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PERSONALIZING AND IMPROVING RESOURCE RECOMMENDATION BY ANALYZING USERS PREFERENCES IN SOCIAL TAGGING ACTIVITIES

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Abstract. Collaborative tagging which is the keystone of the social practices of web 2.0 has been highly developed in the last few years. In this paper, we propose a new method to analyze user profiles according to their tagging activity in order to improve resource recommendation. We base upon association rules which is a powerful method to discover interesting relationships among large datasets on the web. Focusing on association rules we can find correlations between tags in a social network. Our aim is to recommend resources annotated with tags suggested by association rules, in order to enrich user profiles. The effectiveness of the recommendation depends on the resolution of social tagging drawbacks. In our recommender process, we demonstrate how we can reduce tag ambiguity and spelling variations problems by taking into account social similarities calculated on folksonomies, in order to personalize resource recommendation. We surmount also the lack of semantic links between tags during the recommendation process. Experiments are carried out with two different scenarios: the first one is a proof of concept over two baseline datasets and the second one is a real world application for diabetes disease.

Keywords: Folksonomies, social tagging, association rules, resource recommendation, tag ambiguity, spelling variations, medical application

1 INTRODUCTION

With web 2.0 technologies the web has become a social space where users create, annotate, share and make public resources which they find interesting on the web [4]. Kaplan and Haenlein define social media as "a group of Internet-based applications that build on the ideological and technological foundations of web 2.0, and that allow the creation and exchange of user-generated content" [13]. Folksonomies are one of the keystones of these new social practices: they are systems of classification resulting from collaboratively creating and managing tags to annotate and categorize contents. This practice is known as collaborative tagging or social tagging. The basic principle of social tagging relies on three main notions: the user, the resource and the tag. The combination of these three elements enables exploiting annotations of web resources by users with tags.

Despite the strength of folksonomies, there are some problems hindering the growth of these systems: tag ambiguity (or polysemy) is one of the famous problems in folksonomies. It comes from the fact that a tag can designate several concepts (i.e., a tag can have several meanings), for example when a user employs the tag "apple" to annotate a resource, the system will not understand if the user means the fruit or the company. Also the variations in writing a same concept (spelling variations or synonymy) can cause some problems during the search phase, for example "cat" and "chat" both denote the same concept (animal) in English and in French, but when a user searches resources annotated by the tag "cat", the system will not offer him those tagged with the word "chat" because it cannot understand that the tag "cat" has the same meaning that the tag "chat". In addition, tags that are freely chosen in these systems are likely to contain spelling errors and therefore make the retrieval of resources more doubtful than the metadata recovering from a lexicon examined by information professionals. Therefore resource retrieval within folksonomies needs some improvements to increase the quality of the results obtained in these systems.

In this paper, we propose a method to analyze user profiles according to their tags in order to predict interesting personalized resources and recommend them. In other words, our objective is to enrich the profiles of folksonomy users with pertinent resources. We argue that the automatic sharing of resources strengthens social links among actors and we exploit this idea to reduce tag ambiguity and spelling variations in the recommendation process by increasing the weights associated to web resources according to social similarities. We base upon association rules which are a powerful method for discovering interesting relationships among a large dataset on the web. We insist on the fact that our final aim is not to suggest tags to users: each time a resource is presented to a user, the tags already used to annotate this resource are indicated but the user is free to tag the resource by choosing a tag among them or by using a new one. Our aim is to recommend resources which are annotated with tags suggested by association rules, in order to enrich user profiles with these resources. Our approach comes from a new view on the community effect in folksonomies since it aims at automatically strengthening existing correlations between different members of online communities, without involving the user in this process. The fact of suggesting to each user some resources considered useful or interesting for him without specifying explicit tags, this can significantly improve folksonomy-based recommender systems, because the man-machine interaction and therefore the user effort are considerably reduced.

This paper is organized as follows: Section 2 is an overview of the main contributions related to our work. Section 3 is dedicated to the presentation of our approach. In Section 4 we present and discuss the results of some experiments we conducted to measure the performance of our approach. Conclusion and future works are described in Section 5.

2 RELATED WORKS

Despite the relative newness of folksonomies, there are a lot of works attached to this domain. Most of these contributions are distributed between tag recommendation, resource recommendation and searching semantic relationships between folksonomy terms. In the following subsections, we will give an overview of the main contributions related to our work.

2.1 Tag Recommendation

The general aim of tag recommender systems is to help users choose the appropriate tags when annotating resources. Among the many works addressing this problem, let us cite that of Schmitz et al. [19] who showed how association rules can be adopted to analyze and structure folksonomies and how these folksonomies can be used for learning ontologies and supporting emergent semantics. Another noticeable contribution is that of Jaschke et al. [12] who present a formal model and a new search algorithm called FolkRank, especially designed for folksonomies. It is also applied to find communities within a folksonomy and is used to structure search results. Gemmell et al. [9] proposed a tag-based recommendation method based on the adaptation of the K-nearest neighbors algorithm so that it accepts as input both a user and a resource and gives out a set of tags. The interest of this approach is to orient users to use the same tags, and thus increase the chance of building a common vocabulary used by all the community members.

2.2 Resource Recommendation

The general aim of resource recommender systems is to insure the quantity and relevance of the recommended resources. Among the works addressing this problem, let us cite Tso-Sutter et al. [21], who described a method that allows tags to be incorporated into standard heuristic-based collaborative filtering algorithms, and apply a fusion method to re-associate these correlations. Zhao et al. [24] proposed a Clustered Social Ranking (CSR), a new search and recommendation technique specifically developed to support new users of social websites finding contents. The system detects who the leaders are; it then clusters them into communities. User queries are then directed to the community of leaders who can best answer them.

De Meo et al. [8] proposed an approach based on the principle of query expansion to enrich user profiles by additional tags discovered through the exploration of the two graphs: Tag Resource Graph (TRG) and Tag User Graph (TUG) representing the relations respectively between tags and resources and between tags and users.

Huang et al. [11] proposed a recommender system that considers the user recent tag preferences. The proposed system includes the following stages: grouping similar users into clusters, finding similar resources based on the user resources, and recommending the top-N items to the target user.

Zanardi et al. [25] proposed a method aimed to extend the searching capabilities of digital collections targeting educational and academic domains. Given a document, the approach finds similar documents that may be relevant to the user. Versin et al. [22] developed a personalized web-based recommender system that applies recommendation and adaptive hypermedia techniques to orient learner's activities and recommend pertinent links and actions to him during learning. The proposed approach is based on using data clustering, collaborative filtering and association rule mining techniques.

Beldjoudi el al. [4] proposed a method to analyze user profiles in order to improve resource recommendation in folksonomies. Their objective is to enrich user profiles with pertinent resources by resolving the tag ambiguity problem during recommendation.

2.3 Resolving Tag Ambiguity

Among the most important contributions on resolving tag ambiguity and extracting the semantic links between tags in a folksonomy, we start with Mika [17] who has proposed to extend the traditional bipartite model of ontologies to a tripartite model. In his paper, Mika focuses on social network analysis in order to extract lightweight ontologies, and therefore semantics between the terms used by the actors. Gruber [10] recommended to build an ontology of folksonomy. According to him, the problem of the lack of semantic links between terms in folksonomies can be easily resolved by representing folksonomies with ontologies. Specia and Motta [20] proposed a method consisting in building clusters of tags, and then trying to identify possible relationships between tags in the same cluster. The authors have chosen to reuse available ontologies in order to represent the correlations which hold between tags. An attempt to automate this method has been done by Angeletou et al. [2].

Buffa et al. [6] present a semantic wiki with the aim of exploiting the force of ontologies and semantic web standard languages in order to improve social tagging. According to the authors, with this approach, tagging remains easy and becomes both motivating and unambiguous. The niceTag project of Limpens et al. [15] is focused on using ontologies to extract semantics between tags in a system. In addition, the interactions among users and the system are used to validate or invalidate automatic treatments carried out on tags. The authors have proposed methods to build lightweight ontologies which can be used to suggest terms semantically close during a tag-based search of documents. Pan et al. [18] addressed the tag ambiguity problem by extending folksonomy with ontologies. They proposed to expand folksonomies in order to avoid bothering users with the rigidity of ontologies. During a keyword-based search of resources, the set of ambiguous used terms is concatenated with other tags so as to increase the precision of the search results. Wu and Zhou [23] tried to estimate the semantic relations among tags to judge if tags are related from semantic view or isolated. The authors proposed to perform several measures of semantic relatedness to discover semantic information within a folksonomy.

