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Enhancing points of interest recommendation by integrating users' proximity into the calculation of their similarities

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ABSTRACT

In recent years, tourists have increasingly used location-based social networks (LBSNs) to share their travel experiences with friends. Within the context of smart tourism, collaborative filtering (CF) is widely recognized as one of the most commonly used methods for point-of-interest (POI) recommendation systems. This approach analyzes user similarities using measures such Jaccard, or cosine similarity to predict the probabilities of choosing POIs to visit. However, traditional similarity measures fail to account for the physical distances between users and the locations of POIs. To address these limitations, we propose a novel similarity measure called IPUMC (integrating proximity of users in modified cosine similarity). This measure builds on the cosine similarity approach while incorporating geographic proximity between users into the calculation. Experimental results conducted on the Foursquare dataset reveal that IPUMC improves precision by 8.14%, mean average precision (MAP) by 18.01%, and normalized discounted cumulative gain (NDCG) by 16.99% compared to traditional similarity measures, specifically Pearson correlation, Spearman correlation, Euclidean distance, cosine similarity, adjusted cosine and Jaccard.

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1. INTRODUCTION

In recent years, the rise of location-based social networks (LBSNs) has sparked growing interest in the development of effective point-of-interest (POI) recommendation systems [1]. These systems aim to suggest locations that users may find interesting [2]. Among the various approaches, collaborative filtering (CF) techniques have been extensively studied and applied to POI recommendation tasks [3]. Traditional CF methods, including user-based and item-based CF, identify similar users or items based on shared behavioral patterns [4]. Specifically, user-based collaborative filtering compares interaction histories to find users with similar preferences [5]. When two users display comparable behaviors, one can receive recommendations based on the other's choices [6].

The effectiveness of CF recommendations largely depends on the underlying similarity measures. Traditional metrics, such as Pearson correlation, cosine similarity, and Euclidean distance, calculate user similarity based on ratings or check-in data [7]. However, these measures often overlook geographic and contextual factors, which are crucial for POI recommendations. For instance, users are more likely to visit geographically proximate POIs or those recommended by their social network rather than purely historical interaction-based suggestions.

To address these limitations, recent research has focused on integrating additional contextual factors, such as geographic influence and user proximity, into recommendation systems [8]. These approaches aim to improve the relevance and precision of POI recommendations [9], [10]. Furthermore, advancements such as spatial-temporal hypergraphs have significantly enhanced systems' ability to capture user preferences across time and space [11]. Integrating geographic proximity as a core component of recommendation models has proven highly effective, as users tend to visit locations near their current or past check-ins [12]. Similarly, incorporating user proximity, whether through social connections or behavioral similarity, adds another layer of personalization [13].

Additionaly, check-in behavior patterns are essential for understanding user preferences and clarifying the relationship between geographic relevance and similarity measures in POI recommendation systems. Zhou *et al.* [14] emphasize the importance of utilizing check-in data through clustering and tensor factorization to enhance user similarity metrics. These findings highlight the crucial role of check-in data in refining similarity measures and providing more personalized and accurate recommendations. Finally, combining geographic and social proximity in traditional CF algorithms has demonstrated considerable performance improvements [15], [16] and highlight the importance of blending CF techniques with advanced modeling approaches to better address the dynamic and context-dependent nature of POI recommendation.

Building on this line of research, we propose a novel similarity measure that directly integrates user proximity into the collaborative filtering process. Unlike previous methods that treat geographic factors as separate components or post-processing steps, our approach embeds these factors into the core similarity computation. This allows for improved precision and relevance in recommendations, particularly in tourism and LBSN applications. The article contributes to the literature in three main ways:

- Proposing an innovative similarity measure that enriches traditional metrics by explicitly integrating user proximity, considering both geographic distance and behavioral similarity.
- Incorporating this measure into a collaborative filtering framework to evaluate its practical applicability, leveraging both the strengths of traditional CF and added spatial context.
- Conducting experiments on two recognized Foursquare datasets (New York and Tokyo) and comparing this measure to traditional ones, such as Pearson correlation, Spearman correlation, and cosine similarity, using evaluation metrics like precision, MAP, and NDCG.

