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Design and Case Study of Long Short Term Modeling for Next POI Recommendation

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***Abstract*—In recent years, research on the next POI recommendation has received widespread attention. Its goal is to recommend the next POI to users at a specific time based on their historical check-in data. Therefore, modeling the long-term behavior habits and recent continuous behavior of users is crucial. However, existing methods for modeling user short-term preferences either ignore their long-term preferences or the semantic distribution between recently visited POIs, resulting in unreliable recommendation results. To address these issues, we conducted research and analysis on existing relevant literature, planned potential further research ideas and technical routes, and summarized the methods for such research tasks. Described the model framework of the research case, introduced the commonly used datasets and evaluation indicators in POI recommendation methods, and analyzed the experimental results of existing research cases.**

***Index Terms*—Location Based Social Network, Point of Interest Recommendation, Spatio-Temporal Models.**

I. INTRODUCTION

In recent years, with the booming development of location-based service (LBS) platforms such as Yelp, Foursquare, and Uber, the importance of user behavior patterns in the decision-making process has become increasingly prominent, especially in the field of point of interest (POI) recommendation. Researchers have a strong interest in how to use users' historical trajectory data to predict their future interests. The massive historical check-in data accumulated by these services provides valuable resources for service providers to gain in-depth insights into user preferences and needs. In the vast location-based social networks (LBSNs), the attendance data of millions of users provides excellent opportunities to explore user behavior patterns. Through detailed analysis of these data, we can not only significantly improve user experience, but also provide more accurate marketing strategies for service providers. Therefore, this article aims to explore and elaborate on how to use these check-in data to optimize POI recommendation algorithms, thereby improving the quality of LBS services and overall user satisfaction.

In the realm of Point of Interest (POI) recommendation, the subsequent POI recommendation task[1] emerges as a natural extension of traditional POI recommendation, aiming to provide highly personalized POI suggestions to users based on their historical check-in sequences. Models based on Markov chains are extensively employed in next POI recommendation, wherein the construction of transition matrices enables accurate prediction of users' future mobility patterns. Qiao et al.[2] proposed a trajectory prediction algorithm based on Hidden Markov Models (HMMs). By segmenting and clustering trajectory sequences based on the hidden states of the model, an efficient prediction model was constructed. This approach not only enhances the accuracy of trajectory prediction but also improves the adaptability and generalization capability of the model to complex trajectory patterns. However, due to their inability to capture temporal dependencies, these Markov-based methods can only perform well in certain scenarios.

With the advancement of technology, researchers' focus has gradually shifted towards Recurrent Neural Networks (RNNs). Due to their outstanding performance in Natural Language Processing (NLP), RNNs have gained widespread recognition. Moreover, given the similarities between POI recommendation problems and NLP tasks in various aspects, many cutting-edge POI recommendation models opt for RNNs as their foundational architecture. The Flashback model proposed by Yang et al.[3] has attracted widespread attention in the field of POI recommendation. This model is based on the Basic Recurrent Neural Network (RNN) architecture, which efficiently utilizes sparse user mobility data by deeply mining rich spatiotemporal background information and reverse processing hidden states in the RNN.

With the continuous emergence of new models, they have significantly promoted our cognitive depth in the field of mobile speculation. However, there are still several key issues that have not been properly resolved. Firstly, the current mainstream models mainly focus on spatial or temporal differences in the current state, while considering the long-term behavior patterns of users appears relatively insufficient. Secondly, from the perspective of semantic distribution, previous location inference methods have not fully utilized the distribution characteristics of semantic information, which to some extent limits their accuracy and effectiveness in practical applications. Therefore, future research should focus on addressing these issues to further enhance the accuracy and practicality of mobile speculation.

II. POI RECOMMENDATION METHOD CASE STUDY

A. *Long Short Term Model Architecture*

Due to the inability of RNN models to capture long-term dependencies, Long Short Term Memory (LSTM) [4] has been widely used in recent work on POI recommendations. Most models use basic LSTM for prediction. In order to further improve the long-term dependency model, attention

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mechanism will also be used in conjunction with LSTM. The following is a detailed discussion of a research case that uses the structure of a POI recommendation model based on LSTM for long short-term separation.

In previous studies, the authors of LSPL [5] successfully extended their work by introducing personalized long-term and short-term preference learning (PLSPL) models [6]. The PLSPL model innovatively integrates a user based linear combination unit based on LSPL. The core function of this unit is to accurately capture and simulate the unique preferences of different users by learning personalized weights between long-term and short-term modules. This design not only improves the adaptability and flexibility of the model, but also provides a new perspective and method for in-depth research on user behavior patterns.

