Evaluating Diversification in Group Recommendation of Points of Interest

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Abstract: With the massive availability and use of the Internet, the search for Points of Interest (POI) is becoming an arduous task. POI Recommendation Systems have, therefore, emerged to help users search for and discover relevant POIs based on their preferences and behaviors. These systems combine different information sources and present numerous research challenges and questions. POI recommender systems traditionally focused on providing recommendations to individual users based on their preferences and behaviors. However, there is an increasing need to recommend POIs to groups of users rather than just individuals. People often visit POIs together in groups rather than alone. Thus, some studies indicate that the further users travel, the less relevant the POIs are to them. In addition, the recommendations belong to the same category, without diversity. This work proposes a POI Recommendation System for a group using a diversity algorithm based on members' preferences and their locations. The evaluation of the proposal involved both online and offline experiments. Accuracy metrics were used in the evaluation, and it was observed that the level at which the results were analyzed was relevant. For the top 3, recommendations without diversity performed better, but diversification positively impacted the results at the top 5 and 10 levels.

1 INTRODUCTION

Recommendation systems are designed to help users overcome the difficulties generated by the excessive volume of digital information. They automatically suggest items of interest to users while respecting their individual or group preferences. In recent years, with the development of the mobile Internet, people have been using apps to find Points of Interest (POIs), such as restaurants, shopping malls, and tourist attractions. This trend has led to a significant increase in the demand for POI data and the development of various applications and services that leverage this data to provide users with location-based information and services. In this context, a Point of Interest Recommender System is suitable for suggesting the most appropriate candidate destinations to users, which can help them save time and improve their experiences (Yan et al., 2018).

Recommendation systems typically use user profiles, behavioral histories, and item attributes to calculate the relevance of items to users. However, POI recommendation systems also incorporate geographical location information to understand user preferences better and provide more accurate recommendations. This is because the distance between the points of interest and the user plays a significant role in determining the travel time and user preferences. Most users prefer visiting regions close to activities of interest, such as food, shopping, or tourism, to minimize distance and increase the likelihood of visiting multiple points of interest. (Liu et al., 2024) propose to learn similar users' POI transfer preferences with the Session-based Graph Neural Networks, (Liu et al., 2015) propose a framework for recommending potential customers to suppliers on location-based social networks. (Lee et al., 2006) develops a recommendation system integrating location, personal, and environmental context. However, these approaches only consider the geographical distance provided by location services such as global positioning system (GPS) (Ravi and Vairavasundaram, 2016).

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The problem of POI recommendation becomes more complex when it is not just one user but a group. Group Recommendation Systems are generally used when the decision-making must consider all members' preferences. Examples include choosing a family travel destination or watching a movie with friends. According to (Ravi et al., 2019), the main difficulty of SRGs is associated with the diversity and dynamics of the user group (Ravi et al., 2019), making group preference modeling a challenging task (Quijano-Sanchez et al., 2013). Members' particularity and individuality must be considered when choosing POIs (Masthoff, 2015; Nguyen and Ricci, 2017). Based on the assumption that individuals in a group have varied preferences, it is natural to include mechanisms that promote diversity in the items recommended for the SRG.

These systems typically rely on user preferences and behavioral histories to suggest items. Still, they often neglect the geographical context and distance between the user and the recommended points of interest (POIs). This can lead to suboptimal recommendations that do not consider the practicality and feasibility of visiting the suggested locations. In the context of group decision-making, this issue is particularly relevant. When multiple users are involved, the distance between the POIs and the group members becomes crucial in reaching a consensus on what to do or where to go. For instance, if a group of friends is planning a trip, they may prioritize locations closer to each other to minimize travel time and maximize the overall experience. For example, more distant places make users lose interest in visiting, as do nearby places with low ratings. Thus, aggregating each user's preferences to create a group profile while maintaining a constant balance between what each group member prefers is a task for point-of-interest recommendation systems for groups.

Motivated by the need to diversify recommendations for user groups, this paper aims to develop and evaluate a recommendation model for groups, considering members' preferences on points of interest and the diversity component. The article is organized as follows. The section 2 presents a theoretical basis for the research object. The section 3 presents the state of the art. Section 4 presents the proposal in detail. The section 5 shows the experimental evaluation and discusses the results. The section 6 concludes the article and presents future work.

2 RECOMMENDATION SYSTEMS FOR GROUPS AND DIVERSITY

Group Recommendation Systems aim to find recommendations for the users of a given group. A group can be formed in various ways. In the literature, the definitions presented that are widely discussed and accepted are (Carvalho and Macedo, 2014; Boratto and Carta, 2011): i) **Established group:** a group of individuals who have chosen to come together because of some common interest. ii) **Occasional group:** a group of people who occasionally carry out some activity. For the members of this group, there is some common interest at that moment, and iii) **Random group:** several people who are in the same place at a given time and may not know each other or share any common interest.

2.1 Classification of SRGs

Group Recommender Systems (GRS) can be classified based on how they generate recommendations for a group of users, considering the users' preferences and the recommended items. Some of these perspectives are listed below:

- **Users' Preferences:** The opinions of the group's users may be known in advance, as in the case of Polylens (O'connor et al., 2001), but the system may also recognize them as they use it. In general, it is more common for users' preferences to be already known by the Group Recommendation System.
- **User Interaction with the Recommendation:** In some cases, users can comment on what has been recommended to them, such as *The Travel Decision Forum*(Jameson, 2004).
- **Quantity of Recommended Items:** It is possible that the system only needs to indicate one item that satisfies the group.
- **Aggregation of Recommendations or Profiles (de Campos et al., 2009):** There are two ways: i) aggregate recommendations for individual profiles or ii) aggregate individual profiles as a single one and then perform the recommendation for that profile.

