

# A TRAVEL POINT-OF-INTEREST RECOMMENDATION ALGORITHM INCORPORATING SOCIAL FEATURES AND LOGISTIC MATRIX FACTORISATION

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**Abstract.** With the growing demand for personalised travel experiences, the development and application of travel point-of-interest (POI) recommendation systems have become increasingly important. However, many existing systems often underperform owing to insufficient integration of social features and contextual information. To address this issue, the S-LMF algorithm is proposed, combining social features with logistic matrix factorisation to improve recommendation accuracy. This approach simulates social influence by incorporating joint check-in similarity and friendship factors, while logistic matrix factorisation leverages check-in frequency data to refine POI recommendations. The effectiveness of social features and logistic matrix factorisation (S-LMF) was tested against five baseline algorithms using publicly available data sets from Yelp and Gowalla. Results demonstrated that S-LMF outperformed the best baseline model by improving Precision@20 by 22.95% on Yelp and 28.60% on Gowalla. Moreover, it increased Recall@10 by 17.95% on Yelp and 8.19% on Gowalla.

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**Keywords:** Travel point-of-interest recommendations, social features, logistic matrix factorisation, recommender systems, collaborative filtering

## 1 INTRODUCTION

In today's era of information overload, recommender systems have become indispensable in enhancing personalised recommendations, especially in tourism, where point-of-interest (POI) suggestions are tailored to individual preferences [1]. The advent of mobile devices and advanced location tracking technologies has enabled real-time location data collection, fuelling the growth of location-based social networks (LBSNs) [2]. Users can now share their locations, experiences and POI-related content through check-ins, enabling algorithms to leverage past check-in histories and propose personalised attractions, thereby enriching travel experiences. POI recommendations offer several benefits: [i] They help users discover new and unique attractions. [ii] They boost the visibility of tourist destinations, attracting a broader audience. Given their profound impact, POI recommendations have garnered substantial attention from both academia and industry [3].

The primary objective of POI recommendation systems is to facilitate users in discovering appealing attractions by analysing their behaviour and accurately forecasting their interests. However, these systems face challenges such as data sparsity [4], as users typically interact with only a few POIs, leaving many unrated. This lack of data makes it difficult to fully understand user preferences. This, in turn, makes it challenging to provide personalised recommendations. Furthermore, many systems fail to utilise contextual information, such as geographic location and time preferences, leading to less relevant recommendations. To overcome these challenges, researchers have explored incorporating diverse and rich contextual factors, such as category influence [5], geographic proximity [5], social influence [6] and temporal dynamics [7], to enhance model performance. Some studies [8] have integrated geographic and temporal influences into matrix factorisation to improve recommendation accuracy, while others [9] proposed a fusion model called geographic temporal categorical and social (GeoTeCS) for personalised location recommendations, which combines matrix factorisation with the multi-centric Gaussian model (MGM) to align check-in data with the user's historical check-in behaviour. Furthermore, other studies [10] have incorporated time-influenced context and classified locations to mitigate data sparsity and cold-start problems.

In real-world scenarios, people often rely on friends' travel narratives and recommendations, suggesting the importance of social connections in influencing travel decisions.

As shown in Figure 1, weights  $f_1$  and  $f_2$  represent the influence of recommendations from user B (a friend) and a stranger on user A, respectively. Typically,  $f_1$  is much greater than  $f_2$ , indicating that recommendations from friends carry significantly higher weight compared to those from unfamiliar sources. This dis-

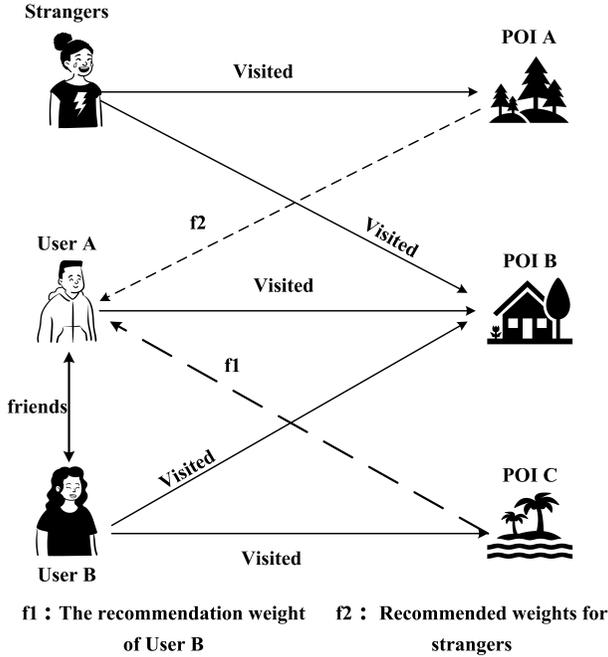


Figure 1. Schematic representing social relevance

parity signifies that user A values suggestions from user B more, particularly when shared interests and mutual understanding are involved. Recommendations from strangers, while present, have a minor influence as user A tends to take advice from friends. This study employs social features to investigate users’ travel preferences by modelling social influence through co-check-in similarity and friendship factors. To enhance the effectiveness of travel POI recommendations, we integrate this social model into a novel matrix factorisation framework. Comparative experiments on two public data sets demonstrate that our proposed method outperforms baseline models in recommendation accuracy and overall performance.

The main contributions of this paper are as follows:

1. We propose a new recommendation algorithm that incorporates social features and logistic matrix factorisation, effectively improving POI recommendation accuracy.
2. By considering the similarity in check-in behaviours and the friendship factor among users, we calculate the weight of similarity between users and their friends. This approach models social influence in a more universal way.
3. To extract more valuable information from check-in data, we use the logistic matrix decomposition method to model the frequency of user-POI interac-

tions, thereby capturing the contribution indicated by higher check-in frequencies.

