GroupRec: Group Recommendation by Numerical Characteristics of Groups in Telegram

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Davod Karimpour
dept. of Computer Engineering
Yazd University
Yazd, Iran
dkarimpoor@stu.yazd.ac.ir

Mohammad Ali Zare Chahooki
dept. of Computer Engineering
Yazd University
Yazd, Iran
chahooki@yazd.ac.ir

Ali Hashemi
dept. of Computer Engineering
Yazd University
Yazd, Iran
alihashemi@stu.yazd.ac.ir

***Abstract*— Today, recommender systems are used in many different businesses to find items of interest to users. The use of these systems is widely found in online economic systems and social networks. Therefore, using these systems in the messaging environment will cause changes and transformations for marketing. Telegram is a cloud-based messenger with more than 500 million monthly active users. This messenger has a relatively acceptable position compared to its other competitors, because the security and features provided in it, have made it different from other messengers and close to social networks. One of the most popular features of messengers is groups. Many marketers are looking for groups that fit their field. One of the main gaps in the messengers regarding advertising and marketing to expand businesses is the impossibility of finding social groups. In this paper, a new method for group recommendation in the Telegram is presented. This method, by receiving a set of users, analyzes their groups and recommends a list of ranked groups. The proposed method is created by combining the previous two methods in the field of group recommendation and computational modeling of numerical variables obtained from each group. This study is dependent on the information of all users due to the use of the membership graph, and the behavior of the system changes by the information extracted from the users. The results of experimental experiments show a significant reduction of RMSE and MAE in the proposed method compared to the previous two methods.**

Keywords*— *Recommendation of social groups, Telegram, social networks (online), computational modeling, business.

I. Introduction

Today, online social networks (OSN) and messengers play an important role in advancing the goals of human life. Every day, a lot of information is generated by users in these environments, and analyzing this information is very important to identify users' interests. In addition, This information is very valuable for marketers to reach their target audience.

In the past, targeted marketing based on messages has been common, and now, due to the increase of virtual businesses, this type of marketing has become more popular on social networks and messengers. For example, for a marketer, it is very important to find a group of targeted customers to promote their products.

Telegram was created in 2013 as an instant messenger. This messenger has 500 million monthly active users, of which more than 50 million are Iranians [3]. Telegram is very popular in Iran and is used as a social network due to providing features beyond a messenger. Telegram offers many services including channel creation, the group with unlimited members, and bots. In recent years, the widespread use of Telegram by users has led to research in the fields of security [4], media [5-6], politics [7], linguistics [8-9], marketing [10-11], and tourism [12].

Most messenger software provides group creation. Users join different groups to discuss and exchange ideas on topics of interest to them. Due to the large number of these groups and the impossibility of searching for groups in the messenger platform, users have difficulty finding their favorite groups. The Telegram search engine has the ability to search for groups, but is very limited and cannot provide all related groups. Therefore, finding a group is important for marketers. Telegram marketing is now non-targeted, with marketers looking for relevant groups in their field without any preconditions to advertise in those groups. To advance this goal, marketers join different groups and post their ads. Some groups charge marketers to send advertisements so that the advertisements can be seen by group members for a certain period of time. These methods are very difficult for marketers to find groups. Especially since the presentation of fake statistics of members of groups and channels by profiteers is very high. To develop marketing in Telegram, a system is needed to analyze the interests of users in different groups and finally recommend a list of groups. The best way to analyze users' interests is to use recommender systems.

Recommender systems are a subset of information filtering systems. The goal in these systems is to filter the information so that only the information remains relevant to the user's interest. Recommender systems have different items to recommend. For example, movie recommendations, news, web pages, friends on social networks are practical examples of these systems. Many social networks, including Twitter, Facebook, Google Plus, and LinkedIn, have been developed through Recommendation systems [13]. Recommender systems have many methods depending on the amount of information extracted from users. This paper provides a solution for recommending groups related to users' interests. The proposed method is in the category of collaborative filtering because it takes into account the records and interests of users.

The Telegram search engine is global. This means that Telegram offers group, channel, and user searches in one section. In addition, Telegram does not provide a feature for marketing, which is why Idekav has emerged as a service to search for channels and groups for marketing. Idekav monitors Telegram's public channels and groups full-time to

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extract all their information. Unlike Telegram, this system provides a separate search engine to find groups and channels.

