Dynamic Communities Formation through Semantic Tags

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ABSTRACT

Taggers in social tagging systems have the main role in giving identities to the objects. Tagged objects also represent perception of their taggers about them and can define identities of their taggers in return. Consequently, identities that are assigned to the objects and taggers have effect on the quality of their categorization and communities formation around them. Tags in social semantic tagging systems have formal definitions because they are mapped to the concepts that are defined in ontologies. Semantic tags are not only able to improve quality of tag assignments by solving some common tags ambiguity problems related to classic folksonomy systems (i.e., in particular polysemy and synonymy), but also to provide some meta data on top of the social relations based on contribution of taggers around semantic tags. Those meta data may be exploited to form dynamic communities which addresses the problems of lack of commonly agreed and evolving meaning of tags in social semantic tagging systems.

This paper proposes an approach to form dynamic communities of related taggers around the tagged objects. Because our perceptions in each specific area of knowledge is evolving over time, the goal of our approach is also to evolve the represented knowledge in semantic tagging systems dynamically according to the latest perception of the related users.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Retrieval models; H.5.3 [**Group and Organization Interfaces**]: Collaborative computing; Computer-supported cooperative work—*WEB*

Keywords

collaborative tagging, community formation, emergent semantics, semantic tagging, social semantic tagging systems

WWW'14 Companion, April 7–11, 2014, Seoul, Korea.
ACM 978-1-4503-2744-2/14/04.
http://dx.doi.org/10.1145/2567948.2567960.

1. INTRODUCTION

Available resources on the Web can be interpreted as knowledge when they are represented with formal agreed upon definitions and enable the related people to use them practically. The exponential growth of online resources on the World Wide Web necessitate categorization of this huge volume of information to facilitate accessibility of the users to the related resources. Bookmarking is one of the most popular methods for classification of the online resources and knowledge management. A study conducted by PEW Research Center revealed that 28% of Internet users have already indexed online content with tags, and 7% stated that they do so several times over the course of a typical day online [18]. Bookmarking online resources with meaningful tags can facilitate accessibility to this valuable part of human knowledge. Users of the social tagging systems (i.e., so called taggers) have the main role in giving identities to the tagged resources (i.e., so called objects). Tagged objects also present perception of the taggers about objects and can define taggers' identities in return. The quality of recommendations in social tagging systems is dependent on the quality of the assigned identities to their users and objects.

1.1 PROBLEM STATEMENT

There exist several reasons that can cause low quality of tag assignments but those that are more related to the area of this research are the followings: 1) the quality of the meanings of assigned tags to an object, 2) the quality of taggers relatedness to a tagged object and 3) the dynamics of recommendations.

1) Using plain words as tags for representing objects in classic bookmarking systems causes ambiguity problems. The sources of such ambiguity include using of different plain words as tags for referring to the same concept (synonymy) or referring to different concepts with the same plain word tags (polysemy). For instance, searching for *"USI"* on classic tagging systems might show results containing tags related to *Università della Svizzera italiana*, a university in Italian part of Switzerland, a province of South Korea, *User System Interaction* (a postgraduate engineering design program in the Netherlands), *U Select It* (a large vending company in the United States), *Union of Students in Ireland*, *Unione Sindacale Italiana*, *United States of Indonesia*, *University of Southern Indiana*, *Unlimited Software Inc*, and so on. One way to narrow results to the university in Southern Switzerland would be if people had tagged their objects with a tag such as <university> and <southern switzerland>. But this has its own problems: not everyone will tag the object with

<southern switzerland> and others may use other synonym tags such as <ticino> (a province in southern switzerland) even if we assume there is a defined naming convention in the system. The new generation of social bookmarking systems that are using semantic tags have solutions for solving tag ambiguity problems by mapping tags to the concepts that are formally defined in ontologies. If tags have meaning, then the <university:USI> would be different from the tag <union:USI> and therefore the result of queries on the semantic tags will be more precise.