2.2 Aggregation Strategies

In the literature, several aggregation techniques are presented (Sen, 1986).

- **Average:** is a technique in which an arithmetic average is made of the values assigned by each user to an item. The Average represents the value of the item's importance to the group.
- **Least Misery:** The lowest rating of the group's users for an item is the group's interest in the item.
- **Most Pleasure:** The group's rating for a given item is the highest rating among the users for this item.
- **Multiplicative:** The rating of an item for the group is obtained as the result of multiplying the users' ratings.
- **Average without Misery:** this strategy is a combination of the *Average* and *Least Misery* strategies. First, a filter is made on the list of possible items to be recommended, where items that score less than or equal to a defined cut-off point are removed from the list. In this way, we prevent items similar to those poorly rated by one of the group members from being recommended. Next, the *Average* technique is applied to the new list of items, and based on this result, the items will be recommended to the group in question.

2.3 Diversity in Recommender Systems

In Recommender Systems, diversity can be defined as a factor in a list of items $p_1, p_2, p_3, ..., p_n$ indicating how different pairs of items are from each other (Bradley and Smyth, 2001). This diversity factor can be calculated based on the distance between items, $dist(p_1, p_2)$, using similarity, as shown in Equation 1.

$$dist(p,k) = 1 - sim(p,k) \tag{1}$$

In addition to the value itself of the distance between items, diversity techniques can vary according to the approach used, as seen in (Kaminskas and Bridge, 2016) and (Ziegler et al., 2005): i) **Random selection:** on a list of candidate items, C, this approach randomly chooses items from the final recommendation list R and **Goal selection:** on a list of candidate items, C, this approach selects the item from C that maximizes the total diversity factor in R, and thus inserts it into R.

3 RELATED WORK

Point of interest (POI) recommendation is widely studied in the literature, especially in location-based social networks (LBSNs). The popularity of LBSNs has driven improvements in POI recommendation systems. Spatial information is fundamental in most models since the probability of a user visiting a location is related to the distance they need to travel, as suggested by Tobler's First Law of Geography (Tobler, 1970). In (Zheng et al., 2010; Kurashima et al., 2013), the authors analyze GPS records, encoded as a time series of geographic coordinates, to identify movement patterns. Our proposal does not use route learning but explicit preference elicitation. The MoveAndShot application, which recommends the best locations for photos, is described in (Silva and Lacerda, 2017). It suggests POIs based on geographical location but on individuals, while our work focuses on groups.

In (Hu and Ester, 2013), the authors explore a spatial topic modeling approach to predict future points of interest based on the textual content of user posts. Although they do not address group recommendations, similar to our proposal, they consider textual descriptions of POIs in the similarity calculation. In (Liu et al., 2013), various aspects of location profiles are analyzed, resulting in a joint model for location recommendation. Like our model, textual information about the POI is used for group recommendations. (Lian et al., 2015) propose a collaborative filtering system based on implicit *feedback* to incorporate semantic content and avoid negative samples. While our work does not analyze negative *feedback*, it can draw inspiration from this study to enrich the descriptions of recommended POIs. In (Ngamsa-Ard et al., 2020), a *framework* is developed to recommend POIs for individuals and groups in location-based social networks. Here, groups are defined by social connections, unlike our proposal, which does not use social networks to form groups. In (Silva et al., 2023), diversification mechanisms on the Pinterest platform are explored to improve the representation of skin tones in fashion and beauty content, positively impacting user satisfaction.

In the context of group recommendation, (Kulkarni and Pervin,) propose a novel Knowledge-based Context-Aware Group Recommender System that utilizes a knowledge graph to learn domain-aware user and POI embedding. These embeddings are infused with visit context in the second stage via a feed-forward transformer. The recommender system learns the group embedding as a weighted aggregate of context-infused embedding of group members. (Chizari. et al., 2023) analyze RS fairness, measuring unfairness toward protected groups, including gender and age. The authors try to quantify fairness disparities within these groups and evaluate recommendation quality for item lists using a Normalized Discounted Cumulative Gain (NDCG) metric. The authors argue that most bias assessment metrics in the literature are only valid for the rating prediction approach, but RS usually provides recommendations in the form of item lists. (Bahari Sojahrood and Taleai, 2021) developed a POI Recommendation System for groups that take into account the difference in users' personalities and their preferences when they are alone or in a group, using historical data from *check-ins* on LBSNs and in terms of category, distance and time. The difference with our work is that the diversity aspect is not considered. (Gottapu and Sriram Monangi, 2017) have developed a subscription-based POI Recommendation System using location-based social networks. The proposal aims to provide recommendations for groups of people of different sizes and with various relationships. Similarly, no aspect of diversity is investigated in that work either, as is done by our proposal. Similarly to our proposal, (Bahari Sojahrood and Taleai,) argue that the geographical proximity of POIs to users' location has a notable influence on the group's decisions to visit the POI and their *check-in* behavior. The application of diversity in the literature is seen in (Oliveira and Durao, 2021), in which the authors developed a group recommendation model using diversification techniques that explore different aggregation techniques on the group preference matrix. In the same way as our research, the authors carry out experiments that evaluate the accuracy and diversity targets for group recommendations. The difference is that they don't recommend POIs but movies. In (Nguyen et al., 2018), the authors address the diversity problem in group recommendation by improving the chance of returning at least one piece of information covering group satisfaction. Unlike our work, the authors combine the preference of each group member with a function of disinterest in the items as a diversity factor. (Liu et al., 2024) bring forward a novel POI recommendation model for random groups based on Cooperative Graph Neural Networks (CGNN-PRRG). The authors propose a new fitted presentation learning method for generating the fitted representations of random groups and an edge-learning enhanced Bipartite Graph Neural Network (EBGNN) to learn similar users' POI comprehensive interaction preferences. Unlike their work, we are not creating graphs to model group preferences. (Si et al., 2017) propose an adaptive POI recommendation method (called CTF-ARA) combining *check-in* and temporal features with user-based collaborative filtering. The authors recommend POIs based on the *check-ins* of active users. Similar to our approach, they use cosine similarity to recommend POIs to users.

