Resource recommender system performance improvement by exploring similar tags and detecting tags communities

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Abstract

Many researchers have used tag information to improve the performance of recommendation techniques in recommender systems. Examining the tags of users will help to get their interests and leads to more accuracy in the recommendations. Since user-defined tags are chosen freely and without any restrictions, problems arise in determining their exact meaning and the similarity of tags. On the other hand, using thesauruses and ontologies to find the meaning of tags is not very efficient due to their free definition by users and the use of different languages in many data sets. Therefore, this article uses the mathematical and statistical methods to determine lexical similarity and co-occurrence tags solution to assign semantic similarity. On the other hand, due to the change of users' interests over time this article have considered the time of tag assignments in co-occurrence tags for determined similarity of tags. Then the graph is created based on these similarities. For modeling the interests of the users, the communities of tags are determined by using community detection methods. So recommendations based on the communities of tags and similarity between resources are done. The performance of the proposed method has been done using two criteria of precision and recall based on evaluations with "Delicious" dataset. The evaluation results show that, the precision and recall of the proposed method have significantly improved, compared to the other methods.

Keywords: Social tagging systems, Recommender systems, Collaborative filtering, Community detection, Folksonomy

1. Introduction

Today, we face a rapid and huge growth of data in social systems. Although there is a lot of useful information in various fields, finding the accurate and desirable data is difficult and time consuming. To conquer this problem, recommender systems have been provided. Those systems are software techniques and tools that assist users in various decision-making processes. In fact, while users need to find the right information, they need a system that supports them. One of the offered solutions in this field is the development of recommender systems to provide personalized services according to users' interests. Recommender systems are used in various fields and applications. One of the most popular well-known systems implemented is Amazon website, which takes advantage of customer's purchase behavior, attractions, and offers according to the users' interests.

The overall structure of a recommender systems follows a set of phases including collection, learning, and recommendation[1][2]. In the first phase, appropriate resources that comprise the relevant information of users are selected. Then, a leaner (supervised or unsupervised learning) analyzes the users' preferences, and extracts their behavioral patterns. Final phase recommends the entities that are the most similar to the users' interests. It is important to recognize that, within a common core structure of recommender system,

there are variations from application to application. Some of the most sophisticated and heavily used recommender systems in industry are Last.fm, YouTube, and Amazon [3].

Generally, recommender systems can generate a list of recommendations by these approaches: content-based filtering, collaborative filtering, hybrid recommender systems and so on [4]. Based on the existing research, the conventional CF¹ approaches, which only use user-item rating information to make recommendations, are in two major categories: the memory-based CF and model-based CF both of which can be used to make recommendations in tagging systems [5]. Memory-based methods make suggestions based on the nearest neighbors and model-based recommends based on the model created by users. In recommender systems, another type of system was introduced as tagged or tagging systems. Mathes discussed the tags on the web in articles in late 2004 [6].

Recently, social tagging systems have become an important instrument of Web 2.0 that allowing users to collaboratively annotate and search the content. In order to facilitate this process, the present research has attempted to improve the performance and quality of resource recommendations. Despite the creation of new opportunities, social tagging recommender systems, revive old problems such as information overload. Recommender systems good applications in making available the information these is related to the users' interests. However, we face new challenges in tagging recommender systems. In these systems, users are interested in finding tags, contents and even other users. Furthermore, while traditional recommender systems typically work with 2D data arrays, the data in these systems act as a third-order tensor or a multilayer graph with user nodes, resources, and tags which have introduced as new aspects of recommendations such as users, resources and introduced the tags. Therefore, new approaches and algorithms were needed to address the threefold nature of the data in these systems. Various social tagging systems such as Delicious, CiteULike, Flickr, etc allow users to assign custom tags for resources based on their background knowledge to manage, organize, share, discover and retrieve resources.

Collaborative tagging systems, also known as folksonomy, have grown dramatically on the Web. Tags in these systems significantly organize the content of websites and other resources and effectively display user behavior. This is considered as an advantage for these systems. Tags are also used as a bridge between users and resources to describe users' interest in resources [7]. Researchers use a variety of strategies to gain the users' interests and make recommendations with greater accuracy. In fact, one of the most important concerns in the field of recommender systems is to provide more accurate recommendations according to the users' interests.