## 2 RELATED WORK

### 2.1 Collaborative Filtering-Based Tourism Points-of-Interest Recommendation

In recent years, collaborative filtering-based travel POI recommendation systems have garnered significant interest in the fields of travel information services and personalised recommendations. By deeply analysing user behaviour and preferences, these methods provide accurate and tailored travel suggestions, enhancing the overall user experience. A study [11] employs cosine similarity to recommend attractions based on the visit history of a user's neighbours. Another work [12] introduces a probabilistic model to bridge user annotations and location taste keywords, addressing data sparsity. In study [13], geographic information is leveraged to capture personal profiles and location popularity, integrating user preferences via matrix factorisation for refined recommendations. Another study [14] enhances collaborative filtering using demographic data to improve accuracy. Other researchers [15] have incorporated memory-based preferences and POI stickiness into a user-based collaborative filtering framework to improve the performance of POI recommendations. Ultimately, the social spatiotemporal probability matrix factorisation model integrates POI similarity and user similarity across social, geographic and POI category spaces to improve recommendation performance [16].

Collaborative filtering methods often suggest that users with similar check-in histories at specific points of interest are likely to visit similar POIs in the future. These algorithms are relatively simple and easy to implement, enabling the rapid construction of recommendation systems. However, despite the existence of numerous accessible locations around the user, users typically visit and check in to only a small fraction of them. This sparsity in user behavioural data often limits the effectiveness of collaborative filtering-based approaches, affecting the accuracy of POI recommendations.

### 2.2 Point-of-Interest Recommendation Based on Contextual Information

With the rapid rise of LBSNs, POI recommendations have become essential for optimising location-based services. Various models have cleverly incorporated geographic influence, a crucial contextual factor, to enhance the accuracy and performance of these recommendations. One approach [17] employs kernel density estimation, factoring in order, category and geographic influence to refine the user's location preference for POIs. The MANC model [18] features a user-centric and a POI neighbourhood module. The latter utilises a feature-level attention network and POI-level attention networks to discern neighbourhood features and gauge the

influence among POIs. A ranking-based method [19] analyses check-in frequency as a proxy for user access patterns and learns factorisation through accurate POI ranking. Another model [20] addresses implicit POI recommendation challenges by leveraging geographical relationships, proposing location-based matrix factorisation (L-WMF), a location neighbourhood-aware weighted probability matrix factorisation method.

The model under consideration ingeniously integrates three critical contextual factors: geographic influence, social influence and temporal information, aiming to enhance precision in capturing users' individualised needs and preferences. A study [21] proposes an innovative VCG (visual contents and geographical) framework to optimise POI recommendations in LBSNs by combining visual content and geographic influence to accurately capture user geographic preferences and provide personalised experiences. Another study [22] employs a Gaussian model (MGM) to model geographic influence, incorporating social information within a generalised matrix factorisation framework. Another approach [23] combines social, geographic and sequential influences to leverage recommendation data for POI selection. A study [24] proposes the SGGCN algorithm for POI recommendations, which integrates social relations and geographic influences. This approach desensitises user activity trajectories and uses graph convolutional neural networks to explicitly learn collaborative signals among users, between POIs and POIs, and between users and POIs, thereby alleviating the problem of data sparsity. A deep learning model analyses user check-in behaviour and develops a deep learning model to integrate both geographic and social influences for improved POI recommendations [25]. Some methods [26] combat data sparsity by integrating social, geographic and temporal information in a matrix factorisation (MF) approach for enhanced accuracy. Personalised POI recommendations consider social, geographical and temporal influences on users' access preferences [27].

While recommendation methods based on contextual information offer significant advantages, they also present challenges. Their advantages lie in precisely matching users' current needs and enhancing personalised experiences. However, they face difficulties in accurately collecting and quantifying certain contextual information, such as user emotions, which adds to the system's complexity and dynamism. Furthermore, privacy protection concerns may limit the diversity of recommendations.

### 3 PROBLEM DEFINITION

Subsequently, to define the notation and describe the problem related to tourism POI recommendations, we can break it down as follows:

**Symbol Definition:** Let  $U = \{u_1, u_2, \dots, u_n\}$  be the set of users,  $L = \{l_1, l_2, \dots, l_m\}$  the set of POI,  $n$  the number of users, and  $m$  the number of POI. Each POI  $l_i$  has geographic coordinates  $l_i = \{\text{lng}_i, \text{lat}_i\}$ , denoting its location. Let the user-POI check-in matrix be denoted as  $E \in R^{n \times m}$ .

**Problem Description:** The tourism POI recommendation problem focuses on building a user preference model for uncharted locations. This involves processing and analysing data related to users, tourism POI and users’ check-in histories. The goal is to identify and recommend uncharted attractions with the highest scores, providing users with personalised tourism location recommendations, satisfying users’ desire for exploration and enriching their travel experiences.

### 4 MODEL CONSTRUCTION

To address the limitations of existing tourism POI recommendation algorithms, which often fail to fully exploit social relationships among users and underutilise contextual information, we propose an innovative algorithm called social features and logistic MF (S-LMF). This algorithm seamlessly integrates social features and harnesses with logistic MF, consisting of two main parts: the social model based on the relationship among users and their friends and the logistic MF model.

#### 4.1 Social Model

In travel planning, social influence from friends significantly affects individuals’ decision-making regarding destination choices. The dynamics of social connections and interactions among users significantly impact their selection of a particular POI. This paper leverages the observed social correlation among users and their friends who have visited the same POI to hypothesise connections with unvisited POI, subsequently informing personalised recommendations. The social model is depicted in Figure 2.

