A Comparative Study of Two Egocentric-based User Profiling Algorithms
Experiment in Delicious

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Abstract: With the growing amount of social media contents, the user needs more accurate information that reflects his interests. We focus on deriving user's profile and especially user's interests, which are key elements to improve adaptive mechanisms in information systems (e.g. recommendation, customization). In this paper, we are interested in studying two approaches of user's profile derivation from egocentric networks: individual-based approach and community-based approach. As these approaches have been previously applied in a co-author network and have shown their efficiency, we are interested in comparing them in the context of social annotations or tags. The motivation to use tagging information is that tags are proved relevant by many researches to describe user's interests. The evaluation in Delicious social databases shows that the individual-based approach performs well when the semantic weight of user's interests is taken more in consideration and the community-based approach performs better in the opposite case. We also take into consideration the dynamic of social tagging networks. To study the influence of time in the efficiency of the two user's profile derivation approaches, we have applied a time-awareness method in our comparative study. The evaluation in Delicious demonstrates the importance of taking into account the dynamic of social tagging networks to improve effectiveness of the tag-based user profiling approaches.

1 INTRODUCTION

The introduction of online social networks (e.g. Facebook, Google+, Twitter, YouTube, Flickr, Delicious, etc.), also called social media, provides an explosion of online information resources. Our work focuses on extracting user's interests from this kind of data in order to derive the user's profile, which is a key element to improve adaptive mechanisms (recommendation, customization, etc.). The better a user's profile reflects user's appropriate characteristics (interests, preferences, etc.), the better these mechanisms will propose relevant information to the user.

User profiling aims to detect/derive user's interests that are generally extracted from his own profile (e.g. interests are directly provided by the user), or from his own activities in the system (e.g. annotating resources) or his social network (e.g. friends). However, detecting user's interests is a crucial problem. Some issues of detecting user's interests could be summarized through two main points.

The first issue is the **cold-start problem**. For new or less-active users that interact less frequently with the system, their profile can be empty or does not contain any useful interests for a mechanism of customization or recommendation. Several works (Tchuente et al., 2013) (Carmel et al., 2009) (Ding et al., 2009) propose to use information from user's social networks. These works demonstrate the effectiveness and advantages of using social network resources to solve the lack of information problem. Indeed, the researchers have analyzed the social environment of the user such as his neighbours (persons connected to the user explicitly or implicitly) (Tchuente et al., 2013) or his own behaviour in social network (e.g. the action of tagging resources) (Kim et al., 2011).

The second issue is related to the **evolution of user's interests over time**. Because the user becomes more and more an active contributor for producing social information, he requires updated information reflecting his current needs and interests in every period of time. This requirement is not widely taken into consideration in existing users' interests

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detection approaches.

In this work, we are interested in studying two social network-based user profiling approaches that aim to overcome the two above mentioned issues. We focus particularly on egocentric-based user profiling. This approach extracts user's interests by analyzing the information provided by his egocentric network, a specific social network that takes into account only the user's direct neighbours[1], by considering that people directly connected to the user in the social network are most similar to him. We consider in this work, the **Individual-based approach** (Cabanac, 2011) (Carmel et al., 2009) that considers egocentric network as a set of similar users and the **Community-based approach** (Tchuente et al., 2013) that considers the existing communities in the egocentric network. These approaches have been experimented in a co-author network of scientific publications. Since the online social networks are considered heterogeneous in terms of data type and network characteristics, we are interested in studying the effectiveness of these two approaches in another kind of social network.

In this paper, we are interested in social tagging networks[2]. There are several motivations to use this kind of social networks. First, social tagging information has been proved relevant to describe the user's interests (Kim et al., 2011). Second, its popularity makes its broad utility in different social network applications. Finally, a social tagging network is considered as an evolving network that provides temporal information. This characteristic could provide a good opportunity to study user's profile derivation process that takes into consideration both social and temporal information.

The motivation of this work is two-fold:

1. to compare two egocentric-based users profiling approaches, that try to overcome the **cold-start problem issue**, in a social tagging network. The aim is to deduce the most efficient approach in the context of a social tagging network.
2. to study the effectiveness of these approaches while applying the time constraint. Since the two studied approaches are time-agnostic, we further have integrated into these approaches, a time-awareness method based on the time-weight strategy, proposed by (Zheng and Li, 2011). Thus, we evaluate the influence of the time to study the relevance of user's interests founded by these two approaches and how they could overcome the user's interests evolution issue.

