A System for Web Widget Discovery Using Semantic Distance between User Intent and Social Tags

Conference Paper · December 2012

DOI: 10.1007/978-3-642-35386-4_1

A System for Web Widget Discovery Using Semantic Distance between User Intent and Social Tags

Zhenzhen Zhao[1], Xiaodi Huang[2], and Noël Crespi[3]

[1] Institut Mines-Télécom, Télécom SudParis
91000 Evry, France
Zhenzhen.zhao@it-sudparis.eu
[2] Charles Sturt University
Albury, NSW 2640, Australia
xhuang@csu.edu.au
[3] Institut Mines-Télécom, Télécom SudParis
91000 Evry, France
noel.crespi@institut-telecom.fr

Abstract. Social interaction leverages collective intelligence through user-generated content, social networking, and social annotation. Users are enabled to enrich knowledge representation by rating, commenting, and tagging. The existing systems for service discovery make use of semantic relation among social tags, but ignore the relation between a user information need for services and tags. This paper first provides an overview of how social tagging is applied to discover contents/services. An enhanced web widget discovery model that aims to discover services mostly relevant to users is then proposed. The model includes an algorithm that quantifies the accurate relation between user intent for a service and the tags of a widget, as well as three different widget discovery schemes. Using the online service of Widgetbox.com, we experimentally demonstrate the accuracy and efficiency of our system.

Keywords: content discovery, folksonomy, service discovery, social tagging, algorithm, widget.

1 Introduction

Social web extends the concept of collective intelligence. Such intelligence is hidden in the Web 2.0. The intelligence is distributed over user activities, such as user-generated contents in YouTube, Flickr, Wikipedia, and Blogs for socializing and knowledge sharing; user-enhanced social relationships through social networking such as Facebook, Myspace, and LinkedIn; and user-enriched knowledge representation through social annotation like social tagging, rating, and commenting.

Nowadays, a huge number of web services keep appearing. This makes it more and more difficult to discover services and resources. Traditional methods for web discovery use the WSDL and UDDI [1]. However, this technique has difficulties in

K. Aberer et al. (Eds.): SocInfo 2012, LNCS 7710, pp. 1–14, 2012.

achieving the precision rate of searching. For improving the accurate rate, the semantic search was introduced, which uses the similarity and relations of queries and resources. Furthermore, advanced languages such as OWL-S [2], WSDL-S [3], and WSMO [4], have been developed. The semantic web ontology has two contradicting features. First, current ontology language models perform well for particular service models in particular situations. But the number of the services based on the semantic web and the ontology language are limited. Second, semantic web ontologies are consistent, but also relatively static and inflexible [5]. Their consistence is because they are often created by a small number of experts.

Social tagging can be seen as a complementing approach to ontology building, termed as Folksonomy [6]. Compared with the traditional meta-data organization, folksonomy enriches meta-data resources collaboratively by all web users in lowering barriers to cooperation [7].

This paper attempts to answer the question as to how to support the discovery of web content/service using social intelligence. In particular, how social tagging is used in discovering services in the Internet? By investigating the current web, the service discovery is based mainly on the keyword-matching algorithms, which accept users' input keywords to look for elements that would contain information of the input words. Social tagging can help in improving the accuracy of retrieved results. How to relate hidden, implicit tag information to user intention becomes the key issue.

In particular, we quantify the semantic relation between an input keyword that indicates the user intent on services and tags that are associated with services in a multi-faceted way. Social tagging has its own problems as uncontrolled vocabulary and non-hierarchical structure [7]. Previous research has addressed some issues on the ambiguity of tags. However, the ambiguities of user information need and how to build a relation between the ambiguous user intent and ambiguous tags have been ignored. A user who is looking for a service issues a query of a keyword to search for a service, for example. In some cases, the user cannot describe exactly what services she wants due to her ambiguous information need. On the other hand, the keyword cannot accurately describe the service she wants due to the ambiguous meaning of the keyword. In order to accurately retrieve services, we make use of an n-m multiple relations among an input keyword, its synonyms, and the tags, instead of a 1-m relation between the keyword and tags.

