Simplified detection and labeling of overlapping communities of interest in question-and-answer sites

Zide Meng
INRIA Sophia Antipolis Méditerranée
France
zide.meng@inria.fr

Fabien Gandon
INRIA Sophia Antipolis Méditerranée
France
fabien.gandon@inria.fr

Catherine Faron Zucker
University Nice Sophia Antipolis, CNRS, I3S
France
faron@unice.fr

***Abstract*—In many social networks, people interact based on their interests. Community detection algorithms are then useful to reveal the sub-structures of a network and in particular interest groups. Identifying these users' communities and the interests that bind them can help us assist their life-cycle. Certain kinds of online communities such as question-and-answer (Q&A) sites or forums, have no explicit social network structure. Therefore, many traditional community detection techniques do not apply directly. In this paper, we propose TTD (Topic Trees Distributions) an efficient approach for extracting topic from Q&A sites in order to detect communities of interest. Then we compare three detection methods we applied on a dataset extracted from the popular Q&A site StackOverflow. Our method based on topic modeling and user membership assignment is shown to be much simpler and faster while preserving the quality of the detection.**

I. Introduction

Question-and-answer sites (Q&A sites) initially aimed at enabling users to ask questions to a community of experts. Since these user-generated contents can be viewed and searched again, people with the same or similar questions can find answers by browsing or searching the questions that were already answered. On one hand, Q&A sites have become huge repositories of question-answer content which support highly valuable and highly reusable knowledge [1]. On the other hand, Q&A sites also contain a large number of users who keep contributing questions and answers. And most of them are more likely to ask questions on topics they are interested in and answer questions in topics they are experts of.

Therefore, we believe that there are two main resources in Q&A sites: the users' network and the Q&A content. From a user's perspective, detecting communities of interests is useful to reveal the sub-structures of the user network and identify relevant peers. From the perspective of content, extracting topics is required to uncover the key subjects from massive content. So we are interested in the following research questions: *Can we detect communities of interests in Q&A sites? Can we identify the common topics that bind them?* Detecting communities of interests can contribute to the question routing problem [2][3], which is very important in Q&A sites optimization problems. It can also contribute to the community management, for instance by allowing to track the interest evolution or community evolution in Q&A sites.

Many community detection algorithms have been developed to discover sub-structures in social networks. Q&A sites support social networking, however, unlike networks such as Facebook, there are no explicit relationship-based links between their users. In fact, Q&A sites capture the connection of users by question-answer links or co-answer links. The users are not mainly concerned with nor aware of the links existing between them. The social network is said to be implicit. As a result, compared with other classical social networks, Q&A networks contain more *star-shape* structures (many users linked to a central user) than *triangle-shape* structures (users linked to each other). Moreover, people have multiple interests i.e. they belong to several communities of interests. It is therefore important to be able to detect their overlapping communities of interests.

We first tried to adapt a document clustering algorithm to the user clustering problem, similarly to [4]: we applied the classic LDA [5] algorithm to assign each user into several topic clusters, by replacing in this algorithm the documents by the users, and the document words by the tags acquired by users. The results were encouraging, however, the complexity of the probabilistic model was prohibitive. When analyzing the LDA model, we found that it largely exploits tags' co-occurrence. This inspired us to design a much simpler and faster algorithm to detect topics. Then, based on the detected topics, we were able to identify the users' interests. So the main contributions of this paper are, (1) a topic detection method to extract topics based on question tags, and (2) a user interest detection method to discover overlapping communities of interests.

The rest of the paper is organized as follows. Firstly, we survey the state of the art of community detection approaches, and point out the differences among these works. Secondly, we introduce an empirical method to detect topics. Then we assign each user to these detected topics based on their interaction behaviors. Thirdly, we report the results of several experiments. They show that our approach is much faster and simpler, compared with other classic approaches, e.g. LDA [5], SLPA [6], and a Hierarchical clustering algorithm, while preserving the quality of the detection. Finally, we discuss about those methods and conclude on our contribution.

II. Related Work

We distinguish between three kinds of approaches for community detection, depending on their characteristics: Graph-based methods are based on network structure; Clustering methods are based on the similarity of user profiles; LDA-based methods use probabilistic graphical model.

A. Graph-based methods

A first and direct solution is to extract an implicit network structure (such as question-answer network, co-answer network, etc.) from interaction traces to come down to a traditional community detection problem on social networks. Since intuitively, users are grouped by interests, and most of their interactions are based on shared interests, it is reasonable to induce a network structure from these interactions and then run community detection algorithms on the network. Many classical algorithms have been developed such as [6][7]. There are many constraints when adopting these methods. First, they do not take into account node attributes nor link attributes. Take co-answer network as an example, where nodes represent users and links represent users answering the same questions. In case two users are connected, these methods can only indicate that they have answered the same questions many times. They cannot provide the information whether they have answered questions on the same topic or on different topics. Second, some of the works adopting this approach cannot detect overlapping communities, while other works such as [6] address this problem.

B. Clustering methods

Community detection can also be envisioned as a clustering problem. By computing similarities between user profiles, one can detect groups according to clustering results. The choice of the similarity metrics is quite important and largely influences clustering results. To find similar interests, we first have to define the distance between user's interests and the definition of this distance has a strong influence on the clustering results. For instance, we can consider a bag of tags with their weights to represent an interest, then compute the weighted tag distance to define the interest distance between two users. Clustering methods, such as [8][9], group users according to their features. They do not take the network structure into consideration. Moreover, some clustering algorithms normally output hard-partition communities, one user can only be assigned to one interest group. However, in the scenario we are interested in, a user often has more than one interest and should be assigned to more than one group simultaneously. This is a constraint for those hard-partition algorithms. [10] use spectral clustering to detect topics from the graph of tag co-occurrence. Compared to it, our approach is more efficient since we only run spectral clustering on a co-occurrence graph of selected tags (only 10% of all the tags). Besides, [10] does not give any details on how to compute the topic tag distribution and user topic distribution, while we do.

