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Colleague Recommender System in the Expert Cloud Using Features Matrix

1. Introduction

Currently, with the rapid development of the IT-based information systems (Navimipour & Soltani, 2016; Zareie & Jafari Navimipour, 2016), many distributed systems such as social networks (Mohammad Aghdam & Jafari Navimipour, 2016; Sharif, Mahmazi, Navimipour, & Aghdam, 2013), grid computing (Navimipour, Rahmani, Navin, & Hosseinzadeh, 2014; Souri & Navimipour, 2014), cloud computing (Asghari & Navimipour, 2016; Chiregi & Jafari Navimipour, 2016; Milani & Navimipour, 2016; Navimipour, 2015; Navimipour & Milani, 2015b), Peer-to-Peer computing (Navimipour & Milani, 2014), and MapReduce (Navimipour & Khezr, 2015) facilitate the information transfer and resource distribution (Navimipour & Milani, 2015a; Navimipour & Zareie, 2015). Among them, cloud computing as a distributed computing paradigm has become very popular. It is built on a wide range of different computing technologies such as high-performance computing, grid and utility computing, distributed systems, virtualization, storage, networking, security, management, automation, service-oriented architecture and etc. (Chiregi & Navimipour, 2016; Yaser Jararweha et al., 2014). In fact, it is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources such as networks, servers, storage, applications and services (Sadeghi Milani & Jafari Navimipour, 2017). The organizations moved to cloud to gain such benefits as cost saving, efficiency, reliability, agility enhancing, flexibility and scalability of services, environmental sustainability and mobile accessible (Chou, February 2015).The primary service models being deployed in the cloud are commonly known as Software as a Service (SaaS)(Martins, Oliveira, & Thomas, 2016; Yang, Sun, Zhang, & Wang, 2015), Platform as a Service (PaaS)(José A. González-Martínez, Miguel L. Bote-Lorenzo, Eduardo Gómez-Sánchez, & Cano-Parra, 2014), Infrastructure as a Service (IaaS)(Chou, February 2015; José A. González-Martínez et al., 2014; Mell & GranceTimothy) and Expert as a Service (EaaS). Expert Cloud gives people the power to share their knowledge and skills and makes the world more open and connected (Nima Jafari Navimipour, Ahmad Habibizad Navin, Amir Masoud Rahmani , & Hosseinzadeh). Many colleagues exist in the Expert Cloud, but colleague recommender -as one of the important challenges in the Expert Cloud- is not developed and implemented so far.

Lately, recommender systems have played an important role in reducing the negative impact of information overload on those websites where users have the possibility of voting for their preferences on a series of articles or services (F. Ortega, J. Bobadilla, A. Hernando, & Gutiérrez, 2013).In fact, recommender systems are developed in parallel with the web (J. Bobadilla, F. Ortega, A. Hernando, & Gutiérrez, 2013). From the network administrator perspective, recommending potential candidates as new friends to users will enable the development of the entire network/community since it results in a more connected network. On the other hand, from the users' side, friend recommendations help them grow their social contacts and explore new friends based on their own interests(Bharath K. Samanthula & Jiang, 2015). The experiments of the social recommendation indicate that the social relationships among users can significantly improve the recommendation accuracy of the traditional recommendation systems (Yu-sheng LI, Mei-na SONG, Hai-hong E, & SONG). It collects information about preferences of its users for a set of items and makes use of different information resource to provide predictions and recommendations for them (Martínez-López, Francisco José, & etal, 2015; *Recommender Systems Handbook*, 2011).Because of increasing scale of Expert Cloud, we encounter a big challenge and therefore, it is very important to help people to find the desired persons and informationare. It seems necessary to make a colleague recommendation system to give useful recommendations to users to improve collaboration in a job experience. Therefore, in this paper, we propose a colleague recommender system in the Expert Cloud using features matrix. We detect potential colleagues through filtering Expert Cloud network and organizing their properties. Then, we calculate a total score for every indirect colleague and finally recommend appropriate experts to the user for collaboration.

The rest of the paper is organized as follows. Section 2 presents the related works; Section 3 describes the proposed method to recommend the colleagues. Section 4 describes the experimental results, and finally conclusions and proposals for future works discussed in section 5.

2. Related work

The related works are divided into three categories: background of Expert Cloud, recommender systems and human Recommender Systems which are described as follow:

2.1 Expert Cloud

Expert Cloud(Nima Jafari Navimipour et al.; Nima Jafari Navimipour , Amir Masoud Rahmani , Ahmad Habibizad Navin , & Hosseinzadeh, 2014) as a new class of cloud systems makes the communication between the HRs(freelancer or employed) more efficient, reduces the expense and cost of service, increases the variety of knowledge and information, facilitates employment of the HR in organizations, decreases customer response time and improves the service delivery methods(Ashouraie & Jafari Navimipour, 2015). To virtualizing the HR, provide EaaS, and share the expertise and skills of HR, Expert Cloud utilizes a layered structure that corresponds to the Cloud architecture (Nima Jafari Navimipour et al., 2014). Expert Cloud can be modeled as an undirected and weighted graph. Fig.1 shows each node labeled by the information and properties of related Human Resources (HR) such as field of study, expertise, and reputation (Nima Jafari Navimipour , Amir Masoud Rahmani , Ahmad Habibizad Navin, & Hosseinzadeh). For example, V3 is a chemical engineer and its expertise and reputation value is 0.091 and 0.143 respectively.