There are abundant researches on web content and service discovery using folksonomy. This paper reviews the state of the art of research work in social tagging. Two comparison tables are presented to compare the different approaches of tag relationship discovery and content/service discovery.

As the important contribution of this paper, an enhanced mathematical model of web widget discovery is proposed, together with an implemented system. In our model, the relation between user intent and tags is measured, and such a relation is then used to discover widgets. To evaluate its performance, we implement the model in our system. The results demonstrate the efficiency of our proposed model by comparing to the current algorithm used in an online service of Widgetbox.com.

The remainder of the paper is organized as follows. Section 2 reviews the literatures on content/service discovery through social tagging. Section 3 presents the proposed enhanced widget discovery model. System design and prototype are described in Section 4 and the relevant results are discussed in Section 5. Finally, we conclude this paper with the future work in Section 6.

2 Relate Work

In this section we present the relevant approaches and systems on discoveries of tag relations, and services.

2.1 Tag Relationship Discovery

Many web services such as Del.icio.us and Flickr.com allow users to tag their desire keywords to an element in the web site. As the service grows bigger, the number of users increases and the number of tags in the system also increases. This raises a question as to how tags are related to each other. The relations maybe exist in terms of synonyms (Chukmol et al. [8]), or through the resource they are notated with (Wu et al. [11] & Dubinko et al. [10]), or even through a word ontology (Li et al. [12], Zhou et al. [7]).

Many researchers have investigated and attempted to implement a number of methods for discovering tag relations. Most of the studies tend to use the information from the existing services like Flickr (Dubinko et al. [10]), and Del.icio.us (Zhou et al. [7]). This could be because implementing existing information is better than creating new one, and using tag relations is more efficient using the large scale of information data (Li et al. [12]). Many researches have provided a great perspective on revealing the possibility of discovering tag relations using different kinds of algorithms, models, and methods. This is done from many different fields of studies such as the semantic network, and information retrieval.

Other research can be classified in terms of ideas, different types of implementation methods, and how each of them looks at the problem differently. For example, some papers present tag ontology (Li et al. [12]), others focus on tag clustering (Wu et al. [11]), and the rests consider both (Zhou et al. [7]). In addition, several works are concerned about the evolution of tag relations over a time window (Dubinko et al. [10]).

Our work here is different from existing works in that we examine the relation between user information intent and tags. We argue that user intent [20] should be accurately described in the first instance, and then we are able to retrieve the services that mostly satisfy user requirements.

Table 1. Comparison on tag relationship discovery

Author(s)	Paper	Goal	Methods
Li et al.	Towards Effective Browsing Large Scale Social Annotation	– Tag semantic – Hierarchy creation	– Tag concept similarity using the term frequency and inverse document frequency in Information Retrieval – Find father-tag by the coverage rule, and sub-tag by intersect rule
Zhou et al.	An Unsupervised Model for Exploring Hierarchical Semantics from Social Annotation	– Hierarchical cluster	– KL-Divergence for finding tag relationship creating cluster of tags – DA Algorithm to create the hierarchical structure
Dubinko et al.	Visualizing Tags over Time	– Tag relation evolution	– Finding the tag relation, using term frequency and inverse document frequency, in accordance to defined time frame

2.2 Content/Service Discovery

There are few research carried on in discovering resources using social tagging. Aurnhammer et al. [9] use users' resource preferences to recommend more resources, while Chukmol et al. [8] implement a web service, WordNet, to find word synonym and resource containing the synonyms of tags. In their paper, Ding et al., 2010 [13], introduce their own technique of QEBT and QPBT for service discovery.

