A New Dynamic Community-Based Recommender System

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Abstract: Due to the rapid changes in users' preferences over time, it becomes increasingly important to focus on the temporal evolution of the users' behavioral patterns to capture the most relevant items to the users. This paper proposes a new framework for dynamic and overlapping community-based collaborative filtering, which models at first the dynamic behavior of users' interests into a temporal network of items. Then, we take advantage of the dynamic and overlapping community detection techniques to find the best partition of similar items. The advantage of doing so is to (i) avoid processing the entire system to select similar items and eventually overcome the scalability problem and (ii) provide users with a recommendation of items similar to the latest appreciated items to match the current users' taste and avoid consequently sparse cases. We conduct experiments to study the sensitivity of some parameters (e.g., the datasets and the similarity measures) on the recommendations' quality. Experimental results show a considerable improvement in the proposed framework recommendation's accuracy compared to the state-of-the-art recommender systems.

1 INTRODUCTION

Due to the huge amount of resources accessible via the internet, finding relevant information becomes a challenging task. Recommender systems (RSs) were introduced to achieve personalization and increase users' satisfaction by recommending items that fit their needs and tastes. Item recommendations can be made using different approaches namely *collaborative filtering*, *content-based* and *hybrid approaches*. Collaborative Filtering (CF) is the widely applied recommendation approach due to the high availability of users' preferences information (Qiang and Yan, 2012) (i.e., the ratings assigned to items). Two main classes of CF exist, namely, *user-based* and *item-based*. We are particularly interested in the item-based approach that consists in computing the preference prediction based on the ratings given to similar items. Basically, the item-based CF analyzes the entire user-item rating data to identify similar items. This can present various challenges, including *data sparsity*, *scalability*, and *cold start* problem. Community detection was used in recommender systems to overcome the recommendation issues (Sahebi and Cohen, 2011; Qin et al., 2010; Deng et al., 2014) and generate more accurate recommendations. The community structure could reveal either the set of items or users that share the same properties. Therefore, the community-based recommendation has a low computational cost compared to the basic recommendation approach since it focuses on pre-detected communities instead of the whole network. However, the existing community-based recommendation methods basically rely on static algorithms to detect communities and fail to consider the temporal evolution of users' interests.

Delving into the dynamic aspect of network behavior has become a necessity, especially for rapidly growing complex networks. The customers' preferences and interests are changing over time. It is crucial to track such temporal changes when defining similar items. It is affirmed that recommender systems taking into account the dynamic behavior of users' interests can provide more relevant recommendations of items (Yehuda, 2009). Based on this idea, we aim to exploit the dynamics of users' interests over time to identify the appropriate communities corresponding to each step of the network evolution. Incor-

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porating such dynamic communities in recommendation tasks may provide the system with a good vision of the most recent neighbors. Furthermore, in real-world networks, the communities overlap such that nodes may belong to several partitions at the same time. For instance, an item naturally tends to belong to several groups of different categories and popularity. The overlapping aspect should also be taken into account when detecting similar items to improve the performance of the provided recommendations (Vlachos et al., 2014).

In this paper, we propose a new framework for dynamic and overlapping community-based collaborative filtering (called for short DO2CF). The proposed framework considers the evolution of users' preferences over time and the overlapping aspect of items when identifying the most similar items. In rough outline, our framework consists of three main steps, namely *dynamic network construction*, *dynamic community detection* and *recommendation*. The first step consists in modeling the dynamic aspect of users' interests into a temporal network where nodes are the items and edges between nodes are established based on the co-rating relationships. In the second step, we use dynamic and overlapping community detection techniques that can track all the topological changes of the temporal network to learn the evolution of users' interests and detect a community structure accordingly. Indeed, each community reveals a set of items having similar interests. Finally, we exploit the network partition to (i) select the items' neighbors more easily and quickly, (ii) identify the candidate items that match the users' current tastes, and (iii) adapt the similarity measure to consider how much the co-users like one item relative to the other similar items instead of all the other items they rated.

This paper is structured as follows. Section 2 presents the basics of recommender systems, community detection, and community-based recommendation. Section 3 further illustrates the different steps of our framework. Finally, Section 4 presents the conducted experiments and their corresponding results.

2 RELATED WORK ON COMMUNITY-BASED RECOMMENDATION

We recall in this section the basic concepts of recommender systems and community detection separately. Then, we expose community-based recommendation and their related works.

2.1 Recommender Systems

The growth of web content and services has raised the interest in recommender systems. RSs are basically classified into three major categories, namely *Collaborative Filtering (CF)*, *content-based filtering*, and *hybrid approach*. The *CF* exploits the user-item rating data to suggest items to the active user. The *content-based filtering* focuses on the item features to characterize the items similar to the ones that the active user likes. The *hybrid approach* takes advantage of the rating information of users as well as the contents of items to produce recommendations. In this work, we focus on collaborative filtering as it is the most popular and used recommendation technique. There are two main CF approaches: *item-based* when the recommendations are generated based on the active user's ratings for similar items, and *user-based* when the recommendations are computed based on the similar users' ratings to the target item. We are particularly interested in the item-based CF approach as it provides a better recommendation quality than the user-based algorithms (Sarwar et al., 2002). Due to the nature of the data, CF could reveal some critical challenges such as *data sparsity* when there are not enough users' ratings, *scalability* when the number of ratings grows, and *cold start problem* when the active user is a new coming in the system (i.e., he does not have any rating data).

