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Enhanced group recommendation system: A hybrid context-aware approach with collaborative filtering for location-based social networks

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Abstract

In recent years, location-based social networks (LBSNs) have gained significant popularity, enabling users to interact with points of interest (POIs) using modern technologies. As more people rely on LBSNs for finding interesting venues, contextually aware and relevant recommendation systems have become very beneficial with practical applications. In this research, we propose an enhanced hybrid recommendation system, designed for LBSNs to improve the accuracy of suggestions by integrating collaborative filtering methods with singular value decomposition to handle sparse data, along with context-aware modeling to tailor recommendations based on user interests, and group recommendation to accommodate multi-user scenarios. In addition, we incorporate contextual aspects, such as spatial proximity and temporal behavior, into the model to ensure recommendations align closely with the user's present surroundings and preferences. The proposed method extends further to group recommendations by considering individual inclinations into cohesive suggestions for groups interested in visiting POIs together. The proposed method is assessed using precision, recall, and F1 score, ensuring a thorough evaluation of its performance. To further highlight context-aware recommendations, we use clustering based on user preference, temporal behavior, and category-wise interaction to identify patterns across various venue types. The proposed method shows improved recommendations, specifically based on data from LBSNs, and develops an efficient solution for balanced user preferences with contextual influences.

Keywords: Collaborative Filtering, Context-Aware Recommendations, Data Sparsity, Group Recommendation, Hybrid Recommendation System, Location-Based Social Networks, Singular Value Decomposition

1. Introduction

Location-based social networks (LBSNs) have become an integral part of daily life, largely due to the widespread use of smartphones and global positioning technology. Platforms such as Weibo, Gowalla, Foursquare, Yelp, and Google Maps allow users to share their locations, check in at various places, and connect with friends. These networks not only track a user's movements but also create a dynamic system in which individuals interact with their physical environment and social networks in meaningful ways (Barai & Bhaumik, 2015). An opportunity and the big challenge are developing recommendations that are more relevant by suggesting points of interest (POIs) – places the user might like based on where they have been, who they know, and what activities the users enjoy frequently – with the help of methods such as content-based filtering and collaborative filtering (CF) traditional recommendation systems, such as those used by Netflix or Amazon, are effective in domains including movies and product recommendations due to well-established preference patterns. However, such models are not directly suitable for LBSNs, which involve more nuanced spatial, social, and temporal dynamics (Ezin, 2024). However, these methods cannot be implemented directly when it comes to location-based recommendations, which involve more complicated factors such as location, social, or temporal aspects related to the users' check-ins. When recommending a venue, systems now consider much more than just general past preferences; factors such as physical proximity and typical visitation times for similar venues are taken into consideration. It is a much more nuanced approach to helping people discover interesting places nearby. These approaches represent a significant shift in how technology understands and anticipates our daily experiences, transforming simple check-in data into sophisticated, personalized recommendation models.

1.1. Challenges in LBSN Recommendations

One of the significant challenges in LBSN recommendation systems is the critical influence of user proximity to other users in the physical world (Dutta et al., 2025). Unlike previous recommendation systems that focused on item features such as type, price, or characteristics, LBSN users tend to frequent POIs located near their current location (Sánchez & Bellogín, 2022). Location plays a pivotal role in generating meaningful recommendations. Previous research has demonstrated that individuals typically travel from their current location before heading to the recommended venue, underscoring the importance of spatial data in recommendation algorithms. A recommendation system might suggest appealing places, but its utility diminishes if it fails to consider geographical distance (Dietz et al., 2025). Beyond geographical considerations, temporal parameters are equally crucial in understanding user decision-making. Individuals' preferences vary throughout the day and week. For example, the users might seek cafés in the morning, restaurants in the evening, or parks on weekends. Therefore, LBSN recommendations must incorporate time-based factors that reflect users' behavioral patterns during specific periods (Zhang et al., 2019). These temporal elements are not merely supplementary but fundamental to recommendation accuracy. Ignoring time-related context can result in inappropriate suggestions that feel disconnected from users' actual behavioral patterns, fundamentally compromising the system's functionality and relevance (Redondo et al., 2020; Zheng & Zhou, 2024). The major challenge lies in developing recommendation systems that can integrate spatial and temporal dimensions, providing suggestions that are not just potentially interesting but practically accessible within a user's context.

However, user preferences and social factors present additional complexities in LBSN recommendation systems. Empirical research demonstrates that individual historical behaviors, such as previous check-ins, repeated visits, and consistent location choices, significantly influence preferred visiting venues (Teoman, 2022; Wachyuni & Kusumaningrum, 2020). Past preference patterns dramatically shape venue selections. Users with a history of social interactions tend to gravitate toward vibrant, interactive venues, such as bars and festivals. On the other hand, those with more solitary past behaviors prefer more contemplative spaces, such as libraries and parks. Location-based data provides significant opportunities to enhance recommendation accuracy by integrating contextual factors, including user location, temporal variables, and local events. Individual preferences can vary substantially between travel and home environments, with local conditions and events further modulating decision-making patterns. The use of this contextual information becomes crucial in creating more accurate recommendations. By combining these factors, recommendation systems can generate suggestions that are aligned with users' circumstances and past preferences. The fundamental challenge lies in developing recommendation systems that can analyze and model the relationship between users' past behaviors, spatial context, and temporal dynamics (Wang et al., 2024).

1.2. Hybrid Recommendation Systems For LBSNs

The complex nature of user preferences in LBSNs makes it crucial to explore hybrid recommendation systems to get more relevant suggestions. In rapidly changing environments like LBSNs, hybrid systems can effectively address the limitations of individual methods by combining the strengths of various recommendation approaches, ultimately providing more accurate recommendations. Most conventional recommendation approaches, such as CF, are typically designed to predict a specific user's preference based on their past activities. However, these traditional methods often fall short in capturing the complex nature of user interactions within the location-based systems. Hybrid recommendation systems offer a more comprehensive solution by integrating multiple recommendation techniques, allowing for a more nuanced and adaptable approach to understanding user preferences. By integrating different methodological strategies, these systems can provide more robust and context-aware recommendations that better reflect the multilayered user behavior in LBSNs (Eliyas & Ranjana, 2022). There are two main types of memory-based CF approaches (Teoman, 2022): User-based CF, which recommends POIs based on preferences of similar users, and item-based CF, which suggests POIs similar to those the user has previously visited. Despite their effectiveness, individual methods often struggle with data sparsity and lack contextual adaptability, both of which are critical for LBSNs. Given the complex nature of user preferences in LBSNs, hybrid recommendation systems have emerged as a promising solution, integrating CF with singular value decomposition (SVD) and context-aware techniques to offer more accurate and personalized recommendations. In this study, we propose a contextual hybrid recommendation strategy that integrates user preferences, geographical location, and temporal behavior factors with CF and SVD matrix factorization to address the unique challenges of LBSNs. Using standard performance metrics, such as precision, recall, and F1 score, we assess the quality of the proposed system's recommendations. This serves as a powerful dimensionality reduction technique that enables the identification of hidden patterns within user-item interaction data that might otherwise remain imperceptible (Wachyuni & Kusumaningrum, 2020). While SVD improves recommendation quality and addresses data sparsity issues, it does not consider contexts, such as spatial or temporal factors, that are essential in LBSN recommendation systems.