Table 2. Comparison on content/service discovery

Author(s)	Paper	Goal	Methods
Aurnhammer et al.	Augmenting Navigation for Collaborative Tagging with Emergent Semantics	– Navigation Map – Combine Image Properties and User's Queries	– Oriented Gaussian Derivative and Euclidean Distance for image distances – Uses nearest neighbour classifier to find the nearest related image
Chukmol et al.	Enhancing Web Service Discovery by using Collaborative Tagging System	– Service discovery through notated tags	– Word's synonym comparing using WordNet finding word's synonym
Ding et al.	A Web Service Discovery Method Based on Tag	– Discovering service using user's query	– QEBT and QPBT algorithms

2.3 Systems

Several researchers have built up systems to investigate how social tagging can improve the performance of the systems. Bouillet et al. [14] develop a system on automated web service composition using social tagging. They later expand this method to facilitate the design and development of compostable services. They also propose a novel approach for service design and composition by meeting faceted, tag-based functional requirements provided by end-users. Using examples from a case study in the financial services domain, they demonstrate the performance of their approach for services that can be composed into myriad workflows based on end-user goals. The authors [5] use tag-based descriptions to describe individual services.

Liu et al. [15] conduct research on automated service composition. The authors introduce a user-oriented approach, which aims to simplify service composition. They leverage the plentiful information residing in service tags, from both service descriptions (such as WSDL) and the annotations tagged by users. Based on Web browsers, they develop a user-friendly prototype so that the users are enabled to accomplish service composition in an interactive way. Later in their work [16], they propose an approach to composing data driven mashups, based on tag-based semantics. Mashup developers including end-users can easily search for desired services with tags, and combine several services by means of data flows. Being equipped with the graphical composition user interfaces in their system, developers are allowed to iteratively modify, adjust, and refine their mashups.

Gomadam et al. [17] presents a faceted approach that searches and ranks Web APIs by taking into consideration the attributes or facets of APIs found in their HTML descriptions. In their paper, the concept of “Facet tag vector” is introduced to define the union of tags that have been assigned to the APIs by users, according to the categories grouped under the facets. The authors evaluate classification, search accuracy, and ranking effectiveness using available APIs. In order to provide more meaningful search results to users, Arabshian [18] presents a framework that performs context-aware search for tagged data by using a tag ontology that includes context information, as well as tagged keywords.

To our best knowledge, no system in discovering widgets through social tagging, however, has been reported. Our system is the first attempt in discovering widgets by using social tagging.

3 Our Algorithm and Model for Web Widget Discovery

In this section, we define the methodology that is used to implement in our experiment in the Widget domain. A widget is a light-weight application or a component of an interface, which enables a user to perform a function or access a service. WidgetBox.com, a widget provider, which allows users to share, tag, and rate their created or preferred widgets.

3.1 Tag Discovery by Measuring Semantic Distances

The user information need for wedges is called an event in this paper, which is characterized by a user input keyword. Normally, the user intention for the requirements of wedges cannot be accurately described. The implicit information from the number of synonyms of the user input keyword can remedy this. These synonyms describe the user information need from multi-faceted aspects. However, each synonym of the user input keyword may be associated with a number of widgets, which each associated widget is also assigned with various numbers of tags. In other words, the synonym of an input keyword and the tags are in an n-m relation via a number of widgets. Different widgets are regarded as different dimensions that measure the semantic similarities between the synonyms and tags. In order to quantify such a diverse relation between a user information need and tags, we make use of the Kullback-Leibler (KL) Divergence metric. As such, we can discover the mostly relevant tags to the user input. The algorithm is given below:

Input: an event
Output: the top 10 tags associated with the event.