Sun et al. [7] used the basic LSTM model in their study and proposed the Long Term and Short Term Preference Modeling (LSTPM) method. LSTPM constructs a model framework consisting of three core modules by dividing all user check-in records into multiple trajectories: long-term preference modeling module, short-term preference modeling module, and prediction module. The long-term preference modeling module comprehensively considers all historical trajectories of the user, while the short-term preference modeling module focuses specifically on the user's final trajectory information and predicts the next potential point of interest (POI) based on it. It is worth noting that the prediction of the next POI is not solely dependent on the user's recent check-in records, but may be influenced by the user's check-in behavior at any previous time. However, traditional RNN/LSTM based methods have limitations in modeling the relationship between discontinuous POIs. To overcome this limitation, Sun et al. combined the geographically extended LSTM scheme with the basic LSTM in the short-term preference modeling module, effectively capturing the potential connections and mutual influences between these discontinuous POIs.

B. *The Influence of Semantic Factors*

Each POI has a unique set of attributes. When two POIs share similar attributes, they exhibit similarity at the semantic level. Meanwhile, considering the personalized characteristics of user behavior, each user has their own unique preferences and tends to access POIs that match their own preferences. Therefore, by analyzing the user's check-in records, it is possible to accurately capture and understand their choices, and then attempt to predict POIs that are semantically similar to the user's previous check-in records, thereby improving the user experience and satisfaction.

Li et al. [8] proposed an encoder decoder neural network model that utilizes embedding methods to merge heterogeneous contextual factors related to each check-in activity to fill in the semantics of check-in. Chang et al. [9] utilized text content that provided POI feature information. They also measure the correlation between words by calculating the Jaccard similarity of POI in the text content.

III. ARCHITECTURE OF THE CASE

Through the analysis of existing research methods, we can observe that the model structure with long and short-term separation is beneficial for addressing the problem of incomplete modeling in our current models. The case model[6] can obtain the long-term and short-term preferences of users through a model structure that separates long and short-term preferences, and integrate these preferences into a unified framework to generate a predicted location list for the next point of interest that the user will visit.

A. *Long-term Model Architecture*

The long-term preference module can be composed of two parts: feature extraction and feature fusion representation. Figure 1 shows the architecture of the long-term module in this case. The multi-dimensional feature extraction layer is mainly used to extract multi-dimensional features from user trajectories, such as spatiotemporal features, semantic features, social relationships, and so on. The feature fusion representation layer can consider assigning personalized weights to each feature by carefully fusing the extracted features to obtain the user's long-term behavioral habits.

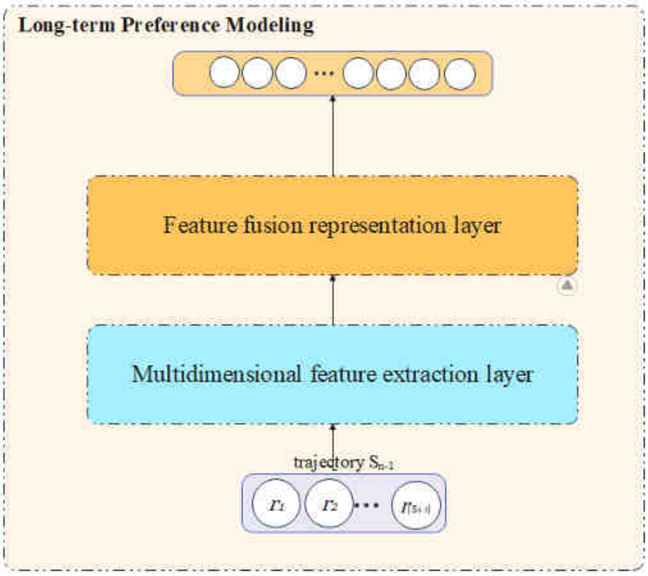

FIG.1 Long term module structure diagram

Existing research mostly focuses on the continuous spatiotemporal relationships between trajectory positions, ignoring the spatiotemporal relationships of non local positions and the hidden behavioral preferences of users. Current research mainly focuses on the continuous spatiotemporal relationships between trajectory positions. However, spatiotemporal relationships between non adjacent positions also contain rich user behavior preference information. Extracting multidimensional features between non adjacent positions in long-term modules can help the model more comprehensively capture user behavior preferences.