2.2 Community Detection

Complex networks are a natural way to represent social, biological, technological, and information systems. An interesting feature, that complex networks present, is the community structure-property. Community detection was proposed as an efficient tool to capture the hidden structure of these networks by partitioning the entities into a set of dense subgroups commonly called communities. A community is generally defined as a set of nodes strongly connected among them and more weakly connected to the remaining of the network (Fortunato, 2010). Studying the forming community structure in complex networks may help to learn the collective behavior of their entities and help the understanding of the modeled systems. The first attempts (Palla et al., 2005; Newman and Girvan, 2004) focused on detecting communities in static networks that are constructed by aggregating all observed data (also called static graphs). However, the democratization of the web 2.0 has produced new challenges for community detection, including the overlap of communities and the temporal aspect of the data (i.e., dynamic networks)

(Aston et al., 2014). The static community detection algorithms cannot support such challenges because they overlook the time information that is crucial to understand the phenomena taking place in the dynamic networks. Recently, many algorithms (Cazabet and Amblard, 2011; Nguyen et al., 2011; Xie et al., 2013) have been proposed to deal with dynamic networks.

2.3 Community-Based Recommendation

In recommender systems, there are two classes of entities: items and users. Indeed, the community structure reveals either the set of items or users with the same properties. Most of the existing works are interested in detecting communities of users since people often tend to form communities in real life. For instance, (Sahebi and Cohen, 2011) considered the different dimensions of social networks to extract latent communities of users using the *Principal Modularity Maximization* method. The resulting communities help recommender systems to overcome the cold start problem when the user has no rating history. (Qiang and Yan, 2012) applied a *Multi-label propagation* algorithm for static community detection in a bipartite network composed of users and items. Based on the active user's communities, the authors recommended items using the collaborative filtering recommendation method. (Ying et al., 2013) proposed a *Preference Aware Community Detection* method (PCD) to extract communities based on both users' rating history and social structure. Besides, they implemented a *Preference Aware Community-based Recommendation* System (PCRS) that uses the discovered communities to recommend items to users. (Guo and Peng, 2014) chose at first the *spectrum analysis* algorithm to extract communities from a user-user network. Then, they employed an evolutionary algorithm to identify the best neighborhood size for each community. Finally, they integrated the best neighborhood size of the active user's community in collaborative filtering to generate recommendations. On the other hand, some studies are interested in finding communities of items and incorporating them into the recommendation model. For instance, (Qin et al., 2010) constructed a YouTube Recommender Network (YRN) based on reviews left as comments in the YouTube videos. Then, they used *CFinder* algorithm to find communities in YRN. These communities are then used to recommend, for the active user, diverse videos that are not restricted to the same tag annotation. In (Fatemi and Tokarchuk, 2013), the authors employed the *Louvain* community detection method to extract communities of movies from the social network of movies that is constructed based on the *Internet Movie Database (IMDb)*. Based on these communities, extensive and diverse movies are recommended to both individuals and groups. The studies presented above overlooked the time dimension of users' preferences when computing recommendation. However, the data collected from recommender systems is often timestamped. The time dimension plays a very important role to properly capture the current need of users based on the most recent data.

Some studies proposed to explore the dynamic aspect of users' preferences in the recommendations generation process. (Abrouk et al., 2010) proposed to use fuzzy k-means clustering from time to time to dynamically capture the last users' preferences when detecting communities. These latter are then exploited to predict the active user's preferences for the unseen items. In (Hamzaoui et al., 2012), the authors have clustered items into groups using the *K-mean* algorithm. Then, they identified the clustering center of each cluster. The center is represented as the average ratings over all the items in the cluster. Finally, they computed the similarity between the target item and all the identified centers to select its neighbors and generate recommendations. The authors assigned a time weight for each pair of <user, item> with the aim to decay the old data when computing the item-item similarity. In (Xin et al., 2014), the authors employed the *Importance Greedy (IG)* algorithm to detect communities in the reader-reader similarity network. The book recommendation list is generated based on top 'k' books which are recently borrowed by the users belonging to the active user's community. The time of book borrowing is considered to highlight the time factor when generating book recommendations. (Yin et al., 2014) employed a modified *Probabilistic latent semantic analysis* (PLSA) model to discover communities. Then, they applied matrix factorization on each community. To model the temporal changes in users' interests, they used a time decay function which weighed the importance of the users latest interests when generating recommendations.

The existing community based-recommendation methods still rely on static community detection algorithms that cannot deal with the dynamic aspect of users' interests. Static community detection cannot support the network's topological changes, and consequently it misrepresents the true image of the network partitions. Using these communities in the preference prediction process may reduce the performance of the generated recommendations.

3 A NEW FRAMEWORK FOR DYNAMIC AND OVERLAPPING COMMUNITY-BASED CF

We propose a new framework for dynamic and overlapping community-based CF (DO2CF) (shown in Figure 1) comprising three main steps detailed below.

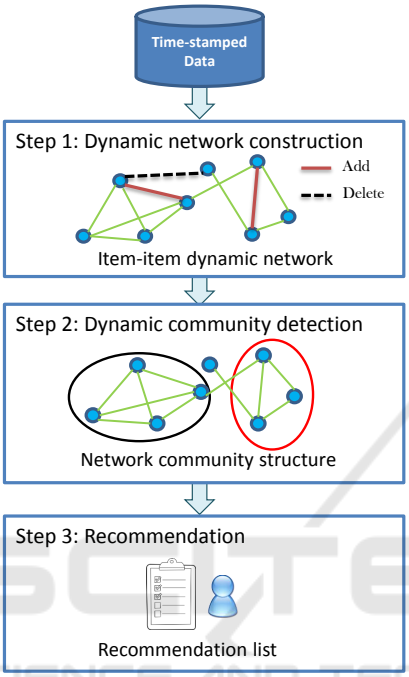


Figure 1: A framework for dynamic and overlapping community-based CF.