C. LDA-based models

A third approach consists in using a probabilistic graphical model for both the user profiles and the network structure to solve community detection problem. For example, [11] transform links to binary node attributes, then use a LDA-based model to detect communities. [12] use a LDA-based method on social tagging systems where users label resources with tags, but they do not consider the problem of overlapping community detection. [13] use an extended LDA-based model to analyze academic social networks in order to find expert authors, papers and conferences. A problem of these LDA-based models is that they normally assume soft-membership [14] which means that a user cannot have high probabilities to belong to several communities simultaneously. That is to say that the more communities a user belongs to, the less it belongs to each community (simply because probabilities have to sum to one). Moreover, [15] and [16] also use statistic model to detect overlapping communities. The difference is that LDA-based models normally integrate topic detection which can be used to interpret detected communities while the two above cited methods only detect overlapping communities without any topic information on each detected communities.

D. Short Summary

Table I summarizes the main features of the three approaches. Graph-based approaches normally use link information while ignoring node attributes. Some of them cannot detect overlapping communities or provide membership ratios which are weights denoting to what extent a user belongs to a community. Most of these methods cannot identify the topic in each detected community. Clustering approaches use node attributes to group similar users. Some of their results are hard-partition communities, with no overlapping and no membership information. LDA-based models overcome the shortcomings of graph-based and clustering approaches, using both node attributes and link information. Besides, LDA-based models normally combine community detection with topic detection, which could be used to interpret detected communities. Our proposed method is similar to LDA-based methods, in that it also enables to detect overlapping communities and identify the topics at the same time. It differs from LDA-based methods in that it enables to consider a user having high probabilities to belong to several communities simultaneously while these methods normally assume soft-membership [14]. In addition, our proposed method is much simpler and faster than LDA-based methods while preserving the quality of the detection.

TABLE I: Comparison of the main approaches and our method

	uses nodes	uses links	overlap	membership	topic
Graph-based	no	yes	few	few	no
Clustering methods	yes	no	few	few	no
LDA-based	yes	yes	yes	yes	yes
Our-method	yes	yes	yes	yes	yes

III. TTD: Topic Trees Distributions model

A. Problem Definition

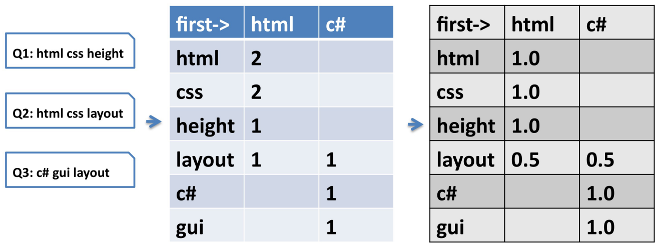
In StackOverflow[1], a user submits a question, then assigns between 1 and 5 tags to indicate the topic of the question. Other users who are interested in the question may provide answers to the question. As the tags attached to the question can reflect its topic, users answering the question can be considered as interested by this topic. Let $U = \{u_1, u_2 ... u_n\}$ be the set of users, $Q = \{q_1, q_2 ... q_m\}$ the set of questions and $T = \{t_1, t_2 ... t_v\}$ the set of tags. We aim at (1) extracting topics distribution $Topic = \{topic_1, topic_2 ... topic_k\}$ from T, and for each $topic_k$, defining $topic_k = \{p_{k1}, p_{k2} ... p_{kv}\}$ where p_{ki} denotes the probability of tag t_i to be related to $topic_k$; and then (2) detecting user's interests. For a user $u_i \in U$, we define

[1]http://www.stackoverflow.com/

$I_i = \{I_{i1}, I_{i2}...I_{ik}\}$ where I_{ik} denotes the probability of u_i to be interested in $topic_k$.

B. First-Tag Enrichment

When sorting the tags of a question by their global frequency, we found that normally the first tag of a question is much more general and indicates the domain of the question. For example, a question tagged with {*c#*, *iostream*, *fstream*} is related to *c#*; A question tagged with {*html*, *css*, *height*} is related to *html*. However, there are also some questions which have less tags and, in this case, the tags are less popular, like a question tagged with {*ant*} or a question tagged with {*qt*, *boost*}. For these questions, the main domain is implicit. Our experiment dataset shows that nearly 12% questions only have one tag, and nearly 25% questions only have two tags. We propose an approach to enrich a question with a first tag when needed. It has two steps, the first one consists in computing the first-tag distribution. For example, as shown in Figure 1,



first->	html	c#
html	2	
css	2	
height	1	
layout	1	1
c#		1
gui		1

first->	html	c#
html	1.0	
css	1.0	
height	1.0	
layout	0.5	0.5
c#		1.0
gui		1.0

Fig. 1: Example of computing a first-tag distribution

let us consider the three tag lists, {*html*, *css*, *height*}, {*html*, *css*, *layout*}, and {*c#*, *gui*, *layout*}, respectively associated to questions Q1, Q2, Q3 . The first-tag frequency map for *html* is {*html*:2}, the first-tag frequency map for *css* is {*html*:2}, and the first-tag frequency map for *layout* is {*html*:1,*c#*:1}. Given a tag, the probability of its first-tag is computed by equation 1, which is the MLE (most likelihood estimation) of the probability $p(first\_tag|tag)$, where $I(tag)$ denotes the occurrence of tag and $I(first\_tag, tag)$ denotes the co-occurrence of $first\_tag$ and tag.

$$p(first\_tag|tag) = \frac{p(first\_tag, tag)}{p(tag)} = \frac{I(first\_tag, tag)}{I(tag)} \quad (1)$$

