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Methods of preference aggregation in group recommender systems

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ABSTRACT

The rapid growth of data volumes has led to information overload, which impedes informed decision-making. To solve this problem, recommender systems have emerged that analyze user preferences and offer relevant products on their own. One type of recommender system is group recommender systems, which are designed to facilitate collaborative decision-making, increase user engagement, and promote diversity and inclusion. However, these systems face challenges such as accommodating diverse group preferences and maintaining transparency in recommendation processes. In this study, we propose a method for aggregating preferences in group recommendation systems to retain as much information as possible from group members and improve the accuracy of recommendations. The proposed method provides recommendations to groups of users by avoiding the aggregation process in the first steps of recommendation, which preserves information throughout the group recommendation process and delays the aggregation step to provide accurate and diverse recommendations. When the object of a collaborative filtering-based recommender system is not a single user but a group of users, the strategy for calculating similarity between individual users to find similarity should be adapted to avoid aggregating the preferences of group members in the first step. In the proposed model, the nearest neighbors of a group of users are searched, so the method of finding neighbors is adapted to compare individual users with the group profile. An experimental study has shown that the proposed method achieves a satisfactory balance between accuracy and diversity. This makes it well suited for providing recommendations to large groups in situations where accuracy is more or less important compared to diversity. These results support the assumption that retaining all information from group members without using aggregation techniques can improve the performance of group recommender systems, taking into account various features.

Keywords: Recommender system; machine learning; neural networks; deep learning; classification; information filtering system; information system

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INTRODUCTION, FORMULATION OF THE PROBLEM

Over the last several years, the proliferation of sensor technology, storage technology, computer technology, and network technology has led to a significant increase in the volume of data. Nevertheless, with the escalating magnitude of data, people are confronted with the challenge of an overwhelming amount of information, so impeding their ability to make informed and appropriate judgments. This occurrence is often referred to as information overload [1].

One of the fundamental challenges in big data analysis is using artificial intelligence to extract abstract information from large datasets and transform it into valuable knowledge.

The emergence of recommender systems is a response to the issue of information overload. The primary objective of this system is to examine the user's past actions and preferences, construct a model, and autonomously suggest goods or products that align with the user's interests. Subsequently, a customized list is generated for the user [2].

The recommender system has the capability to suggest things that align with the user's interests, as well as recommend unfamiliar objects that may be of interest to the user, regardless of their preferences. These issues may be mitigated by recommender systems via their ability to efficiently identify users' probable needs and choose attractive products from a vast pool of candidate information [3].

In recent years, group recommender systems have gained significant relevance in various domains due to their capacity to facilitate collaborative decision-making processes, support teamwork and collaboration tools, enhance user engagement in social networking and community platforms, recommend products or services suitable for group purchases or activities, promote collaborative learning in educational settings, aid in event planning and entertainment recommendations, and contribute to diversity and inclusion efforts by considering the diverse preferences, backgrounds, and perspectives within a group [4].

These systems play a crucial role in analyzing collective preferences and behaviors to provide recommendations that are acceptable and beneficial to the entire group, thereby contributing to improved group experiences and outcomes.

Their evolution is marked by advancements in data analytics, machine learning techniques, and user-centric design principles, which continue to enhance their versatility and applicability across a wide range of contexts [5].

Despite the demand and relevance, group recommender systems face several challenges that can impact their effectiveness. These challenges include addressing the diversity of group members' preferences, handling conflicts or disagreements within the group, ensuring fairness and transparency in recommendation processes, managing scalability with large groups, and maintaining user trust and satisfaction [6].

The expansion of individual recommendation models is a common method for the construction of traditional group recommender systems. This is done in order to facilitate the operation of such systems with groups of users.

To generate a collective preference or suggestion, this extension is often accomplished by combining the information for each individual member of the group [7].

On the other hand, the process of aggregation is not excluded from the possibility of information loss. The distribution, shape, and variety of individual data are all factors that should be taken into consideration while addressing this problem.

Furthermore, the process of aggregation results in a reduction in the diversity of ratings, which in turn reduces the diversity of recommendations [8].

Because of this, the performance of group recommender systems might be enhanced by ensuring that the group recommendation process maintains the greatest amount of information that is supplied by the members of the group and by advancing the aggregation process to the final proposal stages [9].

Thus, **the purpose of this study** is to provide a technique for aggregating preferences in group recommender systems that preserves the highest level of information given by the members of the group and advances the aggregation process towards the final recommendation stages.

1. LITERATURE REVIEW

According to [10], group recommender systems execute four fundamental recommendation subtasks: gathering member preferences, producing recommendations, providing explanations for group suggestions, and assisting in making the ultimate decision.