Key contributions to this research:

(i) This research introduces a novel hybrid recommendation framework that integrates user-based, item-based CF with SVD, and context-aware user modeling. This combination is specifically designed to address and mitigate the limitations found in traditional recommendation approaches within LBSNs, enabling more accurate and context-sensitive recommendation strategies.

(ii) By incorporating factors such as spatial proximity and temporal behaviors, our framework enhances the personalization of recommendations. This integration allows for recommendations that adapt to varying user contexts, aligning suggestions with location-based and temporal dimensions to closely reflect diverse user needs and preferences, accumulating to group recommendations.

(iii) Through extensive experimentation with standard evaluation metrics (precision, recall, F1 score, and accuracy), we demonstrate that the proposed hybrid model outperforms traditional methods. This thorough assessment highlights the framework's potential to maintain high recommendation quality and accuracy in data-sparse and dynamic environments, marking a significant improvement over the conventional method in LBSN settings.

The next section of this paper presents a review of the relevant literature, followed by Section 3, which describes the material and methods, including the detailed steps in the architecture of the proposed system. Section 4 provides the results and comparisons, followed by the conclusion and potential future directions.

2. Related Work

The research on efficient recommendation engines is becoming increasingly important as LBSNs emerge as a primary platform for real-world user interactions. LBSNs present unique recommendation challenges by integrating contextual factors such as user location, check-in timing, and personal preferences, extending beyond traditional user-item interaction models. The CF approaches are widely used in most recommender systems, excel at generating similar-based recommendations tailored to user behaviors (Papadakis et al., 2022). However, the contextual aspects inherent in LBSNs, when the user preferences dynamically shift with location and time, present significant limitations for traditional CF techniques. The complexity of LBSNs has motivated research into integrating contextual information to enhance recommendation accuracy and relevance (Mahajan & Kaur, 2023). While CF techniques have been successfully applied across domains, including media streaming and e-commerce (Hu et al., 2019), their direct application to location-based networks remains challenging. Matrix factorization methods, including SVD, have improved CF effectiveness by reducing user-item interaction matrix dimensionality and uncovering hidden factors. Nevertheless, the data sparsity problem in LBSNs, where users visit few POIs, creates substantial gaps in interaction matrices (Tourinho & Rios, 2021). These constraints highlight the need to develop innovative recommendation methodologies that can effectively capture real-world contextual features and manage sparse data environments.

To address the limitations of conventional CF for large-scale social networks, context-aware recommendation systems have been proposed in a previous study (Ezin, 2024). These systems integrate external contextual factors, such as user time and location, into recommendation mechanisms. LBSN users typically prefer locations spatially closer to their current position, making geo-influence a critical system component. As demonstrated by Yuan & Chen (2017), users visit different places at varying times, establishing temporal factors as essential in LBSN recommendations. Some studies have expanded contextual considerations beyond spatial and temporal parameters. For example, individual personality differences significantly impact location preferences: Extroverted individuals might seek active environments, while introverted users prefer calmer settings (Deldjoo et al., 2020). For instance, people with different personality traits, such as extroverted individuals, typically prefer vibrant environments, while introverted people seek serene settings. Previous studies by Hossein (2018) and Arabi (2018) discuss that integrating personality traits can enhance recommendation targeting, potentially improving overall user satisfaction in LBSNs. While exploring recommendations for LBSN, considering factors such as proximity might enhance user satisfaction.

LBSN research demonstrates that social connections are a valuable source of information for improving recommendation quality. Social network analysis, as discussed by Wang et al. (2019), can be integrated into LBSNs to leverage user relationships, particularly in scenarios with limited user-item interaction data. Wang et al. (2019) suggested that users' preferences are significantly influenced by their social circles, friends, coworkers, and contacts, which can inform and shape location choices. Social trust-based models, introduced by Kanfade et al. (2018) and Bhaumik (2016), extend traditional CF by incorporating trust scores between users, enabling more nuanced preference generalization. Wang et al. (2013) proposed a circle-based recommendation system that generates suggestions by grouping friends into distinct circles, focusing on preferences within these social networks. Recent developments in recommender systems increasingly recognize that multiple factors beyond traditional user-item interactions shape user preferences in LBSNs. Recently, decision-making in these systems incorporates multi-criteria considerations, such as cost, ambiance, accessibility, and user reviews. Multi-criteria rating systems enable more complex, detailed recommendations compared to traditional CF techniques (Dadoun et al., 2019). Unlike the conventional CF approach by Nian (2021), multi-criteria CF (Davtalab & Alesheikh, 2023) extracts multiple dimensions of user preferences to capture the trade-offs users consider when selecting locations. In LBSNs, this approach allows users to prioritize criteria such as distance, reflecting the nature of location-based decision-making.

Traditional CF methods do not consider handling contextual features, leading to the development of hybrid recommendation approaches that combine multiple strategies to enhance overall performance (Zheng, 2022). These hybrid systems integrate advantages from CF, context-aware modules, and content-based strategies to mitigate limitations in individual methods. CF and context-aware approaches, including SVD, are frequently used to capture complex interactions between users and items. This approach is especially vital in LBSNs where user-item interactions are typically sparse and latent factors can mask user-POI relationships (Sun et al., 2022). The increasing trend of collaborative destination planning has shifted focus from individual to group recommendation systems (Zhao et al., 2023). Group recommendation systems face the complex challenge of satisfying multiple users' preferences, often complicated by conflicting individual desires. Various grouping methods have emerged to address these challenges, including social preference analysis and voting processes. These aggregation techniques aim to compute group-level recommendations while carefully balancing individual preferences (Zhou et al., 2024). By incorporating contextual and social aspects, group recommendation algorithms become more sophisticated in suggesting relevant choices for a group along with various venue categories.

The advancement in hybrid systems that integrate CF and social trust modeling has enhanced personalization that is hindered by the limitations of traditional CF in handling sparse data and contextual factors, such as time and location in LBSNs. However, hybrid systems still face challenges in combining contextual and social dimensions, especially for group recommendations. In line with these findings, it is necessary to propose a hybrid recommendation framework that not only leverages CF and SVD for handling data sparsity but also integrates contextual factors, including time and location. In addition, the inclusion of group recommendation methods ensures that our system can balance individual preferences in multi-user scenarios, offering a scalable and contextually adaptive solution for LBSNs.