Beldjoudi et al. [3] proposed a technique to improve resource search in folksonomies with user interests. The presented approach shows the usefulness of social interaction in folksonomies for reducing the tag ambiguity problem. In another contribution Beldjoudi el al. [5] proposed a new technique for developing social semantic web technologies in order to see how they overcome some semantics problems in folksonomies even when representing these latter with ontologies. The authors also illustrated how they can enrich any folksonomy by a set of pertinent data in order to improve and facilitate resource retrieval in these systems.

To sum up, most of the works aspire to bring together ontologies and folksonomies as a solution to resolve tag ambiguity and overcome the lack of semantic links between tags. Sure enough the approaches described in this section show that the social nature of resource sharing is not in contradiction with the possibilities offered by ontology-based systems. But the rigidity that characterizes ontologies and the need for an expert who must control and organize the links between terms as in [10] seem a little cumbersome and too much expensive. Even the structures automatically extracted as in [17] still suffer from the ambiguity of concepts. Regarding the work of [20], we can say that the use of semantic web ontologies for extracting relationships between terms is not sufficient, because as the semantic web includes some specific domain ontology, that will push back the problem. Also the expertise of users which was introduced in [15] is characterized by the complexity of its exploitation. As a result we propose an approach of tag-based resource recommendation where we aim to resolve tag ambiguity and spelling variations without explicitly using ontologies. We base upon association rules which are a powerful method to discovering interesting relationships among a large dataset on the web. Our aim is to enrich user profiles based on similarities between users and association rules and by doing so to increase the community effect when suggesting resources to a given user.

3 RESOURCE RECOMMENDATION IN SOCIAL NETWORKS BASED ON ASSOCIATION RULES

3.1 Principles and Objectives

Our objective is to develop a new approach based on social interactions between different members in a community to make semantics emerge in folksonomies, with the aim of personalizing resource recommendation. The key idea of our approach is to make each member benefit from the resources tagged by other users who have similar interests. We measure similarity between community members in order to compare their preferences and then suggest relevant resources. This allows limiting the problems of ambiguity, spelling variations and the lack of semantic links between tags in folksonomies.

Our approach comes with a new view on the community effect in folksonomies, which consolidates the social interactions between the different members of a community without involving the user in the automatic realization of this process. Also, the fact of proposing to each user resources considered useful to him without him identifying specific tags can significantly improve folksonomy-based systems, because this reduces the man-machine interactions. The user's effort is reduced to a mouse click instead of a keyboard input and therefore this should encourage users to use these systems.

3.2 Description of Our Approach

We define a folksonomy by a tripartite model where web resources are associated with a user to a list of tags. Formally a folksonomy is a tuple $F = \langle U, T, R, A \rangle$ where U, T and R represent respectively a set of users, a set of tags and a set of resources, and A represents the relationships between the three preceding elements, i.e. $A \subseteq U \times T \times R$ [17].

We extract three social networks from a folksonomy, which represent three different viewpoints on social interactions: one network relating tags and users, a second one relating tags and resources and a third one relating users and resources. We represent these social networks by three matrices TU, TR, UR:

$$TU = [X_{ij}]$$

where

$$X_{ij} = \begin{cases} 1 & \text{if } \exists r \in R, \langle u_j, t_i, r \rangle \in A, \\ 0 & \text{otherwise,} \end{cases}$$

$$TR = [Y_{ij}]$$

where

$$Y_{ij} = \begin{cases} 1 & \text{if } \exists u \in U, \langle u, t_i, r_j \rangle \in A, \\ 0 & \text{otherwise,} \end{cases}$$

$$UR = [Z_{ij}]$$

where

$$Z_{ij} = \begin{cases} 1 & \text{if } \exists t \in T, \langle u_i, t, r_j \rangle \in A, \\ 0 & \text{otherwise.} \end{cases}$$

RU, RT and UT are the transposed matrices of UR, TR and TU.

This enables us to analyze the correlations captured from the different social interactions. We use Pajek, a tool which has already been used by Mika to analyze large networks [17]. To apply an association rule method to folksonomies, we represent each user in a folksonomy by a transaction ID and the tags he uses by the set of items which are in this transaction [4]. Table 1 provides an illustrative example of a dataset of user tags.

Transaction ID	Itemset
U_1	Computer, Programming
U_2	Computer, Apple
U_3	Kitchen, Apple
U_4	Programming
U_5	Kitchen

Table 1. An illustrative example of a dataset with user tags

Our goal is to find correlations between tags, i.e. to find tags frequently appearing together, in order to extract those which are not used by one particular user but which are often used by other users close to him in the social network. For example, let us consider a dataset in which it occurs that many users who use the tag Software also employ the tag Java. We aim at extracting a rule *Software* ⇒ *Java* so that we can enrich the profiles of users who employ the tag Software but not the tag Java, by the resources tagged with Java. Among the wide range of algorithms proposed to extract interesting association rules, we use the one known as Apriori [1].

Once the rules are extracted, our recommender system proceeds as follows: For each extracted rule, we test whether the tags which are in the antecedent of the rule are used by the current user. If it is the case then the resources tagged with each tag found in the consequent of the rule are candidate to be recommended by the system. The effectiveness of the recommendation depends on the resolution of folksonomies problems. In our approach we tackle the problems of tag ambiguity, spelling variations (or synonymy) and the lack of semantic links between tags. The detail of our approach is described in the following subsections.

3.3 Resolving Tags Ambiguity in Recommendation

According to Mathes [16], "The problems inherent in an uncontrolled vocabulary lead to a number of limitations and weaknesses in folksonomies. Ambiguity of the tags can emerge as users apply the same tag in different ways. At the opposite end of the spectrum, the lack of synonym control can lead to different tags being used for the same concept, precluding collocation".

A tag can have several meanings, i.e. refer to several concepts. Therefore, a basic tag-based recommender system would equally recommend resources relative to fruits or to computers for a user searching with the tag "apple". The resolution of tag ambiguity is especially crucial in our approach where some tags which are used to recommend resources are not directly used by the user but deduced with association rules. To resolve the problem of tag ambiguity in recommendation, we propose to measure the similarity between users to identify those who have similar preferences and therefore adapt the recommendation to user profiles [4].

First step: For each extracted association rule $A \Rightarrow B$ whose antecedent applies to an active user u_x, we measure the similarities between this user and the users of his social network who use the tags occurring in the consequent of the rule (see Figure 1). The resources associated to these tags are recommended to the user depending on these similarities. To measure similarity between two users u_1 and u_2, both are represented by a binary vector representing all their tags (extracted from matrix UT: see Figure 1) and we compute the angle cosines between the two vectors:

$$\mathrm{sim}(u_1, u_2) = \cos(v_1, v_2) = \frac{v_1.v_2}{\|v_1\|^2 . \|v_2\|^2}.$$

According to Cattuto et al. [7] and Koerner et al. [14], the cosine similarity gives good quality results at a reasonable computational cost since it has linear complexity.

We insist on the fact that the distribution of tags over resources and users in folksonomies follows a power law [8]: most resources are tagged by only a small number of users, and many tags are only used by a few users, a property which leads to a low values of r (the number of resources in matrix RU: see Figure 1) and n (the number of users in the matrix UT: see Figure 1). Therefore, our approach can scale to very large datasets.

Second step: To avoid the cold start problem which generally results from a lack of data required by the system in order to make a good recommendation, when the user of the recommender system is not yet similar to other users, we also measure the similarity between the resources which would be recommended by the system (as related to a tag occurring in the consequent of an association rule) and those which are already recommended to the user. To measure the similarity between two resources r_1 and r_2, we represent each of them by the binary vector representing all its tags (extracted from matrix TR) and we calculate the cosines of the angle between the two vectors.

Third step: Each resource recommended by the system is first associated an initial weight based on the similarities between users. Above a threshold fixed in [0..1], we qualify the resource as highly recommended. Under this threshold, we consider the similarity between resources and we similarly highly recommend the resources which weights calculated on the product matrix $RR = RT \times TR$ are above a given threshold.

We note that our recommender system is flexible, since the user can interact to accept or reject the recommended resources. Also, the very power low distribution of resources over users in folksonomies leads to a low value of r (the number of resources in matrix RU). Therefore, the product matrix $RR = RU \times UR$ is not expensive in our case, which makes the approach efficient and scale to very large datasets.