3.1 Step 1: Dynamic Network Construction

The users' interests in items are rapidly changing over time. This step consists in modeling the dynamic aspect of users' interests into a temporal network as it is the most appropriate representation when data evolves rapidly. Indeed, the snapshot-based representation cannot track all the interactions that appear over the multiple stages of the network life. Such representation is more adapted to time windows data composed of long-lasting relations (for instance, a weekly/monthly/yearly complete crawl of a system) and cannot fit the evolving nature of users' interactions in recommender systems. To build the temporal network, we start by modeling items as nodes and items relationships as edges. Nodes and edges can be added to (+) or removed from (-) the graph. We consider that a link exists between two items as long as these items interact frequently enough during a given period. Items interactions are defined based on the co-ratings relationship delivered from users' profiles. An item-item interaction is created if one user gives the same rating to both items in the same period. To model the network topology changes, we define two parameters N as the number of interactions and P as the number of days.

Table 1: Example of rating database.

UserID	ItemID	Rating$(1-5)$	Timestamp
Alex	*Titanic*	3	12/03/2014
Alex	*Troy*	3	12/03/2014
Amel	*Troy*	3	16/03/2014
Doudi	*Titanic*	3	16/03/2014
Kim	*Batman*	5	17/03/2014
Sam	*Titanic*	4	14/03/2014
Sam	*Troy*	4	14/03/2014
Kim	*Titanic*	5	17/03/2014
Doudi	*Batman*	3	16/03/2014

- An edge is inserted if there are at least N interactions between two items over a period of P days.
- An edge is removed if, over a period of P days, they occur less than N interactions between two items.

Example 1. *Let us consider a movie rating database that contains three movies (Titanic, Troy, Batman) and five users (**Alex**, **Amel**, **Doudi**, **Kim**, **Sam**). The users' ratings data are presented in Table 1.*

In order to construct the temporal network of the period T from $12/03$ to $17/03$, we first model the movies as nodes and we consider that $N = 2$ and $P = 3$. Thus, to create an edge between two movies, we need at least two interactions between these ones over a period of three days. To this end, we will check if Titanic and Troy can be linked. So, we start by extracting all Titanic-Troy interactions:

- ***Alex** rates both Titanic and Troy with the same rating (i.e., 3) in the same date (March the 12^{th}), so the first interaction between Titanic and Troy is created on $12/03/2014$.*
- ***Sam** gives the same rating (i.e., 4) to both Titanic and Troy in the same date (March the 14^{th}), so the second interaction between Titanic and Troy is created on $14/03/2014$.*

Over the first 3 days (i.e., from $(12/03)$ to $(14/03)$), there are two interactions between Titanic and Troy. Then, the edge between these nodes is created. Over the 3 following days (i.e., from $(14/03)$ to $(17/03)$), the edge between Titanic and Troy is removed since there are less than two interactions. Moreover, an edge is created between Titanic and Batman since there are more than two interactions between them over the period from $(14/03)$ to $(17/03)$. The network is finally constructed since there are no more

rating data after (17/03). *The different steps of the temporal network construction are presented in Figure 2.*

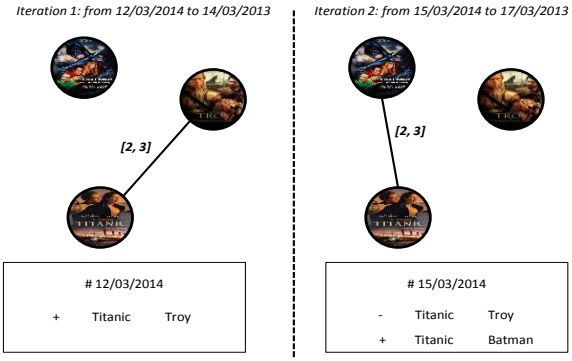


Figure 2: An example of the temporal network construction.

The parameters P and N are considered key to creating more semantic links between nodes. The estimation of these parameters highly depends on the datasets. Recommendation datasets are often characterized by three features, including the number of users, the number of items, and the number of ratings (i.e., numerical evaluations given by users to items). At first, we process all the data to find out the number of interactions N corresponding to each pair of items (i.e., how many users give the same rating to both of these items) and the period P in which these N interactions occurred. Then, we select many significant values for N and P: N_{min} (resp. N_{med}, N_{Q3} and N_{max}) which indicates the minimal (resp. median, 3rd quartile and maximal) number of interactions and P_{min} (resp. P_{med}, P_{Q3} and P_{max}) which indicates the minimal (resp. median, 3rd quartile and maximal) number of days. Knowing that the 3rd quartile indicates the values below which 75% of observations in a set of data fall. A temporal network is constructed based on each possible combination between N and P.

