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RESEARCH ARTICLE

Long-Term Preference Mining With Temporal and Spatial Fusion for Point-of-Interest Recommendation

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ABSTRACT The growth of the tourism industry has greatly boosted the Point-of-Interest (POI) recommendation tasks using Location-based Social Networks (LBSNs). The ever-evolving nature of user preferences poses a major problem. To address this, we propose a **L**ong-**T**erm **P**reference **M**ining (LTPM) approach that utilizes the **T**emporal **R**ecency (TR) measure in the visits along with the location-aware recommendation based on **S**patial **P**roximity (SP) to the user's location. The temporal dynamics and changing preferences are exploited based on the modified Long Short-term Memory (LSTM) that utilizes the time decay. The spatial considerations are modeled in two aspects: geographical proximity based on enhanced representation learning using orthogonal mapping. Second, the Region-of-Interest (ROI) is based on spatial griding and metric learning to capture the spatial relationships between POIs to enhance the metric space representation. The final recommendations are based on a multi-head attention mechanism that allocates the weights to different features. The combination of three models, called, LTPM-TRSP approach captures the user-POI, POI-POI, and POI-time relationships by focusing on the informative representation of sequential and spatial data. The category-aware final recommendations based on comprehensive historical behavior and geographical context are quite efficacious. The experimentation on three real-world datasets, Gowalla, Foursquare, and Weeplaces, also suggests the potency compared to other state-of-the-art approaches.

INDEX TERMS Attention mechanism, metric learning, orthogonal mapping, point of interest, representation learning.

I. INTRODUCTION

The growth of faster communication paradigms and the emergence of the Global Positioning System (GPS) have expedited the growth of Location-based Social Networks (LBSNs) such as Foursquare, Gowalla, Yelp, and Geolife. As per sources,[1] Yelp has 33 million unique devices (average monthly) registered, with 40% of users above 55 as of June 2023. These platforms have provided immense opportunities for users to share their experiences that can be explored for varied applications, especially for personalized Point-of-Interest (POI) recommendations. Figure 1 depicts the expanse of the Foursquare dataset. The density of check-in points is concentrated near the areas of the United States (US).

Further city-wise analysis shows that the maximum check-ins recorded are from California (CA), and the lowest is from Georgia (GA). It suggests that there are ample potential POIs that have been visited. The results from the POI recommendation find utility in the travel and tourism industry, smart city development, and location prediction. The social media content of LBSN harnesses six dependencies among the locations and the users: user-user, user-location, location-location, user-media, media-media, and location media dependencies. The major stakeholders in POI recommendation are the potential POIs, the users themselves, the chronological order that maintains the sequential user trajectory, the peer group of the target user, and the word-of-mouth opinions of the users in the form

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[1]https://www.yelp-press.com/company/fast-facts

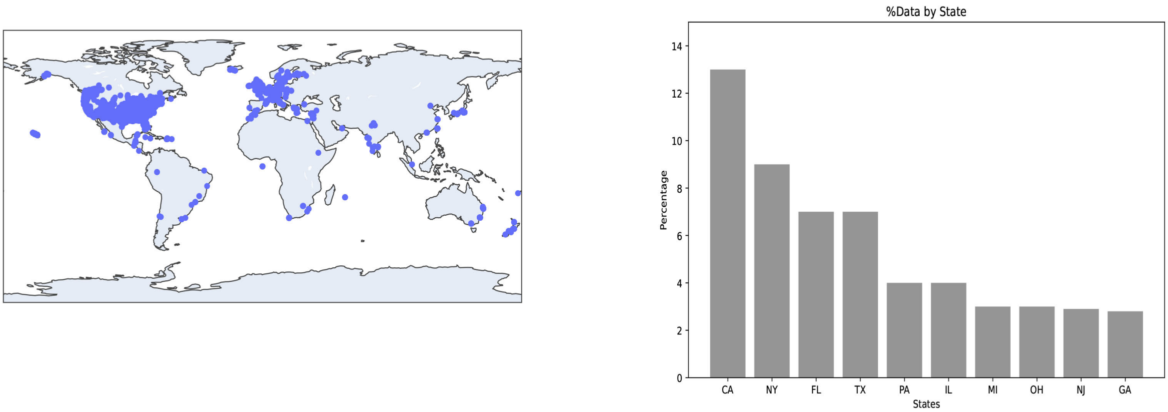

FIGURE 1. Foursquare Dataset analyses. a) Dataset distribution. b) Dataset distribution over the US.

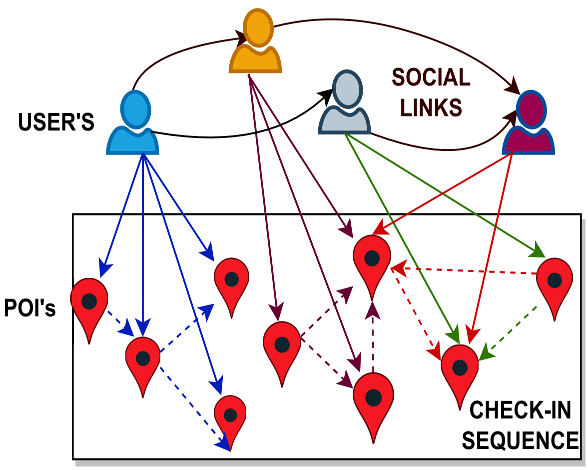

FIGURE 2. Generalized framework of POI recommendation.

of tips, tags, reviews, blogs, comments, etc. The framework of POI recommendation is illustrated in Figure 2. For each user, the respective check-ins are illustrated by the arrows headed to different POIs. The dotted arrows in different colors between the POIs refer to the sequential visit pattern of particular users. The curved arrows denote the peer group of the users.

Spatial influence is of paramount importance in POI recommendation. It has two dimensions: the geographical proximity of the POIs to the user's current location and the other geographical popularity of the POIs that depends on the propensity of POIs in the spatial region and the POIs nearby. Strictly spatial-constrained POI recommendation methods proposed in [1], [2], and [3] rely on spatial/geographical content in the entirety. Temporal content also holds critical weightage in recommendation tasks, representing both periodicity and asymmetry in check-in trajectory. Owing to the temporal aspect, the recency in the historical check-ins has also been exploited in [4] and [5]. Semantic content has also been explored in combination with spatiotemporal data for user preference mining in several approaches. It includes textual content like tips and user reviews. Works on social neighborhood-based preference extraction have also been undertaken to excavate the influence of social peers on the user's preference of visit [6], [7]. POI recommendation is a complex task as, unlike conventional recommendation models, it requires the user's check-in location, location information, the user's description of the locations, and the user's continuous trajectory information that encapsulates the spatial and temporal aspects. The dearth of explicit ratings and limited physical accessibility aggravates the issue of data sparsity. The sparse check-in matrix aggravates the cold-start problem [8]. POI recommendation must cater to the needs of the cold-start users, and the recommended POIs must involve the POIs that are new or have limited rating data, termed as *cold-start POIs*.

