DAPred: Dynamic Attention Location Prediction with Long-Short Term Movement Regularity

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ABSTRACT

Predicting users' future locations has become an important task in various aspects, such as ride-sharing, tourism recommendation and urban planning. However, existing methods disregard that users' interest over next location is dynamic. The dynamic preference over next location involves two aspects: First, preference over distance is dynamic when users move; Second, preference over related terms vary on different target times. Hence, directly predicting next location with static network would result in unsatisfactory accuracies. Dynamic location prediction problem is still open now.

We propose a multilayer recurrent attention model DAPred to solve the problem. The effectiveness of DAPred is underpinned by the following reasons: (1) An embedding recurrent module to map history movements into latent place, which helps build the attention module for the following layers; (2) A historical attention module that detects multiple distance preference from dynamic movement history; (3) A prediction module for learning different weights on different time gaps. Compared to the state-of-art baselines, DAPred reaches 49.8% improvement in hitting ratio accuracy, and 18.5% improvement in average distance predictor error on three real-life datasets.

ACM Reference Format:
Jiayi Liu, Quan Yuan, Carl Yang, He Huang, Chao Zhang, and Philip Yu. 2020. DAPred: Dynamic Attention Location Prediction with Long-Short Term Movement Regularity. In *KDD '20: ACM SIGKDD Conference on Knowledge Discovery and Data Mining, August 22–27, 2020, San Diego, CA.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Location prediction is a task on predicting users' movements based on their preceding GPS trace, which has many applications in real life. For example, in car-pool services, by applying an optimized strategy and planning, location prediction is useful in selecting the pick up locations and destination based on the users' report. Another example is logistic planning and location-aware recommendation for advertisements. With accurate location prediction, advertisements can be precisely-targeted for individuals based on their past movements. Moreover, location prediction is also beneficial for urban planning and traffic jam prediction for governments. In the past, the obstacle in location prediction is the lack of data source. Recent years, with the burst of geo-annotated social media data, such as Foursquare, Facebook, Twitter[5, 24, 28, 29, 31, 32, 34], location prediction has been made possible.

Existing studies predict locations in a static way without realizing that users' preferences may change with time and their past movements. To begin with, when considering time, both users' long-term and short-term preferences should be considered for location prediction. Most studies only consider long-term preferences for location prediction [9, 10, 14, 24, 32]. As short-term preferences indicate users' current interest, studies which lack short-term preference modeling fail to capture users' current interest, resulting in unsatisfactory prediction accuracies. Although some proposed to predict location with both long and short-term preferences by introducing long trajectories and short trajectories [9, 23], they still failed to realize that users preferences would change dynamically when they move.

We study the problem of Dynamic Location Prediction (DLP) by discussing user's dynamic preferences. Figure 1 shows an example. Given a user, with the user's past movements, we want to predict his or her future location at different target times. Although some previous methods embed time in their model, they cannot explicitly model the inherent relationships among movements, preferences and target times. For different target times, previous methods apply static preferences over all the terms, instead of changing preferences with times. As a result, they fail to truely predict locations at different target times.

In this paper, we propose **D**ynamic **A**ttention Location **Pred**iction (DAPred) to solve DLP problem. There are three key challenges need to be addressed. First, *integrating diverse types of user preferences is important.* Users' movement preferences include multiple terms: long-term preference and short-term preference. Before mining the users' dynamic preferences, exploiting the difference and correlation between users' long-term/short-term preferences and

KDD '20, August 22–27, 2020, San Diego, CA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

effectively integrating them are challenging. Second, *finding the dynamic influence of past movements over distance preference has not been discussed before.* Users' past movements may have an influence on the distance selection of next movement. For example, if users keep moving in a long time, they would feel tired to visit a place far away. Extracting the dynamic influence of records over distance preference is worth-considering. Third, *modeling the influence of target time over user's term preference is important.* The target time could not be considered as a simple factor, it should interact with other factors. For example, if the gap time between current time and target time is short (e.g., 15 min), users tends to visit nearby locations that can meet their short-term interests, while if the gap time is long (e.g., 5 hours), users will rely more on their long-term interests.

DAPred adopts three modules to tackle the above challenges. The first module is an embedding-recurrent module to integrate terms into latent place and capture transitions. Then, DAPred employs the historical attention module to discover the movement influence over distance preference. Finally, DAPred sets the prediction module to capture different interests over terms on different time gaps.

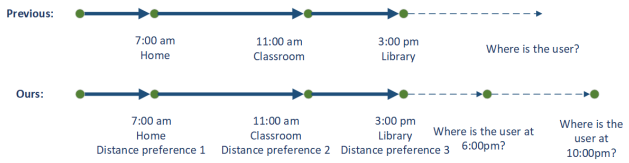


Figure 1: A comparison between next location prediction and dynamic attention location prediction

The major contributions are summarized as follows:

(1) We propose dynamic attention location prediction(DLP) problem, where users' location preferences would change dynamically when they move.
(2) We propose a long-short memory enriched attention recurrent model DAPred to solve the DLP problem. DAPred learns the users' dynamic preferences in two terms: first, users' preferences over distance is dynamic when they move; second, users' long/short-term preferences are dynamic when target times are different.
(3) We test our algorithm on three large-scale geo-tagged tweet datasets: Foursquare, Gowalla New York and Gowalla Los Angeles. Comparing with other algorithms, DAPred makes significant improvement.

