

Location Prediction in the Long Term Evolution Network using ST-RNN and Markov Model

E. Akinola

S. S. Daodu

ABSTRACT

Location prediction has received a great attention in research due to its application in diverse areas. Its usage is found in courier firms, taxi companies, detective organizations and advert placement firms. These organizations are challenged with some issue of concerns such as not been able to capture semantic information and also keeping track of mobile users movement. This work focuses on the use of a Spatio- Temporal Recurrent Neural Network (ST-RNN) and a machine learning model known as the Markov Model (MM) to predict a users' location. This work provides solution to the obvious challenges of past works by developing an efficient and robust model for location prediction. Sequel to the adoption of the aforementioned techniques, preprocessing of the dataset was done by removing the irrelevant features from the datasets, separating the time and the date that were initially merged in the raw dataset and formatting the longitude and latitude columns into the required format. Consequently this system combines the strength of STRNN and Markov Model for predicting user's location; the experimental results yielded a high level of accuracy, took less computational time as well as a reduced system error rate. System evaluation using computational time, root mean square error, prediction accuracy and mean square error of the system when compared with other state of the art technique revealed that combining ST-RNN with Markov Model produced a model with a higher level of accuracy.

Keywords

Location, Prediction LTE, ST-RNN, Markov Model

1. INTRODUCTION

Over the years there has been a great revolution in the generations of mobile networks. Mobile network has greatly evolved and this has led to an increase in its usage. Its revolution has effectively touched virtually all areas in various sectors of life ranging from health sector, office, entertainment industry, educational sector etc. There has been a considerable increase in the number of mobile devices along with the use of wireless communication and a rapid development of location based social networks which collects a large amount of individual movement data. The ability of exactly predicting user's future location could provide more natural and customized services for Location based applications. Generally individual movement data consists of a series of geographic coordinated points stamped with time (Zheng 2015). The predicted movement can then be used to increase the efficiency of location prediction. By using the predicted movement, the system can effectively allocate resources to the most probable to move cells instead of blindly allocating excessive resources in the cell neighborhood of a mobile user.

Cellular network has evolved significantly from 1G to 4G. 4G is referred to as an all internet protocol (IP) packet switched network, mobile ultra-broad band (gigabit) speed access and multi carrier transmission access (Bhalla and Bhalla 2010). The 4G network which is also known as Long Term Evolution (LTE) is considered as the evolution of universal mobile telephone

system (UMTS). LTE is completely an all IP based system. Since there are provisions in LTE for inter-operation with existing systems, there are various paths available to connect to LTE. An operator with a GPRS/EDGE network or a non-3GPP system can connect to a LTE network. Due to this increased flexibility, LTE is the choice of majority of operators worldwide. By using Orthogonal Frequency Division Multiple Access (OFDMA), LTE will be able to provide download rates of about 100 Mbps for multi-antenna (2x2), multiple-input multiple output (MIMO) for the highest category terminals. For these terminals upload rate is about 50 Mbps. Moreover, it provides better mobility, efficient radio usage, high level of security, flexible spectrum utilization, reduced delay/latency, cost efficient deployment and various other advantages which make LTE more reliable and user friendly.

There are several advantages of the use of LTE in data collection and some of these advantages include high spectral efficiency, easy to have internet access and very low latency amongst others.

Markov model uses a discrete stochastic process which are used for future state prediction. It can also be described as a memory less system that the future state depends on the current state and it is also independent of the past state (Shakraih 2013). ST-RNN is a variant of Recurrent Neural Network which is used in this research because it incorporates the concept of space and time features into the model. Different methods or approaches have been studied for location prediction. There are also numerous research that has been done on location prediction.

Bahl et al. (2000), were able to predict a user location with the use of Radar. An RF tag was used to locate a user within a building. The methodology involved creating a database of locations in the building called Radio Map which include records of the estimated signal strength of the beacons emanating from the access points (APs) at the locations. The model locates the position of the mobile user by measuring the signal strength of each APs within range. It then searches through the Radio Map database using an algorithm called Nearest Neighbor in Signal Space (NNSS) to determine the signal strength tuple that best matches the signal strengths it has measured. Matthew et al. (2012) predicted a user location with the use of Markov Model and LZ algorithm which are domain independent algorithms. The authors were able to group the users based on their mobility pattern and also their spatio-temporal characteristics. Although the authors were focused on location prediction, this work also was used to determine which method has the highest level of prediction accuracy and also to determine the one that consumes less energy and resources. For the Markov Family, The order-k Markov predictor is independent of time, and it assumes that the current location depends only on the previous k movements and for the LZ family, the algorithms of LZ family are often used for text compression; they are able to make real time predictions and do not need many resources.

