Measuring Social Tag Confidence: Is It a Good or Bad Tag?

Xiwu Gu[1], Xianbing Wang[1], Ruixuan Li[1], Kunmei Wen[1], Yufei Yang[1], and Weijun Xiao[2,*]

[1] Intelligent and Distributed Computing Lab, College of Computer Science and Technology Huazhong University of Science and Technology, Wuhan 430074, P.R. China
{guxiwu,rxli,kmwen}@mail.hust.edu.cn,
{wxb1225,yfyang}@smail.hust.edu.cn
[2] Department of Electrical and Computer Engineering, University of Minnesota, twin cities 200 Union Street SE, Minneapolis, MN 55455, US
wxiao@umn.edu

Abstract. Social tagging is an increasingly popular way to describe latent semantic information of web resources and thus is widely used to improve the performance of information retrieval system. However, there also has been significant variance of the quality of social tags because they can be annotated by folks on the web freely. As a consequence, how to measure the quality of social tags (referred to as social tag confidence) becomes an important issue. In this paper, we propose a statistic model to measure the confidence of social tags by utilizing a combination of three attributes of a social tag: web resource, tag, and tagging user. In order to evaluate the effectiveness of our model, two experiments are performed with datasets crawled from del.icio.us. Experimental results show that our model has a better performance than other approaches with respect to Normalized Discounted Cumulated Gain (NDCG). In addition, F-1 measure of tagged web page clustering performance is also increased when our model is applied to filter the noisy social tags with low tag confidence.

Keywords: tag confidence, semantic similarity, clustering, information retrieval.

1 Introduction

Along with the dramatic increase in the amount of web resources during recent years, web users are overwhelmed by the massive contents on the web. It is a non-trivial task for users to search and select information of their favorites. On the other hand, social tags have emerged as a valuable complement data source because to some extent they can describe latent semantic information of web resources. Consequently, social tags are widely used to improve information retrieval system effectively in various ways, such as optimizing page ranking using social tag [1][2], retrieving more semantically related images for an image retrieval system by exploiting textural social tag information of images[3], enhancing classifying and clustering effectiveness of

* Correspondence author.

H. Wang et al. (Eds.): WAIM 2011, LNCS 6897, pp. 94–105, 2011.

web resources by means of social tag exploration[4][5], and utilizing social tag to improve language model for information retrieval[6].

However, social tag is a form of folksonomy, which refers to an open Internet-based collaborative method allowing folks on the web to describe or categorize web resources such as web pages, photographs and videos with text labels freely. It can be viewed as metadata of web resources generated by normal web users, which means there is a significant difference of quality between social tag and professional creation of metadata. Instead of being generated by specialists with expertise, social tags are usually created by the user arbitrarily without any control or expertise knowledge. Therefore, social tags also reveal problems caused by ambiguity and synonymy. Mathes et al. [7] cited several examples of ambiguous tags and synonymous tags in Delicious. For instance, the tag “Tiger” is used by many users to annotate web resources about creature tiger. However, some users may use it to tag web resources about Tiger Woods, who is an American professional golfer. Synonymous tags, like “mac” and “macintosh”, “blog” and “weblog” are also widely used. On the other hand, some social tags are more likely created based on personal subjective judgment [8] so that these social tags have no semantic association with the tagged web resource. Besides, there also have been other problems of social tags such as mis-tagging due to spelling errors and tagging the same web resource cross different language. As a consequence, there are a large amount of noisy tags with low confidence on the web. More seriously, noisy social tags with low confidence will reduce the performance when they are utilized in IR system.

In order to deal with the problems of social tags, tag recommendation technique has been proposed and widely used to help user to annotate web resource more accurately [9]. However, tag recommendation is mainly based on the analysis the contents of web resource, the credibility of social annotation user usually is not taken into account.