2 RELATED WORK

In this section, we review existing works related to our problem, including: (1) Long-term movement prediction; (2) Short-term movement prediction; (3) Long-term and short-term movement prediction.

2.1 Long-term location prediction

Most studies [3, 13, 15, 20, 21, 23, 24] predict locations based on users' long-term behavior. For those who use only long-term behavior, we call them long-term location prediction.

Generally, existing model-based long-term location prediction could be classified into two categories: HMM model and RNN model. HMM model use the Hidden Markov Model to predict users' locations[2, 12, 18]. Their transition matrices consist of different factors: location type [4], personalized point-of-interest locations[3], social/geo-distance knowledge for unvisited location prediction[13], grouping information[32].

RNN model uses the recurrent network to model trajectories. By introducing recurrent network, these methods are able to capture the sequential characters for each movement[8, 16, 19, 24–27]. Liu et al. [16] construct a temporal recurrent network with distance/time-specific transition matrices; Yao et al. [24] introduce textual information into recurrent network to improve the performance; Yao et al. [27] introduce a unified deep learning framework for mobile sensing data.

The above methods are all designed for discovering the long-term preference of users. However, there exists long-term preference and short-term preference for a user. For example, a user prefers to go to the gym from home at 6 pm, which is his or her long-term preference. When there is a mid-term exam to prepare, he or she would go to the library instead, which is the short-term preference. Hence, users' short-term preference is also an important factor which should be applied separately.

2.2 Short-term location prediction

Lots of studies separate long-term movements into pieces to fully investigate the short-term preference of users. [6] segment long-term trajectories into short ones and concat them again to find the noisy movements. However, this method only works in short trajectory prediction and unable to predict the next location in a wide time range. Besse et al.[1] also use the segmentation trajectories for their next location prediction. By clustering the short trajectories, they are able to predict the next location.

Although the above studies take short-term movements into consideration, they fail in integrating long-term movements together. Short-term movement and long-term movement indicate the short and long-term interest respectively. The lack of either of them would result in an unconformity with real life. Hence, the results of methods with only short-term location prediction stay unsatisfactory.

2.3 Long-term and Short-term location prediction

For long-term and short-term location prediction, most models adopt recurrent network(RNN) to model trajectories, e.g. long-term and short-term trajectories recurrent network [23], attention periodicity [9]. Although they are all designed with both long-term and short-term, but they still fail to solve this problem: how to predict the locations at different target time? While many studies take the history timestamp as an important feature for location prediction, they neglect the future target time as an important input. They could only predict next location in the future but unable to predict future locations with different target time stamps(e.g. 8 pm at the library and 6 pm at the restaurant). Here we propose the problem as target-time location prediction, which is designed for predicting multiple future locations at different time stamps.

3 PRELIMINARIES

In this section, we formulate the dynamic attention location prediction problem, and explore its characteristics, which motivate the design of DAPred.

3.1 Problem Definition

For brevity, we present a table of notations in Table 1.
For users' check-ins, we denote them as $\boldsymbol{R_u}$. Let $\boldsymbol{R_u} = (r_1, r_2, ...r_n)$

Table 1: Notations

Notations	Description
R_u	The sequential records of u
L_u	Long trajectory of user u
S_u	Short trajectories of user u
e_{st}	Short trajectories embedding results
e_{lt}	Long trajectory embedding results
hs	Short trajectories hidden state results
hl	Long trajectory hidden state results
l_{r_i}	The location of in record r_i
F_{r_i}	The attention score of previous movements for record r_i
D_{r_i}	The attention score of previous distance for record r_i
a_{r_i}	The attention vector for record r_i

be sequential records in chronological order for user u. Each record r_i is a tuple of $< l_{r_i}, t_{r_i}, u >$, where l_{r_i} is the geo-location, t_{r_i} is the post time and u is the user id. Given records $\boldsymbol{R_u}$, we aim to predict the locations where users u would be at multiple future time stamps with a dynamic framework. To construct the dynmaic framework, we transform $\boldsymbol{R_u}$ into long trajectory and short trajectory to represent user's long-term and short-term interests relatively [23].

Definition 3.1 (Long Trajectory). *For a user u, long trajectory $\boldsymbol{L_u}$ is his or her whole movement history. Here,*

$$\boldsymbol{L_u} = [l_{r_1} \quad l_{r_2} \quad ... \quad l_{r_n}] \tag{1}$$

where l_{r_k} represents the location of the k-th record.

Definition 3.2 (Short Trajectories). *For a user u, short trajectories $\boldsymbol{S_u}$ are his or her fragmented movements. We split long trajectory into a sequence of short ones if the gap time between consecutive visits is greater than a threshold(e.g., 6 hours), then we would cut them into different group.*

Formally,

$$\boldsymbol{S_u} = \begin{Bmatrix} [l_{r_1} & l_{r_2} & ... & l_{r_{i-1}}] \\ [l_{r_i} & l_{r_{i+2}} & ... & l_{r_j}] \\ [... & ... & ... & ...] \end{Bmatrix} \tag{2}$$

Note that, the length of each short trajectory could be different.

