Leveraging Geographic Feature Embeddings for Enhanced Location-Based Recommendation Systems

Nícolas Moreira Nobre Leite[1], Claudio E. C. Campelo[1], Salatiel Dantas Silva[1]

[1]Systems and Computing Department
Federal University of Campina Grande (UFCG)
Campina Grande – PB – Brazil

nicolas.leite@ccc.ufcg.edu.br,

{campelo, salatiel.dantas}@computacao.ufcg.edu.br

Abstract. *Geographically-aware models are becoming increasingly important in Points of Interest (POI) Recommendation Systems (RSs), particularly with the rise of Location-Based Systems and Social Networks, benefiting various areas and enhancing user experience and engagement. Although current POI RSs are of good quality, they often overlook intrinsic geographic features such as nearby rivers, buildings, and streets in POI's vicinity, which can significantly influence user preferences. In this study, we propose and evaluate the use of POI type geographic embeddings that incorporate geographic features to enhance POI RSs. The results indicate that this approach improves the effectiveness of POI recommender models.*

1. Introduction

Recommender Systems (RSs) play a crucial role in personalizing user experiences, providing highly relevant suggestions across various domains, including e-commerce [Bhuvanya and Kavitha 2023], entertainment [Kulkarni et al. 2023], and music [Saito and Sato-Shimokawara 2023]. These systems are essential for helping users navigate through numerous options, recommending products, movies, and music that align with their preferences. Within the vast field of RSs, the recommendation of Points of Interest (POIs) represents a subarea of growing interest. However, effective POI recommendation presents unique challenges due to the inherent complexity of capturing user preferences, which are influenced by cultural, personal and geographical factors.

Modern POI RSs often rely on embeddings that are built considering similar information, such as user reviews of locations, check-ins, visiting times, and POI types [Liu et al. 2019, Zhang et al. 2023, Yang et al. 2022]. These data are quite relevant as they represent trajectory patterns and characteristics of the visited POIs. For instance, POI types categorize locations in various ways, such as commercial (e.g., restaurants, hotels), recreational (e.g., parks, museums), and transportation (e.g., airports, train stations), facilitating searches in geographic databases and groupings. However, despite recent researches have shown good results [Yang et al. 2022, Yan et al. 2023, Yin et al. 2023], they do not consider the use of geographic features in the POIs' vicinity. Geographic features refer to any part of the Earth's surface or any element present on it that can be represented on a map[1]. They are normally regarded as geographic entities with precise

[1]https://support.esri.com/pt-br/gis-dictionary/search?q=feição

boundaries, such as rivers, squares and roads. In geographic databases, they are associated with geometric objects of different types, such as points, lines and polygons.

Geographic features can be crucial for characterizing user preferences and may even motivate the choice of the next POI to be visited. For example, some people may be more likely to visit restaurants near lakes than restaurants in denser urban areas. That said, we conducted a study to answer the following question: can the use of POI type geographic embeddings that encapsulate geographic features improve POI recommendations? In this context, we propose an approach to incorporating such embeddings into a POI recommendation model and experimentally evaluated our solution by comparing the effectiveness of a state-of-the-art POI RS before and after this adaptation.

To do this, we selected a recently developed approach to incorporating geographic features into POI type embeddings [Silva et al. 2023], which has shown promising results in other application scenarios. The model selected for implementing the approach was GETNext [Yang et al. 2022], referenced in the literature as one of the leading options for POI recommendation. The results obtained indicate that the approach appears promising, successfully capturing the importance of geographic features present in the context of a POI for choosing the next POI a user will visit.

The remainder of this paper is organized as follows. Section 2 describes related work in the area of POI representation and POI RSs. In Section 3, we present our methodology, including the model architecture and the method of generating geographic embeddings. Section 4 presents the results of our experiments and Section 4.4 discusses them. Finally, Section 5 concludes the paper and points to future research.