Example 2. *Let us re-consider the same rating database of Table 1. We compute the parameters N and P corresponding to each pair of items in the dataset. The number of interactions N for [Titanic, Troy] (resp. [Titanic, Batman] and [Troy, Batman]) is equal to* 2 *(resp.* 2 *and* 1*). The period P in which these interactions occurred between [Titanic, Troy] (resp. [Titanic, Batman] and [Troy, Batman]) is equal to* 3 *(resp.* 2 *and* 1*). Thus, the number of interactions N_{min} (resp. N_{med}, N_{Q3}, N_{max}) is equal to 1 (resp. 2, 2, 2) and the number of days P_{min} (resp. P_{med}, P_{Q3}, P_{max}) is equal to 1 (resp. 2, 2, 3).*

The resulting item-item dynamic network is then considered as a generic temporal network that represents the evolution of users' preferences over time.

3.2 Step 2: Dynamic Community Detection

Given the temporal network that models the dynamic evolution of users' interests (i.e., the output of step1), this step consists in using a community detection algorithm to extract communities. The community identification process strongly depends on the nature of the network (i.e., dynamic or static) and the overlapping aspect of the network entities (if the entities may belong to different subgroups at the same time). It is well understood that items in the recommender system are naturally characterized by multiple community memberships since they may satisfy the needs of several users with different tastes. Thus, overlapping community detection might be more appropriate to reveal interesting and useful patterns of similar items.

Moreover, the users' interests in items are changing over time. We need an algorithm that can consider the dynamic aspect of this behavior when detecting communities. The ongoing changes of a network may be among the most interesting properties to consider to detect more significant and appropriate communities. We consider for instance the evolution of two steps (t_1 and t_2) of a small graph composed of five nodes represented in Figure 3. If we only have a simple view of the last step (t_2), we will not be able to identify the appropriate community structure in the network. This is mainly because this network is strongly connected since it merges the whole observed links during the studied period. However, if we have an overview of the evolution process, we will be able to detect the network community structure that represents the real situation. Hence, by seeing t_1 and t_2, we can say that we probably have two communities (i.e., (abc) and (de)). Consequently, a considerable impact on recommendations is envisaged depending on the type of community detection algorithm.

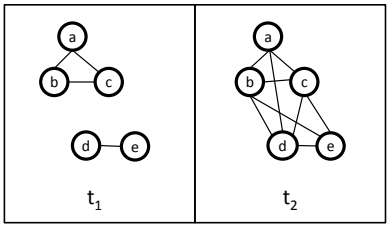


Figure 3: Example of two different steps of a network evolution.

In this step, we focus on community detection algorithms that deal with two basic characteristics: the dynamic behavior of the network and the overlapping aspect of communities. In this work we focus on al-

gorithms that can support the temporal network (i.e., output of step 1) as input, namely *iLCD* (Cazabet and Amblard, 2011) and *AFOCS* (Nguyen et al., 2011).

- In (Cazabet and Amblard, 2011), the authors propose an *Intrinsic Longitudinal Community Detection (iLCD)* that uses a multi-agent-based method to handle the evolution of communities. The general principle of the algorithm is essentially based on local computations. Indeed, the communities can perceive only the nodes that they contain and they can interact only with other communities having at least a node in common. When they perceive a topological change in their local environment (edge/node addition/removal), the candidate communities take decisions to add/lose nodes, split into two distinct communities, or merge with another community based on a set of rules:
  - For any link addition (i, j) in the network, if i is in a community C and j does not belong to C, *iLCD* checks if j must be integrated into C and it finds then the set of these newly-formed communities by the appearance of this new link (i.e., resulted from the fusion of the modified communities).
  - For any deletion of a link, if this edge is found within a community, *iLCD* checks if the concerned community C loses one or many nodes which may lead to self-division.
- In (Nguyen et al., 2011), the authors proposed the *Adaptively Finding Overlapping Community Structure* (AFOCS) algorithm that can detect overlapping communities in a dynamic network through two phases. The first phase consists in discovering all possible basic communities in the original input network by extracting at first all possible densely connected sub-graphs of the network and then combining those that share a significant common substructure. The second phase consists in examining, after every network topological change, the internal density of the current community structure to update the basic community structure:
  - If new node addition $(V + v)$: AFOCS checks if v should (i) be considered as outliers or (ii) joins existing communities or (iii) forms a new community with a substructure of the network.
  - If new edge addition $(E + e)$: AFOCS checks if e (i) has no impact on the current structure or (ii) allows the combination of two existing communities or (iii) allows an existing community to grow up.
  - If node deletion $(V - v)$: AFOCS checks if this change (i) has no impact on the current structure or (ii) allows an existing community to contract or to disappear.
  - If edge deletion $(E - e)$: AFOCS checks if this change (i) has no intact on the current structure or (ii) allows an existing community to split into two distinct communities.

3.3 Step 3: Recommendation

This step consists in generating the recommendation list for the active user based on the network community structure of items (i.e., the output of step 2). The discovered communities are exploited to (i) determine the candidate items that can suit the active user's latest feedback and (ii) select the items involved to compute the active user's preferences prediction for these candidate items.

Typically, the preference prediction is computed for each unseen item. However, it is not necessary to handle the items that could not match the active user's current needs. Indeed, the user's preferences change over time and what was interesting before may not be the case now. For this reason, we assume that the active user would be interested in items similar to his/her current taste, namely candidate items. The candidate items are therefore identified based on the communities of the recently appreciated item. By doing this, (i) we avoid browsing all the unseen items and eventually overcome the scalability problem. And (ii) we keep away from sparse cases since there is at least one similar item already liked by the active user. Then, the active user's preference for each candidate item is computed to generate the top k recommendation list.

$$P_{u,i} = \frac{\sum_{j \in C} s(i,j)\, r_{u,j}}{\sum_{j \in C} |s(i,j)|} \quad (1)$$

where C is the set of items pertaining to the communities of i, $r_{u,j}$ is the rating given by the active user u to the item j and $s(i, j)$ is the similarity degree between items i and j.