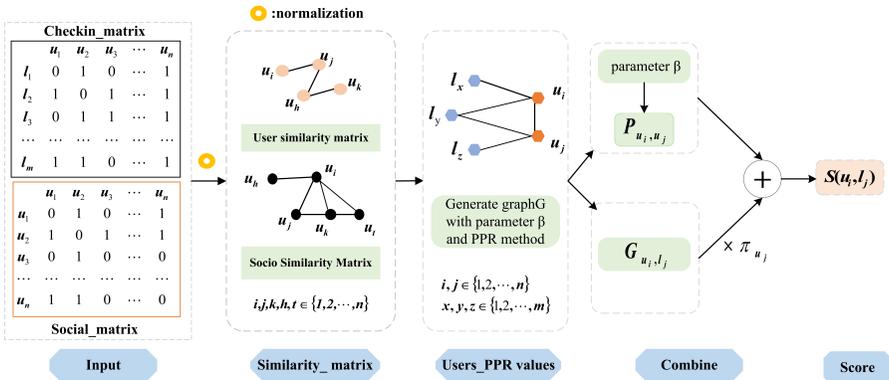


Figure 2. Flowchart of the social model

The personalised page rank (PPR) [28] method is used to calculate element  $\pi_{l_j}$  that reflects the closeness between node  $l_j$  and node  $u_i$ . Equation (12) is used to

update the weights of all the similar edges. When a user links both friendship edges (explicit social relationships among users, which are direct connections in a social network) and similar edges, these are combined by assigning different weights. Similarity edges are merged into a similarity edge. Ultimately, the preference score  $S(u_i, l_j)$  for user  $u_i$  towards POI  $l_j$  is determined.

To evaluate the preference of user  $u_i$  for location  $l_j$ , a user-based collaborative filtering recommendation algorithm considers the visit history of user  $u_i$  and calculates the similarity with other users. Based on the POI visited by user  $u_i$  and their frequency, a vector  $P_{u_i}$  of length  $m$  is constructed to represent his visit profile:

$$P_{u_i} = (G_{u_i, l_1}, G_{u_i, l_2}, \dots, G_{u_i, l_m}). \quad (1)$$

In this expression, if  $G_{u_i, l_j}$  is equal to 0, it means that there is no edge between user  $u_i$  and POI  $l_j$ . Otherwise,  $G_{u_i, l_j}$  denotes the number of check-ins by user  $u_i$  to location  $l_j$ , which is normalised as follows:

$$G_{u_i, l_j} = \frac{\text{freq}(u_i, l_j)}{\sum_{k=1}^m \text{freq}(u_i, l_k)}, \quad (2)$$

where  $\text{freq}(u_i, l_j)$  denotes the frequency of check-ins by user  $u_i$  to location  $l_j$ .

Jaccard similarity is used to measure the behavioural similarity between two users, with values ranging between 0 and 1. A value closer to 1 indicates higher similarity, while a value closer to 0 indicates lower similarity. In this study, we utilise Jaccard similarity to calculate location access and social similarity among users, allowing a more accurate assessment of the preference of user  $u_i$  for location  $l_j$ .

$$J(u_i, l_j) = \frac{|u_i \cap l_j|}{|u_i \cup l_j|}. \quad (3)$$

A user's location check-in patterns are influenced by both proximate and distant companions. To generate recommendations, we leverage a stochastic random walk with restart (RWR) model, as proposed in [29]. Given an LBSNs graph  $G = (U', L', E_F, E_V, W_V)$ ,  $U'$  represents user nodes in  $U$ ,  $L'$  denotes location nodes in  $L$ ,  $E_F \subseteq U \times U$  indicates friendship edges between users,  $E_V \subseteq U \times L$  signifies access edges of users to locations, and  $W_V$  is the weight of each edge in  $E_V$ . RWR integrates these nodes and edges, and  $G$  is a simple network. Figure 3 represents the friendship relationship between a user and an access location, with orange nodes representing users and green nodes representing POI that users may visit. A friendship relationship exists between user  $u_i$  and user  $u_j$ , indicated by a friendship edge between their nodes. Moreover, user  $u_i$  visits POI  $l_j$ , represented by an access relationship between their nodes.

To capture the friendship and similarity relationships among users in  $G$ ,  $G$  is changed to  $\tilde{G} = (U', L', E_S, E_V, W_S)$ , where the friendship edge  $E_F$  is replaced by the similarity edge  $E_S$ , and  $W_V$  is replaced by the similarity edge  $W_S$ . By fusing user similarity and friendship, we explore the influence of social information on users'

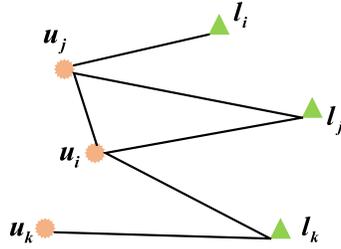


Figure 3. Original diagram G

choices of places to visit. In addition to friendship edges, weighted edges indicating the similarity of users' choices are introduced, as depicted in Figure 4.

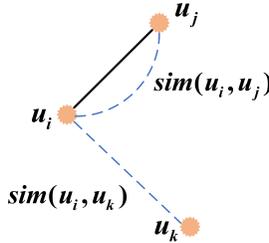


Figure 4. Weighted plot of similarity and friendship among users

In Figure 4, the solid line represents the friendship edge, while the dashed line symbolises the weighted edge reflecting user-selected similarity, which is calculated using the following formula:

$$\text{sim}(u_i, u_j) = J(p_{u_i}, p_{u_j}), \quad 1 \leq i, j \leq n, i \neq j. \tag{4}$$

