Uncertainty Analysis For The Keyword System Of Web Events

B.Viswanath[1], Dr.M.Sreedevi[2] M.C.A,M.Phil,Ph.D.
[1] Student, Dept of Computer Science,SVU College of CM&CS,S. V.University,TIRUPATI,A.P.
[2]Assistant Professor, Dept of Computer Science, SVU College of CM&CS,S.V.University,TIRUPATI,A.P.

Abstract- *Webpage recommendations for hot Web events can assist people to easily follow the evolution of these Web events. At the same time, there are different levels of semantic uncertainty underlying the amount of Webpages for a Web event, such as recapitulative information and detailed information. Apparently, the grasp of the semantic uncertainty of Web events could improve the satisfactoriness of Webpage recommendations. However, traditional hit-rate-based or clustering-based Webpage recommendation methods have overlooked these different levels of semantic uncertainty. In this paper, we propose a framework to identify the different underlying levels of semantic uncertainty in terms of Web events, and then utilize these for Webpage recommendations. Our idea is to consider a Web event as a system composed of different keywords, and the uncertainty of this keyword system is related to the uncertainty of the particular Web event. Based on keyword association linked etwork Web event representation and Shannon entropy, we identify the different levels of semantic uncertainty, and construct a semantic pyramid (SP) to express the uncertainty hierarchy of a Web event. Finally, an SP-based Webpage recommendation system is developed. Experiments show that the proposed algorithm can significantly capture the different levels of the semantic uncertainties of Web events and it can be applied to Webpage recommendations.*

Keywords- Social event, uncertainty analysis, Web event, Web mining, Webpage recommendation.

I. INTRODUCTION

AWEB event could be a hot story or a social activity which attracts broad attention on the Web and there could be an extraordinary number of Webpages covering this Web event. For example, the Libya War (in 2011) is a Web event with thousands of Webpages, blogs, and posts. The large scale of Webpages makes it impossible for users to grasp the evolution of a Web event through manually surfing these Webpages.

Current researches on Web events mainly focus on detecting them from the amount of Webpages [1]–[5] and do the automatic summarization by selecting appropriate sentences [6]–[8]. In this paper, we focus on the uncertainty analysis of the Web events and its application to Webpage recommendations. Uncertainty is a big concept which is used to encompass many subconcepts [9], [10]. According to different sources, uncertainty is categorized as epistemic uncertainty [11], linguistic uncertainty [12], decision uncertainty [13], and variability uncertainty [14]. Of these, variability uncertainty refers to the diversity or heterogeneity of knowledge [10]. Uncertainty analysis is first defined as a process to quantify the uncertainty of a risk estimate and estimate the effect of this uncertainty on the outcomes [9], [10]. In this paper, there are many methods proposed for uncertainty analysis. For example, analytical methods include delta method [15] and point estimation method [16]; probabilistic methods include Monte Carlo simulation [17] and probability bounds/boxes [18]; graphical methods include Bayesian networks [19] and loop analysis [20]; and fuzzy methods include fuzzy set [21] and fuzzy cognitive maps [22]. To the best of our knowledge, there have not been any works proposed for the uncertainty analysis of Web events. A Web event also has its semantic uncertainty. A Web event can be considered as a system composed of different keywords, and this keyword system, like other systems, has its own uncertainty. In this paper, the uncertainty of the keyword system is seen as the uncertainty (a kind of variability uncertainty) of this Web event. This uncertainty is the measurement of the states of keyword systems which is the relative weights of different subtopics of a Web event. For example, on March 20, 2011, the Web event Libya War has two subtopics: 1) Chinese stock market and 2) military attack. If they have similar weights in this Web event, which may be expressed by the same number of Webpages or same number of audiences, this Web event is not certain. If they have different weights in this Web event, which may be expressed by the different number of Webpages or different number of audiences, this Web event is more certain than the former case. Since this uncertainty is a measure of the keyword system of a Web event and keywords are the basic semantic atoms of a Web event, it can also be called a semantic uncertainty. Note that the Web event can be seen as a topic, like Libya War, and this Web event/topic may have some subtopics. Although there are many works on Webpage recommendations, the semantic uncertainty of Web events is seldom considered. The literature of Webpage recommendations can be roughly classified into two categories:

1) Noncontent based methods and
2) content-based methods.