This paper is structured as follows. In the second section, we present related works about tag-based user profiling approaches, the two different egocentric-based approaches adopted in our comparative study and the time-awareness user's interests extraction process. In the third section we present the comparative study. In section four, we present and comment on the results of the comparison study. The last section consists in concluding and presenting our future work.

2 RELATED WORK

User's shared information and interactions in social network can represent his behaviours. Some works have been done to extract his interests to build/derive his user's profile in a social dimension.

In this section, we discuss researches done in order to derive user's profile from his behaviour of tagging (tagging information) and also from his behaviour of making friends (through the information of the egocentric network).

2.1 Tag-based User Profiling

According to (Kim et al., 2011) (Mezghani et al., 2014), among a variety of information in available online social networks, social annotations or tags are interesting elements for building and enriching a social user's profile. The reasons of choosing tags as information that could be used to detect user's interests could be summarized through two main points:

1. **Popularity and Variety:** Tags are becoming more and more popular and widely used in different social networks (Gupta et al., 2010) (Laniado and Mika, 2010): in popular tagging social networks such as Flickr and Delicious, in social media sharing sites such as YouTube or Instagram, in microblogging networks such as Twitter (hash tags), or even in social networking services such as Facebook, Google+. So, extracting user's interests from tag information would be very useful since it could be reused in a lot of different kinds of social media applications.
2. **Utility:** According to (Gupta et al., 2010), tags are used for many purposes (e.g. contributing and sharing, giving an opinion, marking a place for a future search, etc.). They are also a meaningful tool to mark resources, on one hand

[1] In this paper, we consider a neighbour as an individual in the user's egocentric network

[2] Social tagging networks = social networks based on tagging information

for guiding other users to get information, on the other hand, to receive information about a user from the history of tagging (Gupta et al., 2010). In addition, tags allow users to categorize information in a free way without the need of an intermediary entity (i.e. an administrator to define some words taxonomy).

Tag-based user's interests detection may use tags assigned by the user himself or tags deduced from his neighbours. The approaches that exploit the user's own tags may seem to be powerful to capture user's interests. However, they could be less effective to reflect a comprehensible user's profile due to the ambiguity associated to these social tags. The approaches that exploit the tags of the neighbours could overcome the previous issue by capturing the collective knowledge from the network. So, we will use in this paper, tags from neighbours in order to detect user's interests not provided by the user himself.

Like a great number of online social networks, social tagging networks are considered as evolving and providing more and more information over time. (Ding et al., 2009) analysed tags frequencies across time and found that changing trends in user's interests can be identified and tracked over time. To extract the relevant information from this kind of data, we have to take into account this dynamic characteristic (see section 2.3).

2.2 Egocentric-based User Profiling

According to (Tchuente et al., 2013), we consider that people directly connected to the user in the social network are the most similar to him. Thus, we consider in our work, the notion of user's egocentric network as a specific social network that takes into account only his direct neighbours.

The egocentric-based approaches build/derive a user's profile by extracting the information from his immediate neighbours (called egocentric network). We describe the egocentric network of a user as follows: for each user (u) we consider the undirected graph $G(u) = (V,E)$ where V is the set of nodes directly connected to u, and E is the set of relationships between each node pair of V. We emphasize that u is not included in V. According to this graph, the user u is called "ego". The neighbours in V are called "alter". The user's interests can be extracted either by using people selected individually in G (Cabanac, 2011) (Carmel et al., 2009) or rather by using communities in G (Tchuente et al., 2013). This distinction is described in figure 1 and explained below:

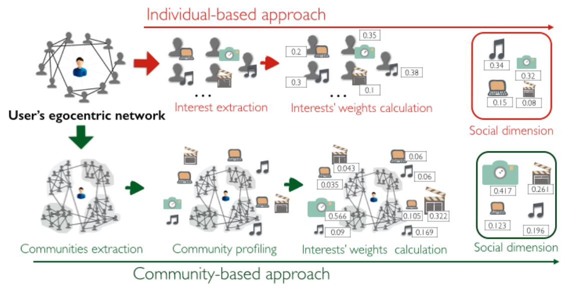

Figure 1: Individual-based algorithm (IBSP) and Community-based algorithm (CoBSP).

2.2.1 Individual-based Approach (IBSP)

This approach uses people individually selected in the user's social network to derive his interests that could be relevant to him. This kind of social profile is used in (Carmel et al., 2009) to improve search engine results and in (Cabanac, 2011) to propose a social recommender system in a co-author network that uses a co-author graph and a graph of venue (in conferences) to recommend relevant authors to a researcher. In these two works, people are selected individually according to their topical similarity, their proximity, their connectivity or the strength of their tie in their social graph (see figure 1).

