Report on the Project: An Hybrid Approach to Sequential Group Movie Recommendations

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Abstract: In the era of digital media consumption, personalized recommendations play a key role in enhancing user experience. This paper introduces a new approach to sequential group movie recommendations, leveraging a hybrid method that combines aspects of averaging and least misery strategies. We deep into the implementation details, rationale behind method selection, and present experimental results demonstrating the efficacy of our approach.

1. Introduction: In the current landscape of online streaming platforms, users can choose among an extensive catalog of movies, TV shows, and other content options. Having so many choices can often lead to misleading decisions or difficulty in discovering content that aligns with their interests. To reduce this challenge and enhance the user experience, streaming platforms leverage recommender systems. These systems analyze users' past behaviors, preferences, and interactions with content to deliver personalized recommendations tailored to their individual tastes. Traditionally, recommender systems have primarily focused on catering to the preferences of individual users. These systems use techniques such as collaborative filtering or content-based filtering to suggest items that are likely to be of interest to a specific user based on their past interactions. While effective for individualized recommendations, this approach may overlook opportunities to serve groups of users who share similar preferences or are engaged in collaborative decision-making scenarios. However, there is a growing recognition of the importance of providing recommendations to groups of users, particularly in social contexts or collaborative environments. In social settings, such as families or friend groups, individuals often seek entertainment options that appeal to the collective interests of the group. Similarly, in collaborative environments such as project teams or study groups, members may benefit from jointly selecting content that aligns with their shared objectives or learning goals. Therefore, the evolving landscape of recommender systems has sparked interest in developing techniques and algorithms capable of generating recommendations tailored to groups of users. These group recommendation approaches aim to consider the collective preferences, behaviors, and interactions of multiple users simultaneously, thereby facilitating more inclusive and satisfying recommendation experiences in social or collaborative contexts.

2. Methodology: Our proposed methodology for sequential group movie recommendations integrates elements from averaging and least misery aggregation techniques. The process begins by calculating individual recommendations for each user in the group. Subsequently, an aggregation method is employed to combine these recommendations into a cohesive set of group suggestions. We introduce five aggregation strategies: averaging, least misery, sum, maximum and an hybrid approach that dynamically adjusts based on user satisfaction levels.

2.1. Pearson Correlation and Predicted Ratings: We utilize the Pearson correlation coefficient to measure the similarity between users' ratings and predict movie ratings for target users. This technique allows us to identify users with similar preferences and estimate how a target user might rate a movie based on the ratings of similar users.

2.2. Aggregation Strategies:

a. Averaging: This method computes the average predicted score for each movie across all users, providing a balanced recommendation based on collective opinions.

b. Least Misery: In contrast, the least misery approach selects the minimum predicted score for each movie, ensuring that even the least satisfied user's preferences are considered.

c. Sum: This method computes the sum predicted score for each movie across all users, providing a balanced recommendation based on collective opinions.

d. Maximum: This method computes the max predicted score for each movie across all users.

e. Hybrid Approach: The hybrid method dynamically combines averaging and least misery for the first and sum and maximum method for the second, based on the disparity between maximum and minimum satisfaction levels within the group (parameter alpha). This adaptive approach aims to optimize recommendations by balancing individual preferences and group consensus.

2.3. Sequential Group Recommendations with the two different approaches:

We extend our methodology to generate sequential group recommendations over multiple rounds. In each round, recommendations are generated for each user, and the recommended movies are removed from subsequent iterations to prevent redundancy.

The first hybrid aggregation method is employed iteratively, adjusting the balance between averaging and least misery based on user feedback.

We extend our methodology to generate sequential group recommendations over multiple rounds. In each round, recommendations are generated for each user, and the recommended movies are removed from subsequent iterations to prevent redundancy.

The first hybrid aggregation method is employed iteratively, adjusting the balance between averaging and least misery based on user feedback. To achieve this, we introduce a parameter called "alpha" that serves as a weight to balance the contributions of the two methods, namely averaging method and least misery method. When alpha is set to 0, only the contribution of the averaging method is considered; conversely, when alpha is set to 1, only the contribution of the least misery method is considered. In general, it is preferable to choose a value of alpha between 0 and 1, calculated as the difference between the maximum and minimum satisfaction levels within the group: alpha = max(group_satisfaction) - min(group_satisfaction). This approach dynamically adapts the hybrid aggregation process based on the variation in group satisfaction levels over the iterations.

The second hybrid approach calculates sequential group recommendations using a mixed approach that combines two different aggregation methods: sum aggregation method and max aggregation method. We used always the alpha parameter to combine the two aggregated methods. When alpha is set to 0, only the contribution of the sum method is considered; conversely, when alpha is set to 1, only the contribution of the maximum method is considered. In general, it is preferable to choose a value of alpha between 0 and 1, calculated as the difference between the maximum and minimum satisfaction levels within the group: alpha = max(group_satisfaction) - min(group_satisfaction).