An extensively used method for group recommendation involves the expansion of individual recommender systems [11].

Thus, the issue of group recommendation is resolved by simplifying it to an individual recommendation problem via the consolidation of individual data.

There are two methods of aggregation:

1. Rating aggregation: users express their preferences about certain products. The ratings are combined to form a collective preference in a group profile called “pseudo-user”, which is then utilized by an individual recommender system (Fig. 1) [12];

2. Recommendation aggregation: based on the individual preferences, the recommender system calculates personalized recommendations for each member of the group.

3. These unique suggestions are then merged to customize the recommendations specifically for the group (Fig. 2) [13].

Prior studies have shown that neither strategy is superior to the other in all circumstances. Conducting research is essential to determine the most optimal solution in each situation.

Furthermore, these systems depend on various aggregation processes that may potentially be customized based on the unique recommendation circumstance [14]:

1. Least misery: this approach aims to minimize member displeasure with the suggested goods. The group's level of satisfaction is determined by the least pleased member. Thus, the group's choice for a certain item is the lowest individual preference.

2. Average: the collective choice of the group is determined by calculating the mean of all individual preferences.

Mean without distress: this process calculates the average of individual evaluations while removing items with individual preferences that fall below a certain threshold.

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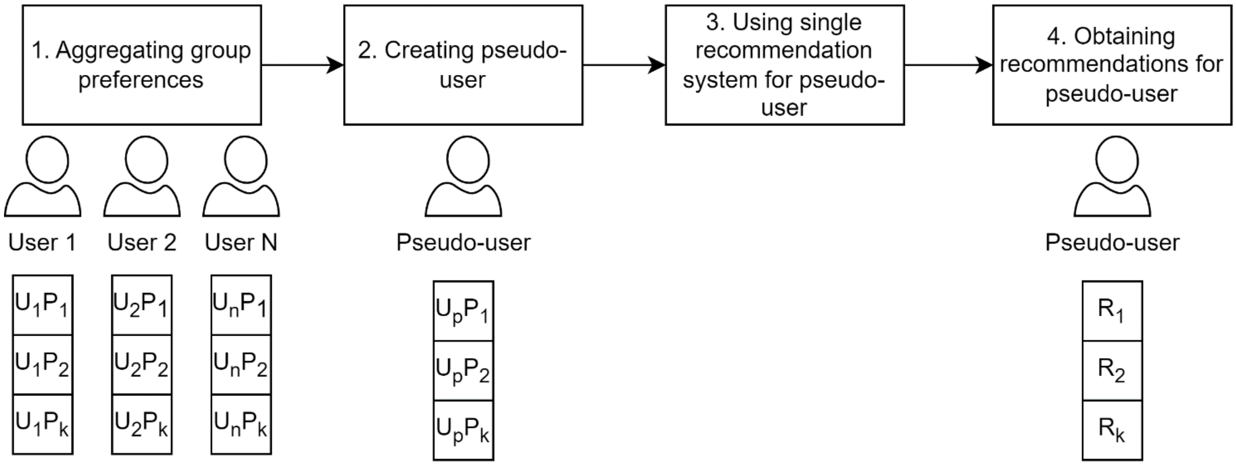

Fig. 1. **Scheme of the rating aggregation method**
Source: **compiled by the authors**