The subsequent sections of the article detail related studies (section 2), the proposed method (section 3), the experimental procedure (section 4), results and discussion (section 5), and conclude with future perspectives (section 6).

2. RELATED WORK

CF is a widely used technique in recommendation systems, particularly in the domain of POI recommendations [7]. Traditional CF methods rely on similarity measures to predict user preferences based on historical interaction data [17]. While these measures have been successfully applied in various contexts, such as e-commerce, social media, and location-based services, they often face limitations when adapted to POI recommendation tasks. Specifically, traditional methods struggle to incorporate spatial factors like geographic proximity, which is a critical element in location-based recommendation systems. One of the key limitations of traditional similarity measures is their inability to account for physical distances between users and POIs [9]. In POI recommendations, geographic proximity is an essential factor, as users are more inclined to visit nearby locations [12]. Recognizing this limitation, recent research has focused on integrating geographic information into similarity measures to enhance the performance of CF models in POI recommendations. Several studies have proposed novel methods that incorporate spatial proximity within the CF framework. For instance, Chen *et al.* [18] developed an approach that combines spatial and temporal factors, enabling the model to capture users' dynamic behavior over time and space. This integration leads to improved accuracy in recommending POIs tailored to specific times of day or particular regions. Similarly, Ding *et al.* [16] introduced a spatial-temporal distance metric embedding that models spatial proximity between POIs while also considering time-specific user preferences. Their approach significantly enhances the accuracy of time-sensitive POI recommendations compared to baseline methods. The integration of geographic and temporal preferences has also been explored in real-time recommendation systems. Jiao *et al.* [19] presented R2SIGTP, a novel real-time system that incorporates geographical and temporal preferences, dynamically adapting to users' evolving interests to provide relevant POI suggestions in real time. Lai *et al.* [11] proposed an adaptive spatial-temporal hypergraph model that captures user preferences across time and space, resulting in significantly improved POI prediction accuracy. In addition to real-time systems, researchers have also focused on integrating geospatial data into CF models. Hybrid models, which combine multiple recommendation strategies, have also shown promise in addressing the weaknesses of individual approaches. For example, Panyatip *et al.* [20] proposed a conceptual framework for hybrid recommendation systems that effectively balances various recommendation methods to improve performance. Other studies have introduced innovative approaches that combine spatial and temporal aspects with user-specific behaviors. Zhang *et al.* [21] proposed a personalized geographical influence model that incorporates both the distance between POIs and the individual geographical preferences of users. Similarly, Li *et al.* [22] introduced a spatio-temporal intention learning framework that captures spatial and temporal intentions simultaneously. This model utilizes historical user data and spatial movement patterns to enhance next POI predictions.

This comparative overview demonstrates that various methods incorporating spatial, temporal, social, and textual data have significantly enhanced the accuracy and relevance of POI recommendation systems, particularly within location-based social networks. Building on this body of work, our research introduces a novel similarity measure that explicitly integrates user proximity into the similarity calculation. This measure advances the state of the art by leveraging existing research while addressing the limitations of traditional similarity measures used in collaborative filtering models.

3. METHOD

This section outlines the methodology for calculating IPUMC similarity. We begin by detailing the formulas used to compute this similarity. Then, we present the IPUMC framework.

3.1. The proposed architecture of the new similarity

In this subsection, we calculate the IPUMC similarity by incorporating two distinct types of similarity measures. The first type, inspired by cosine similarity. The second type of similarity is based solely on the users' first and last check-in choices. These two types of similarity are then combined to produce the IPUMC similarity. This combined similarity measure is subsequently utilized to generate the predictions required for the POI recommendation process.