In this paper, we propose a model to measure the confidence of social tags so that it can identify and filter the noisy tags with low confidence. Our model is based on the following assumptions: (1) Tags created by the user with higher credibility should have higher confidence score. (2) The tags with higher semantic relation with tagged resource should have higher confidence score. Following these assumptions, we utilize a combination of three attributes of social tag: resource, tag and tagging user for measuring the confidence of social tags. In order to evaluate our model, we conducted two experiments on a dataset crawled from del.icio.us. Experimental results show that our model can achieve much higher NDCG value for tag ranking and improve the accuracy for web page clustering after filtering the noisy tags with lower tag confidence. To the best of our knowledge, this is the first work to measure the tag confidence for enhancements of an information retrieval system by making full use of three attributes of social tag: resource, tag, and tagging user.

The rest of the paper is organized as follows. Section 2 summarizes related work on social tags and the applications of confidence of web resources and social tags. Section 3 sets out the definition of the confidence of social tags. The core of our paper, Section 4, proposes a method that is used to measure the confidence of social tags. Section 5 presents the experiments and numerical results. Finally, we draw a conclusion and discuss future work in Section 6.

2 Related Work

2.1 Research on Social Tags

As a new way of user-generated data, social tag can benefit many applications, such as information retrieval [10][11], semantic web [12], web page clustering [13] and user interest mining [14].

Besides the work mentioned above, Krestel et al. [15] introduce an approach based on Latent Dirichlet Allocation (LDA) to extract latent topics from resources with a fairly stable and complete tag set to recommend topics for new resources with only a few tags, which is more useful for searching and recommending resources to users. Ramage et al. [5] address one central question of how tagging data can be used to improve web document clustering and propose a novel generative clustering algorithm based on Latent Dirichlet Allocation. Körner et al. [16] analyze the influence of individual tagging practices in collaborative tagging systems on the emergence of global tag semantics. They raise a hypothesis that the quality of the emergent semantics depends on the pragmatics of tagging and propose four different statistical measures to assign users to two broad classes of categorizers and describers. Koutrika et al. [17] present that tagging systems become more susceptible to tag spam, they propose a framework to model tagging systems and user tagging behavior, and describe a novel approach to rank documents based on taggers' reliability.

Additionally, social tags are also widely used in the image retrieval area. Wu et al. [18] introduce a tag recommendation approach based on the learning, which generates ranking features from multi-modality correlations, and learns an optimal combination of these ranking features from different modalities. Liu et al. [19] propose a tag ranking approach in which the tags of an image can be automatically ranked according to their relevance with the image content by performing a random walk over a tag similarity to refine the relevance scores.

2.2 Research on the Confidence of Web Resources and Social Tags

The research on the confidence of web information has not been explored widely in the information retrieval area. Akamine et al. [20] describe an information confidence analysis system named WISDOM, which can automatically evaluate the confidence of information available on the Web from multiple viewpoints.

Meanwhile, there also has been a few works on the confidence (or the quality) of social tags. Lee et al. [8] propose a method measuring tag confidentiality from visual semantics of image by analyzing the associated visual information and ontology information in image retrieval. Zhu et al. [21] use tag to summarize web document, they measure tag confidence by calculating the user-tag adjacency matrix iteratively. This work has achieved some interesting results, however, this kind of tag confidence measurement doesn’t consider the contents of web pages. In order to identify appropriate tags and eliminate spam and noise, Xu et al. [22] formulate some general criteria for a good tagging system, and by using these criteria, they propose a collaborative tag suggestion algorithm to single out high quality tags.

Different from the works mentioned above, we propose a model to measure the confidence of social tags using the combination of the credibility of users, the content items of web pages, and the relationships among users, tags, and resources.

3 Definition of Tag Confidence

In this paper, the confidence of a tag *t* with respect to a web page *d* is denoted by *Conf*(*t, d*), which represents how much the tag *t* is semantically related to the tagged web page *d*. The value of *Conf*(*t, d*) is ranged from 0 to 1. If the tag *t* is quite bound up with the web page *d*, its confidence value is close to 1. Otherwise, tag confidence value is close to 0.

The main idea of our work is inspired by the paper of Lee et al. [8], in which they propose a method measuring tag confidence from visual semantics of image by analyzing the associated visual information and ontology information in image retrieval. However, they haven't considered the impact of tagging user on the confidence of tag.