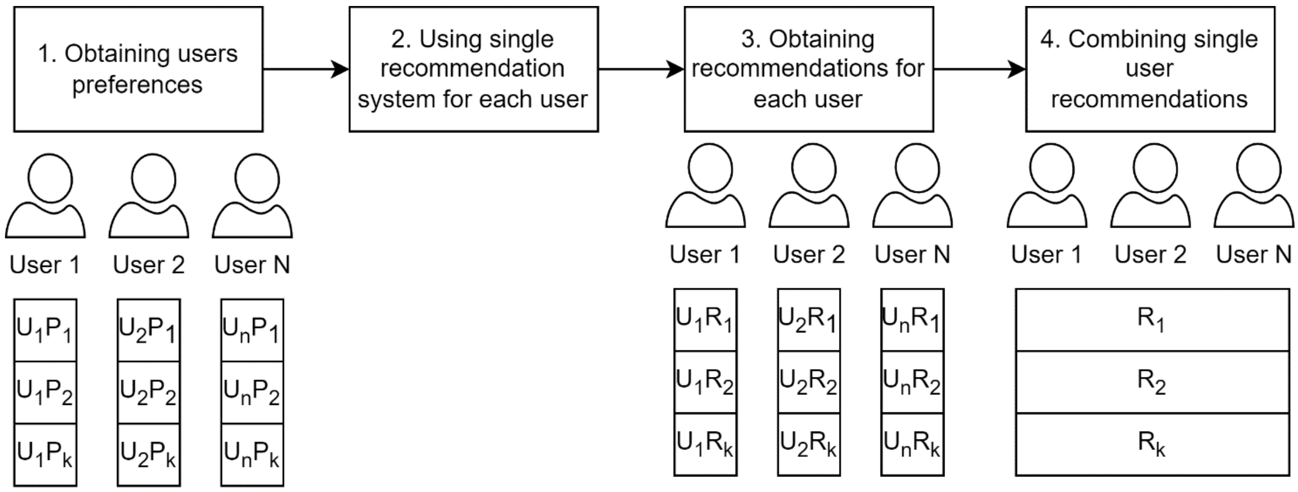

Fig. 2. **Scheme of the recommendation aggregation method**
Source: **compiled by the authors**

Each aggregation approach offers distinct characteristics to the process. The least misery technique is more appropriate for small groups due to the increased likelihood of negative ratings for items as the group size increases. This might result in a group profile that is mostly constituted of negative preferences. This conduct would introduce a bias into the group suggestion.

Additionally, the method of aggregating the least amount of misery is very responsive to new ratings.

This is because the inclusion of a new negative rating has the potential to alter the overall characteristics of the group and hence impact the suggestion [11].

Conversely, the average strategy considers the evaluations of all members, rather than simply the lower ones. When trying to strike a compromise between considering low ratings and all ratings given, the “average without misery” technique combines ratings for things whose overall rating is over a particular level. This is done to prevent the inclusion of the least favored items in the group profile. As a result, this method helps to avoid disliked things.

Several researchers use these methodologies to implement a group recommendation system. Authors of [15] introduced a system designed to consolidate and oversee multimedia material in a family.

This content may be spread across several devices, including hard disks, mobile devices, laptops, or network linked storage. The recommendations are generated using a combination of collaborative filtering and content-based recommendation techniques.

Authors of [12] concentrated on enhancing the fundamental technique for group recommendation by using matrix factorization. This study investigates the process of breaking down the user's profiles into smaller components to identify the important characteristics, and then assesses several methods for combining these broken-down profiles.

Authors of [16] offer a system that considers social interactions, individuals' competence, and differences in interests among group members. The system is assessed by user research conducted in a real-world setting. The experiment concludes that optimal outcomes are attained for each group using distinct algorithms.

The decision-making process varies across different groups. Therefore, a group recommendation system that is recommended to different groups must consider this aspect. Typically, when the system is designed for several types of groups, the recommendation strategy is manually adjusted for each group.

The system administrator examines the groups utilizing the system and chooses the recommendation model that is most suitable for the data.

The model presented in [17] utilizes the personality traits of the individuals inside the group. Using this data, the system utilizes a social influence model to alter the preferences of the members. Individuals are characterized based on their personal traits, including personality, knowledge, and vulnerability.

The authors of [18] are used to analyze these characteristics and guide the social influence model. This method leads to an implicit portrayal of persons.

Authors of [19] assess the methodology for determining suggestions in online communities. The user compares the performance of alternative methods for constructing a community profile, considering inactive members, active members, and community owners.

Similarly, in [20] authors examines several approaches to group suggestion with the goal of identifying the characteristics that impact the selection of an aggregation technique. To do this, they conduct an experiment to evaluate the most effective method of merging individual profiles.

The primary objective of group suggestion is to ensure the satisfaction of all members while minimizing their dissatisfaction with the advice, regardless of the technique used. Two ways that pursue this objective are the “least misery” [13] and “average without misery” [21] approaches. These approaches accomplish a certain amount of justice but do not ensure a strong consensus among members on the proposal. As previously indicated, the methods used for combining recommendations for a group sometimes fail to consider the connections between the preferences of group members, such as shared experiences or comparable interests.

An acknowledged constraint of group recommender systems is that the suggestions may not align with the preferences of all members. In such instances, some suggested goods may fail to meet the expectations of one or more individuals within the group. To reduce the likelihood of this occurrence, in this paper the least misery or multiplicative aggregations is used [22]. The objective of this paper is to use consensus reaching techniques in order to prevent such scenarios by taking into account the interests of all persons involved.