4 THE PROPOSAL

The main objective of this work is to recommend points of interest to groups of users so that they form a diversified recommendation list. Figure 1 illustrates a scenario that motivates the proposal. Consider 3 friends who want to meet at a POI. One lives in the *Graça* neighborhood, the other in *Rio Vermelho*, and the third in the *Federação* neighborhood in Salvador-Ba, Brazil. Although they all like *Amaralina Beach* very much, the proposal would recommend meeting at *Parque Zoobotânico* (park) or *Praia de Ondina* (beach) because although they are not the group's preferred location, they would be the most suitable considering the distance from each to the destination. Thus, throughout this section, the proposal is presented in detail.

Figure 1: Motivating scenario that illustrates the proposal.

4.1 Notations

The formal notations are presented in Table 1.

Table 1: Notations used in the description of the proposed system.

Symbol	Description
P	Set of points of interest
p	A point of interest
G	A group
U	Set of users
u	A user
d	Text description of p
loc	Location of u or p
R_u	Set of ratings r of user u
$r_{u,p}$	A score r assigned by u to p
MA	Matrix of all ratings $r_{u,p}$
MD	Matrix of distances $d_{u,p}$
MG	Matrix of ratings $r_{u,p}$ of a group G
MGD	Matrix MG weighted by distance
MGA	Matrix of the aggregate group
RP	Recommendations of Points of Interest
RPD	Diversified Points of Interest Recommendations

A group G comprises n users $u \in U$. Each point of interest $p \in P$ has a unique geographic location given by the latitude and longitude $loc = (latitude, longitude)$ and a description d, the POI being represented as $p = (d, loc)$. Each user $u \in U$ also has a geographical location and is represented as $u = (u_i, loc)$. The set of ratings for user u is given as $R_u = (r_{u,p1}, r_{u,p2}, ..., r_{u,pm})$, where $r_{u,p}$ is a score given by user u to a POI p, which are in the range $[1,5]$.

4.1.1 Problem Formalization

For the problem addressed in this study, the database is conceived as a $MA = UxP$ matrix containing user ratings of points of interest. The MA matrix is generally sparse because users do not naturally rate the points of interest they visit. The matrix $MG \subseteq MA$ is a subset of the general matrix of evaluations, containing only the points of interest evaluated at least once by users of a group $G = \{u_1, u_2, \cdots, u_n\}$. We aim to recommend a set of points of interest for this group, i.e., $RP \xrightarrow{p \in PC} G$.

4.2 Recommendation

Algorithm 1 details the steps for generating recommendations for POIs with diversity.

Algorithm 1: RECPOI proceduere.

1: **procedure** RECPOIS(MA, G)
2: $\quad MG \leftarrow KNN(G, MA)$
3: $\quad MD \leftarrow distance(loc_u \in MG, loc_p \in MG)$
4: $\quad MGD \leftarrow ponder(MG, MD)$
5: $\quad MGA \leftarrow grouping(MGD)$
6: $\quad RP \leftarrow relevance(MGA, PC)$
7: $\quad RPD \leftarrow diversity(RP)$
8: $\quad$ **return** RPD
9: **end procedure**

4.2.1 Preparing the Group Matrix

As previously mentioned, the MA rating matrix is naturally sparse, and to obtain the preferences of the G group using aggregation techniques, the MG group matrix must have no unrated points of interest. For this reason, in Line 2, we applied the *K Nearest Neighbor* (KNN) algorithm responsible for predicting a user's evaluation of a point of interest. KNN calculates the "distance" between the POI to be inferred and the other POIs and returns the K nearest neighbor POIs as the most similar recommendations. In our empirical tests, K=5 obtained the best results using cosine similarity. Once we have the K most similar POIs, we apply a weighted average considering the similarity value and the evaluations $r_{u,p} \in MG$ to arrive at the predicted value. At this point, we understand that the MG matrix is dense, and there are no points of interest without an evaluation from any user in the group.

4.2.2 Construction of the Distance Matrix and Preference Weighting

In-Line 4, the MG group's preference matrix is weighted by the distance from the user's location to the point of interest. The premise is that points of interest, although very attractive to a group, can have their concept reduced as the distance increases. We then built a distance matrix MD, represented in Line 3, using the *Google Maps* function called *matrixDistance*. Finally, we generate a final MGD matrix where each position is populated with the weighting value according to:

$$r_(u, p, r_{u,p}) \in MGD = \frac{r_u, p}{matrixDistance(u_loc, p_loc)} \tag{2}$$

4.2.3 Application of Aggregation Techniques

With the MGD matrix, we have defined the individual preferences weighted by distance; the next step is to generate the group preference. To do this, we need to use Aggregation Techniques (see Section 2.2) on the MGD matrix to obtain a representative value $r_{G,p}$ of group preference on each of the points of interest in the MGD preference matrix. As seen in Line 5, the result of the grouping is an aggregated group matrix MGA.