Intuitively, *Conf*(*t, d*) should be determined by the following three factors:

(1) The credibility of the tagging user. Since social tags of web resources are created by users, the confidence of tags will be determined by the tagging users. The higher credibility of the user, the higher confidence of the tag generated by the user should be.

(2) The semantic similarity between web pages. Tag *t* of web page *d* can be viewed as keywords or summarization of *d*. Given a web page *d'* which is mostly semantically similar to *d*, if the tag *t'* has high confidence with respect to web page *d'* and tag *t'* is highly similar to the tag *t*, then tag *t* should also has high confidence with respect to web page *d*. Therefore it is necessary to assess the semantic of web page content items in order to measure the confidence of a tag.

(3) The semantic similarity between tags. Under the above consideration, the semantic similarity between tags will also make contribution to the measurement of tag confidence. In order to calculate the semantic similarity between tags, the co-occurrence relationship between tags can be utilized. Two tags have co-occurrence relationship when they are annotated to a same web page.

Based on these considerations, the confidence value of social tag *t* with respect to document *d* is determined by a function *F* with three factors, which can be defined by:

$$Conf(t,d) = F(C(u), CS(d,d'), TS(t,t')) \tag{1}$$

where *Conf*(*t, d*) is the confidence value of tag *t* with respect to *d*, *C*(*u*) is the credibility of user *u*, *CS*(*d*, *d'*) is the semantic similarity between web page *d* and *d'*, *TS*(*t*, *t'*) is the semantic similarity between tag *t* and *t'*, tag *t* and *t'* are annotated to the web page *d* and *d'*, respectively. In particular, the higher value of three factors of *F*, the higher value of *Conf*(*t, d*) should be.

In the next section, we will provide a specific implementation of this idea to measure the confidence of social tags.

4 Proposed Method

As mentioned in section 3, we will use a combination of the credibility of users, the semantic similarity among web pages and the semantic similarity among tags to measure the confidence of social tags. The calculating procedure of our model is described as follows.

In order to calculate the confidence of a target tag *t* with respect to a target web page *d*, we need to calculate the credibility of users who use the target tag *t* to annotate the target web page *d* at first. In the next step, we select top *N* semantically similar web pages of the target web page *d* by calculating the semantic similarity between *d* and each other web page in our dataset based on vector space model. Furthermore, we build a similarity measurement model based on probability statistics to calculate the semantic similarity between each pair of tags, in which one is annotated to the target web page *d* and the other is annotated to the one of the selected top *N* semantically similar web pages. Finally, we use a model named UCTM (user, page content items and social tag) to combine the aforementioned three results to calculate the confidence of target tag *t* with respect to a target web page *d*. The procedure of our method is illustrated in Fig. 1.

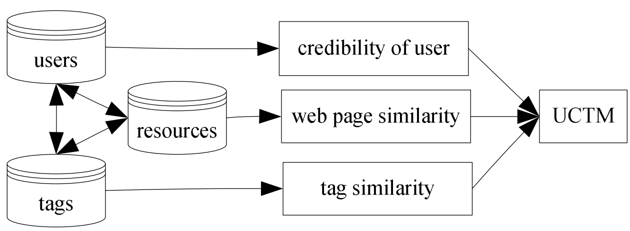
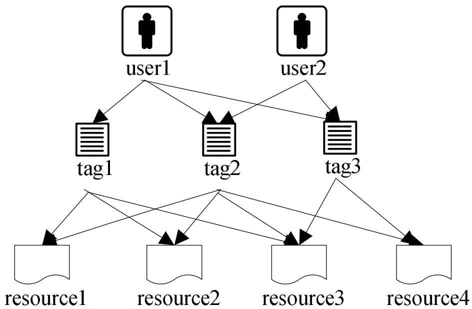


Fig. 1. The procedure for calculating social tag confidence

4.1 The Credibility of Users

In general, users play a significant role in social annotation system. A high credibility user is apt to create high quality tags. Therefore, the higher credibility of a user, the higher confidence of social tags generated by the user will be.

