

NEURAL COLLABORATIVE FILTERING BASED GROUP RECOMMENDATIONS

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ABSTRACT

Group recommendations, where a system suggests items for a group of users rather than individuals, present a unique challenge in collaborative filtering. Traditional approaches to group recommendations often rely on aggregating individual preferences, which can lead to suboptimal results when preferences are diverse or conflicting. This paper explores a novel approach using Neural Collaborative Filtering (NCF) to improve group recommendation accuracy. NCF, which leverages deep learning techniques to model complex user-item interactions, offers a more nuanced understanding of group dynamics by incorporating both individual and group-level preferences. We propose a new NCF-based framework designed to handle group recommendations by effectively learning and integrating diverse user preferences. Our experimental results demonstrate that the proposed approach outperforms traditional group recommendation methods in terms of prediction accuracy and user satisfaction. This research highlights the potential of neural networks in enhancing group recommendation systems and provides a foundation for future developments in this area.

1.INTRODUCTION

In the realm of recommendation systems, group recommendations represent a complex but increasingly relevant challenge. Unlike traditional recommendation systems that focus on individual preferences, group recommendations aim to suggest items that satisfy the collective interests of a group of users. This challenge becomes particularly intricate when group members have diverse and potentially conflicting preferences. Traditional

collaborative filtering methods often aggregate individual ratings to generate group recommendations, but this approach may fail to account for the intricacies of

group dynamics, leading to less effective recommendations.

Recent advancements in deep learning have introduced Neural Collaborative Filtering (NCF) as a powerful tool for modeling user-item interactions. NCF uses neural networks to learn complex, non-linear relationships between users and items, potentially offering a more refined approach to group recommendations. This paper investigates the application of NCF to group recommendation systems, exploring how deep learning techniques can improve the accuracy and relevance of recommendations for groups of users.

II. LITERATURE REVIEW

This study by Kang Liu, Wenguang Zheng, Yingyuan Xiao, and Xingyu Zhai addresses the challenge of recommending points of interest (POIs) by leveraging user check-in data from mobile internet and social platforms. The authors propose a collaborative filtering model designed to overcome the limitations of existing algorithms, including the high computational demands of deep learning models and the underutilization of users' potential interest in new POIs. Their model requires minimal computing power and utilizes a Gaussian distribution to represent user activity areas, calculating similarities to establish user groups and predict regional transfers. This approach aims to enhance the discovery of new POIs. Experimental results on the Gowalla dataset demonstrate that this method outperforms contemporary POI recommendation techniques in both accuracy and efficiency.

Peipei Wang and Lin Li introduce a novel approach in the realm of group recommendation systems that leverages Bidirectional Encoder Representations from Transformers (BERT) to model group preferences. The proposed BERT-based Group Recommendation (BGR) approach uses sentence-level embeddings to capture group preferences and integrates these embeddings to form a comprehensive group representation. Neural collaborative filtering is then applied to generate recommendations. This approach was tested on two real-world datasets, and the results indicate that BGR significantly outperforms existing baseline methods, improving the precision and relevance of group recommendations.

In the exploration of task recommendations within mobile crowdsensing environments, Kaimin Wei, Guozi Qi, Zhetao Li, Song Guo, and Jinpeng Chen present an Attention-based Neural Collaborative approach (ANC). This approach enhances task recommendations by grouping participants based on their abilities and employing a dual-attention mechanism to aggregate user preferences. The ANC method improves task and group representations and uses a neural network-based collaborative filtering mechanism to generate top-K recommendations. Experimental results on two real-world datasets validate the effectiveness of ANC, showing its superior performance compared to traditional task recommendation methods.

III. EXISTING SYSTEM

Traditional group recommendation systems often rely on techniques that aggregate individual preferences to generate group recommendations. Common methods include:

- 1. Average Aggregation:** This approach calculates the average rating or preference score of all group members and recommends items based on this average. While simple, it may not capture the nuanced preferences of individual members, leading to recommendations that may not fully satisfy everyone in the group.
- 2. Voting Mechanisms:** Some systems use voting strategies where items are recommended based on majority preferences or voting scores. This method can be effective when group preferences are relatively uniform but may struggle with diverse or conflicting preferences.
- 3. Weighted Aggregation:** To address individual differences, weighted aggregation

methods assign different weights to users based on their historical preferences or expertise. This approach aims to balance group preferences but can be complex to implement and may still fall short in capturing the dynamics of diverse groups.