To fuse the similarity edges and friendship edges among users, parameter  $\beta$  is introduced to adjust their contributions. Specifically, at the node of user  $u_i$ , similar location-friend links are tracked with weight  $\beta$ , and original friendship links are tracked with weight  $1 - \beta$ . Let  $S_{u_i} = \sum_{u_j \in LF_{u_i}} \text{sim}(u_i, u_j)$ ,  $F_{u_i}$  be the set of all friends of user  $u_i$  ( $u_j \in F_{u_i} \setminus LF_{u_i}$  denotes that user  $u_j$  is a friend of user  $u_i$  (i.e., there is a friendship edge between them), but  $u_j$  does not belong to the set of friends  $LF_{u_i}$  who share a location with user  $u_i$ ),  $LF_{u_i}$  represents the set of friends who share a POI with  $u_i$  or who have visited the same location. The final probability of being at  $u_i$  is denoted by  $P_{u_i, u_j}$ . The  $P_{u_i, u_j}$  formula is used to merge similarity edges and friendship edges, where the weights of the edges among users are defined based on their similarity and friendship edges. Then, the probability of the target user

visiting the desired location is as follows:

$$P_{u_i, u_j} = \begin{cases} (1 - \beta) \cdot \frac{1}{|F_{u_i}|}, & \text{if } u_j \in F_{u_i} \setminus LF_{u_i}, \\ \frac{(1-\beta)}{|F_{u_i}|} + \frac{\beta}{S_{u_i}} \cdot \text{sim}(u_i, u_j), & \text{if } u_j \in F_{u_i} \cap LF_{u_i}, \\ \frac{\beta}{S_{u_i}} \cdot \text{sim}(u_i, u_j), & \text{if } u_j \in LF_{u_i} \setminus F_{u_i}. \end{cases} \quad (5)$$

### 4.2 Logistic Matrix Factorisation Model

In LBSNs, check-in data is frequently regarded as implicit user feedback, presenting a unique recommendation challenge [30]. This study employs a logistic MF model, as introduced in [31], to infer user preferences for POI using a logistic function. The model aims to capture the frequency of visits to these POIs, thereby gauging user interest. It decomposes the check-in data into two compact matrices: a user matrix  $H \in R^{n \times d}$  and a POI matrix  $K \in R^{m \times d}$ , with  $d$  denoting the number of latent factors underlying the model.

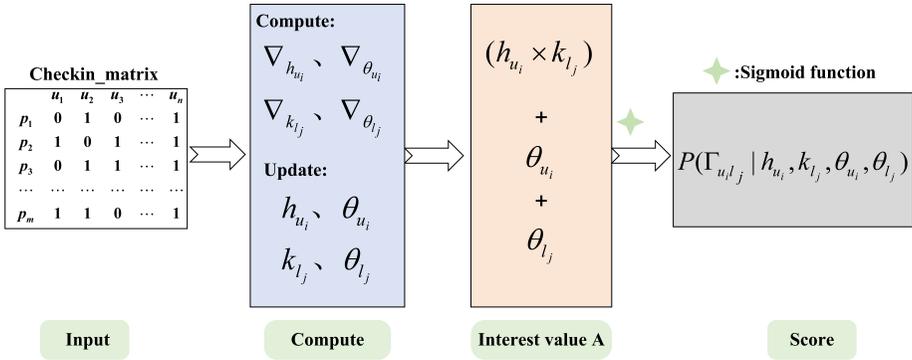


Figure 5. Logistic matrix factorisation model flow chart

The logistic MF model is illustrated in Figure 5, where,  $h_{u_i}$  and  $k_{l_j}$  represent user vectors and interest point vectors, respectively;  $\theta_{u_i}$  and  $\theta_{l_j}$  denote user bias and interest point bias, respectively;  $\nabla_{h_{u_i}}$  and  $\nabla_{k_{l_j}}$  represent user vector gradient and interest point vector gradient, respectively;  $\nabla_{\theta_{u_i}}$  and  $\nabla_{\theta_{l_j}}$  represent user bias gradient and interest point bias gradient, respectively. In this context,  $\Gamma_{u_i l_j}$  indicates the event that user  $u_i$  interacts with interest point  $l_j$  (user  $u_i$  prefers interest point  $l_j$ ). Its probability  $P(\Gamma_{u_i l_j} | h_{u_i}, k_{l_j}, \theta_{u_i}, \theta_{l_j})$  is defined as the preference of user  $u_i$  for interest point  $l_j$ :

$$P(\Gamma_{u_i l_j} | h_{u_i}, k_{l_j}, \theta_{u_i}, \theta_{l_j}) = \frac{\exp(h_{u_i} k_{l_j}^T + \theta_{u_i} + \theta_{l_j})}{1 + \exp(h_{u_i} k_{l_j}^T + \theta_{u_i} + \theta_{l_j})}. \quad (6)$$

In Equation (7), to exploit the contribution of check-in frequency in the logistic MF model, a logarithmic scaling function is used, calculated as follows:

$$Z = 1 + \rho \log(1 + c_{u_i l_j}), \quad (7)$$

where tuning parameter  $\rho$  is used to balance the observations to obtain the rec results, and  $c_{u_i l_j}$  denotes the frequency of check-ins of user  $u_i$  at POI  $l_j$ .

In addition, parameters  $H$ ,  $K$ , and  $\theta$  are learned by solving the following optimisation problem:

$$\arg \max_{H, K, \theta} \log P(H, K, \theta | E), \quad (8)$$

where  $\log P(H, K, \theta | E)$  is defined as follows:

$$\begin{aligned} \log P(H, K, \theta | E) = & \sum_{u_i, l_j} \left[ Z(h_{u_i} K_{l_j}^T + \theta_{u_i} + \theta_{l_j}) \right] \\ & - (1 - Z) \log \left( 1 + \exp(h_{u_i} K_{l_j}^T + \theta_{u_i} + \theta_{l_j}) \right) \\ & - \frac{\lambda}{2} \|h_{u_i}\|^2 - \frac{\lambda}{2} \|K_{l_j}\|^2 \end{aligned} \quad (9)$$

where  $\lambda$  is a regularisation constant to avoid overfitting.