3.1.1. User similarity based on check-in history

In this section, we analyze user profiles, which consist of the check-in history from visits made by tourists. We hypothesize that the similarity between users can be determined by examining the overlap in the POIs they visited during their trips.

First, we used the process of normalization describe in [23] to normalize the check-in for each user into the range [0, 5]. Then, we calculate the similarity between two users, u_a and u_b by using a modified cosine similarity method, denoted as $MCos(u_a, u_b)$. This method incorporates normalized check-in data to capture the preference of users for various POIs. The formula is as follows:

$$MCos(u_a, u_b) = \frac{\sum_{i \in I} (W_{u_a P_i} \times W_{u_b P_i})}{\sqrt{\sum_{i \in I} (W_{u_a P_i})^2} \times \sqrt{\sum_{i \in I} (W_{u_b P_i})^2}} \quad (1)$$

- I: Represents the set of POIs that are visited by both users u_a and u_b. This ensures that the similarity is calculated only based on shared interactions.
- $W_{u_a P_i}$ and $W_{u_b P_i}$: these are the weights assigned to a user's interaction with a POI P_i. They reflect the user's level of preference for P_i, calculated as:

$$W_{u_a P_i} = \frac{NormCheckin_{u_a}(P_i)}{MaxCheckin_{u_a}} \quad (2)$$

where,

- $NormCheckin_{u_a}(P_i)$: the normalized number of check-ins by user u_a at P_i. The normalization process transforms the raw check-in data into a value within the range $[0, 5]$, ensuring standardization across users.
- $MaxCheckin_{u_a}$: the maximum number of check-ins recorded by u_a across all POIs. Dividing by this value scales the preference weight relative to the user's most frequently visited location.

3.1.2. User similarity based on first/last visit

Our proposed approach assumes that the similarity between users u_a and u_b can be determined based on the geographical proximity of their first and last visited POIs. Specifically, the methodology assumes that if the initial and final POIs in the respective activity sequences of u_a and u_b are located near each other, users will likely exhibit similar behavioral preferences. By focusing on both the starting and ending POIs, the approach provides an overview of users' mobility patterns, improving the accuracy of similarity assessment in location-based applications. First, we calculate $dis(FP_a, FP_b)$, that represent the distance between the first POIs FP_a and FP_b visited by u_a and u_b respectively, by using the Haversine formula [24], which is commonly employed in navigation and geographical information systems. Then, we calculate $Sim_F\left(u_a,\ u_b\right)$, that represent the similarity between u_a and u_b based on their first checkins FP_a and FP_b. The $Sim_F\left(u_a,\ u_b\right)$ is calculated by using the formula below:

$$Sim_{FP}\left(u_a,\ u_b\right) = \frac{1}{1 + dis\left(FP_a,\ FP_b\right)} \tag{3}$$

Using 3, we calculate $Sim_L\left(u_a,\ u_b\right)$, that represent the similarity between u_a and u_b based on their last POIs visited LP_a and LP_b respectively. Finaly, the similarity finale denoted as $Sim_{FL}\left(u_a,\ u_b\right)$ between u_a and u_b is calculated by using the formula below:

$$Sim_{FL}\left(u_a,\ u_b\right) = \alpha(Sim_{FP}\left(u_a,\ u_b\right)) + \beta(Sim_{LP}\left(u_a,\ u_b\right)) \tag{4}$$

where, $\alpha,\ \beta \in [0, 1]$, and $\alpha + \beta = 1$: are adjustable parameters that ensure a weighted balance between the two components.

$SimFL(u_a, u_b)$ refers to the geographical similarity between the users. It is determined by evaluating the spatial proximity of their first and last visited POIs. This component accounts for users' location-based behavior, reflecting the likelihood of shared geographic preferences.