2. Related Work

This section describes related work in the areas of POI representation and POI RSs.

2.1. POI Representation

Several studies have explored POI representation through embedding techniques, highlighting them as a promising approach to enhance the effectiveness of POI RSs. Studies such as [Wang et al. 2020], who introduced Urban2Vec, exemplify significant innovations in this field. Urban2Vec is an unsupervised technique that generates representations of neighborhoods using a combination of street view images and textual information from POIs. This approach is notable because it integrates visual and textual features with geospatial data, outperforming existing baselines and competing with fully supervised methods in downstream prediction tasks such as urban planning, business model development, and social well-being improvement.

In the context of POI RSs, embeddings generated by these techniques are used to capture the essence of POIs and contextualize recommendations according to user preferences and local characteristics. For example, [Feng et al. 2017] introduced the POI2Vec model, which uses embeddings to represent POIs based on user interactions and check-ins, allowing for a deeper understanding of movement patterns and preferences.

On the other hand, [Silva et al. 2023] proposed GeoContext2Vec, a method that leverages the importance of geographic features in the vicinity of a POI for generating embeddings. Unlike methods that rely on check-in data or textual descriptions, GeoContext2Vec evaluates the proportion and uniqueness of the space occupied by these geographic features. This method demonstrated superiority over ITDL ([Yan et al. 2017]), a state-of-the-art method based on POI co-occurrences, in terms of POI type similarity evaluation by human analysis. Additionally, the use of public domain maps such as OpenStreetMap (OSM) for vector creation is highlighted as a practical and reproducible alternative.

Despite the advancements in POI representation and recommendation models, a significant gap persists in effectively integrating fine-grained geographic features into the recommendation process. Existing approaches primarily rely on general geographic information such as POI coordinates [Luo et al. 2021, Wang et al. 2020]. However, these methods often overlook the impact of hyperlocal geographic features, such as the presence of parks, bodies of water, or highways, on user preferences. This gap limits the ability of current models to capture the nuanced relationships between users and their surrounding environment, hindering the potential for truly personalized and context-aware recommendations. Therefore, we employed GeoContext2Vec to generate embeddings of POI types that include geographic features, using them in the context of POI recommendations in this research to improve recommendations.

2.2. Conventional POI Recommendation Systems

Initial research in the area of POI RSs utilized Markov chains and matrix factorization techniques [Davtalab and Alesheikh 2021, Koren et al. 2009, Zhao et al. 2016]. However, these approaches have become limited in representing users' visitation patterns when compared to deep learning and embedding-based approaches [Feng et al. 2020].

Additionally, many approaches model the relationships between visited POIs and potential POIs by incorporating and prioritizing temporal factors. [Yuan et al. 2013] identified a significant gap in existing methods, which often neglected the influence of the specific time of day on user preferences. They proposed a collaborative recommendation model that integrates temporal information, allowing for more accurate recommendations at different times of the day. [Shi et al. 2021] introduced an attentional memory network with correlation-based embeddings (AMN-CE) for time-aware POI recommendation, proposing a temporal attention mechanism to adjust the influence of different times on user preferences. [Wang et al. 2021] developed a model that incorporates users' temporal check-in preferences by designing a cross-graph neural network to control the information flow across different semantic spaces, enhancing recommendation accuracy by considering the relationship between check-in times and POIs.

[Halder et al. 2021] addressed the task of next POI recommendation by considering the queue time users spend entering a POI, a critical factor influencing user mobility behavior. Using a Transformer model, the TLR-M, the authors not only recommend the next POI but also predict the queue time required for a user to enter a POI.

While temporal factors are important, the geographic influence of POIs is also crucial for improving recommendations. Various geographic embedding generation techniques have been applied considering the context of POIs, neighborhood characteristics, and temporal factors to capture user preferences and enhance recommendations.

