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Providing effective recommendations in discussion groups using a new hybrid recommender system based on implicit ratings and semantic similarity

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A R T I C L E I N F O

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A B S T R A C T

Discussion groups are one of the most important elements of collaborative learning which utilize recommender systems to improve their performance in several aspects. This type of learning facilitates a comfort communication between users to share their problems and questions and receive the appropriate solutions. Most of recommender systems of discussion groups are based on using collaborative filtering techniques and a few numbers of them use content-based or hybrid filtering. Experimental results of previous works show that using hybrid recommender systems on discussion groups' databases cause significant improvement in accuracy of recommended posts in comparison with other filtering techniques (Kardan and Ebrahimi, 2013). To improve performance of (Kardan and Ebrahimi, 2013), in this paper, a new recommender system is represented, which includes three parts, namely content-based, collaborative, and hybrid filtering parts. The proposed recommender system uses the tagging features to provide more appropriate recommendations on discussion groups. For this purpose, semantic relevance of tags is extracted using WordNet lexical database and the tags are organized in a hierarchical structure based on their semantic relevance. The hierarchical structure is used for searching relevant posts in content-based filtering part, and the user's query is extended using related semantic tags. The implicit ratings of the users are calculated in the collaborative filtering part using similarity measures. Finally, the results of these two parts are combined in the hybrid filtering part of the proposed system to recommend the posts of the discussion group which are similar to the query of the active user. Experimental results show higher precision of the proposed system comparing to the former recommender systems.

1. Introduction

Various communicative environments in different domains have been provided for users via the Internet platform using different web technologies. Asynchronous discussion groups are important examples of these communicative environments which allow users to find proper answers for their raised questions (Kardan and Ebrahimi, 2013). Knowledge extraction from discussion groups and communities is an important research issue that is considered in a variety of recent studies (Kaššák et al., 2016; Christensen and Schiaffino, 2011; Ortega et al., 2016; Wang et al., 2016; Jhamb and Fang, 2017; Lee and Brusilovsky, 2017; Xu, 2018; Li et al., 2018). Unstructured nature of the posts of the members and large volume of information are the main problems of the knowledge extraction process from discussion groups. Recommender systems can be exploited to extract useful knowledge from discussion groups.

This study aims to deliver the appropriate contents that are posted by members of discussion groups to the inquirer users. For this purpose, the related contents are identified at the first step and then, according to the member's interests, the appropriate recommendation will be provided. Most of recommender systems use the similarity of users to make recommendations in discussion groups. Considering similarities of content, or user and content, for this purpose has not received much attention in these systems. The structure of discussion groups is similar to a tree structure and their contents can be as main groups, subgroups, discussion topics, and posts (Fanaeetork and Yazdi, 2013). Each discussion in the subgroups is called a "thread" which has the date and subject by default. This structure allows users to search related topics more quickly. There are some drawbacks in this structure. For example, the users cannot search whole of the group when one topic is included at several threads and while the size of the group is extra-large and thus, they cannot find their related information. Since users cannot

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usually explain their interests using keyword-based queries. In these situations, common keyword-based searching of discussion groups cannot works properly. Recommender systems work based on users' activities, behaviors, and preferences.

Sparsity and cold start problems have made collaborative filtering techniques inappropriate for developing recommendations in discussion groups. The semantic of each post should be discovered in order to increase the quality of recommendations in discussion groups. Therefore, in content-based filtering techniques, in order to extraction of related content, the semantic similarity should be applied instead of other methods which use keyword-based measures. Furthermore, the contents of the posts are ignored by the collaborative filtering recommender systems of discussion groups. A proper solution to overcome the mentioned challenges is to use hybrid techniques which consider information of both user and content. The hybrid recommender system is rarely presented in discussion groups' domain.

In this study, we are going to resolve the mentioned challenges. For this purpose, a new hybrid recommendation technique for discussion groups is suggested. Since the users' explicit information is usually unavailable, their implicit information should be used. Some ideas of collaborative filtering part of the proposed technique are based on activity analysis and user's behavior in discussion groups, which retrieve the user's implicit information. Based on this implicit information, some functions are introduced to calculate implicit ratings of posts. Similar users are identified according to the extracted implicit ratings. The semantic similarity of posts is the basis of suggested plan of the content-based filtering part of the proposed method. For this purpose, the present tags in each subgroup should be identified separately and they should be also organized according to their semantic relationships. Then, during searching for the similar posts, these identified semantic relationships are used and related tags are discovered and similar posts are found based on them. The results of two mentioned parts are combined in hybrid filtering part and the final recommendations are made in the last step.

The main contributions of this paper can be summarized as follows:

- A new hybrid method is proposed to provide recommendation in discussion groups. This method includes 3 main parts, namely, collaborative filtering part, content-based filtering part, and hybrid filtering part.
- In collaborative filtering part of the proposed method, the users' implicit ratings obtained based on presented ideas and users which are similar to the active user are identified.
- In content-based filtering part, similar posts to the user's query are identified according to the semantic relevance between user's question and existing posts.
- Finally, in the hybrid filtering part a relation is provided in which obtained posts are recommended to active user based on what extent similar users to the active user have contributed in them.

The remaining of this paper is organized as follows: In Section 2, related works are explained. Section 3 introduces the proposed method. In Section 4, the experimental results and their related evaluation and analytical discussions are described. Finally, the work is concluded in Section 5.

2. Related works

In this section, different types of recommender systems are explained first and some of provided studies are reviewed and then, some examples of discussion groups are given. Moreover, the employed techniques in suggested system are stated briefly.

Content-based filtering (Pera and Ng, 2013; Son and Kim, 2017; Boratto et al., 2017), collaborative filtering (Yang et al., 2014), and hybrid filtering (Yang et al., 2017; Xu, 2018) are the main filtering types of recommender systems (Adomavicius and Tuzhilin, 2005; Camacho and Alves-Souza, 2018; Zhang et al., 2019; Portugal et al., 2018; Nikzad-Khasmakhi et al., 2019). The main difference of content-based and collaborative filtering recommender systems is in their used information for recommending the items to an active user. Although both approaches have their own advantages, both of them suffer from some drawbacks which affect the quality of their recommendations. For this reason, hybrid methods have been provided and the techniques of both approaches have been combined in these methods to make more efficient recommendations.

2.1. CBF (content-based filtering) recommender systems

In CBF recommender systems (Antonopoulus and Salter, 2006; Lang, 1995; Meteren and Someren, 2000), recommendations are provided based on the previous behavior of users. In these recommender systems, the profile of each item is made considering its features and the profile of each user is made according to features of items on which the user had shown interest. In the next step, the amount of similarity among user's profile and item's profiles is calculated using an appropriate similarity function. The top-N items which have the most similarity score to the active user's profile are finally recommended. Therefore, the recommendations are based on related data to item's features and related data to behavior of each user. Insufficient features, over-specialization, and new or unusual user are the most common challenges of CBF recommender systems. Insufficient features problem occurs when number of achieved features is not adequate to create profiles. Over-specialization means that recommended items are only limited to the similar items that active user had interested in them. Also, new users that are not interested in items or users that have unusual preferences cannot probably receive proper recommendations. The traditional CBF recommender systems usually consider user's profile and item's content and calculate their similarity by comparing the VSM-based (vector space model) user and item keyword vectors. In other techniques, such as ontology-based recommender systems, an intermediate ontology is utilized to compare the similarity of user's and item's profiles. Both of mentioned methods have some disadvantages. In the first method, there is a semantic gap between profiles of user and item and thus, the system will be sensitive to keywords in user's and item's profile. In the second method, the system will be vulnerable when the ontology has a low accuracy or quality. In this case, if the quality of ontology is low, many of the concepts maybe lost during the comparing process. The proposed method in Fanaeetork and Yazdi (2013), is based on vector space model which the users' profiles are enriched using ontologies. The ontologies are made by combining the text mining and NLP (natural language processing) techniques and a lexical database like WordNet. The proposed method of Fanaeetork and Yazdi (2013) decreases the semantic gap of the user's and item's profiles. The system's sensitivity to ontology's quality is also less than other methods. When the high-quality ontology is not available, the system can provide more acceptable recommendations. Its main purpose is to improve dynamicity of discussion groups environments and enhances productivity of discussions. Based on the results, the quality of provided recommendations by ontology-based methods is very close to simple VSM-based methods. Therefore, in large projects, which the computational time is important and a high-quality ontology is not available, the ontology-based methods, such as Shoval et al. (2008), the amounts of calculations of which are less than VSM-based methods, are the best choice. In Fanaeetork and Yazdi (2013), the implicit ratings of users have been utilized. In Middleton et al. (2004) and Abel et al. (2008), the impact of using implicit ratings of users on improving the quality of provided recommendations has been demonstrated. To discover similar posts, the proposed system of this paper exploits the semantic contents of posts in its CBF part. For this purpose, at the first step, the existing tags are categorized and then, semantic relations between each subgroup's tags are identified by WordNet dictionary. Next, the active user's question is extended according to its tags, and related semantic of the tags are discovered to find similar posts.