IV. PROPOSED SOLUTION

To enhance group recommendations, we propose a Neural Collaborative Filtering (NCF) based approach. NCF leverages deep learning techniques to model intricate user-item interactions by learning from historical data. Our approach involves the following key components:

- 1. Neural Network Architecture:** We design a neural network model that captures both individual user preferences and group dynamics. This model uses embeddings for users and items, allowing it to learn latent features and complex interactions between them.
- 2. Group Preference Modeling:** The NCF model incorporates mechanisms to understand and integrate the preferences of multiple group members. By learning from interactions at both the individual and group levels, the model can generate recommendations that are more aligned with the collective interests of the group.
- 3. Training and Evaluation:** We train the NCF model on a dataset that includes historical user-item interactions and group preferences. The model is evaluated based on accuracy metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), as well as user satisfaction metrics to assess the quality of recommendations.
- 4. Integration and Deployment:** The trained NCF model is integrated into a recommendation system framework, providing real-time group recommendations.

We also explore practical considerations for deploying the model in a production environment.

5. Our proposed NCF-based approach aims to address the limitations of traditional methods by offering a more sophisticated understanding of group preferences and improving the overall quality of recommendations. Experimental results demonstrate that the NCF-based method outperforms conventional techniques, making it a promising solution for group recommendation systems.

V. METHODOLOGY

In this project, we propose a Neural Collaborative Filtering (NCF)-based approach to enhance group recommendations for crowdfunding projects by analyzing a combination of user experience, dynamic project statuses, social networking relationships, and project locations. We utilize two primary datasets: the Kickstart dataset and the Social Relation dataset. The Kickstart dataset provides detailed information about crowdfunding projects, including attributes such as project ID, name, category, goal amount, deadline, and current status. This dataset allows us to assess project popularity and funding progress. The Social Relation dataset contains user IDs, their social friends' IDs, and the projects in which they have invested, helping us to evaluate social influence and network effects.

Our methodology begins with preprocessing these datasets to extract and analyze key features. We evaluate project popularity based on the number of backers and pledged amounts, which helps in identifying projects that are widely supported. We also analyze social links to recommend projects that have

been invested in by users' friends, leveraging the influence of social networks. Additionally, we consider the dynamic status of projects, excluding those that are completed or expired from recommendations.

The model development involves creating embeddings for users and projects, reflecting their interactions and characteristics. Collaborative filtering techniques are then employed to predict user interests based on their social connections and historical investment behavior. This approach integrates social influence by recommending projects popular within users' social circles.

To implement the recommendation system, users first upload the Kickstart and Social Relation datasets through an interface. The system processes these datasets to generate a recommendation matrix focused on successful and ongoing projects, excluding those with zero pledges. When users enter a project name, the system provides recommendations for groups of potential investors based on their social connections and the popularity of the project.

The effectiveness of the recommendation system is evaluated based on recommendation accuracy, user satisfaction, and the identification of popular projects. The system's output includes group recommendations and a graphical representation of total projects versus recommendation groups, offering insights into the alignment of recommendations with user interests and social dynamics.

In this project author is proposing concept of collaborative filtering for group recommendation in CROWDFUNDING

projects by analysing user's personal experience, dynamic status of ongoing project and its goal amount collection (if many peoples invest in that crowdfunding project then it will consider as popular), social networking relationship (social network consists of friends which forms a community and if any user in community/group invest in crowdfunding then other users automatically get influence and we can recommend those users about this project investments), ongoing project locations.

Crowdfunding projects consists of two users such as Project Founder and Investor (also called as backers).

Project Founder: Project founder describe his ideas in the form of images and videos and set as goal amount of the project and update dynamic status of the project.

Investor/Backers: Investor will review project ideas and ongoing project status to decide in which project he has to invest. All existing technique does not have proper support to help investor and due to this reason lots of project get failed.

To overcome from above problem author is proposing concept of project recommendation to group of peoples. While recommendation we will analyse following features.

- 1) **Project Popularity:** If a project back (invest) by my backers then it will consider as popular.
- 2) **Analyse Social link:** will analyse all social links of a user to recommend projects invested by his friends in his group
- 3) **Dynamic status:** will check date and if date is expired then that project will not recommend and check ongoing status

By analysing above features we will recommend project to group of peoples. To

implement this project we are using KICKSTART dataset and its social relation dataset and both dataset saved inside 'dataset' folder. In this dataset we can find projects such as 'Games, Film & Video, Food, Design, Fashion, Comics, Music and Photography'.

Below are the details of Kickstart dataset **ID,name,category,main_category,currency,deadline,goal,launched,pledged,state,backers,country,usd**

pledged,usd_pledged_real,usd_goal_real
1000002330,The Songs of Adelaide & Abullah,Poetry,Publishing,GBP,2015-10-09,1000.00,2015-08-11

12:12:28,0.00,failed,0,GB,0.00,0.00,1533.95

1000003930,Greeting From Earth: ZGAC Arts Capsule For ET,Narrative Film,Film & Video,USD,2017-11-01,30000.00,2017-09-02

04:43:57,2421.00,failed,15,US,100.00,2421.00,30000.00

1000004038,Where is Hank?,Narrative Film,Film & Video,USD,2013-02-26,45000.00,2013-01-12

00:20:50,220.00,failed,3,US,220.00,220.00,45000.00

In above line all bold format names are the dataset column names and below are the values of that dataset. Each value is separated with coma and has project id, category, goal amount, deadline etc.