Accept the keyword input of an event $e \in \mathcal{E}$ *where* $\mathcal{E}$ *is a universal set of events.*
Find the synonyms of the event keyword to form a set of S of event e
for each $s_i \in S$
  Retrieve all widgets that contain tag e_i
  Store the retrieved widgets into a set W
end
for each $w_i \in W$
  Retrieve all tags associated with w_i
  Reduce the number of the tags by removing stop words
  Store the rest of tags into a set T
end
// Calculate the semantic distance of the relation between each synonym and each tag
for each $s_i \in S$
  for each $t_i \in T$

$$d(s_i, t_j) = \sum_{k=1}^{|W|} \left(p(w_k|s_i) \times log \frac{p(w_k|s_i)}{p(w_k|t_j)} \right) \quad (1)$$

end
end
//calculate the average distance between event s and each tag

$$DA(e, t_j) = \sum_{i=1}^{|S|} \sum_{j=1}^{|T|} p(s_i|t_j) \times d(s_i, t_j) \quad (2)$$

Extract the nine tags with the highest DA scores.

As an example, we assume that a user wants to look for widget on travel. She may input the keyword is 'Travel'. From WordNet, Miller [22], the algorithm receives a set of synonym words of "travel" such as "travelling", "change of location", "locomotion", "go", "move", "locomote", "journey", "trip", "jaunt", and "move around". These words are stored in a set of S. There words are used for retrieving the widgets, the tags of which are also retrieved. The tags with suffix of '-ing', '-s', and '-ed' are considered to be the same tag. The basic idea of Eq.(1) in the algorithm is that the semantic distance between a synonym of an input keyword and a tag is measured by the distributions of their associated widgets. The smaller the distance is, the closer their relation is. The DA value in Eq.(2) quantifies the average degree of a relation between a tag and an event. In other words, the value implies the closeness between user intent for a wedge (an event) and each tag. The user intent is represented as an event, which is described by an input keyword, as well as its synonyms, rather than just the keyword.

Only the top ten tags associated with an event are selected for experiments. The reasons for this are as follows.

- Tackle the problem of overflowing tags for widgets. A number of widgets are attached with too many tags. The use all of the tags in the set T may result in retrieving the widgets that do not have the greatest relevance to the event. As an example, Fig. 1 illustrates a widget with 15 tags that results from issuing an event of “travelling”. Note that we use all 15 tags for this example. It is obvious that the retrieved result is quite different from the user input of an event. This is because the tags have the diverse meanings.
- Reduce the computation time for retrieving widgets. By reducing the size of the set to only ten tags from more than ten thousands will speed up the algorithm.

Fig. 1. An example of a widget with overflowing tags

3.2 Widget Discovery by Ranking

As a list of top tags has been extracted, the next step is to use them to discover widgets. In this process, three schemes are considered. Three schemes assign a different, respect value to a tag for ranking. The three schemes are described as follows:

1. Assign the same value to each top tag, say 1.
2. Assign its calculated DA score to each top tag. This score has been calculated by the proposed algorithm.

3. Assign its ranks to each top tag, i.e., the value depends on its ranking in the list. For instance, if the rank of a tag is 1, its value is 11; the rank 2, the value 10, and so on until the rank is 11(value = 1).

The three schemes follow the same procedure. One of three proposed schemes could be selected as the main one, or all of them would be combined together. This selection depends on experimental evaluation result. The steps of the procedure are as follows:

1. As the value of each tag is available to the system depending on each schemes is used, this first steps is to go through each widget and determined their total tags value. Note that at this stage some widget might not have any value at all, which is considered as being irrelevant to the solution.
2. The system rearranges the list of widgets in descending order starting from the highest value of the total sum to the smallest one.
3. The threshold value is set as 1000, which is used to determine whether a widget is selected in the final list or not. This threshold value is currently set as 1000 to get rid of the widgets that are considered as unpopular, and may not be useful to the social. This could also means that they would not be useful for users.
4. Starting from the top of the list, the system extracts the widgets that have the installation number higher than the threshold number. This step continues until the final list has ten widgets, or all of the widget in the list is empty.
5. The final list of widgets is the combination of all three lists of widgets. To create a final combination of the widgets, the system multiples the widget values as the widget installation number, of which will give out the final widget result. This widget result is used to rank the widgets in order to get the widgets that are mostly useful.