There are several methods to compute the relative similarity among items in the literature (Sarwar et al., 2001). Basically, the similarity of items i and j is computed by looking essentially to the co-users who have rated both these two items. We present a brief description of the most common similarity measures as follows:

- *Pearson correlation* measures the similarity between items based on the correlation between the co-users ratings.

$$s(i,j) = \frac{\sum_{u \in U} (R_{u,i} - \overline{R_i})(R_{u,j} - \overline{R_j})}{\sqrt{\sum_{u \in U} (R_{u,i} - \overline{R_i})^2} \sqrt{\sum_{u \in U} (R_{u,j} - \overline{R_j})^2}}$$

where U is the set of co-users, $R_{u,i}$ is the rating given by user u to item i, $\overline{R_i}$ is the average ratings given to i and $\overline{R_j}$ is the average ratings given to j.

- *Cosine measure* estimates the similarity of two items by looking to the distance between the feature vectors of these items.

$$s(i,j)=cos(\vec{i},\vec{j})=\frac{\vec{i}*\vec{j}}{\|\vec{i}\|^2*\|\vec{j}\|^2}$$

- *Tanimoto coefficient* is the implementation of *Jaccard* similarity that computes the similarity between two items based on the intersection of their preferences.
- *Likelihood ratio* computes the similarity between items based on the overlapping users' preferences.
- *Adjusted cosine similarity* uses the average of the u^{th} co-user's ratings to make the correlation between the co-users' preferences. However, in this work we focus on computing the similarity of two items within the same community. Intuitively, we modify the *Adjusted cosine similarity* to integrate the community structure in addition to the co-users rating information. In fact, we replace the mean of the user's ratings with the mean of the user's ratings for items belonging to the common communities to measure how much the co-users like one item relative to the other similar items they rated.

$$s(i,j)=\frac{\sum_{u\in U}(R_{u,i}-\overline{R_{u,C_{ij}}})(R_{u,j}-\overline{R_{u,C_{ij}}})}{\sqrt{\sum_{u\in U}(R_{u,i}-\overline{R_{u,Cij}})^2}\sqrt{\sum_{u\in U}(R_{u,j}-\overline{R_{u,C_{ij}}})^2}}$$

where U is the set of co-users, $R_{u,i}$ is the rating given by user u to item i, $\overline{R_{u,Cij}}$ is the average ratings given by user u to items belonging to common communities of i and j.

The preference estimation is also affected, on the one hand, by the number of items in the same communities and, on the other hand, by the number of common communities. Algorithm 1 presents the recommendation step.

Example 3. *Let us consider the network community structure composed of 2 communities C_1 and C_2. Movies Ted2, Batman and X-men belong to C_1 and movies Gladiator, Batman and Ted2 belong to C_2. Table 2 presents the rating data of **Jane** on the available movies.*

*We can note that the Ted2 and Batman movies are more similar than any other movies since they have more common communities. For instance, Batman will be considered twice in the preference computation as it has two common communities with Ted2 while X−men will be considered just once as it shares one common community with Ted2. Knowing that the similarity between the pair of items (Ted2, Batman) (resp. (Ted 2, X−men) and (Gladiator, Batman)) is 0.4 (resp. 0.53 and 0.6), the preference of **Jane** on movies Ted2 and Gladiator are computed as follows:*

$$P_{Jane,Ted2} = \frac{\sum_{b\in C_1,C_2} s(Ted2,b)*r_{Jane,b}}{\sum_{b\in C_1,C_2}|s(Ted2,b)|}$$
$$= \frac{(0.4*3)+(0.4*3)+(0.53*5)}{0.4+0.4+0.53}$$
$$= 3.79$$

$$P_{Jane,Gladiator} = \frac{\sum_{b\in C_2} s(Gladiator,b)*r_{Jane,b}}{\sum_{b\in C_1}|s(Gladiator,b)|}$$
$$= \frac{0.6*3}{3}$$
$$= 3$$

*Thus, the movie Ted2 is selected as the best recommendation alternative to **Jane**.*

Algorithm 1: Pseudocode for the recommendation step.

Require: : Network community structure $C=\{c_j\}$, Active user u, active user's ratings R_u
Ensure: : Recommendation list L
$i^* \leftarrow Max\_preferred(R_u)$
$C^* \leftarrow target\_communities(C,i^*)$
for j $\in candidate\_items(C^*,R_u)$ **do**
$P_{u,j} \leftarrow Preference(R_u,C,j)$
end for
$L \leftarrow Max\_Preference(P_{u,j})$

% $Max\_preferred(R_u)$: Returns the most recent liked item by the user u
% $target\_communities(C,i^*)$: Returns the communities of i^*
% $candidate\_items(C^*,R_u)$: Returns the set of items belonging to C^* and has not yet been rated by u.
% $Preference(R_u,C,j)$: computes the preference prediction as the weighted sum of the u's ratings given to the items belonging to the communities of j.
% $Max\_Preference(P_{u,j})$: Selects the top-k items with the higher preference prediction values in the recommendation list.

Table 2: Jane' Ratings data.

Movie title	**Rating**$(1-5)$
Batman	3
X-men	5
Ted2	?
Gladiator	?