We compute the probabilities just by normalizing the first-tag frequency map. In the example, the first-tag frequency map for *css* becomes {*html*:1.0} and the first-tag frequency map for *layout* becomes {*html*:0.5,*c#*:0.5}. In order to lower the probabilities of low frequency tags as first-tag, we use the squashing function 2:

$$\begin{aligned} p(first\_tag|tag) &= \frac{I(first\_tag, tag)}{I(tag)} * \sigma(I(first\_tag)) \\ &= \frac{record\_freq}{sum(record\_freq)} * \frac{1}{(1+e^{-k*freq})} \end{aligned} \quad (2)$$

where, $record\_freq$ denotes the co-occurrence of *first-tag* and *tag*, $sum(record\_freq)$ denotes the sum of these recorded frequencies, $freq$ denotes the global occurrence of the first-tag, $\sigma(x)$ is sigmoid function, which is used as a squashing function for numerical stability. The value of sigmoid function is between 0 and 1. However, the shape of this function is largely determined by parameter k. Considering the maximum value of tag frequency (tag c#:$31,801$) in our dataset, we chose k as 0.001 (dotted line), which will lower the probabilities of low frequency tags as first-tag while maintaining the probabilities of high frequency tags as first-tag. Figure 2 recalls the shape of the sigmoid function for different values of k.

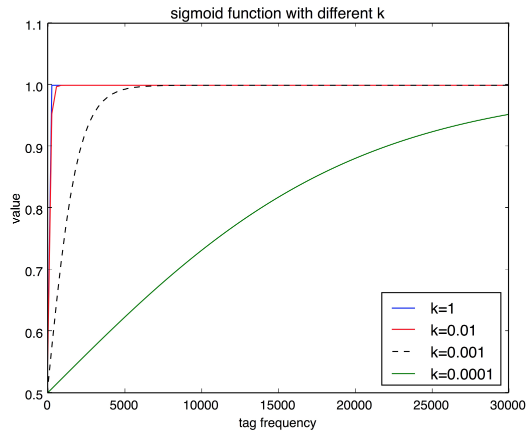


Fig. 2: Shape of function $\frac{1}{(1+e^{-k*z})}$ for different values of k

For example, if the first-tag frequency map for *css* is {*html*:10, *jquery*:2}, then, when normalizing first-tag *html*, $record\_freq = 10$, $sum(record\_freq) = 12$, $p(html) = 5,552$. As a result, $p(html|css) = 0.8301$. Similarly, for each tag, we provide a list of enriching first-tags with estimated probabilities.

The second step of our approach consists in choosing a first-tag to enrich each question. Given a question's tag list, we fetch the top 5 first-tags (with the highest probabilities). Then we accumulate the corresponding probabilities with a discount taking into account the position of the tag in the tag list associated to the question, as shown in equation 3.

$$p_j = p_{1,j} + p_{2,j} * dis + ... + p_{k,j} * dis^{k-1} for j \in [1, V], k \in [1, K] \quad (3)$$

where p_j denotes the probability of the first-tag for a given question, $p_{k,j}$ denotes the probability for tag k to have the tag j as its first-tag, V denotes the number of all the first-tags, K denotes the number of tags in the given question and dis denotes the discount due to the position.

Then we consider the first-tag with the highest probability as the enriching first-tag. If this first-tag already exists in the original tag list, we simply skip the insertion, or else we insert it at the first position of the question's tag list. We processed $242,552$ tag lists from the StackOverFlow Q&A site, and our method enriched $33,622$ of them (13.5%). Table II presents the results of the enrichment of 8 tag lists (enriched tags are in bold).

C. Topic Extraction

From the observation of our dataset, we confirmed the natural intuition that high frequency tags are more generic and low frequency tags are more specific, and most of the low frequency tags are related to a more generic tag. Similar observation was also found in [17]. Besides, [18] shows that tag frequency in Q&A sites also satisfies power law

TABLE II: Original and enriched tag lists

ant	**java**, ant
qt, boost	**c++**, qt, boost
django, hosting	**python**, django, hosting
xslt, dynamic, xsl	**xml**, xslt, dynamic, xsl
sql-server-2005, sorting	**sql**, sql-server-2005, sorting
tomcat, grails, connection	**java**, tomcat, grails, connection
cocoa, osx, mac, plugins	**objective-c**, cocoa, osx, mac, plugins
spring, j2ee, module, count	**java**, spring, j2ee, module, count

distribution [19]. For example, for a question tagged with $\{c{+}{+}, iostream, fstream\}$ (with tags sorted according to their frequencies), we could find that it was related to *c++* and to the *iostream* topic of *c++*, and more specifically, that it focused on *fstream*. This inspired us to build a tag tree to represent it and compute the probability for a tag to be related to a topic. Figure 3 illustrates the process of building a tag tree. Figure 4 illustrates an example of *html*'s tree. Our topic extraction

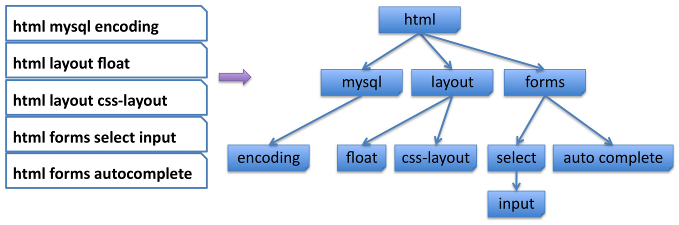


Fig. 3: Example of a tag tree

method is described in Algorithm 1. In the *build trees* process

```
   input  : enriched tag list of questions,topic number K
   output: topic-tag distribution
1  /*build trees process, shown in Fig 3*/
2  trees = null /* initialize */
3  foreach  question's taglist do
4      trees.insert(taglist)
5  end
6  /*build affinity matrix for root_tags*/
7  root_tags = trees.get_root_tags()
8  affinities_matrix = build_affinity(root_tags)
9  /*run spectral-clustering on affinity matrix*/
10 groups = spectral_clustering(affinities_matrix,K)
11 /*combine tree according to groups*/
12 new_trees = combine_tree(trees,groups)
13 /*compute topic-tag distribution*/
14 topic_distributions = compute_distribution(new_trees)
```
Algorithm 1: Topic extraction