2. PROPOSED METHOD

When the intended recipients of a group recommender system are not individual users but a collective group, the approach for calculating similarities between individual users in order to identify a neighborhood must be modified to prevent the combination of members' preferences as the first step. This approach involves identifying the closest neighbors of a certain group of users. The process of discovering these neighbors is tailored to compare individual users with the overall profile of the group. In order to do this, Hesitant Fuzzy Sets are used to represent the preferences of the group [23]. Proposed method enhances the user-based collaborative filtering strategy by substituting the Pearson's correlation coefficient with its modified form. This modified version allows for comparing individual profiles with group profiles.

Fig. 3 illustrates the overall structure of the suggested technique. Overall, the concept is structured similarly to user-based collaborative filtering, but with the distinction that the neighborhood of a target group is calculated using the preferences of all group members without an initial aggregation phase.

The method comprises four sequential steps:

1. Tentative representation of the preferences of both groups and individual users. The preferences of the members of the group and other users are represented as hesitant fuzzy sets;

2. Formation of neighborhood using a modified version of Pearson's correlation coefficient. The nearest neighbors method is adapted to determine the K nearest neighbors to the group by using a modified correlation coefficient;

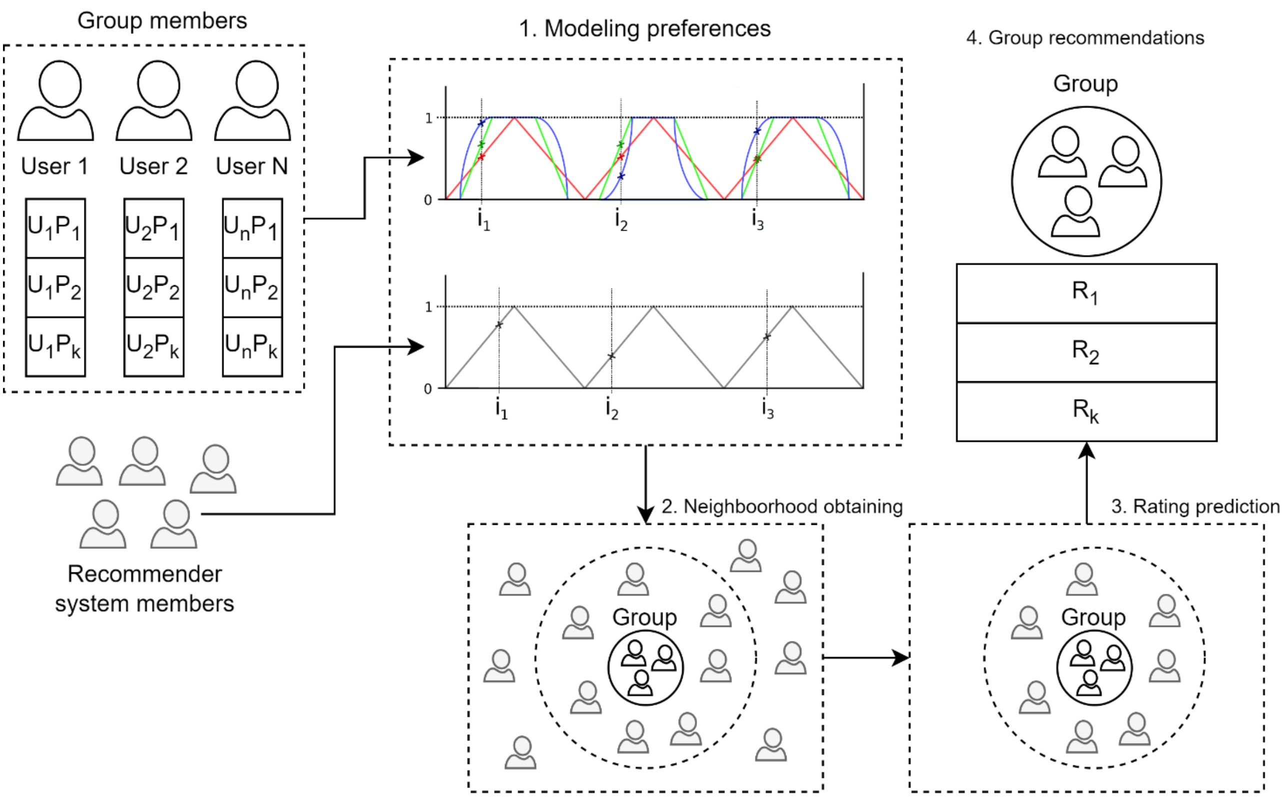

Fig. 3. **Proposed method overall structure**
Source: **compiled by the authors**

3. Prediction of ratings. The concept of group neighborhood is used to forecast ratings for unfamiliar objects by using the ratings of neighboring users;
4. Recommendation for a group. The group is suggested the N items with the highest rating prediction.