For noncontent based methods, the rating-based recommendations rely on the Webpage-user ratings [23] that come from the user feedback. However, it is impractical to collect the feedback for Webpages of Web events. Other methods, such as association rules [24] and Markov models [25], focus on capturing the sequential relations from the scanning/session history. These noncontent based methods do not consider the content of Webpages. For the content-based methods, the texts of Webpages are represented as vectors by VSM [26]. The recommendation is based on the matching between the user profiles and the Webpages. Some other clustering-based methods [27] and ontology-enhanced methods [28] are used to improve performance. The problem is that ontology is difficult to construct from the dramatically evolving Web events and the clustering is not enough. Therefore, it would be better to incorporate more analysis of the contents of Web events. The uncertainty analysis for a Web event can assist Websites to recommend appropriate Webpages of Web events to their visitors. Through the uncertainty analysis of the keyword system of a Web event, we can unveil which parts of the contents of a Web event are active and attractive. For example, as mentioned above, there are about 7000 Webpages covering the Libya War in a simplified Chinese Web environment in one day. In order to know what this event, it is difficult and impractical for a user to read all of these Webpages. There are two kinds of information in these Webpages. 1) One is the certain part information, which will not change drastically with the evolution of a Web event and can serve to provide the main content of the Web event. For example, Libya, antigovernment, and armed conflict will exist in Webpages most of time. 2) The other is the uncertain part information, which will markedly change with the evolution of a Web event and will provide more details about the Web event. For example, stock and economy only exist in Webpages for a limited amount of time. For the past Web events, we can easily distinguish certain and uncertain information through statistics. But, for a currently ongoing Web event, we can only predict it by current data alone, especially in the initial stage. Thus, we need to do the uncertainty analysis for the Web events based on their content. The current problem is how to define and perform the uncertainty analysis for Web events, and how to apply this uncertainty analysis to the Webpage recommendations for Web events.

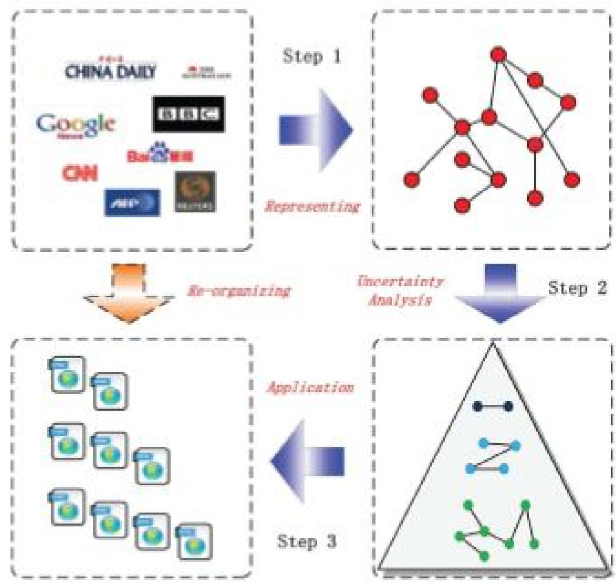


Fig. 1. Proposed method and framework of this paper. At first, the original Webpages about a Web event are collected, which may come from different sources, e.g., China Daily, BBC, and Google news. Second, a flat KALN is constructed as the computational model for preserving the semantics of this Web event. Then, an SP is constructed for the uncertainty analysis. Finally, according to the mapping relations between Webpages and keywords, the Webpages with different uncertainties are recommended to the users.

II. FLAT KALN MINING AND UNCERTAINTY MEASURING

In this section, we will introduce step 1 in Fig. 1 in detail, where a basic flat keyword network representation for the Web events is proposed and constructed. Suppose we have a collection of Webpages about a Web event, e, which could come from news Websites, blogs, or forums. In this paper, this Web event at a given time, t, is represented as follows.