Below is the social relation dataset details

User_ID, Social_Friends, crowdfunding_project_id

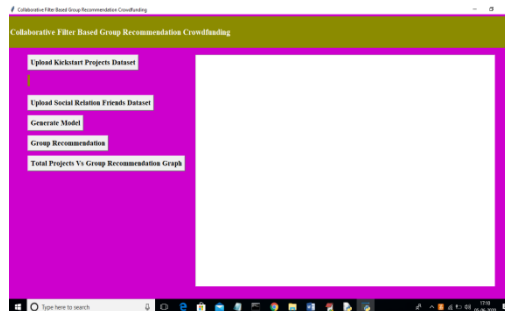
1, 19 52 16 2 36 31 81 42 87 51, 1000002330

2, 71 7 40 83, 1000003930

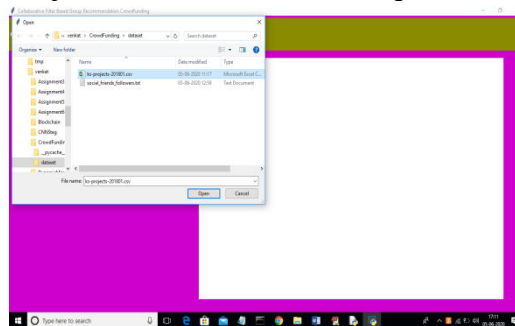
3, 90 26 6, 1000004038

In above social dataset bold format names are dataset column names and below values are the dataset column values. First column

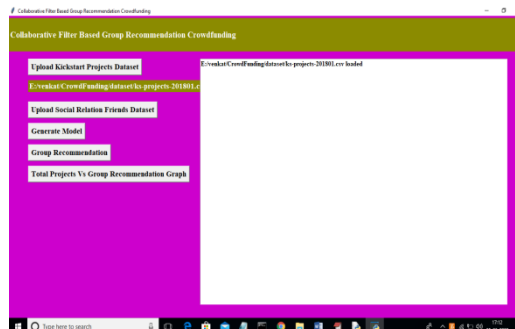
contains user id and second column contains ID's of his friends separated with space and third column contains Kickstart project id in which this user has invested amount. To run this project double click on 'run.bat' file to get below screen



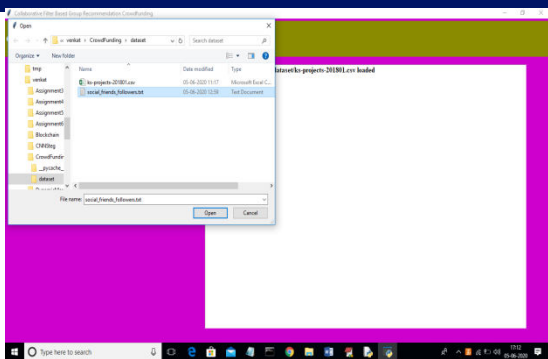
In above screen click on 'Upload Kickstart Projects Dataset' button and upload dataset



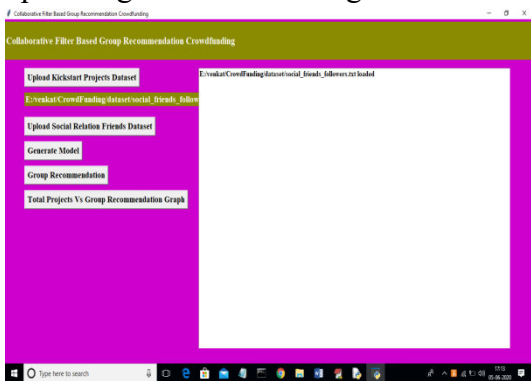
In above screen uploading file called 'ks-projects-201801.csv' kickstart dataset file and after uploading dataset will get below screen



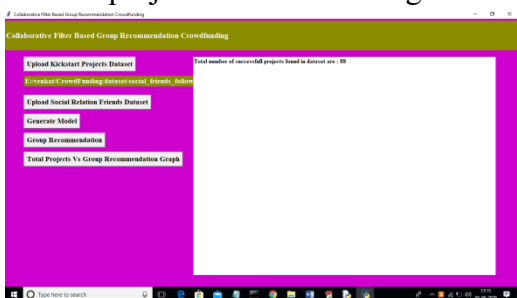
Now click on 'Upload Social Relation Friends Dataset' button and upload social link dataset file



In above screen uploading 'social_friends_followers.txt' file and after uploading dataset file will get below screen