For instance, let us consider a folksonomy with five users who annotate five resources using four tags. Each triple (u, t, r) represents a connection between a user, a resource and a tag (see Table 2). Let the extracted association rule *computer* $\Rightarrow$ *apple* and the folksonomy be described in Table 2. Since the tag "computer" is used by user U_1, then resources R_3 and R_5 tagged with the tag "apple" (in the consequence of the rule) are candidates for a recommendation to U_1. Matrix UT (Table 4) shows that "apple" is used by users U_2 and U_3. Then we calculate the similarity between U_1 and U_2 and the similarity between U_1 and U_3, based on matrix $UU = UT \times TU$ (Table 5).

$$\mathrm{sim}(U_1, U_2) = \cos(UU_1, UU_2) = \frac{(2\ 1\ 0) \times (1\ 2\ 1)}{\sqrt{4+1+0} \times \sqrt{1+4+1}} = \frac{4}{\sqrt{30}} = 0.73,$$

$$\mathrm{sim}(U_1, U_3) = \cos(UU_1, UU_3) = \frac{(2\ 1\ 0) \times (0\ 1\ 2)}{\sqrt{4+1+0} \times \sqrt{0+1+4}} = \frac{1}{5} = 0.2.$$

Users	Tags	Resources
U_1	computer	R_1
U_1	programming	R_2
U_2	computer	R_1
U_2	apple	R_3
U_3	kitchen	R_4
U_3	apple	R_5
U_4	programming	R_1
U_5	kitchen	R_4
U_5	kitchen	R_5

Table 2. Example of a folksonomy

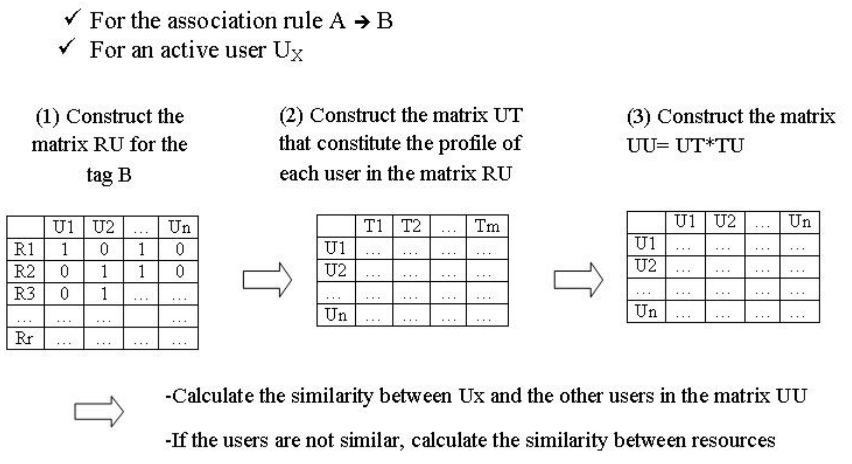

Figure 1. Process of surmounting the tag ambiguity problem

	U_2	U_3
R_3	1	0
R_5	0	1

Table 3. Matrix RU of tag *apple*

U_1 and U_2 show higher cosine similarity than U_1 and U_3. Then, among the resources tagged with "apple", namely R_3 and R_5, those tagged by U_2 are highly recommended to U_1: it is the case of R_3.

U_1 and U_3 are not similar, then, among the resources tagged with "apple", we compute the similarity of those tagged by U_3, namely R_5, with those already recommended by the system, namely R_3. This computing is based on matrix $RR = RT \times TR$:

$$\mathrm{sim}(R_3, R_5) = \cos(RR_3, RR_5) = \frac{(1\ 0) \times (0\ 1)}{\sqrt{1+0} \times \sqrt{0+1}} = \frac{0}{1} = 0.$$

Then R_5 and R_3 are not similar and R_5 is weakly recommended to U_1 [4].

	computer	kitchen	programming	apple
U_1	1	0	1	0
U_2	1	0	0	1
U_3	0	1	0	1

Table 4. Matrix UT

	U_1	U_2	U_3
U_1	2	1	0
U_2	1	2	1
U_3	0	1	2

Table 5. Matrix UU

In order to make our approach scale to very large databases by avoiding repeated recalculations, we enrich our dataset with facts extracted from similarities that have been already calculated. These facts assert that a resource X is similar to a resource Y. For example, let us suppose that we want to know if resource R_x is relevant for user U. In this case before going to calculate the similarities between this user and the other taggers who employed this resource, we first search for resources similar to resource R_x, by checking if there exists a triple (R_x, IsSimilarTo, R_y) in the database. In this case our system will not recalculate the similarity between user U and the taggers who used this resource, nor recalculate the similarity between these two resources. It will directly propose resource R_y to U with the same recommendation level of R_x.

Let us note that the choice of this kind of facts was based on resources and not on users because we are aware that user profiles can be changed at any time by adding or removing new tags or new resources and therefore we cannot assert that two users will always have the same tastes. On the contrary if a large set of users has already agreed that two resources are similar, this information becomes an assertion even if the profiles of these users can be changed in the future. And so we can assume that two resources are similar if they have already been judged as similar by an important group of users.

In order to make our proposal more understandable, let us consider the following example: Suppose that two resources R_1 and R_2 are two papers about web 2.0. At a given time, 5 000 users agree that these two resources are similar: they tagged these resources by common tags.

After a period the profiles of these users have changed (resources and/or tags have been added or removed) and some of them changed their interests. This can affect the similarity value between resources R_1 and R_2 which becomes lower than the similarity threshold. These resources then become dissimilar in the system which is contradictory because these two papers treat the same subject. In our approach we represent and save such similarities in order to avoid loosing them.

3.4 Resolving Language Variations in Recommendation

Multilingualism, dialects and spelling variations are the cause of the most annoying effects in recommender systems. The user perceives the negative effect when the system cannot give him the resources related to a specific tag used in his search.

3.4.1 Recommendation of Similar Resources

Let us consider the illustrative example in Figure 2. When a user searches for all the resources related to the tag "football", the resources tagged with "foot" and "soccer" will not be proposed to him. In order to show the negative effect of this situation on resource recommendation based on association rules, let us consider for example that the association rule *sport* $\Rightarrow$ *football* holds (see Figure 2).

According to the method described in Section 3.3, the recommendation system would propose only the resources related to tag "football" to users having tag "sport" in their profiles. The resources tagged with "foot" and "soccer" would not be proposed to this user.

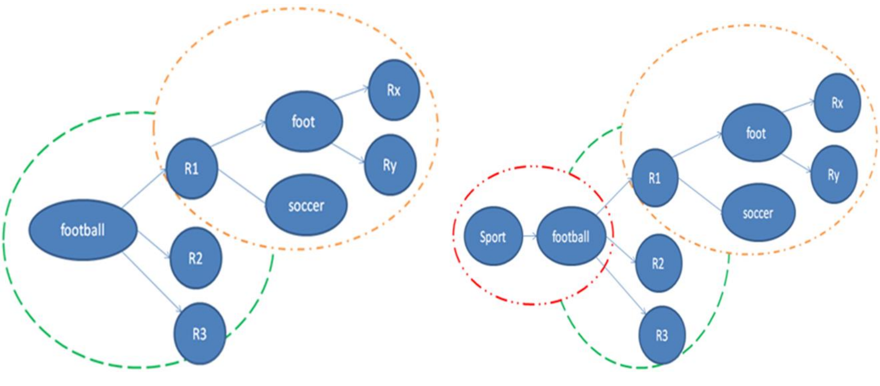

Figure 2. An illustrative example with and without an association rule *sport* $\Rightarrow$ *football*

To answer this problem, we introduced the following steps in our process:

- for each user, for each tag found in the consequence of a rule: calculate the similarity between each resource which is tagged by it and is highly recommended and the other resources having another common tag with this recommended resource,
- select the resources which are similar to the first one,
- recommend these resources to the corresponding user with the same level of recommendation.

For instance, in the above example, suppose resource R_1 is highly recommended. The process becomes as follows:

- the similarities between R_1 and R_x and R_y which are tagged like R_1 with "foot" are calculated,
- R_x is selected which is similar to R_1,
- R_x is recommended to the user with the same level of recommendation as R_1.