The authors also were able to extend Recurrent Neural Network (RNN) and propose a novel method called Spatial Temporal Recurrent Neural Networks (ST-RNN) which can model local

temporal and spatial contexts in each layer with time-specific transition matrices for different time intervals and distance-specific transition matrices for different geographical distances. Considering distance information is an essential factor for location prediction, in this model, geographical distance and time between locations were modeled into the conventional RNN. Time-specific transition matrices and distance-specific transition matrices for different geographical distances between locations were used in this model. Distance-specific transition matrices used in this model capture geographical properties that affect human behavior.

Matthew et al. (2012) clustered location histories according to their characteristics for location prediction of a user. The authors employed the use of the Hidden Markov Model to predict user's location. The initial clustering of sequence is based on the temporal period associated to the last place visited in the sequence in order to group sequences accordingly. A maximum length of 25 different locations visited and a minimum length of 10 locations were kept and this method gives a prediction accuracy of 13.85% when considered over a region of 1280 square meters.

Gambs et al 2012 authors designed a novel algorithm called the n-MMC which is an extension of a mobility model which was used for the prediction of a user location. This algorithm was able to incorporate into the Mobility Markov Chain (MMC) the number (n) of the previous visited locations which gave birth to the n-MMC model used. Although this research was the unable to introduce more explicitly the notion of time in the constructed Mobility Markov chain which reduced the prediction accuracy of the model, it was able to keep track of the n previous locations visited.

2. METHODOLOGY

Network dataset chosen for the analysis and evaluation of the proposed system is a 4G LTE dataset with channel and context metrics. It is an LTE network dataset which is composed of client-side cellular key performance indicators (KPIs) with 135 traces. Commute traces used for the dataset were collected during morning to evening hours while going from home and back to work. Traces of the dataset are categorized into Bus, Train, Pedestrian, Car and Static but Static was not used in this research. The dataset is split into training set (80%) and test set (20%), where the training set is used to build the model, the testing set is used to evaluate the performance of the system.

The need for data preprocessing ensued from the fact that the proposed system is expected to handle very large network dataset containing redundant, irrelevant, and unscaled features which could affect classification rate and also increase the system processing time. The data preprocessing step is responsible for selecting relevant features that are appropriate for location prediction and also formatting the relevant columns into a usable format.

2.1 Markov Model

The Markov model used is the order-k (or "O(k)"). This model assumes that the location can be predicted from the current context, that is, the sequence of the k most recent symbols in the location history ($a_{n-k+1} \dots a_n$).

A user's location history in this model is denoted by $L = a_1, a_2 \dots a_n$ (1)

A substring $L(i, j) = L(i, j) = a_i, a_{i+1} \dots a_j$ for an $1 \leq i \leq j \leq n$. is created. The user's location is denoted as a random variable X.

Let $X(i, j)$ be a string $X_i X_{i+1} \dots X_j$ representing the sequence of random variables $X_i, X_{i+1} \dots X_j$ for any $1 \leq i \leq j \leq n$

The context $c = L(n - k + 1, n)$ is defined. Let A be the set of all possible locations. The Markov assumption is that X behaves as follows, for all $a \in A$ and $i \in \{1, 2, \dots, n\}$.

$$P(X_{n+1} = a | X(1, n) = L) \quad (2)$$

$$= P(X_{n+1} = a | X(n - k + 1, n) = c) \quad (3)$$

$$= P(X_{i+k+1} = a | X(i + 1, i + k) = c) \quad (4)$$

The notation $P(X_i = a_i \dots)P$ denotes the probability that X_i takes the value a_i .

Coordinates of serving eNodeBs and distance between them was calculated using Haversine formula expressed in the equation below

$$d = 2r \sin^{-1} \left(\sqrt{\sin^2 \left(\frac{\varphi_2 - \varphi_1}{2} \right) + \cos(\varphi_1) \cos(\varphi_2) * \sin^2 \left(\frac{\lambda_2 - \lambda_1}{2} \right)} \right) \quad (5)$$

where r is earth radius (6371 km), φ is latitude, and λ is longitude.