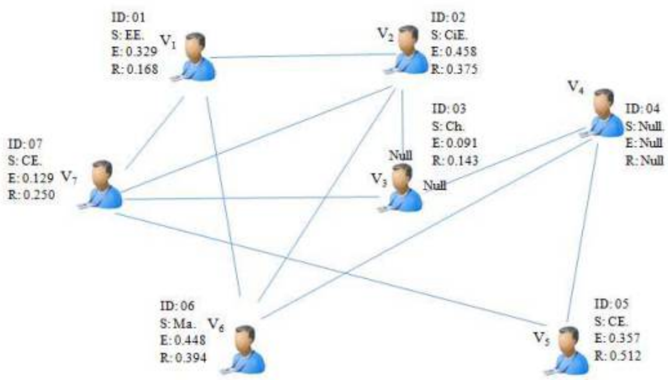

Fig.1 A graph model of the Expert Cloud with seven HR(Nima Jafari Navimipour et al.).

2.2. Recommender Systems

Recommender systems have been developed in the variety of domains to automatically generate personalized suggestions of products, services or people to customers and play an important role in filtering and customizing the requested information. The core of a recommender system is its filtering algorithms. Recommendation mechanisms are usually categorized into three types (Yung-Ming Li, Han-Wen Hsiao , & Lee) including content-based, collaborative-based and hybrid mechanisms.

2.2.1. Content-based mechanisms

This mechanism suggests items based on the similarity to the users' previous preference profiles. Content-based filtering recommends the similar items to the ones the user preferred in the past. In fact, this approach uses historical preference data (Jesus Bobadilla, Fernando Ortega , Antonio Hernando , & Alcalá; Yung-Ming Li et al.). However, sometimes systems suffer from the item cold-start problems which occur when recommendations must be made on the basis of few recorded ratings and as a result similarity analysis is not accurate enough. In these cases, the use of a content-based approach is an alternative. Content-based approaches suffer the limitation of making accurate recommendations to users with very few ratings(Luis M. de Campos , Juan M. Fernández-Luna, Juan F. Huete , & Rueda-Morales, 2010). Furthermore, two different items are indistinguishable if they are represented by the same tags (Zhoubao Sun et al., 2015).

2.2.2. Collaborative-based mechanisms

These mechanisms recommend the items based on the general tastes of similar users' profiles. Collaborative recommender systems can be grouped into memory-based and model-based approaches. These systems employ statistical techniques to find a set of users that have a history of agreeing with the target user and uses information on the general tastes of similar users (Shuchuan Lo & Taipei, 2006; Yung-Ming Li et al.). CF methods can be roughly classified as user-based and item-based(Chin-Hui Lai, Duen-Ren Liu , & Lin, 2013). The most significant part of CF algorithms refers to the group of metrics used to determine the similitude between each pair of users (Jesus Bobadilla et al.). Generally, collaborative systems report a better performance than content-based approaches, but their success relies on the presence of a sufficient number of user ratings(Luis M. de Campos et al., 2010). CF systems have not been explicitly incorporated feature information and face the sparsely and cold-start(Linyuan Lü et al., 2012).

2.2.3. Hybrid mechanisms

To overcome the drawbacks of the aforementioned techniques, a hybrid recommender system combines two or more recommendation techniques to obtain more accuracy (Ahmad A. Kardan & Ebrahimi, 2013). Researchers in different domains presented different approach in hybrid recommendation systems, such as identifying the user similarity neighborhood from implicit information by focusing on the concepts rather than the key words (Ahmad A. Kardan & Ebrahimi, 2013; Kaššák, Michal Kompan, & Bieliková, 2015), combination of two well-known collaborative and content-based filtering methods and employing product taxonomy, attributes of product categories and web usage mining to providing more personalized recommendations(Amir Albadvi a & Shahbazi, 2009).Other approaches are combining user-based and item attribute-based ratings (Zhaobin Liu , Wenyu Qu , Haitao Li , & Xie, 2010), collecting opinions from the users in the form of user-item rating matrix, clustering them offline into predetermined number clusters and storing them in a database, then generating an online recommendations for active user using similarity measures by choosing the clusters with good quality rating to get further effectiveness and quality of recommendations for the active users (Subhash K. Shinde & Kulkarni, 2012). Deriving implicit ratings by applying CF when no explicit rating information is available and integrating collaborative filtering and SPA (Sequential Pattern Analysis) are other methods for improving recommendation quality (Keunho Choi, Donghee Yoo, Gunwoo Kim, & Suh, 2012). Although, it requires many users to rate many items and it has inherent problems such as new user, new item, and sparse problems.