This article focuses on one of the major challenges of recommender systems, which is to improve the performance of the recommender algorithms. To improve the performance, it has relied on modeling user' interests and tagging clustering based on user tagging behaviors. Clustering and providing more accurate analysis we have used the community detection method. This is consider as an important achievement. In fact, by examining the tagging behaviors of users more closely, using the suggested similarity criteria, forming a graph, and using the community detection method, we have paved the way to obtain users' interests and finally we have increased the strength of the recommendations with the nearest neighborhood method.

Tagging activities in folksonomies are not guided by any formal regulations (no dictionaries, no thesaurus) meaning that users can tag resources with any tags they like. This leads to a wide variety of tags like inflections, spelling errors, abbreviations creative use of compounding, and etc. We can interpret the tags in the folksonomy as concepts [8]. As a result, in tagging-based recommender systems, the main problems arise from discovering the meanings of tags. Due to the ambiguity in the meanings of the tags and lack of correct discovery of their meanings, the performance of these systems are affected. The co-occurrence tag method has been used for semantic communication in most previous studies. The number of studies, ontologies or external knowledge have been used to strengthen this method. In semantic theory, in order to find the relationship of tags based on external knowledge, an attempt is made to adapt them with meaning. In [9] they have tried WordNet concepts for deriving relationships. However, WordNet is a static resource, and only less than half (48.7%) of tags can match the direct study in [10]. In [10] described a

¹ Collaborative Filtering

domain ontology development approach that extracts domain terms from folksonomies and enrich them with data and vocabularies from the Linked Open Data cloud. As a result, this article obtains lightweight domain ontologies that combine the emergent knowledge of social tagging systems with formal knowledge from ontologies [10]. In general, it is difficult to choose the right concept that matches the tag due to the lack of tagging context. This is because the process of tagging users is very different from the lexicologists or domain specialists. This problem of separating the concept of tag is discussed in [10] [11]. Even if a tag can be lexically consistent with a concept in external sources, the conformity of their intended meanings is unclear [12].

Our work is different from the previous methods for a number of reasons, because we have not used any external linguistic resources such as Word Net or semantic resources (like ontology) and this makes our method stronger and covers most of the tags. On the other hand, WordNet or other external knowledge is maintained manually by experts and thus remains unchanged in long term. In fact, the low coverage of WordNet inevitably leads to the poor performance of the WordNet based on tag sense disambiguation methods. On the other hand, as in the previous methods, we have used the co-occurrence tag methods by considering the time of tag assignments parameter and lexical similarity to strengthen their communication.

Another strength of the proposed method is the use of community detection method to analyze tags and find appropriate clusters of them. All these are to improve the quality of system performance. In this work, we presented a new method of collaborative filtering resource recommendation systems called social collaborative based on community detection with semantic and lexical connections of tags. It should be noted that when users employ tags for resources, these tags clearly show their preference and interest. By examining the interactions between users and tags, it is possible to understand the semantic correlation between resources and users, and also to extract users' interests more accurately than recommending systems based on rating.

The rest of the article is organized as follows: section 2 summarizes the work done in this area. Section 3 deals with the proposed system with sub-sections for creating tag graphs, identifying tag communities and providing recommendations. Section 4 describes the experimental analyses and the results of the proposed method. Finally, in Section 5, we have presented the results and conclusions.

2. Related works

Nowadays, tag-based recommender algorithms are evolving rapidly. In general, tag-based recommender systems provide recommends to users by analyzing tags assigned to resources. In traditional recommender systems, especially CF, only two-dimensional data was used based on user resource rating and often with a rating resource user matrix, in tagged systems, i.e. collaborative tagging, another dimension of information, namely, social tags, has been used as a powerful mechanism for making more accurate suggestions. Although some studies has been perform on tagged recommendation systems, more research is still needed since there are many challenges in these systems. Many researchers have been trying to come up with solutions for better recommendations according to users' interest. Some of these investigations have been somewhat successful, and some have been able to respond under certain conditions. In this section, we review some related studies.