Further, the heterogeneity in the data and the dynamic nature of the user's preference are two sought-after features. User's historical check-in information has been utilized in many traditional recommendation paradigms like collaborative filtering (CF). Still, these techniques overutilize the rating and check-in content for similarity calculations and neglect the geographical aspect of the POIs and user-POI relations. Hence, the static nature of CF-based POI recommendation methods is inefficacious in addressing data sparsity and dynamic preference modeling. To alleviate such issues, auxiliary information such as social, categorical, semantic, and other contextual factors have been utilized along with spatiotemporal data to provide efficacious results [9], [10], [11].

POI recommendation requires long-term preference mining that in turn requires investigating users' predilections over an extended period. But many impediments linger over. First, preference modeling from isolated user check-in sequences is not static. It dynamically depends on external factors like time, region, weather, etc. Integration of these factors is quite tricky. Second, the user check-in matrix is quite sparse; thus, long-term preference mining is tedious. Third, historical check-in data is infected by noise or outliers like accidental halts, stay points, etc. Hence, data analysis and pre-processing is critical. Fourth, intention disentangling is an important issue in long-term preference mining, as users' historical check-ins are ambiguous.

The POI recommendation has become the researcher's hotspot in the past decade as its outputs can be utilized in various fields. The tourism industry provides a generic application as the tourists can visit the local hangouts and the traditional tourist hotspots. Urban planners can utilize the results of POI recommendations to make decisions for resource allocation, infrastructure planning, etc. The user's mobility analysis has also sprung up as a promising field that requires the POI recommendation results to analyze and predict traffic and manage routes. Based on customer mobility patterns, POI recommendations can also help optimize sales and business proliferation.

In this paper, we attempt to solve the problems in long-term preference mining by incorporating temporal recency and data sparsity. The novel approach, **L**ong-**T**erm **P**reference **M**ining with **T**emporal **R**ecency estimation and **S**patial **P**roximity fusion (LTPM-TRSP), utilizes category statistics for static preference modeling, modified LSTM for recency inclusion, and the Region-of-Interest (ROI) based griding in conjunction with the contrastive learning for vicinity estimation for enhanced POI recommendation.

- In the long run, the user preferences are captured by the LSTM that utilizes the information about the popular POIs sorted based on the number of POIs checked in the different categories.
- To model the temporal period, the popularity of different POI categories is accounted for and sent as a vector to the LSTM unit. The LSTM network is further modified to incorporate the time decay factor so that the user-check-ins are allocated more weightage earlier than the reference point. The recent visits denote the current preference of the user, exploit the POI-time dependency, and capture the temporal asymmetry.
- The POIs near the users' current location are more likely to be visited by the users than far-off places. Further, the areas with more user check-ins represent the actual Region-of-Interest (ROI). The spatial data with the categorical information is fed to the Multi-Layer Perceptron(MLP) to capture the user-POI dependency.
- Orthogonal mapping based on triplet loss enhances representation learning. It boosts the models efficiency and thus the POIs with similar classification (as previously visited) are kept more closer than others. It also captures the POI-POI dependency.
- Using the Geohash for geospatial hashing, the entire region is divided into spatial grids, and using the grid area and the number of embeddings in the region, we find the grid priority. The embeddings in the high-priority regions provide more gravitas in LMNN-based metric learning.
- The LTPM-TRSP exploits user-POI, POI-POI, and POI-time dependencies. The approach has been experimented on three real-world datasets and the results have been juxtaposed to several baselines.

The rest of this paper is summarised as follows: Section II presents the literature works prominent in the field of POI recommendation. Section III elucidates the framework of LTPM-TRSP framework. Section IV illustrates the results of experimentation and the discussion on parameters tunned. Section V concludes the research work.

II. RELATED WORK

POI recommendation methods proposed in the past few years exploit several factors using different techniques. Yu et al. [12] proposed the CPAM model that combines a skip gram-based POI embedding model (SG-PEM) to learn the contextual influence of POIs and Logistic Matrix Factorization (LMF) for personalized POI modeling. Ren and Gan [13] proposed an MPGI framework for the Next POI recommendation to capture the distance and correlations between the POI pairs and position-aware attention units to monitor check-in trajectories. Wang et al. [14] proffered a reinforcement learning framework to capture nuances of the geo-human trajectories for enhanced geospatial context modeling for POI recommendation. Wang et al. [2] explored the geographical, categorical, and sequential influence to proffer a new POI recommendation paradigm based on CF and Kernal Density Estimation (KDE). Chen et al. [15] investigated the temporal, spatial, and propensity information for the TeSP-TMF framework that combined grey relational analysis and matrix factorization to alleviate data sparsity.

Rahmani et al. [16] proposed the LGLMF model that combined the Local Geographical (LG) information based on activity regions with LMF to explore the geographical influence on POI recommendation. Safavi and Jalali [17] proffered the DeepPOF framework that utilized deep learning and the CNN model to excavate friendship relationships based on spatial and temporal aspects. The user's similarity is detected using mean-shift clustering. The predictions were made based on the proximity analysis of the prospective POIs. Han et al. [18] proposed an AUC-MF-based framework with a new lambda for AUC optimization using MF and lambda methods. The method considered local and global similarity to emphasize geographical information in two folds. The region-based sampling method and linear combination proposed in this method successfully incorporated contextual factors along with temporal-spatial similarity calculation.

After proving their mantle in other fields, deep learning models like LSTM, CNN, attention network, and GRU have also been deployed in POI recommendations over the past years. Hossain et al. [4] addressed the issue of non-consecutiveness and non-adjacent visits in user behavior in their proposed framework CARAN that utilized an attention network to cater to the recency in the visits along with the weather conditions influence. The non-adjacent check-ins and spatial distance consideration were monitored using spatiotemporal matrices, liner interpolation method, and positional encoding of check-in sequence. CARAN achieved 7-14% enhanced results. Li et al. [9]

exploited spatial and temporal features for users by using Voronoi diagram construction for spatial regions and virtual trajectory construction for context-aware similarity mining. The efficacious POI recommendations were made using similar users mined on spatial-temporal fronts and reference time and location sought from the target user. Yu et al. [3] investigated categorical information in addition to user preferences and time series data. The CatDM model utilized LSTM-based two-deep encoders to process different parts. The attention mechanism was personalized to exploit the temporal patterns effectively. It modeled user-POI, user-category, POI-time, and POI-user dependencies to mine user preferences. Liu and Wu [19] deployed a Bi-LSTM attention mechanism to analyze long-and short-term preferences. In conjunction with the Bi-LSTM, the encoder and decoder sequence further analyze the POI sequence data to recommend the top-N POIs. The last step involves negative sampling and Bayesian personalized ranking loss calculation for better optimization. SSANet method proposed by Yue et al. [20] deployed the Gaussian Kernel technique for geographical method, attention mechanism to capture the interaction modules, and Node2vec for harnessing the social information. DANSNR proposed in [21] has two parallel channels for modeling long and short-term user preferences and social influence. The multi-head self-attention unit, in combination with the Vanilla attention unit, was used in both channels. Privacy is also one of the major concerns in recommendation tasks. Acharya et al. [22] proposed the DPSND-Rec method that protected privacy using Laplacian noise and exploited the spatiotemporal neighbors for social linkage mining. The social links were mined based on spatio-temporal similarity using similarity indices.