4 EXPERIMENTAL STUDY

To evaluate the accuracy of the proposed framework, we conduct experiments on two real-world data sets

namely, MovieLens data set[1] and Video games reviews data set[2]. All the experiments are implemented in Java JDK 1.8 on a windows 10 based PC with intel Core i3 processor having a speed of 2.40 GHz and 4GB of Ram and compiled in eclipse framework. In what follows, we first describe the data sets and the evaluation metrics. Then, we present the experimental results.

4.1 Datasets and Metrics

The data sets used in our experiments are:

- MovieLens data set extracted from movies recommender system containing 10 million of ratings collected from 72 000 users on 10 000 movies (items) from 2000 to 2009. Each user has rated at least 20 items and made a rating at five discrete levels from 1 to 5.
- Video game reviews data set extracted from Amazon including 1 million ratings spanning from June 1997 to July 2014. The ratings are collected from 129 496 customers on more than 1371 video games, and they are on a numeric five-point scale (i.e., from 1 to 5).

Each data set is divided into two subsets: a training set and a testing set. The training set is used to construct the dynamic network of items, detect communities and finally, predict the user's rating for an item to generate the recommendation list. The testing set is used to evaluate the closeness of the predicted rating compared to the user's provided rating. To this end, we first split the data chronologically into testing (20% of the recent instances) and training (the remaining ones). The efficiency of the proposed framework is evaluated using classification accuracy measure, namely *F-measure* and predictive accuracy metric, namely *Mean Absolute Error* (MAE) (Chena and Liu, 2017). F-measure denotes the weighted harmonic mean of the precision and recall of the generated recommendations. MAE measures the deviation of the estimated preference from the true preference value specified by the active user. The lower the MAE is, the better the generated recommendations are. Formally:

$$F-measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

$$Precision = \frac{RR}{RR + FR}$$

$$Recall = \frac{RR}{RR + RN}$$

where RR denotes relevant and recommended items, RN denotes relevant and not recommended items, and FR denotes not relevant and recommended items.

$$MAE = \frac{\sum_{i=1}^{n} |p_i - q_i|}{n}$$

where p_i denotes the predicted rating for item i, q_i denotes the true rating for item i, n: the corresponding ratings-prediction pairs.

4.2 Experimental Protocol

Before presenting the experimental results and comparing them with state-of-the-art recommendation algorithms, we propose to test the impact of some parameters on the quality of the proposed framework. The parameters representing the optimum values are then taken for the rest of the experiment.

4.2.1 The Parameters N and P

To detect the values that can capture communities with the most interesting size and internal topologies, we count, for each pair of items, the number of interactions N and the corresponding period P. Subsequently, we select various significant values (i.e., the minimal, the median, the 3rd quartile, and the maximal) for these parameters as follows:

- For MovieLens data, we found 171 787 pairs of movies interacted together. The maximal number of interactions N_{max} (resp. the minimal N_{min}, the median N_{med}, and the 3rd quartile N_{Q3}) is 414 (resp. 1, 2 and 2). The maximal period of days P_{max} (resp. the minimal P_{min}, the median P_{med}, and the 3rd quartile P_{Q3}) is 1035 (resp. 1, 119 and 517).
- For video game data, we found 3580 pairs of video games that have interacted together. The maximal number of interactions N_{max} (resp. the minimal N_{min}, the median N_{med}, and the 3rd quartile N_{Q3}) is 55 (resp. 1, 1, 2). The maximal period of days P_{max} (resp. the minimal P_{min}, the median P_{med}, and the 3rd quartile P_{Q3}) is 5329 (resp. 1, 2290 and 2664).

A temporal network is constructed for each possible combination between P and N (i.e., 4^2 temporal networks built for each dataset). We first apply iLCD and AFOCS to detect dynamic communities from each temporal network. The resulting communities are then used to compute recommendations. We kept only the valid temporal network of items (i.e., with existing links and a non-empty community structure) since it is hard to find connections that hold on between nodes if N is maximal and/or P is minimal.

[1] https://movieLens.umn.edu

[2] https://snap.stanford.edu/data/web-Amazon.html

Table 3: The impact of N and P on the recommendation quality in MovieLens.

Algo / $[N,P]$	iLCD		AFOCS	
	MAE	*F − measure*	*MAE*	*F − measure*
$[1,119]$	0.68	0.267	0.88	0.15
$[1,517]$	0.6	0.29	0.7	0.2
$[1,1035]$	0.56	0.299	0.66	0.22
$[2,517]$	0.683	0.277	0.81	0.154
$[2,1035]$	**0.48**	**0.39**	0.57	0.258

We present in Tables 3 and 4 the accuracy of the recommendation for different community detection algorithms and different temporal networks in MovieLens and Video Game reviews data sets, respectively. Table 3 shows that the prediction accuracy in MovieLens dataset reaches its maximum when N is fixed to 2 and P is fixed to 1035. While Table 4 shows that the prediction accuracy in the Video Games data set reaches its maximum when N is equal to 2 and P is equal to 5329. Thus, we conclude that the prediction accuracy reaches its maximum when N is the median value and P takes the maximum for both databases. Indeed, we need to consider the most frequent value of item-item interactions and the maximal period P to keep the highest number of connected nodes. We can also observe from Tables 3 and 4 that by using the dynamic *iLCD* algorithm the recommendation quality reaches its maximum compared to *AFOCS*. This is justified by: (i) its aptitude for considering the network evolution over time that has a major impact on the detected network community structure and (ii) its ability to distinguish between representative nodes and hubs (i.e., highly centralized nodes) to decide against merging communities with many outside neighboring nodes.

