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Elevating Group Recommendations and Collective Decisions Through Prioritized User Activities in Groups

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Group modeling encompasses various areas of interest, including recommendations, movie watching, exercise performance, and the formation of social media groups with similar interests. Similarly, the GRS has numerous practical applications, such as books, movies, and television program recommendations. Various collaborative techniques, such as Least Misery, Average Voting, and Most Pleasure, to name a few, have been employed to enhance group recommendations. However, these methods are not without limitations, often introducing biases and yielding irrelevant suggestions. For example, group of people watching television, the active user having a remote control is paramount. Active user(s), who engage in activities like channel switching, rating, expressing preferences, and commenting, should hold significant influence. This study proposed and integrates active user engagement and feedback into the recommendation process, by considering user activities as feedback. The proposed system employs a filtering mechanism that emphasizes the user's activities, facilitating the prediction of relevant suggestions to group users. The experiments utilized the well-established benchmark dataset Movie Lens. The effectiveness of the proposed approach is evaluated using standard metrics such as precision, recall, and F-score. The results show that recommending active items to actively engaged user(s) significantly benefits most of the group users, yielding an improved suggestion. This study may help practitioners to build more robust recommender systems for groups.

Group Recommendation System (GRS)
Recommendation systems (RS)
Group Lens (GL)
Plurality Voting Strategy (PVS)
Average Strategy (AS)
Multiplicative Strategy (MS)
Least Misery (LM)
Most Pleasures (MP)
Poly Lens (PL)
Average Voting (AV)
Average Strategy (AS)
Group Recommendation Techniques (GRT)

Keywords: Group Recommender System, Group Modeling, User Modeling.

Introduction:

User modeling encompasses various areas of interest, including recommender systems [1]. The user modeling approaches extend to group modeling and play a key role in group recommendations [2]. The GRS has numerous practical applications, such as books, movies, and television program recommendations [3][4]. Recommendation systems (RS) play a key role in the digital age by providing users with personalized suggestions for a wide range of online content, such as movies, books, products, clips, and songs [5]. A plethora of research and state-of-the-art systems have emerged to offer users relevant recommendations. The RS has evolved into an integral component of technology giants, such as YouTube, Netflix, Amazon, social media networks, e-commerce platforms, news websites, etc. The RSs are in a state of continuous evolution, with systems becoming intelligent and contributing to the emergence of Web 3.0 [6]. They are designed to adapt and respond to the unique preferences on choices of individual users [7]. The era characterized by an overwhelming abundance of choices, consumers often find themselves confronted with the challenging task of navigating a huge list of options, e.g., in the domain of music, users were once faced with the staggering challenge of selecting from thirteen million songs on iTunes, a number that has since grown exponentially. The scale of options extends to books as well, with Amazon offering a catalog of over three million titles [8]. This profusion of choices underscores the critical role of RS in simplifying the decision-making process for users. RS not only aids in the discovery of relevant content but also enhances the overall user experience by helping users effectively to navigate through the list of items.

In today's digital landscape, many online activities are inherently social, involving group interactions and shared experiences. Whether it's watching movies, enjoying music from specific groups, or researching books within similar domains, the web frequently caters to collective preferences [9]. Consequently, the concept of group recommendations has emerged as a compelling area of interest for both researchers and industry practitioners. Despite the inherent diversity in individual tastes, temperaments, cultural backgrounds, and social values, the group recommendation is still evolving. Nevertheless, research efforts are steadily growing, intending to achieve higher accuracy and user satisfaction [10].

The GRS plays a crucial role in elevating user experiences, fostering engagement within online communities, and assisting users in discovering content that aligns with their collective preferences [11][12]. With ongoing research and innovation, the field of group recommendations holds the promise of further enhancing the way we interact with digital content as a collective audience [13]. The GRS represents a potent technique for suggesting products or content that aligns with a user's preferences. Numerous leading online companies and brands, including Amazon, Google, and YouTube, have harnessed the potential of GRS to enrich their online platforms and expand their market reach [14][15]. GRS operates based on two primary types of feedback: implicit and explicit.

Implicit feedback entails the collection of user data as they interact with a website, even when users might not be consciously aware of it. In contrast, explicit feedback relies on user actions such as likes, comments, and ratings [16][17]. Some systems leverage both forms of feedback, creating hybrid recommender systems that combine implicit and explicit data sources to deliver more refined recommendations [18]. When a user visits a social media networking website, such as Amazon or any other e-commerce platform, and initiates a product search, the website initiates a recommendation process for related products targeted at users who share similar preferences. For instance, if a user conducts a book search, the system progressively learns from the user's browsing patterns and search queries, subsequently suggesting other books within the user's area of interest [19][20]. It's important to highlight that these recommendations may not always be 100% accurate.

Numerous web applications collect valuable user data during their interactions, including keywords, user preferences, likes, and dislikes [21]. Prominent examples include Google and numerous other websites that leverage this data for various purposes, primarily for future recommendations [22]. This approach is often referred to as a singularity approach, as exemplified by [23]. For enhancing recommendation accuracy, researchers have explored various methodologies, including hybrid models, approaches based on social networks, and diverse techniques for group recommendations [24]. Significantly, several well-known recommender systems, such as GL, the Netflix movie recommendation system, Google's news recommender system, and Facebook's friend recommendation system, have risen to prominence in recent years [25]. These systems frequently employ techniques like content-based, collaborative, and critique-based recommendation systems [23], which will be comprehensively discussed in the Literature Review section of this study.