Kim et al. [23] proposed a local differential privacy (LDP) model called SPIREL that uses transition patterns and visit counts of POIs as input to factorization. This model captures user-POI and POI-POI dependencies simultaneously. The LDP integrated with ALS and SGD utilized sampling and perturbation methods for successive POI recommendations. Dai et al. [24] proffered the PPR method based on graphs. The approach combined the socio and spatial-temporal features obtained from the user's check-in data. The method modeled sequential patterns in four perspectives: POI-user, POI-time, user-user, and user-POI dependencies. Xu et al. [25] proposed an NHRM model that exploited spatiotemporal attributes and is a combination of three different models: the first model captured the user's perspective, the second harnessed the location-user dependencies, and the last model utilized categorical information to substantiate the POI recommendation. Li et al. [26] proposed an attention-based spatial-temporal gated graph neural network (ATST-GGNN) where user-check-ins were modeled using a graph, and dynamic node updation relied on spatiotemporal context information. The long and short preference was an exploited-based attention mechanism. It also uses the window pooling method to enhance local embedding representation, and the attention mechanism enhances global embedding representation. Lu and Huang [27] proposed a successive POI recommendations model based on graph-based latent representation (GLR) to investigate temporal successive transition influence and user preference combined with the geographical influence of POIs, the *GLR_GT* model.

Further, the *GLR_GT_LSTM* version employed LSTM to extract the complex transition behavior. Zhang et al. [28] proposed an STMLA model that utilizes an LSTM and attention network variant for the next POI recommendation. It investigates the user's check-in sequences with selective consideration of non-consecutive factors and explicitly integrates the spatial and temporal information for user preference mining.

III. FRAMEWORK OF LTPM-TRSP

A. BACKGROUND

The following section defines the preliminary terms and the identified problems. Table 1 summarizes the symbols used in this paper.

Definition 1 (Point-of-Interest(POI)): POI is any real-world location, say, v, such that $\mathcal{L} = \{v_1, v_2, \ldots v_n\}$ where $\mathcal{L}$ denotes the set of n available POIs. Each $v_i \in \mathcal{L}$ is identified with a triplet (v_{id}, lat_i, lng_i) where v_{id} refers to a unique POI id alloted to each POI, and lat_i and lng_i denotes the latitude and longitude of the POIs respectively.

Definition 2 (Check-In): The user's visitation at a POI is termed *check-in* and is characterized by the user's unique *user-id*, POI's unique ID, its coordinates, the user's time of visitation, and the category of the POI.

Definition 3 (Region-of-Interest(ROI)): Users' check-in activity is often restricted within geographical bounds, termed ROIs. They are critical to the preference mining process as they represent the regions from which we can extract the potential categories in which the users might be interested. Further, these regions also represent the POIs that the users have visited, and thus, newer POIs closer to them also have a higher chance of visitation, a human instinct influenced by the first law of geography.

Definition 4 (Data Sparsity): The number of POIs that the user visits in the real world is much less than the total number of POIs available. Thus, the user-POI check-in matrix is quite sparse. Moreover, for each user, the check-ins are confined within the activity zone, further aggravating the sparsity issue. Data sparsity leads to overfitting of the model, thereby degrading its performance for cold-start users and POIs. It also enhances the long-tail distribution within the data distribution, and this imbalance makes it difficult to capture the pattern for cold-start POIs.

Definition 5 (Dynamic Preference Mining): Dynamic preference mining is critical in POI recommendation as the predilection of the users is ever-evolving. Newer visits hold a higher precedence than older interactions. Recent and closer visits can be investigated from the historical check-in records to provide relevant and preferred POIs. However,

TABLE 1. Summary of the symbols used.

Symbol	Definition
$\mathcal{L}$	Set of available POIs
v_i	Unique POI
t	Timestamp of the LSTM
i_t	Input gate of LSTM
x_t	Input sequence to the LSTM
$\sigma_i, \sigma_f, \sigma_o$	Activation function for input gate, forget gate, and output gate respectively
h_t	Hidden state of LSTM
W_{xi}, W_{xf}, W_{xc}, W_{xo}	Weight matrix for input at input, forget, cell state and output gate respectively
b_i, b_f, b_c, b_o	Bias factor for input, forget, cell state, and output gate respectively
α_t	Rate adjustment factor
s_t	The user's successive check-in timestamp
t	Temporal timestamp
λ_1	Control parameter for hybrid triplet loss
T_l	Triplet loss
P_s	Spatial proximity term
Z_r	Regio-of-Interest (ROI)
$\mathbb{L}$	Linear Transformation

these preferences remain unchanged and are subject to time and space. For example, coffee shops are popular in the morning, but bars are common in the evening. Similarly, a closer POI is preferable to the far-off.

B. LONG-TERM PREFERENCE MINING

To address the impending issue of vanishing gradient problem, Hochreiter and Schmidhuber proposed LSTM in 1997 [29], a variant of Recurrent Neural Network (RNN) used to capture long-term dependencies. It consists of three gates: a *forget gate, an input gate*, an *output gate,* and a *memory cell.* It is a traditional feedforward neural network layer consisting of a hidden layer and current state cells. Equations (1)-(6) depict the mathematical process behind the gates.

$$i_t = \sigma_i(x_t W_{xi} + h_{t-1} W_{hi} + c_{t-1} \odot w_{ci} + b_i) \quad (1)$$

$$f_t = \sigma_f \left(x_t W_{xf} + h_{t-1} W_{hf} + c_{t-1} \odot w_{cf} + b_f \right) \quad (2)$$

$$\acute{c}_t = x_t W_{xc} + h_{t-1} W_{hc} + b_c \quad (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \sigma_c (\acute{c}_t) \quad (4)$$

$$o_t = \sigma_o(x_t W_{xo} + h_{t-1} W_{ho} + c_t \odot w_{co} + b_o) \quad (5)$$

$$h_t = o_t \odot \sigma_h (c_t) \quad (6)$$

In this approach, we imbibe the recency-aware mechanism in LSTM to capture the temporal aspect.

To capture the user's long-term preferences, we consider the propensity of the category of POIs for that user, i.e., which category is more visited by the user. For this, the POI category information is one-hot encoded and transformed into a vector V_c and the preference vector for POI category $\mathbf{vc_i^u}$ is then computed as in Equation (7). The dimensions of $\mathbf{vc_i^u}$ is same as the total number of categories.

$$\mathbf{vc_i^u} = \frac{\sum_{j=1}^{n} u_{ji}}{\sum_{k=1}^{m} \sum_{j=1}^{n} u_{ji}} \quad (7)$$

where u_{ji} has a value between 1 or 0 and indicates where the POI of *j-th* check-in of the user u lies in the category i. The inner product of $\mathbf{vc_i^u}$ and V_c depicts the historical check-in frequency of the user in the similar category as the POI and is mathematically denoted by $S_{vc} = \mathbf{vc_i^u}.\ V_c$.