(lines 1-5), we build a tag tree according to the position of tags in a question, and record the occurrence of each node. For example, let us consider again the tag lists of question Q1, Q2, Q3 in Figure 1. Based on them, we construct two trees. The root of the first tree is *html*, the occurrence of this node is *2*, it has only one child *css*, which has *2* occurrences, and this node has two children, *layout* and *height*, and each one occurs *1* time. The root of the second tree is *c#* with *1* occurrence. By processing all the tag lists, many trees are generated. We then construct an affinity matrix of the root nodes (lines 6-8). Since we applied first-tag enrichment, the number of root tags is not very large. The similarity of two root nodes is computed according to equation 4,

$$Simi(root\_i, root\_j) = \frac{I(root\_i, root\_j)}{(I(root\_i) + I(root\_j))} \quad (4)$$

where $I(root\_i, root\_j)$ denotes the co-occurrence of the two root tags, and $I(root\_i)$ and $I(root\_j)$ denote the occurrence of tag $root\_i$ and tag $root\_j$ respectively. Then we perform a spectral clustering [20] on the affinity matrix to group these root nodes (line 9-10). Each group form what we will call a topic. As spectral clustering requires to select the desired number of topics, we choose the same number *30* as [10], which has proved to be a reasonable setting for the Stackoverflow dataset. We then combine trees if their root nodes belong to the same topic (lines 11-12). This process leads to a forest where each tree represents a topic. Then, in the *compute topic-tag distribution* process (lines 13-14), for each topic tree, we compute $p(tag|topic)$ by using MLE (the most likelihood estimation), according to equation 5:

$$p(tag|topic) = \frac{p(tag, topic)}{p(topic)} = \frac{I(tag) + 1}{I(sum(tag) + N)} \quad (5)$$

where $I(tag)$ denotes the number of occurrences of tag in the topic tree, and $I(sum(tag))$ denotes the total number of occurrences of all tag occurrences in the topic tree. Compared with

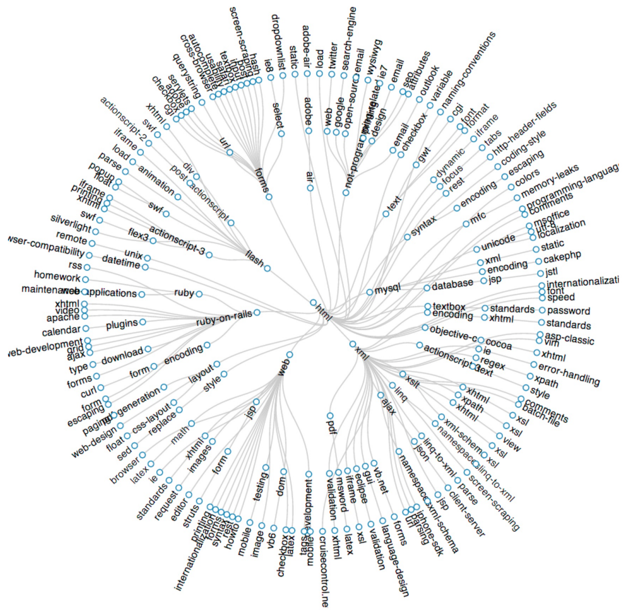


Fig. 4: *html*'s tag tree

LDA-based model, our model could have zero-probabilities problem, which means that there exists some less popular or new tags that are related to certain topics with 0 probability due to no evidence of co-occurrence. For example, if tag *zombie-process* never occurs in a *html*-related tag tree, then the probability of tag *zombie-process* to be related to *html-related* topics is 0, which could lead to some problems when dealing with young datasets. It is quite easy to fix it just by using Laplace smoothing, as shown in equation 5. Table III shows the top tags and their probabilities detected by out method.

We used the spectral clustering implementation of scikit-learn toolkit[2]. We only run it on the root nodes, which have quite a small size (around 1175 nodes with the tag enrichment process), which means we only need to build affinity matrix on these root nodes and the overall cost is acceptable.

D. User Interest Detection

In StackOverflow, users answering a question can be considered as interested in the tags of the question. As a result, a starting point for user interest detection is to model the initial situation as follows: a user answering a question acquires the tags attached to this question and gradually, each user acquires a list of tags. So we represent a user by a tag list: $U = \{U_i | i = 1, ..., n\}, U_i = \{tag_i | i = m, n, ..., k\}$, and our goal is, for each user U_i, to find $I_i = \{I_{i1}, I_{i2} ... I_{ik}\}$ where I_{ik} denotes the probability of user U_i to be related to $topic_k$. As we already have a topic-tag distribution we simply compute user-topic distribution according to equation 6 where $P_{t,k}$ denotes the probability of tag t to be related to topic k. We then normalize the probabilities between 0 and 1 by dividing the global max value. We use the log function for numerical stability. Here we do not apply normalization at the level of the user, because like [14], we believe that each user could have a high interest in two or more topics simultaneously, while most of the probabilistic graphical models including LDA and PLSA require the sum of all the probabilities is 1, which means that a user cannot have high probabilities to many topics simultaneously. Our method does not have this limitation. Then we identify users' communities of interests based on the user-topic distribution: a user having a high probability for a topic should be a member of the community of the topic.

$$I_{i,k} = log \left\{ \sum_{t=1}^{v} P_{t,k} + 1 \right\} \tag{6}$$

IV. Experiments and Evaluation on StackOverflow data

We conducted experiments on the dataset of the activity on the popular Q&A site StackOverflow between 2008 and 2009, which is available [3], to evaluate the performance of our approach compared to three other community detection algorithms. The total number of users is 103K. Among them, 47K users submitted at least one question, and 54K users answered at least one question. The total number of tags attached to questions is 24K, and 20% of them are used more than 10 times. The frequency of tags follows a power law distribution. The total number of posts is 1.1M; among them there are 242K questioners and 870K answers.