Idekav in the group search section shows a list of groups by receiving a query. Also in this system, there is an option for each group to recommend related groups. Group recommender in Idekav [1], recommends all group members at a glance. To meet this need and add users' past records, a paper [2] has been created. In paper [2], a method has been developed to model the maximum migration of users between groups. The problem with both [1] and [2] is that in the list of final recommender groups, there are always groups with a large number of members at the top of the list, and this means that groups with a small number of members have no When they cannot get to the top of the list of recommendations. In this paper, by solving the problem and improving the results by numerically varying the number of members in each group, and normalizing it, we have not only solved the existing problem but also significantly reduced the error compared to the previous two methods. In addition, by analyzing the results of the recommendations, the proposed method has more thematic variety and diversity in the recommended groups than the previous two methods. The proposed method is very effective in offering social groups to users for targeted advertising.

In this paper, considering the membership graph and user records, the two methods of the recent researches in [1] and [2] have been combined, then the results have been improved by using computational modeling. The dataset of this paper is the information of groups and real Telegram users that has been crawled by Idekav. In this study, a heterogeneous graph has been used that this graph has two types of group nodes and user nodes. The number of user and group nodes in this graph includes more than 125 million users and 920,000 groups.

The rest of the paper is as follows. Section 2 describes the related works. Section 3 explains the proposed method. Section 4 describes the dataset and the experimental results, and then the conclusions and future work are presented in Section 5.

II. RELATED WORKS

In recent years, the study of instant messaging networks as a new line in research has aroused the interest of researchers and the analysis of data extracted from these environments. Telegram, as an instant messenger, has attracted the attention of many researchers and marketers. This messenger has two popular components, group, and channel among its users. Many studies have been conducted with data extracted from channels and groups. Some of these studies include channel recommendation [14], spam message categorization [15], user recommendation [16], group quality [17], and identification of viral features of posts in the channel [18].

In previous studies, recommender systems have been examined from various aspects of social networks. These systems have been created to reduce the search and make it easier to find items of interest to users. In general, in many recommendation systems, the user's favorite items are books [19], music [20], and friends. But specifically in some social networks, the recommendations are based on the features of that social network, such as the tweet recommendation on Twitter [21] and the job recommendation on LinkedIn [22]. In this paper, the items recommended to users are the Telegram group. Due to the novelty of the subject, only studies [1] and [2] such as this study have considered the group's recommendation and so far no other research has been conducted in accordance with the intended purpose.

In the following, the methods of recommender systems in social networks and messengers are examined. Recommender systems are divided into different categories based on the amount of information extracted from users. The three most widely used categories in these systems are content-based filtering, collaborative filtering, and hybrid filtering. Many studies have been presented in the context of recommending systems based on three methods based on content, collaborative, and hybrid filtering, some of which are reviewed below.

A. Content-based filtering

This filtering only makes decisions based on a user's activities and information. This method mostly uses the user's profile information, posts, and personality information for recommend and does not pay any attention to other users' information [2]. Jiménez-Bravo et al. [23] have provided a method to model and recommend expert users using each user's profile information on the LinkedIn social network. The recommended expert is selected based on the content of the tweets they publish and whether this content is of interest to the user.