3.4.2 Enrichment of the Folksonomy

Let us now consider the following situation. Suppose that both the association rule *software* $\Rightarrow$ *computer* and the user profiles in Table 6 hold. In this case, according to our approach, resources R_3 and R_4 will be recommended to user U_1, but not resource R_6 despite the fact that it seems relevant to U_1's preferences. Also resource R_7 used by U_4 gives the impression that it is significant and adequate to enrich U_1's profile even if it is not a language variation of "computer".

USERS	TAGS	RESOURCES
U_1	software	R_1
U_1	software	R_2
U_2	computer	R_3
U_2	computer	R_4
U_2	software	R_2
U_2	programming	R_1
U_3	java	R_5
U_3	computer-science	R_6
U_4	informatics	R_7

Table 6. Example of a folksonomy

To answer this problem we enrich the folksonomy by applying the following rule: If (R_X, IsSimilarTo, R_Y) $\wedge$ (T_1, IsSimilarTo T_2) $\wedge$ (R_X, TaggedWith, T_1) $\wedge$ (R_Y, TaggedWith, T_2) Then (R_X, CanBeTaggedWith, T_2) $\wedge$ (R_Y, CanBeTaggedWith, T_1)

Let us consider the facts extracted from the above example of a folksonomy: (R_1, TaggedWith, Software) $\wedge$ (R_2, TaggedWith, Software) $\wedge$ (R_3, TaggedWith, Computer) $\wedge$ (R_4, TaggedWith, Computer) $\wedge$ (R_2, TaggedWith, Software) $\wedge$ (R_1, TaggedWith, Programming) $\wedge$ (R_7, TaggedWith, Java) $\wedge$ (R_6, TaggedWith, Computer-science) $\wedge$ (R_7, TaggedWith, Informatics), and the following association rule: *software* $\Rightarrow$ *computer.*

Let us now suppose that the two facts (R_3, IsSimilarTo, R_6) and (R_3, IsSimilarTo, R_7) have been extracted from a previous calculations. The above rule enable to infer and add the following two facts in the folksonomy: (R_6, CanBeTaggedWith, Computer) and (R_7, CanBeTaggedWith, Computer).

Our recommender system will then recommend R_6 and R_7 to user U_1 because it detects that these two resources are relevant to enrich U_1's profile.

4 EXPERIMENTS

In this section, experiments are described with two different scenarios: the first one consists in a simple application over two baseline datasets and the second one is a real world application carrying novel ideas about diabetes disease. Both experiments are described and the results are analyzed and discussed.

4.1 Experiment Over del.icio.us and Flickr Databases

In order to evaluate the performance of our recommender system, we have conducted the first experiment with the two most famous datasets in folksonomies field: del.icio.us and Flickr databases.

4.1.1 Del.icio.us Database

To validate our approach, we have conducted the first experiment with del.icio.us data. Our test base comprises 58 588 tag assignments involving 12 780 users, 30 500 tags some of which are ambiguous and have many spelling variations, 14 390 resources each having possibly several tags and several users. Our system has extracted a set of 946 association rules from the analysis of the dataset with a support equal to 0.5 and a confidence equal to 0.6. We have for example the rule *computer* ⇒ *programming*: 60 % of the users using the tag "computer" also use the tag "programming".

To demonstrate the validity of our approach, we have distinguished two classes of users: the first one contains the users who employed ambiguous tags and the other one the users who did not. The ambiguity of tags has been subjectively decided based on the use context of the tags and their definition in external sources like WordNet. For example the tag "apple" has been used to annotate both the resource `www.nutrition-and-you.com/apple-fruit.html` which is relative to fruits, and other resources like `www.apple.com` that is relative to computers. So we can conclude that the tag "apple" has several meanings, i.e., it refers to several concepts and thus is an ambiguous term. On the other hand, the users who used the tags "computer", "java" and "programming" are annotating similar web resources, and so we can conclude that these tags are not ambiguous.

4.1.2 Flickr Database

We have conducted a second experiment with the Flickr database. Our test base comprises 37 967 tag assignments involving 11 567 users, 26 876 tags some of which are ambiguous or have spelling variations and 9 321 resources: here again each resource possibly has several tags and several users. In this second experience we have also distinguished two classes of users: those who employed ambiguous tags and those who did not. Our system has extracted a set of 476 association rules from the analysis of the dataset with a support equal to 0.5 and a confidence equal to 0.6.

4.1.3 Experimental Methodology

Normally, in order to evaluate the quality of a recommender system, we must demonstrate that the recommended resources are really being accepted and added by the users. Because the knowledge of this information requires asking the users of the selected databases if they appreciated the proposed set of resources, which is impossible in our case because we do not know this community, we have randomly removed some resources from the profile of each user, and we applied our approach on the remainder dataset in order to show if it can recommend the removed resources to their corresponding users or not. If it is the case, so we can conclude that our approach enables to extract the user preferences.

In order to test the performance of our approach we have proposed to follow the following steps:

a) Evaluating the capacity to overcome the ambiguity problem

To achieve this goal, we started by selecting a set of tags containing ambiguous tags; this set consisted of 1 154 tags from the del.icio.us database and 563 tags from the Flickr dataset. Then we have randomly removed sets of resources tagged by these ambiguous tags. Let us note that all the removed resources were randomly selected in order to preserve the justice and the integrity of our evaluation. We repeated this process five times for each tag in order to make a cross-validation. In other words for each tag we have divided its corresponding set of resources randomly to five parts and then selected one part to be removed in each evaluation in order to use it as a test set. This process was repeated five times and in each time we have selected a different test set from the divided parts.

Experimental Results: In order to evaluate the quality of our recommender system, we have used the following three metrics: recall, precision and F1 metric that is a combination of recall and precision.

Based on our test datasets, we extracted 107 association rules from the die.icio.us dataset and 98 one from the Flickr dataset, with a support equal to 0.5 and a confidence equal to 0.6. Afterwards we calculated the three metrics for each participant in our test. Table 7 presents the average values of the metrics.

	Precision	Recall	F1
Del.icio.us dataset	77 %	83 %	80 %
Flickr dataset	84 %	90 %	87 %

Table 7. Average precision, recall and F1 of the recommendations

These results showed that, by applying the extracted association rules, the resources associated to non ambiguous tags are highly recommended. It has also showed that, in the case of rules involving ambiguous tags, our system recommends to the user the resources which are close to his/her interests with a high level of recommendation and, on the contrary, those which are far from his/her interests with a low level of recommendation.

b) Evaluating the capacity to overcome the spelling variations problem

To achieve this second goal, we started by selecting a set of tags containing terms with many spelling variations; this set consisted of 2 417 tags from the del.icio.us database and 1 186 tags from Flickr dataset. Then we have randomly removed resources tagged with these tags in order to test whether our system recommends them to their right users. We repeated this process five times in order to make a cross-validation.

Experimental Results: Based on our test datasets, we have extracted 127 and 101 association rules respectively from the del.icio.us and Flickr database, this with a support equal to 0.5 and a confidence equal to 0.6. Afterwards we calculated the three above metrics for each user. Table 8 presents the average values of the three metrics.

	Precision	Recall	F1
Del.icio.us dataset	69 %	80 %	75 %
Flickr dataset	66 %	77 %	72 %

Table 8. Average precision, recall and F1 of the recommendations

4.1.4 Discussion

From the analysis of the above results we can conclude that, in all scenarios, precision, recall and F1 of our approach are very promising both in del.icio.us and Flickr datasets. These results indicate that the use of association rules and social similarities performed by our approach are really able to take into account users profiles when recommending resources.

Not surprisingly, our experiment has showed that the resources associated to no ambiguous tags are highly recommended. It has also showed that, in the case of ambiguous tags, our system proposes to the user the resources which are close to his/her interests with a high level of recommendation and, on the contrary, those which are far from his/her interests with a low level of recommendation. It has also showed that when a user wants to obtain relevant resources concerning a specific tag, the majority of pertinent resources related to the tags which are spelling variations of the entered one are given to this user.

To sum up, the consensus among users who have similar interests for using the same tags or the same resources plays an important role in the elimination of the ambiguity problem. Also increasing the weights of these tags or these resources makes the semantics emerge even when there are tags that can have several meanings. The results presented in the above tables (Tables 7 and 8) show a rate of precision and recall very optimistic in the data set tested in this experience. Indeed these results show that our approach succeeds in distinguishing between ambiguous tags and taking into account spelling variations during the resources recommendation. An analysis of our approver's correctness will be presented in the next subsection.