2.2. CF (collaborative filtering) recommender systems

The second type of filtering in recommender systems is collaborative filtering (Bobadilla et al., 2011; Bobadilla et al., 2012; Candillier et al., 2007; Herlocker et al., 2004; Su and Khoshgoftaar, 2009; Xie et al., 2007; Nilashi et al., 2015; Khanian-Najafabadi and Mahrin, 2015; Liao and Lee, 2016; Ma et al., 2017; Yoldar and Özcan, 2019). At the first step of the process of making recommendations in this type of recommender systems, the users' profiles are created using the calculated ratings of users on items. Then, using a similarity function, similar users to the active user, who have rated the items similar to active user, are identified. Top-N items, which similar users have preferred them, are recommended to the active user. Tapestry system for news articles recommendation, GroupLens for internet news, and Ringo for music are some examples of CF-based recommender systems. The CF techniques have been also applied successfully for recommending other items such as movie and document. Since it is necessary in CF-based method that a lot of users have rated a lot of items, items can be recommended to a user which has been rated by adequate similar users.

The applied methods in CF systems are divided into two categories (Sheugh and Alizadeh, 2018; Nilashi et al., 2018; Alonso et al., 2019; Portugal et al., 2018; Isinkaye et al., 2015; Katarya and Verma, 2017). The first category is memory-based methods which use users-items ratings matrices for making recommendations. The second category is model-based methods which utilize machine learning or probabilistic models to make the relation model of items and users and precast the items based on the rating model. The process of making the model is offline. The data mining techniques have been also used in model-based methods. In order to predict the user's preferences, a model of user ratings can be provided using data mining techniques, such as association rule mining and frequent pattern mining (Sohrabi, 2018), especially sequential pattern mining (Sohrabi and Ghods, 2016; Tsai and Lai, 2015; Shou and Di, 2018; Anwar and Uma, 2019). Neural networks were one of the first tools used in recommender systems (Billsus and Pazzani, 1998). Bayesian networks were the basis of another common approach that is mostly applied for recommendation models inference (Condliff et al., 1999). The main weakness of this technique is the high cost of creating the network creation. The KNN is one of the most well-known algorithms exploiting for collaborative filtering methods (Bobadilla et al., 2011; Adomavicius and Tuzhilin, 2005; Schafer et al., 2007). Using the KNN algorithms, k nearest neighbors of active user are identified and their ratings about the items which are not rated by active user is collected and top-N which have the highest ratings are recommended to the active user. New users, new items, and sparsity are the main challenges of CF-based recommender systems (Nguyen et al., 2017; Sheugh and Alizadeh, 2018). Resolving the problems of collaborative filtering using machine learning methods are stated in (Melville et al., 2001). Performance of CF-based recommender systems is usually higher than content-based systems, but the higher performance occurs when there is sufficient number of user ratings (Adomavicius and Tuzhilin, 2005, Marlin, 2004, Ahn, 2008, Li and Kim, 2003, Gunawardana and Meek, 2009).

The user's opinions can be expressed explicitly (Guo et al., 2014) or implicitly (Jin and Chen, 2012). If the user's opinions are expressed explicitly, the system just needs to collect the values and save them in an opinion matrix. Otherwise, the system should measure the user's implicit interests and save them in the matrix. For example, the number of times a user has listened to music (Jin and Chen, 2012), the number of used tags (Ghorbani-Moghaddam et al., 2013) or the number of times a user visited a webpage can be considered as implicit interests. There are also various metrics for finding the similarity of users which can be calculated using available data. Three of the most common metrics that have been widely used in different studies are cosine similarity, Pearson correlation coefficient and mean square difference (MSD) (Choi et al., 2012; Jooa et al., 2016). The limitation of mentioned metrics is their dependence to user's ratings. The users with different rates on items may also be considered similar by some of these similarity metrics. This is an important weakness of cosine similarity and Pearson correlation coefficient metrics, which cause decreasing the quality of recommendations. On the other hand, MSD metric may consider some users as similar users who have rated a few numbers of items (Kardan and Ebrahimi, 2013). Recent studies tried to omit the dependency of CF techniques to the user's ratings and explicit information. For this purpose, they have provided some techniques for extracting implicit information obtained by analysis of user's behaviors in system and are based on their interests.

Several works have exploited CF technique in discussion groups. It has been shown in Webb et al. (2004) that collaboration in discussion groups increases the learning performance. It has been stated in Bradshaw and Hinton (2004) that discussion groups enrich the collaborative learning. It has been stated in Zaiane (2002) that recommender systems can be applied for recommending actions that a learner must do in an e-learning environment. In Soonthornphisaj et al. (2006), only the CF recommender methods have been used. Since the user's implicit ratings are not available (Zaiane, 2002) and the number of users is not sufficient in e-learning systems, the number of these methods is limited in this area. Hence, the learning methods such as clustering and rule-based techniques are used in these systems. It has been explained in Brush et al. (2002) how to use collaborative filtering in e-learning. In Abel et al. (2010), the advantages of using a discussion group in an e-learning system is explained, and it is stated that this work can improve the relationships among learners. The recommendations allow the learners to efficiently access the information in huge discussion groups or weak-structured ones. Content-based recommendations can be considered to improve the quality of recommendations, and by analyzing the posts contents, a user's interests can be inferred using a content-based filtering. However, since there is not access to explicit information in discussion groups, some functions are defined in CF part of the proposed system of this paper, considering behaviors and activities of users in discussion groups, to calculate the implicit ratings of users about posts.

2.3. HF (hybrid filtering) recommender systems

HF recommender systems (Wei et al., 2016, Barragans-Martınez et al., 2010; Lee et al., 2002, Taghipour and Kardan, 2008, Puntheeranurak and Tsuji, 2007, Tran and Cohen, 2000) are the third category of recommender systems which provide some solution to address drawbacks of content-based and collaborative filtering systems. Different hybrid methods have been proposed in the literatures (Adomavicius and Tuzhilin, 2005; Burke, 2002, 2007; Li and Kim, 2003; Paradarami et al., 2017), all of which have a common problem. The hybridization control parameters should be properly regulated in these recommender systems. There are several methods for combining the outputs of content-based and collaborative filtering systems, including using a weighted method (Claypool et al., 1999), voting mechanisms (Pazzani, 1999), selecting different recommenders (Billsus and Pazzani, 2000; Lekakos and Caravelas, 2008), and filtering a recommender's results to another one (Burke, 2002). In some studies boosting algorithms have been used to hybrid recommendations in order to improve cold start problem (Melville et al., 2002; Park et al., 2006). It has been stated in (Bobadilla et al., 2013) that hybrid methods are usually based on bio-inspired and probabilistic methods such as genetic algorithms (Gao and Li, 2008; Ho et al., 2007), fuzzy genetic (Al-Shamri and Bharadwaj, 2008), Neural networks (Christakou and Stafylopatis, 2005; Lee et al., 2002; Ren et al., 2008), Bayesian networks (Campos et al., 2010), clustering (Shinde and Kulkami, 2012), and latent features (Saranya and Atsuhiro, 2009). Support vector machine (SVM) is a linear classifier that has been also used in hybrid recommender systems (Xu and Araki, 2006). SVM is a supplementary technique for other methods, which is used in several studies.