B. Collaborative filtering

This filtering takes into account the information of all users, unlike the content-based approach. In this method, by modeling the past and present interests of the user, the desired items are recommended to the target user based on other users' experiences [2]. A state-of-the-art method using trust information to solve the problem of scattering and cold start using data extracted from the social networks Epinions and FilmTrust has been proposed recently [24]. In this paper, for enhancing the recommender systems, after pre-processing the data, the non-negative matrix analysis algorithm and combining it with trust information is used, which well illustrates the ranking of users, for the target user. In another study [25], a novel way to protect users' privacy in recommender systems using Epinions social network data has been proposed. This study uses an unidentified way to change secondary data without user identity information. The trust data are measured in terms of similarity and trust-weighted criterion and then transformed from perturbation-based chaos to secret data. Finally, fuzzy c-ordered means and particle swarm optimization algorithms are used for data clustering. Shambour [26] has offered a method to movie recommendation on TripAdvisor and Yahoo social networks. This study proposed a deep learning based algorithm for multi-criteria recommender systems. Joorabloo et al. [27] have offered a method to solve precision-diversity problem on Movielens, Netflix, and Goodbooks social networks. This study proposed a new method to recommend items which are fit to users' preferences, and consists of two steps. In the first step, user preferences are obtained. In the second step, there is a graph-based recommending system to recommend items with the desired level of precision and diversity. Isufi et al. [28] have offered a method to Accuracy-diversity on MovieLens social network. This study creates a method that learns joint convolutional representations from the nearest neighbor and the furthest neighbor graph to establish a novel accuracy-diversity for recommender systems. Hamidzadeh et al. [29] have offered a method to predict user preferences over data extracted from six social networks. This study provides a new one-class classifier to predict ratings. This method estimates the shared informative neighbors of each user by a probability fuzzy rough set method. An online recommender system using user preferences on twelve real datasets extracted from social networks has been presented recently [30]. The purpose of this method is to find and adopt the changes in user's ratings, while predicting the next plausible items by examining differences in the user's preferences. Moreover, a novel way to solve the Top-k recommendation problem in recommender systems using seven real datasets has been proposed [31]. This study introduces a method to impute ratings to missed components of the rating matrix. To better enhance the accuracy of Top-k recommender systems, first filled the missing ratings and then made the Top-k recommendation list.

C. Hybrid filtering

This filtering tries to eliminate the shortcomings of other methods by combining two or more filtering methods. Karimpour et al. [16] offered a hybrid method for recommending users to a user group based on the content extracted from the groups. Their method is a combination of two content and collaborative filtering. They used natural language processing methods to make a bag of words for each group, and then recommended users from the groups by searching the most obtained groups. Berkani [32] offered a hybrid method to friend recommendation on the Yelp social network. The method proposed in this paper is a combination of community-based filtering and semantic and social recommendation. The semantic section explains a friend's recommendation based on the similarity between each user and his friends, and the social section examines the user's behavior, including the degree of friendship.

III. Proposed method

In general, this research combines the methods of the papers [1] and [2] and has improved the results by computational modeling. In the following, the recommender of the group presented in [1] is expressed by the first method and the recommender of the group presented in [2] is expressed by the second method. Finally, the third method describes the proposed solution and method. The following variables are considered to facilitate the expression of each of the methods.

- P_i: Incoming users. The i index represents each user ID.
- C_{ij}: The status of user i in group j is current.
- F_{ij}: The status of user i in group j is Former.
- A_{ij}: The status of user i in group j is admin.
- T_j: Number of members in group j.
- NR_j : Numerical rank of group j in the final recommended list

A. Method 1

This method has been created as the first method to recommend the group in messengers. An overview of this method is shown in Fig. 1. In this method, a set of users (P_i) is first entered into the system. The groups that have the most common members with P_i users are then ranked in order (based on most common members).

This method has two main problems. The first problem is that it examines all users from one perspective and it does not do any analysis of the different situations of users in groups. The second problem is that groups with a lot of T_j are always at the top of the list. In other words, the group at the top of the list of recommended groups may have more F_{ij} than C_{ij} and A_{ij}, and that group may be at the top of the list due to incorrect information.

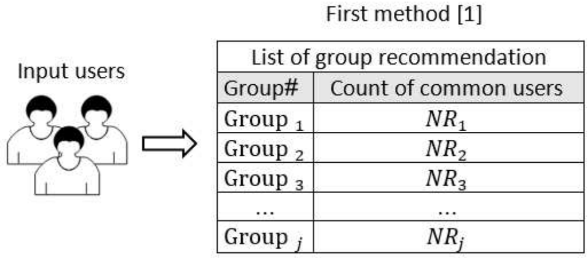

Fig. 1. Overview of the first method

B. Method 2

This method is the second method to recommend the group in the messengers and specifically on the data extracted from the Telegram. In this method, users' membership records in Telegram groups are considered and then the migration of users between groups is modeled. Migration means what groups users who left a group are currently in. In order to solve the problem of the first method, this method considers users in each group with different situations. According to the data used in this method, each user in the group has one of three states F_{ij} or C_{ij} or A_{ij}. An overview of this method is shown in Fig. 2. First, by checking the status of incoming users (P_i), users with F_{ij} status are extracted. Then, it is checked in which groups these users have A_{ij} and C_{ij} status. Finally, groups are ranked based on the largest number of migrated users. This method examines the maximum migration of users between groups by modeling the user behavior of the P_i collection. While the proposed solution in this method solves the first problem of method 1, it still has the problem of ranking groups with a large number of T_j.

