# *CSCF: Clustering based-Approach for Social Collaborative Filtering*

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***Abstract*— Nowadays, Collaborative Filtering (CF) has become a widely used technique in the field of recommender systems. It aims to recommend items that are relevant to the tastes and preferences of the users based on the social relationships between them. One crucial issue in CF is the Cold Start Recommendation which includes two key aspects: new user and new item. Cold user is a new comer who enters the system and cannot get relevant items, while cold item is a new item that cannot be recommended since it has no ratings yet. In this paper, we present "CSCF" a graph-based approach for social collaborative filtering. CSCF offers many interactive tasks aiming to improve the user satisfaction and solves the cold start challenges by identifying the most effective delegates with clustering. Computational results are demonstrated to confirm the effectiveness of our proposed approach.**

***Keywords*— Cold Start Problem, Delegates, Graph theory, Recommender System, Social Collaborative Filtering.***

## I. INTRODUCTION

Collaborative filtering systems "CFS" have recently gained significant attention in the research and industrial communities due to their ability to identify the user preferences and provide adequate suggestions to him. These systems have a special recommendation policy; as they recommend to a user items may be of his interests based on votes left by other users with similar profiles. The objective is to minimize the time spent on research and also to suggest relevant items that would not spontaneously consulted which increase the user satisfaction. Thus, CFS are based on the assumption that people who are looking for information should be able to use what others have already found and evaluated [1].

According to this principle, the users provide ratings to items explicitly or implicitly to build their profiles. Then, their evaluations are compared to those of other users to compute similarities. These latter allow to make recommendations. In fact, a set of friends is identified for each user, and the decision to propose or not an item to a user depends on the assessments given by his friends on this item.

In Social collaborative filtering systems "SCFS", the users who have similar preferences form a social community in which they are linked to each other by trust scores. Like any other recommender systems, SCFS are suffering from the cold start problem for a new user who starts with an empty profile and finds himself isolated from the community members and the cold start of a new resource that may not be visited [1,2]. Indeed, making effective recommendations in cold start situations is a basic task in a recommender system since offering bad recommendations could risk severely the webshop's revenue, market share and overall reputations, because disappointed customers may turn to other competitors and never come back [3] and one recent efficient way to alleviate these problems is to detect the most influential users, called opinion leaders or delegates, within the trust network. These latter are highly confident users with strong opinions [3] and effective connections.

In order to identify the most important set of delegates, many approaches in the literature are based on graph theory [5,6]. According to this view and unlike existing methods which aim to detect delegates using classical graph concepts, we propose in this paper a new delegates based-approach for SCFS. Our method is built on advanced graph concepts. Indeed, we decompose the system into communities and we detect the most powerful heads in each community using "eigenvector centrality". In addition, we add to a higher level; the connector users who connect communities and assist communities' heads in their tasks. These connectors are identified by the critical nodes. Furthermore, we attempt to benefit from psychology field by introducing the personality traits in order to identify the set of social heads and connectors.

The rest of this paper is divided as follows: Section II presents related research works. Section III elicits the basic concepts. Section IV is devoted to the modeling of the proposed approach. Section V presents the proposed credibility measurement, while Section VI presents the proposed Trust score measurement. In Section VII we detail our approach of delegates' identification. In section VIII, we present and discuss our experimental results. We conclude the paper in Section IX with a summary and several interesting directions for future work.

## II. Related Work

The challenge in delegates' detection is how to identify the smallest set of users who influence the other users by their judgments and estimations. To this end, the existing studies on delegates' identification use centrality and fragmentation measures.

Indeed, the different centrality metrics such as distance centrality [4], eigenvector centrality [5] and degree centrality [6] have been used to detect the set of delegates; who are the users having a lot of strong ties with other members. The latter property ensures the selection of users with powerful neighbors. However, centrality is not influential in terms of network connectivity because deletion of central nodes may not guarantee a fragmentation of the network or even disconnectivity [7].