4.2.4 Recommendation List

The line 6 shows the recommendations generated by calculating the relevance of the PC candidate points of interest for the MGA groups. Relevance is calculated as:

$$relevance(G, p) = \frac{1}{n}\left(sim(G, p) + \frac{r_{G,p}}{max(r \in MGA_G)}\right) \tag{3}$$

so that MGA_G corresponds to the aggregate group matrix of group G and the similarity function *yes*. In this context, the cosine similarity was used:

$$sim(G, p) = \frac{\sum_{i=1}^{n} w_i \cdot sim_i(G_i, p_i)}{\sum_{i=1}^{n} w_i} \tag{4}$$

The cosine calculation considers the description of the points of interest in G and the description of the candidate point p. The similarity calculation is applied to all candidate points $p \in PC$. At the end, an ordered ranking of points of interest is generated, thus constituting the set PR.

4.2.5 Diversity

Although Equation 3 produces a list of points of interest *PR* closest to the group's profile, this list can present the problem of overspecialization, i.e., recommendation of POIs in the same category. Preliminary analyses observed that the *PR* list mostly comprised POIs in a single category, such as bars or churches. Because of this, we applied a diversity function to the *PR* list to offer the user alternative POI categories. To do this, we applied the algorithm proposed by (Bradley and Smyth, 2001) to the *PR* list:

$$diversity(PR) = \frac{\sum_{x \in PR} \sum_{y \in R/\{x\}} dist(pr_i, pr_j)}{|PR| \cdot (|PR| - 1)} \quad (5)$$

The result of the diversity function generates the *PRD* diversified points of interest recommendation list. The line 7 of the base procedure shows the receipt of the *RP* list by the diversity function and the return of the *RPD* diversified list.

5 EXPERIMENTAL EVALUATION

The experiment aimed to assess the accuracy of the proposed recommendation model. In particular, it sought to answer the questions:

1. Does diversity applied to group recommendation techniques increase accuracy over techniques without diversity?
2. What difference does the proposed recommendation make to groups of different sizes?

To evaluate the model, two approaches were adopted:

1. An **online** experiment to obtain an evaluation of the recommendations generated for participants through their feedback, as well as to collect this information to create a data set;
2. An **offline** experiment to carry out a counter-proposal of the literature and proposal variations.

Accuracy and ranking metrics were used to evaluate the recommendations generated.

5.1 Experiment 1 (Online)

5.1.1 Methodology

The experiment was carried out in *on-line* and hybrid format. The three stages of the experiment are presented below.

In the first stage of the evaluation, we invited the participants. Although we didn't conduct a more in-depth analysis of the participants' profiles, there was no resistance or difficulty in participating in the experiment. Participants provided their *e-mail* and geographical location (latitude and longitude). After registering, participants rated points of interest with scores from 1 to 5 registered in the experiment database (Section 5.1.2).

In the second stage, groups of 3 and 5 users were formed to evaluate the recommendations in asynchronous *on-line* sessions under the authors' supervision. No criteria were applied to create the groups. The users themselves could form the groups naturally based on their affinities. As the participants were classmates, no impediment was reported that would make the experiment unfeasible.

In the third stage, the groups were invited to evaluate the recommendations in synchronous online sessions. Group members were instructed to discuss the recommendations generated until they reached a consensus on a final score. They were asked to consider their interest in the location and the distance from the point of interest to their geographical position, as reported in the first stage. In total, 19 groups were formed, 10 with 3 participants and 9 with 5 members. For each group, two recommendation lists with 10 items each were generated, giving 38 recommendation lists.

In all, 66 participants aged between 18 and 40 were asked to rate at least 20 points of interest per user in the first stage of the experiment. Although the experiment did not go through an ethics committee evaluation, all participants were informed that their *e-mails* and their preferences about the POIs would be recorded in our database for the sole purpose of authentication and generating recommendations, and that once saved, the data would be automatically anonymized. Everyone agreed to take part in the experiment without exception.

5.1.2 Dataset

To ensure the validity of the *on-line* experiment, creating a dataset containing points of interest in the same city as the participants was necessary. This was the way to obtain a faithful assessment of the recommendations generated. Although several studies in the literature use the Gowalla *dataset* [1], this dataset does not have points of interest located in the city of Salvador-Ba, where the participants in the experiment live. Given this restriction, a new dataset was created and is available at POIS-SALVADOR [2]. The POIs were collected from Google Maps. Table 2

[1] https://snap.stanford.edu/data/loc-gowalla.html
[2] https://github.com/jadna/poi-salvador.git

shows an example of the POIs for the city in question.

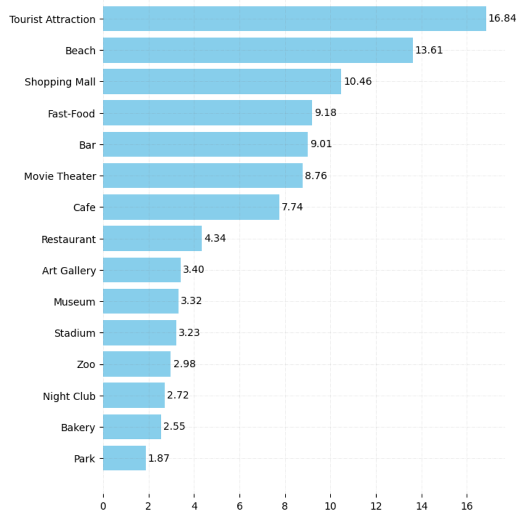

Figure 2: Distribution of points of interest in category.