Definition 1 (KALN):
A KALN, , which is composed of the keywords (as nodes) and their association relations (as links) between keywords, is defined as KALNe t =Se k,t,Se r,t

(1) where Se k,t is the keyword set of Web event, e, and Se r,t is the association relation set of keywords at time, t, which are both extracted from the Webpages of this event at time t.

A. KALN Construction Given a collection of Webpages about an event at a given time, t, by utilizing existing keyword extraction algorithms (i.e., term frequency (TF) and inverse DF [30]), we can get the nodes (keywords) of KALN from this data set. Once the nodes are fixed, the next step is to link these nodes by extracting the association rules between them. There are many state-of-theart works on this subject. Since they are not the main concern of this paper, we will just select the Apriori algorithm [31] to get the association rules from the Webpages. Association rule/relation mining is a basic task of data mining and text mining. In the Apriori algorithm [31], there are two weights given to each associated relation, like “nuclear − > radiation,” including support and confidence. Finally, we connect keywords together by association rules to form the KALN. Apparently, the more precise the keywords and the association rule extraction algorithms are, the better the event is described, and the KALN can express more about the real semantic uncertainty of an event. Before the uncertainty analysis of Web events, it is necessary to have a deep understanding of their representation KALN. A KALN is an expression of an event’s semantics at a given time, which is composed of the keywords and association relations between them. Some other models or methods choose the distribution of keywords in the Webpages to represent Web events. In fact, not only the keywords but also their association relations should be considered in describing an event, because they are both basic semantic elements of an event and they almost play the same role on the semantic expression of Web events. The reason why we call the constructed KALN as flat KALN is because we do not identify the uncertainty hierarchy in this section. With the above definition in hand, we can consider the evolution of a Web event as the variations of the KALN. Meanwhile, the semantics with different uncertainty hidden in these Webpages can preserve more than the model which only considers keywords, because the association relations of keywords are considered here. Finally, the different level semantic uncertainty of KALN at a given time can be identified.

$$I_j = \alpha_j \Big/ \sum_{i \in S(\mathrm{KALN})} \alpha_i$$

B. Using Entropy as Frame to Measure Uncertainty of KALN The entropy has been used to measure the uncertainty of a system. Here, we consider KALN as a system composed of keywords with different properties. Actually, a keyword in KALN has many different properties, such as TF, DF, and node degree (ND). It should be noted that the association relations between keywords (i.e., network structure) can also be reflected by properties of keywords through the structure of a KALN. For example, the ND can reflect the network structure of KALN. We combine the different properties (i.e., TF, DF, and ND) of keywords together to generate a new property for reflecting all the properties simultaneously. This combined property is defined as follows.

III. THREE STRATEGIES TO OBTAIN KEYWORD WEIGHT

As discussed in the previous section, the semantic uncertainty of Web events is defined by the keyword distribution entropy, which is determined by the values of the keywords’ weights. Apparently, different keyword weight computation strategies will lead to different keyword distributions and then lead to different keyword distribution entropies. In this section, three different strategies, which have taken various properties of keywords into consideration, are designed to compute the weights of keywords. This section is for step 2 in Fig. 1, where the hierarchy of the keywords is identified in order to consider the properties of keywords.

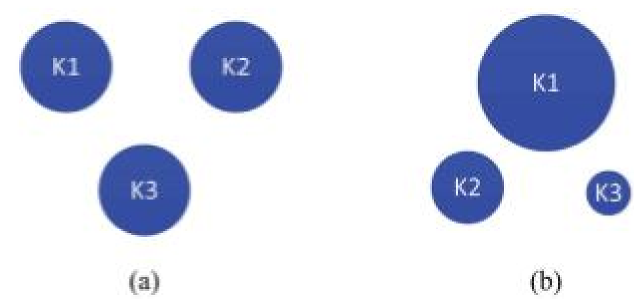


Fig. 2. Schematic of the ratio of DF of keywords in order to express the semantic uncertainty of a Web event. Two graphs/KALNs in this figure represent two statuses of a Web event. Each circle in the graph represents a keyword in a KALN, and the circle size denotes the value of DF of a keyword. (b) Right KALN is more certain than the (a) left one.

