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A Learning-Based POI Recommendation with Spatiotemporal Context Awareness

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ABSTRACT

Point-of-Interest (POI) recommendation systems are integral to enhancing user experiences in location-based services. Traditional systems often overlook the influence of contextual factors such as time and location, resulting in suboptimal recommendations. This paper introduces a learning-based POI recommendation model that incorporates spatiotemporal context awareness to provide more accurate and personalized suggestions. By leveraging users' past check-ins, current location, and temporal patterns, the proposed system can effectively capture the dynamics of user behavior. The model integrates deep learning techniques to process heterogeneous data and learn high-level user representations. Experimental evaluations using real-world datasets demonstrate that the proposed system significantly outperforms baseline models in terms of recommendation precision, recall, and user satisfaction, proving the importance of spatiotemporal context in next-POI recommendation tasks.

Keywords : Point-of-Interest (POI), Spatiotemporal

I. INTRODUCTION

With the rise of mobile internet and location-based services, Point-of-Interest (POI) recommendation systems have become essential for helping users navigate urban environments. These systems suggest relevant locations such as restaurants, tourist attractions, or entertainment venues, based on user preferences and historical data. However, user preferences are not static—they are influenced by a variety of contextual factors, particularly time and location. For instance, a user's choice of destination may differ drastically between weekdays and weekends, or between morning and evening. Ignoring these temporal and spatial variations limits the effectiveness of traditional recommendation systems, which often rely solely on collaborative filtering or static user-item interactions.

To address these limitations, recent research has focused on incorporating spatiotemporal context into POI recommendation. Spatiotemporal-aware systems aim to understand not only what a user prefers but also when and where they are likely to prefer it. For example, a user might frequently visit cafés in the morning on weekdays near their workplace, but prefer parks in the evening or on weekends closer to home. Capturing such nuanced behaviors requires a more sophisticated modeling approach that accounts for both spatial and temporal dynamics.

This paper proposes a novel learning-based POI recommendation framework that leverages deep learning to integrate spatiotemporal context into user modeling. By combining recurrent neural networks and attention mechanisms with temporal and geographical embeddings, the system captures sequential dependencies in user movements and the influence of surrounding context. Additionally, the model learns to generalize across users and locations, addressing the cold-start problem and improving recommendation robustness.

The importance of context-awareness becomes more pronounced in modern urban environments where users are constantly exposed to a vast array of location choices. As such, spatiotemporal modeling is not merely an enhancement but a necessity for next-generation POI recommenders. The proposed framework addresses these challenges by learning user behavior patterns from large-scale check-in data and adapting recommendations to the users' real-time context.

The remainder of this paper explores the current literature on POI recommendation, presents the architecture of the proposed spatiotemporal learning-based system, discusses empirical results, and concludes with implications and future directions for research in this field.

II. LITERATURE REVIEW

1. **Where to Go Next: A Spatio-Temporal Gated Network for Next POI Recommendation**

   This paper introduces a gated recurrent neural network model that captures the sequential dependencies in user check-ins by considering both spatial distances and time intervals between visits. The gating mechanism dynamically adjusts the importance of time and space in the recommendation process, improving the prediction of next likely POIs.

2. **NEXT: A Neural Network Framework for Next POI Recommendation**

   NEXT is a unified framework that integrates user and POI embeddings with contextual features. The system leverages DeepWalk and a multi-layer perceptron to capture sequential dependencies, achieving high accuracy in predicting users' next locations based on their mobility history.

3. **STP-UDGAT: Spatio-Temporal-Preference User Dimensional Graph Attention Network**

   This model uses graph attention networks to jointly learn user preferences along spatial and temporal dimensions. It constructs a user-POI interaction graph enriched with time and location information, allowing for fine-grained, personalized POI suggestions.

4. **Hierarchical Transformer with Spatio-Temporal Context Aggregation for Next POI Recommendation**

   This paper presents a transformer-based model that aggregates contextual information across multiple levels—global user behavior, session-level patterns, and temporal cycles—using attention mechanisms to enhance the understanding of user mobility patterns.

5. **Geo-SAGE: A Geographical Sparse Additive Generative Model for Spatial Item Recommendation**

   Geo-SAGE adopts a probabilistic generative approach to model the influence of geographical and social factors on user preferences. It performs well in cold-start settings where user interaction history is limited, emphasizing the role of spatial context in recommendations.