Definition 3.3 (Time). *Given a user u with records $\boldsymbol{R_u}$, the time stamps for each records are $\boldsymbol{T_u} = [t_{r_1}, t_{r_2}, ...t_{r_n}]$.*

3.2 The Overall Architecture

In a nutshell, DAPred embeds all terms into a latent space, and uses recurrent network to capture the sequential information. By using attention mechanism, DAPred chooses what to pay attention with based on different timestamps.

The intuition behind our architecture is, users' interests over next location are dynamic in two terms: 1) Users' preferences over distance vary when users move. Comparing to the users move in a relatively short route, those who move a long route would be more sensitive to distance. 2) The next locations users would visit differ with target times. Different target times would influence the users' preference over long/short-term memory and distance. For example, when the time gap between target time and current time is small, users tend to make their decision based on short-term memory and more sensitive to distance, otherwise, their preference would be more on long-term memory. Later, this intuition will be proved in experiment part.

To construct our model, our steps are as following: Given a user u, we transform the records $\boldsymbol{R_u}$ into $\boldsymbol{L_u}, \boldsymbol{S_u}$ and $\boldsymbol{T_u}$. As mentioned earlier, dynamic attention location prediction still poses several challenges: 1) How to introduce long-term and short-term interests for dynamic attention location prediction? 2) How to detect the dynamic attention over distance preferences when users move? 3) For different target times, how to apply dynamic preferences over multiple terms? In the following, we introduce embedding-recurrent, historical attention and prediction modules to address the three challenges above respectively. Figure 2 shows a concise architecture of our model.

4 PROPOSED METHOD

DAPred aims to predict users' location dynamically. To this end, we exploit users' movements and spatial-temporal features in a unified framework, which consists of embedding-recurrent module, historical attention module and prediction module.

4.1 Embedding-Recurrent Module

Embedding-recurrent network has been investigated in lots of studies. In this section, we would not introduce the detailed procedures about how and why embedding-recurrent network works, instead, we discuss how long-term/short-term interests work in dynamic attention location prediction[23, 33].

Multimodal embedding jointly maps all the features into latent space. To represent users' mobility, exisiting algorithms only embed three terms: long trajectory $\boldsymbol{L_u}$, time stamps T_u and user u, which represent movements, time and user's personal preferences respectively. Nevertheless, this strategy is problematic because long trajectories $\boldsymbol{L_u}$ could not reveal the user's short-term preference over mobility. Motivated by [23], we add short trajectories $\boldsymbol{S_u}$, which are fragmented from long trajectory $\boldsymbol{L_u}$, to uncover the short-term preferences of users. To help model the transitional relationship between the above four features, we design the multimodal embedding module to jointly embed them. Then, we get $\boldsymbol{e_{st}}, \boldsymbol{e_{lt}}, \boldsymbol{e_t}$ and $\boldsymbol{e_u}$ as the embedding results of short trajectories, long trajectory, times and user.

Given $\boldsymbol{e_{st}}, \boldsymbol{e_{lt}}$, we then capture their sequential information through GRU and RNN respectively and obtain the hidden states of each step i, denoting $\boldsymbol{hl^{(i)}}$ and $\boldsymbol{hs^{(i)}}$. To compute the hidden states, we adopt two layers:

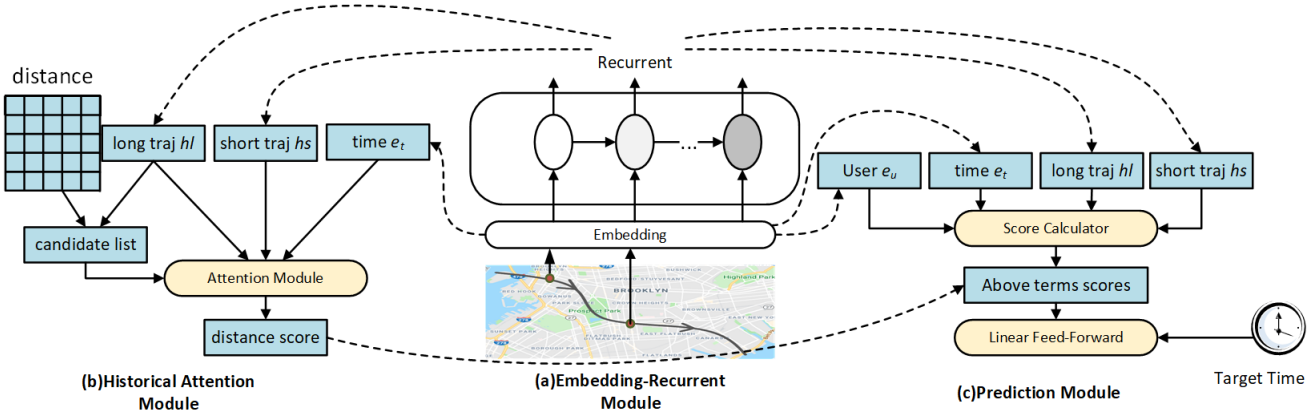


Figure 2: The overall architecture. The inputs consist of users and all their check-ins. The outputs are the probability lists of locations for different target time. (a) Embedding-Recurrent Module uses embedding and RNN/GRU to encode inputs for other modules. (b) Historical Attention Module leverages embedding-recurrent results of trajectories and time to learn users' preference over distance. (c) Prediction Module learn the locations' possiblities by capturing all previous modules' results.