4.1.5 Analysis of the Approach Accuracy

In order to analyze the accuracy of our approach, we compared our results against the null hypothesis where every resource tagged with an ambiguous tag is returned. We consider a *naive folksonomy* without any method to overcome the semantics problems between tags. The average rates of precision, recall, and metric F1 obtained are presented in Table 9.

Tags Ambiguity: When omitting the steps proposed in our approach, the rates of precision become very low, which confirms that the folksonomy suffers from the precision of results and so the ambiguity problem in the step of resources retrieval, and no respect of users' preferences in the resources recommendation process. Also the metric F1 rate decreases according to the diminution of precision. On the contrary the rates of recall are very high (100 %), this can be explained by the ability of our system to retrieve and so recommend all the existing resources by a simple selection query.

Spelling Variations: When omitting the steps proposed in our approach, the rates of precision become very low, which confirms that the folksonomy suffers from the precision of results in the information retrieval and so in resources recommendation. The rates of recall are also much lower than with our approach. This can be explained by the inability of the system to retrieve all the relevant resources tagged with tags related to the one found in the rule consequence. The rate of the metric F1 also decreases.

Problem	Database	Precision	Recall	F1
Tags ambiguity	Del.icio.us	12 %	100 %	21 %
Spelling variations	Del.icio.us	44 %	10 %	16 %
Tags ambiguity	Flickr	33 %	100 %	50 %
Spelling variations	Flickr	25 %	20 %	22 %

Table 9. The average values of the three metrics concerning the problem of tags' ambiguity and spelling variations without following our proposed approach

To conclude, the values of precision and recall achieved with our approach are very promising. Especially when we consider the F1 metric, we can observe that our approach achieves the best values. This implies that it is the most adequate when the user wants to obtain a trade-off between precision and recall. the use of association rules and social similarities really enable to satisfy the user's need when recommending him a set of resources.

Tables 10 and 11 present the deviation value of precision, recall and the F1 metric in both del.icio.us and Flickr datasets for tags ambiguity and spelling variations problems, respectively.

In both cases, these values are very small which indicates that the values of these measures for each user tend to be very close to the average. Since the averages

	Precision	Recall	F1
Del.icio.us	5 %	6 %	5 %
Flickr	7 %	5 %	6 %

Table 10. The standard deviation value of the three metrics concerning tags ambiguity problem

	Precision	Recall	F1
Del.icio.us	8 %	5 %	4 %
Flickr	9 %	4 %	5 %

Table 11. The standard deviation value of the three metrics concerning spelling variations problem

(presented in Tables 7 and 8) are very promising for the community in general, the small values of standard deviations indicate that the metrics are also promising for each user individually.

4.1.6 Choice of the Optimal Value for Support and Confidence

The aim of associations rules mining is to find all the rules that satisfy certain minimum support and confidence restrictions. The more we augment the support value, the more the extracted rules are evident, and thus, the less they are helpful for the user. As a result, it is necessary to put the support value low enough in order to extract important information. Unfortunately, when support threshold is very low, the volume of rules becomes very large, making it difficult to analyze the obtained rules.

The confidence is only an estimate of the rules' accuracy in the future. It represents the confidence that we want in the rules.

A certain amount of expertise is needed in order to find the relevant support and confidence settings, to obtain the best rules that impact the rate of F1 measure.

To find optimal values of minimum support and minimum confidence, two experiments are done. In the first experiment, we search the optimal value of minimum support using the two datasets, del.icio.us and Flickr. We choose different value of minimum support ranging from 0.1 to 1 to select the value for which our approach has the best performance. Figure 3 shows the F1 metric evolution based on the selected minimum support using the two experimental datasets.

As can be seen in this figure, the most suitable value of minimum support that produces the highest value of F1 metric is 0.5.

The second experiment concerns the search of the optimal value of minimum confidence using also the two experimental datasets, del.icio.us and Flickr, where minimum support = 0.5. In this experiment, different values of minimum confidence are used ranging from 0.1 to 1. Figure 4 shows the value of F1 metric evolution based on the selected value of minimum confidence.

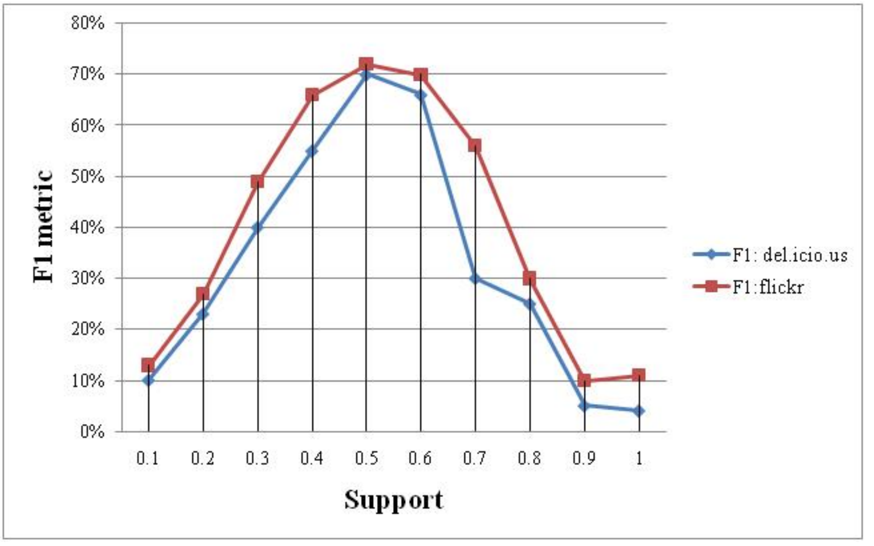

Figure 3. Optimal value of minimum support

From this figure, the optimal value of minimum confidence that provides the best performance is 0.6. In the resulting experiments, the relevant support and confidence settings are 0.5 and 0.6, respectively.

4.1.7 Similarity Threshold

The distribution of tags over resources and users in folksonomies follows a power law [8, 25]: most resources are tagged by only a few number of users, and many tags are only used by a few number of users. This intensely impacts on the similarity degree between two users. Figure 5 shows that almost all pairs of users examined in the experimental datasets (del.icio.us and Flickr) showed a very low similarity degree.

In order to choose the relevant threshold value of similarity among users and among resources, we have selected many thresholds distributed in the interval [0, 1]. In our experiment we remarked that:

- When we choose law values of similarity threshold, our approach generates many incorrect similarity relationships among users and among resources.
- On the other hand, when we choose high values, our approach cannot detect some similarity relationship either among users or among resources.
- Intermediate values let our approach detect many correct similarity relationships and to remove most of the incorrect ones.

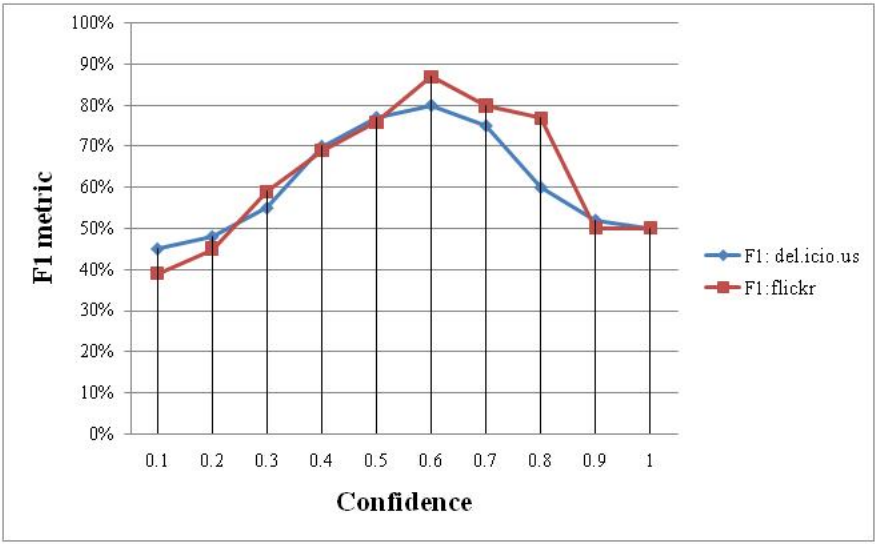

Figure 4. Optimal value of minimum confidence

In the literature, we find that most similarity measures are based on set intersection, union and cardinality. These similarity measures range between a minimum and a maximum value. Generally these two values are 0 and 1, i.e., the similarity between two objects X and Y is limited as follows:

$$0 \leq \mathrm{sim}(X, Y) \leq 1.$$

To determine whether two objects are similar or not, we must compare their similarity with a defined threshold. The problem of finding the relevant threshold setting is generally resolved empirically. We propose a new formula that limits the choice of similarity threshold S during the calculation of similarity within folksonomies. The idea is to calculate the ratio between the number of common tags between two users and the number of tags used by the user who has the richest profile.

$$\frac{\min |U_x \cap U_y|}{\max |U_z|} \leq S \leq \frac{\max |U_x \cap U_y|}{\max |U_z|}.$$

Based on the matrix UU:

- $\frac{\min |U_x \cap U_y|}{\max |U_z|}$ is the minimum value found in the matrix without including diagonal.
- $\frac{\max |U_x \cap U_y|}{\max |U_z|}$ is the maximum value found in the matrix without including diagonal.
- $\max |U_z|$ is the maximum value found in diagonal.