3. Research Methodology

This section presents the methodology and framework for designing the LBSN group recommendation system. The framework in Fig. 1 represents the proposed hybrid approach designed to generate highly personalized and contextually relevant recommendations in LBSNs. To demonstrate the effectiveness of the model, we used the user check-in data from an LBSN named Gowalla (Zhou et al., 2024). The user-influence modeling component built a detailed profile for each user by analyzing key factors that contribute to a long-term understanding of user preferences. Parallelly, CF was employed, encompassing user-based CF, item-based CF, and SVD. This combination allowed the framework to uncover hidden relationships within user-item interactions, making it particularly effective in sparse data environments. In addition, the context-aware module dynamically adjusts recommendations based on the user's immediate context, including their current location and time, ensuring relevance.

Once the system had gathered insights from user influence modeling, CF, and context-aware modules, it combined these in the recommendation

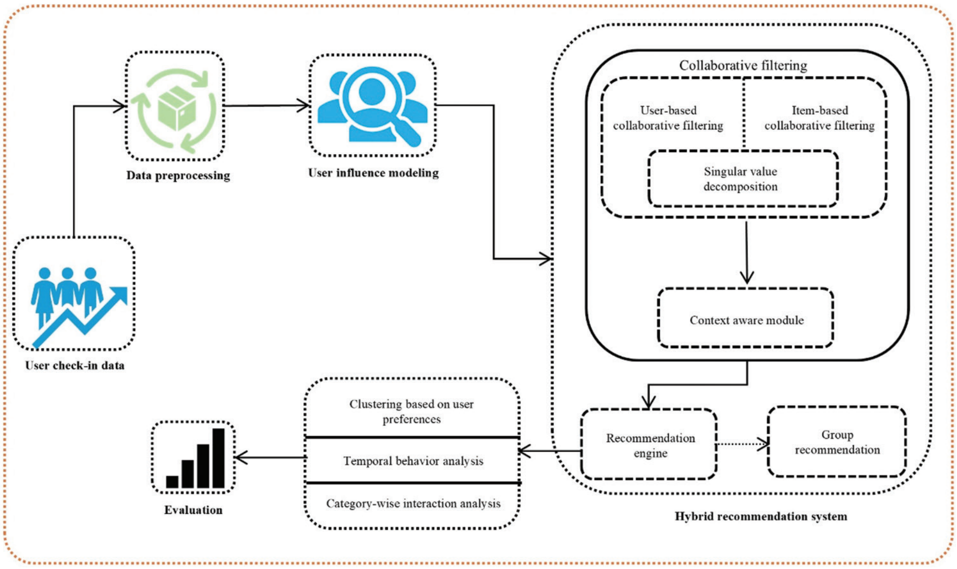

Fig. 1. Proposed framework of LBSN group recommendation system

engine to generate a final set of recommendations tailored to the individual. For group scenarios, the group recommendation module compiled individual preference scores to provide unified recommendations that met the collective needs of multiple users, balancing diverse tastes within the group. Finally, the evaluation component measured the system's performance using metrics, such as precision and recall, along with analyses based on user preferences, temporal behaviors, and category-specific interactions. Together, these components formed a robust, scalable recommendation system that effectively balanced long-term personalization with adaptive, recommendation contextual adjustments, resulting in recommendations that were both accurate and highly relevant to the user's preferences.

3.1. Hybrid Recommendation System For LBSN

The hybrid recommendation system integrates multiple recommendation techniques to provide highly personalized and contextually relevant recommendations for LBSNs. The dataflow diagram in Fig. 2 shows the steps to achieve this goal. The first step involved preprocessing the user-item interaction matrix and extracting contextual information of the user, such as geographical location and temporal behavior. These contextual factors were key to understanding the user's preferences more comprehensively. CF methods were applied to predict scores for POIs, as shown in Eq. (1). We computed the final recommendation score for each user-item pair by integrating user-based CF, item-based CF, and SVD using a weighted sum, as follows:

$$F_{final} = w_1 \cdot F_{up} + w_2 \cdot F_{ip} + w_3 \cdot F_{svd} \tag{1}$$

where F_{final}: final predicted score, F_{up}: user-based CF score, F_{ip}: item-based CF score, F_{svd}: score from SVD, and w_1, w_1, w_1: weights for each method.

In our hybrid approach, the weights assigned to each component method (user-based CF, item-based CF, and SVD) were initially set based on empirical tuning, with equal or proportional to the assigned values derived from preliminary experiments. This initialization provided a balanced integration of the three methods, ensuring that the system did not overly depend on any single approach in the beginning. However, to adapt to our datasets, the weights were fine-tuned during training, considering characteristics such as data sparsity and interaction density. This weighting approach demonstrated the potential to improve recommendation accuracy by enabling the system to respond to various user behaviors and contexts.

User-based CF searched for similar users to the target user and utilized their preferences to generate recommendations, while the item-based CF searched for items that the user had interacted with. The SVD was used to uncover latent relationships between users and items, helping in cases where the data were sparse. The Fig. 2 incorporates contextual information to adjust the recommendations, making them more relevant based on the user's preferences. The final scores were calculated by combining the scores from user-based CF, item-based CF, SVD, and context-aware modeling, using weighted averages. If the recommendation was intended for a group, the preferences of all group members were aggregated, and the final scores were adjusted accordingly. This ensured that the recommendations satisfied the entire group's preferences. Finally, the POIs were ranked based on the adjusted scores, and the top recommendations were

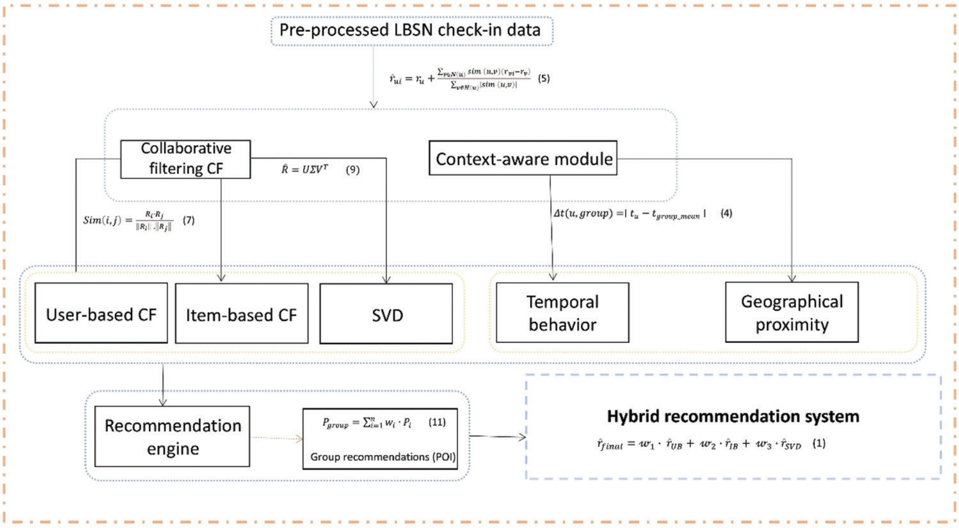

Fig. 2. Dataflow diagram of the proposed method to achieve the hybrid recommendation system
Abbreviations: CF: Collaborative filtering; LBSN: Location-based social networks; POI: Point of interest; SVD: Singular value decomposition

computed. Fig. 2 illustrates the process of generating personalized and group recommendations in LBSN. The process integrated user check-in data, CF (user-based and item-based), context-aware module SVD, and context-aware modeling (spatial proximity and temporal behavior) to produce highly accurate and tailored recommendations for both individuals and groups.