In this approach, the weight of an interest is computed by combining his structural weight and his semantic weight. The structural weight of an interest i from an individual v, is the centrality value of v in the egocentric network. The semantic weight of i is its weight in the profile of v. The combination weight of the structural and the semantic weight can be adjusted with some parameter, as presented in the following formula (1):

$$w(i,c) = \alpha * Struct_{weight(c)} + (1-\alpha) * Semantic_{weight(i,c)} \quad (1)$$

2.2.2 Community-based Approach (CoBSP)

Instead of considering only some individually selected people in the user's social network, (Tchuente et al., 2013) propose a community-based algorithm to derive user's interests. This work considers that the user is better described by communities of people around him, especially the people who are in his egocentric network. This work introduced a user's social dimension building process (named CoBSP, Community Based Social Profile), consisting of four steps (see figure 1):

1. Step 1 consists in extracting communities from the user's egocentric network. This phase is

realized by applying iLCD algorithm (Cazabet et al., 2010), that performs very well with overlapping communities and outperforms other algorithms particularly for egocentric networks.

2. Step 2 consists in computing the profile of each community found in the first step. The profile of a community is computed by analysing the behaviour of all members of this community.
3. Step 3 consists in computing the weight of each interest in the social dimension of the user's profile. The weight of an interest i in the community c is a combination of structural weight and semantic weight. The structural weight of an interest i from a community c, is the centrality value of c in the egocentric network compared to others communities extracted from user's egocentric network. The semantic weight of an interest i in a community c, depends on the weight of this interest in the comminuty. The weights combination is made by the same way as in the individual-based approach.
4. Finally, in step 4, we derive the social dimension by using the weights calculated in the third step.

2.3 Time-awareness User's Interests Extraction

As time goes by, user's behaviours and interests change. Especially, in online social network, user behaviours tend to change rapidly. Several works propose time-awareness approaches to cope with the dynamic and evolution of the studied information. Most of these works rely on time-forgetting approach. In this approach, outdated information is completely forgotten. For example, (Maloof and Michalski, 2000) use a function of aging all the information and fix a threshold for the up-to-date one. The ones that are older for the fixed threshold are forgotten. However, in some cases, the ignored information could be eventually valuable. Thus, this could lead to the lost of useful knowledge. To avoid this inconvenient, some works propose a time gradual approach (Koychev, 2009). This approach supposes that the natural forgetting is a gradual process. Nevertheless, the recent information should be more important than the older one. Several works consider the user's interests drift in an exponential way (Li et al., 2013).

In a social tagging context, (Zheng and Li, 2011) consider that both the latest bookmarks and the old bookmarks are important. They propose to use a time-score method to assign a weight (time-score) to a tag according to its posted date and time. The more a tag is recent, the more its time-score is high. This time-score method is presented by the following formula 2:

$$time_w(t) = e^{-(ln2*time(t))/hl(u)} \tag{2}$$

Where time(t) is a non-negative integer representing the tagging time of the tags shared by a user u. The time (t) takes the value of 0 for the most recent tagging time and time (t) sets to be 1 for the previous one, and so on. hl(u) represents the half-life of the user u which adapt to each user life cycle in his social tagging network (the time duration since he started tagging).

In this paper, we are interested in adopting this time-weighted method in our time-awareness comparative study of the two egocentric network-based user profiling approaches. The used method is modified to be able to deal with the egocentric network user profiling context. We calculate the parameter *time(t)* from all the information of the egocentric network of the user u (instead of his own information).

2.4 Proposed Work

We have shown the importance of the tags and the relevance of the egocentric network to find relevant user's interests. We propose to study in this work, the two different approaches for egocentric network-based user profiling in order to select the most efficient one in a social tagging context.

The experiments in the individual-based approach proposed by (Cabanac, 2011) and in the community-based approach (Tchuente et al., 2013) have been conducted on co-author network, namely *dblp*[3]. In this network nodes represent the authors. Two authors are connected if they publish together. The user's interests are extracted from the titles of their publications. The performance of the community-based algorithm has been proved with empirical results compared to the individual based approach (Tchuente et al., 2013). In this work, we are interested in: i) applying the two existing approaches in the context of a social tagging network and compare the results to find out the most performing one in this context. ii) comparing these same approaches but with a temporal constraint using a time-awareness method.