After this procedure, there are in total 30 widgets in the list at the end, whereas the list is in the order of the total tag summation. This list is used in the future at the stage of final widget discovery. Fig. 2 illustrates the method flow.

4 System Design

This section presents the developed system and architecture. This system is implemented as a web application. The system makes use of the widget services from WidgetBox.com. The main objective of the system is automatic in that it can discover services that would match with a user's requirement and tolerance the social adaptability.

4.1 System Flow

There are two main flows in this system: back-end side and front-end side. On the back-end side, the system uses scraped widgets and their information from WidgetBox.com, while the front-end calculates the input information and creates a final widget discovery. Fig. 3 illustrates the flow diagram of the back-end system. Note that this process flow has to be repeated each time when a user enters a keyword. The input of this flow is the keyword entered by the user. In the case of this research, the keyword is 'travelling'. The output of this process is a list of widgets that is the most relevant to the input keyword.

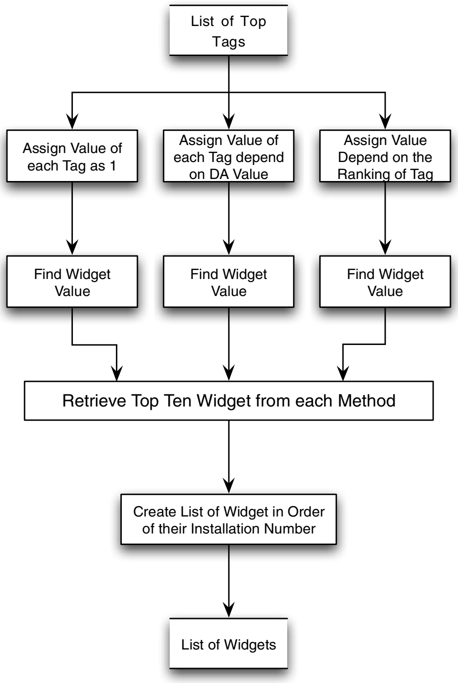

Fig. 2. Calculation schemes of the widget values

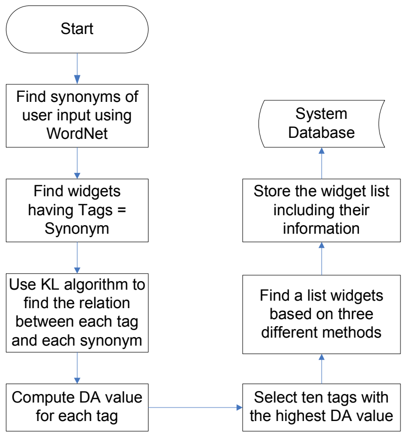

Fig. 3. Flow diagram of the back-end system

4.2 System Interface

Fig. 4 is one of screenshots of the system. The four inputs are as follows:

Event title: the name of an event that a user selects;
Event Type: This is provided by the system currently.
Place: this is the location of a service. As mentioned before, it can be either abstract or specific locations
Party involved: Name of person involving in the event.

After all required information are filled and submitted, the system will generate a list of discovered widgets by running our algorithm and schemes.

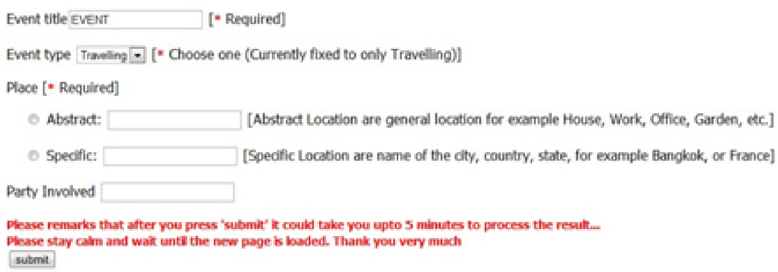

Fig. 4. A screenshot of the system

5 Experimental Results and Discussion

In this section, in terms of retrieved results, we compare our system with the WidgetBox.com system, which is based on the keyword matching discovery.