- *Long-term Trajectory Layer: The GRU Layer.* In this module, we construct a gated recurrent unit network for long trajectories. The intuition behind the adoption of GRU network is that, compared to RNN with vanishing gradient problem, GRU is better at memorizing and learning long-term hidden state dependencies[23]. For long trajectories, their lengths are quite large and shouldn't be forgotten. So we adopt GRU network to model long trajectory. As stated above, the embedding result for long trajectory is $\boldsymbol{e_{lt}}$. So the computation of hidden states would be [7]:

$$\begin{aligned} z^{(i)} &= \sigma(W_z e_l t^{(i)} + U_z hl^{(i-1)}) \\ r^{(i)} &= \sigma(W_r e_l t^{(i)} + U_r hl^{(i-1)}) \\ \tilde{hl}^{(i)} &= \tanh(W_t e_l t^{(i)} + U_t(r^{(i)} \odot hl^{(t-1)})) \\ hl^{(i)} &= (1 - z^{(i)}) hl^{(i-1)} + z^{(i)} \tilde{hl}^{(i)} \end{aligned} \tag{3}$$

  In which, $r^{(i)}$ is the reset gate, $z^{(i)}$ is the update gate of $i-th$ step, $\odot$ is the element-wise multiplication, σ is the sigmoid function, W_z,U_z,W_r,U_r,W_t,U_t represent the parameter matrices for update gate, reset gate and candidate gate. Finally, we get the long trajectories features, which would flow to the attention module.
- *Short-term Trajectory Layer: The RNN Layer.* In this layer, we construct an RNN network for short trajectories. As recurrent network could capture the sequential information, we adopt RNN to model the complicated transitions of short trajectories, which is an advantageous model for sequential data in a short time window[23]. As stated above, the embedding result for short trajectory is $\boldsymbol{e_{st}}$. So the computation of hidden states would be:

$$hs^{(i+1)} = f(W \cdot hs^{(i)} + G \cdot e_{st}^{(i)} + b) \tag{4}$$

  where $hs^{(i)}$ represents the i-th hidden state, W and G reprent the parameter matrices and b represents the parameter vector. Finally, we get the short trajectories features, which would flow to the attention module.

The process of embedding-recurrent module is summarized in Algorithm 1.

Algorithm 1: Embedding-Recurrent Module

Input: Check-ins $\boldsymbol{R_u}$; User u
Output: Embeddings $\boldsymbol{e_t}, \boldsymbol{e_u}$, hidden states $\boldsymbol{hl}, \boldsymbol{hs}$

```
/* Pre-processing*/
Extract long trajectory L_u and time T_u from record R_u.
Split short trajectory S_u from L_u.
/* Embedding-Recurrent*/
Embed S_u, L_u, T_u and u into latent place to obtain
  e_st, e_lt, e_t and e_u.
foreach e_st^(i) ∈ e_st do
    Train e_st^(i) to obtain hidden steps hs^(i) via Eq.(4).
end
foreach e_lt^(i) ∈ e_lt do
    Train e_lt^(i) to obtain hidden steps hl^(i) via Eq.(3).
end
```

4.2 Historical Attention Module

The historical attention module helps learn users' dynamic interest over locations. Instead of keeping a static interest over time [9, 24, 32], we model users' dynamic preferences over distance when they move. The key idea is to find the attention of distance preference on previous records [17, 22]. However, it would be too expensive to directly iterate over all possible locations. To alleviate this problem, for each location l_{r_i}, we generate the next-location candidate list $F_{l_{r_i}}$ from the whole location set based on geo-distance and previous

records. That is, we first estimate the probablity of locations to be chosen as candidates:

$$dis(l_k|l_{r_i}) = \frac{e^{-d(l_k,l_{r_i})}}{\sum_{k=1}^{n} e^{-d(l_k,l_{r_i})}} \tag{5}$$

$$pop(l_k|l_{r_i}) = \frac{f(l_k \wedge l_{r_i})}{f(l_{r_i})} \tag{6}$$

In which $d(l_k, l_{r_i})$ is the distance between l_k and l_{r_i}, n is the total number of locations, $f(\cdot)$ is the frequency.

The process of historical attention module is summarized in Algorithm 2.

Algorithm 2: Historical Attention Module

Input: Embeddings $\boldsymbol{e_t}$, hidden states $\boldsymbol{hl}, \boldsymbol{hs}$, geo-distance matrix d
Output: Distance score S_d

```
Construct distance vector and popularity vector for each location l based on Eq.5 and Eq.6.
foreach record r_i ∈ R_u do
    Construct attentional score F_{r_i}, D_{r_i} via Eq.(7)-(8).
    foreach r_ij ∈ r_i do
        Train attention vector a_{r_i} by decoding F_{r_ij} and D_{r_ij}.
    end
    foreach l_c ∈ l do
        Predict distance score S_{d,l_c} via Eq.(10).
    end
end
```

After we select candidates for l_{r_i}, we introduce the distance-aware attention module to find the correlation between mobility and distance preferences. When involved with distance, previous studies usually concat distance factors with others[16]. However, users' preference over distance may change when they move. Thus, directly concating these factors lacks in discovering the intrinsic interaction between distance and other factors.