In [13] Tso-Sutter et al. used tag information as an additional source along with user rating information matrix in a content-based recommender system. In their work, they extended the user-item matrix to the user-item-tag matrix and used the Jaccard similarity criterion to find neighbors. However, due to the issue of tag quality, their proposed content-based method based on memory was not very successful in improving performance. Niwa et al. [14] made an effort to recommended web pages based on the analysis of tag used and degree of relationship between tags with users. However, in this works the accuracy of the recommendations was between 40% and 60% that was not a good result. The only advantage of their proposed method compared to similar methods was the reduction of complexity due to the lack of page browsing and the use of tags. Sen et al. [15] used a special tag ranking function to obtain user tag preferences. In addition, they used additional information such as search history and click-streaming, which is difficult to use in real systems compared to other methods.

Some researchers have examined various aspects of tagged systems [16][17][18][19][20]. In field of recommendations, the information contained in these systems, has shown its significance in recommending resources, tags and users [16]. In [17], the efficiency of tags in organizing the items to be encoded was examined. Article [16] has studied the reasons for the effectiveness of social tagging systems. In [18], the authors examined the relevance of tags in music information retrieval. In [21], the authors analyzed the structure and pattern of use of social tagging systems in Delicious and compared the differences between collaborative and taxonomy tags.

In [22] Zhu and colleagues used an algorithm to recommend tags using the collaborative tagging information method. Their proposed algorithm considered the tags of a large number of users in the target document and tried to minimize the recommended concept overlapping tags to increase the level of coverage of small documents. Unfortunately, this method did not cover new documents. This is important for us to analysis in terms of tags, but we seek to recommend resources, that are different.

In [23], instead of analyzing tags, the authors used the features of the resources being tagged and combined them with the CF method to model user interest. This method identified implicit relationships that were absent in the traditional CF method. Determining the features of the resources was one of the problems that reduced the efficiency of the system.

Wu et al. [24] proposed the tag2word model based on a content-based method for determining the semantic relationships between tags. Their method was able to reinforce the recommendations. It wouldn't have worked properly if the tags had been used in the content of the documentation. This problem is obvious because many of the tags had been used by users are not in the content of the resources. Therefore, this method does not apply to all types of systems. According to the authors' research, the used dataset gives better recommendations when the usage of tags in the titles or text of sources is high. This solution was presented in a content-based method in recommender systems.

De Gemmis et al. [25] combined semantic analysis of tags with a content-based approach. They were assisted in analyzing the meaning of the Word Net for disambiguation tags. In this approach, they combined the traditional content-based method with semantic analysis of tags and provided recommendations according to user interest. But the proposed method could not also be successful in disambiguating of tags.

Wartena et al. [26] used the idea of distributing co-occurring tags and proposed a tag recommendation system. In fact, they combined the CF method with the proposed idea. Their method did not succeed compared to other methods. They proved that when the number of tags given to resources by a single user is higher, the proposed method works better.

Usually, if we want to examine the tag based recommender systems in terms of the type of recommendation, these systems are divided into three categories: tag suggestions, resource, and user. The type of offering these systems do not really matter because all three categories make recommendations based on the tags [27].

Ignatov et al. [28] created profiles for radio stations and users from the tags of songs they listened to, and used the online release of tags to dynamically update profiles. Vall et al. [29] and Su et al. [30] implicitly created tag-based profiles for music recommendations. Xie et al. [31] added emotions to user profiles and tagged resources. Ignacio et al. [32] proposed a way to extend user profiles and tag-based resources to build cross-domain recommendations.

In general, nowadays there are two main approaches in the field of tagged systems, which include approaches based on graph and content [33]. In the field of graph-based solutions, graph analysis methods can be used, which is one of the methods of community-based graph analysis. There is also another issue in tagged systems, and that is related to the methods of discovering and mapping meaning to the tag.

In this object, three methods have been proposed: 1) Methods based on clustering 2) Methods based on ontology. 3) Hybrid methods that combine techniques 1 and 2. Ontology-based methods are not suitable for determining the relationship between terms.

To achieve ontology-based sustainable systems, ontology building should be done by people having domain knowledge and not just by knowledge experts [34]. This is costly and time consuming and these methods are used in the hope of solving the problem of semantic ambiguity when they could not solve the

problem [35]. In addition, because these methods use external knowledge such as Word net and Wikis, they can't completely cover the tags used and lead to increased workload without complete problem solving.

In most cluster-based methods, external knowledge sources such as Word net and Wikis are used to determine the semantic relationships of tags as in ontology-based methods, which have the same problems mentioned in ontology-based methods in this category of solutions.