On the other hand, the fragmentation measure employed in existing studies on delegates' detection aims to identify one single node at a time. The researchers' community of this topic has studied the drop in the network performance caused by the removal of single nodes, the more important a node is in the network; the higher the falling in performance in the network when that node is deleted. However, single nodes removal is not as beneficial as simultaneous removal of a set of nodes. In fact, we can have two different nodes where the deletion of each single node doesn't results in disconnected communities but deletion of both guarantees a network fragmentation.

The latter reason has led us to think about exploiting an advanced graph parameter "Critical Nodes" in order to achieve the set of most effective delegates whose removal results in the maximum network disconnectivity. In addition, we keep using centrality measure, especially "Eigenvector centrality" as it enables us to take into account the trust score between users. Furthermore, we add the nodes cost that represents users credibility.

## III. Basic Concepts

### A. Critical Nodes Problem

Graph parameters aim to analyze a given graph which induces sometimes the decomposition of this graph on particular structures. The objective of Critical Nodes Parameter (CNP) is to find a set of k nodes in a graph whose deletion results in the maximum network fragmentation [8]. Indeed, deletion of these nodes generates the graph having the minimum pairwise connectivity between the remaining vertices [9].

Consequently, CNP finds several applications in social networks such as the Covert Terrorist Networks [7, 10 and 11] and Immunization Networks [12]. In this paper, we propose a novel method aiming to apply CNP on trust social networks.

### B. Eigenvector Centrality

Eigenvector centrality is a very efficient way aiming to measure the influence or importance of a node [13] since it takes into consideration the edges influence. The idea is that even if a node influences just one other node, who subsequently influences many other nodes (who themselves influence still more others), then the first node in that chain is highly influential [14].

Eigenvector centrality is largely applied in social networks [15,16] in order to identify the set of most important actors. It has been also used in order to alleviate cold start problem in recommender system [5]; by focusing on the influential edges having the stronger scores. In our approach we propose a new view of this measure by adding the nodes weights (users' credibility).

## IV. Graph Modeling of the Proposed Approach

We have chosen to model our approach CSCF with advanced exploration techniques of graph theory. In our proposal, the delegates consist of two key users (Community-heads and Connectors) and based on the collaboration between these two principal types of users, the system will be able to alleviate the cold start problems. The roles of connectors and community-heads are defined as follows:

- ***Community-heads*** are the representatives of their community, they aim at:
  - Representing the community by dealing with its different activities.
  - Putting new users in contact with the appropriate members.
  - Estimating the performance of an item in the course of time.
  - Appreciating the relevance of new items.
- ***Connectors*** are responsible of linking the trust network communities, they have the following tasks:
  - Passing information, items and opinions from a community to another;
  - Helping the new user to choose the right community;
  - Transferring the user who has changed his interests to a new community which is appropriate to his new interests.

According to this view, we propose representing the social trust network of the collaborative filtering system by a weighted graph as shown in (Fig. 1).

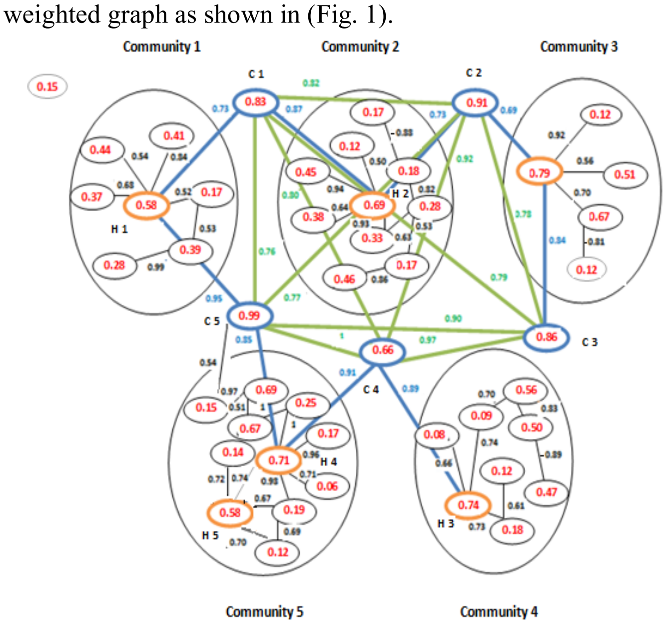


Fig. 1. Graph Modeling of the proposed approach

We have represented our system by a weighted graph in which:

- Social communities are represented by sub-graphs, more especially connected components;
- Users are represented by nodes;
- Links between users are represented by edges;
- Trust Scores between the users are represented by weights of the edges;
- The credibility of a user is represented by the weight of his associated node.