E-learning systems have also used hybrid filtering to provide their recommendations (Khribi et al., 2007). In Khribi et al. (2009) learner's navigation history is used to find similarities of user's interests and contents of learning materials for automatic online recommendations. Web mining techniques have been implemented along with content-based and collaborative filtering in Khribi et al. (2009) to find the related links for recommending to active learners. Rule-based methods have been also utilized in combining CBF and CF techniques (Choi et al., 2012). In this category of methods, rules are extracted using data mining techniques from usually large transaction databases. Association rules of these methods can be itemsets or sequential pattern. A rule-based hybrid recommender system has been proposed in Choi et al. (2012), in which, a CF-based method calculated the implicit rating information from the transaction dataset. Better quality recommendations were obtained by combining CF techniques and sequential pattern analysis (SPA). Liu and Zhoub (2012) proposed a network-based recommendation algorithm for predicting user-object links by considering heterogeneity in initial resource configurations. The numerical results showed that optimized initial resource configurations provided more personalized and more accurate recommendations. In Salehi and Nakhai-Kamalabadi (2013) a hybrid recommender system has been proposed that is based on sequential pattern of the accessed material and the learner's preference tree. This hybrid method addressed sparsity and overspecialization problems, which are drawbacks of collaborative filtering and content-based filtering, respectively. Furthermore, the method improved the precision and recall measures in comparison with its previous algorithms. The proposed method in Lucas et al. (2013) attempted to address some common weakness of recommendation systems, such as scalability and sparsity for a tourism system. Fuzzy logic and associative classification methods have been used in this system to propose an efficient recommender system.

Some hybrid recommender systems have been also proposed in the literature to be used in discussion groups. A hybrid rule-based recommender system has been proposed in Zhang and Chang (2005). Data source, data modeling and recommendation strategy were handled in this study using a one-round table scanning strategy. Another hybrid recommender was provided in Castro-Herrera (2010), in which, similar users in a discussion group are identified based on the posts which they have contributed in. In this study, TF_IDF technique was used in content-based part of the hybrid system and similar contents have been organized based on the keywords. At the collaborative filtering part, the users who have same interests and have contributed on the same posts are identified and their similarity is calculated. Content similarity metrics in the content-based part of this system were the number of shared keywords, their weights, and frequency of their occurrences. Classifying different contents, which utilize similar keywords to explain different concepts, in the same cluster is the result of using this strategy and these metrics. Using semantic similarity of contents resolved this problem. Another hybrid recommender system has been proposed in Kardan and Ebrahimi (2013), which exploited ARM (association rule mining) techniques in combination with WSD (word sense disambiguation) techniques to recommend related posts of a discussion group to similar users, accurately. ARM technique was used to identifying similar users in CF part of the mentioned system and the CBF part of that utilized semantic-based techniques to find useful and related posts. Cold start and sparsity problems of CF and CBF techniques were addressed by combining the results of these two parts in HF part of the system. The HF part of the system has higher precision than its CF and CBF parts and the recommender system of Abel et al. (2010).

3. Proposed method

A few researches have been provided about using recommender systems in domain of discussion groups which consider both content information and user information in their recommendations. A hybrid recommender system is proposed in this section that consists of three main parts, namely, content-based filtering, collaborative filtering, and hybrid filtering. Furthermore, existing information in database of discussion groups is used in pre-processing section to organize existing tags to be exploited in the proposed method.

3.1. Dataset

The dataset of MetaFilter[1] site have been used in this study, and AskMetaFilter[2] part has been chosen for evaluating the proposed method. MetaFilter dataset contains datasets-related transactions on various issues that are mentioned in this site. The MetaFilter discussion group has different parts like MetaFilter, AskMefi, FanFare, Projects, Music, Jobs, IRL and MetaTalk. There are a lot of discussion threads in each of these parts about different issues. At the time of conducting this study, AskMetaFilter dataset contains 299,515 posts, 247,159 users and 4,339,124 comments.

3.2. Research scenario

To ask a question as a post, a member of MetaFilter discussion group should use the AskMetaFilter section as follows: The active user sends a post to ask a question and states the question's title and description. It is possible for the active user to also put a link in the question. The active user will be also asked to identify several keywords or tags for the question. During submitting of user's question, a list of similar posts, called related questions, is recommended to the active user. If the user finds the appropriate answer for the question in these recommended posts, the post will not be submitted. Otherwise, if the recommended posts be irrelevant or the right answer cannot be found in them and their related comments, the question will be submitted to the group. The part of this process that is recommending similar posts to the active user's question will be considered in the proposed method of this paper and an efficient mechanism will be provided to recommend the most similar and the most proper posts to the active user. The purpose of this study is to increase precision and efficiency of provided recommendations and users' satisfaction. Also, this study helps the process of sharing the useful knowledge among discussion groups' members. On the other hand, if the user posts his question, it should be stored in the system as a new thread. Hence, if the recommendation mechanism resolves the user's need by recommending proper posts, system resources are saved.

The proposed recommender system of this paper for discussion groups is a hybrid system that consists of three components: CBF, CF, and HF parts. In the proposed system, similar users to the active user are identified in CF part considering their implicit ratings about common posts with the active user. In CBF part, content of the active user's question is considered, and according to its tags, similar posts are recommended to the active user. To obtain similar posts to the user's question, the obtained hierarchical structure of each subgroup, made based on semantic relations of existing tags in the system, and related tags to the active user's tags are exploited and the user's question will be extended and related posts will be extracted. In HF part, the results of CBF and CF parts are combined and obtained posts recommended to the active user considering the number of similar users contributed in them.

3.3. Participants

According to applied categorization in Abel et al. (2010), users can be divided to several groups based on their behaviors and activities in discussion groups. This categorization was used in Kardan and Ebrahimi (2013). Regular, casual, regular favorite marker, casual

[1] http://www.Metafilter.com.

[2] http://Ask.Metafilter.com.