2.2 Recurrent Neural Network Classification

RNN consists of the input nodes, hidden layers, and the output layers, such that the hidden layers have connections back to themselves, thereby allowing the states of the hidden layers at one time step to be used as input to the hidden layers at the next time step.

In the context of this research, the RNN model is to predict or classify a class label at each time step. That is the model reads an input S_t , update its hidden state h_t , and produce an output c_t which is the predicted class label at each time step t .

The test set is then modelled into the ST-RNN using the formula in equation (6) below

$$h_{t,q_t}^u = f \left(\sum_{q_{t_i}^u \in Q; 0 < t_i < t} (S_{q_{t_i}^u - q_{t_i}^u} * T_{t-t_i} * q_{t_i}^u) + Ch_b^u \right) \quad (6)$$

where $h_b^u = h_0$ denotes the initial status which is constant as any behavioural information for personalized prediction does not exist before. The final prediction can be calculated through the inner product of user and item representation (Liu et al., 2016).

Due to the fact that ST-RNN models encounters data sparsity problems, a distinct matrix was learnt for each possible continuous time interval and geographical distances. Time interval and geographical distance is partitioned into discrete bins respectively.

2.3 Transition Probability Matrix

Each Markov chain prediction model has transition matrix tables that are generated from the Markov chain algorithm. A transition matrix table shows the entire probability distribution of the Markov chain prediction model. With transition matrix tables it becomes possible to evaluate the accuracy of the prediction of the future state of a mobile device.

3. RESULTS

In this model both techniques used are evaluated with the same

performance metrics. The model was simulated using MATLAB. Data collected was merged into a master file as the data collected were collected daily and it was stored differently. Simulation is done after the preprocessed data is inputted into the system. Simulation of the preprocessed datasets shows how the actual data is been matched using both prediction techniques. The merged file is now converted into a MATLAB file from the excel format it was collected with. The model can be used based on the metric that is of utmost importance to the user. Evaluation in this model is done using the four (4) different mobility patterns which are car, bus, train and pedestrian.

Table 1: Prediction Evaluation for Bus Dataset

Model	Comp Time (Secs)	Prediction Accuracy (%)	Root Mean Squared Error	Mean Absolute Error
Markov	54	97.54	0.024522	0.01827
STRNN	279	99.47	0.005337	0.004252

When the preprocessed datasets is run in the model using the two techniques, the above results are gotten. For this dataset, Computational time for the markov model is short as compared to that of ST-RNN which is to say that using Markov model for this dataset is faster, If time is of utmost priority to the user, using Markov model for location prediction of a particular user will be recommended. The Prediction Accuracy for this dataset using Markov model is lower as compared to that of ST-RNN, for this model using ST-RNN gives a more accurate prediction rate. If the user of the model desires to get a more accurate result, ST-RNN is recommended for that purpose. Error computation for this model using Root Mean Squared and Mean Absolute Error are lower when ST-RNN is used as compared to when Markov Model is used. Using ST-RNN in this model gives a relatively low error rate than when Markov Model is used.