3.2. IPUMC similarity formula

To compute the IPUMC similarity between two users (u_a and u_b), we integrate two distinct components: *MCos*, which measures preference similarity based on user interactions with POIs, and *SimFL*, which quantifies geographical similarity based on the spatial proximity of the users' first and last visited POIs. The integration of these components is controlled by the parameters γ and δ, as defined in (5).

$$IPUMC(u_a, u_b) = \gamma \cdot MCos(u_a, u_b) + \delta \cdot SimFL(u_a, u_b) \tag{5}$$

where, γ and δ are adjustable parameters within the range $[0, 1]$, ensuring a weighted balance between the two components. The parameters satisfy the constraint $\gamma + \delta = 1$.

The IPUMC similarity is designed to provide a comprehensive measure of user similarity by combining behavioral and geographical aspects. By tuning γ and δ, the model can prioritize either preference or geographic information, enabling flexible and context-aware POI recommendation. This dual approach enhances the accuracy and relevance of recommendations by leveraging both implicit user preferences and explicit geographic cues.

3.3. IPUMC similarity architecture

Figure 1 presents the main steps of the recommender system that integrate IPUMC similarity to calculate similarities between users. The process of generating personalized POI recommendations begins by transforming the user check-in dataset into a user-POI matrix, where each entry reflects the frequency of visits by a user to a specific POI. To standardize the data, the visit numbers are normalized into the range [0,5], ensuring comparability across users with varying check-in behaviors. The IPUMC similarity metric is then employed to measure the similarity between users based on their interaction patterns within the matrix. For each target user, predictions are generated by aggregating the preferences of the N most similar users identified through the similarity calculation. From these predictions, the system selects the top K POIs that are most likely to align with the user's interests. Finally, the top K POIs are recommended to the user. This structured workflow ensures that recommendations are both relevant and aligned with user behavior, enhancing the effectiveness of the POI RS.

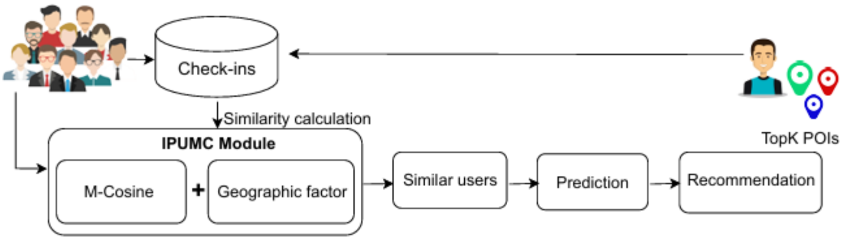

Figure 1. The working mechanism of RS using IPUMC model

4. EXPERIMENTS AND RESULTS

In this section, we have provided a description of the dataset used in our experiments, the evaluation metrics used to evaluate the performance of the IPUMC model, and the experimental procedure employed.

4.1. Data collection

To evaluate the effectiveness of our proposed IPUMC model, we use a publicly available dataset from Foursquare [25]. No filtering criteria were applied to the dataset, allowing a complete evaluation of the proposed method's performance under real-life conditions such as cold start-up and sparsity challenges. The detailed description of the dataset is shown in Table 1.

Table 1. Dataset used in the experiments

	New York Dataset	Tokyo Dataset
Users	1,083	2,293
POIs	38,333	61,858
Check-ins	227,428	573,703

4.2. Parameters

Parameters α and β are used to tune the weight between modified cosine similarity and geographical-distance influence. We tune α from 0 to 1 by step 0.1. After conducting extensive experimental tests, the parameter configuration that achieves the optimal system performance has been identified as follows:

- For New York Dataset (γ =0.85 and δ =0.15), and for Tokyo Dataset (γ =0.8 and δ =0.2).
- α = 0.6, β = 0.4, N = 30 and K = [5, 10, 15, 20] for both Datasets.

4.3. Evaluation metrics

To compare the IPUMC with other similarity, we employed three evaluation metrics: precision which represent the fraction of relevant instances among the retrieved ones [26], MAP that take into account the top K results returned [27], and NDCG which give higher weight to items ranked at the top [28].