The Group Recommender System employs a variety of aggregation strategies to enhance the relevance of its results. Majority-based strategies center around popular items or categories among group members [13][26]. For example, the PVS involves each member voting for their chosen item or category, and the one with the most votes from members is selected [27]. This process is then repeated for the remaining items to generate a ranked list. Additionally, the Group Cast strategy comes into play when users are in proximity to a public screen and tailoring content is shown to their preferences [28]. Consensus-based strategies involve aggregating preferences from all group members [29].

For instance, the Additive Practical Strategy (APS) combines individual user evaluations [30], while the AS computes the average of these individual preferences [31][32]. The MS takes into account the top-rated products based on individual user evaluations [33]. The borderline strategy focuses on integrating a subset of user-preferred items within individual user profiles, taking into account user roles or other relevant criteria [34]. The LM and MP strategies aim to identify items that match the preference and generate the highest interest level among all group members [35]. The PL strategy builds upon LM, catering to small groups and recommending content that collectively satisfies users more than individual preferences, particularly in the context of the Movie Lens database [36]. MP sets the preference of items with high ratings from all individuals who have already expressed a liking for those items, while the AV strategy assigns the preference rating of an item based on the collective ratings of all group members.

Certainly, aggregation techniques such as LM, AV, and MP have shown their effectiveness in various group scenarios. However, it is important to note that these methods are not universally applicable, and there are situations in which their recommendations may not resonate with the majority of group users [37]. For example, in a scenario involving diverse group members watching TV, these existing aggregations and merging techniques do not consistently produce satisfactory recommendation results. To address such scenarios, this study proposed a new priority-based technique that assigns priorities to users' participation within a group. Nevertheless, the field faces a series of pressing issues that warrant immediate attention

Objectives and Novelty Statement:

- **Ranking User Profiles:** A significant challenge lies in the effective prioritization of user profiles based on their participation and the provision of relevant item recommendations to user groups.
- **Enhancing Conversion Rates:** Another critical concern revolves around boosting conversion rates by suggesting items that are not only relevant but also more likely to engender user engagement or action.
- **Improving Relevant Group Recommendations:** It is imperative to enhance the relevance of recommendations to user groups by factoring in user prioritization,

ensuring that the recommendations align with the preferences and priorities of the users within the group.

This paper introduced a recommender system designed to provide relevant recommendations by analyzing user preferences, assessing item similarities, and merging user profiles. While many existing approaches focus on individual recommendations, there has been relatively less emphasis on precision and recall in group recommendations. This research contributes to the field by highlighting user modeling and delivering pertinent item suggestions to user groups. It addresses the challenges related to user profiles, aiming to offer accurate and relevant recommendations customized to the group's dynamics. An essential aspect of this research explores how recommendations can be improved by incorporating user priorities within social networking groups. By understanding and integrating user priorities into the recommendation process, the proposed system seeks to fine-tune and personalize recommendations, ultimately enhancing the overall user experience within these dynamic online communities.

The first step involves creating a user rating table that incorporates user priorities and categorizes users into different groups. Manually assigning priority values to each user can be impractical and time-consuming. To address this challenge, the system devised a method based on the number of movies a user has rated. Essentially, users who have rated the most movies will be assigned the highest priority, while those who have rated the fewest movies will receive the lowest priority. These priorities range from 0 to 5, where 5 represents the highest priority (highly active in groups) and 0 indicates the lowest (inactive in groups). A prototypical movie recommendation system has been developed, which places more importance on the movie preferences of users with higher priority levels. The user categories are divided into three types: super-users, active users, and passive users, as outlined in Table 1. Each category has its priority range and distinct characteristics that influence the recommendation process.

Overview of the Work

The dataset used for this study is the Movie Lens [38] dataset taken from Group Lens. In this dataset, each movie is rated on a scale of 1 to 5, and we have set a minimum threshold of 20 ratings per user. The movies are organized, each with a unique ID, along with information such as the movie title and the genre it belongs to. We achieved almost 100% accuracy for super-users because we directly selected positive and negative movies from the ratings.csv dataset and displayed them in the hierarchy. Similarly, an accuracy of 85% is obtained for active users by selecting positive movies for all active users from the ratings.csv dataset and presenting them in the hierarchy. For passive users, we obtained a precision of 0.51%, recall of 0.58%, and F1 Score of 0.54%. The results demonstrate that priorities play a significant role in TV-watching scenarios. While this approach may not be universally applicable to every group scenario, it proves its effectiveness for active users within groups engaged in dynamic activities, such as those found on social networking sites. The goal is to further expand this research by introducing contextual group recommendations and tailoring the recommendations to specific contexts and activities within user groups.

The subsequent sections of this paper are the "Related Work" section which critically reviews relevant pertinent literature, extracting key insights. Following this, the "Proposed Methodology" proposes a novel approach employed, detailing its design and rationale. The "Results and Analysis" section then presents empirical findings. The "Discussion" section delves into the implications of results, drawing connections with existing knowledge. The "Conclusion" synthesizes key discoveries and underscores their significance. Lastly, the "Future Work" section outlines potential research directions. The references are enlisted at the end of this paper.