Inspired by human attention mechanism, we develop a distance-aware attention module to solve the problem. The detailed flow of this layer is shown in Figure 3. The attention model aims at summarizing the influence of movement history over users' distance preference. To begin with, the influence containing two parts: 1) Trajectory and time. 2) Distance. For trajectory and time, we adopt the results from embedding-recurrent network. For distance, we select the geo-distance between next location and other locations in trajectory to measure the influence. Let $\boldsymbol{f^{(i)}} = [\mathbb{R}(\boldsymbol{hl^{(i)}}), \mathbb{R}(\boldsymbol{hs^{(i)}}), \mathbb{R}(\boldsymbol{e_t^{(i)}})]$ be the concatenation of embedding result $\boldsymbol{e_t^{(i)}}$, long-term GRU result $\boldsymbol{hl^{(i)}}$ and short-term RNN result $\boldsymbol{hs^{(i)}}$ at $i-th$ step, in which, $\mathbb{R}(\cdot)$ indicates the ReLU function: $\mathbb{R}(x) = x^+$.

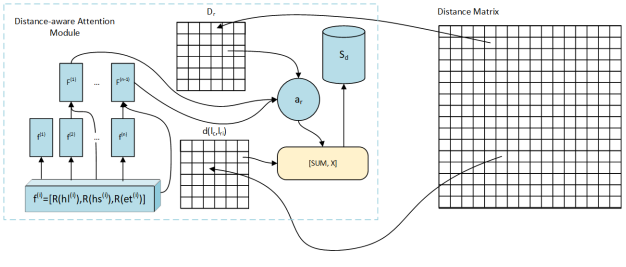


Figure 3: The detailed architecture of Distance-aware Attention Module

Formally, for record r_i, given the embedding-recurrent feature $f^{(i)}$ at a time step t_i and location l_i, to capture its attentional score, we consider the correlations between its previous step and all movement history. Then we define the attentional score as:

$$\boldsymbol{F_{r_i}} = \boldsymbol{f^{(i+1)}} \cdot \left[\boldsymbol{f^{(1)}} \quad \boldsymbol{f^{(2)}} \quad \dots \quad \boldsymbol{f^{(n)}}\right]^T \tag{7}$$

$$\boldsymbol{D_{r_i}} = \left[d(l_{r_{i+1}}, l_{r_1}) \quad d(l_{r_{i+1}}, l_{r_2}) \quad \dots \quad d(l_{r_{i+1}}, l_{r_n})\right] \tag{8}$$

Then we encode $\boldsymbol{F_{r_i}}$ and $\boldsymbol{D_{r_i}}$ to get the attentional vector over distance.

$$\boldsymbol{a_{r_i}} = \boldsymbol{W_a} \cdot \boldsymbol{F_{r_i}} + \boldsymbol{W_b} \cdot \boldsymbol{D_{r_i}} + \boldsymbol{C} \tag{9}$$

where $\boldsymbol{W_a}, \boldsymbol{W_b}, \boldsymbol{C}$ respectively represent the weight for past history, geo-distance and bias.

After obtaining the attentional vector $\boldsymbol{a_{r_i}}$, our goal is to optimize the distance scores of next-location candidates such that we could predict users next target-time location based on their movement history and the geo-distance between locations. Suppose the current location is l_{r_i}, for a location candidate l_c in the candidates list $F_{l_{r_i}}$, we define its distance score $\boldsymbol{S_d^{l_c}}$ as:

$$\boldsymbol{S_d^{l_c}} = \sigma(\boldsymbol{a_{r_i}}) \cdot [e^{-d(l_c,l_{r_1})} \quad e^{-d(l_c,l_{r_2})} \cdots e^{-d(l_c,l_{rn})}]^T \tag{10}$$

where, $\sigma(\cdot)$ is a normalization. The intuition behind this formula is that: the likelihood of a candidate to be chosen is based on two aspects: 1) The attention vector, which represents the history preference over next location. 2) The distance between this candidate and the locations user visits. We apply attention vector on distance preference to indicate the possibility of this candidate to be chosen.

4.3 Prediction Module

The prediction module aims to predict the next locations at different target times. By using a linear feed-forward neural network, we concatenate embedding-recurrent scores above and distance score together. Note that, for different time gaps, we train different weights over feed-forward neural network [29]. Here, we set 1 hour as the smallest unit to deal with underfit. For those with decimal, we adopt the following strategy: Given a gap time gt, suppose its upper bound is $gt_u = ceil(gt)$ and its lower bound is $gt_l = floor(gt)$ the weight w_{gt} of its linear network would be:

$$w_{gt} = w_{gt_u} \cdot (gt_u - gt) + w_{gt_l} \cdot (gt_l - gt) \tag{11}$$

where w_{gt_u} is the weight at gt_u and w_{gt_l} is the weight at gt_l.

Finally, for different time gap, we obtain their own preferences over the terms by:

$$S_l = [\boldsymbol{S_t} \;\; \boldsymbol{S_u} \;\; \boldsymbol{S_{hs}} \;\; \boldsymbol{S_{hl}} \;\; \boldsymbol{S_d}]^T \cdot \sum_{1}^{n} w_{gt} \mathrm{L}(\mathrm{W_L}, \mathrm{b_L}) \tag{12}$$

where $S_t, S_u, S_{hs}, S_{hl}, S_d$ indicate the prediction score for time, user, short trajectories, long trajectories and distance, $\mathrm{L}(\mathrm{W_L}, \mathrm{b_L})$ refers to the linear network for a time gap, W_L and b_l are the weight and bias for this network.