This dataset was used in the first stage of the experiment to collect user preferences. Out of 422 points of interest in the database, only 51 were used in the *on-line* experiment. A minimum criterion of at least 2 points of interest in the same category was set. Categories such as bars, restaurants, squares, and shopping centers describe points of interest. Figure 2 shows the distribution of points of interest by category.

5.1.3 Comparison Algorithms and Metrics

As the focus of the evaluation was to assess the impact of diversity on the POI recommendation list, each group evaluated 2 lists of 10 items, one non-diverse, defined here as **Standard (STD)**, and the other diverse, called **Diversified (DIV)**. We used only one aggregation technique for both lists: *Most Pleasure (MP)*. The choice of this technique is based on a preliminary analysis in pilot tests between 4 aggregation techniques: *Most Pleasure (MP)*, *Least Misery (LM)*, *Average (AV)*, *Average Without Misery (AWM)*. The MAP and Precision@N metrics were used to evaluate the results. To obtain a single metric that contributes to the accuracy of the recommendation method across the entire user group, the MAP (Parra and Sahebi, 2013) is used.

The MAP value is obtained by calculating the average over the average accuracy of the recommendation list for each user in the group as in Equation 6. In the Equation, $AveP(u)$ is the average precision for user $u \in U$, i.e., the average precision values obtained for the top-K recommendations after each relevant suggestion is retrieved (Manning et al., 2008). Equation 7 and 8 correspond to the calculation of the average precision, which is a sum of the precision at each position in the list $p@i$ where r is the number of relevant points of interest up to position i. The metrics presented were applied to the recommendation lists. Each list has 10 items, occupying one position in the recommendation list.

$$MAP = \frac{1}{U} \sum AveP(u) \tag{6}$$

$$AveP(u) = \frac{1}{N} \sum p@i \tag{7}$$

$$p@i = \frac{r}{i} \tag{8}$$

5.1.4 Experiment Results *On-line*

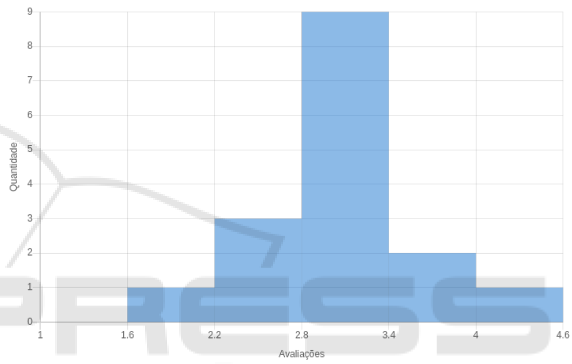

Figure 3: Distribution of the group evaluation averages.

Figure 3 shows the distribution of the averages of the groups' evaluations of the POIs. This analysis was necessary to determine the relevance of the recommendations. As can be seen from the distribution, the ratings were primarily concentrated in the 2.8 to 3.4 range. We, therefore, adopted 3.0 as the relevance threshold for calculating accuracy. Thus, the scores given to recommended POIs with a value equal to or greater than 3 were classified as relevant to the group, if not irrelevant.

Precision. Table 3 shows the precision metric values (Section 5.1.3) for positions 3, 5 and 10 ($p@3, p@5, p@10$), considering groups with 3 users. According to the results obtained, the diversity algorithm did not produce an expected impact on the **Standard** method for analyzing accuracy in positions 3 and 5. However, promising results were observed when analyzing the accuracy of the first 10 items. In particular, group 18 judged the recommendations in diversified mode to be 80% accurate. Group 19 attested to 90% accuracy. The standard deviation showed no great variability in accuracy in positions 3 and 5, but there was an increase in position 10.

Table 2: Example of the geo-localized data set for Salvador-Ba, Brazil.

Name	Latitude	Longitude	Category	Address
Archaeological Museum of Embasa	-12.9566984	-38.4949036	Museum	R. Saldanha Marinho s/n Caixa Dagua Salvador - BA 40320-475 Brazil
Salvador Zoo and Botanical Park	-13.0094574	-38.5047836	Park	Tv. Alto de Ondina s/n - Ondina Salvador - BA 40170-110 Brazil

Table 4 shows the accuracies at positions 3, 5, and 10 for groups with 5 users. The results obtained with groups of 5 people were better than those obtained with groups of 3. In particular, the accuracy of the **Diversified** method was generally better than the results shown in Table 3. Again, the most noteworthy results were observed when analyzing the accuracy of the top 10. On this point, in particular, the diversity algorithm performed better than the **Standard** method. The standard deviation showed no significant variability in accuracy at positions 3 and 5, but there was an increase in variability at position 10.