5.1 Datasets

In this research all of the data is retrieved from WidgetBox.com. The data and information are taken from that website using the scraping technique. The data are retrieved and stored in the database for computing the information and the future references. Table 3 lists the number of data that are used in this research. Note that the number of widgets in this system counts the only widgets that have relations with the input keyword of 'Travelling'.

Table 3. Dataset information

Total # Widgets in Widget-Box.com	# Widgets in Database	# Tags	Average # Tags per Widgets
234, 944	2, 924	29, 748	10.2

5.2 Tag Discovery Results

After following the methodology presented in Section 3, the final result of the tag discovery is a final list of ten tags that have the highest relation values with the input term. From the experiments, the top ten tags can best make use of tags information. More tags make no much difference because they include redundant information. Table 4 displays the result, which is ordered from the most related tag to the least one. Again, the data is generated as a result of the enquiry keyword of 'travelling'.

Table 4. Top 10 tags retrieved

Tag	DA Value
Blog	0.020015
Hotel	0.020577
Culture	0.020877
Vacation	0.021136
Photography	0.0216759
Entertainment	0.0225166
Life	0.0248366
Food	0.0249321
Art	0.0254775
Photo	0.0254775

The list in Table 4 shows that term 'blog' has the strongest relationship with the event 'travelling'. It has to be pointed out that the synonym may exist in the list. As might be noticed, the tag 'Photo' and 'Photography' have the similar meaning and the content is generally the equal. However, the system cannot separate them from each other, on one hand to reduce the affect of ambiguous from the system of trying to detect the word with similar meaning from each. On the other hand, since the objective is to have the system running dynamically it would be more realistic and stick to the tag retrieved dynamically.

5.3 Widget Discovery Results

Table 5 gives 10 widgets that have been retrieved using the tag retrieved and through the widget discovery method. The underlined words in the table are the top tags retrieved.

Table 5. Top 10 widgets retrieved

Widget Name	Tag	Installation	Rating (Out of 5)
Been-Seen: Travel By Design	travel, travel blog, hotel, world, travelling, travels, travel tips, travel photos, blog, blogging, blogosphere, culture, design, entertainment, film, widget, art, blogosphere beenseen, travel by design, writing	7,693	3.5
USA Smarts	learning, geography, usa, quiz, us quiz, blog, community, culture, education, entertainment, marketing, reference, social networks, travel, web20	1,676	4
French Word-A-Day	france, french, language, paris, provence, europe, culture, life in france, european, travel, wordaday, french words, pronunciation, books, food, interests, photography, pictures, writing, widget	4216	4
Forbes.com: Lifestyle	life, travel, art, beauty, celebrities, diet, fashion, fitness, food, home, real estate, shopping, style, sports, trends, women, forbes, interests, info	1,591	5
Britannica Blog	britannica, ideas, blogging, books, culture, entertainment, events, film, internet, leadership, reference, religion, science, social, travel	1,286	1.5
Trip Countdown	college, student, travel, widget, organize, plan, vacation, countdown, clock, uk, us, sta travel, interests, info	20,712	4
Live TV/Radio	live tv, radio, radio stations, worldwide, entertainment, humor, music, online, politics, religion, rss, video, videos, travel, technology, sports, social networks	13,448	3.5
The Bargainist Deals, Sales & Coupons	shopping, deals, bargains, coupons, discount, fashion, food, gadgets, internet, movies, travel, tech, sports, software	13,337	3.5
Trippermap - mapping Flickr	mapstraffic, photo, map, flickr, travel, photos, journey, world, google, earth, maps	2,206	4.5
Been-Seen: Travel By Design	travel, travel blog, hotel, world, travelling, travels, travel tips, travel photos, blog, blogging, blogosphere, culture, design, entertainment, film, widget, art, blogosphere beenseen, travel by design, writing	7,693	3.5

5.4 Comparison

In the current WidgetBox.com system, the widget discovery is based on keyword matching. If a user inputs 'travelling', for example, it would find only the widgets that have the tag travelling. Table 6 reports the comparisons of the information from both systems based on the input of "Travelling".