### 4.3 Recommendation Framework

The primary objective of recommendation systems is to estimate the preference score  $r_{u_i, l_j}$  for user  $u_i$  towards an unvisited POI  $l_j$ , and subsequently rank the top N POI based on these scores. To achieve this, the social model and the logistic MF model are integrated, as depicted by the following equation:

$$r_{u_i, l_j} = S(u_i, l_j) \times P(\Gamma_{u_i l_j} | h_{u_i}, k_{l_j}, \theta_{u_i}, \theta_{l_j}). \quad (10)$$

## 5 EXPERIMENTATION

To assess the proposed model's accuracy and effectiveness, a series of simulation experiments are conducted on two well-established public data sets. The subsequent section delves into the detailed experimental procedures.

### 5.1 Description of the Data Set

In the experimental phase, two widely adopted public data sets, Yelp and Gowalla were chosen as the data sources. These data sets contain data on users, geographic coordinates, POI categories, social relationships and timestamps. The basic statistical information of the data set is shown in Table 1.

Statistical Item	Gowalla	Yelp
Number of users	5 628	7 135
Number of POIs	31 803	16 621
Number of check-ins	620 683	301 753
Social relation	46 001	46 778
Data density %	0.347 %	0.254 %

Table 1. Basic statistical information on the data set

When preprocessing the data sets, key steps include cleaning and filtering, which involve removing users with less than 15 check-in POIs and POIs with less than 10 visits to optimise data quality. Following this, the processed data set is partitioned into 70 % training data, 10 % tuning data and 20 % testing data. This helps ensure that the model demonstrates good recommendation performance and enhances the reliability of practical applications.

## 5.2 Evaluation Indicators

To assess the model performance, two key evaluation metrics are used, Precision@N and Recall@N, where N represents the number of recommended POI. TP refers to the number of samples that are actually true and the prediction result is true, representing the number of POIs that users actually visited and were correctly recommended by the system. FP refers to the number of samples that are actually false and the prediction result is true, representing the number of POIs that users did not visit but were incorrectly recommended. FN refers to the number of samples that are actually true, and the prediction result is false, representing the number of POIs that users actually visited but were not recommended by the system.

Precision measures the accuracy of the recommendations by calculating the proportion of N recommended POIs that users are genuinely interested in. This metric is particularly crucial for tourism recommendation systems as it helps users quickly find desired locations, avoid irrelevant suggestions and enhance satisfaction and trust.

$$\text{Precision@N} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad (11)$$

Recall measures the recall rate, namely how effectively the system captures the user's true interests. In the context of tourism recommendations, a high recall rate indicates that the system understands user preferences well, providing diverse recommendations that cater to their exploration needs.

$$\text{Recall@N} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (12)$$

### 5.3 Baseline Model

To validate the effectiveness of the S-LMF method proposed in this study, we compared it with the following tourism POI recommendation algorithms. The selected baseline algorithms are the following:

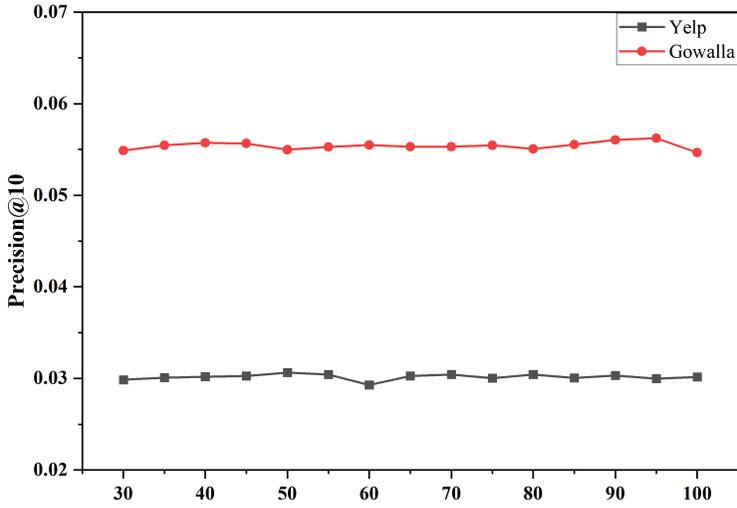
- LORE [23]: This approach blends social, geographic and sequential influences to make recommendations on POI.
- GeoSoCa [5]: This algorithm uses geographic, social and categorical correlations to learn from a user's historical check-in data and predicts their correlation score with unvisited POIs to make recommendations.
- LGLMF [13]: This recommendation algorithm combines the user's geographic and geolocation information and integrates user preferences through logical MF.
- STACP [32]: This spatiotemporal activity-centred approach enhances POI recommendations by modelling user behaviour more accurately and incorporating geographic influences in matrix decomposition models, with two settings: static time and dynamic time.
- SUCP [26]: This algorithm combines social, geographic and temporal information into MF techniques to address issues such as data sparsity and improve recommendation accuracy.

### 5.4 Parameter Tuning

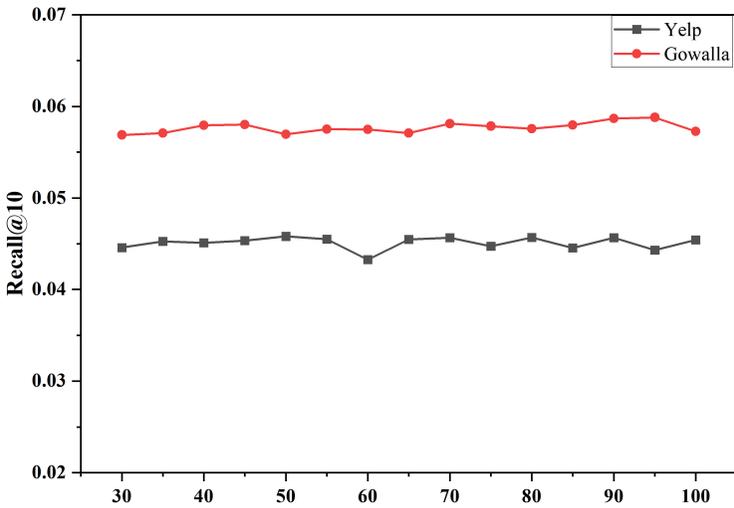
**The effect of the tuning parameter  $\rho$ .** Figure 6 shows the effect of the parameter  $\rho$  on both data sets concerning metrics Precision@10 and Recall@10. As seen in the figure, on the Gowalla data set, S-LMF performs optimally when  $\rho = 95$ , but performance decreases when  $\rho$  exceeds 95. Conversely, on the Yelp data set, the performance of S-LMF first improves as  $\rho$  increases but declines when  $\rho$  surpasses 50, reaching peak prediction accuracy at  $\rho = 50$ . Optimising parameter  $\rho$  is crucial for accurately estimating user check-in frequency at POIs, underscoring the efficacy of logistic MF in emphasising high-frequency weights in POI recommendations.

