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An Augmented UCAL Model for Predicting Trajectory and Location

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Abstract**:** *Predicting human mobility between locations plays an important role in a wide range of applications and services such as transportation, economics, sociology and other fields. Mobility prediction can be implemented through various machine learning algorithms that can predict the future trajectory of a user relying on the current trajectory and time, learning from historical sequences of locations previously visited by the user. But, it is not easy to capture complex patterns from the long historical sequences of locations. Inspired by the methods of the Convolutional Neural Network* (*CNN*)*, we propose an augmented Union ConvAttention-LSTM* (*UCAL*) *model. The UCAL consists of the 1D CNN that allows capturing locations from historical trajectories and the augmented proposed model that contains an Attention technique with a Long Short-Term Memory* (*LSTM*) *in order to capture patterns from current trajectories. The experimental results prove the effectiveness of our proposed methodology that outperforms the existing models.*

Keywords**:** *Deep learning, LSTM, attention mechanism, human mobility prediction location, trajectory.*

1. Introduction

Predicting user activity and location preferences is very important in location-based services and in the understanding of the human mobility [1-4]. Predicting mobility plays an important role in many areas. For example, tourism businesses would like to know the journey characteristics of their customers in order to design appropriate advertising strategies. Sociologists have conducted extensive research on migration in order to identify the general characteristics of human mobility. Police also strive to determine the future location of a criminal fleeing a crime scene. In addition to these examples, the prediction of the user's location mobility is used in traffic problems. City transport is important for everyday life and many people go to work using different means of transport which causes traffic jams during rush hours. Predicting the location of an accurate mobility can help plan routes, vehicles distribution, reduce congestion and transfer frequency, which leads to improved urban traffic management [5, 6].

The prediction of users' movements [7] is governed by their complexity. Indeed, these movements are characterized by a regular appearance for some users, but random for others depending on certain parameters such as travel period (day week, weekend, vacation, etc.), as well as kind of person who travels (student, wage earner, senior citizen, etc.). It should be noted that users' movements are often underlain by socio-economic needs and are governed by the road's topography and infrastructure as well as the different amenities provided in the location area, such as: schools, factories, supermarkets, highways, etc.

To model the human mobility behaviour, several information sources such as mobile phones data [8] and Location Based Social Networks (LBSNs) can be exploited. Common LBSNs, like Foursquare and Twitter, for instance, can provide the number and type of activities existing in a target area, giving an insight on the number of people who are likely to visit that zone. In human mobility, the most straightforward way to predict the next location is to build a grid over an area of interest, then treat the problem as a multiclass classification one, where the aim is to predict the next visited cell. In this context, many works have focused on collecting the users' locations and learning their mobility patterns as achieved in [9-16].

Recently, with the introduction of deep learning neural networks like the Recurrent Neural Network (RNN) based methods, many research efforts [17-19] have been made in the prediction of the next location. However, the results of these efforts have not been flawless since the prediction of human mobility is difficult due to the sparsity and heterogeneity of the data and the complex mobility patterns of historical trajectories.

As a solution, the authors in [20] propose the Union ConvGRU Net (UCG) for modelling trajectory and human mobility prediction based on historical and current trajectory. The CNN architecture is used to track historical trajectory with long sequences of locations. While, the Gated Recurrent Unit (GRU) architecture focus on sequential transitions of a current trajectory.

From the above works, it is clear that the prediction of a trajectory does not give the best accuracy since a great deal of information is generally neglected. To improve the results accuracy and obtain a better performance than previous works, the attention mechanism is used. This mechanism makes it possible to focus on specific parts of complex data and therefore does not neglect any piece of information. In our case, it leads to produce a score for each element of the current input and focuses only on particular information from the summary of the inputs.

Previous works use the attention mechanism with the LSTM model for establishing a historical trajectory. However, the historical trajectory length of each user cause the LSTM to generate poor performances and results in the inability of the mechanism to proceed with long sequences directly due to the vanishing gradient [19].

For these reasons, we propose as a solution, the use of the attention mechanism combined with the LSTM for long or complex sequences in a current trajectory. In this case, an augmented model called Union ConvAttention-LSTM (UCAL) has been developed. This model consists of two parts. The first introduce the same existing 1D CNN that allows defining the locations from historical trajectories with short locations sequences as proposed in [20]. The second part suggests a new proposed model that contains an Attention technique combined with the LSTM in order to capture and predict the future locations based on the current ones.