3 COMPARATIVE ANALYSIS

In this section, we first present the experimentation

[3]Digital Bibliography and Library Project

setup, which allows us to explain the main steps of building users' profiles and also to explain the evaluation process. Then, we present the results of the comparison through two main criteria: time-agnostic (ignoring the time constraint) and time-awareness (taking into account the time constraint). We consider in this comparative analysis the notion of user dimension and social dimension to distinguish between the user's explicit interests (user dimension) and the interests extracted from his egocentric network (social dimension).

The goal of evaluation is to compare the effectiveness of the two algorithms mentioned in the section 2.2, in a social tagging context. We compare these algorithms on the Delicious[4] social database. Nodes in the social tagging network graph represent the users. The links between these users are extracted from their contacts list.

The evaluation strategy consists in comparing the results of the two algorithms CoBSP and IBSP with the user's real profile (user dimension), and selecting the one that allows building a social dimension that is the closest to the user dimension.

3.1 Experimentation Setup

To build the user and social dimension of each user's profile, we extract the interests from theirs tags posted in their Delicious profile. Our data set contains the tags data posted in different time stamps between 2003 and 2010 extracted from (Ivan et al., 2011). We consider the tags indicated in each user's profile as his real interests and use them to build the user dimension. To build the social dimension, we use the tags from all users' contacts (user's egocentric network). To extract the best performance of community based approach, the studied user in our work has to possess a significative number of neighbours. The user considered relevant to the experiment of (Tchuente et al., 2013) had at least 50 neighbours (ones who possess less neighbours could lead us to the misinterpretation in the community extraction step). Subsequently, we have decided to take into account, users having more than 45 neighbours in our dataset.

3.1.1 Profile Building Process

In this work, we adopt the same process of building and evaluating users' profiles as presented in (Tchuente et al., 2013), except that we extract the user' interests from users' tags instead of users' publication titles.

[4]www.delicious.com

User Dimension Construction. The user dimension in this experiment consists in representing the real interests of the user. This dimension is build by mining keywords in the list of tags posted by the user as presented in (Tchuente et al., 2013). The first step of the user dimension construction consists in collecting the tags posted in user's Delicious profile. As presented in the section 2.1, the social tagging networks are considered as evolving networks. We can identify and track the changing trends in user's interests over time. Consequently, for each user, we only consider his recent posted tags in his user dimension. In the second step, we extract interests from the collected tags using a tag-mining engine: we first use dictionaries/thesaurus to merge tags having the same meaning. Then we apply filters to remove empty words, in order to retain only consistent interests. In the third step, we compute interests weights using a semantic weight. The semantic weight of each interest is computed by its tf measure that represents the time frequency of the each interest in the set of all found interests.

Social Dimension Construction. To build a social dimension, interests are detected by mining texts that appear in tags of communities or individuals according to the algorithm used to derive social dimension presented in the section 2.2 (CoBSP, IBSP). The first step of the user dimension construction consists in collecting the tags from user's egocentric network (the tags posted by his direct neighbours). In the second step, we extract interests using a tag-mining engine. We use the same process as defined in the second step of user dimension construction process. In the third step, we compute interests weights by using the combined weight between the structural weight from user's egocentric network and the semantic weight using the formula 1.

3.1.2 Evaluation Process

To evaluate the relevance of each social dimension (Social Dim.) compared to user dimension (User Dim.), we use the precision and the recall measures. The precision assesses the proportion between the relevant found interests and the total number of found interests. The precision formula is presented as follows (3):

$$Precision = \frac{Nb.Interests(SocialDim. \cap UserDim.)}{Nb.InterestsSocialDim.} \quad (3)$$

The recall assesses the proportion of relevant founded interests compared to the total number of real relevant interests (user dimension). In our experimentation context, the recall formula is presented as follows (4):

$$Recall = \frac{Nb.Interests(SocialDim. \cap UserDim.)}{Nb.InterestsUserDim.} \quad (4)$$

To compute the precision and the recall, we only consider the most relevant interests. The total number of interests in the user dimension top N (user's interests) + m first interests obtained after building the social dimension (m=5 in this experiment). For example, if the user dimension of an author's profile contains 10 interests, we will consider the social dimension as only the top 15 first interests computed in the social dimension. Figure 2 summaries the evaluation process.