Cattuto et al. [36] observed that the words folksonomy include many community-specific terms which are not present in any lexical resource. For example, [37] found that Word Net only covers English, while tags for datasets such as Del.icio.us covers from different languages, and at most 61% of the 10,000 repeated tags in Del.icio.us can be found in WordNet. In addition, tags are not considered as words at all rather considered as string of characters in Del.icio.us. Therefore, by examining the existing methods, we came to the conclusion that the simple and effective approaches many researchers use in catching semantics to folksonomy are based on mathematical and statistical formulas. Mathematical and Statistical formulas play an important role. The best thing about them is that they were clear and unambiguous [36]. Therefore, using statistical and mathematical methods, the semantic and lexical relationship of tags can be determined. In the proposed solution, we did not use any external semantic sources such as ontologies or thesaurus, however we used accurate and formal methods in determining the semantic relationships of tags, which strengthen the proposed solution in managing a large amount of tags in folksonomy. Because mathematical and statistical methods have good accuracy for extracting semantic and lexical relations of tags, they are suitable to be use in the proposed solution. After determining the semantic and lexical relationships of tags, we used an effective method in clustering tags called community detection methods. That is also one of the solutions in graph-based tagging systems. With community detection methods, more accurate analysis of relationships between graph elements can be provided. In general, it is possible to make more personalized suggestions in recommending systems by using community-based solutions, a good way to analyze networks. Thus the quality of recommendations increase and this is the advantage of our proposed solution.

3. Proposed method

In this Section, we examined the users' tagging behaviors that could determine their interest. To achieve this aim, we used tags for resources and categorized them, determining users' interests.

A social tagging system consists of a set of users (U), a set of tags (T), and a set of resources (R). We define these sets as follows:

$$U=\{u_1, u_2,...,u_n\}$$
 $T=\{t_1, t_2,...,t_m\}$ $R=\{r_1, r_2,...,r_k\}$

where n is the number of users, m is the number of tags, and k represents the number of resources. In these systems, a folksonomy is defined as $\langle U, R, T, Y \rangle$, where Y is a ternary relation between them, i.e., $y \subseteq U \times T \times R$ [38]. Although there are various general datasets available for evaluating recommender algorithms, we chose Delicious dataset to evaluate our work. Because the proposed method does not use any external thesaurus or ontologies, it supports other languages than English, so it is suitable for evaluating.

Our proposed approach consists of two main phases. The first phase includes two steps:1) creating a graph of tags and 2)identifying communities of tags. The second phase is to make recommendation based on the communities created from the tags and available resources in each community. In the following, we will explain the phases of the proposed solution.

3.1. Generating tags graph

As it was previously explained, the proposed solution includes two phases. The first phase includes two stages, the first which is the formation of tag graphs. Graph nodes of tags, and the weight of its edges are determined by the amounts of lexical, semantic similarity and the time of tag assignment. For example: the weight of two tags, t_i and t_j , is shown with $w(t_i, t_j)$. After generating the graph, in the second stage, the tag communities are identified. In other words, the basis of our work is detecting communities of user tags and building communities of resources based on them. For each community of tags, a community of relevant resources and users are created. Finally, resource suggestions are recommended for the target user based

on the probability of membership of each resource to the communities and the power of the local neighborhood. In fact, with this new method, it is possible to identify the interest of users accurately and provide precise recommendations. To create a graph, in the first phase, for determining the relationship between the tags, use their semantic and lexical similarity and the time of tag assignment. In fact, the first innovation of the proposed method is to determine the relationship of tags by a combination of semantic (considering the time of tag assignment) and lexical similarity and not by using foreign linguistic or semantic sources. In addition, this approach can manage a large part of tags in this way. To obtain semantic relevance, the property of co-occurrence tags were used. However, unlike the previous methods, we took into account the fact that users' interests change over time. As a result, when using the co-occurrence tags, we added the time of tag assignment parameter. If the two co-occurrence tags are close to each other in the parameter, they will have a higher score and therefore, the power of semantic correlation will be higher. Jaccard similarity is used to find similarity of co-occurred tags. The formula is defined as follow:

$$sim_{Jac}(t_i, t_j) = \frac{|R(t_i) \cap R(t_j)|}{|R(t_i) \cup R(t_j)|}$$
(1)

where $R(t_i)$ stands for the set of resources tagged by the t_i tag. When two tags co-occur, first their semantic similarity is calculated with the Jaccard similarity formula. Then the lexical similarity with Levenshtein distance is calculated and called sim_{Lev} For calculating lexical relevance and morphological tags, we used high-threshold sim_{Lev} criterion. This can resolve minor morphological changes as well as misspellings (these are two common problems with social tagging systems). Moreover, for tags that do not have semantic relevance but they have a strong lexical similarity, this lexical similarity is considered as the weights of the edges. The formula for sim_{Lev} is defined as follow:

$$sim_{Lev} = \frac{Levenshtein\ distance(t_i, t_j)}{maxLength(t_i, t_j)}$$
(2)