The remaining of this paper is structured as follows: Section 2 reviews the related works on human mobility. Section 3 summarizes our methodology based on the attention mechanism with the LSTM to capture locations from current trajectories. Section 4 is devoted to the experimental results and discussion. A comparison with the achieved results in the literature is also provided. The last section draw the main conclusions and suggests some future perspectives.

2. Related works

The increasing availability of trajectory recordings has led to the mining of a massive amount of historical track data, allowing for a better understanding of travel behaviours. In the context of human mobility analysis, the problem of next location prediction assumes a central role and is beneficial for a wide range of applications such as personalized services or targeted recommendations. This prediction may suffer from certain drawbacks due to long and complex trajectories.

As a solution, many existing research efforts have been invested in the recognition and prediction of human mobility patterns like neural network-based methods [17-19, 21-27].

LSTM and GRU are specifically the most commonly used architectures.

In [17], authors propose a Spatial Temporal RNN (ST-RNN) for the future prediction locations. Their experimental results show that the proposed ST-RNN model yields significant improvements over the competitive comparable methods on two typical datasets, i.e., Global Terrorism Database (GTD) and Gowalla dataset.

In [18], authors propose a Semantic-Aware Recurrent Model (SERM) that use the sequential and semantic influence for the next trajectory prediction. Experiments on two real-life semantic trajectory datasets show that the SERM achieves significant improvements over state-of-the-art methods.

More recently, Feng et al. [19] has proposed a DeepMove model to capture the multi-level periodicity of historical trajectory based on the attentional mechanism. Experiments on three representative real-life mobility datasets, and extensive evaluation results demonstrate that DeepMove model outperforms the state-of-the-art models by more than 10%. Moreover, compared to the state-of-the-art neural network models, DeepMove provides intuitive explanations into the prediction and sheds light on interpretable mobility prediction.

Since the complication of the DeepMove, the authors in [24] use a generative probabilistic model together with neural network and propose a VANext to improve it. They are the first to integrate CNN to capture long human trajectories with

Graphics Processing Unit (GPU). The experiments conducted on real-world datasets prove that VANext and VANext-S outperform the state-of-the-art human mobility prediction models.

The framework of UCG Net, in [20], uses a 1D CNN to capture the user mobility from historical trajectory. First, to capture short patterns of trajectory locations, they use a Multi-Layer Perceptron (MLP) to integrate the hidden states and encode them with a convolutional layer. Then, they use an FC layer to capture locations of separated hidden states. Finally, they generate long sequences of locations with a Max Pooling layer and concatenate them as inputs of a current trajectory learning Module. The last uses the GRU architecture. The experiments have proven that the UCG model performs best compared with other architectures.

3. Methodology

To obtain better results for the long complex sequence of locations from current trajectories, an augmented model called Union ConvAttention-LSTM (UCAL) net was proposed (Fig. 1). Its architecture consists of the embedding layer, 1D CNN, Attention mechanism, LSTM, Concat and FC layers and the predicted trajectory with Softmax layer and a set of locations C.

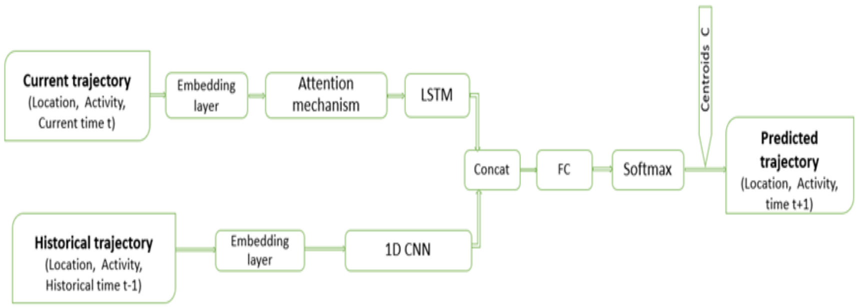

Fig. 1. Global architecture

Embedding layer. The current and historical trajectories have been presented by three features: location, activity and time. However, these features are categorical. So, we have modelled the features with a dense representation vector [28] based on an embedding layer.

1D CNN. In this work, we have used the same model 1D CNN as in [20].

Attention mechanism. It has been applied to a very wide range of applications, such as speech recognition [29], machine translation [30], text summarization [31], and image description [30]. This mechanism has been successfully used also for human mobility [19], in order to capture the important periodicities that govern human movements [29, 33]. The aim of the attention module is to learn which part of the trajectory is more important to focus on. This has been achieved by transposing the input and feeding it to a dense layer as softmax, which estimates the weight distributions that are then combined with the input sequence.