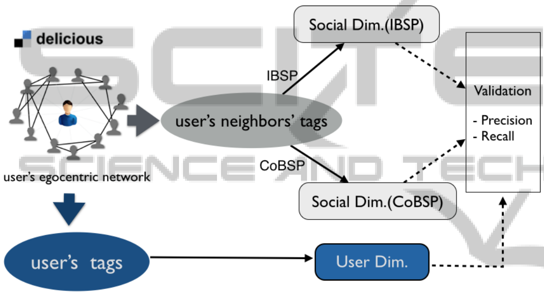

Figure 2: Evaluation process.

3.2 Results

In this section, we first present the comparison results of CoBSP and IBSP algorithms without the temporal constraint. Then, we present the time-weight strategy used in our time-awareness comparison approach and the results of this approach.

3.2.1 Time-agnostic Method Results

We present the comparison results of the CoBSP and IBSP algorithms in the *Delicious* social tagging network in figure 3. This figure presents comparative curves (precision, recall) of these algorithms for all users' egocentric networks studied in this work. The alpha value (α) indicates the weight of structural weight compared to the semantic weight as presented in the formula 1. We can see that the community-based approach (CoBSP) provides the worst accuracy in terms of precision and recall compared to the individual approach (IBSP), when the alpha value is low, that is when we consider more the semantic weight than the structural one during the interest weighting step.

The results are conflicting compared to the work of (Tchuente et al., 2013) where CoBSP outperforms

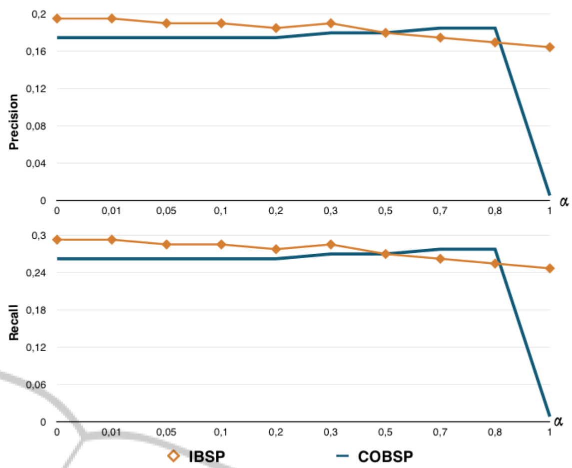

Figure 3: Comparison of the precision (top) and the recall (bottom) of calculated social dimensions (Orange: IBSP, Blue: CoBSP).

IBSP with the experimentation on co-author network, when the alpha value = 0.1. This can be explained by the fact that in the scientific publications network, users' research field are quite similar, an author tends to work in the same field than his co-author in order to publish papers together. Thus, the interests extracted from this kind of network are in the same domain. For example, computer scientists tend to publish in computer science field. The interests extracted from this kind of network are for the majority in the computer science domain. So, we can detect meaningful user's communities that lead to an effective social dimension of the user's profile (computed by CoBSP).

In case of tagging information, we can find different domains of interest from the same user (e.g. sport, art, music, etc.), with different motivations of tagging. The more the number of users there are, the more different domains of tags can be provided. As the community extraction algorithm used in CoBSP algorithm is only based on the network structure, it could be possible that the communities extracted from this process are irrelevant. Thus, this could lead to a misinterpretation of the results. When the alpha value is very high (i.e. structural weight is considered more than the semantic weight during the interests extraction step) we can see that the CoBSP algorithm outperforms the IBSP one.

3.2.2 Results with Time-awareness Method

To take into account the evolution of social tagging network in the user profiling process, we propose to apply a time-awareness method to evaluate the relevance of each tag according to his posted time.

To reach this goal, we apply a time-weighted method to assign a weight to a tag according to his posted date. The more a tag is recent, the more its time-weight is high. We adopted the time-weight strategy proposed by (Zheng and Li, 2011) in formula (2). We use the similar evaluation strategy as presented in the section 3.1, except in the semantic weight computing step of social dimension construction where we give a weight to each interest extracted from users' social tags by multiplying its time-score with its tf weight. The results of this comparison are presented in the figures 4 and 5.

