde, R. de Paz Alberola, A. J. Jara, S. Fedor, S. K. Das, and D. Pesch, "Service discovery protocols for constrained machine-to- machine communications." IEEE Communications Surveys and Tutorials, vol. 16, no. 1, pp. 41–60, 2014.

[4] P. K. Verma, R. Verma, A. Prakash, A. Agrawal, K. Naik, R. Tripathi, M. Alsabaan, T. Khalifa, T. Abdelkader, and A. Abogharaf, "Machine- to-machine (m2m) communications: A survey," Journal of Network and Computer Applications, vol. 66, pp. 83–105, 2016.

[5] K. Oztoprak, "Profiling Subscribers According to Their Internet Usage Characteristics and Behaviors," in Proceedings of the IEEE Big Data. IEEE, 2015, pp. 1492–1499, Santa Clara, October 2015.

[6] K. Oztoprak, "Subscriber Profiling for Connection Service Providers by Considering Individuals and Different Timeframes," IEICE Transactions on Communications, vol. 99, no. 6, 2016.

[7] X.Chang, Y.Yi, Y.Lingyun, S.Purui,and F.Dengguo,"Automated User Profiling in Location-Based Mobile Messaging Applications," in Trust, Security and Privacy in Computing and Communications (TrustCom), 2014 IEEE 13th International Conference on. IEEE, September 2015, pp. 18–26.

[8] P. Burge and J. Shawe-Taylor, "An Unsupervised Neural Network Approach to Profiling the Behavior of Mobile Phone Users for Use in Fraud Detection," Journal of Parallel and Distributed Computing, vol. 61, no. 7, pp. 915–925, 2001.

[9] P. Loskot, M. A. M. Hassanien, F. Farjady, M. Ruffini, and D. Payne, "Long-term drivers of broadband traffic in next-generation networks," Annals of Telecommunications - Annales Des Télécommunications, vol. 70, no. 1-2, pp. 1–10, 2014.

[10] J. Ghosh, M. J. Beal, H. Q. Ngo, and C. Qiao, "On Profiling Mobility and Predicting Locations of Wireless Users," International Workshop on Multi-hop Ad Hoc Networks: from Theory to Reality, pp. 55–62, 2006.

[11] S. Lee, J. Lim, J. Park, and K. Kim, "Next place prediction based on spatiotemporal pattern mining of mobile device logs," Sensors, vol. 16, no. 2, p. 145, 2016.

[12] "Open RTB API Specifications v2.3.1, accessed online on August 1st of 2016," The Interactive Advertising Bureau (IAB) Web Site, 2015. [Online]. Available: http://www.iab.net/

[13] L. Vintan, A. Gellert, J. Petzold, and T. Ungerer, "Person movement prediction using neural networks," Technical Report of University of Augsburg, vol. April, no. 10, 2004.

[14] A. Gellert and L. Vintan, "Person Movement Prediction Using Hidden Markov Models," Studies in Informatics and Control, vol. 15, no. 1, pp. 17–30, 2006. [Online]. Available: http://webspace.ulbsibiu.ro/arpad.gellert/html/SIC_HMM.pdf

[15] S. Akoush and A. Sameh, "Mobile user movement prediction using bayesian learning for neural networks," Proceedings of the 2007 international conference on Wireless communications and mobile computing - IWCMC '07, p. 191, 2007. [Online]. Available: http://dl.acm.org/citation.cfm?doid=1280940.1280982

[16] N.Phamand, T.Cao, Knowledge and Systems Engineering: Proceedings of the Fifth International Conference KSE 2013, Volume 1. Cham: Springer International Publishing, 2014, ch. A Spatio-Temporal Profiling Model for Person Identification, pp. 363–373. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-02741-8_31

[17] L. Cortesão, F. Martins, A. Rosa, and P. Carvalho, "Fraud Management Systems in Telecommunications: a practical approach," in Proceeding of 12th International Conference on Telecommunications, 2005, pp. 167– 182.

[18] M. Lin, H. Cao, V. Zheng, K. C.-c. Chang, and S. Krishnaswamy, "Mobility Profiling for User Verification with Anonymized Location Data," in Proceedings of the 24th International Conference on Artificial Intelligence. AAAI Press, 2015, pp. 960–966.

[19] C. S. Hilas and J. N. Sahalos, "User profiling for fraud detection in telecommunication networks," 5th International Conference on Technology and Automation, pp. 382–387, 2005.

[20] M. M. Ko and M. M. S. Thwin, "Anomalous Behavior Detection in Mobile Network," in Genetic and Evolutionary Computing. Springer International Publishing, 2015, pp. 147–155.

[21] J. H. Schumann, F. von Wangenheim, and N. Groene, "Targeted Online Advertising: Using Reciprocity Appeals to Increase Acceptance Among Users of Free Web Services," Journal of Marketing, vol. 78, no. 1, pp. 59–75, 2014.

[22] H.Haddadi, P.Hui,and I.Brown, "MobiAd: private and scalable mobile advertising," Proceedings of the fifth ACM international workshop on Mobility in the evolving internet architecture, pp. 33–38, 2010.

[23] I. Ullah, R. Boreli, M. A. Kaafar, and S. S. Kanhere, "Characterising user targeting for in-app mobile ads," in Computer Communications Workshops (INFOCOM WKSHPS), 2014 IEEE Conference on. IEEE, 2014, pp. 547–552.

[24] H. Fujimoto, M. Etoh, A. Kinno, and Y. Akinaga, "Web user profiling on proxy logs and its evaluation in personalization," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 6612 LNCS, pp. 107–118, 2011.

[25] G.Castellano,A.M.Fanelli, C.Mencar, and M.A.Torsello,"Similarity-Based Fuzzy Clustering for User Profiling," 2007 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology - Workshops, pp. 75–78, 2007.

[26] K. Makvana and P. Shah, "A novel approach to personalize web search through user profiling and query reformulation," in Data Mining and Intelligent Computing (ICDMIC), 2014 International Conference on. IEEE, 2014, pp. 1–10.

[27] M.D.Hall and N.Kanar, "Method delivering location-base targeted advertisements to mobile subscribers," US Patent: US7027801 B1, 2006.

[28] J. Wilson, C. Kachappilly, R. Mohan, P. Kapadia, A. Soman, and S. Chaudhury, "Real World Applications of Machine Learning Techniques over Large Mobile Subscriber Datasets," arXiv:1502.02215 [cs], pp. 1–9, 2015.

[29] Z. Zhang, L. Zhou, X. Zhao, G. Wang, Y. Su, M. Metzger, H. Zheng, and B. Y. Zhao, "On the validity of geosocial mobility traces," in Proceedings of the Twelfth ACM Workshop on Hot Topics in Networks - HotNets-XII, 2013, pp. 1–7.

[30] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, "Mining user mobility features for next place prediction in location-based services," Proceedings - IEEE International Conference on Data Mining, ICDM, no. April, pp. 1038–1043, 2012.

[31] B. Zheng, K. Thompson, S. S. Lam, S. W. Yoon, and N. Gnanasambandam, "Customers' Behavior Prediction Using Artificial Neural Net- work," IIE Proceedings of the 2013 Industrial and Systems Engineering Research Conference, pp. 700–709, 2013.

[32] K. D. Bahn, "Characterizing Consumer Interest Through the Use of Canonical Correlation: Application for Small Business," in Proceedings of the 1982 Academy of Marketing Science (AMS) Annual Conference Part of the series Developments in Marketing Science, 1982, pp. 519– 524.