2.1. Modeling preferences

The first stage of proposed method involves representing the preferences of both groups and users using Fuzzy Sets. This is done to prevent the loss of information that would occur if members' preferences were aggregated as the first step. In this undertaking, the profiles of both groups and users are specified in terms of fuzzy sets.

The profile of a group PF_G, enables the handling of numerous ratings given by the members of group G for a single item. Therefore, PF_G is a hesitant fuzzy set that includes the ratings provided by the users of group G:

$$PF_G = \{\langle e_k, h_{PF_G}(e_k)\rangle : e_k \in E\},$$
$$h_{PF_G} : E \to P([0,1]), \quad (1)$$
$$h_{PF_G}(e_k) = \left\{\widehat{r_{m_g e_k}} \ s.t. m_g \in G\right\},$$

where $\widehat{r_{m_g e_k}}$ is the normalized rating $r_{m_g e_k}$.

The member's profile, PF_{m_j}, represents the ratings of member m_j:

$$PF_{m_j} = \left\{\langle e_k, h_{PF_{m_j}}(e_k)\rangle : e_k \in E\right\},$$
$$h_{PF_{m_j}} : E \to P([0,1]), \quad (2)$$
$$h_{PF_{m_j}}(e_k) = \left\{\widehat{r_{m_j e_k}}\right\},$$

where $\widehat{r_{m_j e_k}}$ is the normalized rating $r_{m_j e_k}$.

2.2. Neighborhood calculation with modified Pearson's correlation coefficient

The second step of proposed method involves constructing the neighborhood of the group using modified Pearson`s correlation coefficient.

Modified correlation coefficient was proposed in [24] in order to operate on hesitant fuzzy sets.

In this method, the modified correlation coefficient is used to calculate the correlation between the preferences of the group and other members of recommender system.

Modified Pearson`s correlation coefficient regarding preferences of the group and preferences of the members, defined as follows:

$$\rho_{FZ} = \frac{Cov_S\left(h_{PF_G}, h_{PF_{m_j}}\right)}{ST_S\left(h_{PF_G}\right) * ST_S\left(h_{PF_{m_j}}\right)}, \quad (3)$$

where Cov_S is the covariance of both fuzzy sets and defined as:

$$Cov_S\left(h_{PF_G}, h_{PF_{m_j}}\right) = \sum_{e_k}^{E}\sum_{m_g}^{G}\sum_{m_j}^{\{m_j\}}\left(\left(h_{PF_G}(e_k)\right)^{(m_g)} - \overline{h_{PF_G}}\right)\left(\left(h_{PF_{m_j}}(e_k)\right)^{(m_j)} - \overline{h_{PF_{m_j}}}\right), \quad (4)$$

and $ST_S\left(h_{PF_G}\right)$ and $ST_S\left(h_{PF_{m_j}}\right)$ are the standard deviation of the fuzzy sets defined as follows:

$$ST_S\left(h_{PF_G}\right) = \sqrt{\frac{1}{|h_{PF_G}|}\sum_{e_k}^{E}\sum_{m_g}^{G}\left(h_{PF_G}(e_k)^{(m_g)} - \overline{h_{PF_G}}\right)^2}, \quad (5)$$

$$ST_S\left(h_{PF_{m_j}}\right) = \sqrt{\frac{1}{\left|h_{PF_{m_j}}\right|}\sum_{e_k}^{E}\sum_{m_j}^{\{m_j\}}\left(h_{PF_{m_j}}(e_k)^{(m_j)} - \overline{h_{PF_{m_j}}}\right)^2}, \quad (6)$$

where $\overline{h_{PF_G}}$ and $\overline{h_{PF_{m_j}}}$ are the average of hesitant fuzzy set values of the sets and are defined as:

$$\overline{h_{PF_G}} = \frac{1}{|h_{PF_G}|}\sum_{e_k}^{E}\sum_{m_g}^{G}\left(h_{PF_G}(e_k)^{(m_g)}\right), \quad (7)$$

$$\overline{h_{PF_{m_j}}} = \frac{1}{\left|h_{PF_{m_j}}\right|}\sum_{e_k}^{E}\sum_{m_j}^{\{m_j\}}\left(h_{PF_{m_j}}(e_k)^{(m_j)}\right). \quad (8)$$

By using the stated similarity across hesitant fuzzy sets, the group G's neighborhood is obtained by calculating the similarity between PF_G and the profiles of each other member of recommendation system, PF_{m_j}. The neighborhood of group consists of the K users with the greatest resemblance to the group, denoted as NB_G. According to [25], negative correlations do not provide favorable outcomes. Consequently, neighbors exhibiting negative similarity are excluded from the neighborhood.