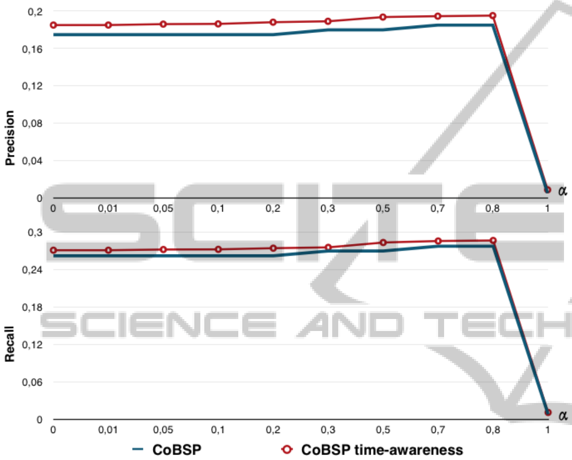

Figure 4: Comparison of the precision (top) and the recall (bottom) of calculated social dimension of the COBSP algorithm (Blue: CoBSP time-agnostic, Red: CoBSP time-awareness.)

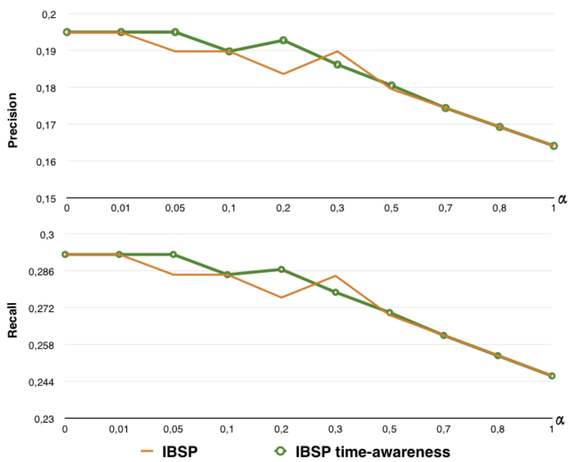

Figure 5: Comparison of the precision (top) and the recall (bottom) of calculated social dimension of the IBSP algorithm (Orange: IBSP time-agnostic, Green: IBSP time-awareness).

For the community-based approach, the time-awareness method (CoBSP time-awareness) outperforms the time-agnostic one (CoBSP) for all values of α (figure 4). For the individual-based approach, the results are improved after applying the time-weight method when $\alpha \in [0.01, 0.2]$ (figure 5). We have also calculated the average gain of the time-awareness approach compared to the time-agnostic one for each algorithm (IBSP and CoBSP). The average gain is computed according to the difference between the IBSP time-awareness curve (respectively CoBSP time-awareness) and the IBSP time-agnostic curve (respectively CoBSP) for all α. The results show that:

- for the comparison of the CoBSP vs. CoBSP time-awareness approach (figure 4): the gain according to the precision values is 6.0% and the gain according to the recall values is 3.7%
- for the comparison of the IBSP vs. IBSP time-awareness approach (figure 5): the gain according to the precision values is 0.73% and the gain according to the recall values is 0.47%

The positive average gain values show that the time-awareness approach can improve the performance of all algorithm compared to the time-agnostic one. The results demonstrate the benefit of taking into account the evolution of social tagging networks by applying the proposed time-awareness method to extract the interests to build a more relevant user social profile. Nevertheless, the gain rates are still low and require more studies to improve the effectiveness of this approach.

4 CONCLUSION AND PERSPECTIVES

In this work, we are interested in user's profile deriving process using user's social tagging network. We have compared two egocentric-based user's profile derivation approaches: the individual-based approach and the community-based approach. This comparative study aims to find out the most effective approach in a social tagging context. In order to take into account the dynamic characteristic of tagging information, we further integrate a time-weight strategy into the two studied approaches.

Our experiment in Delicious database shows that the individual-based approach performs well when the semantic weight of user's interests is taken more in consideration and the community-based approach performs better in the opposite case (more importance to structural weight).

In the time awareness comparison study, the results show that the time-awareness user's profile is more relevant than the time-agnostic one. These results demonstrate the importance of taking into account the time criteria (temporal information) in tag-based user's profile derivation or even in other kinds of online social network that are considered evolving. However, the gain rates of the time-awareness approach studied in this work are still low and require more studies to enhance its effectiveness. Our perspective is to improve the effectiveness of the time-awareness approach by study of different time-awareness methods to select ones that fit the best with each adopted social network.

The popularity of online social networks offers a variety of available data that are heterogeneous in terms of structure and utility. To build a relevant user's profile from each social network data, it's necessary to take into account the data characteristics in the user profiling process. Our long-term perspective consists in taking into account this suggestion in order to find out an effective user's interests extraction technique for each type of data. Finally, we expect to propose a platform that extracts the information and derives a social dimension of user's profile according to the type and the specific characteristics of each studied social network.

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