Table 3: Precision ($p@i$) of groups with 3 users.

	p@3		p@5		p@10	
	STD	DIV	STD	DIV	STD	DIV
Group 1	0.3	0.2	0.3	0.4	0.7	0.6
Group 2	0.3	0.3	0.5	0.4	0.8	0.7
Group 3	0.2	0	0.4	0.1	0.7	0.5
Group 4	0.1	0	0.1	0	0.2	0.4
Group 5	0.2	0.2	0.4	0.3	0.6	0.6
Group 8	0	0	0	0.1	0	0.2
Group 9	0.2	0	0.2	0.2	0.7	0.6
Group 13	0.3	0.2	0.5	0.4	1	0.9
Group 18	0.3	0.3	0.3	0.5	0.5	0.8
Group 19	0.3	0.3	0.5	0.4	0.8	0.9
Average	0.22	0.15	0.32	0.28	0.6	0.61
Standard deviation	0.10	0.14	0.18	0.17	0.30	0.21

Table 4: Precision ($p@i$) of groups with 5 users.

	P@3		P@5		P@10	
	STD	DIV	STD	DIV	STD	DIV
Group 10	0	0.2	0	0.3	0	0.4
Group 11	0.3	0.2	0.4	0.4	0.8	0.8
Group 12	0.3	0.1	0.3	0.3	0.5	0.6
Group 14	0.1	0.1	0.1	0.1	0.2	0.3
Group 15	0.2	0.2	0.4	0.4	0.6	0.6
Group 17	0.2	0.2	0.3	0.4	0.7	0.7
Average	0.18	0.17	0.25	0.32	0.47	0.58
Standard deviation	0.12	0.05	0.16	0.12	0.31	0.20

MAP. Table 5 shows the results for MAP@3, MAP@5, and MAP@10 (Section 5.1.3) for the groups with 3 users.

Table 5: MAP of groups of 3 users.

	MAP@3	MAP@5	MAP@10
Standard	0.22	0.32	0.6
Diversified	0.15	0.8	0.61

According to the results in Table 5, the **Diversified** method obtained superior results to **Standard** only in position 5, whereas it was inferior in position 3.

Table 6 shows the results for MAP@3, MAP@5, and MAP@10 groups with 5 users. As with accuracy, we can see better results for the MAP metric when analyzing groups with 5 users. In particular, the **Diversified** method obtained higher MAP values than **Standard** in positions 5 and 10. Nevertheless, we observed lower values in position 3.

Table 6: MAP of groups of 5 users.

	MAP@3	MAP@5	MAP@10
Standard	0.18	0.25	0.47
Diversified	0.17	0.32	0.58

5.2 Experiment 2 (Offline)

In addition to the online experiment, each component of the proposed model should be evaluated, i.e., the model being tested only with the user preference factor and the model being tested only with the distance analysis factor. We also analyzed how the decomposed model would behave for different aggregation techniques. The quality of the recommendations with and without the diversity component was analyzed for each combination mentioned. The methodology, the data set, and the results are presented below.

5.2.1 Methodology

The main objective of the offline experiment was to analyze the determining factors of the model individually (preference and location) and evaluate how the proposed model behaves when other aggregation techniques are considered. The model with and without diversification was always compared for all the variations analyzed.

1) GRSPOI - model proposed in this work without diversification.
2) GRSPOID - model proposed in this work with diversity.
3) DSTD - equivalent to GRPOID considering only the distance factor without diversification.
4) DDVS - equivalent to GRPOID considering only the distance factor with diversification.

5) PSTD - equivalent to GRPOID considering only the preference factor without diversification.
6) PDVS - equivalent to GRPOID considering only the preference factor with diversification.

Three aggregation techniques were used for the variations of the proposals: *Least Misery (LM)*, *Average (AV)*, *Average Without Misery (AWM)*. The dataset used in the offline experiment was the same as that described in Section 5.1.2. In addition, the groups used in the offline experiment were the same as those formed in the online experiment. In total, 15 groups were formed, with 9 containing 3 participants and 6 with five members. The reason for carrying out the offline experiment after the online experiment was precisely to obtain the groups' evaluations of the recommended items. In this way, it was possible to distinguish which item would be relevant or not for each group.

5.2.2 Metrics

The metrics used were Precision and MRR. Precision is described in Equations 7 and 8 presented in Section 5.1.3, which correspond to the calculation of the average precision, being a sum of the precision in each position of the list $p@i$ where r is the number of relevant points of interest up to position i. The metrics presented were applied to the recommendation lists. Each list has ten items, so each item occupies a position on the recommendation list.

The *Mean Reciprocal Rank (MRR)* is a statistical measure for evaluating any process that produces a list of possible answers to a sample of queries, ordered by probability of correctness. The reciprocal rank of a query answer is the multiplicative inverse of the rank of the first correct answer: 1 for first place, $\frac{1}{2}$ for second place, $\frac{1}{3}$ for third place and so on. The average reciprocal ranking is the average of the reciprocal rankings of the results for a sample of Q queries. If none of the proposed results are correct, the reciprocal rank is 0. Equation 9 of the MRR is described below.

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \tag{9}$$

5.2.3 Results

Below are the results of the offline experiment with groups of 3 and 5 users.

Groups with 3 users. Figure 4 shows the accuracy metric values (Section 5.1.3) for position 10 ($p@10$), considering groups with three users. According to the results obtained, the diversity algorithm produced an expected impact on the **Standard** method for analyzing accuracy in positions 10. However, promising results were observed when analyzing the accuracy of the first ten items. Group 19 attested to an accuracy of 90%. In particular, group 18 judged the recommendations in diversified mode to be 80% accurate.

Table 7 shows the number of times the diversified model obtained better, worse, and similar results over the non-diversified models for each variation. For each aggregation technique, the data was presented. There were more ties between the accuracies of the variations of the proposal with diversity than without diversity, followed by the performances. However, the MRR saw more victories for the diversified models, followed by similar results between the models.