Related Work:

In the contemporary digital landscape, coping with the ever-expanding volume of information available on the internet has emerged as a formidable challenge. RS emerges as a pivotal player in addressing this challenge, leveraging sophisticated filtering techniques to effectively and efficiently assist users in navigating this vast information landscape [39]. Over the years, numerous researchers have employed their efforts to developing and refining filtering techniques aimed at enhancing the overall user experience. The history of Recommender Systems traces back to 1992 when the first system, known as Tapestry, was pioneered by Goldberg [40]. In the present day, various tech giants, such as Google, Twitter, LinkedIn, Netflix, and Amazon, have harnessed the power of RS to optimize product recommendations and augment their sales strategies [41]. RS typically employ three primary approaches:

- Content-based recommendation systems, which compare items based on user feedback and preferences. This approach focuses on user profile items that have been rated or liked, evaluating the similarity between different items [41][42][43].
- Collaborative filtering techniques rely on both implicit and explicit feedback. Implicit feedback is derived from user queries within groups, while explicit feedback is based on user ratings within a group [44][45]. Collaborative filtering aims to identify groups of similar users whose opinions can inform RS recommendations [46]. It finds application in diverse fields, including finance, e-commerce, and weather prediction, using user ratings as a foundational element [47].
- Hybrid approaches that combine elements of both content-based and collaborative filtering for recommendations. However, it's important to note that these approaches can introduce heavy computational overhead, potentially generating additional challenges [26].

The ever-increasing volume of information on the internet poses a growing challenge for humans [48]. RS play a pivotal role in addressing this challenge by filtering information to cater to individual user preferences and needs [49]. RS is designed to respond to user choices and options, tailoring content and suggestions accordingly [39]. One of the most famous and widely recognized examples of RS is YouTube. YouTube utilizes an RS to recommend videos to users based on their viewing preferences. For instance, if a YouTube user consistently watches sports-related videos, the RS will proactively recommend a stream of sports-related content upon opening the platform [50]. This represents a significant advancement in the field of artificial intelligence, with widespread global usage that helps individuals to discover content aligned with their interests [51].

The GRS occupies a significant role in the realm of user experience enhancement, community engagement, and content discovery for users with shared preferences. With persistent research and innovative developments, the domain of group recommendations holds substantial potential for reshaping collective interactions with digital content [14]. GRS stands as a robust technique for recommending products or content that align with individual user preferences. Prominent online entities, including Amazon, Google, and YouTube, have strategically leveraged GRS to enrich their online platforms and broaden their market outreach [14][15]. The operational foundation of GRS relies on two fundamental types of feedback: implicit and explicit. The Group Recommender System employs a range of aggregation strategies aimed at enhancing the relevance of its recommendations. Several notable approaches are as follows:

- **Majority-Based Strategies:** Majority-based strategies center on identifying popular items or categories within the group. For instance, the PVS involves each member casting their vote for their preferred item or category, with the most-voted option being selected. This process is iterated for the remaining items to generate a ranked list.

Additionally, the Group Cast strategy is utilized when users are in proximity to a public screen, allowing for content tailored to their preferences [28].

- **Consensus-Based Strategies:** Consensus-based strategies entail aggregating preferences from all group members. Examples of this approach include the Additive Practical Strategy, which combines individual user evaluations, and the A), which computes the average of these individual preferences. The MS takes into account top-rated products based on individual user evaluations [33].
- **Borderline Strategy:** The borderline strategy focuses on the summation of a subset of user-preferred items within individual user profiles, considering user roles or other relevant criteria [34].
- **Least Misery and Most Pleasures:** The LM and MP strategies aim to identify items that align with preferences and generate the highest interest level among all group members. The PL strategy builds upon LM, particularly catering to small groups and recommending content that collectively satisfies users more than individual preferences, particularly in the context of the Movie Lens database. MP sets the preference of items with high ratings from all individuals who have expressed a liking for those items, while the AV strategy assigns the preference rating of an item based on the collective ratings of all group members [52].

These strategies play a pivotal role in group recommendation systems, offering diverse approaches to ensure that recommendations align with the preferences and dynamics of the user group. Major technology companies like Google, Twitter, LinkedIn, Netflix, and Amazon extensively employ RS to maximize product sales and enhance user experiences [53]. Concurrently, group recommendations have garnered increasing attention from researchers and companies alike. Prominent platforms like Group Lens, ARS, Netflix, GNRS, and Facebook incorporate GRT [54]. Diverse approaches, including LM, AV, and MP, among others, are employed to improve group recommendations. However, it's important to note that these techniques may introduce biases and lead to recommendations that are irrelevant to many group users [55].

Indeed, while techniques like LM, AV, and MP have proven effective in many scenarios, they are not universally suitable, and their recommendations may sometimes be irrelevant to the majority of group users [37]. In today's digital era, the abundance of options and choices can be overwhelming for users. For instance, when a user searches for a specific item on Amazon, they might be presented with thousands of results, making it challenging to identify the most suitable product among the multitude of choices. In this context, recommender systems play a crucial role in assisting users in making informed decisions and selecting the best option from the extensive array of possibilities [56].

The literature survey underscores that RS fundamentally operates through the analysis of user preferences, the assessment of item-to-item similarities, and the evaluation of user profile similarities, all with the overarching goal of delivering pertinent item recommendations to groups of users. To tackle these challenges, this study introduces a novel approach that prioritizes social networking group discussions as a mechanism to augment recommendations. By harnessing the dynamics and interactions inherent in group discussions, the objective is to optimize recommendations and, in turn, ameliorate the user experience for groups of users.