Using the embedding layer, we transform the *user-id*, v_{id} and the encoded category information into continuous vectors, $\mathbf{u_t^u}$, $\mathbf{v_t^u}$ and $\mathbf{vc_i^u}$ respectively. Then, to learn the non-linear dependencies in user-POI and category data, we feed the embedding layers to LSTM as in Eq (8). The hidden vector $\boldsymbol{h_t^u}$ is the representation for user u at step t and captures the POI category preferences of the user over the long term. Figure 3 represents the LTPM architecture.

$$h_t^u = LSTM(\mathbf{W_u u_t^u} + \mathbf{W_v v_t^u} + \mathbf{W_t vc_i^u}, \mathbf{h^u_{(t-1)}}) \quad (8)$$

where $\mathbf{W_u}$, $\mathbf{W_v}$ and $\mathbf{W_u} \in \mathbb{R}^{d \times d}$ are the transition matrices.

C. CAPTURING TEMPORAL FEATURES

The user's check-in history has a timestamp imbibed into it. We rely on timestamps for temporal preference mining. This phase has two components. To compute the preferred POIs based on temporal periodicity, we divide the user's trajectory into temporal sequences such that the consecutive POIs are visited more than τ times units apart. We choose $\tau = 8$h and travel sequences $S_{v1}, S_{v2}, \ldots S_{v+1}$, are ordered chronologically. Using the sequences estimated for each user, we compute the average periodicity score V_t of visits as in Equation (9)-(10).

$$V_t = \frac{1}{n} \sum_{u \epsilon U} \sum_{p_1, p_2 \epsilon\ S_v} (p_1 - p_2) \rho(v), \quad \forall\, v \epsilon\ \mathcal{L} \quad (9)$$

$$\rho(v) = \begin{cases} 1 & \textit{if the user has visted the POI} \\ 0 & \textit{otherwise} \end{cases} \quad (10)$$

where n is the number of POIs visited, p_1 and p_1 represents the POIs of same sequences for the user, and $\rho(v)$ denotes whether the user has visited the POI or not.

The periodicity score is then used to find the category popular at that time by computing the category interest C_v^t as in Equation (11)-(12).

$$C_v^t = \sum V_t\, \gamma(c_v), \quad \forall\, c \epsilon\ C \quad (11)$$

$$\gamma(c_v) = \begin{cases} 1 & \textit{if category c is visited} \\ 0 & \textit{otherwise} \end{cases} \quad (12)$$

The inner product of C_v^t and the respective category vector V_c, $(x_t = C_t^v.\ V_c)$, represents the periodic popularity of the POIs. This component successfully captures the temporal periodicity.

To capture the temporal asymmetry, we modify the traditional LSTM model. We utilize an exponential decay function that emphasizes the diminishing effect of older interactions and incorporates the temporal features in the dynamic preference modeling. For this, we measure the difference between successive instances concerning the reference time allotted

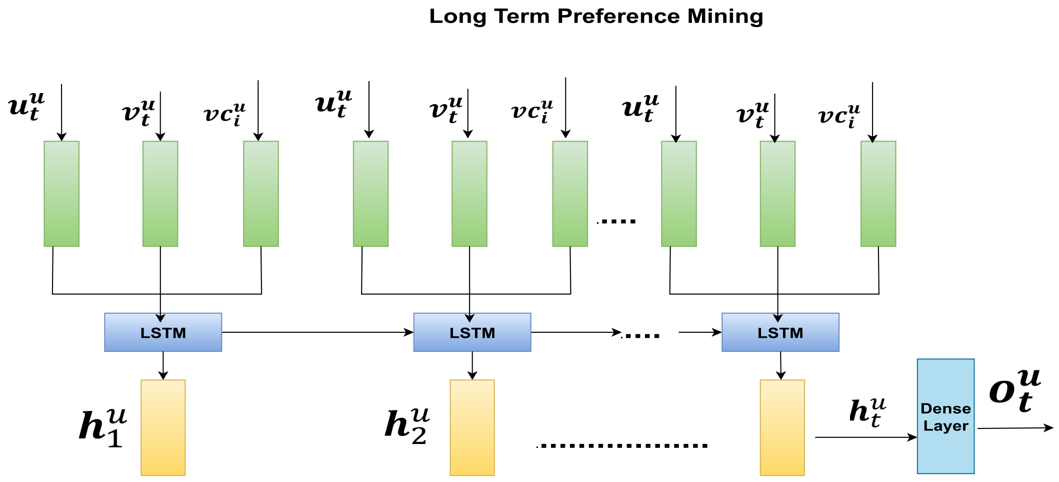

FIGURE 3. LTPM framework for POI recommendation.

by the user. We utilize a decay function to assign higher weights to user check-ins that are more recent to the current reference time specified by the user, as the older interactions have lower importance in preference mining. The exponential decay function calculates the time decay for every check-in. We measure the distance between the temporal instances t to find the difference between the successive user check-in timestamp s_t. Then, using the exponential decay function, a rate adjustment vector α_t is formed, and the input sequence x_t of LSTM is multiplied by this vector to form a dynamic weight update mechanism that encapsulates the user preferences over time. To provide more emphasis on recency, we apply exponential smoothing. The sigmoid activation function (σ) is used for training LSTM. Equation (13)-(15) depicts the modified LSTM gates.

$$i_t = \sigma(W_{ii} * x_t + W_{hi}h_{t-1} + W_{si}s_t * \alpha_t + b_i) \tag{13}$$

$$f_t = \sigma(W_{if} * x_t + W_{hf} * h_{t-1} + W_{sf}s_t * \alpha_t + b_f) \tag{14}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{15}$$

where i_t, f_t and c_t denote the input gate, forget gate, and output gate, respectively. W and b represent the weight matrices and bias terms.

D. CAPTURING THE SPATIAL FEATURES

The historical user check-in can be used to find the region of interest based on the area of maximum activity and proximity to the current location. For this, we follow a parallel input stream to process the spatial and sequential data parallelly. Spatial data is passed through the MLP that captures the latent features intertwined in user-POI check-ins. We feed user, POI, and rating vectors to the MLP layer, which forms the three embeddings that capture the latent representations and learn the non-linear relationships in user-POI information. The resultant embeddings are passed to orthogonal mapping that deploys triplet loss to enhance the discriminative power of the embeddings. In triplet loss, the triplet of the sample comprising an anchor sample, a positive sample, and a negative sample is used to minimize the distance between the anchor and positive sample and marginally maximize the distance between the anchor and negative sample. It also enforces the orthogonality constraints among the learned embeddings and better captures their inherent relationships. To imbibe the spatial proximity in this method, we modify the triplet loss function T_l by adding the spatial proximity term P_s. P_s denotes the spatial proximity between the anchor and positive samples using the Haversine distance [30] as depicted in Equation (16), as shown at the bottom of the next page.