A. Performance of Topic Extraction

We use the Perplexity [5] metric to measure the topic extraction performance. It is a common metric in the topic modeling area, measuring how well the words in test documents are represented by the word distribution of extracted topics. The intuition is that a better model will tend to assign higher probabilities to the test dataset, corresponding to a lower perplexity value. We split the dataset (question tag lists), 80% as training set, 20% as testing set. We run LDA and our method on the training set to get the topic distribution. Then for a test set of M questions' tag lists (N_d denotes the number of tags in d^{th} question) the Perplexity score is computed as shown in equation 7:

$$Perplexity(D_{test}) = exp \left\{ - \frac{\sum_{d=1}^{M} \log p(tag)}{\sum_{d=1}^{M} N_d} \right\} \tag{7}$$

In our model, $p(tag)$ is computed by $p(topic|question) * p(tag|topic)$. In order to obtain $p(topic|question)$ distribution, we just compute it similarly to user interest detection (see Section III-D), by replacing user tag lists by question tag lists. The only difference is that we normalize the question topic distribution to make sure that the sum of a question's topic distribution is 1. We show and compare the average perplexity score in Figure 5. *empirical* represents our method, *empirical_noEnrich* represents our method without first-tag enrichment. We find that our method could outperform the state-of-the-art topic model LDA. The reason is, compared with traditional document topic modeling use cases, question tag lists in Q&A sites are very short, and LDA performs poorly in this situation. Besides, our first-tag enrichment method can improve the performance when the topic number is not very large. Another point is that, benefiting from a tree structure for topics, we can easily extract sub-topic from a given topic. Besides, our community detection method is based on a topic model, so extracting these sub-topics can help us find sub-communities within a detected community. Table IV shows the top tags of *java*'s sub-topic *html* and of topic *html*. We can find that the differences are noticeable for topics: a user who is interested in topic *html* is not necessarily interested in *java*'s sub-topic *html* and vice versa.

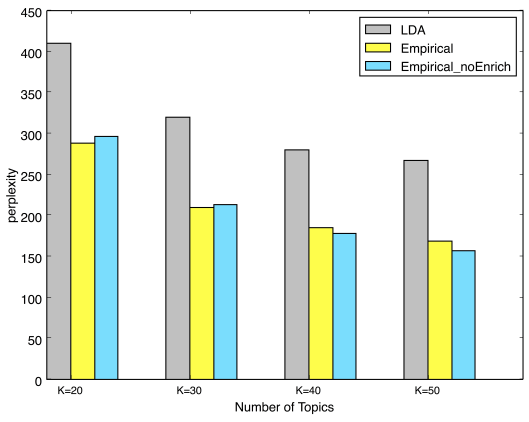


Fig. 5: Topic extraction performance comparison

B. Performance of User Interest Detection

Traditional community detection algorithms are based on the network structure. As there is no explicit network in our dataset and in order to compare our work with other approaches on the same dataset, we extracted a network of interactions between users: a co-answer network inspired by the notion of co-view network introduced in [9]. The idea behind is that if two users answer the same question they

[2]Scikit-learn toolkit: http://scikit-learn.org/stable/modules/clustering.html#spectral-clustering
[3]https://archive.org/details/stackexchange

TABLE III: Top tags and their probabilities for some topics computed by our method

topic4		topic5		topic6	
iphone	0.203	git	0.198	sql	0.177
objective-c	0.112	svn	0.096	mysql	0.122
ios	0.109	version-control	0.045	sql-server	0.074
xcode	0.042	github	0.033	database	0.040
cocoa-touch	0.021	tfs	0.033	oracle	0.030
ipad	0.020	maven	0.029	sql-server-2008	0.029
cocoa	0.018	tortoisesvn	0.018	tsql	0.026
uitableview	0.012	msbuild	0.016	query	0.025
ios5	0.010	jenkins	0.015	sql-server-2005	0.019
core-data	0.009	tfs2010	0.014	database-design	0.011

topic12		topic13		topic14	
html	0.214	javascript	0.264	machine-learning	0.247
css	0.201	jquery	0.114	artificial-intelligence	0.130
xhtml	0.017	html	0.035	neural-network	0.062
web-development	0.016	ajax	0.031	classification	0.046
ie	0.012	css	0.016	data-mining	0.037
css-layout	0.010	firefox	0.013	svm	0.031
div	0.010	dom	0.011	weka	0.025
layout	0.010	php	0.011	libsvm	0.015
firefox	0.009	ie	0.010	nlp	0.024
ie6	0.009	web-development	0.008	bayesian	0.011

TABLE IV: top tags for *java*'s sub-topic *html* and *mysql*, denoted by java_html, and java_mysql respectively, compared with topics *html* and *mysql*

java_html	jsp swing xml parsing jsf jeditorpane pdf applet dom
html	css xhtml web-development table div ie layout css-layout firefox
java_mysql	jdbc hibernate database tomcat prepared-statement spring connection-pooling connection security
mysql	database query mysql-query ruby-on-rails database-design performance stored-procedures innodb optimization

share some of their interests. So, the co-answer network, to some extent, can reflect the common interests between users. We filtered the co-answer links with a rule stating that a link is kept if two users answer the same questions more than 10 times (we varied this parameter by 15, 20, 25, the results are similar, so here we report results with 10). Based on the noise-less dataset obtained, we implemented three well known community detection methods in order to compare our approach with them. In order to evaluate the results of overlapping community detection, for each user, a method should output $1 \sim 3$ community labels with corresponding probabilities to indicate to what extent the user is interested in the community. Then we define three levels of interests: *High*, *Medium*, *Low* according to the probabilities. In addition, we set the community number to 30 for all these methods empirically.