Our trust social graph is composed of many communities. Each one regroups a set of users who have the same preferences. There are four kinds of nodes:

- ***Followers (dark nodes):*** they represent the users of the system who interact in communities in order to get recommendations and benefit from the different goods of the system. These users trust their accountancies with confidence scores.
- ***Independent nodes (gray nodes):*** they are of two types:

  -*Newcomers* which represent the new users in the systems (cold start users). These nodes have no links.

  - *Changed-Nodes* which represent the users who have changed their interests and whose preferences become different from their community centers. These nodes have low trust scores with their friends.
- ***Community-heads (orange nodes):*** they are the most influential nodes in their community. They correspond to its representative users, their task is to manage the community by putting its newcomer in contact with the other users having similar interests and propagating items.
- ***Connectors (blue nodes):*** they are the intermediates nodes between the heads of the communities. They have the ability of passing information as well as news and also propagating items from a community to another. In addition, they help *Independent users* to transfer to the adequate community.

In addition, there are three types of edges:

- ***Edges between friends (dark edges):*** they link the nodes representing the system users;
- ***Edges between Connectors (green edges):*** they are the graph bridges that transmit information between connectors;
- ***Edges between Community-heads (gray edges):*** they allow the heads of a same community to communicate to each others;
- ***Edges between Connectors and Community-heads (blue edges):*** they transmit information and items from a community to another.

## V. CREDIBILITY MEASUREMENT

User credibility is computed by aggregating the five credibility components which are the connection to the system, the seniority in the system, the number of rated and proposed items in the system, the experience and the personality type. The credibility score ranges between 0 and 5 where each of the five components ranges between 0 and 1.

### *A. The connection to the system*

This component is related to the number and duration of user connections in the week. Generally, the users who are interested in a system connect frequently to it. Table 1 illustrates the scores of the number of connections and Table 2 presents the scores of the duration of connections by week.

TABLE I. SCORES OF THE NUMBER OF CONNECTIONS BY WEEK

| **Number of days of connections by week** | **Score** |
|---|---|
| [1-2] | 0.33 |
| [3-5] | 0.66 |
| [6-7] | 1 |

TABLE II. SCORES OF THE DURATION OF CONNECTIONS BY WEEK

| **Duration of connections by week** | **Score** |
|---|---|
| Less than 4 hours | 0.33 |
| Between 4 hours et 10 hours | 0.66 |
| More than de 10 hours | 1 |

The final score of the first credibility component « Connection to the system » is given by the average of its two sub-components « Number of connections» and « Duration of connections ».

### *B. The seniority in the system*

This component indicates the existence period of a user in the system as former users have good acknowledge of the system and its different functionalities as well as its communities. Each year of existence in the system is noted by the score (0.1).

### *C. The number of the rated and proposed items in the system*

A user who writes and recommends a lot of items in his community is active and beneficial in the network. Users can rate items by explicit votes that range between [0-10], where:

- [0-3]: Not interesting item.
- [4-6]: Interesting item.
- [7-10]: Very interesting item.

The scores of the number of rated and proposed items in the system are presented in Table 3.

TABLE III. SCORES OF THE NUMBER OF RATED AND PROPOSED ITEMS

| Number of rated and proposed items | Score |
|---|---|
| Less than 10 items | 0.33 |
| Between 10 and 30 items | 0.66 |
| More than 30 items | 1 |

### *D. The experience of the user*

Experts in the interests of a community are very important as they can recommend relevant research papers and guide new researchers such as new PhD students. The scores of the users experience are detailed in Table 4.