2.3. Human recommender systems

Human recommender systems provide a human recommendation in a virtual media environment where experts and individuals with common interests seek and share knowledge(Charband & Navimipour, 2016; Navimipour, Navin, Rahmani, & Hosseinzadeh, 2015). A large online community may have millions of participants who have accrued a large knowledge repository with millions of text documents. The methods in human recommending could be further classified into two categories: profile-based and document-based methods. Profile-based methods directly build the expert candidate profile based on associated documents and then generate the ranking score according to the profile in response to a user query. Document-based methods first rank documents in the corpus given a query topic. Then, associate candidates are found from the subset of retrieved documents (Zhai & Fang, 2007).

In (G. Alan Wang, Jian Jiao, Alan S. Abrahams, Weiguo Fan, & Zhang), the Page Rank algorithm is modified to evaluate one's authority so that it reduces the effect of certain biasing communication behavior in online communities. Another approach to an expert recommendation based on the fuzzy linguistic method and fuzzy text classification in knowledge management systems is proposed by Ming Li, Lu Liu and Chuan-Bo Li (Ming Lia, Lu Liu, & Li) to assist the user to find the required experts. The method adopts the fuzzy linguistic method to construct the expert profile, that is, to model expert’s expertise. In addition, the fuzzy text classifier is used to get the relevant degree of the document to each knowledge area when the document is registered, which is the base on the following user's profile construction. Then, the user's profile consisting of the time and the relevance factors of the rated documents are constructed to derive the overall knowledge of the user. Consequently, the expert is recommended based on the similarity between the derived expert profile and the user profile(Ming Lia et al.). Similar functionality has been realized by expert finding systems.

Jianshan Sun et al.(Jianshan Sun, Wei Xu , Jian Ma, & Sun, 2015) have used the quality analysis module and relevance analysis module for measuring the expertise level of a potential expert. They used the rank algorithm to rank expert in the collaboration network. Also, Duen-Ren Liu et al (Duen-Ren Liu, Yu-Hsuan Chen, Wei-Chen Kao, & Wang, 2013) have proposed an expert finding mechanism by taking user's expertise and reputation into consideration. Their approach has been extended to developing a question dependent approach in question answering websites that consider the relevance of historical questions to the target question in deriving user domain knowledge, reputation and authority. In(Xiwang Yang, Harald Steck, & Liu, 2012), a recommendation method in online social networks by inferring social trust circles from available rating data combined with social network data and expertise was presented. To infer the trust value of a link in a circle, they have estimated a user's expertise level in a category based on the rating activities.

3. Proposed method

In this section, the proposed method for the colleague recommendation in Expert Cloud is explained. Various criteria have been used to measure users' importance score. Our aim is to combine the number of the features to obtain an applicable similarity between users and satisfactory results and increasing the accuracy of predictions. In this section, we use topological information of social networks. Topology-based approaches for recommendation systems have already been suggested by other researchers (Bharath K. Samanthula & Jiang, 2015; Naruchitparames, Gunes, & Louis, 2011; Silva, Tsang, Cavalcanti, & Tsang, 2010). We choose the friend-of-friends (FOF) concept, which is a simple and widely used idea. This algorithm does the filtering procedure by employing the concept of the clustering coefficient, which is characteristic in small world networks (Silva et al., 2010). We generalize this algorithm to find all colleagues who are related to the target user. In our method, because of reducing the scale of the network, we consider 5 stages of colleagues for the target user. By using this algorithm, we obtain all possible colleagues of target user up to 5th stage. In Fig. 2, a path from target user to 5th recommendable indirect colleagues in the Expert Cloud is illustrated. Indirect colleague-user is a user whose name is not in the list of target user's colleagues, but she/he is reachable through colleagueship relations in the next stages.