**The effect of the latent factor dimension  $d$ .** Figure 7 shows the effect of the latent factor dimension  $d$  on both data sets for Precision@10 and Recall@10. In the experiments,  $d$  ranged from 10 to 50, with 20 being the optimal setting for both data sets. The performance of S-LMF gradually decreases as  $d$  increases from 20 to 50. We hypothesise that an appropriate latent factor dimension reflects latent relationships more accurately, but when  $d$  exceeds 20, reconstructed user preferences for POI may become less accurate, affecting recommendation accuracy.

**The effect of the parameter  $\beta$ .** Figure 8 examines the effect of parameter  $\beta$  on both data sets for Precision@10 and Recall@10. The S-LMF model performs

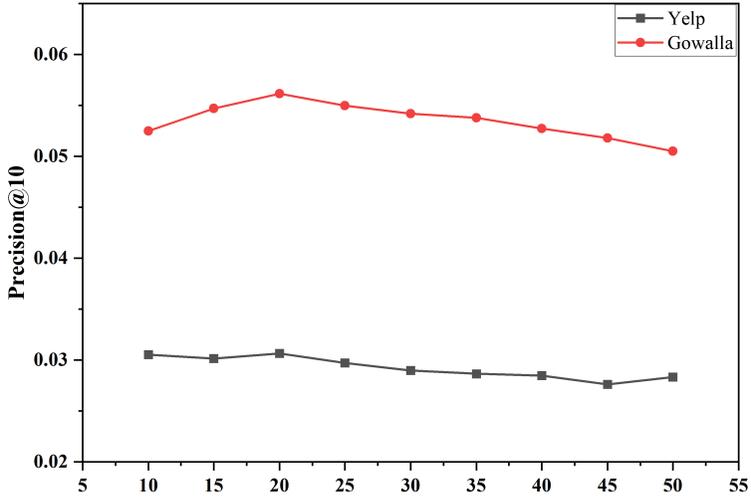


a)

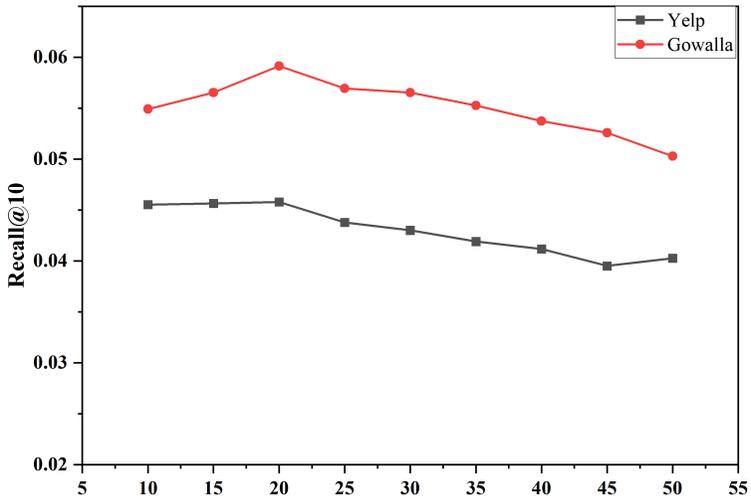


b)

Figure 6. Effect of tuning parameter  $\rho$  on the data set



a)



b)

Figure 7. Impact of latent factor dimension  $d$  on the data set

optimally when  $\beta = 0.7$  on the Gowalla data set and  $\beta = 1.0$  on the Yelp data set. This suggests that both similarity and friendship connections significantly affect user-POI relationships. The influence of similar users on visiting new POIs varies across data sets, subsequently impacting the recommender system’s performance. These findings underscore the need for dataset-specific parameter tuning.

## 5.5 Performance Comparison

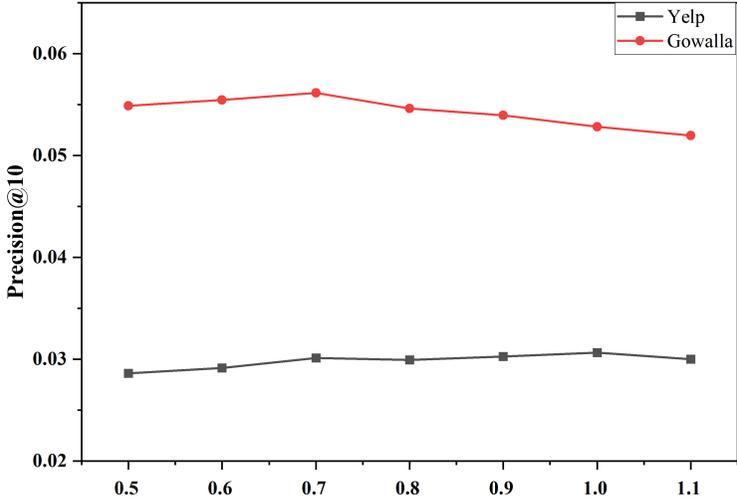
Each model underwent a comprehensive evaluation through extensive experimentation on two distinct data sets. Performance indicators, such as Precision@10, Precision@20, Recall@10, and Recall@20, were meticulously documented for each model. The findings are systematically compiled in Table 2, facilitating in-depth analysis.