3.2. Overview of the Dataset

To show the effectiveness of the proposed method, we utilized the Gowalla dataset (Cho et al., 2011), which contains detailed check-in information of the users of the LBSN. Gowalla is a location-based service where users share their activities with friends by checking in at various POIs in the real world. The dataset includes check-in records from users across the globe, enabling a rich context for studying user mobility, spatial influences, and location recommendations, as shown in Table 1.

The dataset used in this study included 196,591 users, each identified with a unique user ID. Users in the dataset interacted with different locations by checking in at various POIs. User check-ins were timestamped, which allowed for the analysis of temporal behavior in conjunction with spatial movement patterns. There were 6,442,892 check-ins at 1,280,969 different POIs in the dataset. Each POI was associated with geographical coordinates (latitude and longitude) and represented a real-world location such as a restaurant, park, or other venue. The dataset consisted of over 6.4 million check-ins. This social network structure enables the modeling of user behavior based on social influence and peer interactions, which is valuable for group and social-aware recommendation systems.

Table 1. Overview of the dataset

Attribute	Description
Number of users	A total of 196,591 users with unique user IDs. Each user has a record of check-ins at various POIs.
Number of POIs	A total of 1,280,969 POIs with geographical coordinates (latitude and longitude).
Total check-ins	A total of 6,442,892 check-ins where users interacted with different POIs.
Geographical data	Latitude and longitude for each POI, which allow calculation of spatial proximity for the recommendation model.
Temporal information	Timestamps for each check-in that allow analysis of user behavior over time.
Categories of POIs	Food, entertainment, professional, shopping, etc.

Abbreviation: POI: Point of interest.

3.3. Data Preprocessing

Before conducting the analysis, several preprocessing steps were undertaken to ensure the quality and consistency of the data. First, the spatial data, including the latitude and longitude information for POIs, was normalized to standardize distance calculations and enable accurate spatial proximity analysis. Temporal information, specifically the timestamps for each check-in, was converted into standard date-time formats to facilitate the study of temporal patterns, such as user check-ins at different times of the day or week. To maintain data integrity and ensure the focus remained on active users and their mobility patterns, users who exhibited very low levels of activity were excluded from the dataset. The dataset used for this study included 196,591 users and 1,280,969 unique POIs, with a total of 6,442,892 check-ins. Although the dataset did not explicitly categorize POIs, they were grouped into various categories based on their nature and purpose. These categories included food (e.g., restaurants, cafés, and fast-food outlets), travel (e.g., parks and tourist spots), entertainment (e.g., concert halls, theatres, and cinema), professional (e.g., banks and offices), shopping and services (e.g., malls and retail stores), educational (e.g., schools, universities), hotels, residential (e.g., apartments), and sports. These groupings provided a clear understanding of user preferences and behaviors in different locations. Each attribute in the LBSN dataset indicated the interaction frequency between a specific user and a POI. After preprocessing, the user-POI interaction matrix, R, was constructed with Eq. (2), where each entry $R_{u,i}$ represents an interaction between a user (u) and a POI (i) with binary values indicating whether an interaction exists (1) or not (0), while m and n represent the number of users and the number of items (POIs), respectively.

$$R = \begin{bmatrix} R_{1,1} & R_{1,1} \cdots & R_{1,n} \\ R_{2,1} & R_{2,2} \cdots & R_{2,n} \\ \vdots & \vdots & \vdots \\ R_{m,1} & R_{m,2} & R_{m,n} \end{bmatrix} \quad (2)$$

The system was initialized by acquiring user check-in data from LBSNs. This data captured user interactions with various POIs, including restaurants, parks, and cafés. Each check-in record typically contained location coordinates, timestamp, and supplementary user demographic or behavioral data. These historical interactions formed the cornerstone of our recommendation process, revealing patterns in user preferences, frequently visited locations, and peak activity periods. Through systematic analysis of this data, the system uncovered underlying user preferences and their affinities for specific POIs.

3.4. User Influence Modeling

The next stage was user influence modeling, where our recommendation system improved user influence modeling by incorporating contextual factors that enhanced recommendation relevance. While traditional systems primarily analyzed user-item interactions, LBSNs required consideration of external influences. The framework evaluated spatial proximity, acknowledging that users typically preferred venues near their current location. It also accounted for temporal patterns, recognizing that preferences shifted throughout the day, such as favoring coffee shops in morning hours and restaurants in the evening. By integrating these contextual factors, we personalized recommendations based on two key influences: spatial proximity and temporal behavior patterns.

In LBSNs, physical proximity significantly influenced user preferences, with users typically favoring recommendations for nearby POIs. We evaluated the distance between users and POIs as a key factor in our recommendation system, recognizing that users closer to specific locations were more likely to interact with them and provided relevant recommendations. To quantify spatial relationships, we calculated each user's distance from the group's centroid location using latitude and longitude coordinates. This spatial proximity measurement employed the Haversine formula (Wirastuti et al., 2023), as expressed in Eq. (3).

$$d(u,group) = Haversine(lat_u|, lon_u|, lat_{mean}|, lon_{mean}|) \quad (3)$$

where: lat_u and lon_u represent the latitude and longitude of the user u, while lat_{mean} and lon_{mean} centroid the coordinates of the group.

Temporal patterns significantly influenced human behavior, with distinct location preferences emerging during work hours versus leisure time. Our recommendation system analyzed these temporal patterns by tracking when users typically interacted with various POIs. The system assigned higher priority to locations where a user's preferred check-in times aligned with peak activity periods. To quantify this temporal relationship, we evaluated the time differential between individual check-in patterns and group user behavior using Eq. (4).

$$\Delta t(u,group) = |t_u| - tgroup\_mean_{|} \quad (4)$$

We calculated user influence scores by analyzing interactions across location, time, and behavioral patterns. This scoring enabled us to prioritize recommendations that aligned with each user's preferences and behavioral patterns. Our recommendation accuracy relied on three key dimensions: geographic proximity, temporal activity patterns, and individual behavioral characteristics.

3.5. CF

CF techniques integrated user-item interaction data with sophisticated user influence factors. The basic idea of user-based CF centered on identifying users with statistically significant similarities in their spatial interaction patterns, particularly those demonstrating consistent check-in behaviors across comparable venues. The user-based CF recommended POIs that were frequently visited by users with similar traits, but remained unexplored by the target user. On the other hand, the item-based approach suggested POIs that exhibited substantial similarity to locations previously visited by the user, effectively extending the user's existing interaction profile. For example, when a user consistently visited specific types of restaurants, the model identified and recommended similar venues across diverse spatial contexts. This approach enabled the recommendation system to determine behavioral patterns, generating contextually refined and relevant recommendations as formalized in Eq. (5).

$$\hat{r}_{ui} = r_u + \frac{\sum_{v \in N(u)} sim(u,v)\left(r_{vi} - r_v\right)}{\sum_{v \in N(u)} \left|sim(u,v)\right|} \quad (5)$$

where: $\hat{r}_{ui}$ is the predicted rating for the user u on item i, $sim\ (u,v)$ is the similarity between users u and v, r_u and r_v are their average ratings, and $N(u)$ is the set of similar users.