The final loss is then computed combining the triplet loss and spatial proximity as in Equation (17), as shown at the bottom of the next page, where λ_1 is the hyperparameter to adapt the required trade-off. where R is the radius of the earth, (lat_1, lon_1) and (lat_2, lon_2) depict the coordinates of different POIs.

The region of maximum user activity, i.e., the ratio of maximum check-ins to the area of the grid, is referred to as ROI Z_r. The entire spatial region is divided into spatial grids using the Geohash library in Python.[2] We analyze each grid cell for user check-ins to measure the spatial density of check-in distribution. From Z_r, we prioritize the grids of high check-in density and allocate them to higher weights. The embeddings of the high-priority grids are given more weightage than the others in the next step, which involves Large Margin Nearest Neighbour (LMNN) metric learning. LMNN takes the embeddings along with the category labels to minimize the distance metric between the POIs of the same category.

E. FINAL RECOMMENDATION

The outcomes of LMNN and LSTM are concatenated to provide the final recommendation. The final recommendation involves the multi-head attention mechanism wherein each

[2] https://www.restack.io/docs/superset-knowledge-superset-python-geohash-integration

attention head will emphasize different aspects like temporal, spatial, and categorical content. The attention scores of different heads are concatenated to compute the weighted sum and apply the averaging technique. The output is combined to provide the final recommendation. Figure 4 depicts the framework of the LTPM-TRSP.

IV. EXPERIMENT AND RESULTS

In this section, we explain the experimental setup, hyper-parameter settings and the results obtained. We also compare our model with state-of-art approaches, and results surface our claims.

A. EXPERIMENTAL SETUP

The experimentation was carried out on an Intel(R) Core (TM) i7-6700 CPU @3.41 GHz processor with 64-bit Windows operating system installed and one NVIDIA GeForce RTX 2070, 8GB Graphics Card. The memory capacity is 16 gigabytes. The programming was done in Python 3.7 using the Jupyter Notebook environment. We utilized different libraries like numpy for computing operations, pandas for data manipulation and visualization, and scikit-learn for model analysis and computing performance. We also deployed the deep learning framework TensorFlow 6 1.2.0.

B. HYPER-PARAMETER SETTINGS

We fix the embedding size to 64, and embedding parameters are initialized with the Xavier method [31]. LTPM-TRSP and its variants LTPM-TR and LTPM-SP are optimized with Adam optimizer, and we use the default learning rate of 0.0001 and batch size of 1024. L_2 regularization coefficient is searched in the range of $(1e^{-6}, 1e^{-5}, \ldots.., 1e^{-2})$ and the optimal value found is $1e^{-4}$. The number of epochs was searched between 100 and 300, but after 250 epochs, the results showed fluctuations and performance degradation. Thus, optimal epochs were set to 250. The value for R for the Haversine distance is 6,371 kilometers.

C. DATA SOURCE AND DESCRIPTION

Three publicly accessible real-world LBSN datasets-Foursquare NYC,[3] Gowalla, and Weeplaces[4] were used in the experiment. Gowalla was recorded from February 2009 to October 2010. The Foursquare NYC data used in this study ranges from April 2012 to December 2013. The Weeplaces databases cover the time from November 2003 to June 2011. Records are defined by quantifying the number of users of a particular service, the number of POIs available, and the number of times users have checked in.

[3]https://sites.google.com/site/yangdingqi/home/foursquare-dataset
[4]https://www.yongliu.org/datasets

TABLE 2. Datasets characteristics.

Datasets	#Users	# POI's	#check-ins	Sparsity	Location Categories
Gowalla	319063	2844076	36001959	99.78%	629
NYC	2293	61858	573703	99.51%	247
Weeplaces	15799	971309	7658368	98.39%	96

TABLE 3. Datasets category-wise characteristics.

Gowalla		Weeplaces	
Category	#Check-ins	Category	#Check-ins
Corporate Office	1750707	Home/ Work/ Other: Corporate/ Office	437824
Coffee Shop	1063961	Home/Work/Other: Home	306126
Mall	958285	Food: Coffee Shop	267589
Grocery	884557	Nightlife: Bar	248565
Gas and Automotive	863199	Shops:Food& Drink:Grocery Supermarket	161016

A check-in is a single entry in the dataset containing the user's user ID, the POI-ID, the POI's latitude and longitude, the timestamp showing the check-in time, and other information as depicted in Table 2. Table 3 shows the dataset's statistical analysis. For recommendation, we remove the users with less than 10 check-ins as such users might behave as noise, impacting the accuracy of predictions and mitigating the effects of the spatial clustering phenomena [32]. Further, the removal also addresses the problem of stay points and accidental check-ins. Similarly, we remove the POIs with less than 10 check-ins because these POIs also act as outliers. The top five most popular categories and the total number of check-ins for each are shown in Table 3 for the Gowalla and Weeplaces dataset. We use one hot-encoding for the category information to facilitate the investigation of POIs propensity category-wise. We convert the timestamp information to time intervals of weeks, months, days, and hours to better analyze the temporal periodicity and asymmetry. The datasets were split into training and testing halves in an 80:20 ratio.

The analysis of user check-ins in the US extracted from the Weeplaces dataset is depicted in Figure 5, and March recorded the highest check-ins. Further, the city-wise analysis depicts that New York has the highest check-in count, and the Los Angeles dataset has the lowest check-in count. This analysis is done on a sample of 20000 user check-ins.

$$P_s = 2R\arcsin\left(\sqrt{sin^2\left(\frac{lat_1 - lat_2}{2}\right) + cos\,(lat_1) * cos\,(lat_2) * sin^2\left(\frac{lon_1 - lon_2}{2}\right)}\right) \tag{16}$$