TABLE IV. SCORES OF THE USERS EXPERIENCE

| User | Score |
|---|---|
| Graduate student | 0,33 |
| Post graduate student | 0,66 |
| PhD, Assistant Professor, associate professor and Professor | 1 |

### *E. The personality of the user*

A social user is more beneficial than a lonesome user since persons who have a social personality type are dedicated delegates, humanistic, responsible and supportive. In fact, they enjoy informing, helping, training, developing and curing people in their work, they may, then, be very effective delegates.

To specify the personality type of a user we have used the Eysenck Personality Questionnaire (EPQ) [17] in order to extract the different personality traits such as (sociability, responsibility, dominance and activity). EPQ is a short and simple psychological questionnaire; that classifies the personality into three dimensions as shown in Table 5.

TABLE V. PERSONALITY DIMENSIONS DEFINED BY EPQ

| Psychoticism | Extraversion | Neuroticism |
|---|---|---|
| Aggressive | Sociable | Anxious |
| Energetic | Dominant | Depressed |
| Unsympathetic | Expressive | Moody |
| Turned into success | Active | Autonomous |

In CSCF, we are interested in the "Extraversion Dimension" which indicates if a user is sociable or solitary person. To this end, we ask our users to reply only on the 24 questions concerning extraversion dimension in EPQ; by choosing one of these five answers: “Strongly disagree, Disagree, Neither disagree nor agree, Agree, Strongly agree”. Thus, since Extraversion dimension includes 24 questions, the scores of sociability rage between 0 and 24. Table 6 defines the degree of sociability of a user according to his obtained score.

TABLE VI. DEGREE OF SOCIABILITY

| Range of Extraversion Score | Sociability Score |
|---|---|
| [0–5] | 0.25 |
| [6–11] | 0.5 |
| [12–17] | 0.75 |
| [18–24] | 1 |

The score of each answer is identified in Table 7 as follows.

TABLE VII. SCORES OF THE ANSWERS

| Answer | Score |
|---|---|
| Strongly disagree | 0 |
| Disagree | 0.25 |
| Neither disagree nor agree | 0.5 |
| Agree | 0.75 |
| Strongly agree | 1 |

Furthermore, each credibility component has been normalized using *sigmoid function* that varies between [0,1]. It is defined by [19]:

$$y = \frac{1}{1+\varepsilon^{-x}} \qquad (1)$$

## VI. TRUST SCORES MEASUREMENT

The trust scores between users have been computed using Pearson correlation coefficient as shown in formula 2. This coefficient gives scores between (-1) and (1).

$$w(u,v) = \frac{\sum_v (r_{u1,v} - \overline{r_{u1}})(r_{u2,v} - \overline{r_{u2}})}{\sqrt{\sum_v (r_{u1,v} - \overline{r_{u1}})^2 \sum_v (r_{u2,v} - \overline{r_{u2}})^2}} \qquad (2)$$

Where:

$r_{u1,v}$ : is the rating of user *u1* on item *v*.

$r_{u1}$: is the ratings average of user*u1*.

$r_{u2,v}$ :is the rating of user *u2* on item *v*.

$r_{u2}$ : is the ratings average of user *u2*.

## VII. DELEGATES IDENTIFICATION

### *A. Communities and connectors detection*

Communities' detection process aims to cluster the graph nodes representing the users into social groups. In our proposal, we use the critical nodes parameter in order to partition our network into communities and detect the most important connectors in each one.

Our proposed approach requires the information about the nodes representing the users to be clustered and the existing links between them. Thus, we cluster our weighted graph based on the nodes weights (users' credibility) and the edges weights (trust scores between users).