In the sum_aggregate_method we sum up the predicted scores for each movie across all users. For each movie, it calculates the total score by summing up all predicted scores.

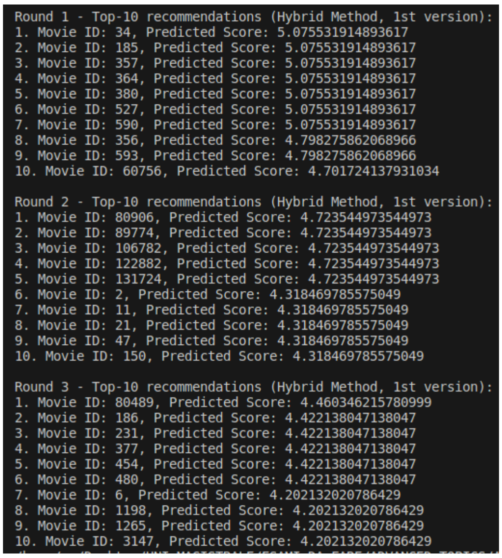
In the max_aggregate_method we aggregate recommendations by selecting the maximum predicted score for each movie across all users. For each movie, it selects the maximum score from the list of predicted scores.

I chose this combination of methods because it offers a more nuanced way to aggregate recommendations compared to simply using the average or least misery methods alone. By incorporating both the sum and max aggregation methods and adjusting the alpha parameter between 0 and 1, we can strike a balance between maximizing group satisfaction and considering individual preferences. This hybrid approach allows for greater flexibility in recommendation generation, as it can adapt to different scenarios and user requirements more effectively. Compared to the hybrid method using the average and least misery, this approach provides a wider spectrum of recommendation possibilities, catering to a broader range of user preferences and group dynamics. In the hybrid method with average and least misery, recommendations are aggregated by taking the average predicted score for each movie across all users, while also considering the movie with the highest predicted score for each user individually. This approach aims to balance group satisfaction and individual preferences. On the other hand, in the current method with sum and max aggregation, recommendations are combined by summing up the predicted scores for each movie across all users and selecting the movies with the highest total scores. Additionally, the movie with the highest predicted score for each user is also considered. This method emphasizes maximizing overall group satisfaction while still taking into account individual user preferences.

In summary, while both methods aim to balance group satisfaction and individual preferences, the current method offers a different approach by focusing on maximizing total group satisfaction through sum aggregation while still considering individual preferences through max aggregation.

3. Experimental Evaluation: To evaluate the effectiveness of our approach, we conducted experiments using the MovieLens 100K dataset. We selected groups of 3 users **[2,8,24]** and generated sequential recommendations over multiple rounds (3). We compared the performance of our first hybrid method against the second hybrid method.

3.1. Results: Our experimental results demonstrate that the first hybrid approach finds lower results respect to the second hybrid method. In summary, the second hybrid method (sum and maximum) might yield higher results than the first hybrid method (average and least misery) due to its greater sensitivity to maximum scores and potential distribution of predicted scores in the data.



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Round 1 - Top-10 recommendations (Hybrid Method, 1st version):
1. Movie ID: 34, Predicted Score: 5.075531914893617
2. Movie ID: 185, Predicted Score: 5.075531914893617
3. Movie ID: 357, Predicted Score: 5.075531914893617
4. Movie ID: 364, Predicted Score: 5.075531914893617
5. Movie ID: 380, Predicted Score: 5.075531914893617
6. Movie ID: 527, Predicted Score: 5.075531914893617
7. Movie ID: 590, Predicted Score: 5.075531914893617
8. Movie ID: 356, Predicted Score: 4.798275862068966
9. Movie ID: 593, Predicted Score: 4.798275862068966
10. Movie ID: 60756, Predicted Score: 4.701724137931034

Round 2 - Top-10 recommendations (Hybrid Method, 1st version):
1. Movie ID: 80906, Predicted Score: 4.723544973544973
2. Movie ID: 89774, Predicted Score: 4.723544973544973
3. Movie ID: 106782, Predicted Score: 4.723544973544973
4. Movie ID: 122882, Predicted Score: 4.723544973544973
5. Movie ID: 131724, Predicted Score: 4.723544973544973
6. Movie ID: 2, Predicted Score: 4.318469785575049
7. Movie ID: 11, Predicted Score: 4.318469785575049
8. Movie ID: 21, Predicted Score: 4.318469785575049
9. Movie ID: 47, Predicted Score: 4.318469785575049
10. Movie ID: 150, Predicted Score: 4.318469785575049