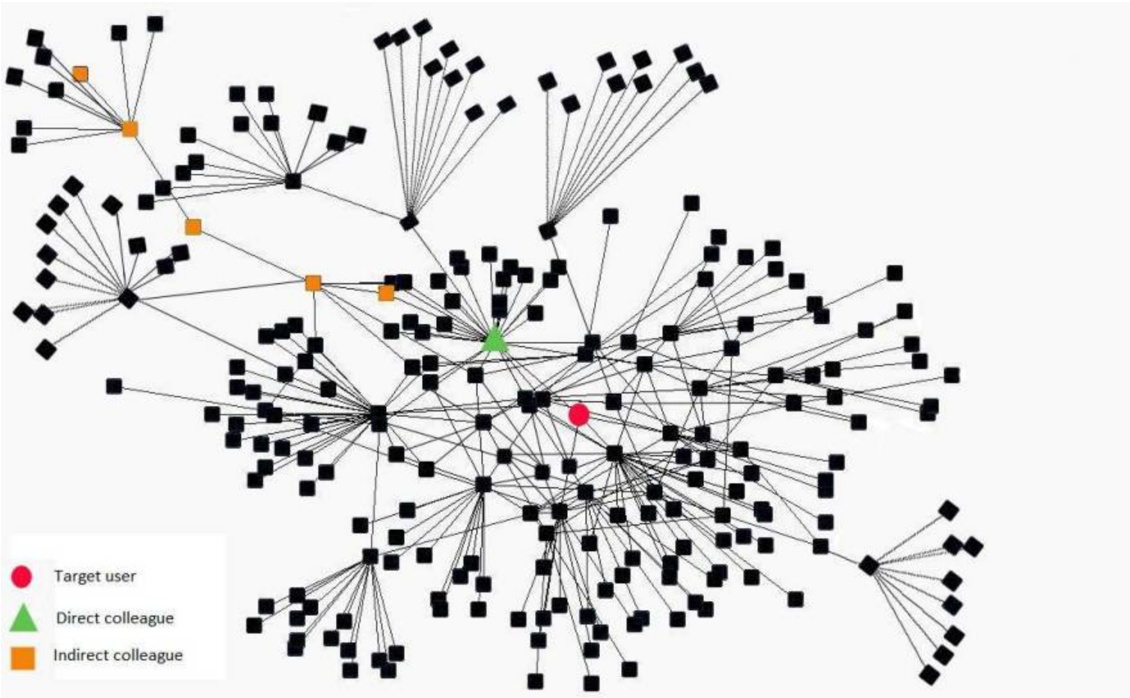

Fig. 2. A graph that shows a target user and his/her colleagues up to 5th stage

In the rest of this section, we introduce All Possible Colleagues at First (APCF) method for recommending colleagues in Expert Cloud by introducing main features and used matrixes.

3.1. Main features

Main features considered for recommending colleagues are reputation, expertise, trust, cost, agility and field of study which are presented and explained in this section.

3.1.1. Reputation

Reputation(Fulan Qiana, Shu Zhaoa, Jie Tangb, & Zhanga, 2016) is the public opinion about the character and status (such as truthfulness, ability, dependability, reliability) of an HR. These ratings are obtained from the questions that are provided in quality control component. Eq (1) evaluates the reputation value of HR_i (R_i)(Nima Jafari Navimipour et al.).

$$R_i = \frac{1}{x} \sum_{n \in ct} w_n \times RA_{nt} \quad (1)$$

$$Where\ Wn=\begin{cases}0 & RA_{ni} < \lambda \\ 1 & otherwise\end{cases}$$

$$Ci=\{HR \mid HR\ is\ the\ colleague\ of\ HR_i\} \quad (2)$$

RA_{ni} is the result of the questions that HR_i answers about HR_n, λ is in the range of 0 …1; for example, if $\lambda = 0.4$, only the *HR* can contribute to reputation evaluation process which their own R value is not less than 0.4, and denotes the number of HR which $HR \in Ci$ and its *R* value is not less than λ.

3.1.2. Expertise

Information about the employees' expertise needs to be extracted from well-chosen existing data resources(Tim Reichling, Michael Veith, & Wulf). We obtain these data from the questions answered by other HR. Expertise not only shows the type of skill, expertise, and dexterity of any HR, but also determines her/his intensity and level of skills and knowledge (Jafari Navimipour & Charband, 2016; Jafari Navimipour, Rahmani, Habibizad Navin, & Hosseinzadeh, 2015; Zareie & Navimipour, 2016). Eq. (3) evaluates the expertise value of HR_i (E_i)

$$E_i=\frac{1}{x}\sum_{n=1}^{|Ci|} Wn \times EAni \quad (3)$$

Where, EA_{ni} denotes the answer for the expertise of HR_i from HR_n in the range of 0…1. λ is in the range of 0…1, and *X* denotes the number of HR which $HR \in C_i$ and its *R* value is less than λ.

3.1.3. Trust

A dominant approach in the social network-based recommendation is to develop trust models and estimate user interest based on his/her trusted people's preference (Xin Lia, Mengyue Wanga, & T.-P. Liangb, 2014). Xin Li, Mengyue Wang and T.-P Liang in (Xin Lia et al., 2014) categorized the recommender system in two approaches: trust and similarity approach. Many recommendation systems allow each user to compile a trust list of his/her trusted users. In this way, a web of trust, which indicates the trust relationships among users, can thus be derived by aggregating the trust lists (Chien Chin Chen, Yu-Hao Wan , Meng-Chieh Chung , & Sun, 2013). Computing trust is a reasoning problem under uncertainty, requiring the prediction and anticipation by an agent (the evaluator) of the future behavior of another agent (the target) (Punam Bedi & Pooja Vashisth).In general, $T_{i,j}$ from U_i to U_j is computed as per Eq. (4):

$$T_{i\,j} = \prod_{n,m \in P(U_i,U_j)} T_{n,m} \tag{4}$$

Where, $P(U_i, U_j)$ represents the path between U_i and U_j; for example:

$P(U_1, U_4) = \{(U_1, U_2), (U_2, U_3), (U_3, U_4)\}$

It is possible to be more than one path between two users. In such cases, each path has its own trust value. For example, there is more than one path between U_1 and U_4, therefore there is more than one trust value and we can choose the path with greater trust value.