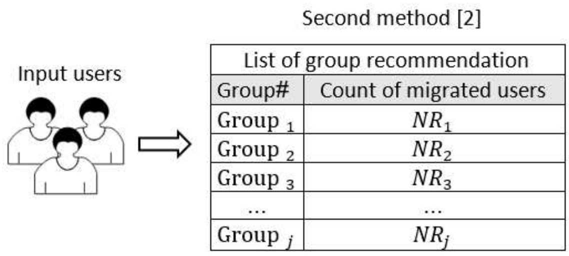

Fig. 2. Overview of the second method

C. Method 3

The proposed method applies the idea of the second method to all the results of the first method and then improves the ranking of each group in the results by computational modeling. The workflow of the proposed method is shown in Fig. 3. In this method, according to Fig. 3-(a), the first method is implemented first and a list of ranked groups is obtained. Then, according to Fig. 3-(b), for each of the groups in the list obtained from the implementation of the first method, the idea of the second method is implemented. In this way, for each group in the list of results of the first method, first users with status F_{ij} are extracted, then it is checked in which groups these users have status A_{ij} and C_{ij} at most. Eventually, the group to which most users have migrated will be replaced by the desired group. For each of

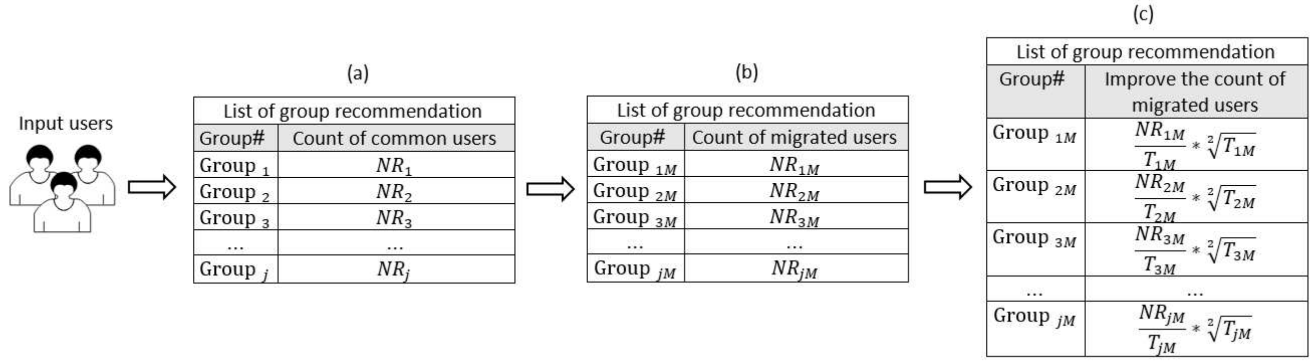

Fig. 3. Overview of the third method

the groups obtained from the first method, migration is examined and that group is replaced by a new group. After doing this on all the groups obtained from the first method, the new groups obtained are ranked based on the most common members with the users of the P_i collection. According to Fig. 3-(b), the numerical rank of the new groups obtained is denoted by NR_{jM}. Finally, a list of groups ranked by numerical rank (NR_{jM}) is obtained. Up to this point, there is still the problem of ranking groups with a large number of T_j.

To solve this problem, according to (1), we divide NR_{jM} for each group, which represents the number of common members of each group with the set P_i, by T_{jM} of the same group. T_{jM} is the number of group members that most users have migrated from group j to that group. The reason for this division is that, when groups with a large number of T_{jM} are placed at the top of the recommended list, it is true that they have a large number of members in common with the P_i set, but the number of members of those groups (T_{jM}) has resulted in their ranking. For example, in the first and second methods, a group with values of $T_j = 2000$ and $NR_j = 200$, has a higher priority in the ranking than a group with values of $T_j = 200$ and $NR_j = 190$. Because the first group has 200 common members per 2,000 users and the second group has 190 common members per 200 users, this means that groups with a large number of T_{jM} are always at the top of the list. After dividing NR_{jM} in each group by T_{jM} of that group, we have ranked all the groups with a common percentage with the set P_i instead of a common number. After completing (1) for each group, a list of groups is obtained in which all groups with a very small number of T_{jM} are at the top of the list. The reason for ranking groups with very low T_{jM} is that when NR_{jM} is divided by T_{jM}, the value of T_j is very high compared to NR_{jM}, and the value of NR_{jM} can never increase as much as T_{jM}.