2.3. POI Recommendation Systems that consider geographic information

[Luo et al. 2021] proposed the Spatio-Temporal Attention Network (STAN), a model that addresses spatial scarcity and temporal relations by employing a two-layer attention architecture. This model excels in facilitating interactions between non-adjacent locations and non-consecutive check-ins, capturing the explicit spatiotemporal effects influencing user behavior. [Wang et al. 2022] proposed a POI recommendation method leveraging sequential, categorical, and geographic influences. Their process begins by extracting latent vectors of POIs and user preferences from check-in sequences using a word embedding model. Collaborative filtering is then applied to predict user preferences for different POIs based on their behavior.

[Qin et al. 2023] proposed the Disentangled Dual-Graph (DisenPOI) framework for next POI recommendation, enhancing POI recommendation by disentangling sequential and geographic influences, often conflated in traditional approaches. The framework uses two distinct graphs: one to model the user's visit sequence and another to represent the geographic relationships between POIs. Through contrastive learning, the framework extracts disentangled representations of these influences, allowing for a clearer understanding of user preferences and resulting in more accurate and interpretable recommendations. [Yang et al. 2022] presented the Graph Enhanced Transformer (GETNext) model, which also uses graphs for next POI recommendation, leveraging a global trajectory flow map and a Transformer-based architecture. To capture generic user movement patterns between POIs, the authors constructed a graph representing user trajectories, where nodes reflect POIs with attributes such as geographic location, POI category, and check-in frequency. They then used a Graph Convolutional Network to learn POI embeddings encapsulating these global transitions and recommend the next POI to visit.

[Yan et al. 2023] developed the Spatio-Temporal HyperGraph Convolutional Network (STHGCN), a model for next POI recommendation that employs a hypergraph to analyze detailed trajectory information. The model learns from historical and collaborative trajectories, addressing the cold start problem [Lika et al. 2014] and improving recommendations for various user trajectory durations. Using a Transformer with hypergraph integration, STHGCN incorporates hypergraph structures with spatiotemporal data, outperforming previous methods in practical tests. [Yin et al. 2023] developed the Sequence-based Neighbour search and Prediction Model (SNPM) for next POI recommendation, using graph embedding techniques and Eigenmap methods to analyze POI relationships from sparse check-in data. The model includes a Dynamic Neighbour Graph and Multi-Step Dependency Prediction, considering both current states and historical visit sequences to POIs.

While the aforementioned approaches have significantly advanced the incorporation of geographic data and graph-based architectures to improve recommendations, there remains a crucial gap in integrating geographic features into POI recommendation models. Therefore, we propose an approach that uses geographic embeddings of POI types incorporating geographic features, as described in [Silva et al. 2023]. We then integrate these embeddings into the graph and Transformer-based architecture of the GETNext model [Yang et al. 2022] to determine if the addition of these embeddings enhances POI recommendations.

3. Methodology

In our methodological approach, we employ the generation of POI type embeddings using GeoContext2Vec and then integrate these embeddings into the graph-based and Transformer architecture of the GETNext model. The details of these processes are presented in the following subsections.

3.1. Generation of POI Type Embeddings

As mentioned earlier, geographic features play a fundamental role in representing POI types. POI recommendation systems can significantly benefit from this as they attempt to capture user preferences based on different attributes.

To achieve this, we utilize GeoContext2Vec to represent POI types, considering its potential to leverage geographic features present in a POI's context. Unlike traditional methods that rely on co-occurrences, check-ins, and POI popularity, the method explores geographic information available in maps like OSM to generate embeddings of POI types more accurately. OSM has four main tables that we use to extract relevant geographic features for our context. These are: planet_osm_polygons, containing features like buildings, parks, rivers, lakes, etc.; planet_osm_lines, including streets, smaller highways, railways, etc.; planet_osm_roads, encapsulating the main roads and highways of the city; and planet_osm_points, containing traffic lights, trees, fountains, etc.