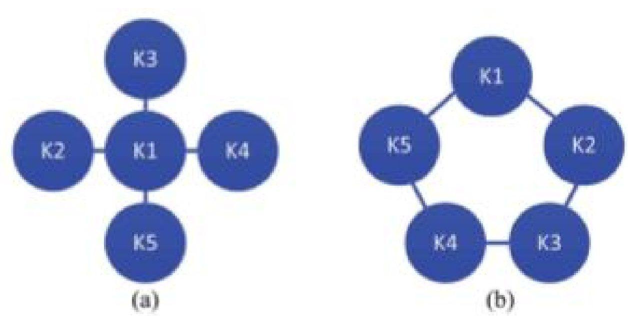


Fig. 3. Schematic of the function of ND in order to express the semantic uncertainty of Web events. Two networks/KALNs in this figure represent two statuses of a Web event. Each circle

in the graph represents a keyword in a KALN. (a) Left one is more certain than the (b) right one.

$$I_j = \frac{1}{2}\left(\frac{\alpha_j}{\sum_{i\in S(\mathrm{KALN})}\alpha_i} + \frac{\beta_j}{\sum_{i\in S(\mathrm{KALN})}\beta_i}\right)$$

After removing a keyword k, the degree log–log curve will change due to the missing of keyword k. Then, we refit a straight line for degree log–log curve, and re-evaluate the fitting error, errnew. Finally, the PLC of keyword k is PLCk =|err−errnew.

$$I_j = \frac{1}{2}\left(\frac{\alpha_j}{\sum_{i\in S(\mathrm{KALN})}\alpha_i} + \frac{\gamma_j}{\sum_{i\in S(\mathrm{KALN})}\gamma_i}\right)$$

where γj is the PLC of keyword j and i∈S(KALN) γi is the summation of PLC of all keywords. The formula of (6) is used to make sure that pj is a probability (pj =1). The DF and the PLC are set to have the same status in the equation here. The aim of PLC is similar with ND, and the keyword with a big ND tends to have a big PLC, too. But there are significant differences between these two measurements of network structural information. At the theoretical level, the PLC, which considers the global network structure, is from the node/keyword contribution of the KALNs power-law distribution, but ND, which considers the local network structure, is from the degree of the node/keyword. At the computational level, the PLC computation not only has a relation with the degree of the keyword, the degrees of neighbors are also considered. The keyword with a big degree does not definitely have big PLC, and vice versa.

D. Measurement of Influence of Each Keyword to KALN Entropy

After three different strategies of computing the weight of keywords are introduced, we can utilize the keyword distribution entropy, HKALN, to evaluate the influence of each keyword to the KALN entropy (i.e., the semantic uncertainty of Web events). In order to do that, a procedure is designed to increase the number of keyword in KALN (i.e., the value of KALN entropy) one by one with the keyword weight in descending order. Then, a series of entropy values of KALNs with a different number of keywords is obtained and forms a curve.

Algorithm 2 Compute KALN Entropy With a Given Keyword Input:

keyword set,Sk assigning each A keyword a weight value, Ij, by Eq. (3), (4) or (6) Output: The values of keywords' influences to the KALN entropy

1. Initial an empty KALN without keywords
2. while Sk is not empty do
3. Select the keyword with maximum Ij from Sk to add into KALN
4. Remove this keyword from Sk
5. Compute the entropy, Hi, of KALN by Eq. (2)
6. end while
7. Finally, we get < H0,H1,...,Hn >.