Based on this consideration, we quantify the credibility of users through an iterative model. The iterative algorithm is inspired by the work of Zhu et al [21]. They propose an algorithm named EigenTag to calculate user scores and tag scores. They deem that there exists a mutually reinforcing relationship between users and tags and describe this relationship as a tag-user graph with an adjacency matrix. However, they only consider the relationship between user and tag, the annotated web resource has not been taken into account. In order to calculate the credibility of users, we firstly model the relationships between users, tags and resources by three adjacency matrixes, as shown in Fig. 2. The relationships are illustrated by the user-tag-resources graph and the three corresponding adjacency matrixes *M*, *N*, *P*. which are tag-user matrix, resource-tag matrix and user-resource matrix, respectively.



$$M=\begin{bmatrix}1 & 0\\ 1 & 1\\ 1 & 1\end{bmatrix}\quad N=\begin{bmatrix}1 & 1 & 0\\ 1 & 1 & 0\\ 1 & 1 & 1\\ 0 & 1 & 1\end{bmatrix}$$

$$P=\begin{bmatrix}1 & 1 & 1\\ 0 & 1 & 1\end{bmatrix}$$

Fig. 2. Users-tags-resources relationship graph and adjacency matrixes

If a user u uses a tag t to annotate resource r, then the entry (t, u) of matrix M, the entry (r, t) of matrix N and the entry (u, t) of matrix N are all equals to 1. Let U be the vector of user scores $(u_1, u_2, \ldots, u_x)^T$, T the vector of tag scores $(t_1, t_2, \ldots, t_y)^T$, R the vector of resource scores $(r_1, r_2, \ldots, r_z)^T$. Then the user score can be calculated by the following equations iteratively:

$$T = MU \quad R = NT \quad U = PR \tag{2}$$

We initialize the vector U as (1, 1, ... 1), which means that we are impartial to every user at first and they have the same credibility. In each iteration step, the score of each tag is updated to the sum of the scores of all users annotating it, the score of each resource is updated to the sum of scores of all tags annotated to it, and the score of each user is updated to the sum of scores of all resources annotated by the user. The three vectors need to be normalized after each iteration step. We iterate the above three equations until the user scores converge. The credibility of a user will be set to the corresponding score in the final user score vector.

4.2 Select Top N Semantically Similar Web Pages

In order to select top N similar web pages of the target web page, we model a web page as a vector in vector space and calculating the similarity of each pair of web pages. There are two general approaches to weighting the components of vector: tf and tf-idf. In our paper, we use term frequency to weight the components of each vector because tf-idf approach over-emphasizes the rarest terms.

Once we have vector representation of web pages, we apply cosine similarity to calculate the semantic similarity between the target web page and the each other web page in our dataset. We set a threshold to select top N web pages which are the most similar to the target web page.

4.3 Tag Similarity

Social annotation is viewed as a set of triples constituted by users, tags and resources. Each triple (u, r, t) represents user u annotates resource r with tag t. The similarity measure between each pair of tags can be elicited by exploiting the relationships of these triples. In order to simplify the calculation, we use dimension reduction method and represent a tag as a vector of resources.

The tag similarity calculation is based on the work proposed by Markines et al. [23]. We define the notations as follows: t represents a tag and T is its vector representation with resource components r_1 to r_n. In order to weight the components of vector T, we use the entropy of resource r, denoted by $-\log p(r)$, as the weight of the component r in vector T, where $p(r)$ is the fraction of tags annotated to r. Additionally, since there may be many users who use the tag t annotating the resource r, we need to take the number of users into account in order to enlarge the weight of the resource r. Hence the vector T of tag t can be represented as:

$$T = (R_1, R_2, \ldots, R_n) \tag{3}$$

$$R_i = -N(t, r_i) * logp(r_i) \tag{4}$$

where $N(t, r_i)$ is the number of users who use tag t to annotate resource r_i.