Proposed Methodology:

The significance of this research lies in its dedicated contribution to reshaping the RS landscape, placing a strong emphasis on the prioritization of user models and the delivery of well-suited recommendations to user groups. This user-centric approach holds the potential to address persistent challenges related to user profiles, particularly in terms of modeling issues that have hindered the accuracy and relevance of recommendations within user groups. Importantly, the scope of this recommender system extends across various domains, encompassing diverse areas such as movies, travel, music, and more.

Acknowledging the need for efficiency and effectiveness, the proposed methodology introduces a filtering technique customized to individual users' priorities. This innovative framework recommends various item types to each group member based on their unique priority settings, followed by the application of an algorithm for predictive rating assignments. To validate the effectiveness of this algorithm, this study utilized a publicly available dataset (Movie Lens) containing user comments.

In the proposed approach, high-priority items receive broad recommendations to all users, while low-priority items are selectively suggested to members who exhibit profile similarities. This recommendation strategy relies on the strategic application of a filtering mechanism and the careful prioritization of information, ultimately aiming to enhance the quality of recommendations. The framework illustrated in Figure 1 represents a significant advancement towards enhancing the quality of recommendations, with the ultimate objective of converting casual visitors into loyal customers, a transformation commonly referred to as the conversion rate. The key components underpinning the proposed system are outlined in Figure 1.

- **Viewer's Profile:** The viewer's profile is a group profile, typically stored on devices meant for group enjoyment, such as a smart TV. It encompasses all records of viewers and can be populated either manually or automatically through various sensors, like cameras.
- **Group Discussion:** Group discussions involve the participation of a diverse array of members, each contributing valuable insights. The initial step involves information retrieval from various sources to construct user profiles and capture preferences derived from these group discussions. This model harnesses datasets from social media networks, mining group discussions for invaluable data.
- **User Profiles:** User profiles emerge as a crucial facet of the proposed methodology, generated by aggregating data from group discussions and reflecting user preferences. These user profiles serve as the foundation for the recommendation engine, which leverages them to provide relevant item suggestions to groups, aligned with individual user preferences.
- **Usage Logs:** The usage log is a central module that keeps track of all activities of group members. For example, it records how much time a particular group member spends on a specific activity.
- **Priority Extraction:** Priorities are extracted from the observed usage patterns. The priorities related to specific group members are tracked, allowing for a more refined understanding of their preferences.
- **Group Prioritization:** Group prioritization introduces an alternative approach to enhancing recommendations. By prioritizing users within the group discussion, the recommendation system tailors its predictions to align with user prioritization. These prioritized user groups subsequently inform the recommendation engine.
- **Recommendation Engine:** The proposed approach lies the recommendation engine, which draws upon user profiles and group prioritization to deliver finely tuned recommendations to the appropriate groups of users. Once the users within the group are prioritized, and their profiles created, the recommendation engine seamlessly accesses data and recommends items of relevance to the group. As we go deeper into the proposed approach, the potential for more robust and effective recommendations becomes increasingly evident.

At its core, this work aims to empower group discussions and activities by introducing prioritization and relevance. By providing a practical means of recommending appropriate items to specific groups of users, this approach squarely falls within the domain of user and group modeling.

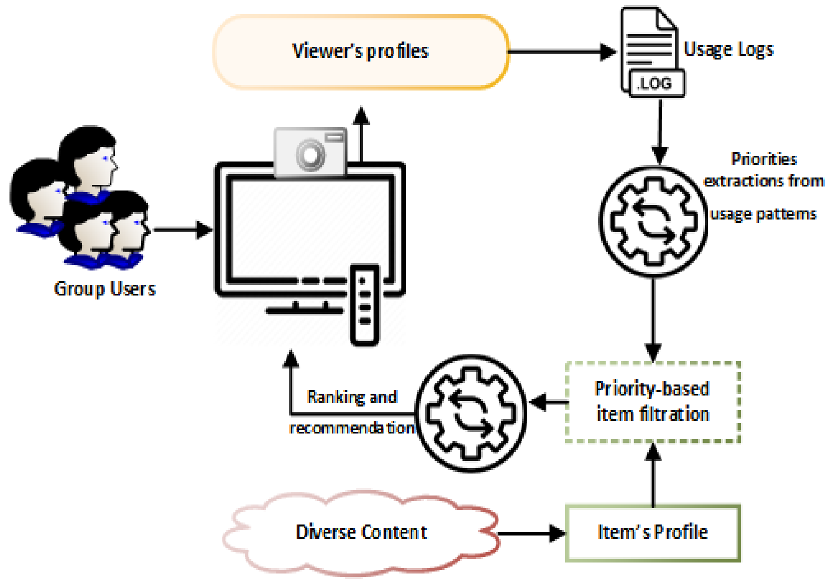

Figure 1: Schematic Diagram of the Proposed Approach

The comprehensive concept is presented in Table 1, outlining a path toward a more user-centric and impactful RS landscape.