$$Rec_1 = \frac{NR_{jM}}{T_{jM}} \tag{1}$$

To solve this problem, according to (2), we multiply the fraction obtained by (1) for each group by the radical T_{jM}. This causes groups with a lower T_{jM} number to be reduced and normalized from the beginning of the list. According to Fig. 3-(c), all groups are ranked in descending order after performing (2).

$$Rec_2 = \frac{NR_{jM}}{T_{jM}} * \sqrt[2]{T_{jM}} \tag{2}$$

IV. Experimental Results

In this section, first, the dataset used is introduced, and then the evaluation method and the results of the evaluation are examined.

A. Dataset

The data used in this paper is a collection of real data from the Telegram messenger that has been crawled by Idekav system. Idekav has a cluster of crawlers like web crawlers, and each crawler operates independently. Each crawler becomes a member of the group by finding new links and receives all its information, including the new user and group messages, as a moment after joining each group. This information is sent by the crawler to the information management section. In the management section, the data obtained by the crawler is checked and spam groups are sent to leave the group, and new links are sent to the crawler to join. Crawler information is stored in a cluster of inverted indexes, making keyword searches faster. Finally, the search service, which is based on the Lucene searcher, queries directly from the indexes [17]. The information used in this paper includes more than 920,000 supergroups and 125 million users. In this paper, we have used a graph that connects users based on a common group. According to the graph, each user is in at least one member group.

B. Evaluation Method

In this paper, the evaluation method as in [2] has been done by specialized groups in Telegram. Specialized groups are high-quality groups in Telegram in which members send messages about the subject of the group and there is no message unrelated to the subject of the group. In this paper, we have found 90 specialized groups through expert review. The reason for choosing specialized groups for evaluation is that all members of these groups are users who are really interested in the topic of the group and do not send messages that are not related to the topic of the group. We have measured the final recommended groups based on the users of the groups.

Evaluation of the amount of prediction and error of the proposed method has been done separately by each of the 90 specialized groups. To evaluate the methods by each specialized group, group members are divided into two sections: 80% for training and 20% for examining the amount of prediction and error. In general, the evaluation method is such that for each specialized group, the first 80% of the group users are given input to each of the methods (first method [1], the second method [2], and the proposed method). Then, in each method, ranked groups are obtained separately. The users of the groups are merged in the order of the list until they reach the user collections with the desired number. For example, the desired number of users can be set 10, 20, 30 times the input user set or any desired value. In this paper, the desired number of users is 10 times the input user set. Finally, for each method, after accessing the end-user set, the amount of prediction and error is evaluated using 20% of the retained user.

We used the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) criteria to check the error rate of the proposed method and other previous methods. These two criteria are methods for examining the model prediction that shows its effectiveness by stating the amount of error. RMSE and MAE are calculated according to (3) and (4), respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \qquad (3)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Predicted_i - Actual_i| \qquad (4)$$

In (3) and (4), Predicted is a set of zeros and ones whose zeros denote the correctness of the prediction and the ones denote its inaccuracy. Also, Actual is a set of zeros that represents 20% of the set of stored users. N represents the set of errors in the recommended list.

C. Evaluation Results

In this paper, the evaluation of the proposed method and each of the previous methods have been performed separately on each of the 90 specialized groups. Fig. 4 shows the average of the evaluation results on 90 supergroups. According to Fig. 4, the proposed method, although it has solved the problems in [1] and [2], has been able to significantly reduce the error. The proposed method reduces the mean RMSE error on 90 groups to 0.072 compared to [1] and to 0.061 compared to [2]. Furthermore, the proposed method reduces the mean MAE error on 90 groups to 0.081 compared to [1] and to 0.067 compared to [2]. Given the errors obtained from each method, we find that as the number of groups with a large number of members decreases from the beginning of the final recommended list, the prediction increases and the error decreases.