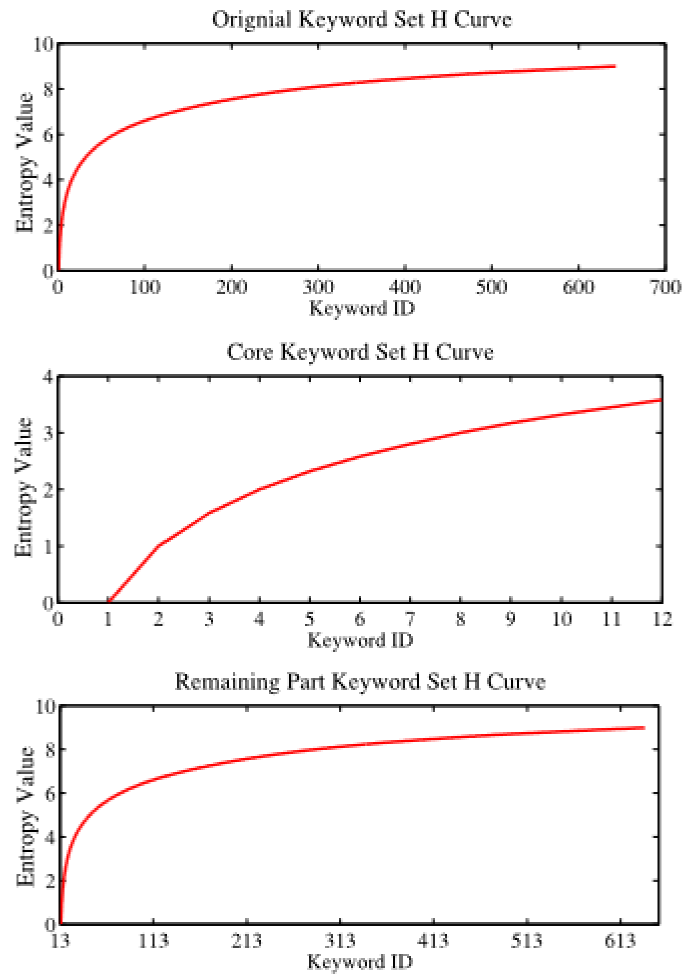
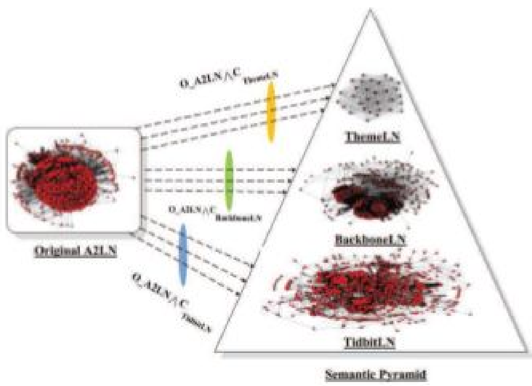


Fig. 4. Entropy values with the variation of the keyword set of KALN with the first strategy. The new keyword is added into the keyword set in the descending order of DF. The contribution of a keyword to the semantic uncertainty is reflected by the change of entropy value after a keyword is added into KALN.

IV. SEMANTIC PYRAMID OF WEB EVENTS

This section is for step 2 in Fig. 1, where three layers of keywords are recognized from the flat keyword network.

We first analyze the hierarchical property of KALN through the entropy value curve constructed in the previous section. Then, the SP of a Web event is constructed and discussed to express the hierarchical uncertainty of this Web event. How to utilize this pyramid will be given in the next section.



A. Fig. 5. Mined SP from the flat KALN. The left part network is flat KALN. In the right part SP, three networks are theme layer network, backbone layer network, and tidbit layer network from top to bottom (Web event: Japan earthquake, date: March 9, 2011, using first strategy).

At first, we get two split points for division

$$\vartheta_{p1} = \frac{\sum_{i \in S_k^{\mathrm{KALN}}} \vartheta_i}{N^{\mathrm{KALN}}}$$

$$\vartheta_{p2} = \frac{\sum_{i \in S_k^{\mathrm{KALN}'}} \vartheta_i}{N^{\mathrm{KALN}'}}$$

Definition 4 (Theme Layer KALN, I):
The theme layer KALN comprises the keywords, which satisfy the condition that ϑ is bigger than ϑp1, and the association rules between them. This layer network is the core of the flat KALN. It expresses what this KALN or this event is referring to and has less semantic variation over time.