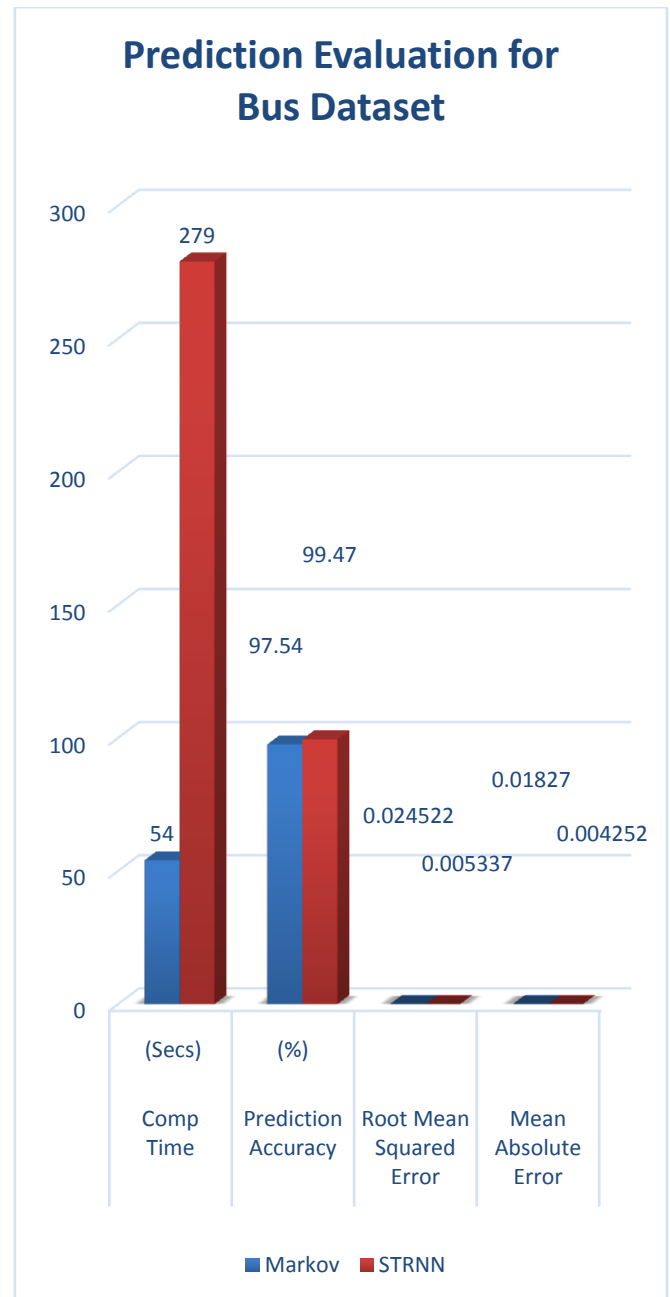


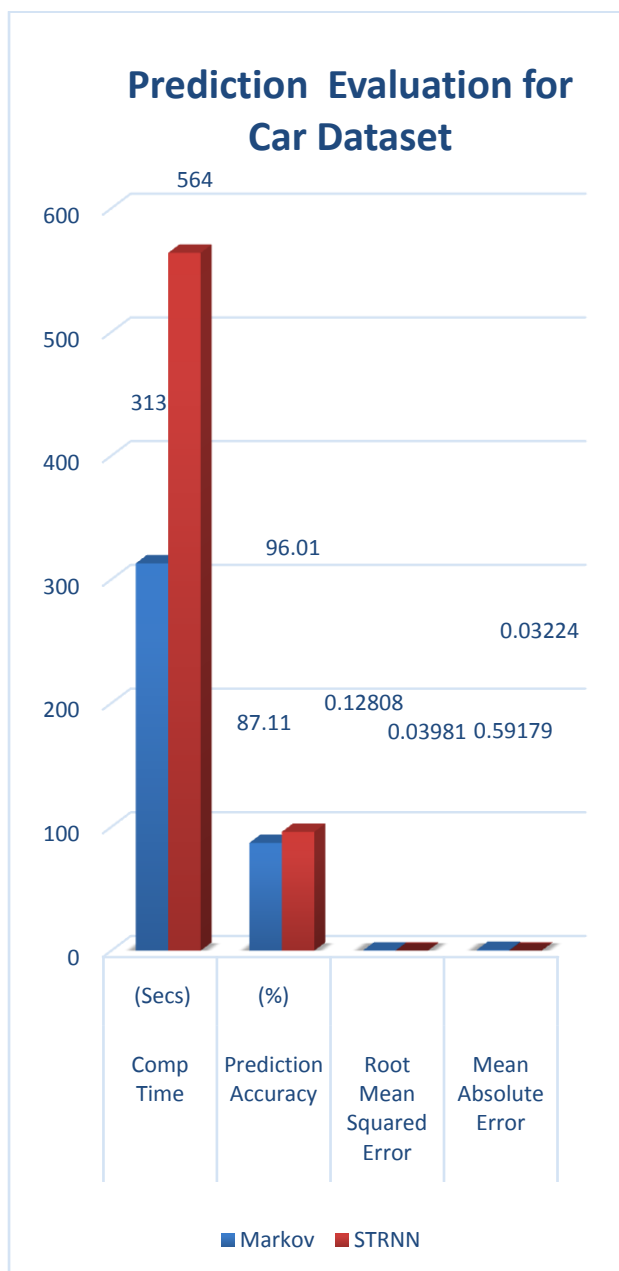
Table 2: Prediction Evaluation for Car Dataset

Model	Comp Time (Secs)	Prediction Accuracy (%)	Root Mean Squared Error	Mean Absolute Error
Markov	313	87.11	0.12808	0.59179
STRNN	564	96.01	0.03980	0.03224

When the preprocessed datasets is run in the model using the two techniques, the above results are gotten. For this dataset, Computational time for the markov model is shorter as compared to that of ST-RNN which is to say that using Markov model for this dataset is faster, If time is of utmost priority to the user, using Markov model for location prediction of a particular user will be recommended.