After obtaining both similarities, each lexical or semantic similarity that is larger, selected as the similarity between two tags. If two tags do not co-occur and the lexical similarity is greater than a threshold value of α , then the value is selected as a similarity between two tags. Since the users' interests change over time, we considered another similarity based on the time of tag assignments for co-occurred tags. This similarity is shown with $\operatorname{sim}_{\text{time}}(t_i,t_j)$. Suppose that Timestamp(t_j , t_k) shows the last time the tag t_i is assigned to the resource t_k . The set of the common resources for two co-occurred tags t_i and t_j , whose assignment is too close, is shown by $\operatorname{nco}(t_i,t_j)$. The formulas of $\operatorname{nco}(t_i,t_j)$ and $\operatorname{sim}_{\text{time}}(t_i,t_j)$ can be defined as follows:

$$\mathsf{nco}\big(t_i,t_j\big) = \{\mathsf{r}_k | \mathsf{r}_k \in \mathsf{R}(\mathsf{t}_i) \ \land \ \mathsf{r}_k \in \mathsf{R}(\mathsf{t}_j) \land \ \big| \mathsf{Timestamp}(\mathsf{t}_i,\mathsf{r}_k) - \mathsf{Timestamp}(\mathsf{t}_j,\mathsf{r}_k) \big| \ \leq \tau \} \quad (3)$$

$$sim_{time}(t_i, t_j) = \frac{|nco(t_i, t_j)|}{|R(t_i) \cap R(t_j)|}$$
(4)

Therefore, sim_{time} is considered when two tags are co-occurred. Finally, a graph of the tags is created and the weight between two desired nodes calculated by Eq. 5.

$$w((t_{i}, t_{j})) = \begin{cases} \lambda \times sim_{jac}(t_{i}, t_{j}) + (1 - \lambda) sim_{time} & \text{if } t_{i} \text{ co-occurred with } t_{j} \text{ and } sim_{jac} > sim_{lev} \\ \lambda \times sim_{lev}(t_{i}, t_{j}) + (1 - \lambda) sim_{time} & \text{if } t_{i} \text{ co-occurred with } t_{j} \text{ and } sim_{jac} < sim_{lev} \\ \lambda \times sim_{lev} & \text{if } t_{i} \text{ not cooccurred with } t_{j} \text{ and } sim_{lev} > \text{threshold} \\ 0 & \text{otherwise} \end{cases}$$

$$(5)$$

After generating a graph of tags then, we specified their communities. In the following, we will explain the community detections algorithms and the reasons for using it in the proposed method.

3.2. Community detection

The scope of social networks is known as a significant evolution in the last decade, and community detection has emerged to analyze many fields as well as the individual's interactions within social environments [39]. We also decided to use this method to analyze tags. Therefore, the second stage of the first phase of the proposed approach is to detect tag communities. The best way to analyze the network of tags and to cluster them, is to use community detection methods. The purpose of detecting communities is to extract groups whose their communities internal communication is stronger and more powerful than external communication. In fact, with this method, the existing divisions in a network can be identified and separated to get a better view of the structure of a network for its analysis. Various methods have been proposed for community detection. Here, community means a group of network nodes of tags that are tightly connected. The strength of the joints is obtain through their degree of similarity. In other words, the strength of the power connections shows the semantic and lexical similarity. In fact, the nodes belonging to the same community are similar and related to the same interest. The better the identified communities, the more accurate results are obtained in the recommendation section of the research system. Here, the criterion for distinguishing a good community is modularity, which is widely used in community detection methods. Modularity is defined based on [40] in Eq. 6.