Table 1: The proposed model approaches

Categories	Classes	Priority	Recommendation
Group of Users and Items	Super-user (group creator)	5 (highest)	Recommend items to whole groups of users
	Active Users	3 to 4.9 (medium)	Positive items Recommend to whole Groups of users
	Passive Users	1 to 2.9 (lowest)	Recommendation based on user's profile similarity

Table 2: Movie Lens/Group Lens dataset

25 Million Movie Ratings:	**A Wealth of User-Generated Ratings Provides Invaluable Insights into User Preferences.**
01-million tag applications:	A comprehensive set of tags applied to 62,000 movies, offering rich metadata.
15-million relevance scores:	These scores encompassing 1,129 tags provide a nuanced understanding of item relevance.
Data-set size:	A manageable 250MB, available in a convenient zip format.

To comprehensively evaluate the performance of our recommendation approach, the selection of a well-defined dataset is of paramount importance. As discussed, a well-established dataset Movie Lens/Group Lens dataset (see Table 2) has been used. It is a publicly available and stable benchmark dataset widely recognized for its appropriateness in evaluating recommendation systems. This dataset comprises an extensive collection, including:

This dataset serves as the cornerstone for evaluating our recommendation algorithm, as it offers a diverse range of user interactions and preferences, making it an ideal choice for conducting comprehensive assessments. The dataset can be directly accessed from the official website at (https://group-lens.org/datasets/movie-lens/).

Results and Analysis:

This section presents the performance results of our proposed Recommendation algorithm, comparing it with recent algorithms from the literature. To facilitate the work in Python, we have utilized various libraries, each serving a specific purpose, such as Pandas, NumPy, Matplotlib, Scikit-learn, and Operator. The proposed movie recommendation system places a strong emphasis on prioritizing movies for users with high priorities. Each user type has a distinct priority range and unique characteristics in the recommendation process. The suitable dataset for our case is the Movie Lens dataset. In this dataset, each movie has been rated on a scale from 1 to 5, and there's a requirement that each user must have rated a minimum of 20 movies. The movies are well-organized, with each movie having a unique ID along with its corresponding title and genre. Tables 3, 4, and 5 represent the rating data:

Table 3: Rating Dataset with Unique ID

S.No	User-Id	Movie-Id	Rating
0	1	31	2.5
1	1	1029	3.0
2	1	1061	3.0
3	1	1129	2.0
4	1	1172	4.0

Table 4: Count the user's ID and movie ID with the Rating

	Movie-Id	User-Id	Rating
Min	1	1	5
25%	15500	40500	3
50%	31000	81000	4
75%	46500	121500	4
Max	62000	162000	5

Table 5: Movie data-set frame

Movie-Id	Title	Genres	Year
1	Toy Story	Adventure, Animation, Children, Comedy, Fantasy	1995
2	Jumanji	Adventure, Children, Fantasy	1995
3	Grumpier Old Men	Comedy, Romance	1995
4	Waiting to Exhale	Comedy, Drama, Romance	1995
5	Father of the Bride Part II	Comedy	1995

The proposed methodology explains the process of assigning priorities to users and how to recommend items to users based on these priorities to ensure the delivery of relevant recommendations to the group of users.

Assigning Priorities:

The initial step in this process involves creating a user rating table that includes priority values and categorizes users into specific groups. Manually assigning priority values to each user can be a daunting and time-consuming task. To address this challenge, we have devised a method to automatically determine priorities based on the number of movies a user has rated. Essentially, users who have rated a higher number of movies will receive a higher priority, while those who have rated fewer movies will have a lower priority. The formula mentioned in the study [34] has been employed for assigning priorities is as follows:

$$P_{a,j} = \overline{r_a} + k \sum_{i=1}^{n} S_{(a,i)} \times r_{i,j} - \overline{r_i} \quad \textbf{(1)}$$

This approach ensures that users with more extensive engagement are accorded higher priorities, aligning the recommendations more closely with their preferences and interests. After applying these formulas to all users, we obtain a priority value for each user ranging from 0 to 5, reflecting the level of their engagement and activity. As previously mentioned, we categorize users based on their priority values, and the categorization process is as follows:

- If a user's priority is equal to 5, they are designated as a "super-user."
- If a user's priority falls within the range of 3 to less than 4.9, they are categorized as an "Active User."
- If a user's priority is less than 3, they are classified as a "Passive User."

Data Creation:

To streamline our process, we processed the entire rating data frame and extracted all the necessary information, which was then organized into JSON data format. The format for the JSON data is as follows: In addition to this, the categorization of users based on the priorities assigned can be found in Table 6.

Table 6: Category of the Users with Priority

User Id	Rating	Num-of-Movies	Priority	Star
547	3.366792	2391	5.000000	Super-user
564	3.552463	1868	3.897090	Active User
624	2.894236	1735	3.616617	Active User
15	2.621765	1700	3.542809	Active User
73	3.374224	1610	3.353016	Active User
452	3.189179	1340	2.783636	Passive User
468	2.965918	1291	2.680304	Passive User
380	3.366416	1063	2.199494	Passive User
311	3.006379	1019	2.106706	Passive User
30	3.765084	1011	2.089836	Passive User

The JSON dataset contains comprehensive user information. It includes the user ID, a list of positively rated movies with their corresponding movie IDs and ratings, a list of negatively rated movies with the same details, and each user's priority level. The users are organized based on their priorities, with the super-user user occupying index 0 and the user with the least priority at index -1.