Denote an undirected graph $G = (V,E)$ with a set of vertices $V$ = (v1, v2,…n) and a set of edges $E$ = {uv : u, v ∈ V }. With $W_v \in [0,5]$ the weights on the vertices and $W_e \in [-1,1]$ the weighs on the edges. We aim to detect a subset S⊆V with total weight w(S) to be removed in order to generate a set of connected components CC = (C1,C2, . . . ,Cp), with the maximum internal cost of the edges weights denoted CCC as described in the following formula.

$$\begin{cases} w(S) \geq \propto \\ max \sum_{i=1}^{p} CCC \end{cases} \quad \text{: Where } \alpha \text{ is a constant} \qquad (3)$$

Noting that we have identified the connected components using the depth first search algorithms. At the end, the set of generated critical nodes *S* represent the set of connectors and the resulting connected components are the detected communities.

### *B. Community-Heads detection*

Once the communities and the connectors are detected, we apply “Eigenvector Centrality” in order to identify the set of most influential heads in each community. The number of heads in a community depends to its size noting that this number has to be as small as possible while being reprsesentatives of a lot of users in the community. As mentioned before, Eigenvector Centrality is more efficient than classical centrality measures as it focuses on strong links in the graph. In our case, strong links are represented by the edges having strong trust scores.

Formula 4 represents the use of the first parameter “Eigenvector Centrality” aggregated with nodes weights that represent “users' credibility”. In our proposal, an influential user has the maximum strong weights with other users in the community while his credibility is high.

Denoted H the set of heads in a connected component CC such that $|H| \leq \beta$ where $\beta$ is a constant. The set of nodes included in $H$ has to satisfy the following property:

$$\mathrm{H} = \max \frac{1}{\lambda} \sum_{1}^{\beta} \sum_{j=1}^{M} a_{ij}\, W_{ij} + \max W_i \qquad (4)$$

Where $A = (ai,j)$ is be the adjacency matrix of the graph.

$ai,j = 1$ if the node $i$ is linked to the node $j$ node, otherwise, $ai,j = 0$, $M$ is the set of nodes in the connected component, λ is a constant, $W_{ij}$ is the weight of the edge linking $i$ and $j$ "the trust score" and $W_i$ is the weight of $i$ "the credibility value".

## VIII. Results and Discussion

Since existing datasets in the field of recommender systems lack information about psychology traits and users connectivity. We have proposed our own dataset (ResPap) consisting of 160 users and 793 ratings on 58 items to test our approach. The set of users includes researchers in computer science area and the set of items contains researcher papers. The dataset has been collected during 6 months and was divided into 80% training set and 20% test set.

The accuracy of the system is evaluated in terms of precision [18] and fragmentation utility [5]. The precision can be interpreted as the fraction of relevant items among the $k$ recommended items for user $u$, as described in equation 5.

$$Precision\ (k,u) = \frac{N\ (k,u)}{k} \qquad (5)$$

Table 8 shows the precision average of our approach compared to a Random User and Eigenvector centrality [5]. From Table 4, it can be clearly seen that Random User is less effective since its precision averages is only 41%. At the opposite, Eigenvector Centrality Technique presented in [5] could reach about 79% of precision. The accuracy of our approach was estimated by 82% of precision average when we use only connectors as delegates and 84% when we choose only community-heads as delegates. In addition, CSCF could achieve 86% of precision average when it uses both connectors and communities' heads. These results confirm the feasibility and effectiveness of our clustering based-delegates approach.

TABLE VIII. Comparison of CSCF with other approaches in terms of precision average with ResPap dataset

| Random delegates | [5] | CSCF (with heads) | CSCF (with connectors) | CSCF (with connectors and heads) |
|---|---|---|---|---|
| 41% | 79% | 84% | 82% | 86% |

The results presented in Table VIII are schematized in the following figure (Fig. 2).