2.3. Rating prediction

During the rating prediction step, the rating prediction for each item in group G is computed using neighborhood preferences. To compute a neighborhood using all group information, the aggregation of group preferences is avoided during the neighborhood formation phase. At this stage, it is not imperative to prevent the aggregation of neighborhood preferences, as it is constructed taking into account all available group information.

As a result, the aggregation of neighborhood preferences does not significantly affect the diversity of recommendations.

Diverse initial strategies for individual collaborative filtering to derive the predicted rating based on the neighborhood have proposed in [26].

For the purpose of direct prediction, a weighted average is computed from the neighborhood ratings regarding the target item, taking into account the ratings' similarity to the target group.

$$PR(G, e_j) = \frac{\sum_{m_k \in NB_G} \rho_{FZ}\left(PF_G, PF_{m_j}\right) \cdot r_{m_k e_j}}{\sum_{m_k \in NB_G} \rho_{FZ}\left(PF_G, PF_{m_j}\right)}. \quad (9)$$

Compensated prediction: when rating, users may be biased in various ways, including being overly optimistic or pessimistic. To account for these variations, the user bias is eliminated from the rating prior to performing the weighted aggregation.

This preemptive strategy is implemented in every technique that is compared throughout the experiment.

$$PR(G, e_j) = \bar{r}_G + \frac{\sum_{m_k \in NB_G} \rho_{FZ}\left(PF_G, PF_{m_j}\right) \cdot \left(r_{m_k e_j} - \bar{r}_{m_j}\right)}{\sum_{m_k \in NB_G} \rho_{FZ}\left(PF_G, PF_{m_j}\right)}, \quad (10)$$

where $\bar{r}_G$ is the mean value of the collection of ratings provided by the members of the group.

2.3. Recommendation for a group

After calculating a prediction for each item, the system generates a categorized catalog of the items in accordance with their predicted rating. The recommendation consists of the N highest-rated items as predicted by the algorithm.

3. EXPERIMENTAL RESULTS

To assess the appropriateness of proposed method, it is compared to the conventional group recommender systems, which relies on rating aggregation. In this experiments, two variations of such systems were used: group recommender system with pseudo-user based on mean preferences [27] and group recommender system with pseudo-user base on RMSMean aggregation [28]. Due to its extensive use in the literature, this model is considered a suitable benchmark for comparison.

Furthermore, two iterations of the proposed method were used, in addition to comparing it with conventional methods. Proposed method acknowledges the presence of duplicate preferences and takes them into account. However, modified proposed method effectively removes these duplicate preferences.

Concisely, the experiment evaluates four method:

1. Method 1: pseudo-user group recommender system using Mean as the method for preference aggregation;
2. Method 2: pseudo-user group recommender system that uses root mean square preference aggregation;
3. Method 3: Proposed method that takes into account duplicate preferences;
4. Method 4: proposed method that removes redundant preferences.

Each of these methods produces a sorted list of suggested things as output. During the experiments, the top-5 suggestions were taken into account.

The dataset is divided into a training set and a test set, and a 20-execution 5-fold cross-validation is performed. The method are being compared using the dataset ml-100k [29], which has 1682 items, 943 users, and 100k ratings. The dataset consists of consumers rating movies on a five-star scale. The rating domain is normalized to facilitate working with fuzzy sets.

The MovieLens dataset only comprises individual tastes, without any information pertaining to groups. This experiment specifically targets random groups, which are considered the most difficult sort of groups for group recommender systems.

The purpose of random group creation is to simulate the scenario when a group of users get together to engage in an activity [30].

The methods are evaluated based on different group sizes, ranging from 1 to 500 members. To provide clarity, only the findings for groups consisting of 20, 50, 100, 250, and 500 members are shown. These group sizes are a representative subset of the sizes that were investigated.

The purpose of the proposed method is to preserve the group's knowledge throughout the recommendation process. To assess the influence of this objective on the recommendation outcomes, several perspectives on the quality of recommendations were examined: precision, ranking quality, and diversity.

There are three assessment metrics that try to evaluate the quality of recommendations based on different perspectives [31]: Normalized Root Mean Squared Error, Normalized Discounted Cumulative Gain, and Intra List Similarity. The following definitions are used to describe these measures.