		AWM		AV		LM		Diversification Analysis	
		P@10	MRR	P@10	MRR	P@10	MRR	Average P@10	Average MRR
Group_1	STD	0.10	0.10	0.10	1.00	0.10	0.10	0.10	0.40
	DVS	0.20	0.13	0.10	1.00	0.20	0.17	0.17	0.43
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.10	0.10	0.00	0.00	0.10	0.10	0.07	0.07
	PSTD	0.20	0.55	0.20	0.55	0.10	1.00	0.17	0.70
	PDVS	0.10	1.00	0.10	1.00	0.10	1.00	0.10	1.00
Grupo_2	STD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Group_3	STD	0.10	0.20	0.10	0.20	0.10	0.20	0.10	0.20
	DVS	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
	DSTD	0.10	1.00	0.00	0.00	0.10	1.00	0.07	0.67
	DDVS	0.10	1.00	0.10	0.33	0.10	1.00	0.10	0.78
	PSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PDVS	0.30	0.16	0.30	0.16	0.00	0.00	0.20	0.11
Group_4	STD	0.70	0.19	0.80	0.18	0.70	0.19	0.73	0.19
	DVS	0.20	0.22	0.20	0.18	0.20	0.22	0.20	0.21
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.10	0.25	0.10	0.25	0.40	0.19	0.20	0.23
	PDVS	0.20	0.22	0.20	0.22	0.10	0.33	0.17	0.26
Group_5	STD	0.10	1.00	0.10	0.50	0.10	1.00	0.10	0.83
	DVS	0.40	0.36	0.20	0.23	0.40	0.36	0.33	0.32
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.10	1.00	0.10	1.00	0.10	1.00	0.10	1.00
	PDVS	0.30	0.61	0.30	0.61	0.30	0.61	0.30	0.61
Group_8	STD	0.10	0.25	0.00	0.00	0.10	0.25	0.07	0.17
	DVS	0.10	0.11	0.00	0.00	0.10	0.11	0.07	0.07
	DSTD	0.20	0.75	0.20	0.75	0.20	0.75	0.20	0.75
	DDVS	0.20	0.67	0.20	0.67	0.20	0.67	0.20	0.67
	PSTD	0.00	0.00	0.00	0.00	0.40	0.28	0.13	0.09
	PDVS	0.40	0.16	0.40	0.16	0.40	0.28	0.40	0.20
Group_9	STD	0.30	0.57	0.50	0.13	0.30	0.57	0.37	0.42
	DVS	0.40	0.46	0.40	0.24	0.40	0.46	0.40	0.39
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.10	0.17	0.10	0.17	0.10	0.20	0.10	0.18
	PDVS	0.40	0.26	0.40	0.26	0.40	0.26	0.40	0.26
Group_13	STD	0.70	0.19	0.80	0.18	0.70	0.18	0.73	0.18
	DVS	0.20	0.22	0.20	0.18	0.20	0.22	0.20	0.21
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.10	0.25	0.10	0.25	0.40	0.19	0.20	0.23
	PDVS	0.20	0.22	0.20	0.22	0.10	0.33	0.17	0.26
Group_19	STD	0.20	0.16	0.60	0.16	0.20	0.16	0.33	0.16
	DVS	0.20	0.23	0.60	0.20	0.20	0.23	0.33	0.22
	DSTD	0.00	0.00	0.20	0.42	0.00	0.00	0.07	0.14
	DDVS	0.00	0.00	0.20	0.42	0.00	0.00	0.07	0.14
	PSTD	0.20	0.15	0.20	0.15	0.20	0.16	0.20	0.15
	PDVS	0.20	0.18	0.20	0.18	0.10	0.25	0.17	0.20

Figure 4: Group of 3 users.

Table 7: The final result of the model with diversification for the group with 3 users.

	Victories	Defeat	Draws
P@10	9	6	12
MRR	13	6	8

Groups with 5 users. Figure 5 shows the accuracy metric values (Section 5.1.3) for position 10 ($p@10$), considering groups with five users. According to the results obtained, the diversity algorithm produced an expected impact on the **Standard** method for analyzing accuracy in positions 10.

The number of times the diversified model obtained better, worse, and similar results to the non-diversified models were presented for each variation and each data aggregation technique. In Table 8, there were more victories between the accuracies of the proposal variations with diversity than without diversity, and the MRR also performed better, followed by similar results.