When constructing a feature fusion representation layer, attention mechanisms can be considered to fuse spatiotemporal and semantic features in trajectories, aiming to capture user behavior patterns in a targeted manner and gain a deeper understanding of their long-term preferences. This fusion representation method enables the model to comprehensively consider the user's behavior patterns at different times, locations, and semantic categories, thereby more accurately understanding the user's long-term preferences.

B. Short-term Model Architecture

In most existing research cases that use long short-term separation, LSTM models are usually used to learn users' short-term preferences when constructing short-term modules. The structure of the short-term module can be summarized as described in Figure 2:

In the short-term preference section, the input sequence of the module includes user ID, location, category, and time information. Before establishing a sequence preference model, existing research cases first learn their potential embedding vectors, and then use LSTM models to maintain dependency relationships in features, ultimately obtaining a short-term preference representation of users. In the short term, by processing trajectories and combining spatiotemporal features based on semantic transition sequence correlation, multi-level semantic features are embedded and represented. The LSTM model is used to maintain the sequential dependency relationships between various features and extract short-term preferences of users.

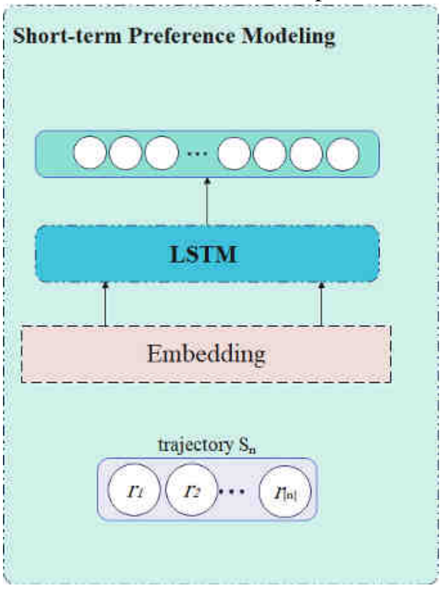

FIG.2 Short term module structure diagram

The input sequence includes semantic attributes of user, location, time, and current location. The original timestamp is mapped to discrete hours, and similar user, location, and semantic attributes are also represented as one hot encoding. Assign such combination vectors to the LSTM model simultaneously, and model user preferences using LSTM as follows:

$$
\begin{aligned}
x_t &= [v^u; v^l; v^t; v^s] \\
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i), \\
f_t &= \sigma\left(W_f[h_{t-1}, x_t] + b_f\right), \\
g_t &= tanh\left(W_g[h_{t-1}, x_t] + b_g\right), \\
o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o), \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t, \\
h_t &= o_t \odot tanh(c_t).
\end{aligned} \tag{1}
$$

IV. CASE EXPERIMENT ANALYSIS

A. Experimental Datasets

Interest point recommendation, as a special recommendation field, requires more time and geographic location data in the dataset compared to other datasets, and algorithms are particularly sensitive to data that affects a person's travel, such as geography, time, and social relationships in the dataset. The commonly used datasets for interest point recommendation currently include the Foursquare dataset, Yelp dataset, and Gowalla dataset. Below are several commonly used datasets.

(1)Foursquare dataset. The Foursquare dataset is sourced from a location-based social networking site. Foursquare itself does not provide an API to access user check-in data, but its association with Twitter allows users to find and utilize Foursquare's check-in data from Twitter. Among them, the basic user information includes the user's ID, name, and address. The basic information of points of interest includes the ID name, address, coordinates, and classification labels of the location. The user's history includes their comment tags, each of which is associated with the ID of the point of interest, detailed comments, and timestamp.

(2) Gowalla dataset. The Gowalla dataset is sourced from the location-based social check-in application Gowalla. The corresponding check-in data was collected by Stanford's Jure Leskovec from February 2009 to October 2010, which contained 6442890 check-in information. Each record in the data consists of the user's ID, check-in time, coordinates of the point of interest, and the ID of the point of interest.

Although the Gowalla dataset is sourced from the social application Gowalla, it does not have a clear social relationship as it is not directly disclosed by Gowalla. Meanwhile, the dataset is no longer updated, and the user's selection of points of interest is time sensitive. Therefore, the model learned from this dataset may deviate significantly from the user's actual selection.