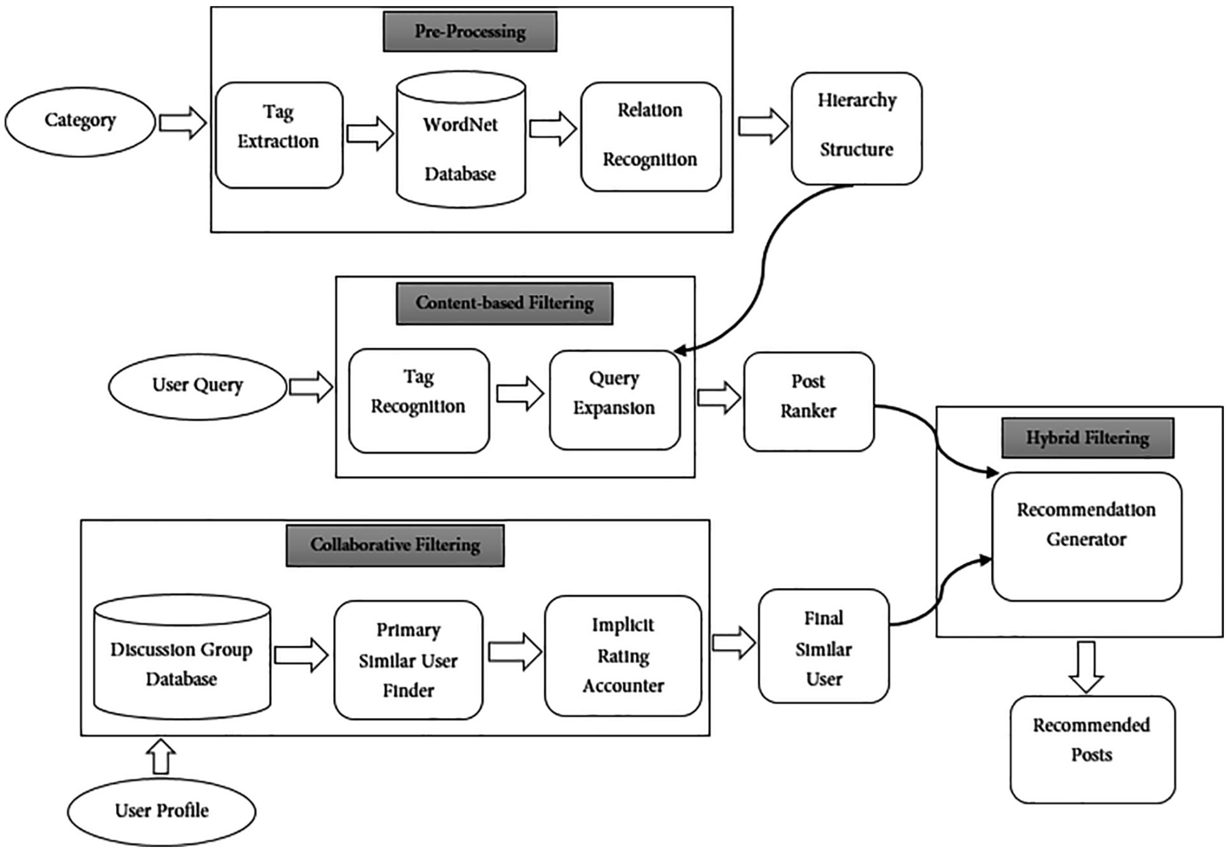

Fig. 1. Architecture of the proposed hybrid recommender system for discussion groups.

favorite marker, and passive users are 5 types of users in discussion groups which were considered in Abel et al. (2010) and Kardan and Ebrahimi (2013). The same classification will be also used to categorize users in discussion groups of the proposed system of this paper. Regular users create the main body of the knowledge of discussion groups and add comments or start threads in these groups. Casual users are the second type of users of these groups whose infrequently create a post or add a comment. Regular favorite marker users and casual favorite marker users are type 3 and 4 of the users and only express their respectively regular and infrequent opinions about posts of other users, instead of contributing to discussions. The last type of user is passive one who has no act on discussion group.

3.4. System's architecture

The architecture of the proposed recommender system of this paper is shown in Fig. 1. This architecture includes four main parts; Pre-Processing, Content-based Filtering, Collaborative Filtering, and Hybrid Filtering. The performance and details of these parts are described in this subsection of the paper.

3.4.1. Pre-processing phase

Pre-processing techniques are executed offline before starting the recommendation process, and the output of this section is used in the CBF part. WordNet (Miller, 1995) is a lexical database in which English words have been classified into sets of synonyms called Synsets (https://en.wikipedia.org/wiki/WordNet). Tags are a type of metadata in information systems assigned to a part of information as a term or keyword to add some additional information to it. Tags are now considered a part of some computer software (Rafailidis and Daras, 2013). To speed up searching process, tags can be organized as a hierarchical structure (Smith, 2008). To create an appropriate hierarchical structure of tags, Tag Extraction unit extracts all tags of the posts of each subgroup, as the first step of the pre-processing phase of the proposed method. In the next step, all relations of the extracted tags of all subgroups will be obtained using WordNet by Relation Recognition unit. The hierarchical structure of the obtained relations of the tags is the output of preprocessing phase which will be used as the input of CBF part of the proposed system. The process of inserting each subgroup's tags to the hierarchical structure is shown in Fig. 2.

3.4.2. Collaborative filtering phase

Similarity of each two users of a discussion group can be determined using their information included in their profiles. Since obtaining explicit information from discussion groups is often difficult and the use of implicit information in recommendation process leads to generate more accurate results, implicit information of the users' profile should be extracted for collaborative filtering phase. At the first step of this phase, the active user's profile is formed based on his activities and behaviors in the system. Based on the profile, it is determined that which posts in which subgroups have been created by the active user and on which posts the active user have commented. It is also recognized that which posts and comments have been selected as favorite or the best answer by the active user and these posts and comments belong to which subgroups. The similar users to the active user are identified based on this information in the Primary Similar User Finder unit. The users who have commented on the same posts as the active user, commented on the posts made by the active user, or chose the same post or comment as the active user as their favorite are identified as the primary similar users in this unit.

To identify the most similar users to the active user, a function should be defined to achieve the implicit ratings of the users through the users' transactions data. In order to define this function, following issues will be considered:

1. The users who have commented more than once on a post are

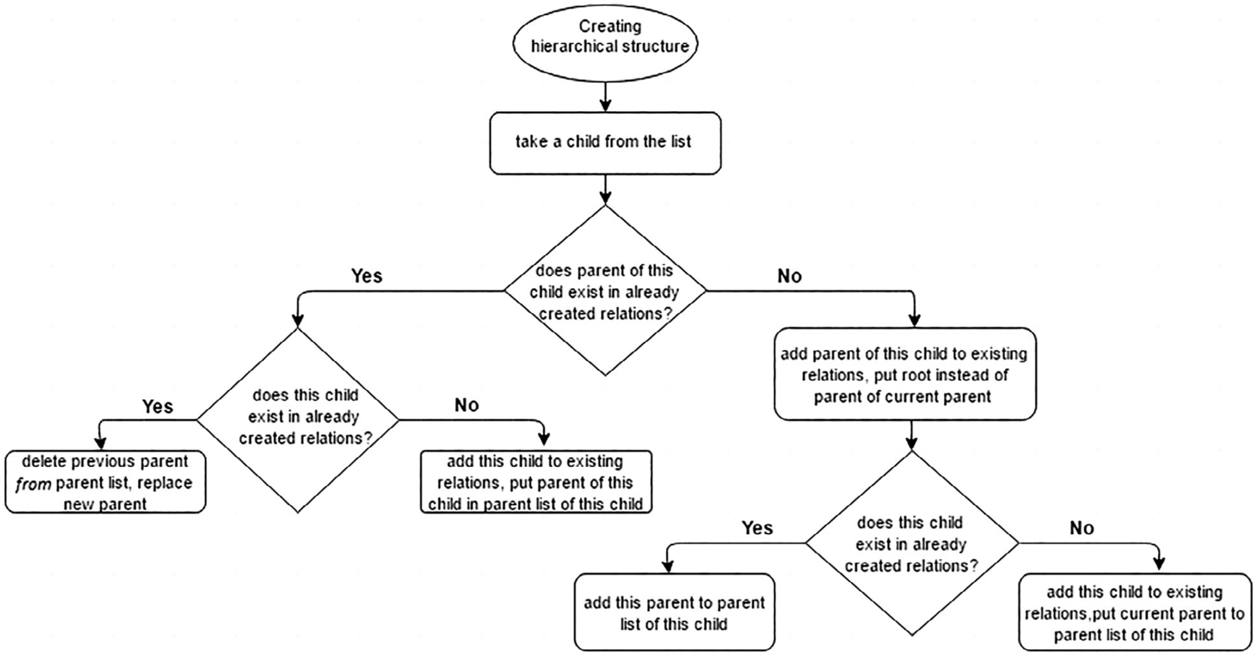

Fig. 2. The process of inserting each subgroup's tags to the hierarchical structure.

considered as interested users in the subject of that post.