Example 4. *For instance, if we consider Figure 4. Titanic, Troy, and Tourist are* 3 *movies of the same community* C_1 *(i.e., many users have evaluated Tourist similarly as Titanic and Troy). Moreover, movies Belle, Titanic and Troy belong to the same community* C_2*). However, Tourist and Belle cannot be similar (i.e., be in the same communities* $C_1 \cup C_2$*) just because both are similar to Titanic and Troy. These latter are popular legendary movies and can be appreciated by many users with different tastes.*

Hence, we chose to use dynamic *iLCD* algorithm (Cazabet and Amblard, 2011) to detect communities in the remaining experiments. Figure 5 shows two snapshots of the network community structure detected by iLCD with the aforementioned optimal results of N and P.

Table 4: The impact of N and P on the recommendation quality in Video games.

Algo / $[N,P]$	iLCD		AFOCS	
	MAE	*F − measure*	*MAE*	*F − measure*
$[1,2290]$	1.22	0.263	1.34	0.19
$[1,2664]$	1.2	0.27	1.29	0.194
$[1,5329]$	1.19	0.284	1.268	0.2
$[2,2290]$	1.4	0.192	1.6	0.166
$[2,2664]$	1.02	0.293	1.24	0.225
$[2,5329]$	**0.99**	**0.32**	1.18	0.3

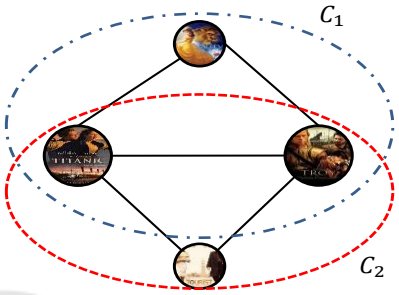


Figure 4: Example of a network structure.

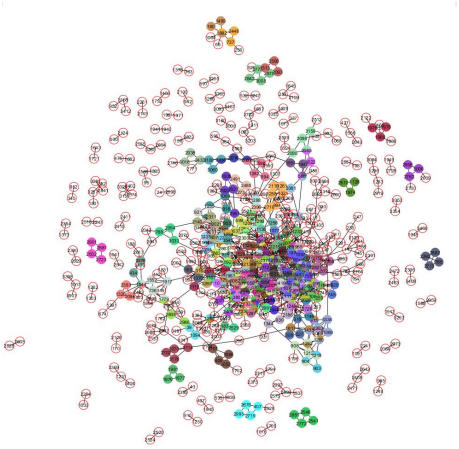
4.2.2 The Effect of the Similarity Measure

In this experiment, we choose to test the similarity measures namely, *Pearson correlation*, *Cosine*, *Tanimoto coefficient*, *Likelihood ratio* and *adjusted cosine*, as they are commonly used in recommender systems in our data sets, and study their effects on the obtained prediction quality. We have implemented the Adjusted cosine similarity measure, and we use Apache Mahout's implementations of other measures. Figure 6 shows the evaluation results.

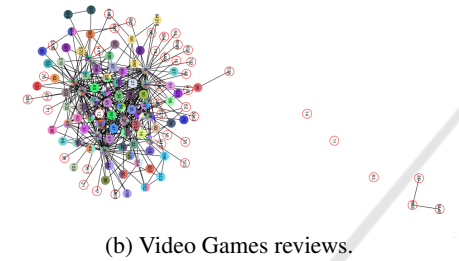
We can see that for both MovieLens and Video Games data sets, using the *adjusted similarity* in the proposed framework achieves the lowest MAE and the highest F-measure value compared to other similarity measures. This result can be justified by the fact that is more interesting to focus on how much the co-users liked similar items instead of all the other items to measure the similarity of items of the same communities. Therefore, the adjusted cosine similarity is used in what follows.

4.3 Comparison with Related Work

In this section, we propose to compare the recommendation accuracy of our dynamic and overlapping community-based recommendation framework with existing related work approaches presented in Table 5.



(a) MovieLens.



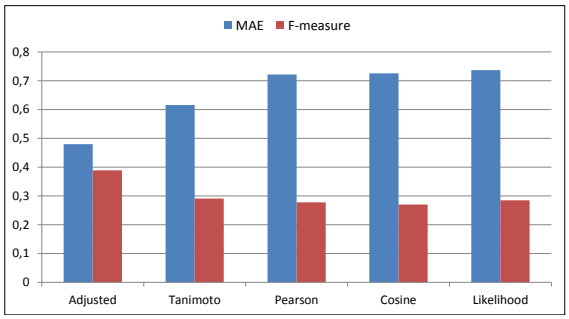
(b) Video Games reviews.

Figure 5: Network Community structure of iLCD with $[N_{med}, P_{max}]$.