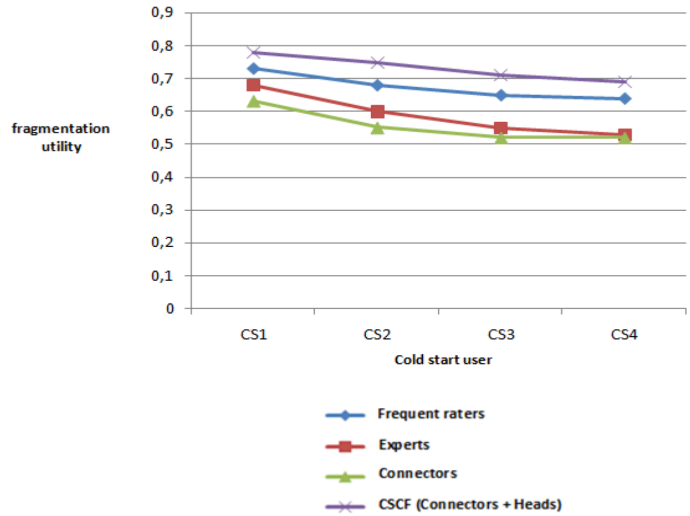


Fig. 2. Fragmentation utility

In the figure above (Fig. 2), CS1 refers to users who have evaluated exactly one item, CS2 refers to users who rated two articles, CS3 refers to users who rated three articles and CS4 are users who rated four articles.

Frequent raters (users who evaluate many articles), experts (users who offer many articles) and connectors (users who have a lot of connections) are the delegates proposed by [5], while connectors (critical nodes) and heads (central nodes) represent the delegates of our proposal.

Based on the results shown in Fig. 2, we observe that our approach is more effective because frequent evaluators and experts are not necessarily the most influential users since they may have a limited number of connections in the system. Moreover, the fragmentation measure used in [5] eliminates a single node each time, which does not necessarily influence the network. However, deleting this same node simultaneously with another node can cause significant disruption in the network.

In addition, the objective of our approach is to identify all of the delegates based on their experience and reliability by detecting users who evaluate, propose and recommend a considerable number of items in their community. Also, they frequently connect to the system, they have a good knowledge of the system, they have a good experience in the interest center of the corresponding community, and they also have a sociable personality. Taking all these criteria into account, we could reach the smallest groups of key users having the most important influence in the system.

Furthermore, the accuracy of CSCF has been evaluated in terms of fragmentation utility as shown in the following results.

Also, we have tested our approach on Dating agency dataset [20] which consists of 172511 evaluations given on 220970 items by1219 users. The results are summarized in the following table.

TABLE IX. Comparison of CSCF with other approaches in terms of precision average with Dating Agency dataset

| Random delegates | [5] | CSCF (with heads) | CSCF (with connectors) | CSCF (with connectors and heads) |
|---|---|---|---|---|
| 37% | 76% | 87% | 85% | 89% |

Furthermore, we have evaluated CSCF approach by using MovieLens dataset [21] which consists of 100000 ratings for 1682 movies by 943 users. The results are summarized in the following table.

TABLE X COMPARISON OF CSCF WITH OTHER APPROACHES IN TERMS OF PRECISION AVERAGE WITH MOVIELENS DATASET

| Random delegates | [5] | CSCF (with heads) | CSCF (with connectors) | CSCF (with connectors and heads) |
|---|---|---|---|---|
| 21% | 69% | 78% | 83% | 85% |

From the results presented in tables IX and X it can be clearly observed that CSCF approach is the most effective in terms of precision average.

## IX. CONCLUSION

In this paper, we have presented a novel delegates based-approach CSCF that allows solving the cold start user and item problems; by using graph theory and psychometric tests. CSCF aims to detect the set of most influential delegates who are able to guide new users and predict the recommendation of new items by clustering the graph of the social network representing the collaborative filtering system.

In order to cluster our social graph and detect the most efficient delegates, we have used advanced graph concepts; namely the critical nodes parameter and eigenvector centrality. Moreover, we have employed a psychology test in order to identify the most sociable delegates.

We assumed that best social delegates are those connecting the communities, communicating with key neighbors and having sociable personality. We also proved that an effective recommendation system has to take into consideration both trust and social information. In addition, we have shown that the mixture of recommender system field with graph theory and psychology domains has improved the quality of recommendations.

As a future work, we plan to test our approach on weighted directed graph that allow modeling trust between each pair of users in both directions using multiple edges. Another interesting perspective is to test our approach on recent big datasets including psychological information. We also plan to introduce content-based filtering to enhance recommendations.

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