		AWM		AV		LM		Diversification Analysis	
		P@10	MRR	P@10	MRR	P@10	MRR	Average P@10	Average MRR
Group_10	GRSPOI	0.20	0.30	0.80	0.34	0.20	0.30	0.40	0.31
	GRSPOID	0.20	0.38	0.50	0.41	0.20	0.38	0.30	0.39
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.30	0.28	0.20	0.15	0.30	0.28	0.27	0.24
	PSTD	0.00	0.00	0.10	0.50	0.00	0.00	0.03	0.17
	PDVS	0.10	0.11	0.10	0.50	0.10	0.25	0.10	0.29
Group_11	GRSPOI	0.00	0.00	0.40	0.12	0.00	0.00	0.13	0.04
	GRSPOID	0.00	0.00	0.40	0.20	0.00	0.00	0.13	0.07
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PDVS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Group_12	GRSPOI	0.00	0.00	0.70	0.16	0.00	0.00	0.23	0.05
	GRSPOID	0.20	0.22	0.30	0.21	0.20	0.23	0.23	0.22
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.10	0.10	0.10	0.50	0.10	0.10	0.10	0.23
	PSTD	0.10	0.13	0.10	0.13	0.10	0.20	0.10	0.15
	PDVS	0.30	0.23	0.30	0.23	0.20	0.25	0.27	0.24
Group_14	GRSPOI	0.00	0.00	0.10	0.10	0.00	0.00	0.03	0.03
	GRSPOID	0.10	0.50	0.70	0.24	0.20	0.42	0.33	0.39
	DSTD	0.10	0.50	0.00	0.00	0.10	0.50	0.07	0.33
	DDVS	0.10	0.25	0.00	0.00	0.10	0.25	0.07	0.17
	PSTD	0.00	0.00	0.00	0.00	0.10	0.10	0.03	0.03
	PDVS	0.20	0.31	0.20	0.31	0.40	0.28	0.27	0.30
Group_15	GRSPOI	0.6	0.38	0.90	0.29	0.70	0.36	0.80	0.34
	GRSPOID	0.3	0.45	0.90	0.00	0.40	0.46	0.65	0.30
	DSTD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DDVS	0.00	0.00	0.10	0.20	0.00	0.00	0.03	0.07
	PSTD	0.60	0.39	0.60	0.39	0.30	0.57	0.50	0.45
	PDVS	0.50	0.40	0.50	0.40	0.40	0.43	0.47	0.41
Group_17	GRSPOI	0.10	1.00	0.10	0.20	0.10	1.00	0.10	0.73
	GRSPOID	0.30	0.42	0.10	0.10	0.30	0.42	0.23	0.31
	DSTD	0.20	0.11	0.00	0.00	0.20	0.11	0.13	0.07
	DDVS	0.30	0.20	0.00	0.00	0.30	0.20	0.20	0.13
	PSTD	0.20	0.58	0.20	0.58	0.20	0.75	0.20	0.64
	PDVS	0.10	1.00	0.30	0.51	0.50	0.42	0.30	0.64

Figure 5: Group of 5 users.

Table 8: Final result of the model with diversification for the group with 5 users.

	Victories	Defeat	Draws
P@10	10	3	5
MRR	11	4	6

5.3 Discussion, Limitations, and Points for Improvement

Based on the results obtained, it was possible to answer the research questions raised in Section 5. Concerning the first question, a satisfactory increase in accuracy was seen with the insertion of diversification techniques in the groups with three users considering ten recommendation items and in the groups with five users considering 5 and 10 recommendation items. As to the second research question, it was possible to observe that using the diversity technique achieved better results in the group with 5 participants. A natural justification for this behavior is the profile of the more diverse group. A limitation of the research regarding method and results is that the diversity algorithm did not achieve the expected impact in smaller groups with POIs in the same category.

Regarding the applications of the proposal, it is not always possible for the user to visit the recommended location and evaluate the recommendation faithfully. In this study, the average rating was around 3.0. To mitigate the abovementioned problem, the group was invited to explore images and videos of the recommended POIs on the web and proceed to the evaluations with greater confidence. Despite this effort, it is not guaranteed that audio-visual information will be available, which threatens the proposal's validity. A limitation of the work is that the descriptions of the POIs are not always fully described. As a point of improvement, it is necessary to enrich the descriptions of the points of interest, as done in (de Almeida et al., 2018). This point of improvement is fundamental for a more assertive similarity calculation and consequent increase in accuracy.

Concerning threats to the experiment's validity, not all POIs in the city of Salvador were considered because we don't have this complete catalog. In addition, some POIs, such as bars and restaurants, may change location or no longer exist. Despite the care taken, this review should be carried out frequently in future evaluations. Regarding the selection of participants, the assessment was restricted to people who lived in or knew about POIs in Salvador to record their interests in the POIs questioned. Another threat to the experiment's validity is the evaluation of popular or generic POIs, such as shopping malls. There is a fear that the assessment will be given by the "fame" of the POIs and not necessarily by an individual analysis and distance.

6 CONCLUSION

This article proposes developing a point-of-interest recommendation System for User Groups using diversity techniques. The recommendation considers the group's preference and the group member's distance from a point of interest. Aggregation techniques are used to generate a group profile. This profile generates recommendations and then reorders using a diversity algorithm. The solution was evaluated using an online experiment with 66 participants and 19 groups. In particular, we assessed the accuracy of the recommendations for the groups and the impact of the applied diversity technique on the original recommendation list. The results point to a better performance of recommendations with diversity, especially for groups with five users. As a contribution to the community, a geo-localized dataset containing POIs from the city of Salvador-Ba was made publicly available.

As future works, we intend to evaluate the proposed solution in a scenario without group preference. In addition, we want to assess the behavior of the recommendations when inserting negative *feedback* into the model. This will help you determine how well the model adapts to the user's preferences and how effective it is in recommending relevant POIs. We also plan to investigate the adoption of a component to explain the recommendations so that the group understands the suggested points of interest. Further, we will need to assess whether the explanations increase the transparency of the recommendation process and enhance the group's confidence in the suggested POIs. An automatic POI extractor will be implemented based on a ground zero and an observation radius to make the application generic. Also, we plan to construct a geographical graph that represents the spatial relationships between POIs. This graph will help in modeling the content-aware correlation between POIs. Last, we intend to include contextual elements in the recommendation model, such as environmental conditions and weather.

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