Let us consider matrix $UU = UT * TU$. It is characterized by the following properties:

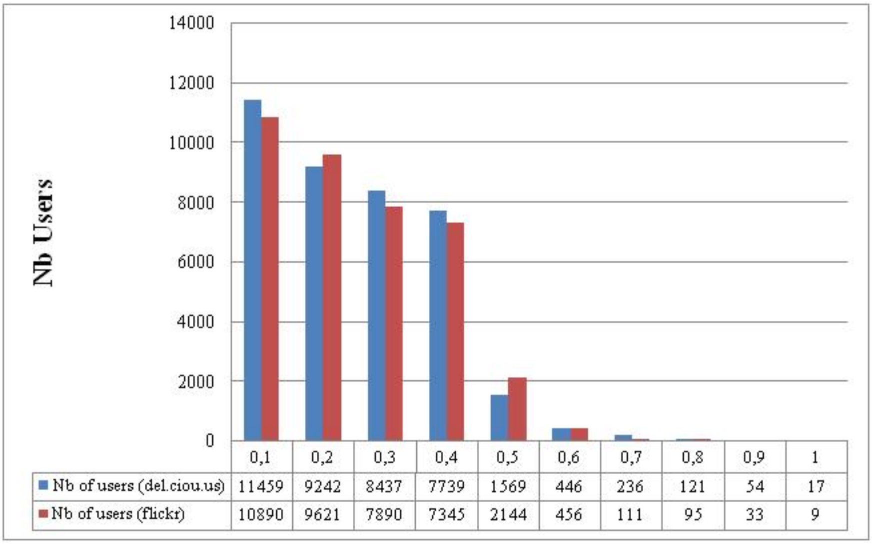

Figure 5. Distribution of users' similarity with cosine formula over many thresholds distributed in the interval $[0, 1]$

- It is a symmetric matrix.
- Each cellule in the diagonal represents the number of tags used by user U_z, which gives us $|U_z|$.
- The values of other cells outside the diagonal represent the number of common tags between two users U_x and U_y (i.e. $|U_x \cap U_y|$).

	U_1	U_2	U_3	U_4	U_5
U_1	278	146	0	132	0
U_2	146	246	100	0	0
U_3	0	100	144	0	44
U_4	132	0	0	132	0
U_5	0	0	44	0	44

Table 12. Example of a matrix UU

$$\frac{\min |U_x \cap U_y|}{\max |U_z|} = \frac{0}{278} = 0$$

and

$$\frac{\max |U_x \cap U_y|}{\max |U_z|} = \frac{132}{278} = 0.47.$$

So the similarity threshold should not overstep 0.47 in this folksonomy. We have empirically determined that the best tradeoff was obtained when the threshold value of similarity among resources is equal to 0.45 and that of similarity among users is equal to 0.5.

4.1.8 Scale-Up Experiment

Recommender systems are intended to be exploited in large datasets. So, it is important to determine how rapidly does our approach provide substantial recommendations. In this subsection we discuss the impact of increasing the number of users on the execution time of our approach. In order to demonstrate the scalability of our approach, we measured the execution time required to make relevant recommendations both in del.icio.us and Flickr databases, with a number of users increasing from 1 000 to 11 500 users.

Figure 6 shows that the execution time (in seconds) of our approach linearly increases as the database size increases, meaning that our approach has relatively good scale-up behavior since the increase of the number of users in the database will lead to approximately linear growth of the processing time, which is desirable in the processing of large databases.

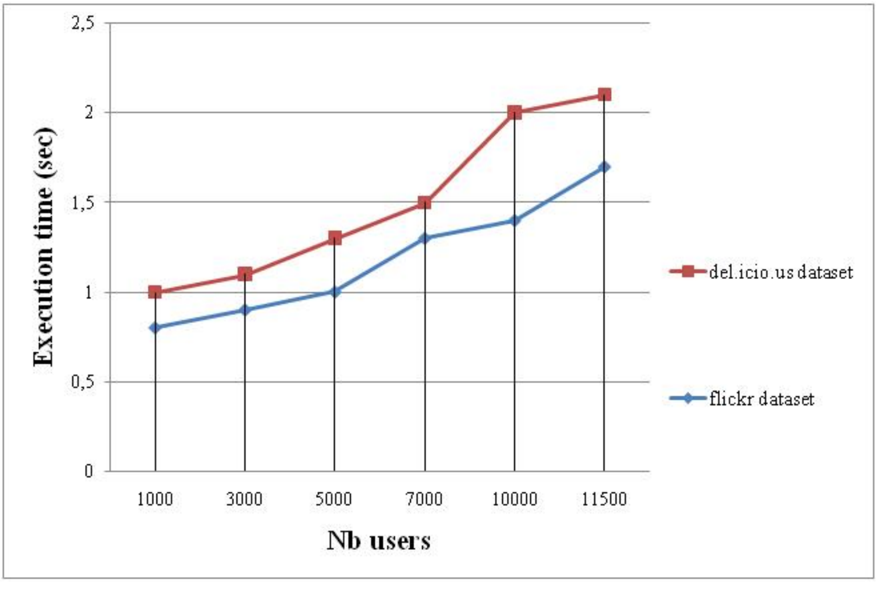

Figure 6. Performance of our approach when the database size increases

4.1.9 Comparative Analysis

In this subsection we propose a quantitative comparison between our approach and some approaches for resource recommendation in folksonomies based on the enrichment of the profiles of involved users; in particular, we consider the approaches described in De Meo et al. [8], Huang et al. [11] and Zanardi et al. [25].

These systems show different behaviors; this depends essentially on the different strategies used by them to surmount the folksonomies problems in resources recommendation process. In this context, we are going to analyze each approach from three points (Resolving Tags Ambiguity Problem (RTAP), Resolving Spelling Variations Problem (RSVP), and Modeling Users' Preferences (MUP)). In Table 13, we report a summarization of three related approaches along with their similarities and differences with ours.

System	RTAP	RSVP	MUP
De Meo et al. [8]	No	No	Yes
Huang et al. [11]	No	No	Yes
Zanardi et al. [25]	No	No	Yes
Our approach	Yes	Yes	Yes

Table 13. A comparison between our approach and three related ones

We implemented the three approaches described in Section 2 and ran both of them and our approach on the del.cio.us dataset described in Section 4.1. Then we computed the corresponding values of Precision and Recall and F1 metric achieved by each system. At the end of this experiment we averaged the values of the above metrics. In Table 14 we reported the obtained results. This table indicates that our approach achieves high values of Precision and Recall and the best value of F1 metric.

Approach	Precision	Recall	F1
De Meo et al. [8]	68 %	71 %	69 %
Huang et al. [11]	60 %	73 %	66 %
Zanardi et al. [25]	72 %	60 %	65 %
Our approach	73 %	82 %	77 %

Table 14. Average Precision, Average Recall and Average F1 achieved by our approach and three related ones

On the other hand, the semantics problems solved in our approach are discussed by previous methods, especially via employing ontologies. In this subsection we will see some comparisons with these methods in order to demonstrate our approach capacity to surmount tags ambiguity and spelling variations when users submit a simple query and not only the final recommendation. In order to make a quantitative comparison between our approach and some approaches aimed to bring together folksonomies and ontologies to overcome the lack of semantics between tags, we considered the approaches described in Limpens et al. [15] and Pan et al. [18]. In this experiment we will use del.icio.us dataset described in Section 4.1.1.