2. The user who has given the greatest number of comments on a post is selected as the first interested user in the subject of that post.
3. The users who comment more than once on the same post are considered as the user with the same interest.
4. The users whose comments are chosen as the best answer more frequently than the other users are placed in higher level of knowledge on the questions related to that field.
5. The users who have marked the comments as their favorite answers more frequently than the other users are identified as more interested users in the subject of those posts comparing to the other users.

Therefore, using the data obtained by the active user's and primary similar users' transactions in the Implicit Rating Accounter unit, and using the solution provided by Choi et al. (2012), rating of post *i* for user *u* is calculated. Preference of user *u* on post *i* is defined as Eq. (1).

$$AP(u.\ i) = ln\left(\frac{T_i(u)}{T(u)} + 1\right) \tag{1}$$

In this equation, $T_i(u)$ is the number of transactions of user *u* on the post (item) *i* and $T(u)$ is the total number of transactions of user *u*. Since Eq. (1) only considers frequency, relative preference is defined as Eq. (2).

$$RP(u.\ i) = \frac{AP(u.\ i)}{\underset{c \in U}{Max}(AP(c.\ i))} \tag{2}$$

U, in Eq. (2), is the set of users that have a transaction on the post *i*, including commenting on post *i*.

Maximum function in the denominator of the right side of Eq. (2) causes normalization of RP in the range of [0,1]. Finally, RP is multiplied by 5 to have the implicit ratings range [1,5], similar to the majority of the current recommender systems.

$$Implicit\quad rating\quad (u.\ i) = Round\quad up\quad (5 \times RP(u.\ i)) \tag{3}$$

Obtaining the implicit ratings for all users, the similarity between the active user and any other user is attained by using similarity measures. There are many similarity measures among which cosine measure (COS) and Pearson correlation coefficient (PCC) are common standard criteria which are frequently applied for measuring the similarity in CF techniques (Liu et al., 2014). In CF part of the proposed system, a traditional similarity function such as Pearson correlation coefficient or cosine similarity is used. Pearson correlation coefficient estimates the similarity based on the rating pattern between two users. Cosine similarity treats two users as two vectors in the *m*-dimensional rating vector space, where *m* denotes the set of all items rated by both users, and estimates the similarity by calculating the cosine value of the angle between two vectors (Choi et al., 2012). Selecting the similarity function should be properly conducted based on available dataset. These similarity functions have been defined in Liu et al. (2014) as Eqs. (4) and (5), respectively.

$$sim(u.\ v)^{PCC} = \frac{\sum_{p \in I}(r_{u.p} - \bar{r}_u)(r_{v.p} - \bar{r}_v)}{\sqrt{\sum_{p \in I}(r_{u.p} - \bar{r}_u)^2} \bullet \sqrt{\sum_{p \in I}(r_{v.p} - \bar{r}_v)^2}} \tag{4}$$

$$sim(u.\ v)^{COS} = \frac{\sum_{p \in I}(r_{u.p})(r_{v.p})}{\sqrt{\sum_{p \in I}(r_{u.p})^2} \bullet \sqrt{\sum_{p \in I}(r_{v.p})^2}} \tag{5}$$

In these Equations, *I* is the set of the common items rated by users *u* and *v*. $\bar{r}_u$ and $\bar{r}_v$ represent the mean value of the ratings assigned by users *u* and *v*, respectively. Also, $r_{u.p}$and $r_{v.p}$ show the rating of item *p* by the users *u* and *v*, respectively.

3.4.3. Content-based filtering phase

The main objective of CBF phase is to extend the user question to the relevant questions based on the hierarchical structure of the tags. This structure has been developed based on the relations available in the WordNet lexical database. The process of CBF part of the proposed system is started by entering the user question as its input. Similar questions which are available in the system should be extracted in this part. Extending the user's question based on its tags can improve quality of this recommendation. If there is no similar question in the system, the output will be NULL or has a low accuracy. This case can be an example of new item in the cold start problem. However, if the question is extended, the tags which are relevant to user question tags are considered and then relevant posts to those tags will be recommended. Furthermore, this possibility should be also considered that a user may not be able to indicate his willing well within the framework of the tags. Extending the active user's question will also resolve this problem. Tags of a question can be divided into 3 categories based on their place in the question: tags which are only placed in the title of the question, tags which are only placed in the text of the question, and tags which are placed in the both title and text of the question. Since posts' titles are usually more expressive than posts' texts, tags of the title should be given greater weights in comparison with text's tags. Therefore, weight 2,1, and 3 are given to tags of the title, tags of the text, and tags of the both, respectively. For example, assume that a user has used Java and C# as tags of his question's title and has talked about Java in his question. Therefore, C# and Java will have 2 and 3 as their weights, respectively. Tag Recognition unit of the proposed system conducts the process of weighting tags to expand the active user's question.

In the Query Expansion unit, using the hierarchical structure of the tags of each subgroup that has already been created according to the meanings and relations available in the WordNet, the parent and sibling tags of the available tags of the question's titles are extracted. For the tags available in the question's text, only the parent tag is extracted. For the tags available in both the question's title and text, the grand parent, parent, and sibling tags will be extracted. In some exceptional cases which a tag has not a relation such as grand parent or sibling, the tags which have the shortest path to target node in the hierarchical structure should be replaced. For example, if a tag has no sibling, other options such as grand parent or child tag can be selected. If a tag has no grandparent, its sibling tags can be extracted.

When an active user asks a question, the CBF phase of the proposed method does as follows. First, existing tags in the question of the user are identified in terms of their places. Then, based on priorities of Table 1, the related posts are extracted. The tags in the user question and extended tags which are corresponding to each column of Table 1 are divided. The tags which are present neither in title nor in text of the active user's question are determined as no-place tags with weight 0. The search process for priority 1 is as follows: each of four columns of Table 1 are considered separately and search for the posts is done based on the OR operation of tags of each list, and then, the intersection of the outputs of the four searches is made and the achieved posts are considered as the output of the priority 1.

Hence, the output of this part is a series of posts which are displayed at several levels. Since the joint posts can be considered as the outputs of various levels, in order to reduce amount of computation, only the highest level of each post is taken and the post is removed from all lower levels.

Since the priority-based search may find a large number of posts as the output depending on the dataset, other filters should be applied on the achieved posts to extract the closest posts to the user question. Post Ranker unit does this operation. Since the posts existing in higher priorities are more likely to be close to the user question than the posts existing in lower priorities, to impose the final filtering, the posts are selected from the highest priority. For this purpose, the value of each post is calculated, posts are sorted in descending order of their values, and top-P posts of the ordered list is selected for final list of this phase, which will be used as input of hybrid filtering phase. The value of P is determined based on the size of the dataset.

Table 1
Priority of posts based on existing tags in the active user's question.

Title-text	Title	Text	No place	Priority
1	1	1	1	1
1	1	1	0	2
1	1	0	1	3
1	1	0	0	6
1	0	1	1	4
1	0	1	0	7
1	0	0	1	8
1	0	0	0	12
0	1	1	1	5
0	1	1	0	9
0	1	0	1	10
0	1	0	0	13
0	0	1	1	11
0	0	1	0	14
0	0	0	1	15
0	0	0	0	–

If an active user asks a question which no similar post with the user's question can be found considering its tags, the semantically relevant tags to the user's tags are used to find similar posts in the proposed system of this paper. As a result, the obtained output will be of higher accuracy and it is more likely to satisfy the need of the user. In general, if the tags which the user has specified in his question have no relevant tags in the hierarchical structure, the following procedures will be considered.