Algorithm. Attention (timestamp, features)
Input: Timestamp, features
Output: Weighted output sequence
For each t ∈ timestamp, f ∈ features
Input (t, f)
Dense layer (t, f)
Multiplication (Input (t, f), Dense layer(t, f))
End for

LSTM. Recurrent Neural Networks are dedicated to sequential data processing. LSTM is an artificial RNN algorithm used in the deep learning. LSTM networks are applied in many fields like classifying, processing and making predictions based on time series data. Therefore, the details of our LSTM unit with forget gates are the following:

Input: The LSTM unit takes the current input vector denoted by x_t and the output from the previous time step (through the recurrent edges) denoted by h_{t-1}. The weighted inputs are summed and passed through tanh activation, resulting in z_t (1).

Input gate: Is calculated by taking the x_t and h_{t-1}, computing the weighted and applying the sigmoid activation. The result is multiplied with the z_t (2).

Forget gate: Is the mechanism through which an LSTM learns to reset the memory contents when these are no longer relevant. This may occur for example when the network starts processing a new sequence. Given x_t and h_{t-1} a sigmoid is applied to compute the inputs weights. The result f_t is multiplied by the cell state at a previous time step, i.e., s_{t-1} which allows erasing the memory content which is no longer needed (3).

Memory cell: The current cell state s_t is computed by forgetting irrelevant information from the previous time step and accepting relevant information from the current input (4).

Output gate: Is calculated by taking the weighted sum of x_t and h_{t-1} and applying the sigmoid activation function (5).

Output: h_t is calculated by applying the tanh function on s_t and multiplying with the o_t which is given by Equation (6).

Therefore, the LSTM is represented by the following set of equations:

(1) $$z_t = \tanh(W_z x_t + R_z h_{t-1} + b_z),$$
(2) $$i_t = \text{sigmoid}(W_i x_t + R_i h_{t-1} + b_i),$$
(3) $$f_t = \text{sigmoid}(W_f x_t + R_f h_{t-1} + b_f),$$
(4) $$s_t = z_t . i_t + s_{t-1} . f_t,$$
(5) $$o_t = \text{sigmoid}\ (W_o x_t + R_o h_{t-1} + b_o),$$
(6) $$h_t = \tanh(s_t) . o_t,$$

with W_z, W_i, W_f, W_o are input weights, the R_z, R_i, R_f, R_o are recurrent weights and b_z, b_i, b_f, b_o are the biases.

Concat and FC layers. In this work, concat layer focuses on concatenation of the outputs of LSTM and 1D CNN to capture mobility regularities from the historical and current trajectories. Afterward, the output of this layer is fed into a fully connected layer to capture patterns of separated hidden states.

Predicted trajectory. The prediction module is the last step of our proposed algorithm. In fact, it resembles the results of the previous modules and closes the prediction stage. In particular, it is structured with a softmax layer and a linear layer. Having a number of neurons which is equal to the number of clusters C, the softmax layer takes the representation generated by the FC layer as its input and generates P_i which represents the softmax probability associated to each cluster defined by

(7) $$P_i = \frac{\exp(e_i)}{\sum_{j=1}^{C} \exp(e_j)}.$$

Based on the softmax layer, an additional output layer with one neuron that represents the predicted trajectory is added. Therefore, its output y is given by the probability distribution over all the clusters given by

(8) $$y = \sum_{i=1}^{C} P_i c_i.$$

4. Experimental configuration

The main objective set for this research work is to tackle the problem of predicting long and complex trajectories. To validate our study, in this section the used dataset and the evaluation metrics are detailed.

4.1. Dataset

The Foursquare dataset [34] consists of check-in data for different cities. One subset contains check-ins in NYC and Tokyo collected over a period of about 10 month (from 12 April 2012 to 16 February 2013). It contains 227,428 check-ins in New York city and 573,703 check-ins in Tokyo. Each check-in is associated with its time stamp, its GPS coordinates and its semantic meaning (represented by fine-grained venue-categories). 80% of the datasets has been used for the training and 20% for the testing set.

4.2. Evaluation metrics

Several evaluation metrics are defined to evaluate the efficiency of a recommender. The recommender system produces an item ranking list. Therefore, it is necessary to consider how to measure directly the quality of the ranking instead of using other proxy measures.