The process of prediction module is summarized in Algorithm 3.

Algorithm 3: Prediction Module

Input: S_d, e_t, e_u, hs, hl
Output: next location scores S_l
Init time gap weight matrix w_t.
foreach *record* $r_i \in R_u$ **do**
  Decode e_t, e_u, hs and hl to obtain scores S_t, S_u, S_{hs} and S_{hl} over location candidates l.
  foreach *target time* $t \in \Gamma$ **do**
    Caculate their own weight vector w_{gt} via Eq.(11).
  end
  Predict next location scores S_l via Eq.(12).
end

5 EXPERIMENT

5.1 Experiment Setting

5.1.1 Datasets. Our experiments are based on three datasets: Foursquare, Gowalla New York and Gowalla Los Angeles. The source of Foursquare dataset is the same as [24, 30]. Gowalla dataset is a location-based social networking website similar to Facebook, the source of this dataset is the same as [5]. For foursquare dataset, it consists of 1.4 million check-ins from 2009-01 to 2012-01 in New York City. For Gowalla dataset, it consists of 1.95 million check-ins in New York and 3.33 million check-ins in Los Angeles from 2009-01 to 2012-01. For each dataset, we firstly merge records with the same user to set trajectories for users. Then, we remove the users with less than 5 records and the locations with less than 10 records[9, 24]. This operation guarantees that each trajectory is long enough to be cut into the training set and testing set.

After such preprocessing, for Foursquare dataset, we obtain 500 users, 3555 locations and 9968 trajectories in training set, 2829 trajectories in the testing set. For Gowalla dataset at New York, we obtain 500 users, 5670 locations and 5019 trajectories in training set, 22851 trajectories in the testing set. For Gowalla dataset at Los Angeles, we obtain 404 users, 777 locations and 18405 trajectories in training set, 5202 trajectories in the testing set.[1]

5.1.2 Experimental Protocol. For each dataset, we randomly select 70% records of users for training, 10% for tunning and the remaining records for testing. To evaluate the performance of each method, we use the hitting ratio @k and average distance error δ_d. Hitting ratio is the percentage of the ground-truth location appears in our top-k location result list, average distance error is the average distance between our top-1 prediction and ground-truth. These two evaluation methods are the same as [9, 24].

[1] **The code is available at https://github.com/JYLEvageline/DAPred**

5.1.3 Parameter Settings. DAPred owns the following major parameters: (1) For the embedding layer, the latent dimension D_v for both long and short trajectories, D_t for time and D_u for users. (2) For the recurrent layer, the recurrent dimension D_h for both RNN and GRU. (3) For attention layer, the number of candidates N. (4) The dropout probability O (5) The batch size of minibatch M. After tuning, we set D_v as 16, D_t as 8, D_u as 32, D_h as 16, N as 16, O as 0.5, and M as 50. We tested on various parameter settings and did not find much difference, the details of our tuning process would be discussed in 5.5.

5.2 Quantitative Results

As aforementioned, we use the ground truth locations in the remaining 20% testing data to evaluate all methods. To quantify the performance of all the methods, we use the hitting ratio @k as our criteria. Here, hitting ratio refers to the percentage of ground truth appears in our top-k list. Here, we present the hitting ratio of top 1, top 5 and top 10. The other criterion is δ_d, which is the average geographical distance between the ground-truth location and the top-1 prediction. The metrics we adopt are same as previous work [9, 24].

$$HR@k = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k} \vee(y_{ij} == \hat{y_i})$$

$$\delta_d = \frac{1}{n}\sum_{i=1}^{n} ||y_{i0} - \hat{y_i}||$$

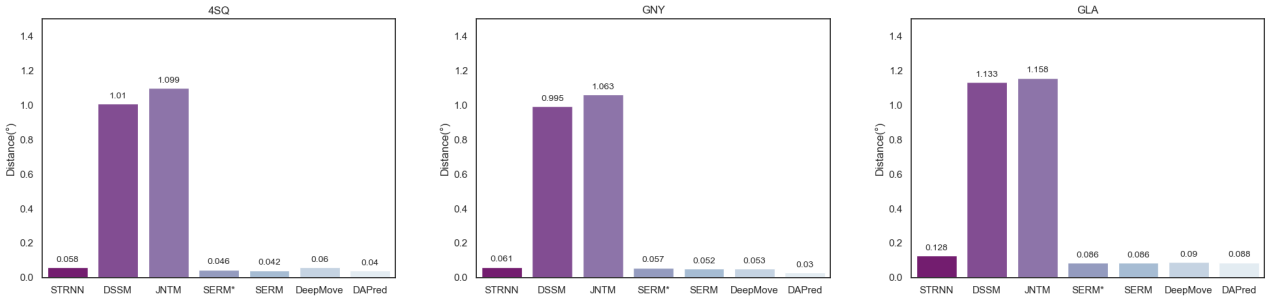
We compare DAPred with the following methods: (1)DSSM[11] (2)JNTM[23] (3)ST-RNN[16] (4)SERM*[24] (5)DeepMove[9].