2) Although semantic tags address the syntactical ambiguity of tags, the semantic ambiguity might remain unaddressed due to the different perception of users about concepts. Often tags represent heterogeneous perceptions of individuals rather than a collective and commonly agreed opinion of a group of users who are knowledgeable about those resources. For instance, the perception of a user who is a student of *University of Southern Indiana* is different from a user who studies in *Università della Svizzera italiana* about tag <university:USI> that is assigned to an object. Therefore, the opinion of these two individuals about the correctness of assigning <university:USI> to a resource about *Università della Svizzera italiana* will be opposite. This example shows the advantage of using opinion of numerous related users over opinion of individuals on tag assignments. Furthermore, if the system provides collaborative tagging services and improves the initial ontology based on users votes on the assigned tags, there might exist a strong agreed upon semantic relation between *"Ticino"* and *"Southern Switzerland"* concepts in the ontology behind those tags, the results of a semantic query on <university:USI> which includes *"Ticino"* or *"Southern Switzerland"* will provide the same precise result related to the *"Università della Svizzera italiana"*.

3) While knowledge of people is evolving, their perception of different objects and concepts also evolves over time. Therefore, if bookmarks also represent perception of the taggers on different objects, they should also evolve and update dynamically according to the latest perception of the taggers. Categorizations that are based on fixed tag assignments can not improve recommendations of the system according to the latest users opinions. For instance if the name of a concept that was known as *"ARPANET"* changes to *"Internet"*, objects that are tagged with the former name should also be updated or still be recommended to the users in a community that are using the new name.

Our approach addresses the above mentioned problems in order to enhance the quality of collaborative semantic annotations and facilitate their growth problems.

1.2 STATE OF THE ART

In this Section we discuss the state of the art tools and methodologies related to our approach.

1.2.1 Collaborative Ontology Development

The quality of the meaning of assigned tags to objects in a social semantic bookmarking system is dependent on the quality of the ontology behind its tags. There are some tools for collaboratively defining ontologies, such as *Protégé*[1] which has a semi-automatic tool for ontology merging and alignment called *PROMPT* [14]. *SWOOP* [6], *Hozo* [8], *DILIGENT* [24], *ONKI* [26] and *KAON* [2] are also tools for collaborative ontology development by using change logs and version controlling methods. Focus of our research is not on defining ontologies from scratch or improving them by using such tools. We use ontologies that are defined by such tools or only the measured semantic relatedness between concepts by Information Retrieval (IR) methods in order to feed the system with some background knowledge. However, collaboration of the related users in the formed communities around semantic tags can improve the ontology behind them. In the initial steps, the background knowledge that is retrieved from other resources, enables us to start giving meaning to tags. Then we will define new relations or refine existing ones according to opinion of the related users and statistical measures. This ontology improvement process for merging new and refined relations with the initial background knowledge can be done by help of one of the mentioned tools.

Online platforms enable us to develop ontologies collectively and refine them according to the opinion of the related users. Receiving feedback from the users on defined semantic relations on online social media and updating a single agreed ontology can remove the need of having a version control system for different versions of static ontologies.

1.2.2 Social Semantic Tagging Systems

Social semantic bookmarking allows for the annotation of resources with tags extended by semantic definitions and descriptions that also evolve collaboratively within the same system [3]. Semantic tags have great potential for supporting information integration and for enhancing the intelligence of the Web. In order to make tags computer-interpretable, we have to make them unique, standardized, and their names have to be agreed upon [27]. To achieve this goal, some approaches like *MOAT* [17] rely on Linked Data principles, using URIs from existing resources to define the meaning of their tags. There exist several reference resources which social semantic tagging systems use to extract taxonomy and meaning of the words like *WordNet* [13], *Yago* [23] and *Wikitaxonomy* [19]. Moreover, those references need to cover different topics. *DBpedia*[2] is a project that extracts structured information from *Wikipedia* in the form of RDF triples. As *Wikipedia* contains articles about many domains of concepts, *DBpedia* can also be seen as a huge ontology that assigns URIs to a large number of concepts. Some social semantic tagging systems like *Faviki*[3] are using *DBpedia* as their knowledge base to give meaning to their tags. There exist a few social semantic tagging systems like *Bibsonomy* [5], *GroupMe*[1], *Twine*[4], *ZigTag*[5], *ginzr*[6], *Annotea*[7][7], *Fuzzzy*[8] [9] and *SOBOLEO* [30] with different features and purposes. The common feature between them is that all of them allow their users to extend tags used for annotating with additional semantics but only two of them have the community formation feature, (i.e., *Fuzzzy* and *SOBOLEO*) [3]. However, the formed communities are static and built around fixed topics with the categorizing approach of classic folksonomy systems.