$$Q = \frac{1}{2m} \sum_{ij} \left(w(t_i, t_j) - \frac{K_{t_i} K_{t_j}}{2m} \right) \delta \left(C m_{t_i}, C m_{t_j} \right)$$
 (6)

$$K_{t_i} = \sum_{k} w(t_i, t_k) \tag{7}$$

$$m = \frac{1}{2} \sum_{ij} w(t_i, t_j) \tag{8}$$

Where $w(t_i,t_j)$ is the weight of two nodes t_i and t_j . In the following K_{t_i} is the degree of node t_i defined in Eq. 7. Also, $\delta\left(Cm_{t_i},Cm_{t_j}\right)$ has a value of 1 if both nodes t_i and t_j belong to the same community; otherwise, its value is zero. In Eq. 6, m is the total weights of all edges in this graph, defined in Eq.8. In this research, the Louvain method has been used to identify the tags community. This method is non-overlapping. It should be noted that according to the authors in [34], community-based recommendation systems are the best recommendation system to consider the needs of the network. After this step, we will explain the next part, which is the presentation of resource recommendations algorithm.

3.3. Resources recommendation stage

In this section, after identifying the communities, the recommendation steps are explained. First C is defined as a set of communities which is detected by the community detection algorithm. Each community is a set of tags. These are defined in Eq.9 and Eq. 10.

$$C = \{c_i | c_i \text{ is a community } \}$$

$$c_i = \{t_k | t_k \in T, \theta(t_k) = i \}$$

$$(9)$$

$$(10)$$

where θ stands for a function determining the cluster number of tags. In the following, for each resource a probability value is calculated for each community that indicates the probability of that resource's membership in the desired community of tags which can be defined by Eq. 11.

$$Pr(\mathbf{r}_i, c_j) = \frac{N(r_i, c_j)}{\sum_{c_j \in C} N(r_i, c_j)}$$
(11)

$$N(\mathbf{r}_i, c_j) = \sum_{\mathbf{t}_k \in c_j} N(\mathbf{t}_k, \mathbf{r}_i, c_j)$$
 (12)

In Eq. 12, $N(t_k, r_i, c_j)$ is the number of tags are used in the community c_j to be tagged the resource r_i , where it is possible to determine which communities are related to the resource. The higher the probability, the more relevant the resource is to that community. In other words, more tags from a community are used to tag the resource. In fact, by examining a user's resources, it is possible to determine the user's interests in various communities.

In this research, it was determined experimentally that the overlap of resource communities is high. The creation of resource communities through tag communities causes this high percentage. Due to the reduced accuracy of the recommendations. Therefore, at this stage, the resource communities are refined. According to Eq. 11, the probability value a resource to a desired community is obtained, which we can consider threshold value. Therefore, resources that are less than threshold dependent are excluded from that community. In this way, the resulting communities will be more reasonable.

After determining the resources' membership for different communities, in the next step, by Eq. 13, which is the Ellenberg similarity criterion, the degree of similarity between two resources r_i and r_j is obtained.

$$Sim_e(r_i, r_j) = \frac{m/2}{m/2 + b + c}$$
 (13)

where m is the sum of the probabilities of membership the two resources r_i and r_j in the common communities. b indicates the probability of membership the resource r_i and c represents the probability of membership the resource r_j in different communities. By calculating the similarity between resources of the target user and resources of the specified communities of the target user a list of recommended candidate resources can be obtained. More formally, let R_{TU} and R_{TC} be the set of the target user resources and resources of the target user communities. This list has two problems. The first problem is that there are too many resources in this list that have the same amount of similarity to the resources of the target user, and it is difficult to choose the exact resources recommended and close to the user's interest. The second problem is that there are many unrelated resources to a reasonable degree of similarity in this list, that if we suffice with a numerical similarity, we will not get the expected result. To solve this problem, the other similarity has been used between two resources by Eq.14.

$$sim_{u}(r_{i},r_{j})=|(U(r_{i}) \cap U(r_{j}))| / max\{|U(r_{i})|, |U(r_{j})|\}$$
 (14)

 $U(r_i)$ stands for the set of users that annotated r_i with tags. Then by Eq. 15, resources with the most similarity to the resources of the target user are calculated.

$$Msr(r_i) = \underset{r_i}{argmax} \{ sim_u(r_i, r_j) + sim_e(r_i, r_j) \}$$
 (15)

where r_i is the resource of the target user ($r_i \in R_{TU}$) and r_j is the resource of the target community ($r_j \in R_{TC}$). Finally, a list of recommended resources is obtained by Eq. 16.