The user-based CF approach leveraged behavioral similarities, predicting future preferences based on the users' historical interaction patterns. The identified user partners were characterized by significant behavioral similarities, particularly in spatio-temporal POI engagement. By analyzing the patterns of user check-in behaviors, the recommendation system identified the relational pattern that captured the interactions between users and venues. It involved identifying users with highly correlated interactions and subsequently utilizing their POI preferences to generate targeted recommendations for the user. This approach effectively transformed the collective user experience into a predictive recommendation mechanism. The user-based CF calculated user similarity by analyzing their interaction patterns with items (POIs), as shown in Eq. (6).

$$\hat{R}_{u.i} = \sum_{v \in similar\_users(u)} Sim(u,v) \cdot R_{v,i} \quad (6)$$

where: $\hat{R}_{u.i}$ represents the predicted score of interactions between user u and item i.

The item-based CF approach varied from traditional user-based methods by focusing on inter-item (venues) similarity relationships. This recommendation strategy, which operated mainly on spatial proximity and contextual similarity between venues, could effectively predict user preferences. By analyzing the characteristics and interaction patterns associated with specific locations, item-based CF could generate recommendations based on the inherent similarities between POIs. Consider a scenario where a user showed a distinct preference for coffee shops. The item-based CF systematically identified and recommended alternative venues that exhibited significant similarities. The similarity of two venues i and j, as well as the correlation between users who had interacted with both items, were measured using cosine, as expressed in Eq. (7). The predicted score for venue i is determined as in Eq. (8).

$$Sim(i,j) = \frac{R_i \mid \cdot R_j}{\| R_i \| . \| R_j \|} \quad (7)$$

$$\hat{R}_{u,i} = \sum_{j \in similar\_items(i)} Sim(i,j) \cdot R_{u,j} \quad (8)$$

The SVD served as a dimensionality reduction technique that effectively uncovered latent patterns and intricate relationships between users and items, particularly in large-scale datasets characterized by sparse user-item interaction matrices. This approach enabled the identification of underlying semantic factors that analyzed the check-in data, revealing features that significantly influenced user preferences. In the context of LBSNs, these latent factors involve attributes such as venue type (e.g., restaurant or park) and contextual environment (e.g., casual or formal). By extracting these hidden patterns, the recommendation system could generate highly contextualized suggestions even in scenarios with limited direct user-item interaction data. The SVD demonstrated outstanding efficacy in enhancing recommendation accuracy by discerning sensitive, non-obvious patterns that remained hidden through conventional analysis. This was achieved by decomposing the user-item interaction matrix R, thereby revealing latent structures. The reconstruction of the user-item matrix, as shown in Eq. (9), facilitated precise predictive recommendations by synthesizing these extracted characteristics.

$$\hat{R} = U \Sigma V^T \quad (9)$$

The top-N recommendations were based on the predicted score with the highest values in $\hat{R}$ calculated as in Eq. (10).

$$\hat{R}^{Hybrid} = \lambda_1 . \hat{R}^{UB} .\ |\ \lambda_2 . \hat{R}^{IB} .\ |\ \lambda_3 \hat{R}^{SVD} \quad (10)$$

where $\hat{R}^{UB}$ is the user-based CF's predicted scores, $\hat{R}^{IB}$ represents the item-based CF's predicted scores, and $\hat{\ }^{SVD}$ from SVD. The combined score is a weighted sum for the hybrid approach, where λ_1, λ_2, and λ_3 represents the weights of each method. This score was then combined with the contextual feature to get the final recommendation score.

3.6. Group Recommendation

In a hybrid recommendation engine, the system employs group recommendation methodology to integrate individual preferences into a cohesive collective recommendation. This process combined individual user preferences to identify a set of POIs that suitably satisfied the collective group's preferences. The group recommendation mechanism leveraged well-known techniques from social choice theory and the collaborative voting method to join and integrate different user preferences. By employing this approach, the model could strategically recommend venues that demonstrated the highest probability of collective appeal based on a comprehensive analysis of individual user profiles, historical patterns, and collective preferences. For each user in the group, the system computed preferences using CF, SVD, and context-aware modeling (spatial and temporal). Then, individual preferences were gathered into a group recommendation using voting techniques. A method for gathering preferences could be represented in Eq. (11).

$$P_{group} = \sum_{i=1}^{n} w_i \; P_i \tag{11}$$

where: P_{group} is the final group recommendation score, P_i is the recommendation score for individual user i based on their preferences, w_i is the weight assigned to each user's preferences, and n is the number of users in the group. The system then recommended items (POIs) that maximize P_{group}, considering each member's preferences and grouping them into a unified group decision.

3.7. User Behavior Analysis

In developing a comprehensive recommendation system, understanding user interaction patterns played a critical role. The system implemented three analytical components: clustering based on user preferences, temporal behavior analysis, and category-wise interaction analysis, each contributing to improved recommendation accuracy and personalization.

3.7.1. User Preferences

We employ K-means clustering due to its scalability and efficiency for partitioning users based on preference features. The number of clusters ($k = 3$) was selected empirically to balance between underfitting and over-segmentation. This step influenced clustering techniques, that is, K-means, to segment users based on their preferences and interaction behaviors. By grouping users with similar location preferences, the recommendation system can generate tailored suggestions that are more aligned with each user's interests. The clustering process often incorporates distance measures such as Euclidean or Cosine similarity to assess the proximity between users in terms of their preferences.

3.7.2. Temporal Behavior Analysis

This component analyzed the influence of time on user behavior, examining when users were most likely to interact with certain categories of locations (e.g., restaurants during lunch hours or entertainment venues in the evening). Temporal patterns helped the system to adjust recommendations based on the time of day or week. In LBSN research, the day was often divided into four distinct time segments: morning (5:00 A.M. – 11:59 A.M.), afternoon (12:00 P.M. – 5:59 P.M.), evening (6:00 P.M. – 8:59 P.M.), and night (9:00 P.M. – 4:59 A.M.), which reflected natural human activity patterns and aligned with previous studies on temporal behavior in location-based services (Choe et al., 2023). The analysis often involved temporal data partitioning, which was then visualized and measured to capture significant behavior patterns, typically using normalized interaction rates over defined periods.

This analysis focused on the categories of locations that users interacted with most frequently, providing insights into which types of venues held the most appeal for different user clusters. By computing metrics such as mean, median, and standard deviation of interactions within each category, the system could discern variations in user engagement across different categories, allowing more significant recommendations. To model these behaviors, equations were integrated to represent similar measures and interaction probabilities. For instance, the relationship between users i and j could be calculated as in Eq. (12).

$$Similarity_{ij|} = \frac{\sum\left(u_i \bullet u_j\right)}{\sqrt{\sum u_i^2} \times \sqrt{\sum u_j^2}} \tag{12}$$

where u_i and u_j are the interaction vectors for users i and j, respectively.