[1]http://protege.stanford.edu/

[2]http://dbpedia.org/
[3]http://www.faviki.com
[4]http://twine.com
[5]http://zigtag.com
[6]http://code.google.com/p/gnizr/
[7]http://www.annotea.org/
[8]http://www.fuzzzy.com

1.2.3 Community Formation and Detection Methods

There exist a variety of community definitions and even larger community formation and detection methodologies in the literature. They differ in their purposes and characteristics of the main transactions and in consequence structure of the social network under study. The purpose of our approach is to form communities around the tagged objects dynamically in order to get opinion of the most related users on them. Papadopoulos et al.[16] categorize community detection and graph clustering methods in five main categories of *Subgraph Discovery*, *Model-based*, *Vertex clustering*, *Quality Optimization* and *Divisive* methods according to the adopted community definition and underlying methodological principles. The graph based community detection methods attempt to identify groups of vertices that are more densely connected to each other than to the rest of the network [16]. Every transaction in social systems typically involves different entities. In our approach, we consider taggers, tagged objects and tags as the three main entities of the social semantic tagging system under study and represent the transactions among them with a tripartite graph (i.e, similar to Mika's approach [12]). The social network topologies also affect messages spreading patterns and in consequence communities formations. For instance the networks that are based on person to person connections (e.g., friendship connections on *Facebook*[9]) give their recommendations based on the position of the user in their network with respect to the other users that is by using one of the centrality measures of vertices like *Degree centrality*, *Closeness centrality*, *Betweenness centrality*, *Eigenvector centrality*, *Katz centrality* or *Alpha centrality* or considering discrete roles of vertices like *hubs* and *outliers* [29] or other roles like *loners*, *big fish*, *bridges* and *ambassadors* [22]. Another topology of social networks is based on common interest. Interest-based networks connect people based on their common interest. We hypothesize that communities formation around specific topics can be more practical in the interest-based networks in which the topics of interest are semantically related. Although the main recommendations on *Twitter*[10] are also based on followers (i.e., person to person) connections, it is also one of the successful platforms for communities formation around specific topics through assigning tags to people, contents and events. Even though, there is no semantic connection between *hash tags* of *Twitter*, there are several approaches that try to discover the semantic meaning between tags mostly by considering concurrence of *hash tags* in different *tweets* (e.g., Posch's approach [20]) and some by mapping hashtags to the larger documents that enable them to apply Information Retrieval (IR) methods on them for measuring similarities between them (e.g., Celik's approach [4] that maps short tweets through their hashtags to larger news documents). Semantic approaches tend to merge interest networks with semantic networks in order to have higher quality of information retrieval for detecting or forming communities. Tsatsou et al.[25] algorithm integrates the results of tag community detection in personalized recommendation systems and compares against conventional nearest neighbor tag expansion schemes. More specifically, tags belonging to the same community are used as a terminological description of semantic concepts within a domain ontology.

[9]https://www.facebook.com/

[10]https://twitter.com/

The notion of "dynamic communities" is more used in studies that are analyzing communities with entities and their relations in different time stamps. But in each of the time windows they cluster the network and form fixed communities with predefined characteristics of the clusters. Dynamics of communities are mostly used for studying transformation and evolution of the network under study (e.g., growth, contraction, merge, split, birth and death of communities in the network [15, 11, 21]). The notion of "dynamic community" in our approach refers to the formation of communities relative to the semantic tags assigned to an object and their adaptation according to the latest identities of the objects, tags and the taggers.

2. PROPOSED APPROACH

In order to improve representation of online resources by assigning meaningful tags closer to the perception of the majority of the related users in social semantic tagging systems, our approach suggests the following four steps: 1) define a new or use an already existing initial ontology that has broad enough collection of concepts in order to give meaning to the tags; 2) recommend related and already defined semantics to taggers based on the context and other properties of the resources; 3) identify the taggers (i.e, based on their contribution and reputation around tags) and the resources (based on the latest meaning assigned to them by tags); 4) form communities of related taggers dynamically around the tagged objects according to their latest identity representation. The first two steps are common in most of the mentioned social semantic tagging systems (in Section 1.2.2). Although the first two steps are also included in our work, the main research contribution is on the third and fourth steps where results also have effect on first two steps.