- JNTM[23] is the first method in location prediction considering both long-term movements and short-term movements by adopting long trajectories and short trajectories as features.
- DSSM[11] is an algorithm for Web Search. Here, we make an analogy between queries and users, documents and trajectories to adapt it for location prediction.
- ST-RNN[16] is a model which employs both time-specific and distance-specific features to predict next location. By constructing a distance matrix between time points, ST-RNN is able to capture both temporal and spatial interests for users.
- SERM*[24]is the variant of SERM, a semantics-enriched recurrent model. As there is no semantic information, we apply SERM*, which is the variant of SERM, only models location, time, and user factors without using textual information.
- SERM[24]is also tested by us with their semantic information.
- DeepMove[9] is the state-of-the-art attentional recurrent network in location prediction. By applying historical attention model, DeepMove captures the periodicity to augment recurrent network.

Table 2 reports the performance comparison of our methods and the State-of-the-Art algorithms on our three datasets. In Foursquare(4SQ) dataset, compared to the best baseline DeepMove, DAPred yields around 29.1% improvement in top 1 hitting ratio, 71.2% improvement in top 5 hitting ratio and 127.6% improvement in top 10 hitting

Table 2: Performance Comparison between DAPred and STRNN, DSSM, JNTM, SERM*, DeepMove. HR is the hitting ratio

		Previous Algorithm						Our algorithm			
Data	Metrics	STRNN	DSSM	JNTM	SERM*	SERM	DeepMove	TPred	TLSPred	TDPred	DAPred
4SQ	HR@1	0.016	0.128	0.06	0.137	0.170	0.148	0.128	0.124	0.186	0.191
	HR@5	0.054	0.245	0.121	0.353	0.405	0.306	0.244	0.236	0.51	0.524
	HR@10	0.083	0.286	0.156	0.486	0.553	0.352	0.291	0.274	0.769	0.801
GNY	HR@1	0	0.052	0.038	0.098	0.113	0.100	0.101	0.083	0.135	0.146
	HR@5	0.004	0.110	0.092	0.185	0.254	0.248	0.19	0.16	0.336	0.362
	HR@10	0.008	0.141	0.126	0.306	0.392	0.313	0.238	0.201	0.641	0.678
GLA	HR@1	0	0.066	0.020	0.126	0.159	0.198	0.066	0.066	0.176	0.182
	HR@5	0.004	0.145	0.061	0.223	0.285	0.262	0.129	0.125	0.254	0.289
	HR@10	0.008	0.188	0.086	0.440	0.572	0.565	0.161	0.157	0.533	0.619



(a) Test on Foursquare (b) Test on Gowalla.NY (c) Test on Gowalla.LA

Figure 4: δ_d(average distance predictor error) comparison among state-of-art algorithms

ratio. In Gowalla New York(GNY) dataset, compared to the best baseline DeepMove, DAPred yields around 46.0% improvement in top1 and top 5 hitting ratio and 116.6% improvement in top 10 hitting ratio. In Gowalla Los Angeles(GLA) dataset, DAPred yields around 10.3% improvement in top 5 hitting ratio and 9.6% improvement in top 10 hitting ratio. Distance predictor error δ_d comparison is shown in 4, in which DAPred outperfroms the best baseline SERM by 13% in Foursquare and DeepMove by 43.3% in Gowalla at New York. Compared to the strongest baseline DeepMove, the huge improvements in DAPred are mainly attributed to two main reasons: (1) The dynamic preferences over distance when users move; (2) The introduction of various interests over all terms on different target times. To further prove our conclusion, we conduct experiments on the variants of our models.

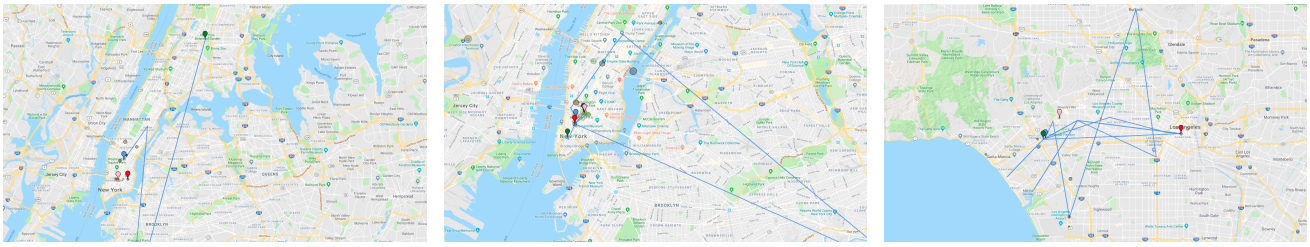
As we stated before, dynamic location prediction own three key challenges to be solved. (1) Integrating diverse types of user preferences. (2) Dynamic influence of past movements over distance preference. (3) Influence of target time. To illustrate the effectiveness of each component, we conduct experiments on four models, including: TPred (Embedding and LSTM), TLSPred (Embedding and LSTM-RNN), TDPred (Embedding,LSTM-RNN and attention) and DAPred

As shown in Table 2, the attention-based model outperform others consistently. Addtionally, DAPred combines both structure of TLSPred and TDPred, achieving the best results among all models. Hence, DAPred is more effective in modeling dynamic relations than simple structures.