$$Loss = \lambda_1\,(T_l) + (1 - \lambda_1)\,P_s \tag{17}$$

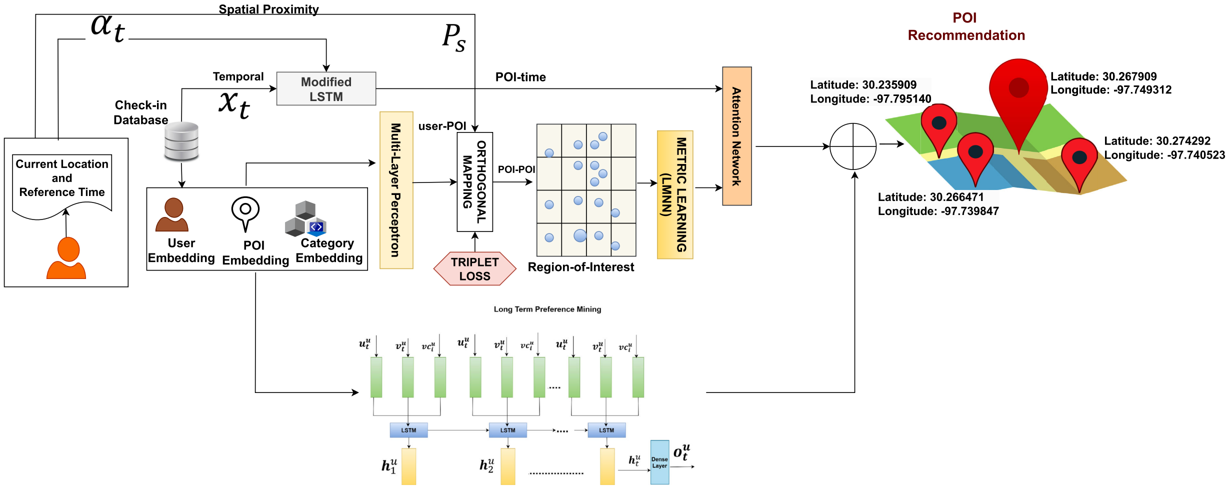

FIGURE 4. LTPM-TRSP framework for POI recommendation.

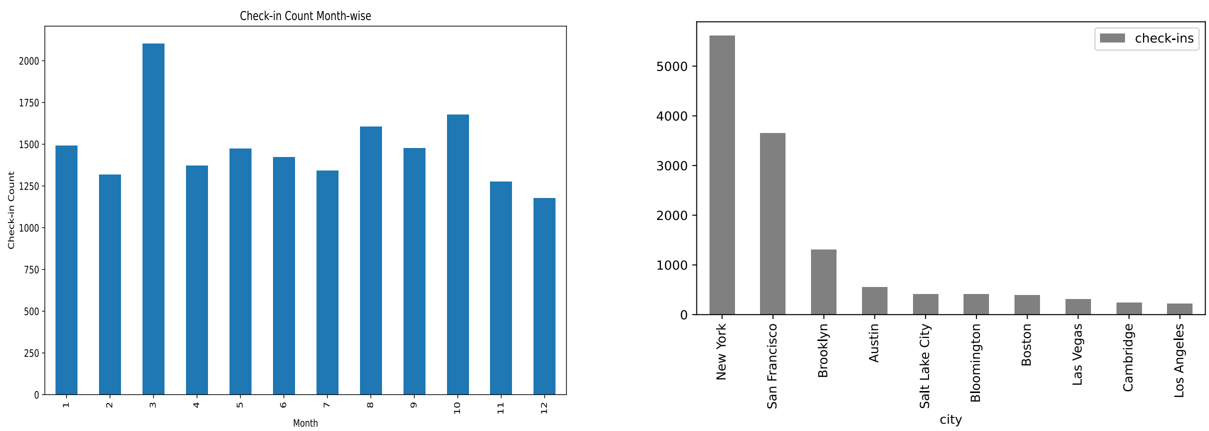

FIGURE 5. Check-in data analysis of Weeplaces. a) Month-wise. b) city wise.

D. EVALUATION METRICS

The proposed approach is evaluated on two metrics defined as follows:

Precision@k: It is the ratio of recovered POIs to the number of recommended POIs, depicted mathematically in Equation (18).

$$Precision@k = \frac{1}{n}\sum_{u=1}^{n}\frac{|I^{recom} \cap I^{test}|}{k} \tag{18}$$

I^{recom} is the top-k recommended POI list of target users, I^{test} is the visited POI list of the target user in the test set, and k is set to 5, 10, 15, and 20.

Recall@k: It is defined as the ratio of recovered POIs to the number of POIs predicted, as represented in Equation (19).

$$Recall@k = \frac{1}{n}\sum_{u=1}^{n}\frac{|I^{recom} \cap I^{test}|}{|I^{test}|} \tag{19}$$

I^{recom} is the top-k recommended POI list of target users, I^{test} is the visited POI list of the target users in the test set, and k is 5, 10, 15, and 20.

Acc@k: It is computed as the ratio of correct recommendations obtained to the total records in the test set $|D_{test}|$. Equation (20) depicts the formula used. Here, k is varied to 5 and 10 only.

$$Acc@k = \frac{\#hits@k}{|D_{test}|} \tag{20}$$

E. BASELINE METHODS

1) CatDM [3]: This is a deep encoder-based LSTM used in this model to capture user preferences based on spatial, temporal, and categorical aspects.
2) ST-RNN [33]: It uses spatial-temporal context with recurrent neural networks.
3) Spatial Binning [1]: The spatial griding-based method that utilizes LSTM to model ROIs.
4) HST-LSTM [34]: It is a hierarchical extension of spatial-temporal LSTM to enhance prediction performance.
5) LSTM [29]: Standard model for deep learning-based recommendation tasks.

6) SDAE-Bi-LSTM [35]: A combination of stacked autoencoders (SDAE) and Bi-LSTM.
7) DeepPOF [17]: It exploits the social links in addition to spatial and temporal content with a deep neural network.
8) RecPOID [36]: It can be defined as a friendship-aware spatial-temporal context-mining approach.
9) Bi-LSTM + Attention [19]: Spatial-temporal context processed through encoder-decoder-based Bi-LSTM model.
10) GT-HAN [37]: This framework models geographical-temporal aspects using an attention network and caters to POI-POI dependencies.
11) DeepMove [38]: It is an attention-recurrent network for mobility prediction in user-check-in trajectory.
12) STAN [39]: A spatio-temporal network uses a self-attention network to harness the interactions between the non-consecutive check-ins.
13) MGCOCO [40]: It exploits the multi-granularity context, correlations, and spatial-temporal aspects to capture the local and global mobility patterns.
14) APRA-SA [41]: It is a POI recommendation method that investigates the activity and spatial features using activity regions, temporal propensity, and distance features.
15) Trust and Spatial-Temporal [42]: It uses direct and implicit trust modeling in combination with spatial and temporal factors.
16) DeNavi [43]: It uses subspace decomposition, distance awareness, and lightweight learning for POI recommendation.

The results have also been compared with LTPM-TR, LTPM-SP, and LTPM-TRSP to confirm our claims.

F. RESULTS

1) PRECISION AND RECALL

The *precision@k* and *recall@k* for NYC and Gowalla datasets are depicted in Table 4. Among the NYC dataset's baselines, HST-LSTM has the lowest precision, followed by a minor spike in LSTM, the basic standard model for deep learning. The spatial binning approach of [1] showed better performance than the other two owing to the spatial griding of the geographical region for POI recommendation. CatDM outperforms the baselines and shows the highest performance. However, it is further surpassed by LTPM-TR, the variant of our approach that uses only temporal recency-based modified LSTM. LTPM-TR outperforms LTPM-SP, which utilizes the metric learning-based spatial proximity estimation. Both versions are further subdued by the complete LTPM-TRSP, combining spatial proximity and recency as two distinct units. A similar trend is visible in *recall@k* for the NYC dataset.