- SLPA [6]: An overlapping community detection method inspired by a classical Label propagation algorithm (LPA). SLPA algorithm can evaluate to which extent a user belongs to a community by the received propagated label (a 'Post-process' in SLPA algorithm). So, it can output more than one community label according to these frequencies.
- LDA: Similar to [18], we run LDA to build a user-topic-tag model on the given dataset, users are represented by their tag list. As the output contains a user-topic distribution, we just sort the distribution for each user and choose the top 3 topic labels as community label together with their probabilities.
- Clustering: We used the implementation of hierarchical clustering from scikit-learn toolkit[4]. As clustering algorithms are hard-partitioned, it can only generate one group label for each user.
- Empirical: it is our method. We just sort the results of user interest detection (section III-D) and choose the top 3 as community label together with their probabilities.

[4]http://scikit-learn.org/stable/modules/clustering.html#hierarchical-clustering

Our aim was to evaluate the similarity between users within a detected community of interest. We mainly used the *jaccard similarity* and *cosine similarity* of two user's tag lists to evaluate the similarity of two user's interests. We used a modified modularity metric to compute the difference between the average similarity between the users within a community (avg_inner) and the average similarity between the users in a community and some user randomly chosen from the whole dataset (avg_rand). This is captured in Equation 8, where N represents the number of users in a community C, and $Simi$ denotes the similarity function. $Rand\_U$ represents users that are randomly chosen from the whole data set. A higher value of avg_inner denotes that users within a community are very similar. A lower value of avg_rand denotes that users of a community are not very similar to random users. So a higher value of $modularity$ means a larger difference between avg_inner and avg_rand, which is considered as a better partition of communities. As the metric has random variables, we run the experiments 10 times and each time we used different random users. Besides, we created a *center* user in each community by averaging all users' tag lists and frequencies, then we computed the average similarity between each user in a community and this *center* user as avg_center. As introduced before, each method gives $1 \sim 3$ community labels for each user to indicate the level of interest. So we evaluated each level of interest respectively.

$$Modularity(C) = \frac{Avg\_inner(\sum_{i=1}^{N}\sum_{j=1}^{N} Simi(U\_i, U\_j))}{Avg\_rand(\sum_{i=1}^{N}\sum_{j=1}^{50} Simi(U\_i, Rand_U\_j))} \quad (8)$$

Experiment results are shown in Table V. We run each method on the co-answer dataset for 10 times, and listed the average value. We found that our method is better than the three other methods in detecting *High* level communities of interests with both metrics. The reason why our method is not very good on *Low* level interest is that it allows users to belong to more than one community with high probabilities. This puts some irrelevant users in *Low* level communities of interests which decreases the similarity between users. Table VI shows some users and their interests detected with our method and their top 10 tags. The first row contains user ids, the second row contains their detected communities of interests with their probabilities. The following ten rows show the top 10 tags for each user. We replaced community labels by names assigned according to the tags in each topic interest.

C. Scalability

We also evaluated the scalability of each method. However, as these methods are written in different programming languages, it is not fair to consider this as a precise evaluation, but more as an indication. To increase the stability of the comparison, we run experiments 10 times, and only listed the average values. We used a Java implementation of LDA algorithm. All the other methods were implemented in Python. For our method, the time of topic detection was also counted

TABLE V: Performances of the compared user interest detection methods

Similarity	Jaccard Similarity											
Level	High Interest				Medium Interest				Low Interest			
Metric	avg_inner	avg_rand	*modularity*	avg_center	avg_inner	avg_rand	*modularity*	avg_center	avg_inner	avg_rand	*modularity*	avg_center
Empirical	**0.162**	**0.033**	**4.909**	**0.218**	**0.135**	**0.039**	**3.462**	0.171	0.107	0.042	2.548	0.131
LDA	0.147	0.035	4.200	0.178	0.131	0.039	3.359	**0.177**	**0.144**	0.041	**3.512**	**0.193**
SLPA	0.131	0.040	3.275	0.166	0.129	0.040	3.225	0.159	0.121	**0.039**	3.103	0.155
Clustering	0.130	0.041	3.171	0.161	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Similarity	Cosine Similarity											
Level	High Interest				Medium Interest				Low Interest			
Metric	avg_inner	avg_rand	*modularity*	avg_center	avg_inner	avg_rand	*modularity*	avg_center	avg_inner	avg_rand	*modularity*	avg_center
Empirical	0.736	**0.574**	**1.282**	0.857	0.573	**0.602**	0.952	0.761	0.475	0.629	0.755	0.695
LDA	**0.836**	0.660	1.267	0.917	**0.900**	0.612	**1.471**	**0.948**	**0.757**	**0.600**	**1.262**	**0.865**
SLPA	0.749	0.624	1.200	0.854	0.590	0.621	0.950	0.687	0.702	0.625	1.123	0.844
Clustering	0.763	0.622	1.226	0.875	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE VI: Examples of user interests detected with our empirical method