However, the Eq. (4) will encounter such a problem that if two tags are not annotated to the same web page, the measure of similarity will yield a zero similarity. In order to resolve the problem of zero similarity, it is reasonable to make the assumption that if many users all employ the same pair of tags, the pair of tags might be related even the pair of tags is not tagged to the same web page. Based on this assumption, we add R^* to the vector T:

$$T = (R_1, R_2, \ldots, R_n, R^*) \tag{5}$$

$$R_i = -N(t, r_i) * logp(r_i) \tag{6}$$

$$R^* = -log\ [1/(N(t) + \lambda)] \tag{7}$$

where $N(t)$ is the number of users who own the tag t, λ is a smooth parameter which is not less than 1.

When we obtain the vector representation of two tags, we can use cosine theorem to calculate the similarity of two tags, the formula is given by

$$\theta(t_1, t_2) = \frac{T_1}{||T_1||} * \frac{T_2}{||T_2||} \tag{8}$$

where $\theta(t_1,t_2)$ represents the semantic similarity between tag t_1 and tag t_2.

4.4 Evaluating Tag Confidence

In order to measure the confidence of tag t with respect to the target web page d, we build a model named UCTM which combine three attributes of social tag: the credibility of user, the semantic similarity among web pages, and the semantic similarity among social tags.

For a target web page TF with tag t, we can get top N similar web pages, which are denoted by $LF_1, LF_2, \ldots, LF_n$, respectively. Suppose each web page $LF_i(i=1, 2, \ldots n)$ is annotated by tags $lt_1, lt_2, \ldots, lt_{im}$, where im is the number of tags annotated to page LF_i. The confidence of tag t with respect to the target web page TF can be defined as follows.

$$Conf(t, TF) = \frac{C(u)}{n} * \sum_{i=1}^{n} \left[CS(TF, LF_i) * max\left(TS\left(t, lt_j\right) \middle| j = 1, 2, \ldots, im\right) \right] \quad (9)$$

$C(u)$ is calculated by:

$$C(u) = max\ (C(u_1), C(u_2), \ldots, C(u_n)) \quad (10)$$

where u_1, u_2, ..., u_n are the users who use tag t to annotate web page TF, $C(u)$ is the credibility of user u whose credibility value is maximum among u_1, u_2, ..., u_n, $CS(TF, LF_i)$ is the semantic similarity between web page TF and page LF_i, $TS(t, lt_j)$ is the semantic similarity between tag t and tag lt_j.

For each top N similar web page LF_i, we firstly calculate the maximum tag similarity among its tags and the target tag t. Next, we integrate the credibility of users, the web page similarity between LF_i and LF, maximum tag similarity to calculate intermediate results of each top N similar web page. Finally, the confidence of tag t with respect to the target web page TF is calculated by averaging all intermediate results of the top N similar web pages. The higher confidence value signifies that the tag is highly related to associate web page.

5 Performance Evaluation

5.1 Experimental Settings and Evaluation Measurement

The experiments are conducted on a dataset partly crawled from the social annotation site del.icio.us during July, 2010. After dataset preprocessing, the experimental dataset consists of total number of 21770 tags, 14818 web pages and 20195 users.

We evaluated our model with two different measurements. The first measurement is Normalized Discounted Cumulated Gain (NDCG), a kind of ranking accuracy performance measure which shows how exactly an ordered list of objects ranked automatically by a certain criteria matches the ordered list ranked manually by users [24]. Once having calculated the confidence of all social tags with respect to each document in our dataset, tags of each document are ranked by confidence value. Then three hundred web pages are randomly selected from our dataset and 20 students are invited to label each tag of each web page as one of four levels of relevance: (1) irrelevant; (2) marginally relevant; (3) fairly relevant; (4) highly relevant. Given a web page annotated by the tags t_1, t_2, ... , t_n, we ranked them according to the confidence value and the NDCG value is calculated by :

$$N_n = Z_n * \sum_{i=1}^{n} (2^{r(i)} - 1) / \log_2(1 + i) \quad (11)$$

where $r(i)$ is the relevance level of the ith tag and Z_n is a normalization constant. After computing the NDCG measures of each web page's tag ranking list, we average 20 students' NDCG value to obtain an evaluation measurement of tag confidence for each web page.