By comparing the data in the table, our algorithm clearly achieves a better performance. In particular, there are in total 78,416 installations (the number of users) for the proposed algorithm, while there are 8,055 installations in the keyword matching algorithm. Further, the installation average is 7,841.6 installations of the new algorithm, which is almost 10 times that of the keyword matching algorithm. This result clearly reflects the popularity of the widgets in the list. In other words, this reflects that the discovered widgets by the new algorithm capture a way better social popularity.

Table 6. Comparisons between key word matching and our algorithm

Algorithm	**Total Number of Installation**	**Average Number of Installation**	**Total Number of People Rating**	**Average Rating per Widget (Out of 5)**
Keyword Matching Algorithm	8,055	805.5	7	1.45
Our Algorithm	78,416	7,841.6	121	3.75

Moreover, the number of user ratings on the widgets retrieved by the new algorithm is 121, which is much higher than 7 by the keyword algorithm. The higher number indicates that the number of users participating in rating the widgets is higher. In other words, the widgets discovered by the proposed algorithm are more popular among users than those by the keyword algorithm.

In Table 6, the average rating of the tag relation algorithm is 3.75 out of 5, which is more than 3 times higher than that of the keyword algorithm. This validates that not only there are more participants, but also users are more satisfied with the widgets retrieved by the tag relation algorithm.

From the above comparison, it could be concluded that the retrieved widgets using the tag relation algorithm is better than those using the keyword algorithm.

6 Conclusion and Future Work

This paper has presented an overview on the use of social tagging in discovering contents and services. A new system that retrieves and ranks widgets from the Widget domain has been described. The proposed algorithm implemented in the system is able to rank the most relevant tags to a user query, and then to retrieve the best widgets. Together with the algorithm, a metric has been presented that quantifies the relation between user intent and the tags associated with widgets. By comparing with the keyword matching algorithm, our system has demonstrated its accuracy and efficiency. For the future work, we plan to test the quality of tags associated with widgets in order to make better recommendation to users.

Acknowledgment. Our sincere thanks to Mr. Anupong Muttaraid for his efforts on the system implementation.