We implemented the two approaches [15] and [18] described in Section 2 and ran both of them and our approach on the dataset described in Section 4.1.1. Next, we have performed some queries for retrieving a set of resources related to a specific tag. This one can be ambiguous and/or have several spelling variations. For each submitted query we computed the corresponding values of Precision, Recall and F1 measure achieved by each system. At the end of this experiment we averaged the values of these metrics across all submitted queries. In Table 15 we report the obtained results which indicate that our approach achieves high values of Precision and Recall, and also the best value of F1 metric.

Approach	Precision	Recall	F1
Pan et al. [18]	75 %	67 %	71 %
Limpens et al. [15]	70 %	69 %	70 %
Our approach	90 %	82 %	85 %

Table 15. Average Precision, average Recall and average F1 achieved by our approach and two related ones

From the analysis of this table it is possible to observe that the three systems show different behaviors; this depends essentially on the different strategies used by them to surmount the folksonomies problems. In this context, we are going to analyze each approach concerning three points: resolving tags ambiguity problem, folksonomy enrichment and resolving spelling variations problem.

Starting with the approach presented in Pan et al. [18] that addressed the problem of tag ambiguity by expanding folksonomy search with ontologies. The author proposed to expand folksonomies in order to avoid bothering users with the rigidity of ontologies. During a keyword-based search of resources, the set of ambiguous used terms is concatenated with other tags so as to increase the precision of the search results. This contribution addresses tags ambiguity problem, however neither the folksonomy enrichment nor the spelling variation problem are tackled. The limits of this approach are listed in the following points: the results of users' queries are not adapted to each user profile; the approach did not tackle the spelling variations problem and there is no folksonomy enrichment in the proposed method.

In another contribution, Limpens et al. [15] focused on using ontologies to extract the semantics between tags. Also, the interactions between users and the system are used to validate or invalidate automatic treatments carried out on tags. The authors have proposed methods to build lightweight ontologies which can be used to suggest terms semantically close during a tag-based search of documents. This work tackled three kinds of relations between tags which are: spelling variations, hyponyms (that include narrower or broader tags) and related tags. The problem of tags ambiguity did not tackled in this approach, therefore the results obtained when a user wants to search resources annotated by an ambiguous tag cannot be personalized according the interest of each user.

Concerning the folksonomy enrichment, we find that the approach of Limpens et al. [15] tackled this point by

1. enriching tag-based search results with spelling variants and hyponyms, or
2. suggesting related tags to extend the search, or
3. hierarchically organizing tags to guide novice users in a given domain more efficiently than with a list of tags or occurrence-based tag clouds.

The problem of spelling variation was tackled in this work, where string-based similarity metrics are applied to tag labels to find spelling variants of tags.

The limits of this approach are listed in the following points: the expertise of users that was introduced is characterized by the complexity of its exploitation; the queries results are not adapted to each user profile, also this approach did not tackle tags ambiguity problem.

In this context, we are going to analyze each approach from the following points (Resolving Tags Ambiguity Problem (RTAP), Resolving Spelling Variations Problem (RSVP), Supporting Related Tags (SRT), Supporting Hyponyms Tags, Supporting Folksonomy Enrichment (SFE) and Modeling Users' Preferences (MUP)). In Table 16 we report a summarization of these two related approaches along with their similarities and differences with ours.

Approach	RTAP	RSVP	SRT	SHT	SFE	MUP
Pan et al. [18]	Yes	No	No	No	No	No
Limpens et al. [15]	No	Yes	Yes	Yes	Yes	No
Our approach	Yes	Yes	Yes	No	Yes	Yes

Table 16. A comparison between our approach and two related ones

4.2 A Real World Application for Diabetes Disease

Diabetes affects millions of people in the world leading to considerable and expensive healthy problems in our life. Recently with the emergence of social networks in the internet and their use in different field, we propose to use this technology in clinical practice by showing a system based on giving doctors relevant medical resources that can be annotated by them. A novel technique is proposed to help doctors discovering the best practices to patient's diseases diagnosis and treatments in their daily tasks by analyzing doctors' profiles according to their tagging activity in order to personalize the greatest medical resources recommendation related to the patients' diseases, treatments or clinical cases. We propose to take profit of community effect strength which characterizes social networks with creating and observing emergence of the intelligence captured from social interactions between doctors in the network by using a powerful method of data mining which are associations rules. We show through an empirical scenario how we can evaluate and demonstrate the efficiency of the medical resource recommender system in clinical decision.

This choice is motivated by the necessity to avoid the problem of knowledge acquisition that gene developers of expert systems since it is relevant to use online knowledge and online community as a valuable source of knowledge and, moreover, to improve traditional explanation with hyperlinks to other relevant web resources. Because the calculation of the three metrics (Precision, Recall, and the metric F1) requires the knowledge of all relevant resources for each user in order to compare the results provided by our recommender system and those which are preferred by each user, we have built a real database by inviting a set of users to participate in our experiment.

We have chosen the diabetes disease as subject of this application, this latter is a group of metabolic diseases in which a person has high blood sugar. Diabetes is no outsider to 40 million people of Algeria. Tackling the diabetes challenge in Algeria is important. In the following sections we will discuss how we can help doctors interested in diabetes in their daily work.

4.2.1 Dataset

Because our application is incorporated within a web 2.0 technology which is folksonomies, we must give an overview about its three main elements: Resources, Users and Tags.

Resources: Firstly, we made a prototype of a folksonomy in the form of a website, where we have collected a set of different kinds of resources related to the diabetes disease. This set of resources was varied between a set of web pages containing a simple text, videos, photos, etc. 543 is the number of the collected resources.

Participants (Users): We have recruited 65 individuals to participate in our study. All participants are doctors interesting in the diabetes disease. The grade of each doctor is varied between internal, general doctor, resident and specialist. We must note that users of this system are only doctors, and patients have no involvement in this application except through their therapists. All these members are asked to use our real world application in order to show the impact of social interactions in helping each doctor to benefit from the expertise of others and so let the system move toward a general consensus of its members.

Tags: The tagging activity is conducted as follows: We have initially asked the specialist doctors to tag a set of resources found on our website in order to let our system benefit from their expertise, and then the system can be used in parallel either by specialists, residents, general practitioners or interns. The number of collected tags is 783 tags.

4.2.2 Experimental Methodology

We have invited a doctors group specializing in diabetes field for participating in our experiment. We have initially asked the specialists doctors to tag a set of resources found in our website, and after that the system can be used in parallel either by specialists, residents, general practitioners or interns. All this lets non-specialist physicians benefit from the specialists' experience within a Web 2.0 application like folksonomies (see Figure 7).

The profile of each physician is constructed from the set of tags and resources used by him when he treats his patients.

Now in order to link the usual task of doctors to our application, we proceeded as follows: When the doctor begins his work, usually he asks his patient some questions about his symptoms, whether he takes already some medicaments, whether he suffers from some parallel disease, etc. Then he saves this information in the patient's profile by tagging resources related to his symptoms, his history, etc. Next, the doctor will make a diagnosis in order to identify the illness of his patient and then save this information in the system in the form of tags linked to resources related to this disease. After the diagnostic phase, it is now the time for therapy. Of course, the treatment proposed by the doctor will differ according to each patient's case. It is the expertise of a physician which will be intervened here for proposing the appropriate treatment according to each case. Also this treatment must be noted in the application by tags related to a set of resources indicating information about the proposed medicaments. And of course, this scenario will be repeated each time when a doctor performs a new consultation with one of his patients.

We must always insist on one of the strongest points in our application which is dynamism aspect of the users' profiles. The profile of each patient can be changed in each new consultation by removing or adding some symptoms, changing one or more therapies, etc. The same, the physician profiles will also be modified according to the arrival of a new patient. Therefore we can say that our system can react according to these updates by adding or removing new tags and new resources. In the next subsection, we will give an overview about the impact of our application on the professional task of doctors:

a) Helping doctors to find the appropriate questions for their questionnairing

Since the specialists' expertise in choosing the relevant questions posed to a patient will be saved in our system, another doctor can benefit from this experience by providing him information (in the form of recommended resources) about the questions or symptoms he can ask his patients to discover a correct diagnosis. For example, if our system discovered that the majority of doctors when found that patients suffered from the symptoms X and Y they asked them if they suffer also from the symptom Z, then as a result the system will generate an association rule $X, Y \Rightarrow Z$. With this association rule our application will recommend the resources tagged by the tag Z for doctors who detected that their patients suffer from the symptoms X and Y. All this helps doctors to gather all necessary information required for a proper diagnostic.

b) Helping doctors to make an appropriate diagnostic

After the questionnaire phase, the doctor arrives at a stage where he must make a correct diagnosis in order to discover the illness of his patient. Our system will greatly help also here to all doctors: internal, general practitioner, resident and even a specialist for discovering the patient disease focusing on the previous physicians' expertise who have treated similar cases. For example, if the system perceived that the majority of doctors who detected that their patients suffered from the symptoms X, Y and Z, they diagnosed the disease D, so the system will generate an association rule $X, Y, Z \Rightarrow D$.