With respect to the first step, to give meaning to the tags, since *DBpedia*[11] knowledge-base is broad and precise enough, ontologies that are provided based on *DBpedia* usually have an acceptable quality. If we use *DBpedia* as the source of our initial ontology, we can use its URIs for mapping tags to the concepts that exist on *Wikipedia*. Some social semantic tagging systems generate their own ontology from scratch. Most of the others use the already existing ontologies (e.g., *DBpedia* or the other ones that we mentioned in Section 1.2.2). In our approach we use the discovered semantic relations of *DBpedia* as the main background knowledge of the system.

With respect to the second step, existence of a recommender can facilitate assignment of semantics to the tags for the taggers. Quality of the recommendation of semantics to the tags in social semantic tagging systems is dependent on the quality of the available knowledge in the system (e.g., an ontology) and the methodology that the system is using to measure semantic similarities between concepts (i.e., semantic tags) in the knowledge-base and keywords that can be extracted from the object that is going to be tagged or tags that are already suggested by taggers for it. Not all of the existing social semantic tagging systems recommend tags to their taggers. Improving quality of the semantic relations among tags, objects and taggers in the following steps will also affect the quality of the recommendations.

With respect to the third step, as we mentioned before, the represented knowledge in tagging systems identifies both

[11]http://dbpedia.org/

taggers and objects. Because our perception in each specific area of knowledge is evolving over time, the goal of our approach is also to evolve the represented knowledge in semantic tagging systems dynamically according to the latest perception of the related taggers.

With respect to the fourth step, we build a model which enables us to record and update transactions in the system frequently and in a short time-window. The main challenges of our approach are: I) the model we use for the main transactions in the system must support frequent retrieval and update according to our goal for community formation; II) the method we use for measuring semantic relatedness between semantic tags must support refinement based on the latest transactions (e.g., opinion of the users). We have chosen the following strategies for each of the mentioned challenges in our approach: I) As we mentioned before, we represent the network model of our system with its main entities and transactions among them with a tripartite graph and its hyperedges. We model the main entities of social tagging systems with three disjoint sets of A (representing Actors, or taggers in the system), T (representing Tags or semantic tags in semantic tagging systems) and O (representing the tagged Objects or resources) that are vertices of this hypergraph. We consider each of these entities as a vertex of the graph and connect them through edges if there exist a transaction among them. Edges of this graph have weight based on the number of times that there were interaction between them. We represent three facets of this hypergraph including its entities and interactions between them with three matrices. Matrices AT, AO and TO represent all transactions among taggers and tags, taggers and objects and tags and objects respectively. Values of the cells in those matrices represent the frequency of their occurrences together. Recording these three main transactions in these separate matrices (i.e., sparse matrices) allow us to retrieve and update them with a high performance according to the goal of similarity measures and community formation in the fourth step. For the large matrices we apply *Latent Semantic Analysis (LSA)* [10] in order to reduce dimension of the tags to a smaller set and improving the performance of measuring similarity between the semantic tags. II) To measure semantic relatedness, first we import the already measured semantic relatedness between concepts in an already existing knowledge base (i.e.,*Wikipedia Link-based Measures* [28] between concepts of *DBpedia*) and matrices of the latest interactions happened in the social semantic tagging system. Then we measure semantic similarity between tags, by considering the imported matrices and occurrences of tags in TA and TO matrices. Therefore, formed communities will be in accordance to the latest transactions in the system. The main contribution is that when a new transaction happens in the system. If in addition to updating the corresponding cells in the matrices we also update the semantically related cells according to our last measures and the transactions in the system, we might be able to improve both quality and quantity of transactions of the system. For example, when a new semantic tag i assigned to an object j by a tagger k, in addition to increasing value of the cell with index [k, i] in the AT matrix by one (i.e., which represents frequency of using tag i by tagger k for different objects), or the cell with index [i, j] in the TO matrix (i.e., which represents frequency of using tag i for object j by different taggers), we also increase the value of the cell with index [k, $i+1$] in the AT and the cell with index [$i+1$, j] in the TO matrix with the value m (i.e, which will be a normalized value between zero and one) if a tag with index i and a tag with index $i+1$ have semantic relatedness according to the last measurements with the value m. We repeat this action for all the tags which are in column j of the matrix TO and in row k of the AT matrix if their measured similarity is above some threshold value. Applying this approach updates also semantically related tags to the used tag in addition to the used tag itself and enables us to form more number of related users around the shared objects. We can modify the value of the threshold according to the number of tags that are semantically related to each tag (i.e, the more the related tags are, the less the threshold value is for that tag). The number of tags that are semantically related to each tag is also representing centrality of a tag in a semantic network or with another interpretation, how general or specific is the semantic of a tag. By defining a threshold for updating the value of the related cells in the matrix, we prohibit saturation of the semantic relatedness values for the very general semantic tags. Therefore, in an abstract level we can consider each of the tagged objects and taggers as a vector in a vector space with n dimensions (i.e., n corresponds to the number of semantic tags in the knowledge-base of the system) according to the semantic tags that are assigned to each object or used by each tagger. Then by applying the mentioned procedure in our approach, we expect to position each of the tagged objects closer to the taggers who are semantically related to the objects each time we update the relatedness measures according to the last opinion of the users. That is the reason we call our communities dynamic.