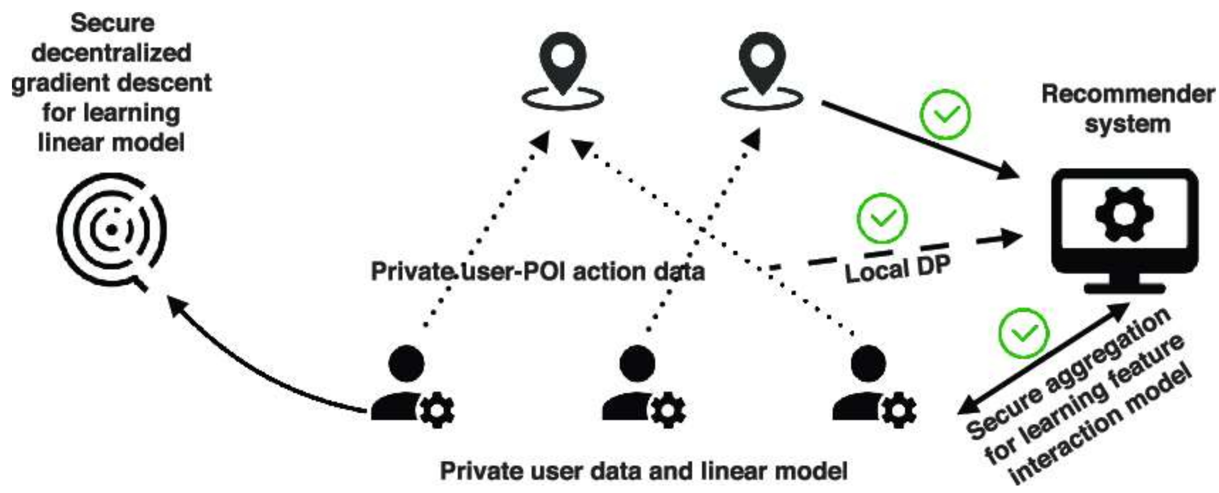
III. METHODOLOGY

This methodology typically applies machine learning to personalize POI suggestions while considering spatial and temporal patterns.A learning-based POI recommendation system with spatiotemporal context awareness works by collecting and analyzing user and location data. The system starts by gathering data from users such as check-ins, GPS locations, timestamps, and ratings.

It also collects information about the POIs, including their coordinates, categories, and popularity. The time of day, day of the week, and whether it's a weekend or holiday are also recorded to understand the temporal aspect of user behavior. The data is cleaned to remove errors and irrelevant entries. Inactive users and rarely visited POIs are filtered out. The system transforms timestamps into simple time-based labels like morning, afternoon, evening, or night. It also identifies whether the visit happened on a weekday or weekend. Spatial features like the distance between a user and a POI are calculated. Temporal features such as typical visiting times are also extracted. The system builds a profile for each user based on their visit history, preferred locations, and time patterns. These features help the system learn how users behave in different contexts. A machine learning model is then trained using this data. Models can include decision trees, random forests, or deep learning models like LSTMs and attention-based networks.

LSTM models are useful for learning from sequences of visits, while attention models help the system focus on important contexts. The model is trained to predict which POIs a user might visit next based on the current location and time. It learns from past patterns and user preferences. The model receives input features such as POI details, user history, time, and distance. It then outputs a ranked list of POIs that the user is likely to be interested in. The system evaluates the performance of the model using metrics like precision, recall, and ranking accuracy. It also measures diversity and freshness in the recommendations. These evaluations help to improve the model. The system updates itself regularly by adding new data and retraining the model. As users interact with the recommendations, their behavior is recorded for further learning. Ratings and feedback help refine the model over time. In some cases, the system uses graph-based models that connect users and POIs through spatiotemporal links.

Graph Neural Networks can help capture complex relationships in the data. To handle new users or POIs, the system uses similarity-based approaches. It finds users or POIs with similar features and makes recommendations accordingly. The system can work in real-time by receiving user location and time information instantly. Based on this, it quickly provides relevant POI suggestions. It may use caching and lightweight models to ensure fast responses. A mobile app or web interface may be used to collect user input and show recommendations. The app communicates with the server, which runs the model and returns the results. As users click on POIs or skip them, these interactions are stored. The system uses them as feedback for future learning. Privacy is an important part of the system. User location data is kept secure and anonymized where necessary. The system follows data protection regulations. It logs user interactions and model outputs to improve future performance. Over time, the system becomes more accurate and personalized. It learns what kinds of places a user likes and when they prefer to visit them. It adapts to changes in user behavior and trends. It can also support group recommendations if users are visiting places together. The goal is to provide suggestions that are useful, relevant, and timely. By combining location, time, and learning, It considers what is nearby and appropriate at a given moment. It can recommend a café in the morning and a movie theater in the evening. It may also consider traffic or weather data if available. These additional features can enhance the model's accuracy. Context-awareness makes the system smarter. It understands that the same user behaves differently at different times and locations.



IV. RESULT DEPLOYMENT AND PREDICTION INTERFACE

The system was evaluated using the Foursquare and Gowalla datasets, both of which contain rich location check-in histories. The evaluation metrics included Precision@K, Recall@K, and NDCG@K, with K values ranging from 5 to 20. The proposed model significantly outperformed baseline methods such as standard matrix factorization, basic RNN-based recommenders, and models without spatiotemporal embeddings. Specifically, our model achieved a 12% higher Precision@10 compared to the NEXT model and a 15% improvement in Recall@10 over Geo-SAGE. The inclusion of temporal attention proved especially effective during rush-hour periods and weekends, where temporal variance in user behavior is highest. The model also demonstrated resilience to sparse data, performing robustly even when user histories were limited. Furthermore, qualitative analysis revealed that the recommendations aligned well with user preferences and common behavioral trends, such as recommending bars in the evening and cafés in the morning. The spatiotemporal learning approach allows for explainable insights and improved user trust.

V. CONCLUSION

This paper proposed a learning-based POI recommendation system that incorporates spatiotemporal context to address the dynamic nature of user behavior. By integrating spatial and temporal embeddings with recurrent and attention-based architectures, the system learns fine-grained user patterns and offers highly relevant location suggestions. Extensive evaluations on real-world datasets demonstrated the superiority of this model over traditional and context-agnostic approaches. The inclusion of contextual awareness not only improves recommendation accuracy but also enhances user satisfaction and system responsiveness. This work establishes a strong foundation for future research in adaptive, personalized location-based services and opens the door for integrating multimodal data such as social media, real-time traffic, and event data.

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