3.1.4. Cost

Cost is an important factor in the collaboration. Experts want to control costs by extending the value of their existing abilities. Also, the first question raised in the customer's mind before using the Expert Cloud is whether it is cost-effective to make use of this human labor. This criterion can be achieved by some criteria regarding the considered human resources such as comparing cost versus the work done, the satisfaction of customer or HR, to give a reward if necessary and etc. (Parisa Fulady & Navimipour). For a human resource or expert, the cost criteria calculation is obtained as follows:

$$\text{Cost} = \sum_{i=1}^{n} \frac{cr_i}{n} \tag{5}$$

Where cr_i is the rating value for cost criteria and n is a number of criteria. We will use this feature negatively because we want to find the best experts for recommending as a colleague with lower cost.

3.1.5. Agility

Agility (Parisa Fulady & Navimipour) of HR causes the customers to expand or change their considered tasks in the shortest time period, while imposing no costs. Agility in the Expert Cloud shows how the HR manages to meet the new requirements of the customers. Agility items can be defined by HR properties like willing to use new knowledge, adapting to new conditions or different technical request, the ability to simultaneously work on different tasks in different teams and etc.

$$\text{Agility} = \sum_{i=1}^{n} \frac{ar_i}{n} \tag{6}$$

Where ar_i is the rating value for an agility criteria.

3.1.6. Field of study

Field of study can determine if two users are studying on common subjects or working on similar projects. This property is obtained from the user profile and helps to match the best colleagues. Also, we can find more information about colleague's profession domain in their profile history. Taking common fields of study into account, we score users from 0 to 1.

3.2. All Possible Colleagues at First (APCF) method

Fig. 3 gives an overview of this method. In this process, at first, we apply FOF filtering to find all possible colleagues for target user up to 5th stage, and then the direct colleague's features are gathered in a matrix named DCF. The DCF matrix is an n×m matrix which is used for denoting values of main features (F) for all of the indirect colleagues. Then, we organize the features of possible colleagues in CU-F matrix and required features of the target user in TU-F matrix. Now, by applying some matrix calculations, every colleague is given a score. As a result, we can recommend top-k(Kaššák et al., 2015) colleagues to the target user.

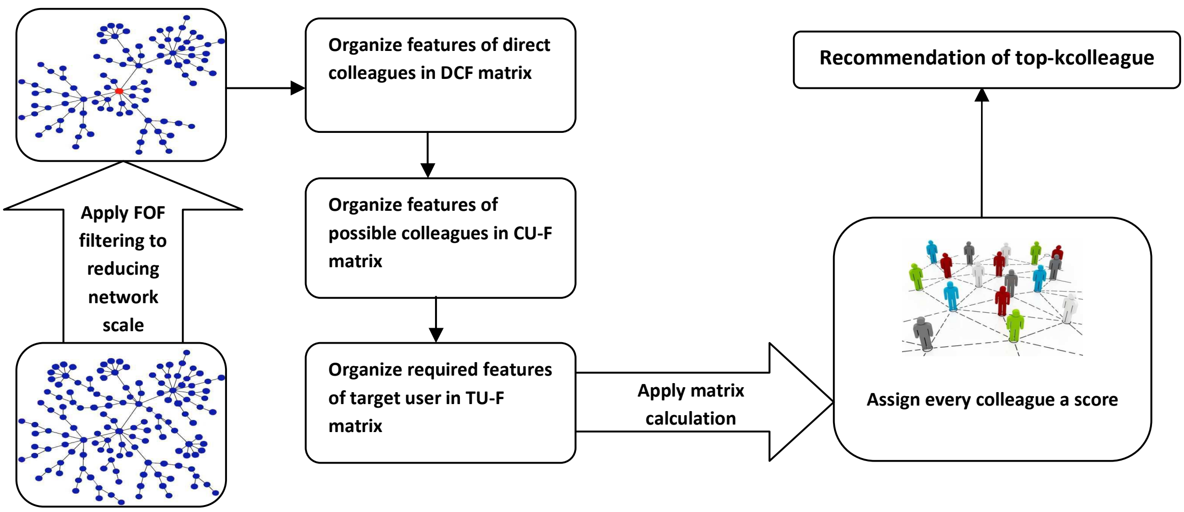

Fig. 3. Overview of the proposed method (APCF)