The process generates a recommendation matrix using the Cosine similarity approach. Leveraging the rating data, a matrix to recommend movies is constructed tailored to each user. This matrix is created through a Cosine similarity calculation, which identifies similarities between users based on their ratings of the same movies. If two users share similar ratings for certain movies, it suggests they have similar tastes. With this insight, we can predict a user's movie preferences if another user has already watched and positively rated those films. To achieve this, we utilize the 'cosine similarity' function from the sci-kit-learn library.

At this point, all user data in JSON format is available, including their rated movies, and we possess the recommendation matrix generated using Cosine similarity. Now, our goal is to provide users with movie recommendations based on their priorities. When we receive a user ID, we first determine the user's category, which could be 'super-user,' 'active,' or 'passive.' Based on this categorization, we tailor our movie recommendations. In our current dataset, user 547 is classified as a super-user, while users 564, 624, 15, and 73 fall into the active category, with the remainder categorized as passive users. We will illustrate how recommendations are generated for each user category, focusing on three user IDs: the super-user (547), an active user (15), and a passive user (30). Note that we won't present all recommendations in detail due to their sheer volume, which could potentially obscure the essence of the recommendation process. Various movie recommendation types specifically aimed at the super-user shown in Table 7.

Table 7: Recommendation of Super-user with Positive Rating Movies

Movies Id	Title	Genres	Years	Ratings

17	Sense and Sensibility	Drama, Romantic	1995	5.0
111	Taxi Drivers	Crime, Dramas, Thrillers	1976	5.0
125	Flirting with disaster	Comedy	1996	5.0
176	Living in Oblivion	Comedy	1995	5.0
194	Smoke	Comedy, Drama	1995	5.0
246	Hoop Dreams	Documentary	1994	5.0
296	Pulp Fiction	Comedy, Crime, Thriller	1994	5.0
318	Shashank Redemption	Crime, Dramas	1994	5.0
448	Fearless	Drama	1993	5.0
527	Schindler's List	Dramas, Wars	1993	5.0

Table 8: Recommendation of Super-user with Negative Rating Movies

Movies Id	Title	Genres	Years	Ratings
6	Heat	Action, Crime, Thriller	1995	2.5
156	Blue in the Face	Comedy, Drama	1995	2.5
222	Circle of Friend	Dramas, Romances	1995	2.5
365	Little Buddha	Drama	1993	2.5
454	The Firm	Drama, Thriller	1993	2.5
549	Short Films About Glenn Gould	Drama, Musical	1993	2.5
708	The Truth About Cats and Dogs	Comedy, Romance	1996	2.5
805	A Time to Kill	Drama, Thriller	1996	2.5
1018	That Darn Cat	Children, Comedy, Mystery	1995	2.5
1050	Looking for Richard	Drama, Documentary	1996	2.5

The super-user, there are four distinct sets of guidelines in place. The foremost principle entails the exclusion of self-recommendations for the super-user, ensuring that their preferences are not factored into the equation. Furthermore, these recommendations are exclusively tailored for active users, thereby avoiding the clutter of suggestions for those who do not actively engage. Moreover, the scope of predictions extends solely to active users, with an emphasis on movies that have garnered positive ratings. It's essential to note that these active users are readily identifiable, as their user IDs are conveniently listed in the active user roster, all of whom exhibit a priority ranking exceeding 3.

Table 9: Recommendation of Active ID 564.0 with Priority 3.89

Movies Id	Title	Genres	Years	Ratings
22	Copycat	Crime, Drama, Horror, Mystery, Thriller	1995	5.0
25	Leaving Las Vegas	Drama, Romance	1995	5.0
30	Shanghai Triad	Crime, Drama	1995	5.0
36	Dead Man Walking	Crime, Drama	1995	5.0
39	Clueless	Comedy, Romance	1995	5.0
45	To Die	Comedy, Dramas, Thrillers	1995	5.0
46	How to Make an American Quilt	Dramas, Romance	1995	5.0
49	Night is Falling	Dramas, Romance	1995	5.0
50	The Usual Suspects	Crimes, Mystery	1995	5.0
52	Mighty Aphrodite	Comedy, Drama, Romance	1995	5.0

Table 10: Recommendation of Active ID 564.0 with Priority 3.89

Movies Id	Title	Genres	Years	Ratings
1	Toy Story	Adventure, Animation, Children	1995	5.0
16	Casino	Crime, Drama	1995	5.0
260	Star War: Epi 4, New Hope	Actions, Adventure's, Sci-Fi	1977	5.0

296	Pulp Fiction	Comedy, Crimes, Drama, Thriller	1994	5.0
593	The Silence of the Lambs	Crime, Horror, Thriller	1991	5.0
599	The Wild Bunch	Adventure, Western	1969	5.0
671	Mystery Science Theater	Comedy, Sci-Fi	1996	5.0
858	The Godfather	Crime, Drama	1972	5.0
1028	Mary Poppins	Children, Comedy, Fantasy, Musical	1964	5.0
1031	Bed knobs and Broomsticks	Adventure, Children, Musical	1971	5.0