4. Experimental analysis

One of the main parts of each recommendation system is the collection of information. If it were done in a regular and accurate manner, the analysis of data will be accomplished with great speed and accuracy [41]. In the proposed system, among the valid datasets that have been published, we used the highly used Hetrec2011-Delicious-2k dataset as in [42][43] in our experiments, which includes 53,388 tags and 69,226 sources, which are gathered from Delicious.com and released in [44]. In this dataset, users not only can save and organize their favorite pages (URLs) but also tag and share them as they wish. Users are connected in a social network created from Del.icio.us interactions, and each user has its own tags, bookmarks and tag assignments.

In the beginning of using this dataset, we first removed the noisy and meaningless tags in the clearing step. Unlike most previous methods, we used tags with any number of repetition. Therefore, the proposed solution is responsive to the cold start problem. Then we specified the test and trained dataset as 20% and 80% of the total data. Recommendations are generated based on the known information in the training set, and then the test set is used to evaluate the performance of recommendation algorithms In the first step, which is generating a graph of users tags, a graph of all user tags was created. In creating this graph, Jaccard similarity and Levenshtein distance was used to determine the edge weight between two tags for cooccurring tags. In order to consider the lexical connection between them, Levenshtein distance was used and the greatest similarity was selected. If two tags co-occur, we also consider the time of tag assignments. For tags that do not co-occur, we consider the lexical similarity (sim_{Lev}) to α threshold. Here, in various experiments, we experimentally considered the lexical similarity threshold, i.e. α , equal to 0.7 for co-occur tags; otherwise, its value is 0.8. If the lexical similarity were greater than this threshold, we calculated it as 50% and applied it as weight. This graph then should be converted into communities. The users who are members of that community are actually interested in that community, and on the other hand, the resources of members of that community indicate that they have provided content in that community. For this reason, after extracting communities, the tags, resources, and users of each community are identified so that the users with the same interest and resources with the same subjects were identified.

The next step was to analyze the tag communities and also obtain resource and user communities. In this point, we calculated the probability of a resource membership in a community. Then, according to the tags of the target user, we specified the interests of the user. In other words, we specified the communities of interest of the target user as target communities. Next, to calculate the nearest neighborhood, we obtained the similarity of the resources tagged by the target user with the resources of the target communities, and determined N of the resources with the highest similarity.

The criteria most often used to evaluate recommender systems are Recall (R) and Precession (P), all of which used to evaluate the quality performance of recommendation systems. In fact, the criterion of Precession determines what percentage of the set of recommenders is presented by a method is correct. This criterion measures the correctness and accuracy of the proposals recommended, as a result, the larger the criterion, the less errors in the method being measured. The next criterion, which is Recall, refers to what percentage of the offers are really users' interest. According to [23], P and R are defined in Eq. 17 and Eq. 18. Since users usually review the highest recommended items, we cut these criteria to a specific rank k. That is, just considering k the number of results at the top of the recommendation list, the precession in k with P@k and recall in k by R@k.

$$P = \frac{|rr \cap tr|}{|rr|} \tag{17}$$

$$R = \frac{|rr \cap tr|}{|tr|} \tag{18}$$

In our experiments, the mean values of P@k and R@k were used to evaluate the performance of the system recommended by users. Where rr is the list of recommended resources and tr is the list of resources being tested.

All experiments are implemented an Intel(R) Core i7 computer with 2.67 GHz CPU and 16.00 GB RAM.

We posed two research questions in this section. RQ1: How effective is the lexical similarity in the proposed method? To answer this RQ1, we compared the proposed method with lexical similarity which is shown as LEXSEM_CDR. The method without this similarity is demonstrated by SEM_CDR. We examined them with using two metrics, Recall@k and Precision@k with four k values, 5, 10, 15 and 20. Table 1. represents the experimental results. These results show that lexical similarity enhances system performance by using semantic similarity. This improvement in output is especially evident when there are spelling mistakes in the tags. In these experiments, we experimentally considered the threshold value to be 0.7 for co-occur tags; otherwise, its value is 0.8. Because in assigning tags to resources, spelling mistakes are obvious, instead of spending time to clean them, using lexical similarity seemed very useful.