1. If the tag is not new, but there is no relevant tag in the hierarchical structure, the search process is conducted only based on the posts in which this tag has been used.
2. If the tag is new, the synonym of tag is found using WordNet and then this synonym is searched in the tags stored in the system. If the synonym is found in the hierarchical structure, the user's tag is replaced by this synonym and it is extended either it is in the text or in the title of question. If it is not in the hierarchical structure, the search is conducted just based on the posts which have this synonym. If the synonym word is not included in the tags of this subgroup, no post can be recommended by the system in this phase.

3.4.4. Hybrid filtering phase

The obtained outputs from the collaborative filtering and content-based filtering phase are used as inputs of hybrid filtering phases and the related posts are recommended to the active user based on the method of this phase. In Kardan and Ebrahimi (2013), in this phase, the posts were suggested in which at least one of the similar users who had been found by the CF part contributed or interested. By applying this method for the users who are not active or have low level of activity in the group, similar users cannot be found and thus, no post is recommended. Since in the CF part of the proposed method of this paper, as mentioned in Section 3.4.2, the similar users are sorted based on their similarities, and in its CBF part, as mentioned in Section 3.4.3, the found posts are sorted in descending order of their values, the method which is applied in the Recommendation Generator unit of this phase works as follows:

1. The posts obtained from the CBF phase are weighed. The weighing process can be also neglected in this part and the obtained value of each post is accepted as its weight. However, since there may be two or more posts with the same value, such posts should be identified and weighted. Since similar users will be also weighted according to the amount of their similarities in this phase, a weighing process must be utilized which is appropriate for the both parts. The weighting process considered in this section divides the range [0-1] into the number of the posts obtained from the content-based filtering and the upper bounds of the obtained sub-ranges are assigned to the posts as their weights according their ranks.
2. The similar users identified in the CF part are weighed too. The weighting process in this part is similar to the weighting process of the posts. The users who are more similar to the active user will have higher weights.
3. For each post that is available in the output of the CBF part, we search how many similar users have contributed in that post and then the sum of the weights of these users will be stored.
4. Eq. (6) is considered to mix the results together.

$$RP(P_i) = (W_{P_i} \times \alpha) + (\sum_{U_i} \times (1 - \alpha)) \tag{6}$$

In this equation, W_{P_i} is the weight of the post *i* which is determined in the step 1 of this phase, $\sum_{U_i}$ is the total weight of the users who have contributed in the post *i*, and α is an adjusting factor in range [0, 1] that specifies the important degrees of W_{P_i} and $\sum_{U_i}$ in the recommendation approach. The value of RP is calculated for all posts which come to this part from CBF using Eq. (6). Finally, the posts are sorted in descending order of their RP values and the ordered list is sent to the Recommended Posts unit in order to be displayed as the created recommendation.

3.5. Implementation

In the implementation process of the proposed method, the dataset related to MetaFilter site is stored in the tables of the database. Microsoft SQL Server 2008 is used to search for the information needed about the posts and the users in the transaction dataset of the discussion group. Java is used as the programming language of implementing the recommender system. There are several APIs to work with WordNet in Java. In this study, the Java library JWI is utilized for this purpose.

3.6. Evaluation metric

Precision and Recall metrics are the most popular and standard evaluation metrics of outputs of recommender systems. Precision indicates how many percent of all created recommendations are accurate. Recall indicates how many percent of user's interested items has been proposed to him. To have a better understanding of these measures, we use the definitions of Kardan and Ebrahimi (2013) for these metrics. A confusion matrix as Table 2 is considered in Kardan and Ebrahimi (2013), and these metrics can be as Eqs. (7) and (8) using this confusion matrix.

$$Precision = \frac{a}{a+b} \tag{7}$$

$$Recall = \frac{a}{a+c} \tag{8}$$

F-measure (F1) is another metric that combines the Precision and Recall values and gives the same weight to each of them as Eq. (9) (Kardan and Ebrahimi, 2013).

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

The value of F1 is in the range [0, 1] and closer values to 1 show better performance of the recommender system.

4. Experimental results, evaluation and analysis

In this section, the approach of analyzing and evaluating the proposed method is explained and the obtained results of experiments will be demonstrated and analyzed.

4.1. Pre-evaluating the proposed system

To analyze the proposed system, we have considered several tests with various conditions of the user's question. In the first step, a variety of questions with various numbers of tags and different places of tags in the questions have been asked from the proposed system. In the second step, various questions for different types of users, who have already been mentioned, have been asked. So, the conditions of CF and CBF parts have been changed several times and the result of the proposed hybrid system for each condition has been measured. The basis of our proposed method measurement is Kardan and Ebrahimi (2013). Evaluating the results obtained from executing the system of Kardan and Ebrahimi (2013) on a dataset similar to our dataset has shown that its hybrid method has better results comparing to CF and CBF. The work has also shown that its hybrid method has better results in comparison with the collaborative filtering presented in Abel et al. (2010). Considering the results of Kardan and Ebrahimi (2013) and other previous researches, we compare the results of our hybrid system with the results of the hybrid method of Kardan and Ebrahimi (2013) that has obtained the best results comparing with the other methods.

Table 2
Confusion matrix (Kardan and Ebrahimi, 2013).

Predicted/actual	Relevant	Irrelevant
Recommended	a	b
Not recommended	c	d

To evaluate performance of the proposed method in answering user's questions in MetaFilter discussion group, different considered questions, which had already asked from the implemented system of this paper, have been also asked in New Question section of the MetaFilter site and the results obtained from these two systems were compared together. The results of the experiments show that in the tag-based systems, choosing appropriate tags for questions is very important and completely affects the results of the recommender system. If the user chooses appropriate tags for a questions and also if the question's title be clear and proper tags are used in it, the results of the search for the relevant posts in the content-based filtering is very likely to be accurate; because the more expressive and accurate tags are chosen at the time of asking the question, the more accurate and precise relevant semantic tags are extracted at the time of extending the tags of the question. As a result, the posts which are searched based on these tags will be semantically similar to the user's question.

Another important point specified in the experiments is that it is not enough to simply choose well-known common tags for a question. Because the more popular tag is, the more relevant semantic tags are obtained at the time of extending the tag and consequently, the number of posts extracted in relation with that tag is significantly increased. This can lead to significant reduction in the results accuracy. For example, in a number of our questions by which we were looking for software to calculate the bandwidth of a network, we investigated the effect of different selected tags of various questions on the accuracy of results. Since the words "Network" and "Software" are well-known tags in Computer and Internet subgroup, they are included in countless posts; and if the user uses only these tags, the precision of the obtained posts is reduced. However, if the word Bandwidth is used along with the other two tags, the accuracy of the obtained posts in the content-based filtering is very high in most of cases.

Another topic that should be mentioned in this sub-section is the hybrid filtering phase of our proposed method. In the question and answer section of the discussion groups, people usually seek the answers of their questions and other members answer the questions being asked. Hence, there are two important parameters which play key roles in a hybrid recommender system in such groups: The first one is the accuracy of the presented suggestions to the inquiring user, and the second one is the similarity of users who have collaborated in the found posts to the active user. Thus, a hybrid recommender system should firstly search for the posts which are semantically similar to the user's question, and then, impose the impact of the similar users to the active user on the obtained posts. For this reason, Eq. (6) has been represented in the hybrid section of our proposed method. The advantage of the proposed equation is that it considers the accuracy of the semantic content of the posts and imposes the impact of the similar users on the posts. In Kardan and Ebrahimi (2013), after searching for similar posts, the posts were suggested as final recommendations in which at least one similar user has collaborated. Since it is possible that none of the similar users has collaborated in the obtained posts and/or the active user asks his question in a subgroup other than the ones he and his similar users have been collaborated, no post is recommended by the system of Kardan and Ebrahimi (2013) in this cases and the user usually resends the post. Since each new question stored in the system is in the form of a thread to be answered by the other users, this leads to waste the system's resources. This also causes more time cost as the active user must wait more to have his question's answer.