Table 11: Recommendation of Active Id 15.0 with Priority 3.54

Movies Id	Title	Genres	Years	Ratings
47	aka Seven	Mystery, Thriller's	1995	5.0
50	The Usual Suspects	Crimes, Mystery, Thriller	1995	5.0
82	Antonia's line (Antonia)	Comedy, Drama	1995	5.0
111	Taxi Driver's	Crimes, Drama's, Thriller	1976	5.0
149	Amateur	Crime, Drama, Thriller	1994	5.0
246	Hoop dreams	Documentary	1994	5.0
260	Star War: Epi4 - New Hope	Action's, Adventure, Sci-Fi	1977	5.0
293	The Professional	Action's, Crimes, Dramas, Thriller	1994	5.0
296	Pulp Fiction	Comedy, Crimes, Drama's, Thriller	1994	5.0

Table 12: Recommendation of Active Id 73.0 with Priority 3.34

Movies Id	Title	Genres	Years	Ratings
1	Toy Story	Adventure, Animation, Children, Comedy	1995	5.0
32	Twelve Monkey's	Mystery, Sci-Fi, Thrillers	1995	5.0
47	aka Seven	Mystery, Thrillers	1995	5.0
50	The Usual Suspect	Crime, Mystery, Thriller	1995	5.0
215	Before Sunrise	Drama, Romance	1995	5.0
293	The Professional aka	Actions, Crimes, Dramas, Thriller	1994	5.0
296	Pulp Fiction	Comedy, Crimes, Drama's, Thriller	1994	5.0
318	The Shawshank Redemption	Crime, Drama	1994	5.0
356	Forrest Gump	Comedy, Drama, Romance, War	1994	5.0
364	The Lion King	Adventure, Animation, IMAX, Drama	1994	5.0

This example pertains to active user recommendations, with a focus on both positively and negatively rated movies for active users, followed by positively rated movies by all active users while excluding positively rated movies by the user itself, as the user falls under the "active" category. In a separate context, it's worth noting that passive users' movie recommendations encompass various categories and types.

Table 13: Recommendation using Cosine Similarity for Passive User

Recommendation using Cosine Similarity for Passive User				
Movies Id	**Title**	**Genres**	**Years**	**Ratings**
1	Toy Story	Adventure, Animations, Children's, Comedy	1995	2
356	Forrest Gump	Comedy, Drama, Romance, War	1994	2.5
480	Jurassic Park	Actions, Adventure, Sci-Fi, Thriller's	1993	2
593	The Silence of the Lambs	Crime, Horror, Thriller	1991	2
608	Fargo	Comedy, Crime, Drama, Thriller	1996	3
1196	Star War: The Empire Strike	Actions, Adventure	1980	2.5
1198	Raiders of the Lost Ark	Actions, Adventure's	1981	2

1210	War: Epi IV Return of the Jedi	Actions, Adventure, Sci-Fi	1983	2
1270	Back to the Future	Adventure, Comedy, Sci-Fi	1985	1
2858	American Beauty	Drama, Romance	1999	2

For passive users, the recommendation process mirrors the pattern mentioned above, with some additional considerations. The sequence of recommendations begins with positively and negatively rated movies by the super-user. Subsequently, positively rated movies by active users are presented as recommendations. Additionally, a final recommendation for passive users involves utilizing the cosine similarity matrix. In the context of performance evaluation and confusion metrics in the research, several key metrics will be employed. The formulas mentioned in the study [34] for precision, recall, and F-measures are outlined as follows:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F - measure = \frac{2(Precision * Recall)}{Precision + Recall} \quad (4)$$

Similarly, the confusion matrix, shown in Table 14, will be used that provide the base for precision, recall, and f-measure.

Table 14: The Confusion Matrix

		Predicted Value	
		Positive	**Negative**
Actual Value	**Positive**	TF	FN
	Negative	FP	TN

Cross-validation involves a process that begins with importing the necessary libraries from the scikit-learn (sklearn) model for cross-validation. Following this, the accuracy of the model is calculated and printed. Subsequently, K-fold cross-validation is performed to derive the mean scores of accuracies. In this context, cross-validation is a crucial step in assessing the performance of a model, and the sci-kit-learn library simplifies this process. By employing K-fold cross-validation, you can obtain a more robust measure of the model's performance by averaging accuracy scores across different subsets of the data.

First, we split the Movie Lens dataset into training and testing sets and then applied K-fold cross-validation techniques. To do this, we begin by randomly shuffling the ratings.csv file. Next, we extract a 5 percent segment of the dataset for testing purposes while reserving the remaining 95 percent for creating the training dataset. Subsequently, we generate predictions for each pair of movie IDs and user IDs. We then process the test set to obtain predictions for each user ID and movie ID pair using the confusion matrix and save these predictions as the predicted ratings shown in Table 15.

Table 15: Cross Validation

K-fold cross-validation accuracy	**0.941**
Mean Training Accuracy	0.951
Mean Training Precision	0.998
Mean Training Recall	0.988
Mean Training F1 Score	0.993
Mean Validation Accuracy	0.938
Mean Validation Precision	0.922

Mean Validation Recall	0.915
Mean Validation F1 Score	0.916

Discussion:

It is crucial to evaluate three distinct components: the recommendation of super-user movies, the recommendation of active-user movies, and the recommendation using cosine similarity.

Super-User Recommendation:

The recommendation for super-user movies demonstrates an almost 100% accuracy rate. This level of accuracy is achieved by directly extracting positive and negative movie selections from the ratings.csv dataset and presenting them in a hierarchical order. This method ensures precise recommendations for the super-user, as it's based on explicit data available in the dataset. The high accuracy in super-user recommendations suggests that this approach is highly effective, benefiting from the clear and direct data source. However, we should further examine the results for the recommendations to active users and those utilizing cosine similarity to provide a comprehensive evaluation.