The proposed method considers the exceptions of the target user. So, we build another matrix named TU-F that is a(m×1) matrix. According to Eq. 6, we use an average of direct colleague's features to make the TU-F's items.

$$\text{TU-F}(i,1)=\begin{cases}\frac{\sum_{j=1}^{k} DCF(j,i)}{k} & 1 \leq i \leq 6 \\ max_{j=1}^{N}\left(DCF(j,6)\right) & i=6\end{cases} \quad (7)$$

DCF(j,i) is the i[th] feature of j[th] direct colleague and *K* is the number of direct colleagues of the target user. Notice that the F features in CU-F matrix are available in neighbor users and F features in TU-F matrix are expected by the target user. We use following features that were discussed in section 3.1 for neighbors (possible colleagues) and target user. We consider F_1 as reputation, F_2 as expertise, F_3 as trust, F_4 as cost, F_5 as agility and F_6 as a field of study. Maybe for the target user, some features have more importance than others in cooperation activities. For this purpose, we assign an importance weight (W_i) to every feature considering TU-F matrix. We obtain these weights by rounding TU-F matrix items to nearest existing value in table 2. The weighted TU-F matrix is calculated:

$$WTU\text{-}F_i = TU\text{-}F_i \times W_i \quad (8)$$

Now we can calculate the final score (CU-S) for every indirect colleague-user:

$$\text{CU-S}_i = \sum_{i=1}^{n}(CU - F_i \times WTU - F_i) \quad (9)$$

The calculated score for every indirect colleague shows the professional and social closeness between all possible colleagues and target users and we can recommend a top-k colleague for target user according to their scores.

For comparing the results, we rewrite the Eq. (10) in a different way:

$$\text{CU-S}_i = \sum_{i=1}^{n}(CU - F_i \odot WTU - F_i) \quad (10)$$

Where ⊙ indicates the cosine similarity (Duen-Ren Liu et al., 2013; *Recommender Systems Handbook*, 2011; Shuiguang Deng, Longtao Huang, & Xu, 2014; Ximeng Wang , Yun Liu, & Xiong, 2016) between every colleague's feature vector and target user's expectation vector. Cosine similarity calculation between two user's features vectors u_i and v_i, is as follows:

$$\text{Cosine}(u_i,u_j) = \frac{v_i \bullet v_j}{\|v_i\| \bullet \|v_j\|} \quad (11)$$

Where • indicates vector dot product and $||v||$ is the norm of vector *v*. we examine this method by the name "APCF-CO".

4. Empirical evaluation

This section establishes the evaluation settings (data set, evaluation metrics, and experimentation aim) and also presents the experimental results for the performance of the APCF method and compares it with other approaches. In this section, we first explain our dataset and then introduce evaluation metrics for obtaining an experimental result and finally we present the implementation of the method in expert cloud website.

4.1. Dataset

To evaluate the method, we collected actual data from www.expertcloud.ir, a website for sharing knowledge and skills of human resources as a service in cloud systems. This website provides a suitable environment for users to search experts and send colleague request to them. Also, users can publish their job offerings on this website. This dataset is placed in http://www.dataset22.expertcloud.ir. For evaluation, we choose 10 target users randomly and then determine their possible colleagues in the number of 100, 200, 300, 400, …,900 and 1000.We evaluate and compare the performances of different expert recommendation algorithms with APCF method that was discussed in section 2.3.

4.2 Evaluation metrics

The experiments are developed using MATLAB7.2. The experimental setting is an Intel Dual core 2.20GHz and 4GB RAM machine with Microsoft Windows7 Operating System. We evaluate the performance of the method in recommending colleagues by hiding the actual colleagues and predicting their colleagueship possibility through the compared recommendation algorithms and our method. Precision, accuracy, incorrect recommendation and runtime metrics are also used.

Precision: This is one of the most popular metrics for evaluating information retrieval systems. The precision metric computes the recommender's capacity to present only useful and relevant items among a set of irrelevant and relevant items. Eq. (11) calculates the precision (Ahmad A. Kardan & Ebrahimi, 2013).

$$\text{Precision}=\frac{relevantrecommendeditems}{relevantrecommendeditems+irrelevantrecommendeditems} \tag{11}$$

Accuracy: The metric of Accuracy is the percentage of correct recommendations to the total possible recommendations (Ahmad A. Kardan & Ebrahimi).

$$\text{Accuracy}=\frac{relevant\,recommended\,items+irrelevant\,not\,recommended\,items}{total\,items} \quad (12)$$

4.3 Experimental results

In this section, we show the results that are obtained by using data from Expert Cloud. Figs.4-6 show respectively the results of comparison between APCF, APCF-CO, EF(Duen-Ren Liu et al., 2013) and CB (Xiwang Yang et al., 2012) by precision, accuracy and time. Note that the APCF and APCF-CO methods use the reputation, expertise, trust, coast, agility and field of study features, while EF method uses only reputation and expertise and CB method uses only expertise and trust features. We can observe the APCF is superior to other algorithms. Because of using more features and simple calculations, the APCF method gives better results in accuracy and precision than other algorithms. APCF-CO is similar to APCF, but it has more calculation complexity and for this reason it has poor results compared to APCF.