The Normalized Root Mean Squared Error (NRMSE) [32] quantifies the difference between the predicted ratings and the real values, with the error being scaled to a range of [0.1]. Therefore, a lower NRMSE value indicates a more accurate Recommender System:

$$NRMSE = \sqrt{\frac{1}{N}\sum\nolimits_{r_{m_i}\in R}\left(\frac{\tilde{r}_{m_i} - r_{m_i}}{d_{max} - d_{min}}\right)^2}. \quad (11)$$

The Normalized Discounted Cumulative Gain (NDCG) [33] quantifies the similarity between the ranking produced by the recommendation system and the ideal ranking based on the actual rating values.In order to make a comparison, the utilities of both lists are evaluated and compared.

The value of NDCG varies from 0 to 1, with a perfect rating achieved when NDCG=1:

$$DCG = \sum_{k=1}^{N} \frac{\tilde{r}_{m_i} - 1}{\log_2(k+1)}, \quad NDCG = \frac{DCG}{IDCG}, \quad (12)$$

where IDCG refers to the DCG of the items when they are ranked based on their genuine rating. It should be noted that in the experiments, we are referring to 1-NDCG, meaning that all metrics are minimized.

Intra List Similarity (ILS) [34] quantifies the degree of similarity among the items in a suggestion. Having a lack of ILS is preferable since diversity is a desirable characteristic.

$$ILS(\tilde{E}) = \frac{\sum_{e_j\in\tilde{E}}\sum_{e_k\in\tilde{E}, j\neq k}(v_j, v_k)}{2}, \quad (13)$$

where feature vectors v_j and v_k represent items e_j and e_k, respectively. These vectors are obtained by performing Singular Value Decomposition [35] with 20 features on the rating matrix.

The outcomes of the methods are first analyzed separately for each of the three measures. Subsequently, to achieve a harmonious equilibrium between the factors considered by each metric in the selection of the optimal approach, we merge the NRMSE and the ILS. As a result, we get a composite measure that encompasses both prediction accuracy and diversity. This is crucial because, as author in paper [36] pointed out, it is not always possible to enhance accuracy and variety simultaneously, and any enhancement in one measure has a detrimental influence on the other.

Table 1 displays the outcomes for NMRSE. The results are shown for group sizes ranging from 20 to

500. It is evident that as the size of the group increases, the prediction error also increases. When comparing the outcomes of different methodologies, both configurations of the proposed method approach exhibit an increase in accuracy when predicting ratings.

Table 1. **Experimental results for NRMSE of reviewed methods**

Method	Group size				
	20	50	100	250	250
Method 1	0.25582	0.25593	0.25639	0.25751	0.25904
Method 2	0.25563	0.25597	0.25645	0.25757	0.25909
Method 3	0.25320	0.25357	0.25389	0.25502	0.25706
Method 4	0.25344	0.25372	0.25399	0.25519	0.25723

Source: **compiled by the authors**

Table 2 displays the results for 1-NDCG. The results are shown for group sizes ranging from 20 to 500. These metrics should be reduced, meaning that a lower value is preferable. It is evident that as the size of the group increases, the quality of the ranking decreases. Nevertheless, the findings indicate that all the procedures examined exhibit comparable NDCG values up to the fourth decimal place. Therefore, there is no noticeable decline in ranking quality amongst the evaluated techniques.

Table 2. **Experimental results for 1-NDCG of reviewed methods**

Method	Group size				
	20	50	100	250	250
Method 1	0.07225	0.07234	0.07237	0.07252	0.07255
Method 2	0.07225	0.07234	0.07237	0.07252	0.07255
Method 3	0.07225	0.07234	0.07237	0.07251	0.07255
Method 4	0.07225	0.07234	0.07237	0.07252	0.07255

Source: **compiled by the authors**

Table 3 displays the experiments for ILS. Overall, as the group size rises, all compared approaches exhibit reduced ILS. It is important to note that with proposed method variants, the larger the group size, the more the ILS decay.

Additionally, the degree of decay is higher for both approaches compared to conventional group recommender systems. Consequently, proposed method variants provide a wider range of recommendations.

As previously indicated, it is necessary to examine the outcomes using all assessment metrics in order to accurately determine the most effective method.

According to the data shown in Table 2, the NDCG findings remain consistent across different methodologies. Consequently, we may disregard the ranking quality while doing the combined analysis of measures.