Table 16: Confusion Matrix for Super-user

	Recall	Precision	F1-Score	Support
Recommended	0.98	0.98	1.00	743
Not Recommended	0.97	0.97	1.00	1542
Accuracy			1.00	2285
Macro Avg	1.00	1.00	1.00	2285
Weighted Avg	1.00	1.00	1.00	2285

Confusion Matrix for Super User

	Recommended	Not recommended
Recommended	743	0
Not recommended	0	1542

Figure 2: Graph of Confusion Matrix for Super-user.

Active User Recommendation:

An accuracy of 85% for the active users has been achieved, because of the selection of positively rated movies for all active users from the ratings.csv dataset and hierarchically present them.

Table 17: Confusion Matrix for Active Users

	Recall	Precision	F1-Score	Support
Recommended	0.85	0.89	0.81	2115
Not Recommended	0.87	0.85	0.81	3445
Accuracy	-	-	0.95	5560
Macro Avg	0.97	0.96	0.95	5560
Weighted Avg	0.968	0.96	0.958	5560

Confusion Matrix for Active User

	Recommended	Not recommended
Recommended	2115	0
Not recommended	0	3445

Figure 3: Graph of Confusion Matrix for Active.

Passive User Recommendations:

To accomplish this, a random shuffling of the ratings.csv dataset has been done. Next, a 5% portion of the data frame for testing purposes, while allocating the remaining 95% for calculating user similarity and creating the cosine similarity matrix. After generating a confusion matrix, predictions are obtained for every pair of movie IDs and user IDs. We then process the test set to acquire predictions for each user ID and movie ID pair from the confusion matrix, and these predictions are saved as the predicted ratings. The construction of this confusion matrix is based on each user's predicted ratings and the true ratings for the respective movies.

Table 18: Test Set to Get the Predictions

	User Id	Movie Id	Rating
60787	441	5952	4.0
46505	342	593	5.0
64532	461	2985	4.5
67765	472	2948	4.0
6201	33	1394	2.0

Table 19: Confusion Matrix for Passive Users

	Recall	Precision	F1-Score	Support
Recommended	0.51	0.58	0.54	2068
Not Recommended	0.52	0.45	0.48	2126
Accuracy	-	-	0.51	4194
Macro Avg	0.51	0.51	0.51	4194
Weighted Avg	0.51	0.51	0.51	4194

Figure 4 presents a comparative analysis of evaluation metrics, namely precision, recall, and F1-score, for all three types of users. In comparison to super and active users, the passive users received a lower score, attributed to the priorities assigned to this user type, as shown in Figure 4.

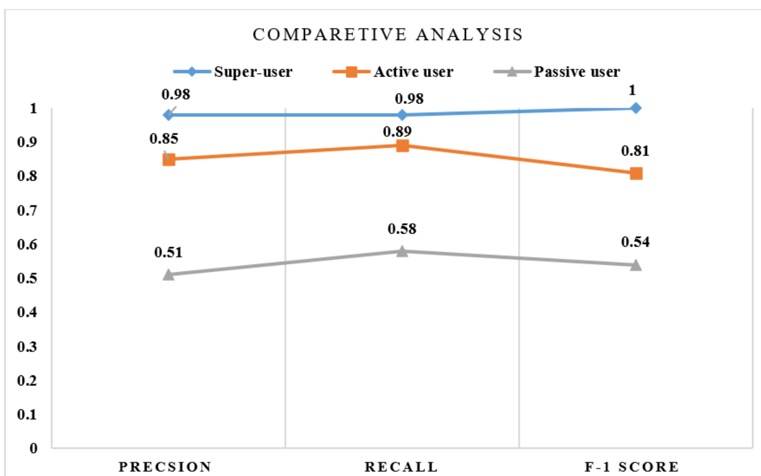

Figure 4: Comparative analysis of Precision, Recall, and F 1- Score for all three types of users

Conclusion and Future Work:

A prototypical implementation of a movie recommendation system has been developed that places special emphasis on movies favored by users with higher priority rankings. The users are categorized as super-users, active users, and passive users, each assigned distinct priority ranks, resulting in unique characteristics influencing the recommendations. This approach holds the potential to improve recommendation outcomes, ultimately converting visitors into customers, a metric often referred to as the conversion rate. The recommender system operates by discerning and accommodating users' preferences, assessing the similarity between items and users' profiles, and subsequently suggesting relevant items. The versatility of this system extends to various domains, including movies, travel, and music. A significant body of research has focused on developing filtering techniques that are both effective and efficient for users. This research contributes to the prioritization of user models, presenting a method for recommending suitable items to specific user groups. This approach addresses challenges related to user profiles, including modeling issues, to ensure the delivery of precise and pertinent recommendations to user groups. The user ranking model is implemented to filter and rank user profiles for recommendation purposes. By leveraging filters and ranking, this recommendation system enhances group recommendations and focuses on ranking social networking group discussions to deliver pertinent items to the right audience.

Limitations:

Besides, potential areas of interest, the study has some limitations and cannot be fit in one-size-fits-all scenarios. The proposed work only fits where we have groups of people.

Declarations:

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