TABLE I
COMPLEX NETWORK PARAMETERS OF THREE LAYER NETWORKS (WEB EVENT: JAPAN EARTHQUAKE, DATE: MARCH 9, 2011, USING FIRST STRATEGY)

Parameters	KALN		
	Theme	**Backbone**	**Tidbit**
Number of nodes	12	48	584
Number of arcs	128	986	5346
Density	0.97	0.437	0.016
Average Degree	10.667	20.542	9.154
Clustering Coefficient	0.973	0.756	0.825
Mean Distance	1.03	1.661	3.325
Diameter	2	4	8

Definition 5 (Backbone Layer KALN, II):
The backbone layer KALN comprises the keywords, which satisfy the condition that ϑ is smaller than ϑp2 and bigger than ϑp1, and the association rules between them. This layer network is the backbone of the flat KALN.

Fig. 6. Main page of Google News. There are a number of Web events with hyperlinks to the recommended Webpages. These Webpages are the most representative and should express the main content of each Web event well.

V. SEMANTIC PYRAMID-BASED WEBPAGE RECOMMENDATION

This section corresponds to step 3 in Fig. 1, where the recognized hierarchical keyword network is applied for Webpage recommendations. For a user who wants to follow a Web event, it will be impossible to read all the related Webpages about this Web event owing to the huge number of Webpages emerging each day. Fortunately in this paper, an SP has been constructed from these Webpages to represent and organize all the semantics of a Web event on a given time. It can be viewed as a mental structure constructed after the reading of all the Webpages by a human.

A Most Certain Webpages Recommendation Based on Theme-Level KALN

For a user who just starts to focus on a Web event, the most certain Webpages will enable them in order to quickly grasp the main semantics of this Web event.

B. Most Uncertain Webpages Recommendation Based on Backbone Level KALN

For the continuously updated Web events, the users who have been following these Web events just want to know the information that is more uncertain and which has a large potential to cause the evolutions of Web events. For our SP, this means the Webpages contain the keywords in the tidbit level KALN. A criterion is proposed for a Webpage.

C. Directional Webpages Recommendation Based on Tidbit Level KALN

Some users just want to know a specific aspect about a Web event, and the correlated Webpages should be carefully selected to recommend to them. Normally, this specific aspect is in the second or third level KALN of SP

$$D(w) = \frac{\sum_{k_i \in w \cap K} w_{k_i}}{\sum_{n=I,II and III} \left(\sum_{k_i \notin K and k_i \in \Omega^n \cap w} \rho^n \cdot I_i \right)}$$

where D(w) is the correlation of a Webpage w to the desired keyword set, K, ki∈w∩K wki denotes the matching degree of w to K, ki, and the denominator is for removing the undesired information from w. ρn are the coefficients of three levels in [0,1].

VI. EXPERIMENT AND EVALUATION

1) Dateset 1:

It is the Webpages of Web event Japan earthquake (in 2011) from March 9, 2011 to April 20, 2011. The number of Webpages is 6884. All these Webpages are collected from search engines, including www.Google.com.hk and www.Baidu.com (the biggest search engine in China), regardless of the sources of these Webpages.

2) Dateset 2:

It is also the Webpages of Web event Japan earthquake (in 2011) from March 9, 2011 to April20, 2011, but these Webpages are collected using the source (i.e., news Websites, blogs, and forums)interface provided by www.Google.com.hk. The numbers are 3059 (from news Websites), 4533 (from blogs), and 3535 (from forums).

For example, at the start point, the keyword set of before is null and the keyword set of "future" is universal set. At the end point, the keyword set of before is universal set but the keyword set of future is null. As for the curves, this will lead to being relatively big in the middle and small at the ends of the curves. But it does not impact the comparison of different layer networks and different sources.