		Precision@10	Precision@20	Recall@10	Recall@20
Gowalla	GeoSoCa	0.03436	0.02741	0.05467	0.08569
	LORE	0.04504	0.03490	0.03287	0.05074
	LGLMF	0.03646	0.03070	0.03549	0.05834
	STACP	0.02086	0.01865	0.02321	0.04003
	SUCP	0.04359	0.03594	0.04485	0.07132
	<b>S-LMF</b>	<b>0.05615</b>	<b>0.04622</b>	<b>0.05915</b>	<b>0.09288</b>
Yelp	GeoSoCa	0.01842	0.01508	0.02146	0.03408
	LORE	0.01829	0.01567	0.02032	0.03349
	LGLMF	0.01777	0.01664	0.02572	0.04756
	STACP	0.02128	0.01834	0.03550	0.06101
	SUCP	0.02498	0.02118	0.03883	0.06488
	<b>S-LMF</b>	<b>0.03064</b>	<b>0.02604</b>	<b>0.04580</b>	<b>0.07560</b>

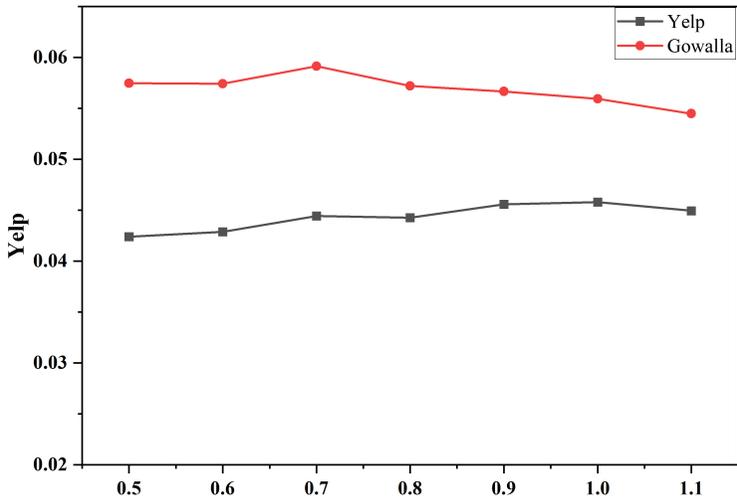
Table 2. Comparison of model performance

Table 2 reveals that the S-LMF model proposed in this study outperforms baseline alternatives across all evaluation metrics on both the Gowalla and Yelp data sets. On Gowalla, S-LMF improves Precision@10 by 24.69% over LORE, the best-performing baseline. For Precision@20, S-LMF surpasses SUCP with a 28.60% improvement. In Recall@10 and Recall@20, S-LMF exceeds GeoSoCa with gains of 8.19% and 8.39%, respectively. On the Yelp data set, although SUCP prevails in all four metrics, S-LMF demonstrates higher accuracy, with improvements of 22.66%, 22.95%, 17.95%, and 16.52% in Precision@10, Precision@20, Recall@10, and Recall@20. These findings underscore the effectiveness of the S-LMF model.

To investigate the impact of varying recommendation counts on model performance, the study employs two representative values,  $N = 10$  and  $N = 20$ , for comparative analysis. Figures 9 and 10 illustrate how different recommendation numbers affect performance.

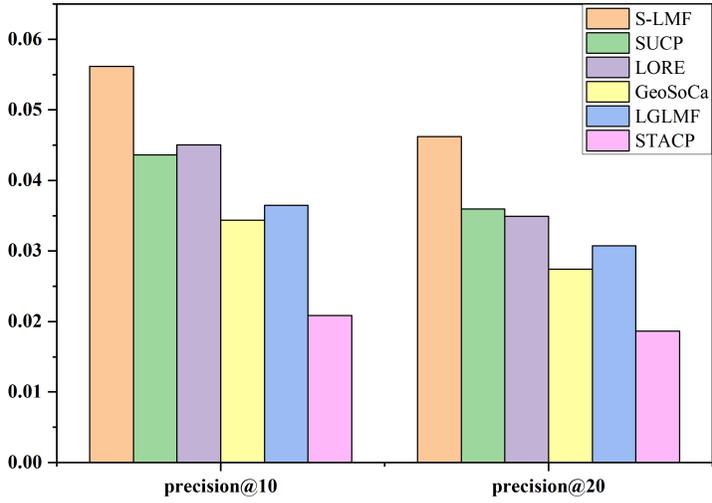


a)

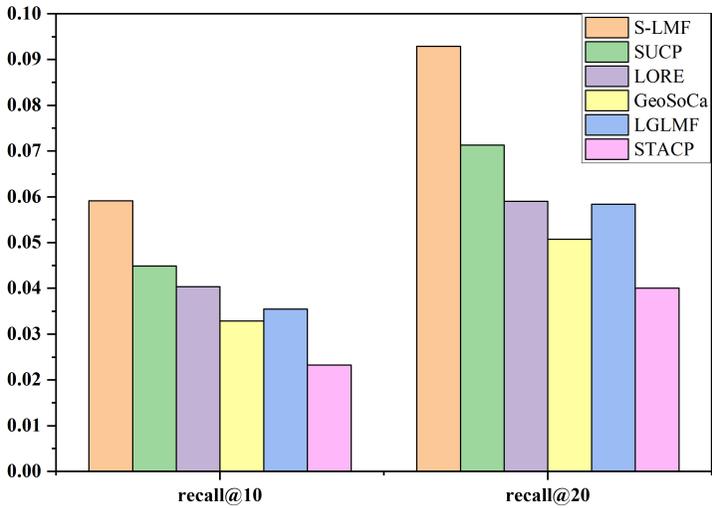


b)