In addition, temporal interaction rates could be computed to normalize engagement across different time intervals. Each of these components contributed to a robust recommendation framework by capturing diverse dimensions of user behavior, thereby enhancing the relevance and personalization of the recommendations.

3.8. Evaluation

The evaluation stage of the research evaluated the system's efficiency and effectiveness through comprehensive performance metrics. These overlapping performance indicators, including precision, recall, F1 score, and accuracy, provided a multidimensional assessment of the recommendation system's ability to align recommended POIs with user preferences. The precision quantified the performance of recommended POIs calculated as the ratio of true positives (TP) to the total number of recommendations (TP + false positives [FP]), addressing the critical research question: "Of all system recommendations, what percentage accurately matches user preferences?" A high precision score indicated the system's capability to generate contextually appropriate suggestions. Recall evaluated the model by determining the ratio of TP to the total number of relevant items (TP + FP), answering: "Of all potentially relevant items, what proportion did the system successfully identify?" The F1 score, which was estimated as the mean of recall and precision, provided the balanced composite metric. This measurement was particularly valuable for assessing system performance in scenarios with irregular precision and recall, in terms of recommendation effectiveness. Accuracy represented the overall system performance by calculating the proportion of correctly identified relevant and irrelevant items. Mathematically derived as the ratio of all correct predictions (TP + TN) to the total number of predictions (TP + TN + FP + FN). This metric offered a comprehensive view of the recommendation system's capabilities.

4. Results and Discussion

This section presents a comprehensive empirical analysis of the hybrid recommendation approach for LBSNs, utilizing the Gowalla dataset. The investigation provides a thorough evaluation of the proposed methodology, systematically examining multiple critical dimensions of recommendation generation. The research explored the interactions between CF techniques, spatial proximity, and temporal behaviors. The study employed key performance metrics, including precision, recall, F1 score, and accuracy, to evaluate the performance of the model and recommendation efficiency.

4.1. User Influence Modeling

To highlight the influence of spatial and temporal features on the recommendation quality, we applied context-aware approaches, as shown in Fig. 3. This analysis optimized the matrices, streamlining their manipulation in subsequent computational phases.

The integration of spatial proximity demonstrated significant improvements in the performance of the recommendation system. Empirical findings uncovered

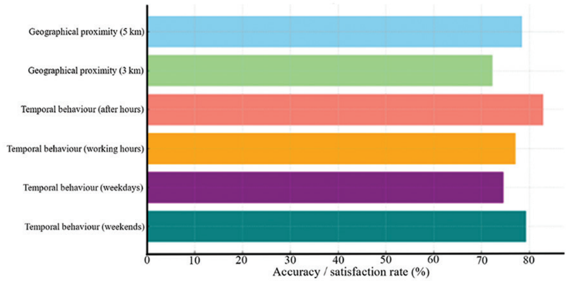

Fig. 3. User influence modeling. This chart shows how spatial and temporal patterns (e.g., proximity and working hours) impact user satisfaction with POI recommendations

that 78.5% of the generated suggestions corresponded to POIs within a 5-km radius of the user's current location, aligning closely with established behavioral patterns in LBSNs. The analysis substantiated that users commonly interact with proximate POIs, with a notable 72.3% interaction rate for locations within a 3-km radius. These results also emphasize the critical significance of spatial proximity in determining recommendation relevance. The temporal features also showed significant implications for recommendation accuracy. The model demonstrated remarkable capability in predicting user preferences across distinct time segments by analyzing check-in patterns. During non-working hours, the recommendation mechanism successfully suggested entertainment and food venues with an accuracy of approximately 82.9%. Similarly, during working hours, it strategically demonstrated work-related location recommendations, achieving a precision of 77.1%. Consistent behavioral patterns were observed across weekday and weekend contexts, confirming the key role of temporal features in enhancing the relevance of recommendations and contextual alignments with users' daily activities.

4.2. Temporal Distribution

The analysis of user activities within different venue categories during various periods of the day can be observed with the help of the temporal distribution of the check-ins. Fig. 4 demonstrates user interactions spread out over time in various categories, including educational, food, shopping and services, hotel, entertainment, travel, sports, professional, and residential venues.

Each cell represents the percentage of interactions within a specific category during the corresponding period, with darker shades indicating higher levels of interaction. Educational venues showed peak activity of 51.61% in the morning, aligning with typical school and university hours, while entertainment venues dominated in the evening and night, with

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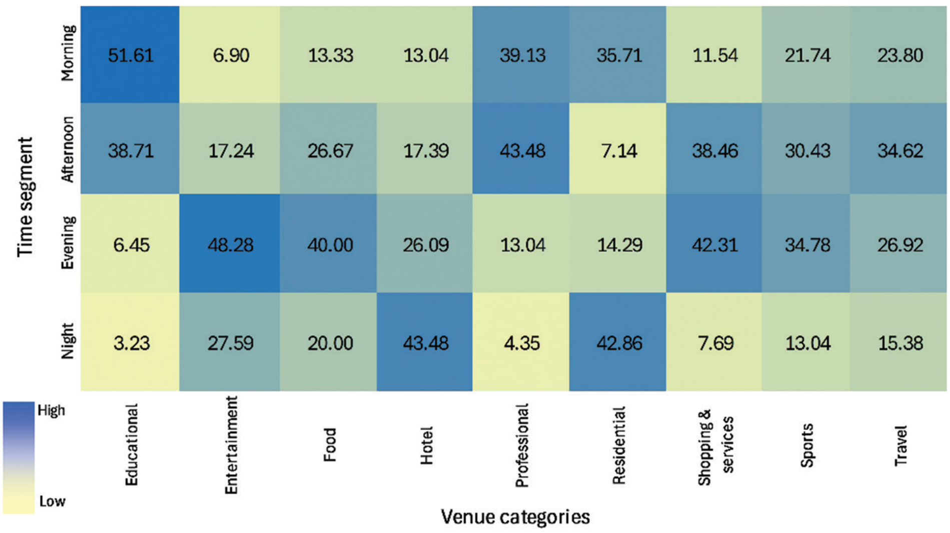

Fig. 4. Temporal distribution of user interaction across categories. Each cell represents the proportion of interactions within a specific venue category during different periods (morning, afternoon, evening, and night), highlighting peak usage patterns

48.28% and 27.59% activity, respectively, reflecting social and leisure behavior. Food establishments were most active during the evening, with 40% activity, and maintained significant activity of 26.67% and 20% in the afternoon and night, respectively, which corresponded to mealtime trends. Residential areas exhibit peak interactions of 42.86% and 35.71% at night and in the morning, respectively, as users returned home or began their day. Professional locations, as well as shopping and services, showed the highest engagement during traditional working and leisure hours, with professional venues showing high activity of 43.48% and 39.13% in the afternoon and morning, respectively. On the other hand, shopping and services venues reported high activity of 42.31% and 38.46% in the evening and afternoon, respectively. Hotels and travel-related venues exhibit steady activity, with hotels demonstrating the highest activity of 43.48% at night, while travel reporting consistent activity across all periods. These distributions underscore the importance of time-aware modeling in understanding user behaviors and optimizing LBSN-based recommendation systems.