4.4. Experimental procedure

We evaluated the performance of the IPUMC model by comparing it with other traditional similarity measures, such as Pearson correlation, Spearman correlation, Euclidean distance, cosine, adjusted cosine and Jaccard. First, we divided the dataset into a training set (70%) and a test set (30%) based on user check-ins. Then, for each similarity measure: we compute the similarity scores between each user and the other users, select the N most similar users, generate predictions, recommend the K most relevant POIs and, finally, evaluate the performance of all similarity measures using precision, MAP, and NDCG metrics.

5. RESULTS AND DISCUSSION

In this section, we provide a comprehensive overview of the Foursquare datasets utilized in our experiments. Following this, we describe the evaluation metrics selected to assess the performance of the proposed IPUMC model. Furthermore, we outline the experimental procedure, highlighting the data preprocessing steps, parameter tuning, and comparative analysis against baseline methods.

Figures 2 to 4 demonstrate that the IPUMC similarity measure consistently outperforms other similarity measures (Pearson correlation, Spearman correlation, Euclidean distance, cosine similarity, adjusted cosine similarity, and Jaccard similarity) across both New York and Tokyo datasets. Specifically, Figure 2 highlights that IPUMC achieves superior performance in precision. Figure 3 indicates that the IPUMC measure achieves higher MAP values. Similarly, Figure 4 illustrates that the IPUMC similarity measure outperforms its counterparts in terms of NDCG. These results underscore the effectiveness of the IPUMC approach in various evaluation metrics.

Using the New York dataset, our user similarity measure named IPMUC improved the following parameters: precision by 6.51%, MAP by 14.27%, and NDCG by 14.28% compared to existing similarity-based methods (Jaccard, Pearson, and Cosine). Furthermore, using the Tokyo dataset, we also observed a significant improvement in these same parameters: precision by 11.98%, MAP by 21.76%, and NDCG by 19.7% compared to the same traditional methods mentioned above.

These experimental results show that the IPUMC similarity measure significantly outperforms other traditional similarity measures. This performance improvement can be attributed to the ability of our method to efficiently consider the geographical influence with the user's historical check-in behavior in the similarity measures computation processes. This ability to combine the user's geographical location with his behavior allows our IPUMC similarity-based approach to provide more accurate and contextual recommendations. This type of approach finds its interest in scenarios such as smart tourism where the preferences based on the tourist's location and his visit history play a crucial role in recommending POIs.