Another evaluation measurement is to apply the confidence value calculated by our model to filter the noisy tags which confidence value is lower than the predefined threshold. After that, remained tags with higher confidence are utilized for a practical application (web page clustering) to see that whether tags with higher confidence can improve the F-1 measure of clustering results.

5.2 NDCG Evaluation Result and Analysis

We use the following three tag ranking criteria as NDCG measurement comparison baseline of our tag confidence strategy.

(1) Tag TF Frequency. The tag TF frequency is defined as how many times a tag is annotated to a web page. We rank the tags by tag TF frequency and compare the NDCG value with our model.

(2) Tag TF-IDF Frequency. A tag's TF-IDF is the term frequency downweighted by the log ratio of the total number of web pages to the number of web pages annotating by that tag. We rank the tags by tag TF-IDF frequency and compare the NDCG value with our model.

(3) EigenTag. In order to compare with the method proposed by Zhu et al. [21], we also have implemented the algorithm described in this paper and calculation result is compared with our model.

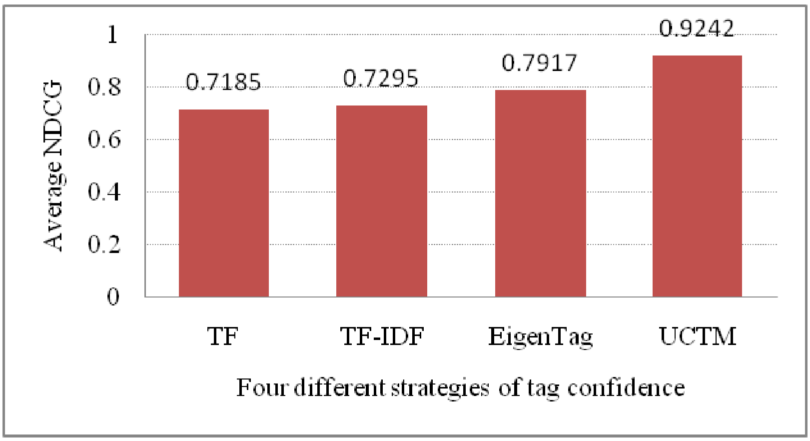


Fig. 3. Performance comparison of different strategies of tag confidence

The experimental results are shown in Fig. 3. One can see that our method outperforms TF, TF-IDF and EigenTag by about 29%, 27% and 17%, respectively. TF and TF-IDF only take statistical information of tags into count. EigenTag, which consider both users and tags, has better performance than TF and TF-IDF. However, it doesn't consider the semantic information of web page content items. Our model achieves the best performance because it considers the information from the quality of users, web page content items, and the relationships among users, tags, and resources.

5.3 Evaluation Results of Web Clustering

In order to evaluate our model more effectively, we took the web clustering algorithm proposed by Ramage et al. [5] as a baseline for comparison. Their method uses K-means clustering algorithm with the combination of social tags and web page words in three ways: Using Word-only, Using Tag-only and Using Tag+Word.

To evaluate the F-1 performance of clustering, we use a subset of partly crawled data collection from del.icio.us that is also presented in Open Directory Project (ODP) (http://www.dmoz.org/). ODP is the largest, most comprehensive human-edited directory of the Web. For every web page presented in ODP, we use the root category of that page as our clustering evaluation gold standard. The clustering evaluation measure we used is F-1 metrics [25].

First, we cluster the web pages without applying the strategy of tag confidence. In order to evaluate our model more objectively, we perform three experiments and in each excrement we use feature selection algorithm to select 500, 800, 1000 words, respectively. We also set the number of tags equal to the number of words. The F-1 values for Word-only, Tag-only, and Tag+Word are shown in Table 1.

Table 1. The clustering result not using the strategy of tag confidence

	tag, word = 500	**tag, word = 800**	**tag, word = 1000**
Word-only	0.1739	0.1904	0.1937
Tag-only	0.2101	0.2101	0.2103
Tag+Word	0.2160	0.2031	0.2039

Table 1 show that the performance of clustering using Tag-only is better than using Word-only. However, the performance of clustering using Tag+Word doesn't always outperform Tag-only method. The main reason is some words occurred in web pages act as noise so that they affect the performance of clustering.