The experiment on the Gowalla dataset also presents some interesting facts. The SDAE-Bi-LSTM model shows the lowest performance, followed by the Bi-LSTM-Attnetion model. The standard LSTM shows better results than these. The RecPOID technique substantially enhances results but is outperformed by the DeepPOF model. ST-RNN model performed equally well to DeepPOF with the slightest increase in the results. Our proposed method and its variants subdued the baselines with a similar trend. LTPM-TR performs better than other baselines but least within the versions of LTPM. LTPM-SP performs better but is lower than the LTPM-TRSP. The results of the NYC datasets are slightly less than those of the Gowalla dataset, owing to the implicit disparity in data distribution. A similar trend is also visible for the Weeplaces dataset.

2) ACCURACY

Applying the LTPM-TRSP algorithm on the Gowalla platform yielded an accuracy rate of 34.8%. Similarly, the Weeplaces platform achieved an accuracy rate of 35.13%, while the Foursquare platform reported an accuracy rate of 31.82%. As elucidated earlier, the observed discrepancy can be attributed to the intrinsic variations in geographical distribution. We have compared the baselines with the complete model LTPM-TRSP.

Figure 6 depicts the variations in acc@5 and acc@10 for the Gowalla and Weeplaces datasets. Our model surpasses all other baseline models and presents a competitive technique for POI recommendation. The results presented were calculated at epochs 250 for better comparisons. The accuracy also varies with epochs, as depicted in Figure 7, which presents the accuracy results over epochs 100, 150, 200, 250, and 300 for Gowalla and Weeplaces. After 300, we observed a stabilization in accuracy. Also, at epoch 280, we observed a decline in the accuracy, and the optimal epoch selected was 250. The accuracy variation with the training and testing ratio is depicted in Table 5.

3) ABLATION STUDY

To assess the efficacy of our suggested methodology, we examine different versions of the LTPM-TRSP framework. Each employs a different component in its entirety. Figure 7 presents epochs vs. accuracy variations for different versions of Weeplaces and Gowalla datasets. As the epochs increased, the accuracy increased. After 250 epochs, the accuracy statistics decreased till 280 epochs and then increased to 35.74 % for Gowalla and 38.16 % for Weeplaces. After 300 epochs, stabilization was achieved. According to the Gowalla dataset, the LTPM-SP method showed higher accuracy than the LTPM-TR method; thus, geographical considerations significantly influence the choice of check-in at a POI. Users prefer visiting a POI close to a previously visited POI near their location, suggesting a tendency for connectedness between nearby locations. LTPM-SP in Weeplaces was slightly lower than in Gowalla due to the geographical distribution patterns in the check-in records. LTPM-TR accuracy for Weeplaces also shows similar behavior. LTPM-TRSP outperforms other approaches; thus, confined geographical regions within proximity and temporal

TABLE 4. Comparison of precision and recall for NYC and Gowalla.

NYC Dataset								
Approach	**P@5**	**P@10**	**P@15**	**P@20**	**R@5**	**R@10**	**R@15**	**R@20**
CatDM [3]	0.12	0.07	0.05	0.02	0.401	0.524	0.561	0.5942
LSTM [29]	0.0510	0.0492	0.0443	0.0407	0.2771	0.2936	0.324	0.3312
HST-LSTM [34]	0.05	0.04	0.036	0.030	0.18	0.31	0.35	0.39
Spatial-Binning [1]	0.065	0.061	0.057	0.052	0.201	0.237	0.282	0.314
LTPM-TR	0.11	0.087	0.052	0.0211	0.2549	0.2973	0.3256	0.3708
LTPM-SP	0.1247	0.0974	0.0778	0.0573	0.2973	0.3141	0.3348	0.3687
LTPM-TRSP	**0.1674**	**0.1258**	**0.1004**	**0.0875**	**0.2856**	**0.317**	**0.3398**	**0.3823**
Gowalla Dataset								
Approach	**P@5**	**P@10**	**P@15**	**P@20**	**R@5**	**R@10**	**R@15**	**R@20**
SDAE-Bi-LSTM [35]	0.024	0.0142	0.0113	0.0085	0.14	0.22	0.24	0.32
DeepPOF [17]	0.11	0.07	0.08	0.07	0.15	0.18	0.25	0.3
RecPOID [36]	0.068	0.062	0.058	0.05	0.05	0.07	0.1	0.12
LSTM [29]	0.0447	0.0411	0.0392	0.0351	0.2417	0.2732	0.3014	0.3245
Bi-LSTM-Attention [19]	0.0254	0.0195	0.0132	0.010	0.19	0.252	0.324	0.362
ST-RNN [33]	0.10	0.08	0.054	0.0178	0.14	0.25	0.2873	0.3271
LTPM-TR	0.147	0.119	0.071	0.0423	0.4071	0.4315	0.4524	0.5013
LTPM-SP	0.168	0.142	0.105	0.081	0.4723	0.5076	0.5345	0.5714
LTPM-TRSP	**0.2141**	**0.1923**	**0.1570**	**0.1143**	**0.4985**	**0.5341**	**0.5863**	**0.601**
Weeplaces dataset								
Approach	**P@5**	**P@10**	**P@15**	**P@20**	**R@5**	**R@10**	**R@15**	**R@20**
APRA-SA [41]	0.055	0.042	0.031	-	0.133	0.159	0.194	-
MGCOCO [40]	0.061	0.047	0.036	-	0.140	0.168	0.206	-
LTPM-TRSP	**0.064**	**0.058**	**0.053**	**0.047**	**0.187**	**0.226**	**0.276**	**0.307**

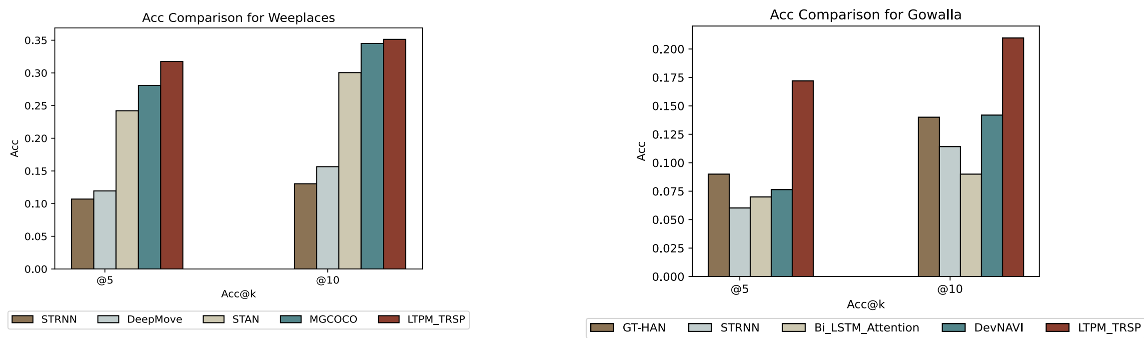

FIGURE 6. Accuracy comparison for a) Weeplaces and b) Gowalla @5 and @10.