user_10224	user_103043	user_113570
database (0.805) c#-dev (0.081)	java-dev (0.664) database (0.105)	c#-dev (0.393) web-dev (0.328)
sql-server (21) sql (21) tsql (6) performance (4) database (4) stored-procedures (3) sql-server-2005 (3) .net (3) mysql (2) sql-server-2000 (2)	java (135) swing (28) oracle (27) sql (23) subjective (15) windows (13) eclipse (12) best-practices (12) plsql (10) regex (10)	c# (107) jquery (89) javascript (56) .net (47) asp.net (27) css (23) regex (20) html (20) iphone (12) string (10)
user_24181	user_34509	user_30461
web-dev (0.743), database (0.072)	c-dev (0.663), linux-dev (0.083)	ios-dev (0.885), linux-dev (0.020)
php (304) javascript (193) mysql (116) html (86) css (57) regex (40) jquery (37) sql (27) ajax (26) apache (23)	c++ (703) c (187) templates (62) stl (53) linux (48) subjective (45) pointers (44) java (42) bash (40) boost (31)	cocoa (333) objective-c (184) iphone (47) cocoa-touch (39) osx (35) mac (34) iphone-sdk (20) xcode (18) cocoa-bindings (18) core-graphics (18)

in. For LDA and SLPA, we set the iteration number at 100. We run the experiments on a computer with 3GHz Intel i7 CPU and 8GB RAM. From the experiment, we could find that LDA, SLPA and our method are linear in terms of the number of users. Although LDA algorithm is theoretically $O(nm)$ in each iteration, with n representing the number of users, and m representing the number of tags for each user, when we test it on large datasets, it clearly appears that only n actually has an impact. m changes very little, so it could be regarded as linear. Besides, [21] proved that LDA model requires a few hundreds of iterations to obtain stable topic distribution. Our model does not have this limitation.

D. Discussion

To sum up, most community detection algorithms work well on real-life social networks which contain many *triangle-shape* structures. The interactions between the users in these networks are mainly based on their relationships. It is also noticeable that the relationships which a user in such network can maintain are limited and most likely restricted by the location (co-author networks in academia is also in this situation), so the overall structure of the network is *flatter*, *scattered* and with many *triangle-shape* structures. Comparatively, in Q&A sites, such as StackOverflow, there are no fixed relationships between users. Users interact with each other based on their own interests. And they are not aware of whom they are interacting with, so they will not maintain explicit relationships. Besides, a user can interact with any other user and mainly interacts with the *"gurus"* (most of

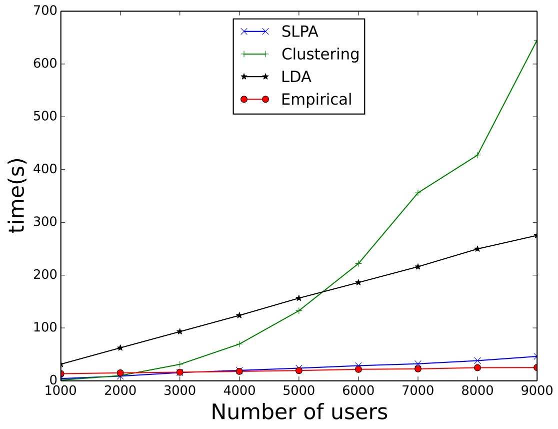


Fig. 6: Scalability of the compared user interest detection methods

questions are answered by a small group of people). So the overall structure of the network is *octopus-shape* [22] with less *triangle-shape* structures. According to [23], the average number of *triangle-shape* structures per user in twitter dataset is around 35714, while in our co-answer dataset, the number of *triangle-shape* structure per user is around 30 which is far less. So, graph-based community detection methods fail in such situation. The result of SLPA algorithm shows that it outputs one or two giant groups, together with many tiny groups that only contain a small number of users as depicted in Figure 7, where each color represents a detected community. We can also see that the network contains less *triangle-shape* structures and a high-density *core*. It also indicates that the network has huge overlaps. Since clustering methods normally generate hard-partitions communities, they cannot detect the overlapping communities which are typical in our case. Concerning the LDA-based methods, on one hand, in our dataset, question tag lists are quite short, and the experiment shows that our topic extraction method gives better results in this situation. On the other hand, the probabilistic graphical model requires hundreds of iterations to get stable results [21] which is more complicated and slower than our method. We also conducted similar experiments on a Flickr dataset in order to show our method is not specific to StackOverflow. Recalling our research questions (Can we detect communities of interests in Q&A sites? Can we also identify the topics that attract them?) we believe we propose a topic detection method which is very suitable for Q&A datasets and an efficient user

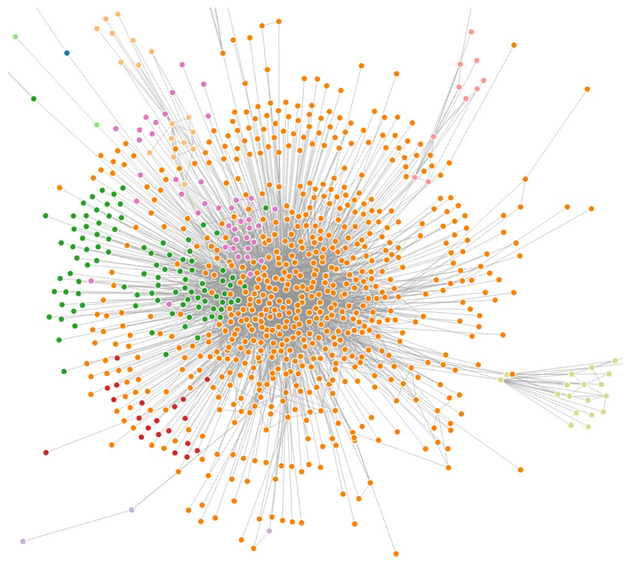


Fig. 7: Illustration of co-answer-network

interest detection method to discover overlapping communities of interests.