Now, when a new doctor detects that his patient suffers from the symptoms X, Y and Z and he thinks about the corresponding disease, our system is going to provide him resources related to the illness D and helps this doctor to make an appropriate diagnosis by giving him interesting information about this disease in the form of relevant resources.

c) Helping doctors to propose the best treatment

We are now at the stage where the doctor should propose the best possible treatment to his patient. In this step each physician must take in account not only the symptoms from which the patient suffers, but also other considerations such as patient's another treatment, whether the patient (if a women) is pregnant, etc. All this is to avoid proposing a bad treatment for the patients. Here, the strength of our approach is to help the doctors to provide the right treatment for their patients. For example, if the majority of doctors provide the medicine M when they detect symptoms X, Y and Z, then our system will generate an association rule $X, Y, Z \Rightarrow M$ and offer it to the physicians who discovered these symptoms, and should suggest an appropriate type of treatment, resources related to the medicine M in order to give them a quick reminder about this remedy and at the same time helping them to propose an appropriate medicament for their patient.

4.2.3 Experimental Results

In order to validate our approach efficiency, we propose two experimental scenarios: In the first one we will incorporate doctors' community in the evaluation process since the calculation of the metrics which will be used in the estimation requires the knowledge of all the relevant resources for each user in order to compare them with the results provided by our recommender system. In the second scenario, we will try to test our approach capacity without involving doctors in this task. More details will be given in the next subsections.

The First Scenario:

The aim of this experiment is to see the impact of association rules in medical field to make a new recommender system. In order to evaluate the performance of this technique, we choose to calculate the rates of three metrics Precision, Recall and the metric F1. Based on our test dataset, we have extracted 114 association rules with a support equal to 0.5 and a confidence equal to 0.6. Afterwards we have calculated the above mentioned three metrics for each physi-

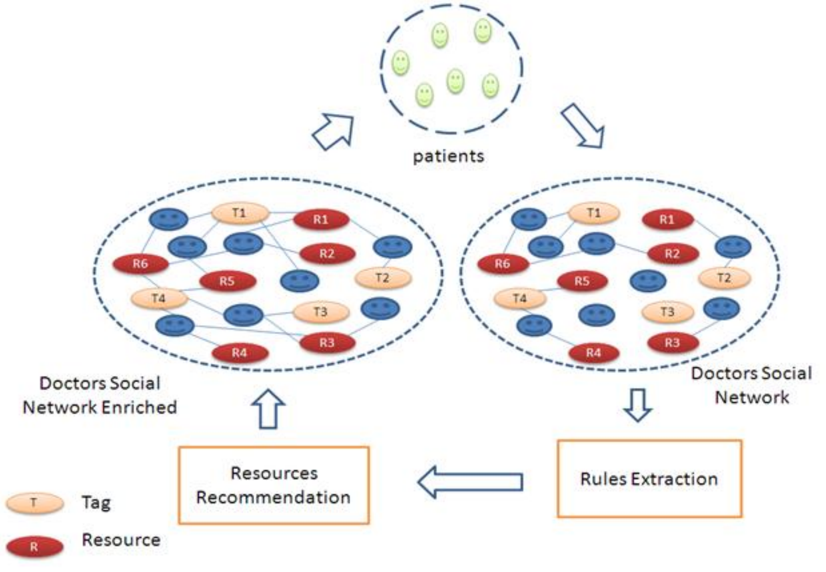

Figure 7. Overview of the system design

cian. Table 17 presents the average values of the metrics we obtained for our 65 doctors.

	Precision	Recall	F1
Average	83 %	81 %	82 %

Table 17. The average values of the three metrics following our proposed approach

These are quite encouraging results showing that our approach to the recommendation process adapted to doctor profiles is truly able to help doctors when searching for resources.

In order to give an efficient analysis to the obtained results, we decided to evaluate our experimental dataset without following the steps and the hypotheses proposed in our approach, and then calculate the rates of precision, recall, and the metric F1. After this evaluation we obtained the results presented in Table 18.

	Precision	Recall	F1
Average	17 %	100 %	29 %

Table 18. The average values of the three metrics without following our proposed approach

As we see in this table, when we omitted the steps proposed in our approach, the rates of precision became very low, which confirms that the current folksonomies suffer from the precision of results in the information retrieval because they cannot surmount the problem of tags ambiguity, spelling variations and the semantics lack between terms. Also the rate of the metric F1 is decreased according to the diminution of precision. On the contrary, the rates of recall show a complete degree (with 100 %) which demonstrates the ability of the system to retrieve all the existing resources by a simple select query.

The Second Scenario:

To evaluate the efficiency of our approach without involving doctors in this procedure, we followed the next scenario: we selected to remove randomly some resources from the profile of each doctor and then applied our approach on the remainder dataset in order to show whether it can recommend the removed resources to their corresponding users. If so, we can say that our approach can really analyze the doctors' preferences. In order to test the performance of our approach, we propose the following experimental protocols:

a) **Evaluating the approach capacity to overcome the ambiguity problem in recommendation**

We started by selecting a set of ambiguous tags; this test set consisted of 30 tags. Then we removed random resources tagged with these ambiguous tags in order to see if our approach will be able to overcome the ambiguity problem in its recommendation process and recommend the removed resources to the corresponding doctors.

In order to evaluate the efficiency of our recommender system, we used the above mentioned metrics: Recall, Precision and F1 measure. Table 19 presents the average values of the metrics.

	Precision	Recall	F1
Average	84 %	90 %	87 %

Table 19. The average values of the three metrics concerning the problem of tags Ambiguity

Not surprisingly, our experiment showed that the resources associated to non ambiguous tags are highly recommended. It also showed that, in the case of rules involving ambiguous tags, our system recommends the resources which are close to doctor's interests with a high level of recommendation, and, on the contrary, those which are far from his interests, with a low level of recommendation.

b) **Evaluating the approach capacity to overcome the spelling variations problem in recommendation**

To demonstrate our approach capacity to overcome spelling variations problem, we also started by selecting a set of tags which have many spelling variations, this set consisted of 85 tags. Then we removed random resources from these tags in order to judge if our approach will be able to overcome the problem of spelling variations in its recommendation. Table 20 presents average values of the used metrics. These are quite encouraging results, showing that our approach of recommendation adapted to doctor profiles is truly able to help users when searching for medical resources.

	Precision	Recall	F1
Average	69 %	80 %	75 %

Table 20. The average values of the three metrics concerning the problem of spelling variations

4.3 General Discussion

The results of our experiments are very optimistic and so we can say that the force of community effect in folksonomies applied with association rules have showed its efficiency in the enrichment of users' profiles. At the same time our approach contributes to increase the weights associated to the relevant resources, it also reduces tag ambiguity and spelling variations problems. The extraction of association rules is based on tags rather than on resources because we believe that tag popularity in folksonomies is greater than resource popularity and the meaning of tags in these systems is more significant than that of resources. The results presented in the above sections show that rates of Precision and Recall are very optimistic. We must note also that the methodology proposed to treat tags ambiguity and spelling variations problems can be applied during a simple research by tags.

5 CONCLUSION AND FUTURE WORK

In this contribution we have exploited the strength of social aspect in folksonomies to let each member in the community benefit from the resources tagged by his other neighbors in the social networks based on resources recommendation. We have seen that it is very important to analyze the users profile in order to realize that a dynamic recommendation can be adapted to each modification in favour of the users' interests.

Starting from this point, we found that it is very significant to overcome the semantics problems within folksonomies during our recommendation. The followed method is based on the similarities between users in some cases and between resources in the other cases. In this paper, we proposed a method to enrich user profiles with relevant resources based on social networks and folksonomies. We exploited association rules extracted from the social relations in a folksonomy to recommend resources tagged with terms occurring in these rules in the social network. Our objective is to create a consensus among users of a same network in order to teach them how they can organize their web resources in a correct and optimal manner. We have tested our approach on two baseline datasets where we obtained good results. In order to continue and improve our work, we aim to enrich folksonomies by other semantic relations.

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