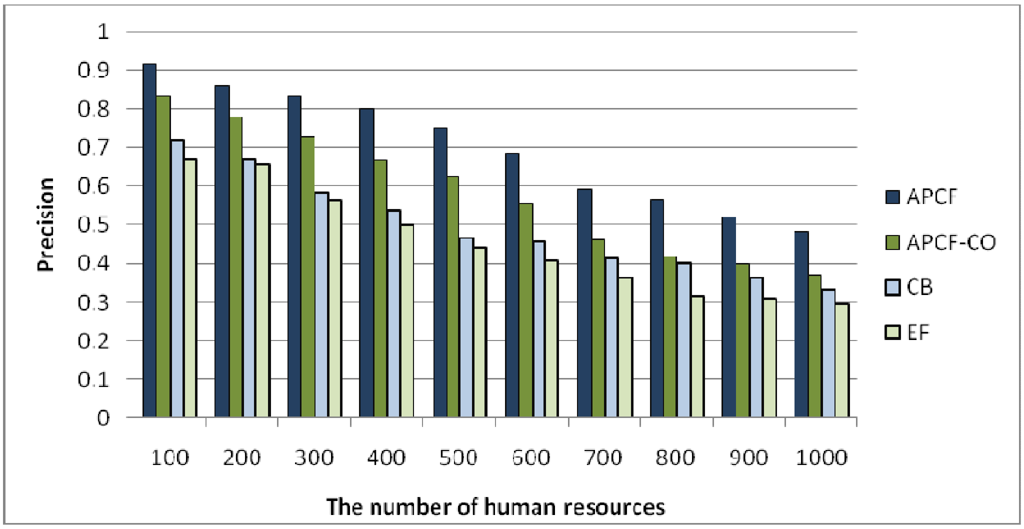

Fig.4. Comparing the precision of APCF, APCF-CO, EF and CB methods

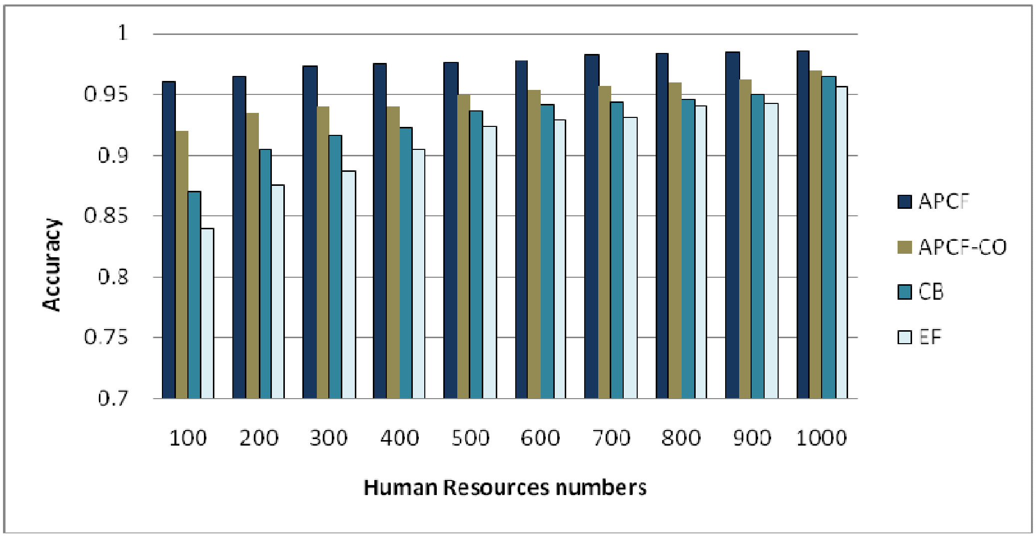

Fig.5. Comparing the accuracy of APCF, APCF-CO, EF and CB methods

Because of using more features, the APCF and APCF-CO methods consume more time than other methods. Fig.6 shows time cost of these algorithms. Each EF and CB use two features in recommendation process and consumes less time than others.