Next, we apply the strategy of tag confidence to cluster our web pages. We firstly filter some tags whose confidence is relatively low for a web page. Next we mark the remained tags of a web page as Tag' and cluster the dataset using Tag'-only and Tag'+Word. The final results of clustering are shown in Table 2 and Table 3.

Table 2. The clustering result using Tag-only and Tag'-only

	tag, word = 500	**tag, word = 800**	**tag, word = 1000**
Tag-only	0.2101	0.2101	0.2103
Tag'-only	0.2150	0.2155	0.2153

Table 3. The clustering result using Tag+Word and Tag'+Word

	tag, word = 500	**tag, word = 800**	**tag, word = 1000**
Tag+Word	0.2160	0.2031	0.2039
Tag'+Word	0.2215	0.2242	0.2338

The clustering results show that our model can improve F-1 score by about 2.4% averagely when using Tag-only and F-1 score is increased more significantly by 2.5% to 14.7% when using Tag+Word. By examining the F-1 results, one can see that Tag'+Word has the best clustering result after applying the strategy of tag confidence to web page clustering. The reason is that there are some noisy tags with lower confidence in our dataset which will downgrade the clustering performance and these noisy tags are filtered according their tag confidence calculated by our model. Thus we can obtain a new tag set with higher confidence which is more beneficial for web clustering.

6 Conclusion

During recent years, social tags are emerged as complement metadata source and widely used for improving the performance of an information retrieval system. However, there also has been considerable variation in the confidence of social tags while the confidence of social tags has a lot of impacts on the performance of information retrieval system. In this paper, we have proposed a novel measurement model of tag confidence for estimating the quality of social tags. In order to measure the confidence more accurately, the model takes full account of three attributes of social tag: resource, tag, and tagging user. Experimental results show that our tag confidence model can assess the quality of social tag more accurately than other methods. In addition, the F-1 measure of tagged web page clustering performance is also increased when our model is applied to filter the noisy social tags.

Acknowledgments. This work is supported by National Natural Science Foundation of China under Grant 60873225, 60773191, 70771043, National High Technology Research and Development Program of China under Grant 2007AA01Z403.

References

1. Bao, S., Xue, G., Wu, X., Yu, Y., Fei, B., Su, Z.: Optimizing web search using social annotations. In: The 16th International Conference on World Wide Web (WWW 2007), pp. 501–510. ACM Press, Banff (2007)
2. Park, L., Ramamohanarao, K.: Mining Web Multi-resolution Community-based Popularity for Information Retrieval. In: The 16th International ACM Conference on Conference on Information and Knowledge Management (CIKM 2007), pp. 545–554. ACM Press, Lisboa (2007)
3. Wang, C., Zhang, L., Zhang, H.: Learning to Reduce the Semantic Gap in Web Image Retrieval and Annotation. In: The 31th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2008), pp. 355–362. ACM Press, Singapore (2008)
4. Noll, M.G., Meinel, C.: Exploring social annotations for web document classification. In: The 2008 ACM Symposium on Applied Computing (SAC 2008), pp. 2315–2320. ACM Press, Brazil (2008)
5. Ramage, D., Heymann, P.: Clustering the Tagged Web. In: The Second ACM International Conference on Web Search and Data Mining, pp. 54–63. ACM Press, Barcelona (2009)
6. Xu, S., Bao, S., Cao, Y., Yu, Y.: Using social annotations to improve language model for information retrieval. In: The 16th International ACM Conference on Conference on Information and Knowledge Management (CIKM 2007), pp. 1003–1006. ACM Press, Lisboa (2007)
7. Mathes, A.: Folksonomies - cooperative classification and communication through shared metadata. Computer Mediated Communication, LIS590CMC (Doctoral Seminar), Graduate School of Library and Information Science, University of Illinois Urbana-Champaign (2004)