For example, precision is the portion of relevant elements in all the retrieved items. It is used to know the number of correct elements among all recommendations.

Taking these definitions into account, Precision@k would be the portion of relevant elements in the top *k* recommendations, and recall@k would be the coverage of relevant times in the top *k*.

In order, to create reasonable comparisons, the assessment execution metrics are used such as Top@k. Recall@k, Precision@k and F1-score@k [20]. Particularly, we display each user with k areas sorted by the anticipated score based on the classifier, i.e., S_u^k. Given a top-k anticipated area list S_u^k and target area list l_u^* of the test set, each assessment metric can be characterized as

(9) $$\text{Top@k} = \frac{1}{|u|} \sum_{|u|} \sum_{j}^{|l_u^*|} \left(\frac{\left| l_{u,j}^* \cap S_{u,j}^k \right|}{|l_u^*|} \right),$$

where *j* signifies each test.

The evaluation metrics are given by the next equations:

(10) $$\text{Recall@k} = \frac{1}{|u|}\sum_{|u|}\sum_{j}^{|\,l_u^*|}\left(\frac{\left|S_{u,j}^{k}\cap S_{u,j}^{\text{visited}}\right|}{S_{u,j}^{\text{visited}}}\right),$$

(11) $$\text{Precision@k} = \frac{1}{|u|}\sum_{|u|}\sum_{j}^{|\,l_u^*|}\left(\frac{\left|S_{u,j}^{k}\cap S_{u,j}^{\text{visited}}\right|}{k}\right),$$

where $S_{u,j}^{\text{visited}}$ represents the list of locations *u* has visited. At last, the F1-score is the consonant cruel of Review and Precision defined by

(12) $$\text{F1-score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}}.$$

5. Results

In this section, we revealed the results of the proposed model and compare its performance with others models.

5.1. Proposed model results

In this work, the objective of the proposed model is to capture the next trajectory based on top@k results and output a ranked list of predicted trajectories. It is worth noting that we set a scale for k that ranges between 1 and 5. For any value exceeding 5 (k=5), the predicted trajectories results would be the worst. To simplify entries, we consider the notations: Tk= Top@k, T1=Top@1, T5=Top@5, Rk=Recall@k, R1=Recall@1, R5=Recall@5, Pk=Precision@k, P1=Precision@1, P5=Precision@5, Fk= F1_score @k, F1= F1@1, F5= F1@5.

Based on our proposed UCAL model and using the two datasets on NYC and TKY, the Tk results are given in the Table 1.

Table 1. Tk performances on NYC and TKY datasets

	NYC		TKY	
Our methodology	T1	T5	T1	T5
	0.250	0.480	0.200	0.400

Based on the two datasets on NYC and TKY, tables 2 and 3 give the obtained results on the performances of the proposed UCAL model presented by the Rk, the Pk and the F1_score @k metrics.

Table 2. Performance of Rk, Pk and Fk based on NYC dataset

	NYC					
Our methodology	R1	R5	P1	P5	F1	F5
	0.250	0.370	0.250	0.480	0.250	0.417

Table 3. Performance of Rk, Pk and Fk based on TKY dataset

	TKY					
Our methodology	R1	R5	P1	P5	F1	F5
	0.200	0.300	0.200	0.421	0.200	0.350

The above tables attest for the performance of the proposed UCAL to detect the next trajectory. It is worth stating that the NYC dataset allows better results compared to those obtained using the TKY dataset. This is because NYC dataset has fewer users which makes the training easier.

5.2. Comparison with other methods

To highlight the merits of our proposed UCAL model, this section is devoted to comparing its results with others achieved by existing methods (table 4). These are:

- ST-RNN is a recurrent neural network that predicts locations from spatial-temporal inputs [17].
- SERM represents a long short-term memory architecture which can predict the next location of the user based on jointly spatio-temporal context and activities as inputs [18].
- DeepMove is a deep learning method relied on the Attention technique which captures historically visited locations from a historical trajectory and is able to find out complex sequential transitions from a recent trajectory [19].
- UCG Net represents a model for predicting the future trajectories relying on historical and current locations with spatio-temporel context [20].

Table 4. presents the comparison Tk metric results using the two datasets.