V. Conclusion

In this paper, we addressed the problem of detecting overlapping communities of interests in Q&A sites. By studying the Stackoverflow dataset and the LDA algorithm, we proposed TTD (Topic Trees Distributions) a tag tree based topic extraction model. We then exploited the extracted topic information to detect overlapping communities of interests. We conducted experiments on a dataset from the popular Q&A site StackOverflow to compare different approaches. The results indicate that for this kind of web communities our method can be a good replacement for more complicated methods in detecting overlapping communities of interests. There are also limitations in our work, in particular our model requires each question to have several tags to the question. There are many potential future directions for this work. An interesting one is to track the evolution of communities of interests and the evolution of users' interests.

Acknowledgment

The authors would like to thank StackOverflow for sharing their data. We also sincerely thank volunteers for helping us label the dataset for evaluation. We thank the ANR-12-CORD-0026 ocktopus project grant for the support of this research. We also appreciate very helpful advices from anonymous reviewers.

References

[1] A. Anderson, D. P. Huttenlocher, J. M. Kleinberg, and J. Leskovec, "Discovering value from community activity on focused question answering sites: a case study of stack overflow," in *KDD*, 2012, pp. 850–858.

[2] B. Li and I. King, "Routing questions to appropriate answerers in community question answering services," in *Proceedings of the 19th ACM international conference on Information and knowledge management*. ACM, 2010, pp. 1585–1588.

[3] T. C. Zhou, M. R. Lyu, and I. King, "A classification-based approach to question routing in community question answering," in *Proceedings of the 21st International Conference Companion on World Wide Web*, ser. WWW '12 Companion. New York, NY, USA: ACM, 2012, pp. 783–790.

[4] D. Li, B. He, Y. Ding, J. Tang, C. Sugimoto, Z. Qin, E. Yan, J. Li, and T. Dong, "Community-based topic modeling for social tagging," in *Proc. of the 19th ACM CIKM*, ser. CIKM '10. New York, NY, USA: ACM, 2010, pp. 1565–1568.

[5] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *the Journal of machine Learning research*, vol. 3, pp. 993–1022, 2003.

[6] J. Xie, S. Kelley, and B. K. Szymanski, "Overlapping community detection in networks: The state-of-the-art and comparative study," *ACM Comput. Surv.*, vol. 45, no. 4, p. 43, 2013.

[7] Y.-Y. Ahn, J. P. Bagrow, and S. Lehmann, "Link communities reveal multiscale complexity in networks," *Nature*, vol. 466, no. 7307, pp. 761–764, 2010.

[8] Z. Xu, Y. Ke, Y. Wang, H. Cheng, and J. Cheng, "A model-based approach to attributed graph clustering," in *SIGMOD Conference*, 2012, pp. 505–516.

[9] U. Gargi, W. Lu, V. S. Mirrokni, and S. Yoon, "Large-scale community detection on youtube for topic discovery and exploration," in *ICWSM*, 2011.

[10] S. Chang and A. Pal, "Routing questions for collaborative answering in community question answering," in *Proceedings of the 2013 IEEE/ACM ASONAM*. New York, NY, USA: ACM, 2013, pp. 494–501.

[11] H. Zhang, B. Qiu, C. L. Giles, H. C. Foley, and J. Yen, "An lda-based community structure discovery approach for large-scale social networks," in *ISI*, 2007, pp. 200–207.

[12] X. Sun and H. Lin, "Topical community detection from mining user tagging behavior and interest." *JASIST*, vol. 64, no. 2, pp. 321–333, 2013.

[13] J. Tang, J. Zhang, L. Yao, J. Li, L. Zhang, and Z. Su, "Arnetminer: extraction and mining of academic social networks," in *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2008, pp. 990–998.

[14] J. Yang, J. McAuley, and J. Leskovec, "Community detection in networks with node attributes," in *Data Mining (ICDM), 2013 IEEE 13th International Conference on*. IEEE, 2013, pp. 1151–1156.

[15] A. McDaid and N. Hurley, "Detecting highly overlapping communities with model-based overlapping seed expansion," in *Advances in Social Networks Analysis and Mining (ASONAM), 2010 International Conference on*. IEEE, 2010, pp. 112–119.

[16] A. Lancichinetti, F. Radicchi, J. J. Ramasco, and S. Fortunato, "Finding statistically significant communities in networks," *PloS one*, vol. 6, no. 4, p. e18961, 2011.

[17] P. Mika, "Ontologies are us: A unified model of social networks and semantics," *Web Semantics: Science, Services and Agents on the World Wide Web*, vol. 5, no. 1, pp. 5–15, 2007.

[18] L. Yang, M. Qiu, S. Gottipati, F. Zhu, J. Jiang, H. Sun, and Z. Chen, "Cqarank: jointly model topics and expertise in community question answering," in *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*. ACM, 2013, pp. 99–108.

[19] L. A. Adamic and B. A. Huberman, "Power-law distribution of the world wide web," *Science*, vol. 287, no. 5461, pp. 2115–2115, 2000.

[20] A. Y. Ng, M. I. Jordan, and Y. Weiss, "On spectral clustering: Analysis and an algorithm," in *ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS*. MIT Press, 2001, pp. 849–856.

[21] T. L. Griffiths and M. Steyvers, "Finding scientific topics," *Proceedings of the National academy of Sciences of the United States of America*, vol. 101, no. Suppl 1, pp. 5228–5235, 2004.

[22] J. Leskovec, K. J. Lang, A. Dasgupta, and M. W. Mahoney, "Statistical properties of community structure in large social and information networks," in *Proceedings of the 17th international conference on World Wide Web*. ACM, 2008, pp. 695–704.

[23] H.-M. Park and C.-W. Chung, "An efficient mapreduce algorithm for counting triangles in a very large graph," in *Proceedings of the 22nd ACM CIKM13*. ACM, 2013, pp. 539–548.