Table 3. **Experimental results for ILS of reviewed methods**

Method	Group size				
	20	50	100	250	250
Method 1	0.84603	0.78699	0.71454	0.63698	0.44152
Method 2	0.84840	0.79291	0.71729	0.63452	0.44419
Method 3	0.83818	0.75524	0.68297	0.59661	0.41455
Method 4	0.83822	0.75533	0.68303	0.59676	0.41462

Source: **compiled by the authors**

Therefore, the evaluation of accuracy and diversity is conducted by using a convex combination of NRMSE and ILS.

$$ACDV = NRMSE \cdot \beta + ILS \cdot (1 - \beta). \quad (14)$$

In this formula, a value $\beta \in [0,1]$, represents the relative relevance of accuracy compared to diversity. The assessed methods have been compared for $\beta = 0.5$.This value represents an equal importance of accuracy and diversity.

The second value signifies an equal importance placed on both accuracy and diversity. The third value indicates a ratio of 1:3, indicating a higher emphasis on diversity compared to accuracy. The experiment results are shown in Table 4.

Table 4. **Experimental results for ACDV with $\boldsymbol{\beta = 0.5}$ of reviewed methods**

Method	Group size				
	20	50	100	250	250
Method 1	0.55082	0.52170	0.48559	0.44730	0.35022
Method 2	0.55204	0.52461	0.48699	0.44805	0.35164
Method 3	0.53562	0.50737	0.45864	0.42377	0.33124
Method 4	0.53571	0.50745	0.45879	0.42384	0.33140

Source: **compiled by the authors**

CONCLUSIONS

The results of the combined experiment indicate that proposed method variants achieve superior values as the group size grows, in comparison to the conventional group recommender systems, which are classic aggregation-based models.

This trend is seen in all groups, indicating that omitting the first aggregation step in user-based neighborhood techniques for group recommendation enhances suggestion variety without compromising accuracy.

For all values of a tested, proposed method variants provides a significant performance advantage over conventional models as the group size grows. Notably, these gains become more apparent for group sizes beyond 100 members.

This disparity indicates that the enhancements of proposed methods in relation to recommendation variety do not adversely affect the accuracy of the system.

Therefore, both proposed method variants effectively achieve a balance between accuracy and diversity when recommending to large populations. This makes them acceptable for recommendation domains that prioritize diversity.

Overall, proposed method achieves a satisfactory equilibrium between accuracy and variety. This makes it well-suited for suggesting to large groups in situations where accuracy is of more or equal relevance compared to diversity.

These findings validate the premise that retaining all information from group members without using aggregation methods would enhance the performance of the group recommender systems by considering various features.

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Методи агрегації вподобань в групових рекомендаційних системах

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АНОТАЦІЯ

Стрімке зростання обсягів даних призвело до інформаційного перевантаження, що перешкоджає прийняттю обґрунтованих рішень. Для вирішення цієї проблеми з'явилися рекомендаційні системи, які аналізують вподобання користувачів і самостійно пропонують релевантні товари. Одним з видів рекомендаційних систем є групові рекомендаційні системи, які призначені полегшувати спільне прийняття рішень, підвищуючи залучення користувачів та сприяючи різноманітності та інклюзії. Однак ці системи стикаються з такими проблемами, як врахування різноманітних групових вподобань та збереження прозорості у процесах надання рекомендацій. В даному дослідженні був запропонований метод агрегування вподобань у системах групових рекомендацій, щоб зберегти максимум інформації від членів групи та підвищити точність рекомендацій. Запропонований метод надає рекомендації групам користувачів, уникаючи процесу агрегування на перших кроках надання рекомендацій, що зберігає інформацію протягом усього процесу надання групових рекомендацій і затримує крок агрегування для надання точних і різноманітних рекомендацій. Коли об'єктом рекомендаційної системи на базі колаборативної фільтрації є не один користувач, а група користувачів, стратегія обчислення схожості між окремими користувачами для пошуку схожості повинна бути адаптована, щоб уникнути агрегування вподобань членів групи на першому кроці. У запропонованій моделі відбувається пошук найближчих сусідів групи користувачів, тому спосіб пошуку сусідів адаптовано для порівняння індивідуальних користувачів з профілем групи. Проведене експериментальне дослідження показало, що запропонований метод досягає задовільного балансу між точністю та різноманітністю. Це робить його добре придатним для надання рекомендацій великим групам у ситуаціях, коли точність є більш або менш важливою порівняно з різноманітністю. Ці результати підтверджують припущення про те, що збереження всієї інформації від членів групи без використання методів агрегування може підвищити продуктивність систем групових рекомендацій, враховуючи різні особливості.

Ключові слова: рекомендаційна система; машинне навчання; нейронні мережі; глибоке навчання; класифікація; система фільтрації інформації; інформаційна система

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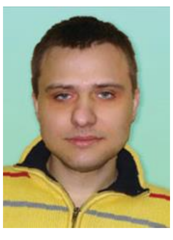

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