Table. 4. Tk comparison results

Methods	NYC		TKY	
	T1	T5	T1	T5
ST-RNN [17]	0.162	0.345	0.142	0.303
SERM [18]	0.170	0.396	0.144	0.298
DeepMove [19]	0.195	0.378	0.168	0.346
UCG Net [20]	0.218	0.456	0.186	0.384
Proposed model	0.250	0.480	0.200	0.400

As shown in Table 4 and in comparison, with the reference approaches, the proposed model achieves the best performance, using the two datasets, since it is able to exploit the previously used trajectories with more precision. Indeed, compared to the UCG which present 21.8% for T1 and 45.6% for T5, the proposed model shows an increment since it presents 25% for T1 and 48% for T5 using the NYC dataset. For TKY dataset, we can observe a similar increasing trend of results of 20% and 40% in the T1 and T5 results respectively compared to the UCG model that presents 18.6 for T1 and 38.4% for T5.

The above tables evidence the good performance of the proposed UCAL in detecting the next trajectory. It should also be noted that the NYC dataset allows better results compared to those attained by the TKY dataset with Tk results. This is because NYC dataset has fewer users which makes the training easier.

Similar to Tk metric, the performance comparison results of Rk, Pk and Fk metrics are given in tables 5 and 6 using the datasets on NYC and TKY, respectively.

Based on the tables above, the proposed algorithm achieves the best results compared to all the reference algorithms. Indeed, the Rk results show that the UCAL performs better to classify the true places.

Using the NYC dataset and compared to the UCG Net which presents 21.8% and 34.8% for R1 and R5, respectively our proposed UCAL model allows an increase since it reaches 25% and 37% for the same metrics. Similarly, the proposed UCAL improved the results using the TKY dataset by achieving an increase in R1 and R5.

Table 5. Rk, Pk and Fk results generated on NYC dataset

Methods	NYC					
	R1	R5	P1	P5	F1	F5
ST-RNN	0.162	0.297	0.162	0.362	0.162	0.326
SERM	0.170	0.318	0.170	0.425	0.170	0.364
DeepMove	0.195	0.299	0.195	0.348	0.195	0.322
UCG Net	0.218	0.348	0.218	0.455	0.218	0.395
Proposed model: UCAL	0.250	0.370	0.250	0.480	0.250	0.417

Table 6. Rk, Pk and Fk results generated on TKY dataset

Methods	TKY					
	R1	R5	P1	P5	F1	F5
ST-RNN	0.142	0.236	0.142	0.349	0.142	0.282
SERM	0.144	0.228	0.144	0.341	0.144	0.273
DeepMove	0.168	0.254	0.168	0.395	0.168	0.309
UCG Net	0.186	0.274	0.186	0.401	0.186	0.326
Our model	0.200	0.300	0.200	0.421	0.200	0.350

For the Pk results, our UCAL model ameliorated the results for P1 and P5 by an increase that expect 25% and 48%, respectively using the NYC dataset. In addition, it provided an increase presented by 20% and 35% in P1 and P5, respectively using the TKY dataset. Therefore, the Pk results testify that the UCAL predicts better the real place.

For F1-score, the proposed UCAL presents an increase since it achieved 25% and 41.7% in F1 and F5, respectively using the NYC dataset. Similarly, it succeeds in increasing the F1 and F5 by 20% and 35%, respectively, using the TKY dataset.

Taking into account all the results analyzed above, it can be deduced that our proposed model achieves a satisfactory classification performance. In summary, it allows for the best performance compared with the strong neural network approaches.

6. Conclusion

Understanding and predicting human mobility between locations is an important issue in complex human behaviors, transportation, economic geography and regional economics. It also has several practical applications in urban planning, population migration, cargo transportation, traffic engineering, infectious diseases epidemiology and emergency management.

Modelling human behavior mobility requires to uncover valuable knowledge, such as daily routine of individuals from historical trajectories and predict their next trajectory.

So, it is not easy to capture long complex patterns from historical trajectories to be able to predict the future ones.

To overcome the problem of long complex sequence of locations, this paper propose an augmented model called Union ConvAttention-LSTM. The objective of the UCAL is the next location prediction by incorporating historical and current ones.

For the historical trajectories, the UCAL use the same existing 1D CNN that allows capturing short sequences of locations. However, to define locations from current trajectories, the proposed UCAL introduces a new module that contains an Attention technique with a Recurrent Neural Network (RNN). The attention mechanism is used to improve accuracy since it focuses on specific parts of complex data that leads to obtain better performances for the true classification location.

The experimental results given by the evaluation metrics show several improvements using the TKY and the NYC dataset.

In order to further improve the accuracy of the obtained performances, we think of using the theory of beliefs functions as a potential study topic for a future perspective.

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