P@5 Models P@10 P@15 P@20 R@5 R@10 R@15 R@20 LEXSEM CDR 24.08 22.80 21.70 20.73 8.11 14.60 18.84 25.54 SEM_CDR 24.02 22.67 21.52 20.07 8.06 14.03 18.44 25.32

Table 1: Recommendation Performance of two Proposal Models (in %)

In the following, we want to pose the second question. RQ2: How effective is the time of tag assignment in the proposed methods? Due to the changes in users' interests over time, we have considered the time difference of the last assignment of two co-occurred tags to generate a graph. Table 2 presents the results of the proposed method (CDR_TIME) and its comparison with LEXSEM_CDR. The results showed that using the time of tag assignment approved accuracy of the recommender system.

Models	P@5	P@10	P@15	P@20	R@5	R@10	R@15	R@20
LEXSEM_CDR	24.08	22.80	21.70	20.73	8.11	14.60	18.84	25.54
CDR TIME	24.23	22.98	21.87	20.89	8 43	14.84	19 21	25 96

Table 2: Recommendation Performance of two Proposal Models (in %)

To show the efficiency of the proposed method, we compared it with the following models: 1) CCS² method: The Cosine similarity method is based on clustering. Hierarchical clustering [45] was used to model users and resources as a vector of cluster-based attributes, and content-based filtering is based on cosine similarity of recommendations. Our method is better than this method for several reasons. First, use the tags graph and create this graph in a powerful way. Secondly, the use of robust graph analysis, which is a method of community detection. The results of these two methods show the superiority of this research method.

² Clustering-based Cosine similarity

- 2) ACF³ method: uses the CF method based on automatic encoder. An automated encoder is usually used to obtain summary introductions from user profiles based in which CF recommendations are used. Experiments on CF method with different number of hidden layers demonstrate that deeper architectures can work better if the depth of the neural network is set appropriately [42].
- 3) CCF⁴ method or CF based on clustering: It is similar to CCS method but here the user-based CF method is used for recommendations [46].
- 4) PMF⁵ method: This technique, which is based on filtering user collaboration, uses a user ranking matrix. This model, based on the assumption that users who have rated similar sets of items are likely to have similar preferences [47]. The method was chosen to demonstrate the superiority of using another dimension of information, namely tags.

These two criteria have been significantly improved in the proposed algorithm, according to the known algorithms. The results of comparing the presented method with the proposed and known methods are shown in Table 1.

Models	p@5	p@15	p@30	p@50	R@5	R@15	R@30	R@50
CCF	0.913	0.757	0.597	0.454	0.439	1.051	1.499	1.803
ACF	1.120	0.909	0.736	0.595	0.590	1.209	1.917	2.364
CCS	2.397	1.903	1.564	1.273	0.938	2.271	3.774	4.774
MF	9.157	7.467	6.784	6.306	1.302	2.851	4.988	7.587
CDR_TIME(proposed)	24.23	21.87	19.75	17.80	8.43	19.21	27.92	37.45

Table 3: Comparisons of Performance of different models (in %)

The results show that the proposed method has significantly improved the two criteria of precision and recall. In addition to the improved results, the great advantage of the proposed method is that it uses only training data and does not use any external knowledge base or resource contents, and is an agile method. As it is explained in the previous sections, tags do not have a specific format and users choose them without restrictions and this was the main reason for not using an external knowledge.

5. Conclusion

We examined the problems in tagged recommender systems and concluded that the performance of these systems is affected by semantic and lexical ambiguities. Various solutions have been proposed in this field, most of which suggested the use of external knowledge and thesaurus. Because the use of tags in some cases does not follow any specific rules, these solutions were not suitable especially in datasets such as Delicious, where most tags are not covered by thesaurus. Therefore, by using co-occurring tags, the time of tag assignment and statistical and mathematical methods, we identified the semantic and lexical similarity of more accurate communications. We reached a suitable modeling of users' interest from the community detection method. Based on this accurate modeling we achieved better results in providing recommendations. The results of experimental examinations also confirmed this. In later studies, we plan to use more advanced community detection methods to cluster tags and get more accurate results and also will provide a plan to eliminate the semantic ambiguity of the tags.

³ Autoencoder-based collaborative filtering

⁴ Clustering-based collaborative filtering

⁵ Probabilistic Matrix Factorization

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