D. Diversity

In addition to checking for forecast error, the variety of recommended items is crucial. Diversity is used to determine the effectiveness of the results of items recommended by recommender systems. There are many methods for examining diversity, and we have used the thematic diversity of groups in this paper. Each group in Telegram has a name and description. In order to study the thematic diversity of the recommended groups, we first extracted the keywords of the group name and description for all the proposed groups. Then we checked the word sharing between all the recommended groups. Thus, the smaller the number of common words of all the recommended groups, the more diversity in the group recommendation. We have examined the diversity of results obtained from the implementation of each of the 90 specialized groups on the last two methods and the proposed method. Fig. 5 shows the results of the thematic average of 90 supergroups evaluated on each of the methods of papers [1] and [2] and the proposed method. According to Fig. 5, the average number of common words of all recommended groups for 90 specialized groups in the first method is 3061.3, in the second method is 1859.9 and for the proposed method is 143.1. According to these values, the proposed method with a large difference of 20918 compared to [1] and 1716 compared to [2] has been able to have more thematic diversity and variety in the recommended groups.

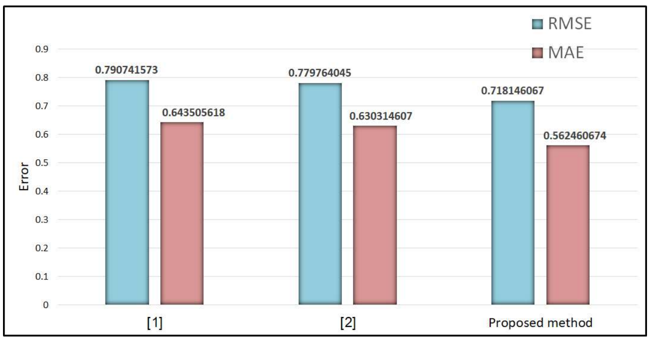

Fig. 4. Average RMSE and MAE for 90 groups in each method

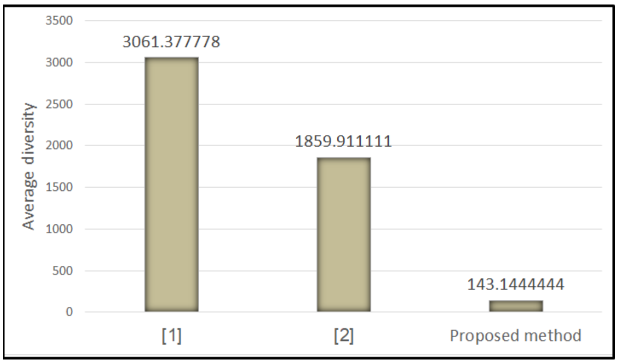

Fig. 5. Average diversity for 90 groups in each method

V. CONCLUSIONS AND FUTURE WORK

Today, the use of recommender systems is widely found in social networks and websites. Using these systems in messaging software is very useful to recommend different items to users. Telegram has features such as group and channel. Therefore, recommending these features to users reduces the production and processing of queries. In this paper, we present a method for recommending Telegram groups by using the graph of user membership and combining the two previous methods. The proposed method recommends a list of ranked groups through computational modeling of variables extracted from the Telegram group level, including user membership records, groups in which the user is currently a member, groups in which the user is an admin, and the number of members in each group. This paper, considering the migration of users between Telegram groups, is able to recommend groups according to the user's interests. We concluded that if ranked groups based on a common percentage instead of the number of common members with incoming users, we would have a better prediction of the results. Also, we found that as the number of groups with a large number of members decreases from the beginning of the final recommended list, the prediction increases and the error decreases. The evaluation of the proposed method and the previous two methods has been performed on 90 specialized and high-quality groups in Telegram. The proposed method, in addition to eliminating all the disadvantages of the previous two methods, has been able to significantly reduce RMSE and MAE. In addition, by examining the final results of the recommender in the previous two methods and the proposed method based on the titles of the recommended groups, we concluded that the thematic diversity of the final recommended groups in the proposed method is greater than the previous two methods.

In order to develop and improve this paper in the future, more users and groups can be considered. In this paper, the user graph is used alone, while the content information in the groups, including users' messages, can also be used. The method proposed in this paper is the starting point in the discussion of computational modeling by mathematical methods, and in the future changes can be made to improve it by using logarithms and power properties in mathematics. The framework of this research is not specific to Telegram data and can be used with the data of other messengers and social networks that can create a group and also their programming interface is available, in addition to proving the effectiveness of this method on those environments, to the weaknesses. And the strength of this method and its improvement was achieved.

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