Figure 8. Effect of parameter  $\beta$  on the data set

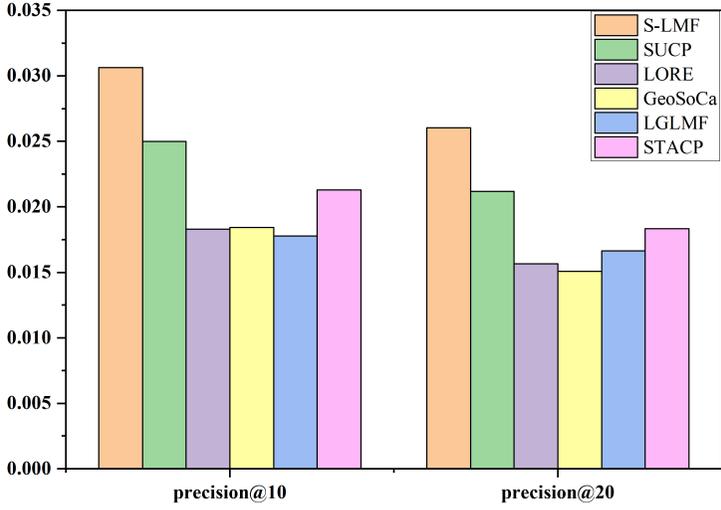


a)

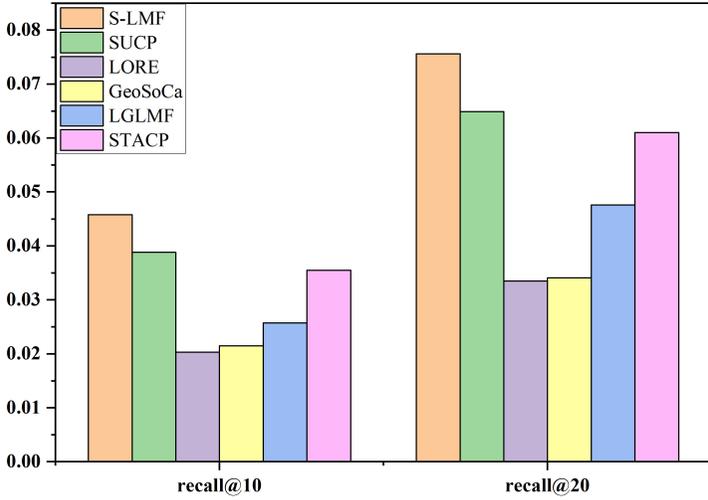


b)

Figure 9. Precision@N and Recall@N results on Gowalla



a)



b)

Figure 10. Precision@N and Recall@N results on Yelp

The comparative analysis in Figures 9 and 10 reveals that the S-LMF model consistently outperforms its baseline counterparts in recommendation precision and recall. On both the Gowalla and Yelp data sets, S-LMF demonstrates a significant advantage over the respective optimal baseline models, showcasing its superior performance.

## 5.6 Ablation Experiments

To evaluate the efficacy of the proposed model, comprehensive ablation experiments were carried out, isolating the impact of each model. All experiments were conducted under controlled training conditions to ensure fairness. The findings are presented in Table 3, providing a clear assessment of each module’s contribution.

1. SM: This test removes the logistic MF model used to capture the contribution of check-in frequencies and perform the experiments on the social model.
2. LMF: This experiment removes the model that describes social influence based on common check-in similarities among users and friendship factors, and conducts experiments on logistic MF model pairs.

		Precision@10	Precision@20	Recall@10	Recall@20
Gowalla	SM	0.04490	0.03661	0.04684	0.07340
	LMF	0.03554	0.03029	0.03591	0.05956
	<b>S-LMF</b>	<b>0.05615</b>	<b>0.04622</b>	<b>0.05915</b>	<b>0.09288</b>
Yelp	SM	0.02981	0.02533	0.04463	0.07333
	LMF	0.01888	0.01774	0.02656	0.05022
	<b>S-LMF</b>	<b>0.03064</b>	<b>0.02604</b>	<b>0.04580</b>	<b>0.07560</b>

Table 3. Performance comparison across different modules

Table 3 shows that on the Gowalla data set, the SM model experienced a decline in Precision@10, Precision@20, Recall@10, and Recall@20 by 1.13 %, 0.96 %, 1.23 %, and 1.95, respectively. Similarly, on the Yelp data set, performance dropped by 0.08 %, 0.07 %, 0.12 %, and 0.23 % in these metrics. The LMF model experienced more significant declines on the Gowalla data set, with decreases of 2.06 %, 1.59 %, 2.32 %, and 3.33 % across the same metrics. On the Yelp data set, the LMF model’s performance fell by 1.18 %, 0.83 %, 1.92 %, and 2.54 %.

In conclusion, these ablation studies clearly demonstrate the indispensable role of both sub-modules in enhancing the model’s overall performance.

## 6 CONCLUSION

To address the limitations of current tourism POI recommendation algorithms, which often overlook social and contextual information, we propose the S-LMF

algorithm. This approach integrates social features and contextual data, leveraging social interactions by calculating user similarities and analysing social relationships to enhance POI recommendations. At the same time, the algorithm employs logistic MF, using a parameterised logistic function to assign higher weights to user check-ins frequencies, thereby accurately mining this data for recommendations.

Experiments on both the Yelp and Gowalla public data sets demonstrate that S-LMF significantly improves travel POI performance. Specifically, compared to the optimal baseline models, S-LMF achieved a 22.95 % and 28.60 % increase in Precision@20 and a 17.95 % and 8.19 % boost in Recall@10. These results demonstrate the algorithm's effectiveness in generating high-quality travel recommendations, making the algorithm viable for practical applications.

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