4.3. Category-Wise Interaction Analysis

We also performed interaction analysis based on different venue categories, which is a vital part of understanding and utilizing user activities and preferences. Fig. 5 presents a comprehensive distribution of user interactions across different venue types, including food, shopping and services, travel, hotel, educational, entertainment, professional, sports, and residential domains. It represented the user

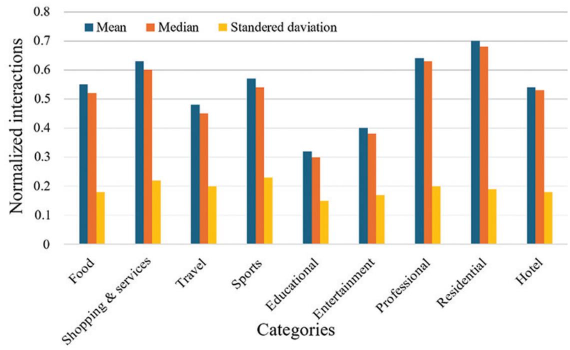

Fig. 5. Category-wise interaction analysis. The analysis displays normalized interaction values (mean, median, and standard deviation) across venue types, reflecting user engagement preferences

interaction patterns across these diverse categorical contexts.

The professional and residential venue categories demonstrate the highest average and median interaction values, indicating the users' tendency to check in at these venues. Shopping and services, as well as food categories, exhibit substantial interaction levels, suggesting that these places are prominent venues for user engagement. This analysis reveals a remarkably consistent interaction pattern across most categories, as evidenced by the minimal standard deviation. However, the sports, as well as shopping and services categories, exhibit marginally higher variability, indicating potentially more heterogeneous user behaviors within these categories. Conversely, the educational and entertainment venue categories show noticeably lower mean and median interaction values, suggesting comparatively reduced user engagement in these specific venue types.

4.4. Temporal Behavior Distribution

Temporal analysis is an important factor in human behavior studies, which can be achieved by analyzing the users' activities during different periods of the day. We divided the time into four segments, including morning, afternoon, evening, and night. Fig. 6 shows the distribution of users' interactions over time across various categories. For educational venues, most interactions (51.61%) occurred in the morning, reflecting typical school and university hours, with a decline to 38.71% in the afternoon and minimal activity during the evening and night. In contrast, entertainment venues show high activity of 48.28% and 27.59% in the evening and night, respectively, corresponding to leisure and nightlife activities. Food establishments reported the highest engagement in the evening of 40%, followed by 26.67% and 20% in the afternoon and night, respectively, aligning with dining patterns. Hotels demonstrate the highest activity of 43.48% at night, indicating late check-ins or overnight stays. Professional locations show the most activity of 39.13% and 43.48% in the morning and afternoon, respectively, which is consistent with standard working hours. Residential areas are highly engaged at night and morning, with activity of 42.86% and 35.71%, respectively, reflecting the daily routines of starting and ending the day at home. Shopping and services venues are most active during the afternoon and evening, with interactions of 38.46% and 42.31%, respectively, reflecting shopping and errand behaviors. Sports activities are distributed across the day, with the highest activities of 34.78% and 30.43% in the evening and afternoon, respectively. Travel-related venues show moderate activity throughout the day, with peaks of 34.62% the afternoon and 23.80% in the morning. These results emphasize the temporal nature of user behavior in LBSNs, providing insights into category-specific trends that can be leveraged for time-aware recommendation systems.

4.5. Clustering Based on Preferences

The users' clustering approach enables the systematic identification of behavioral similarity within the user populations. By leveraging efficient clustering techniques such as *K*-means, researchers can effectively stratify users based on their mutual interaction preferences and spatial patterns. This approach reveals distinct user trends, ranging from individuals mostly interested in food venues to those demonstrating explicit engagement with entertainment or professional venues. The clustering methodology provides the mechanism for generating personalized recommendation strategies that align precisely with the characteristics of each identified user cluster.

Fig. 7 presents a comprehensive scatter plot illustrating the empirical outcomes of *K*-means clustering applied to analyze users' motivational factors for interaction across diverse venue categories, including food, travel, and other domains. Each data point represents an individual user, with the visualization classifying the user population into three distinct clusters, represented by different colors. The coordinate axes represent two critical dimensional components: food interaction, as well as shopping and services interaction, which serve as primary determinants in the cluster formation process in this figure. This visualization provides a graphical representation of user behavioral clusters, facilitating a deeper understanding of interaction patterns across various venue categories.

The clustering method presents user preferences through comprehensive behavioral and categorical interactions. User clusters are calculated based on distinctive venue types, such as clusters characterized by pronounced engagement with food, as well as

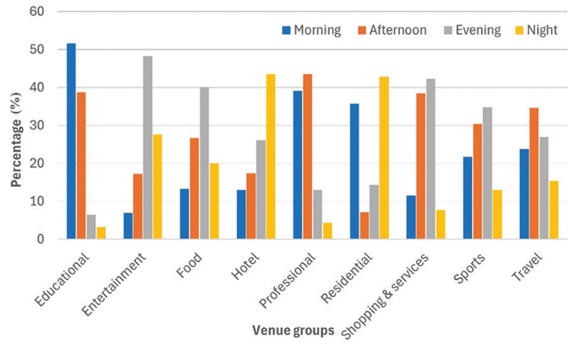

Fig. 6. Temporal behavior distribution across categories. This figure displays percentage interactions across categories segmented by time, revealing trends in check-in behavior

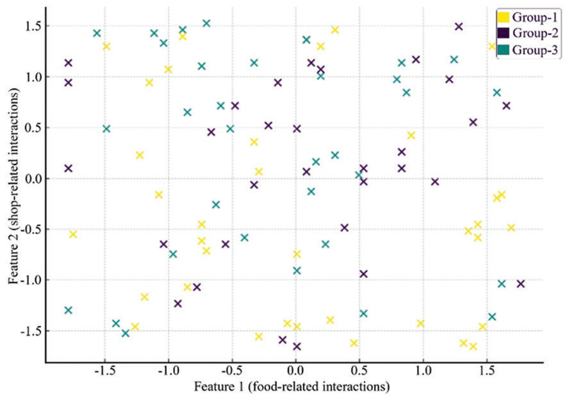

Fig. 7. Clustering based on user preference

shopping and services categories. Similarly, we can compute other clusters demonstrating significant interaction patterns in travel and hotel venues. This clustering approach enables the recommendation system to generate highly contextualized recommendations tailored to the distinct preference profiles of each identified user group. The cluster-based recommendation strategy facilitates a more accurate and relevant user experience by aligning recommendation content with the observed behavioral and categorical preferences of each user segment.