4.2. Adjusting recommendation parameters

In this sub-section, the parameters k (the number of similar users which should be determined in the CF phase), p (the number of posts which should be extracted in the CBF phase), and α (the hybridization coefficient) are adjusted. These parameters are common among all recommender systems and there is not a certain way to determine their exact amount because they depend on the available dataset and they should be empirically obtained.

4.2.1. Determining the number of similar users which should be determined in the CF phase

The number of similar users which must be determined in the CF part is specified by k. It is one of the important parameters, the optimum value of which should be attained for a recommender system. In the proposed method of this paper, by testing different values, $k = 4$ has been considered as the number of similar users. Many similar users with a high level of similarity can be found for an active user who regularly participates in discussions. However, it is expected than a good recommender system to suggest accurate recommendations to all the users whether they collaborate in discussions rarely or frequently. Hence, the results of the active user cannot be generalized to the other users. Therefore, based on our dataset, we select a number of users for each of different types of users, and according to the process explained in the collaborative filtering phase, similar users are calculated and thus, according to our available dataset, four similar users is considered for each user in average.

4.2.2. Determining the number of posts which should be extracted in the CBF phase

The value of p specifies the number of the final posts obtained in the CBF part. Depending on the available dataset and the type of the user's question, the desired number of obtained posts is different. For example, for the questions which include well-known common tags, many posts are found which have similar tags to the user's question's tags. On the other hand, if the used tags in the user's question are not well-known or they are new, the number of the obtained posts will be relatively small. The dataset also effects on the number of the obtained posts. For example, if the proposed system be tested for different questions in different subgroups of the system, a lot of posts may be obtained for a question at a subgroup, but fewer posts may be recommended for that question in another subgroup. Hence, different values can be assigned to p. The value of p should lead to an optimal trade-off between Precision and Recall. In order to be able to compare the results of the proposed method with the results of MetaFilter site (which recommend top-5 related posts to the active user), the value 5 is considered for p at first, and top-5 posts are considered as the output of the content–based filtering phase. If there are other posts that have equal value (weight) with the 5 chosen posts, those posts are also added to the list of the selected posts. According to the method considered in the CBF part for calculating the value of the posts based on their relevant tags, if we have several posts with equal value, they are very likely to be semantically similar and they should be considered as the output of this part. This method of selecting p also leads to increase the Recall value.

4.2.3. Determining the hybridization coefficient

Correct selection of the value of α coefficient in Eq. (6) of the hybrid filtering phase has an important effect on the efficiency of the proposed method. Several values have been tested for α and $\alpha = 0.9$ has been selected as an appropriate value, for which, the semantic similarity of the contents of the posts is of much greater importance than collaborative similarity of their participant users.

4.3. Dataset and test scenario of the proposed and other systems

In Kardan and Ebrahimi (2013), three one-month time periods have been considered to conduct tests for the same users which were not modified during these three periods of time. Also, evaluation tests have been performed for different types of users described in Section 3.3. The obtained results showed that higher values of Precision and Recall have been achieved in HF part for the regular users and regular favorite marker users. For causal users and causal favorite marker users, the obtained results of HF part and CF part were similar. Finally, no post recommended to the passive users by HF part.

Our proposed method attempts to suggest accurate recommendations to all types of users. In the question and answer part of discussion groups, semantic similarity of the contents of the recommended posts to the active user's question is more important than the other things in our proposed system, and non-participation of users in discussion groups should not affect the accuracy of recommendations to this type of users. Since some users may be new members and have not participated in the discussions yet, it is hard to find many similar users to them. Some other users may also raise questions on the subgroups which are different from the ones they had already collaborated in, and as a result, it is hard to find similar users to them who have collaborated in the searched posts. Therefore, we consider the proposed methods in the pre-processing and content-based filtering phases, and then, we use the results obtained from CF part in the hybrid filtering phase and apply the positive effect of the similar users on the extracted posts. Positive effect means that if the similar users to the active user have collaborated in the extracted posts, depending on the number of the similar users and the weight of their collaboration in the posts, the posts will have higher weight comparing to other searched posts, and thus, they are recommended to the active user. Using this approach for recommendation, firstly, some recommendations are created for all types of users, secondly, the created recommendations are accurate as much as possible and thirdly, if the similar users to the active user collaborate in the recommended posts, they make positive effect on the created recommendations. Thus, the generated recommendations satisfy all types of users.

The results of the hybrid technique of Kardan and Ebrahimi (2013) had better Precision and Recall comparing to CF and CBF techniques. Its experimental results showed that using the users' information and posts' contents together can improve the quality of recommendation in all the tests the values of Precision are less than the values of Recall. Precision calculates the ratio of the relevant recommendations to all generated recommendations of the recommender system. Since many recommendations were generated for the active user, the value of precision was reduced. Since Recall is the ratio of relevant items recommended to the total relevant items, the higher value of Recall shows that the most of the relevant posts have been extracted and recommended to the user. Tests of Kardan and Ebrahimi (2013) have been conducted based on the data related to transactions made during a month and the results of the tests of the first month was better than the results of the tests of the second month and the third month.

Our experimentations have been performed based on all the data available before August 2016 in the Computer and Internet subgroup of the AskMetafilter section. The MetaFilter dataset consists of four parts: askme, mefi, meta, and music. In each of these sections there are separate data, such as commentdata, commentlength, postdata, postlength, posttitle, and tagdata. There are also some data, such as usernames and contactdata, about users. The structure of data in all four sections is the same and is stored as the .txt format. An example of the data structure of MetaFilter is shown in Fig. 3.

Different questions have been used for the analysis of our proposed method and the present situations of tags in each question have been

```
postid  userid  datestamp   category   comments   favorites  deleted reason
3705    14180   Dec  8 2003 01:28:06:877PM  15  51  27  0   [NULL]
3706    1   Dec  8 2003 01:31:21:287PM  2   28  0   0   [NULL]
3707    14434   Dec  8 2003 02:20:54:067PM  1   15  0   0   [NULL]
3708    6604    Dec  8 2003 02:22:50:837PM  1   35  0   0   [NULL]
3713    15668   Dec  8 2003 06:47:03:430PM  1   28  1   0   [NULL]
3714    1860    Dec  8 2003 07:50:56:143PM  7   10  0   0   [NULL]
```

```
postid  title
3705    Your favorite DVD commentary tracks?
3706    Questions about HDTV
3707    SVG - amazing, yet not popular?
3708    Started My Own Blog: Need Advice on CSS, Non-FTP Updating & Automated Archiving
3713    Help me understand Perl.
3714    Car Repair?
```

Fig. 3. An example of the data structure of MetaFilter.

```
Title = how can i calculate network bandwidth accurately ?
Question = please tell me exactly how the bandwidth was achieved. there is special software or the windows do it ?

Tags = network , bandwidth , software
```

Fig. 4. An example of user's question.

changed several times for different tests. Several tests are considered for each question and the number of tags, the types of tags, and the location of the tags of the question are changed in each test. We have also asked the same questions from the system using different users' IDs from different types of users. For example, Fig. 4 shows a question that we have asked in one of tests of our experiments.

Several other tests are considered in the proposed system so that the title and body of the question is same as the title and body of question of Fig. 4, but the number of their tags is changed. For example, the tags of theses test can be as follows: Test2: bandwidth, network – Test3: bandwidth, software – Test4: software, network – Test5: bandwidth.

Moreover, different users have been selected considering their level of collaboration in discussions (according to the user types mentioned in part 3.3) and the same questions were asked from the proposed system using their user IDs. The obtained results from these experiments show that the highest Precision value is obtained for the recommendations generated for the first and the third tests, the lowest Precision value is obtained in the fourth test, and the average of obtained Precision values for these tests is 72.5%.