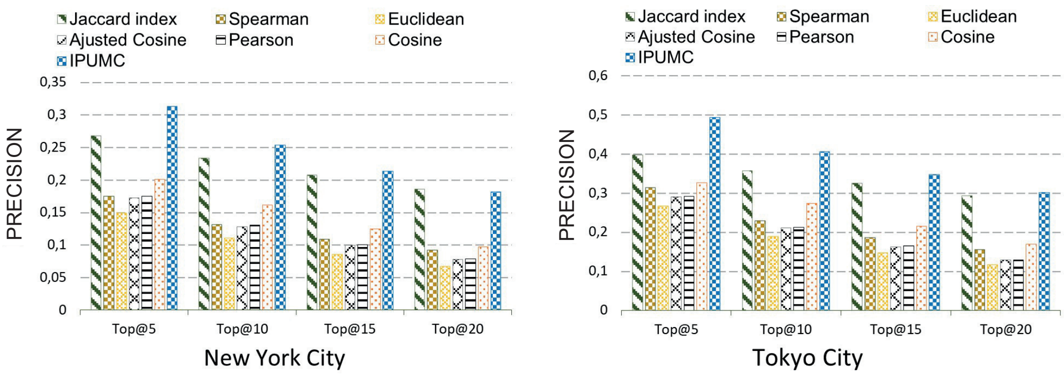

Figure 2. Precision performance on New York and Tokyo datasets

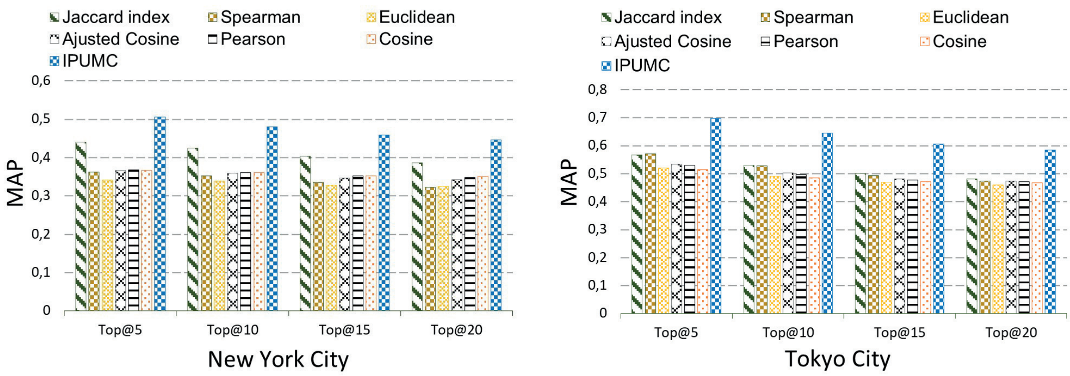

Figure 3. MAP performance on New York and Tokyo datasets

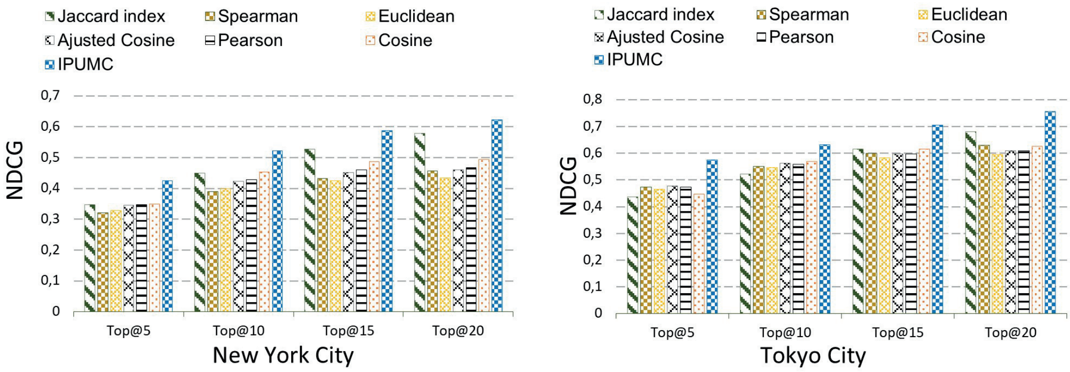

Figure 4. NDCG performance on New York and Tokyo datasets

6. CONCLUSION AND FUTURE WORK

In conclusion, the rapid growth of location-based social networks has significantly influenced users' tourism activities, highlighting the importance of similarity measures in POI recommendation systems. However, traditional similarity methods fail to consider geographical influence, which can limit recommendation accuracy. For this reason, this article proposed a novel similarity measure incorporating a geographical factor into the cosine similarity calculation. This approach leverages (i) the efficiency of cosine similarity and (ii) location data derived from users' check-in histories. Experimental results demonstrate that the proposed similarity, IPUMC, significantly enhances the performance of user-based CF POI recommendation systems. For future research, this measure could be improved by integrating additional contextual information, such as the semantic characteristics of POIs and weather conditions, to further refine recommendation quality.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Djelloul Bettache	√	√	√	√	√	√	√	√	√	√	√	√		
Nassim Dennouni	√	√		√						√	√	√		
Ahmed Harbouche										√	√	√		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject Administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The supporting data of this study are openly available in Dingqi YANG Foursquare Dataset web page, Available: https://sites.google.com/site/yangdingqi/home/foursquare-dataset.

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