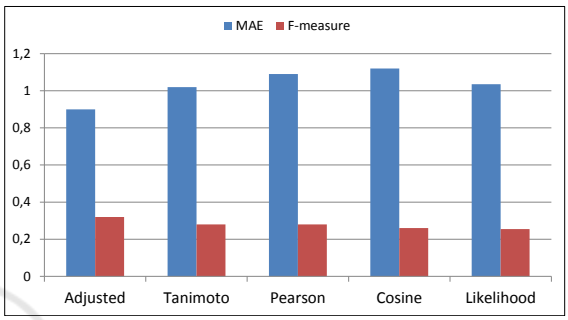
The static community-based CF (so-called S.community) (Fatemi and Tokarchuk, 2013) employed the *Louvain* method to extract communities of movies. The static clustering-based CF (so-called S.cluster) (O'Connor and Herlocker, 2001) consists in using the *Average link* clustering algorithm to group items into clusters based on the similarity matrix. The dynamic clustering-based CF (so-called D.cluster) (Hamzaoui et al., 2012) included a time weight parameter in item-item similarity measure to penalize the impact of historical data and then take into account the dynamics of the active user's purchase habits. The timeSVD++ (Yehuda, 2009) refers to the time-sensitive algorithm that considers temporal information beyond the rating matrix by introducing time-variant biases for each user and each item. The idea is to decay the weight of the user's old ratings to have no effect on his status at the current time.

Figure 7 displays the prediction accuracy results over the state-of-the-art recommendation methods.

First, the prediction quality of S.cluster is unsurprisingly worse than item-based CF as stated by the literature (O'Connor and Herlocker, 2001). For instance, applied to the MovieLens data set, the clustering-based approach yields an MAE of 0.77



(a) MovieLens data set.



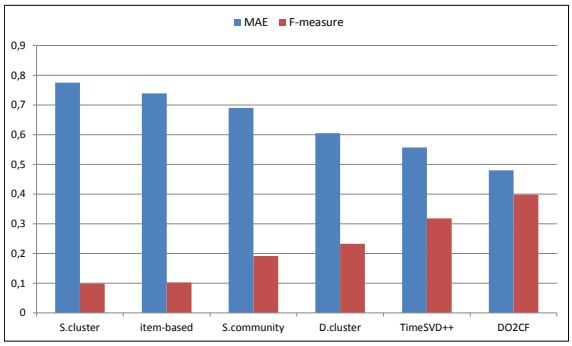
(b) Video Games data set.

Figure 6: Sensitivity of similarity measures.

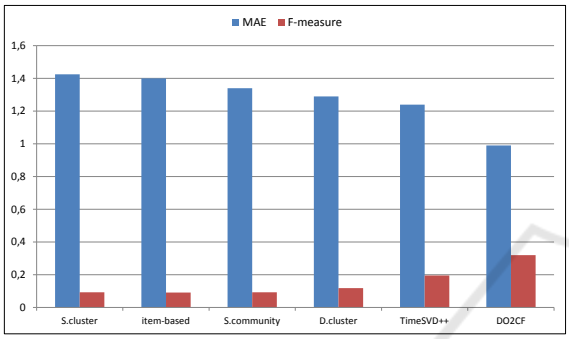
Table 5: State-of-the-art methods.

Name	Overlapping	Time	Method
item-based	No	No	*KNN*
S.community	Yes	No	Louvain
S.cluster	No	No	Average link
D.cluster	No	Yes	K-means
TimeSVD++	No	Yes	–

and the item-based CF yields an MAE of 0.739. Moreover, applied to the Video Games data set, the clustering-based approach gives a higher MAE (i.e., 1.42) and thus a lower accuracy compared to the basic item-based (i.e., 1.39). The decrease in accuracy could be due to the fact that the clustering algorithms group items to be exclusively in one cluster. However, certain items may have significant predictive value for multiple clusters. Subsequently, the predictions computed using a static and overlapping community detection approach (S.community) are more accurate than the basic item-based. This is explained by the fact that the overlapping aspect of the items subgroups (i.e., an item may be a member of more than one community) may reveal interesting neighbors selection (i.e., containing similar items with different popularity and preferences). It can also be observed from Figure 7) that the D.cluster, in both data sets, provides a better quality of prediction compared to both item-based and S.community because it considers the temporal information of users' preferences when com-



(a) MovieLens data set.



(b) Video Games data set.

Figure 7: The performance of the state-of-the-art recommendation algorithms.

puting the similarity between items (i.e., by penalizing the impact of old rating data and highlighting the recent data rating). However, the time-sensitive algorithm TimeSVD++ performs better than D.cluster since it considers the temporal dimension in a large space (i.e., not only when computing the similarity). Finally, the proposed framework for overlapping and dynamic community-based CF (DO2CF) has a lower MAE value (i.e., 0.48 in MovieLens and 0.99 in the Video games data set) compared to D.cluster, and this meant that it yields the best recommendation accuracy in comparison to all the other CF methods. This is justified by the fact that by considering both the temporal changes in users' interests and the overlapping aspect of items, the detected communities can better reveal the items that represent the most recent related neighbors. Accordingly, the quality of the community structure has an impact on recommendation accuracy. Furthermore, DO2CF performs better than TimeSVD++ since the latter aims to capture temporal effects by incorporating a time-variant bias for each user and item at every time window. Indeed, TimeSVD++ cannot track the underlying pattern for different biases of time windows.

5 CONCLUSIONS

In this paper, we propose a new framework for dynamic and overlapping community-based CF that allows (i) modeling the dynamic aspect of users' preferences in a recommender system into a dynamic network, (ii) identifying dynamic and overlapping groups of items using a community-detection algorithm, and (iii) providing a diverse recommendation list that could match the current users' tastes. Through this work, we highlight that by considering the network topology changes and the overlapping membership of items, the detected communities are more significant and appropriate. Consequently, a considerable impact on the recommendations' quality is envisaged depending on the type of community detection algorithm. In addition to the recommendation accuracy improvement, the experimental results for both MovieLens and Video Games data sets indicate that (DO2CF) can scale with large data and address sparsity.

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