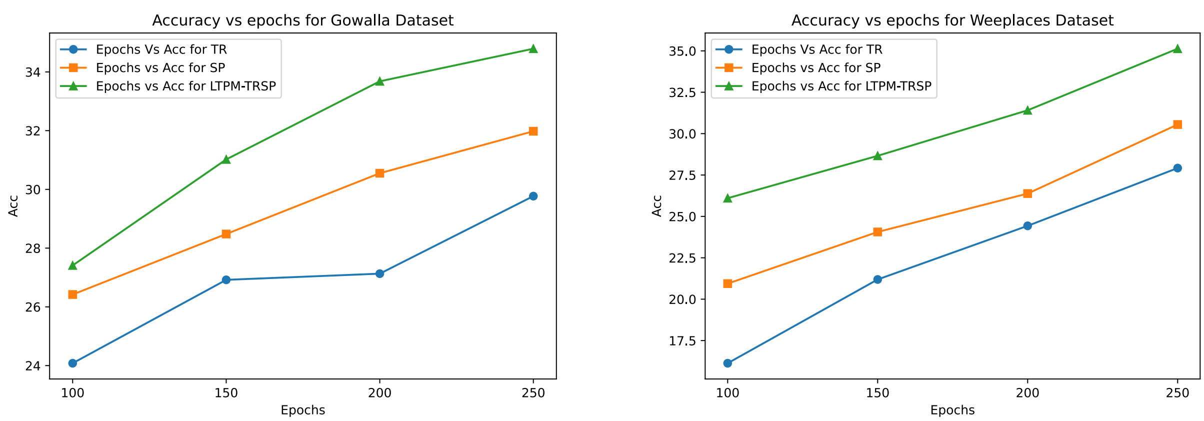

FIGURE 7. Accuracy vs Epochs a) Gowalla dataset b) Weeplaces dataset.

recency provide a higher opportunity for user preference mining. Accuracy also showed fluctuations with the train and test data ratio variations, as described in Table 5.

4) COMPLEXITY ANALYSIS

The complexity of LTPM-TRSP depends on the individual complexity of four different steps. The temporal feature

TABLE 5. Accuracy variations with train-test ratios.

Ratio		Gowalla	NYC	Weeplaces
Training	Testing			
50	50	24.25	22.58	26.10
60	40	31.84	27.29	30.96
70	30	33.7	28.41	33.04
80	20	34.8	31.82	35.13
90	10	35.4	34.6	38.96

incorporation in LSTM has the $O(t \times n^2)$ where t is the sequence length, and n is the number of units. Spatial Feature analysis using MLP, Geohash, and LMNN is $O(n^2)$. For orthogonal mapping, the complexity is $O(d^2 \times n^2)$ that depends on d is embedding space, and the complexity of triplet loss is $O(d)$ per triplet. For multi-head Attention, layer complexity is $O(H \times L \times d^2)$ where H is the number of attention heads, L is the input length, and d is the dimensions of input vectors. The final concatenation of results and recommendations is $O(n)$. This is less than our previous approach to spatial binning proposed in [1]. LTPM-TRSP takes an overall 741.41024752 s of training time at 250 epochs.

5) DISCUSSION

LTPM-TRSP uses an exponential decay function for which the decay rate is a significant factor as it decides the dominance of newer interactions over the older ones. The learning rate for LSTM is set to 0.001, the batch size is 64, and the optimal number of epochs is set to 250. The number of hidden layers in MLP is 4, with 16, 8, 4 and 2 neurons in each layer, respectively. MLP has a learning rate of 0.0001. The embedding dimension is set to 32 for orthogonal mapping to avoid overlapping the dimensions and provide a suitable trade-off. The λ_1 value fluctuates between 0 to 1. The suitable value obtained by hit-and-trial is 0.64; at this value, the RMSE obtained was 0.2 to 0.4, which was substantially acceptable. Further, with this value, the radial distance accepted is neither very small nor very large; hence, the radial distance is suitable.

Using the time decay, the older interactions are neglected, and newer ones are assigned higher weights. The temporal features are searched for both temporal periodicity and temporal asymmetry. The popularity of the category and the time past from the last check-ins are crucial components as revealed by the timestamps. Using these, we integrate the recency in the model. The spatial sensitivity and relevancy based on MLP capture the categorical propensity of POIs. We ensure the discriminative power in the system using orthogonal mapping and capture the user-POI interactions. LMNN reduces the distance between the POIs of similar categories, hence groups the potential POIs in recommendation. The concatenation of both units ensures balanced dynamic preferences based on the current location and the reference time. The final recommendations are obtained by combining the long-term preferences mined from the historical check-ins using category-aware LSTM. Through this model, we infuse the temporal and spatial units as the measure of recency and proximity into the static long-term predilections of the users.

V. CONCLUSION

In this paper, we attempt to solve the issue of data sparsity and long-term preference based on recency in the user's historical check-ins and the proximity of the POIs to the user's current location. The approach deploys modified LSTM to incorporate the time decay in mining the propensity of POIs. Concomitantly, the geographical distance and ROI are mined to boost the representation learning using combined orthogonal mapping and metric learning units. This approach exploits the user-POI, POI-POI, and POI-time relationships latent within the check-in data to substantiate the user's preference mining approach. The objective of the approach is to provide increased priority to recent information and less priority to older data, as this reduces performance and might produce outdated recommendations. LTPM-TR captures the temporal periodicity and temporal asymmetry in the user check-ins. The frequency of check-ins represents the long-term preference of categories of POI. The recommendation considers personalized preferences based on periodic visits, and the difference between reference time and the previous check-ins measures the asymmetry. Thus, recent visits would depict the currently popular POIs. LTPM-SP uses contrastive learning in combination with spatial proximity that optimizes the triplet loss through geographical vicinity score. The final loss provides the trade-off between the two and captures the sequential, categorical, and spatial behavior embedded in the user check-ins. The spatial gridding with higher priority to grids with POIs of high check-in frequency further enhances the location trajectory mining. LMNN-based metric learning aggregates the categorical effect in the POI recommendation process. Thus, the discriminative power of the embeddings learned enables a large margin in POIs of different categories and vice-versa. The final recommendation is made by attention-augmented units using the outputs of LTPM, temporal and spatial sections. The results evaluated on three real-world datasets are quite affirmative. The complexity analysis of the model infers that the process is a bit complicated and requires a significant amount of time in the training process.

VI. FUTURE WORKS

The proposed model relies on the recency in the visitation pattern and uses a decay mechanism. In the future, we wish to explore the methods for dynamic weighing mechanisms to capture user mobility behavior based on Deep Q Network (DQN), ensemble methods, or regularization strategies. The model caters to only temporal and spatial information but neglects contextual parameters like social contexts, tips, reviews, etc. Hence, in the future, we aim to investigate the importance of the auxiliary information too. The data extracted from the historical check-in puts the confidentiality of the user at stake. Including different learning paradigms like federated learning and adversarial learning can be envisaged.

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