Initially, the GeoContext2Vec algorithm considers a radius around the POI (e.g., 100 meters) and identifies the geographic features present in this context (Figure 1). It then calculates the proportion of space occupied by each geographic feature in the context. For example, a river that runs through the entire context will have a higher proportion than a small building.

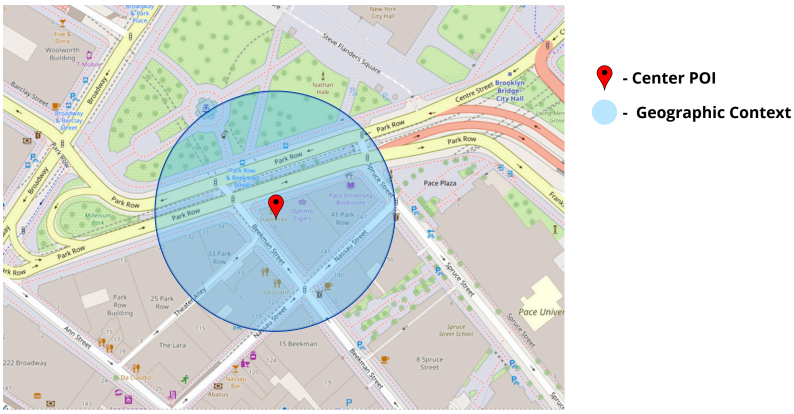

Figure 1: Geographic context of a POI

Additionally, the algorithm considers a parameter ω that determines the emphasis given to the area of geographic features relative to their occurrences. If ω is set to 1.0, only the area of the features will be considered. On the other hand, if ω is 0.0, only the occurrences of the features will be taken into account. Values between 0.0 and 1.0 indicate a combination of the two, where the proportion is determined by the parameter value. The algorithm also evaluates the uniqueness of each geographic feature. For example, a single river will be more relevant for characterizing the context than small trees present in large quantities. By combining space proportion and uniqueness, the algorithm generates a factor that increases the co-occurrence relationship between the POI type and each geographic feature present in the context. Finally, the set of generated co-occurrence relationships is used to train a Word2Vec model [Mikolov et al. 2013], which learns vector embeddings for each POI type. These embeddings capture the contextual relationships between POI types and the geographic features of the context.

The algorithm was applied for generating embeddings considering the POI types present in the dataset used. We defined a radius of 400 meters for the geographic context of a POI and considered all geographic features within the circumference of this radius. This value was established through experimentation, with 400 meters producing the most favorable results. We also defined the parameter ω as 0.8, meaning that 80% is allocated to the feature's area and 20% to occurrences, which also proved most suitable in our experiments. With the ω defined, we extracted all relevant features considering the OSM tables and then generated a training set considering the co-occurences between each POI type and geographic feature. Each co-ocurrence is replicated considering the ω factor, accounting for both the space proportion occupied by the feature and its uniqueness in the POI context. The training set generated was used to train a Word2Vec model using the Skip-Gram architecture, which learns vector representations for each POI type based on associated geographic features, and obtained an embedding for each POI type present in the dataset, reflecting the geographic features of its context.

3.2. Model Architecture

The GETNext model aims to predict the next POI to be visited by a user, integrating context and sequential information. We selected this model as the foundation for our approach due to its state-of-the-art performance in POI recommendation and its inherent suitability for incorporating geographic feature embeddings. Specifically, GETNext's graph-based architecture allows us to seamlessly integrate the learned geographic feature representations, making the geographic features part of the sequence of POI visits by each user and enriching the model's understanding of each location. Furthermore, GETNext's utilization of a Transformer network enables it to effectively capture these sequential patterns in user behavior, making it well-suited for incorporating the contextual information provided by our embeddings.

The architecture employed in the model includes crucial components for this prediction, merging generic movement patterns, user-specific preferences, and contextual data to predict the next POI to be visited. The use of graph neural networks, attention mechanisms, and the Transformer-based architecture enables the capture of complex relationships and personalized recommendations. The three main components of the architecture are: Generic Movement Learning, Contextual Embedding, and Encoder-Decoder. These three components are described in the following subsections.