8. Lee, S., Min, H., Lee, Y.B., Ro, Y.M.: Measurement of Tag Confidence in User Generated Contents Retrieval. In: Proc. of SPIE, pp. 7257–7262 (2009)
9. Wu, L., Yang, L., Yu, N.: Learning to Tag. In: The 18th International Conference on World Wide Web (WWW 2009), pp. 361–370. ACM Press, Marid (2009)
10. Zhou, D., Bian, J., Zheng, S., Zha, H., Giles, C.L.: Exploring social annotations for information retrieval. In: The 17th International Conference on World Wide Web (WWW 2008), pp. 715–724. ACM Press, Beijing (2008)
11. Schenkel, R., Crecelius, T., Kacimi, M., Michel, S., Neumann, T., Parreira, J.X., Weikum, G.: Efficient top-k querying over social-tagging networks. In: The 31th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2008), pp. 523–530. ACM Press, Singapore (2008)
12. Wu, X., Zhang, L., Yu, Y.: Exploring social annotations for the semantic web. In: The 15th International Conference on World Wide Web (WWW 2006), pp. 417–426. ACM Press, Edinburgh (2006)
13. Brooks, C.H., Montanez, N.: Improved annotation of the blogosphere via autotagging and hierarchical clustering. In: The 15th International Conference on World Wide Web (WWW 2006), pp. 625–632. ACM Press, Edinburgh (2006)
14. Li, X., Guo, L., Zhao, Y.E.: Tag-based social interest discovery. In: The 17th International Conference on World Wide Web (WWW 2008), pp. 675–684. ACM Press, Beijing (2008)
15. Krestel, R., Fankhauser, P., Nejdl, W.: Latent Dirichlet Allocation for Tag Recommendation. In: The 3rd ACM Conference on Recommender Systems, New York, USA (2009)
16. Körner, C., Benz, D., Hotho, A., Strohmaier, M., Stumme, B.: Stop Thinking, Start Tagging: Tag Semantics Emerge from Collaborative Verbosity. In: The International Conference on World Wide Web (WWW 2010), pp. 251–260. ACM Press, USA (2010)
17. Koutrika, G., Effendi, F.A., Gyöngyi, Z., Heymann, P., Molina, H.G.: Combating Spam in Tagging Systems. In: The Third International Workshop on Adversarial Information Retrieval on the Web (AIRWeb 2007), Alberta, Canada (2007)
18. Wu, L., Yang, L., Yu, N.: Learning to Tag. In: The 18th International Conference on World Wide Web (WWW 2009), pp. 361–370. ACM Press, Marid (2009)
19. Liu, D., Hua, X., Yang, L.: Tag Ranking. In: The 18th International Conference on World Wide Web (WWW 2009), pp. 351–360. ACM Press, Marid (2009)
20. Akamine, S., Kawahara, D., Kato, Y.: WISDOM: A Web Information Credibility Analysis System. In: Proceedings of the ACL-IJCNLP, Suntec, Singapore, pp. 1–4 (2009)
21. Zhu, J., Wang, C., He, X., Bu, J., Chen, C., Qu, M., Lu, G.: Tag-Oriented Document Summarization. In: The 18th International Conference on World Wide Web (WWW 2009), pp. 1195–1196. ACM Press, Marid (2009)
22. Xu, Z., Fu, Y., Mao, J., Su, D.: Towards the Semantic Web: Collaborative Tag Suggestions. In: The 15th International Conference on World Wide Web (WWW 2006). ACM Press, Edinburgh (2006)
23. Markines, B., Cattuto, C., Menczer, F., Benz, D., Hotho, A., Stumme, G.: Evaluating similarity measures for emergent semantics of social tagging. In: The 18th International Conference on World Wide Web (WWW 2009), pp. 641–650. ACM Press, Marid (2009)
24. Jarvelin, K., Kekalainen, J.: Cumulated gain-based evaluation of IR techniques. ACM Transactions on Information Systems 20(4), 422–466 (2002)
25. Manning, C., Raghavan, P., Schütze, H.: Introduction to information retrieval. Cambridge University Press, Cambridge (2008)