(3) Yelp dataset. The Yelp dataset is sourced from Yelp, the largest review website in the United States, and is publicly available by Yelp. The dataset is recorded in JSON format. As of March 26, 2020, this dataset contains interest point information from 11 major cities in 4 countries, with 520 million user reviews and 174000 interest point information. The dataset consists of interest point information, check-in information, comment information, user comment tags, user information, and image information. Interest point information consists of interest point ID, name, address, coordinates, rating, classification, business hours, and other attribute information. The check-in information consists of a set of interest point IDs and the timestamp at which the interest point was signed in. Comment information consists of comment ID, comment user ID, point of interest ID, comment content, and comment time. The comment tag information consists of tag text, interest point ID, and user ID. User information consists of user ID, name, number of comments, social relationships, etc. The image information consists of the image ID, the corresponding interest point ID, descriptive text, and image classification labels.

B. Evaluating Indicator

Common evaluation indicators include recall, precision and MAP. TP represents the number of positive classes, FP represents the number of predicted positive and negative classes, and FN represents the number of predicted negative positive classes. Rec@k used to measure whether there is a correct POI among the first K recommended POIs. Higher Rec@k Numerical values represent better predictive performance. The calculation formula for Recall is as follows:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The calculation formula for Precision is as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

C. Experimental Results and Analysis

We will compare the two methods, PLSPL and LSTPM, which mainly discuss the use of long short-term separation structures, with traditional POI recommendation methods. It can be observed that on the Foursquare dataset Recall@5 For example, a model that uses long short-term separation exhibits good indicator performance. This further demonstrates the effectiveness of the model structure we are exploring in capturing user behavior dynamics and long-term trends.

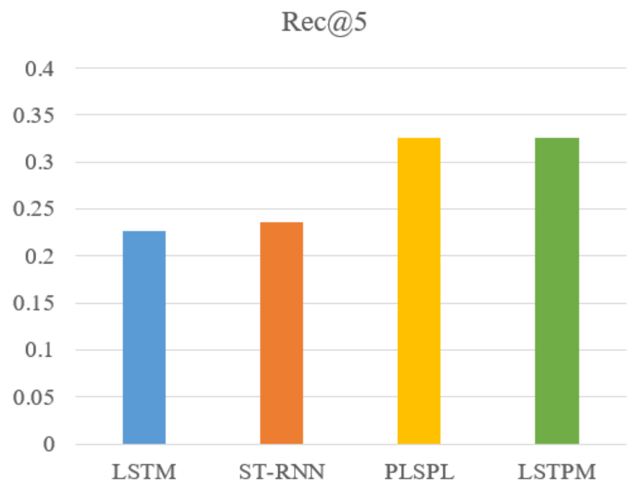

FIG. 3 Different methods on the Foursquare dataset Rec@1 Comparison of performance

The comparison results are shown in Figure 3.We can see that PLSPL and LSTPM perform relatively well. Due to the integration of both long-term and short-term preference modeling to some extent, its experimental results are superior to other methods in terms of recall.

This is because LSTM and STRNN mainly focus on dynamically obtaining short-term user preferences, neglecting to capture long-term user preferences. Therefore, this further demonstrates the importance of considering both long-term and short-term modeling simultaneously.

At the same time, we can observe that the experimental effect of the LSTPM method is slightly lower than that of the PLSPL method. This is because LSTPM did not consider the importance of semantic dimensions and discontinuous POIs. By introducing advanced semantic analysis and discontinuous POI modeling techniques, deep semantic analysis of user behavior data was conducted using natural language processing and deep learning techniques to more accurately capture user interests and needs.

In summary, on multiple datasets, the performance indicators of cases separated by long computation periods are significantly better than baseline methods, especially in capturing users' long-term and short-term preferences, demonstrating excellent capabilities. By introducing semantic analysis and long-term POI modeling techniques, these methods have successfully overcome the limitations of traditional methods and provided users with more accurate and personalized recommendation services.

V. Conclusion

In this article, we conducted a survey of existing relevant literature in this research field and analyzed and summarized it. Proposed potential further research ideas and technical routes, optimized the recommendation performance of the next point of interest by separating the model architecture of long-term and short-term methods. In the design of the long-term module, we conducted in-depth analysis of user behavior habits and achieved accurate capture and learning of user long-term preferences through feature extraction layers and feature fusion techniques. In the short-term module, this article uses feature embedding layers and LSTM models to capture and learn users' spatiotemporal feature preferences and semantic distribution preferences. After a series of experimental verifications, our model has been evaluated for performance on real-world datasets Recall@k. For key indicators, it is significantly better than existing advanced methods. This achievement not only validates the effectiveness of our model architecture, but also further highlights the potential value of long-term and short-term separation strategies in the field of POI recommendation.

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