4.4. Comparing the results of the proposed system with previous works

Table 3 shows the average values of obtained Precision, Recall, and F-measure of the proposed system of this paper, called HRS. As shown in Table 3, the average of obtained Precision of the proposed system has been increased in comparison with Kardan and Ebrahimi (2013), while the average of obtained Recall has been reduced (Kardan and Ebrahimi, 2013). As it was mentioned earlier, the proposed system can recommend several relevant posts and improve its Recall, but since the obtained results should be compared to the results of the MetaFilter site, only 5 posts are recommended to each user that leads to reduce the Recall value.

Considering goals of using recommender systems in discussion groups, the high value of Recall cannot be interpreted as high efficiency of a system. As mentioned about the results of Kardan and Ebrahimi (2013), in all its conducted tests, the values of Precision were low but the obtained values of Recall were high. This means that many posts are recommended to the active user, which seem relevant based on considered measures of Kardan and Ebrahimi (2013), while they are not accurate. Thus, high values of Precision can confirm the efficiency of recommender systems in discussion groups. In Figs. 5–7, the average of obtained results of using the proposed system of this paper (HRS) and the results obtained in Kardan and Ebrahimi (2013) are compared. In these figures, HF1[1], HF2[1], and HF3[1] show the results of the first, the second, and the third tests of Kardan and Ebrahimi (2013). The average values of Precision, Recall, and F-measures of the mentioned systems are shown in Figs. 5–7, respectively.

In addition to the overall performance of the proposed system which have been compared with previous works in Figs. 5–7. Several test scenarios are also designed to detailed evaluation of the results. For this purpose, following 5 test scenarios are considered:

Test 1: Certain questions have been asked by different types of users defined in the system.
Test 2: A number of questions are considered as active user's questions, and only well-known tags have been used in them.
Test 3: A number of questions have been asked, in which proper tags are used in possible areas of tags, such as title, text and title/text.
Test 4: The questions of the discussion groups are divided into general and specific categories. A number of specific questions have been asked.

Table 3
The obtained results of the proposed hybrid recommender system.

Technique	Precision	Recall	F_1
HRS	68.75	36.45	0.47

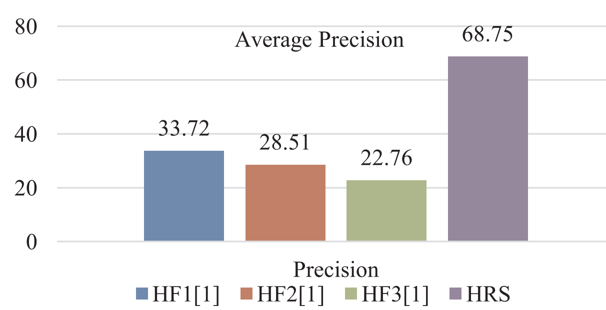

Fig. 5. Comparing the average of Precisions of different recommendation systems.

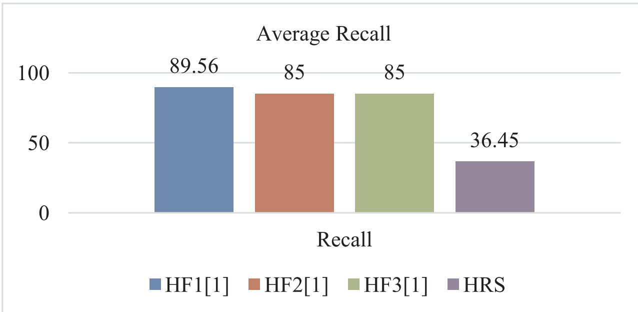

Fig. 6. Comparing the average of Recalls of different recommendation systems.

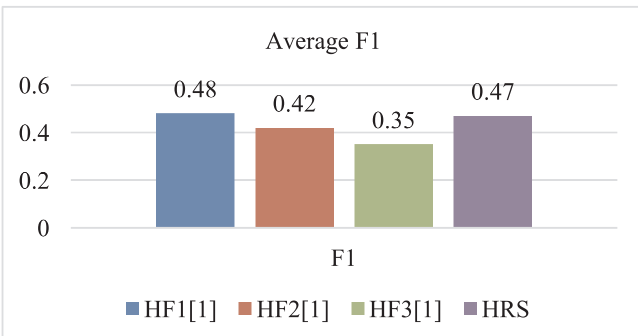

Fig. 7. Comparing the average of F-measures of different recommendation systems.

Table 4
Performance of the proposed recommender system for different test scenarios.

Test type	Precision	Recall	F_1
Test 1	62.53	30.85	0.41
Test 2	38.45	39.16	0.38
Test 3	72.51	41.59	0.52
Test 4	65.27	33.92	0.44
Test 5	57.50	30.67	0.40

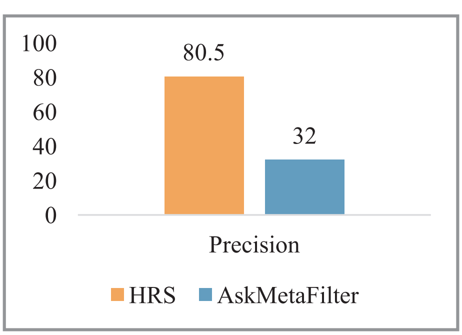

Fig. 8. Comparison the average of obtained Precision.

Test 5: Some general questions have been asked.

The average performance of the proposed system in each test scenario is summarized as Table 4.

4.5. Comparing the results of the proposed system to the results of the MetaFilter site

For further analyzing the proposed system, several questions were provided and were asked using both the proposed system and the New Question part of the AskMetaFilter to find out if the conducted research helps the recommending procedure of similar questions when an active user asks a question. The provided questions for two mentioned systems were completely similar. Each question that is asked from our proposed system were also asked from the MetaFilter site by keeping the same tag numbers, tags locations, and other dominant question conditions. In both parts, questions were asked by the account 239173, which was registered with the name of "msmrhy" in the MetaFilter site. The average of obtained precision through these tests is shown in Fig. 8.

As shown in Fig. 8, the precision of the proposed system is higher than the precision of the Metafilter system. According to the analyses conducted in several cases, some tags are considered as popular tags in the MetaFilter site, and when a user asks a question, it first looks for posts including these popular tags. Since the semantic relations between tags and the semantic similarities between the user's question and the existing posts is also considered by the proposed method of this paper, the precision of its recommendations is higher than the MetaFilter's recommendations.

5. Conclusion

Considering the features of discussion groups, a hybrid recommender system that consists of three parts, namely, content-based filtering, collaborative filtering, and hybrid filtering was proposed in this paper to enhance performance of Kardan and Ebrahimi (2013). This study was conducted based on discussion groups with tagging feature. Semantic relations between existing tags in each subgroup were obtained using WordNet dictionary and tags were organized in a hierarchical structure according to their relations. In CBF part of the proposed system, the hierarchical structure was used during searching of similar posts and the user's question was extended considering semantic relations of tags. In CF part, according to implicit information of users' transactions, implicit ratings of users on posts were obtained and similar users to the active user were identified using similarity metrics. In hybrid filtering phase, the results of two mentioned parts were combined and similar posts to the active user's question are recommended considering similar users' collaborations. For analyzing the proposed system, the values of the important parameters of the system were determined by performing various tests and experiments. The results of the proposed system were compared with the results of other previous recommender systems of discussion groups. The proposed system had higher precision in comparison with the other systems. Several questions were also considered and asked from the proposed system and the MetaFilter site to compare their performance in terms of precision of their recommendations. The results showed higher precision in recommendations provided by the proposed system. Moreover, the sparseness problem of recommender systems can be resolved using the proposed system. If a few information about users are available, recommendations will be created using content information. The semantic-based method, which is used for finding semantically similar contents in the CBF phase, is another advantage of the proposed system of this paper.

CRediT authorship contribution statement

Masoumeh Riyahi: Methodology, Software. **Mohammad Karim Sohrabi:** Writing - review & editing, Supervision, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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