The Prediction Accuracy for this dataset using Markov model is lower as compared to that of ST-RNN, for this model using ST-RNN gives a more accurate prediction rate. If the user of the model desires to get a more accurate result, ST-RNN is recommended for that purpose. Error computation for this model using Root Mean Squared and Mean Absolute Error are lower when ST-RNN is used as compared to when Markov Model is used. Using ST-RNN in this model gives a relatively low error rate than when Markov Model is used.

Using the train mobility pattern dataset showed that Speed is of utmost importance in this research as it affects the results of the computational metrics used. The effect of speed on this research reflects on each performance metric used. The percentage of the accuracy of the model reduced a great deal which makes the model less accurate and also less efficient as it took a longer time to compute, which means that the running time of the model was longer. Also observed in this research when using the pedestrian dataset, the results showed that the accuracy of the model increased and the error rate was also minimal.



4. EVALUATION OF THE MODEL

In this section, evaluation of the performance of this models was done, namely, MM and ST- RNN. For each experiment, Training and test sets were split into 80% and 20% respectively. First, we study the effect of the order of Markov model by varying order from 1 to 5. Respectively for each dataset, different parameters were set for the models: MM (cluster number $K_c = 5$), ST-RNN (Epoch = 1000, batch size = 500, RNN_size =50, Learning rate = 0.001, Number of layers = 4, Relu size = 20)

Since the values of cluster number, learning rate are estimations, we vary them in a range to obtain more comprehensive performance evaluation. The values used here are the values that gave the best evaluation results.

5. CONTRIBUTION

This work has been able to proffer a method with which location of individuals can be predicted easily with a high level of accuracy and a low error rate. With the use of this method, Courier firms can predict the location of their staff and also the items billed for deliveries,

Taxi companies can predict and track their vehicles by noting their routes and trajectories for the day.

6. REFERENCES

- [1] Bahl, P. Padmanabhan, V.N., and Balachandran, A(2000) Tracking System, Microsoft Research, 2 (MSR-T)
- [2] Bhalla, M.R. and Bhalla, A.V (2010). Generations of mobile wireless technology: A Survey. International Journal of Computer Applications, 5(4)
- [3] Gambs, S., Killijan, M.O., and Prado Cortez, M.N. (2012, April). Next Place prediction using mobility markov chains. In Proceedings of the First Workshop on Measurement, Privacy, and Mobility (p.3). ACM.
- [4] Herder, E., Siehndel, P., and Kawase, R. (2014, July). Predicting User Locations and Trajectories in International Conference on User Modeling, Adaptation, and Personalization (pp.86-97). Springer, Cham
- [5] [Liu, Q., Wu, S., Wang, L., and Tan, T. (2016). Predicting the Next Location: A Recurrent Model with Spatial and Temporal Contexts. In AAAI (pp. 194-200).
- [6] Mathew, W., Raposo, R., and Martins, B. (2012). Predicting future locations with hidden Markov models. In *Proceedings of the 2012 ACM conference on ubiquitous computing* (pp. 911-918). ACM.
- [7] Skariah, E. (2013). Mobile Phone Context Prediction Using Markov Chains.
- [8] Szalka, T., Szabo, S., and FÜLÖP, P. (2009). Markov model based location prediction in wireless cellular networks. *Infocommunications Journal*, 40.
- [9] Qiao, Y., Yang, J., He, H., Cheng, Y., & Ma, Z. (2016). User location prediction with energy efficiency model in the Long Term Evolution network. *International Journal of Communication Systems*, 29(14), 2169-2187.
- [10] Zheng, Y., Zhang, L., Xie, X., and Ma, W. Y. (2009). Mining interesting locations and travel sequences from GPS trajectories. In *Proceedings of the 18th international conference on World wide web* (pp. 791-800). ACM.