5.3 Illustrative Cases

In this section, we present several illustrative cases for our algorithm. Figure 5 shows the location prediction for three different users from 4SQ, GNY and GLA dataset. In these figures, the blue markers are starting points and the green marker are end points. Markers with other colors indicate the ground truth of next location and the blue lines are users' past movements. Black circles in the figures refer to the results of our predictions. A larger circle indicates a higher ranking of the prediction.

By visualizing users' movements and our prediction, it is obvious that we can correctly predict users' next location at different target times. Moreover, for the movements in figure 5(b), for the first target time with black circles indicate our prediction, we find the black circles are almost around the short trajectory, showing a preference for short-term memory. For the second target time with green circles, they are almost around the endpoint, indicating a preference over locations in the neighborhood. While for the third target time with brown circles, most of the predicted locations are far away, showing a preference on long-term memory.



(a) 4SQ (b) GNY (c) GLA

Figure 5: Visualization of dynamic attention location prediction with different interest over long-term and short-term preference.

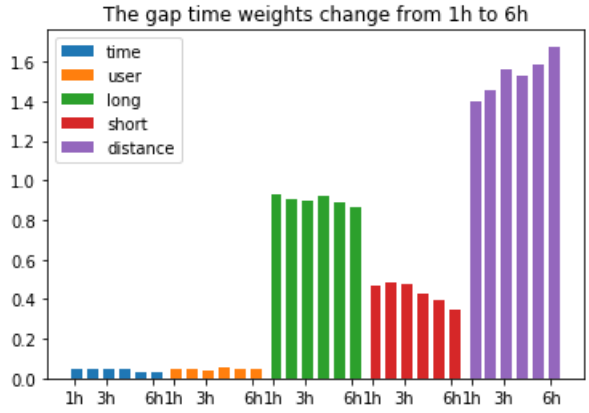


Figure 6: The change of weights with gap times on Foursquare

5.4 Effect of dynamic attention mechanism

As we discussed above, we attribute our improvements to two aspects. In this section, we would further discuss the effects of these two parts.

In Figure 6, we present the change of weights on different time gaps (from 1 hour to 6 hours). When the time gap becomes larger, the weight of distance tends to grow, and the weight of short-term preference tend to decrease. Such a phenomenon further validates the change of users' preference over target time. Due to limitations of space, we don't present the results for all datasets

5.5 Parameter Tuning

As mentioned above, there are three main parameters of DAPred: the embedding demension for long-term and short-term trajectory E_v, the embedding demension for time E_t and the embedding demension for user E_u.

We first study the effects of E_t and E_v. In Figure 7, the orange bar implies the accuracy of HR@10, the blue bar implies the accuracy of HR@5, while the red bar implies the accuracy of HR@1. From the figure, we could find that the when $E_t = 16$ and $E_v = 16$, we could reach the highest accuracy. We could also draw the conclusion that the effects of parameters of E_t and E_v are limited on accuracy. Then we study the effects of E_u. Comparing to the parameters above, the value of E_u influence the accuracy a lot. Based on the figure, we select $E_u = 32$.

6 CONCLUSION

In this paper, we studied the problem of dynamic attention location prediction problem with a new algorithm DAPred. To the best of our knowledge, DAPred is the first method to predict next location with multiple target time. To solve the target-time aware location prediction problem, DAPred enjoys two novel characteristics: 1) An attentional module to model the temporal and historical movements influence over next movement selection 2) Various target time preference over multiple factors. Our extensive experiments with three real-life datasets have proved that DAPred owns a significant improvement over the accuracy of the state-of-the-art method in terms of HR@1, HR@5, HR@10 and average distance predictor error. Further more, we also conduct comparison between different models origined from our algorithm, which further proved the significance of dynamic attention on time.

As part of our future work, we plan to discuss more on the dynamic attention location prediction problem. We would incorporate our dynamic location prediction with inner-purpose in time cycle (e.g. habits, travels, etc).

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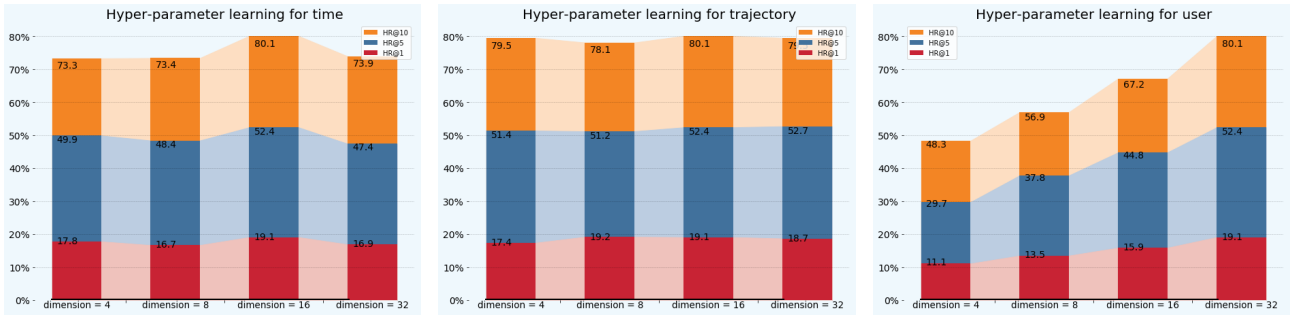

(a) Time dimension (b) Trajectory dimension (c) User dimension

Figure 7: Hyperparameter Tuning

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