3.2.1. Generic Movement Learning

In the Generic Movement Learning layer (Figure 2), a Graph Convolutional Neural Network (GCN) analyzes historical check-in data to learn the embeddings of POIs. These embeddings reflect user movement patterns between POIs, considering aspects such as location, category, and visit frequency. Additionally, the layer includes a Transition Attention Map, which explicitly models the transition probabilities between POIs, reinforcing the influence of collective movement patterns on prediction.

3.2.2. Contextual Embedding

In the Contextual Embedding layer (Figure 2), three additional embeddings are generated, in addition to the POI embeddings generated in the Generic Movement Learning layer. They are: user embeddings, category embeddings, and time embeddings. These embeddings are designed to capture, respectively, user preferences, POI categorization, and temporal preferences. However, to extract deeper insights, it is necessary to combine these embeddings. The POI embeddings are then integrated with user-specific embeddings, derived from individual histories, to personalize recommendations. Additionally, temporal embeddings and category embeddings are also combined, recognizing that user preferences may change depending on the POI category and different times of the day. These integrations adjust the model to align with user preferences and the temporal context of POI visits.

3.2.3. Encoder-Decoder

The encoder-decoder layer, subdivided into a Transformer encoder and multi-layer perceptron decoders, processes sequences of check-ins and extracts relevant features using attention layers and fully connected networks. The decoder employs a multi-layer perceptron to make detailed predictions, including the next POI to be visited, its category, and the visit time.

Given the context of the described architecture, we add embeddings of POI types that incorporate geographic features, generated for the city of New York using GeoContext2Vec, so that the recommendation model is able to identify visitation patterns and associate them with geographic features. The embeddings were added after the concatenation of combined embeddings (POI + user and category + time), as shown in the Contextual Embedding layer in Figure 2. This addition aims to have a final representation that presents both configurations, visitation and features. This approach can be intuitively understood as a means to provide the model with a richer understanding of the geographic context associated with visited locations. By doing so, the model can learn to associate specific geographic aspects with visitation patterns, potentially improving its ability to make accurate and contextually relevant recommendations.

4. Experiments and Results

This section describes the configuration and results of the experiments conducted for the task of next POI recommendation.

4.1. Dataset

We conducted our experiments on the public New York dataset from Foursquare[2], which consists of 1,075 users, 5,099 POIs, 318 categories, and 104,074 check-ins collected be-