References

1. Newcomer, E.: Understanding Web Services: XML, WSDL, SOAP, and UDDI. Addison Wesley, Boston (2002)
2. Martin, D., et al.: OWL-S: Semantic Markup for Web Services. W3C member submission, `http://www.w3.org/Submission/OWL-S/`
3. Akkiraju, R., et al.: Web Service Semantics - WSDL-S, W3C Member Submission, `http://www.w3.org/Submission/WSDL-S/`
4. Bruijn, J.D., et al.: Web Service Modeling Ontology (WSMO). W3C Member Submission, `http://www.w3.org/Submission/WSMO/`
5. Bouillet, E., Feblowitz, M., Feng, H., Liu, Z., Ranganathan, A., Riabov, A.: A Folksonomy-Based Model of Web Services for Discovery and Automatic Composition. In: Proc. IEEE International Conference on Services Computing (SCC 2008), pp. 389–396. IEEE Press (July 2008), doi:10.1109/SCC.2008.77
6. Wal, T.V.: Folksonomy. Online Information. London, UK (2005)
7. Zhou, M., Bao, S., Wu, X., Yu, Y.: An Unsupervised Model for Exploring Hierarchical Semantics from Social Annotations. In: Aberer, K., Choi, K.-S., Noy, N., Allemang, D., Lee, K.-I., Nixon, L.J.B., Golbeck, J., Mika, P., Maynard, D., Mizoguchi, R., Schreiber, G., Cudré-Mauroux, P. (eds.) ASWC 2007 and ISWC 2007. LNCS, vol. 4825, pp. 680–693. Springer, Heidelberg (2007)
8. Chukmol, U., Benharkat, A.-N., Amghar, Y.: "Enhancing Web Service Discovery by using Collaborative Tagging System. In: Proc. 4th International Conference on Next Generation Web Services Practices (NWESP 2008), pp. 54–59. IEEE Press (October 2008), doi:10.1109/NWeSP.2008.29
9. Aurnhammer, M., Hanappe, P., Steels, L.: Augmenting Navigation for Collaborative Tagging with Emergent Semantics. In: Cruz, I., Decker, S., Allemang, D., Preist, C., Schwabe, D., Mika, P., Uschold, M., Aroyo, L.M. (eds.) ISWC 2006. LNCS, vol. 4273, pp. 58–71. Springer, Heidelberg (2006)
10. Dubinko, M., Kumar, R., Magnani, J., Novak, J., Raghavan, P., Tomkins, A.: Visualizing tags over time. ACM Transactions on the Web (TWEB) 1(2) (August 2007)
11. Wu, X., Zhang, L., Yu, Y.: Exploring social annotations for the semantic web. In: Proc. 15th International Conference on World Wide Web (WWW 2006). ACM Press (2006), doi:10.1145/1135777.1135839
12. Li, R., Bao, S., Yu, Y., Fei, B., Su, Z.: Towards effective browsing of large scale social annotations. In: Proc. 16th International Conference on World Wide Web (WWW 2007), ACM Press (2007), doi:10.1145/1242572.1242700
13. Ding, Z., Lei, D., Yan, J., Bin, Z., Lun, A.: A Web Service Discovery Method Based on Tag. In: Proc. International Conference on Complex, Intelligent and Software Intensive Systems (CISIS 2010), pp. 404–408. IEEE Press (February 2010), doi:10.1109/CISIS.2010.18
14. Bouillet, E., Feblowitz, M., Liu, Z., Ranganathan, A., Riabov, A.: A Faceted Requirements-Driven Approach to Service Design and Composition. In: Proc. IEEE International Conference on Web Services (ICWS 2008), pp. 369–376. IEEE Press (September 2008), doi:10.1109/ICWS.2008.117

15. Liu, X., Huang, G., Mei, H.: A User-Oriented Approach to Automated Service Composition. In: Proc. IEEE International Conference on Web Services (ICWS 2008), pp. 773–776. IEEE Press (September 2008), doi:10.1109/ICWS.2008.139
16. Liu, X., Zhao, Q., Huang, G., Mei, H., Teng, T.: Composing Data-Driven Service Mashups with Tag-Based Semantic Annotations. In: Proc. IEEE International Conference on Web Services (ICWS 2011), pp. 243–250. IEEE Press (2011), doi:10.1109/ICWS.2011.31
17. Gomadam, K., Ranabahu, A., Nagarajan, M., Sheth, A.P., Verma, K.: A Faceted Classification Based Approach to Search and RankWeb APIs. In: Proc. IEEE International Conference on Web Services (ICWS 2008), pp. 177–184. IEEE Press (September 2008), doi:10.1109/ICWS.2008.105
18. Arabshian, K.: A Framework for Personalized Context-Aware Search of Ontology-Based Tagged Data. In: Proc. IEEE International Conference on Services Computing (SCC 2010), pp. 649–650. IEEE Press (July 2010), doi:10.1109/SCC.2010.73
19. Miller, G.A.: WordNet: a lexical database for English. Communications of the ACM 38(1) (November 1995)
20. Case, D.O.: Looking for information: A survey of research on information seeking, needs, and behavior, 350 p. Academic Press, Amsterdam (2012)