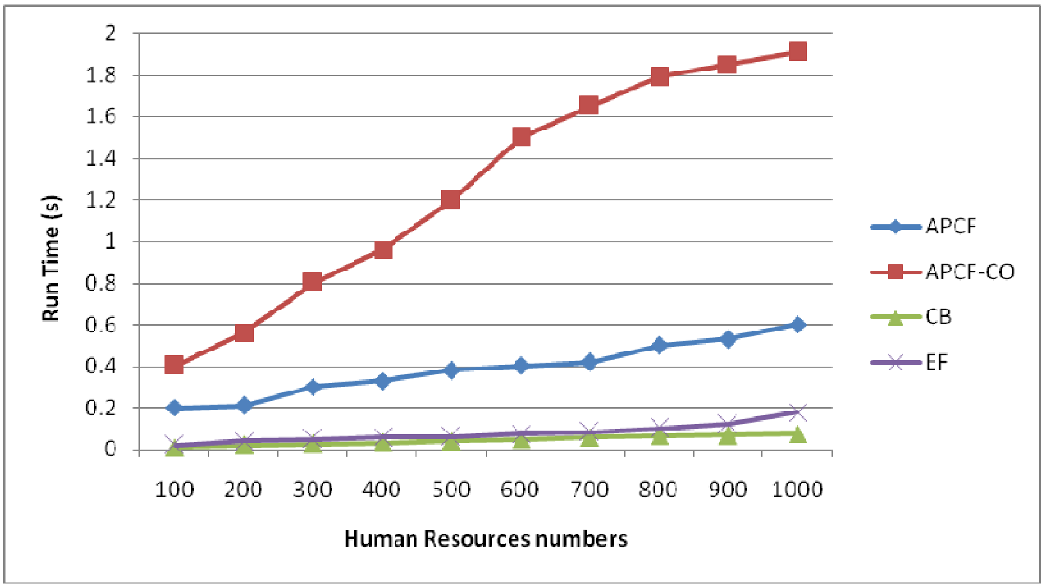

Fig.6. Comparing the run time of APCF, APCF-CO, EF and CB methods

4.4 Implementation

We develop a web-based APCF colleague recommender system on Expert Cloud website to gather appropriate data from real world users. The web-based system collected information by users' profiles and their direct colleagues. We implemented our own experimental software using PHP in www.expertcloud.ir. In fig.7, the recommended colleagues for the user are presented.

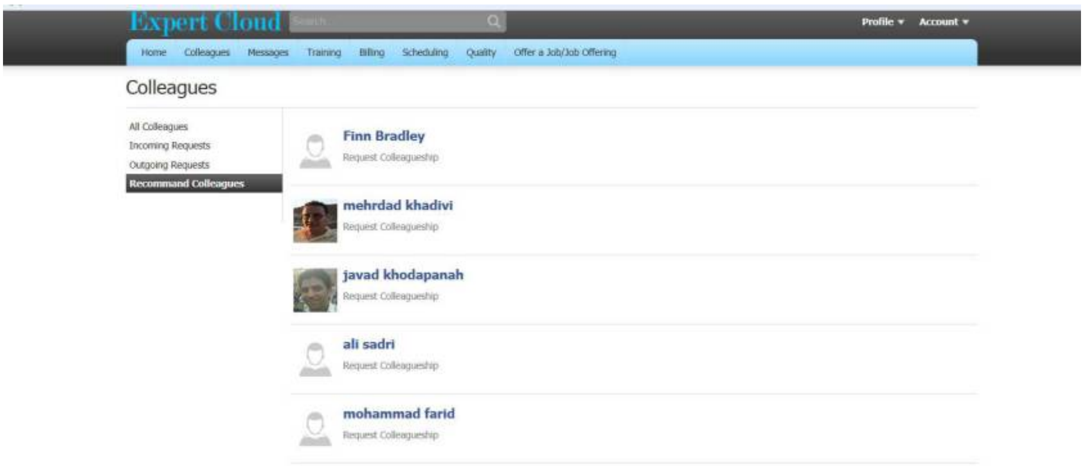

Fig.7 The screenshot of the colleague recommendation page in the Expert Cloud website

5. Conclusions and future works

In this study, we propose a colleague recommendation for Expert Cloud along with a new approach for the expert recommendation. In the Expert Cloud, each user enjoys some features like trust, reputation, expertise, cost, agility and field of study. Considering all these features together makes the recommendation results more real and accurate. In this method, we first apply FOF filtering to find all possible colleagues for target user up to 5th stage, and then gather colleague's features in a matrix. Also, we consider the expectations of the target user in recommendation process, while existing methods for the human recommendation use fewer features than the method for evaluating users. In this paper, the experimental data obtained from the real-world Expert Cloud website and experimental results show that the proposed method can be directly applied in existing human recommender systems and it has high accuracy. Also, the method is implemented in the Expert Cloud website and provides more availability to new colleagues for users. We believe that the method still has much to improve. For example, instead of considering all indirect colleagues up to 5 stages, we can calculate every stage's colleagues separately and propagate its result to next stages. This helps to choose the paths with maximum scores in the social networks and also reduce network's search space. This way, we can calculate a score for every indirect colleague in its own stage for choosing top-k colleague-user. In this way, previous stage's top colleagues are used for finding the next stage's top colleagues, until the final stage.

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