[2]https://sites.google.com/site/yangdingqi/home/foursquare-dataset

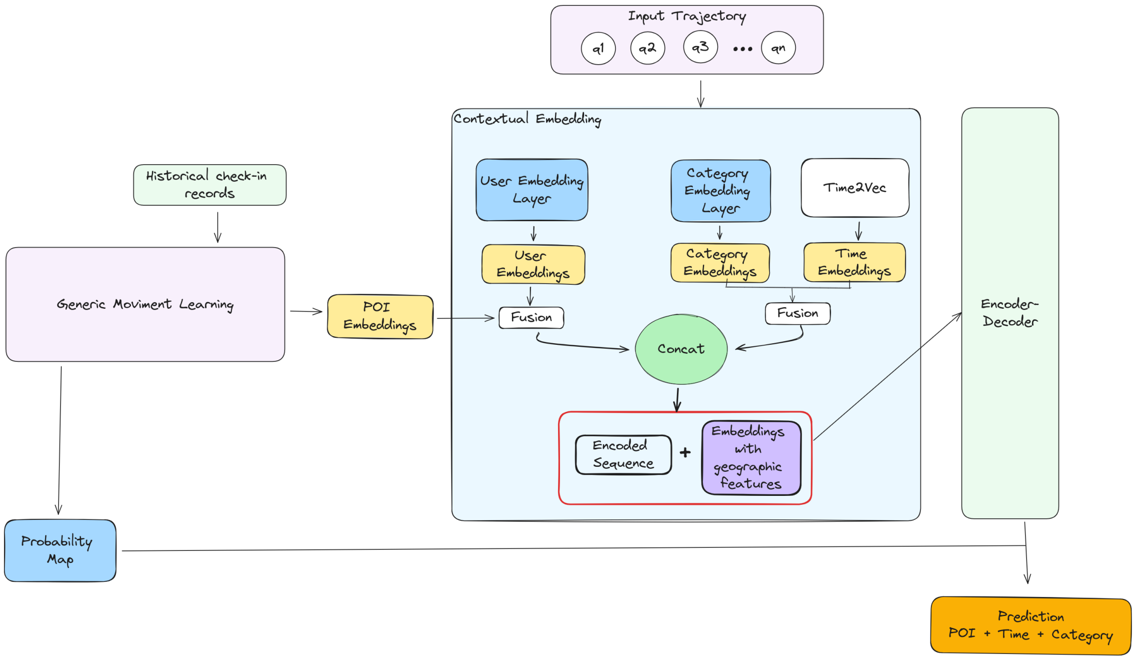

Figure 2: Model architecture based on GETNext with POI type embeddings that integrate geographic features

tween April 2012 and February 2013. The total sequence of check-ins for a user was divided into trajectories of 24-hour intervals, generating a total of 14,160 trajectories. Trajectories containing only one check-in were removed from the dataset. The dataset was split into train, validation, and test sets following a chronological order, with 80% for training, 10% for validation, and 10% for testing. An important point is that if a user or POI did not appear in training but appeared in testing, we ignored it when calculating the metrics.

4.2. Experiment Settings

We used the PyTorch library for training the models (GETNext and Word2Vec) and conducting tests, on a hardware configuration that includes an Intel Core i7-12700F 12th generation processor, 64GB of RAM, and an NVIDIA GeForce RTX 4090 24GB GPU. The main hyperparameter settings for GETNext include the use of 128-dimensional embeddings for POI and user, and 32 for time and POI category, chosen based on the same values defined in the reference work [Yang et al. 2022]. Additionally, we used the embeddings generated by GeoContext2Vec which have 70 dimensions. Finally, the training of the GETNext model with the addition of POI type embeddings that incorporate geographic features was performed for 200 epochs with a batch size of 20. The source code used in this research is available in a Github repository[3].

4.3. Results

Our research focused on integrating POI type embeddings, which incorporate geographic features, into a POI recommendation model [Yang et al. 2022] with the aim of improving recommendations. For evaluation, we employed two widely-used metrics for assessing recommendation systems: accuracy@k (Acc@k) and Mean Reciprocal Rank (MRR).

[3]https://github.com/nicolasmnl/poi-recommendation-TCC

Acc@k checks if the POI that the user visited (or interacted with) is present among the top K recommended POIs. However, since Acc@k does not take into account the order of relevant POIs in the top k results, we also used MRR, which considers the position of the first relevant POI in the recommendations list. The results, shown in Table 1, indicate an increase of up to 1.65% in the calculated metrics for the New York dataset, compared to GETNext, our main baseline, and other commonly used baselines in the area of POI SRs [Koren et al. 2009, Hochreiter and Schmidhuber 1997, Luo et al. 2021, Feng et al. 2015, Rendle et al. 2010, Wu et al. 2022, Zhao et al. 2022, Liu et al. 2016]. The results of GETNext, presented in Table 1, were obtained by reproducing the experiments under the same conditions as those conducted by the original authors.