4.6. Hybrid Recommendation System

The proposed model is implemented to determine its performance based on check-in data. In this section, we presented the results of various methods in comparison with our proposed model and assessed their effect and efficiency. In Fig. 8, user-based filtering identifies users with check-in patterns, achieving 68.5% precision and 70.2% recall. While effective, this method encountered limitations with users having sparse interaction data. It was most successful when analyzing users with highly similar preferences, with 65.9% of recommendations being relevant based on users with comparable experiences. Item-based CF slightly outperformed user-based, reaching a precision of 72.4% and a recall of up to 74.8%. It excelled in scenarios with consistent user behavior patterns, such as frequent visits to similar venue types. Recommending POIs based on item similarity particularly benefited users with clear, repetitive preferences. Applying SVD revealed interesting hidden relationships between users and POIs, and it is the most effective in sparse data environments, achieving 75.5% precision and 71.7% recall. The high efficiency demonstrated SVD's capability to uncover latent interaction patterns, generating improved recommendations for users.

The proposed hybrid model, integrating user-based CF, item-based CF, and SVD techniques with context-aware spatial and temporal features, demonstrated superior performance compared to individual recommendation methods. Achieving precision up to 80.6% and a recall up to 77.3%, with an F1 score achieving up to 78.5%, the hybrid approach consistently delivered the most accurate recommendations, as shown in Fig. 8.

Table 2 provides a detailed assessment of the recommendation system's accuracy across top-5, top-10, and top-20 recommendations, demonstrating the model's effectiveness in suggesting the most relevant items for users.

The proposed model demonstrates remarkable accuracy across different recommendation depths. For the top-5 recommendations, the system achieves 82.3% accuracy, indicating that over four-fifths of

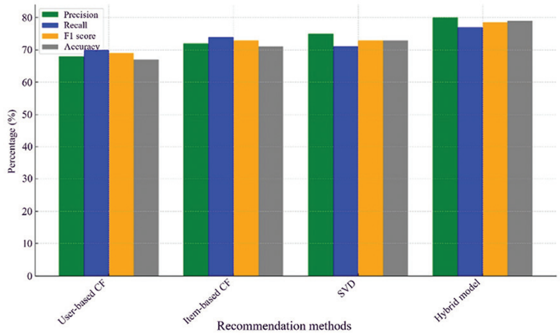

Fig. 8. Performance comparison of recommendation methods
Abbreviations: CF: Collaborative filtering; SVD: Singular value decomposition

Table 2. Top-N recommendation performance

Top-N	Accuracy (%)
Top-5	82.3
Top-10	90.6
Top-20	95.2

the initial suggestions are highly relevant to the user. The accuracy progressively improves, with top-10 recommendations reaching 90.6% and top-20 recommendations achieving an impressive 95.2% precision. This improvement reveals that as the number of recommended options increases, the likelihood of suggesting relevant POIs becomes significantly higher. The expanding recommendation set provides users with greater flexibility and choice, enhancing the overall recommendation experience. By combining different methodological strategies and incorporating contextual factors such as venue and temporal data, the system generates tailored and precise suggestions. Considering features such as users' venue and temporal aspect that enhance the appropriateness of the suggestions, resulting in improved user satisfaction. The results presented in Table 3 present the efficiency of our proposed hybrid model in comparison with baseline methods.

The baseline models demonstrate moderate performance, with accuracy ranging from 65% to 73.4% and respectable precision, recall, and F1 score metrics. The hybrid model significantly outperforms these baseline approaches, with precision up to 80.6%, recall achieving 77.3%, and accuracy of 79.1%. The performance improvement stems from the strategic integration of CF as a hybrid model with context-aware features and techniques, effectively mitigating individual method limitations. By leveraging user-item similarities and uncovering hidden relationships through SVD, the hybrid model generates more accurate recommendations. The approach proves particularly powerful in data-sparse environments,

Table 3. Comparison of the hybrid model with baseline methods

Method	Reference	Precision	Recall	F1 score	Accuracy
LBRS	Tao et al., 2021	68.60	60.80	64.80	67.50
GR-DELM with Gowalla	Zhao et al., 2018	77.84	81.23	79.50	-
TrustWalker	Ravi & Vairavasundaram, 2016	73.98	-	73.41	-
SVD	Rodpysh et al., 2023	75.50	71.70	73.60	73.40
CF	Liu et al., 2014	65.00	60.00	62.00	65.00
PARS	Ye et al., 2011	-	69.00	70.50	72.00
Hybrid model	(The current study)	80.60	77.30	78.50	79.10

Abbreviation: CF: Collaborative filtering; GR-DELM: Geographical-aware recurrent deep extreme learning machine; LBRS: Location-based recommendation system; PARS: Personalized adaptive recommendation system; SVD: Singular value decomposition.

enabling more accurate and relevant suggestions tailored to LBSN contexts. Ultimately, the proposed hybrid methodology emerges as the most reliable and sophisticated recommendation solution for location-based services.

5. Conclusion

In this research, we proposed a novel hybrid approach for group recommendations in LBSNs, addressing the unique contextual needs of these platforms. By incorporating spatial proximity and time-based patterns, our model effectively combines user-based CF, item-based CF, and SVD to enhance both accuracy and personalization. The integration of spatial and temporal factors significantly improves precision, as users frequently engage with nearby locations that align with their daily routines. Our evaluation demonstrated that this hybrid approach outperforms conventional methods, particularly in situations where interaction data are sparse. This model was able to achieve high accuracy and diversity in recommendations. However, limitations persist, especially with cold-start users and scalability as LBSNs expand in size. The system's reliance on sufficient historical interaction data poses a challenge for new or infrequent users, despite the mitigating effect of the hybrid method. Moreover, the hybrid model's computational complexity can limit responsiveness in large-scale, real-time applications, as the combination of user- and item-based filtering with SVD and contextual information may slow down recommendations in extensive datasets. In addition, while our model successfully accounts for user-item interactions, geographic proximity, and temporal behavior, it currently lacks real-time contextual adaptability factors, such as sudden location shifts or external conditions that are not fully captured, which may limit relevance in highly dynamic environments.

Future evaluations will consider deployment in real-time environments and validation on diverse LBSN datasets to assess scalability and generalization. It could address these limitations by enhancing cold-start handling with advanced embedding methods or social network analysis, which would incorporate user metadata or social connections to generate initial recommendations for new users or items. Improvements for real-time recommendations could involve integrating dynamic contextual data, such as weather or event information, to adapt recommendations to users' immediate surroundings and conditions. Furthermore, leveraging deep network-based models and attention mechanisms could improve the model's understanding of complex relationships between users, items, and context, thereby boosting both scalability and accuracy. Overall, this hybrid approach demonstrates strong potential for effectively meeting the dynamic and personalized demands of LBSNs.

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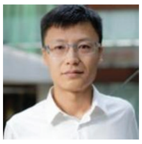

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