Since instead of pre-categorization of users, tags and objects in the predefined sets, we form communities of semantically related taggers around the tagged objects based on the latest identity of the taggers and the tagged objects, we consider our approach a dynamic community formation method.

3. METHODOLOGY

In order to examine the main hypothesis of our approach, currently we are simulating it on a large collection of a *Del.icio.us*[12] dataset including 6,192,002 tags and 922,651 taggers and 46,364,200 tagged objects with 410,700,661 transactions among them. We are trying to optimize the main performance and quality metrics that we defined for evaluating our approach. Since the mentioned collection doesn't have semantic relations between its tags, we divided the collection by fixed-step random sampling to five separate sets: four sets for incremental learning of semantic relations between tags and one for testing. We randomized the sets to avoid effect of a biased behavior according to the chronological order of the dataset. Then we measure the semantic similarity between tags by applying it on training sets. In the next step we set values of testing set according to the measured similarity between tags and measure the cosine similarity between taggers in the testing set once with and once without considering the semantic relations between tags. Finally, we can compare the number of common objects between the most similar taggers with and without considering the semantic relations between tags.

[12]https://delicious.com/

The main metrics for evaluating our approach will be the degree of the precision and recall of the similarity measures and recommendations and also the performance of the running procedures.

4. RESULTS

We have so far formulated our methodology and identified an appropriate dataset for our experiments. According to the results we obtained on a small set of targeted taggers, our experiment shows improvement on discovering related taggers in our formed communities who do not share any tag with each other but are interested in many common objects and could not be discovered by the classical approaches.

5. CONCLUSIONS AND FUTURE WORK

In this paper we have discussed different aspects of our research project. We started with an introduction of one of the most popular internet activities which is bookmarking and how this activity of the users classifies the huge volume of online resources. Then we described problems in classical tagging systems that led to the development of semantic tagging systems. We described the existing problems in such systems by giving some examples. Then we presented the state of the art of tools for collaborative ontology development, social semantic tagging systems and methodologies for community formation and detection. Finally we described our proposed approach to form dynamic communities of the related taggers around the tagged objects in order to have a reliable and agreed upon representation of the online resources according to the contribution of the taggers around semantic tags. Then, we described our methodology for evaluating our approach and the current status and results of the project. If successful, we expect to have representations of the online resources that track the latest opinion of the most related users. Identities that are assigned to the objects and taggers by their semantic tags could be more representative when they are closer to the common perception of the majority of the people related to the corresponding area of knowledge. In the future, we can also try to discover the social graph of expertise by analyzing users' reputation around semantic tags.

With the exponential growth of resources on the Web, the problem of classifying and finding needed information has become increasingly difficult. We have reviewed this problem from the point of view of resources on the Web that are tagged by taggers. The quality of their tagging activity around specific topics may be used as an indication to measure their level of their interest or expertise.

Current approaches are static and record the relationship among resources, tags, and users once and for all. But as people's interest and expertise grows, community detection must also be able to evolve to match this growth. We propose to investigate community formation based on the evolution of tagging activity.

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