Table 1: Performance comparison in Accuracy@K and MRR in New York dataset

	Acc@1	**Acc@5**	**Acc@10**	**Acc@20**	**MRR**
MF [Koren et al. 2009]	0.0368	0.0961	0.1522	0.2375	0.0672
FPMC [Rendle et al. 2010]	0.1003	0.2126	0.2970	0.3323	0.1701
LSTM [Hochreiter and Schmidhuber 1997]	0.1305	0.2719	0.3283	0.3568	0.1857
PRME [Feng et al. 2015]	0.1159	0.2236	0.3105	0.3643	0.1712
ST-RNN [Liu et al. 2016]	0.1483	0.2923	0.3622	0.4502	0.2198
STGCN [Zhao et al. 2022]	0.1799	0.3425	0.4279	0.5214	0.2788
PLSPL [Wu et al. 2022]	0.1917	0.3678	0.4523	0.5370	0.2806
STAN [Luo et al. 2021]	0.2231	0.4582	0.5734	0.6328	0.3253
GETNext [Yang et al. 2022]	0.2268	0.4897	0.5880	0.6545	0.3460
GETNext with geographic features	**0.2329**	**0.4987**	**0.6045**	**0.6670**	**0.3524**
Increase (%)	0.61%	0.9%	1.65%	1.25%	0.64%

4.4. Discussion

This study investigated the potential of integrating POI type geographic embeddings that encapsulate geographic features into a POI recommendation model to enhance its effectiveness and capture the influence on user preferences. Our findings indicated that incorporating these embeddings into the GETNext model led to an improvement up to 1.65%, as evidenced in Table 1. This positive outcome suggests that the model successfully leverages the additional contextual information provided by the geographic features to better understand user preferences and predict their next POI visit. This supports the notion that users are possibly influenced by the presence of specific geographic features when making decisions about where to go next.

Furthermore, our strategy can be easily replicated, requiring only the addition of embeddings of POI types that incorporate geographic features in other approaches with similar characteristics. For example, [Yan et al. 2023] developed a model that employs similar characteristics to this research, also outperforming GETNext, but it differs by not using geographic features and by using a hypergraph to analyze both individual user's historical trajectories (intra-user) and collaborative trajectories between different users (inter-user). This model could be enhanced with the addition of embeddings that consider geographic features, potentially improving the results presented. However, reproducing the work [Yan et al. 2023] with the addition of embeddings that incorporate features was not within the scope of this research.

As limitations of our experiments, we noted that the high density and homogeneity of urban environments in large metropolises like New York City might lead to a reduced diversity of geographic features within the considered POI context, which may hinder the distinction and association between a POI and its geographic context. This factor could potentially limit the model's ability to fully exploit the richness of geographic information in more diverse environments. Additionally, the reliance on a single dataset also poses a threat to the validation of our findings, as it might introduce biases specific to the New York dataset taken from Foursquare, which may suggest limitations in the generalization of the results.

5. Conclusion and Future Work

POI recommendation systems are crucial for enhancing user experience, fostering sociability, and boosting tourism in various regions. However, conventional POI recommendation systems often limit themselves to using information such as user reviews, check-ins, visiting hours, and POI types, disregarding relevant geographic data, such as geographic features in the context of POIs. In this study, we propose the use of embeddings of POI types that integrate geographic features to improve POI recommendation systems. We evaluated our approach primarily in comparison to GETNext, as well as other usual baselines in POI recommendation systems. The results show that the inclusion of geographic features in the embeddings of POI types increased the metrics by up to 1.65% compared to GETNext in the New York dataset used, demonstrating the relevance of geographic features in users' choice of the next POI to visit and addressing the research question raised.

For future work, to address the limitations presented in Section 4.4, we intend to conduct experiments with a wider variety of datasets, including different cities and geographic contexts, to evaluate the robustness and generalization capability of the proposed model. This will provide a deeper understanding of how geographic features affect POI recommendations in various environments. Additionally, we want to evaluate our methods in other state-of-the-art POI recommendation models. Finally, specific studies on which geographic features contribute most to improving recommendations can be conducted. It will involve sensitivity analyses and evaluations of the relative importance of different types of features in varied contexts, providing valuable insights for the continuous improvement of POI recommendation systems.

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