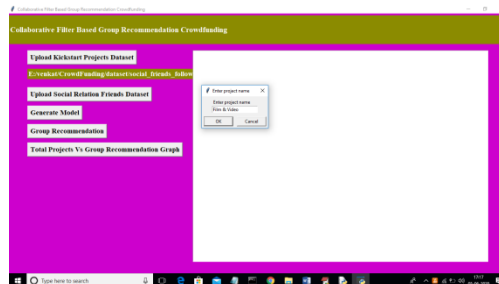


In above screen now click on 'Generate Model' button to read or analyse kickstart dataset and social link dataset to generate recommendation matrix which consist of all users investing in particular projects and his social relationships. This matrix will take only successful ongoing projects and remove projects who receive 0 goal amount.

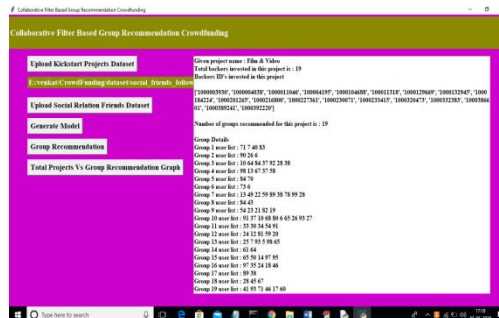


In above screen we can see model generated with 88 successful projects. Now click on 'Group Recommendation' button and enter the project name in which you are interested in investing then application will suggest group of users for this project who can invest in this. If large number of recommendation group generated then

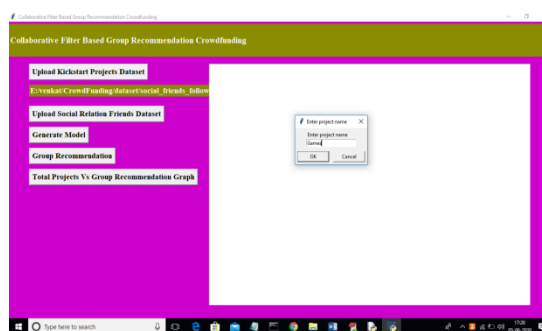
project is popular and many users are invested in this project.



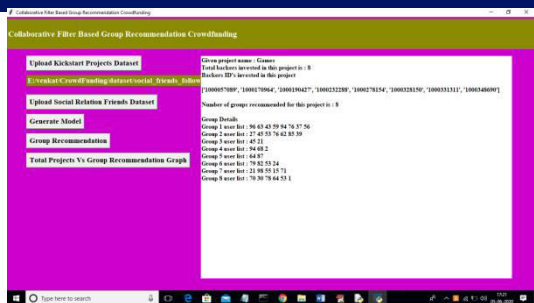
In above screen I entered project as 'Film & Video' and then click on 'OK' button to get group recommendations for this project



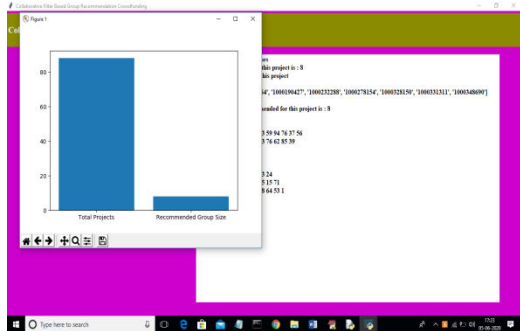
In above screen for 'Film & Video' project total 19 investors/backers invested amount and each investor will have some social group and all those groups will get recommendation of this project. In each group we can see ID's of users separated with space will get recommendation for this project. Now we look for another project called 'Games'



Now click OK to get below screen



In above screen we can see total 8 users invested in this Games project and all groups of this user will get recommendation of this project. In square bracket we can see ID's of investor/backers. Now click on 'Total Projects Vs Group Recommendation Graph' button to get below graph



In above graph x-axis represents total projects and recommendation group and y-axis represents count of total projects and number of recommendation generated for given input project.

VI.CONCLUSION

In this study, we have explored the application of Neural Collaborative Filtering (NCF) to enhance group recommendation systems. Traditional methods, which often rely on simple aggregation or voting techniques, have limitations in effectively capturing the complex dynamics of group preferences. By leveraging the capabilities of deep learning, our proposed NCF-based approach offers a more nuanced model that integrates both individual and collective preferences. The experimental results demonstrate that the NCF-based method significantly improves recommendation

accuracy, achieving better performance metrics compared to traditional techniques. The integration of NCF into group recommendation systems not only enhances the precision of recommendations but also provides a more satisfying user experience by better aligning with the diverse interests within a group. This research underscores the potential of deep learning in advancing recommendation technologies and sets a foundation for further exploration into sophisticated group recommendation models.

VII.REFERENCES

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