Round 3 - Top-10 recommendations (Hybrid Method, 1st version):
1. Movie ID: 80489, Predicted Score: 4.460346215780999
2. Movie ID: 186, Predicted Score: 4.422138047138047
3. Movie ID: 231, Predicted Score: 4.422138047138047
4. Movie ID: 377, Predicted Score: 4.422138047138047
5. Movie ID: 454, Predicted Score: 4.422138047138047
6. Movie ID: 480, Predicted Score: 4.422138047138047
7. Movie ID: 6, Predicted Score: 4.202132020786429
8. Movie ID: 1198, Predicted Score: 4.202132020786429
9. Movie ID: 1265, Predicted Score: 4.202132020786429
10. Movie ID: 3147, Predicted Score: 4.202132020786429
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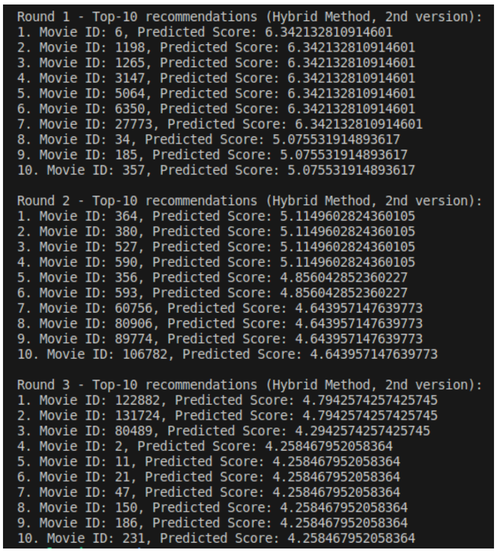

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Round 1 - Top-10 recommendations (Hybrid Method, 2nd version):
1. Movie ID: 6, Predicted Score: 6.342132810914601
2. Movie ID: 1198, Predicted Score: 6.342132810914601
3. Movie ID: 1265, Predicted Score: 6.342132810914601
4. Movie ID: 3147, Predicted Score: 6.342132810914601
5. Movie ID: 5064, Predicted Score: 6.342132810914601
6. Movie ID: 6350, Predicted Score: 6.342132810914601
7. Movie ID: 27773, Predicted Score: 6.342132810914601
8. Movie ID: 34, Predicted Score: 5.075531914893617
9. Movie ID: 185, Predicted Score: 5.075531914893617
10. Movie ID: 357, Predicted Score: 5.075531914893617

Round 2 - Top-10 recommendations (Hybrid Method, 2nd version):
1. Movie ID: 364, Predicted Score: 5.1149602824360105
2. Movie ID: 380, Predicted Score: 5.1149602824360105
3. Movie ID: 527, Predicted Score: 5.1149602824360105
4. Movie ID: 590, Predicted Score: 5.1149602824360105
5. Movie ID: 356, Predicted Score: 4.856042852360227
6. Movie ID: 593, Predicted Score: 4.856042852360227
7. Movie ID: 60756, Predicted Score: 4.643957147639773
8. Movie ID: 80906, Predicted Score: 4.643957147639773
9. Movie ID: 89774, Predicted Score: 4.643957147639773
10. Movie ID: 106782, Predicted Score: 4.643957147639773

Round 3 - Top-10 recommendations (Hybrid Method, 2nd version):
1. Movie ID: 122882, Predicted Score: 4.7942574257425745
2. Movie ID: 131724, Predicted Score: 4.7942574257425745
3. Movie ID: 80489, Predicted Score: 4.2942574257425745
4. Movie ID: 2, Predicted Score: 4.258467952058364
5. Movie ID: 11, Predicted Score: 4.258467952058364
6. Movie ID: 21, Predicted Score: 4.258467952058364
7. Movie ID: 47, Predicted Score: 4.258467952058364
8. Movie ID: 150, Predicted Score: 4.258467952058364
9. Movie ID: 186, Predicted Score: 4.258467952058364
10. Movie ID: 231, Predicted Score: 4.258467952058364
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4. Conclusion and Future Work: In this paper, we presented two novel hybrid approach to sequential group movie recommendations, combining elements of averaging and least misery aggregation and sum and max aggregation. Our methodology offers a flexible and adaptive solution that balances individual preferences and group dynamics. Future research could explore additional factors for dynamic aggregation, such as user trust levels or context-aware preferences, to further enhance recommendation accuracy and relevance.

References: [1] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer, 42(8), 30-37. [2] Burke, R. (2002). Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12(4), 331-370. [3] Resnick, P., & Varian, H. R. (1997). Recommender systems. Communications of the ACM, 40(3), 56-58.