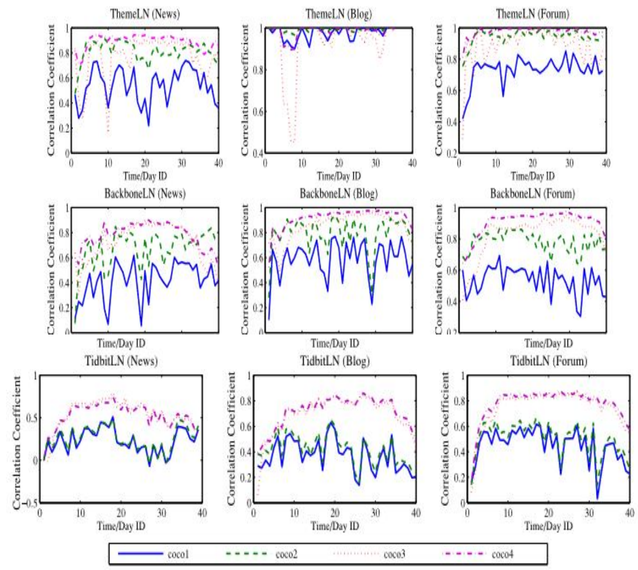


Fig. 7. Four correlation coefficients of three layers KALN, including ThemeLN, BackboneLN, and TidbitLN. It can be found that four evaluation metrics have relatively similar trends. The variation range of the ThemeLN is the smallest in these three layers. The TidbitLN's variation range is the biggest. This suggests that ThemeLN's semantics is the most stable one, TidbitLN's semantics is the most unstable one and BackboneLN's semantics is the medium one. In the evolution process, the different layer networks show different behaviors.

TABLE II
FOUR CORRELATION OF THREE LAYERS KALN (WEB EVENT NUMBER: 50, AVERAGE LENGTH: 30 DAYS, WEBPAGES NUMBER: 202 673, USING FIRST STRATEGY)

Sources	news			blog			forum		
Layers	ThemeLN	BackboneLN	TidbitLN	ThemeLN	BackboneLN	TidbitLN	ThemeLN	BackboneLN	TidbitLN
COCO1	0.47	0.53	0.13	0.92	0.55	0.35	0.7	0.48	0.35
COCO2	0.71	0.65	0.20	0.97	0.68	0.4	0.92	0.72	0.40
COCO3	0.54	0.59	0.53	0.79	0.63	0.6	0.81	0.61	0.67
COCO4	0.80	0.74	0.54	0.9	0.85	0.62	0.85	0.81	0.71

Different strategies can form different SPs. In order to compare the performances of three strategies, an evaluation metric is introduced according to the definitions of three layers KALN and their uncertainty properties.

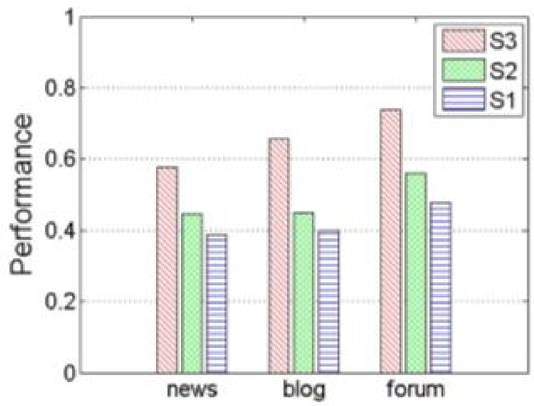


Fig. 8. Performance comparisons of three strategies on different sources, including news, blog, and forum. S1–S3 stand for Strategies I–III, respectively. In all the sources (news, blog, and forum), Strategy III outweighs the other two strategies (Web event number: 50, average length: 30 days, Webpage number: 202673).

In the below diagram, to help people to understand a Web event. Some screenshots are listed at the end of this paper, in Figs. 9–12. The Web address is http://iic.shu.edu.cn:20/webevent (please make sure the Web browser can access on port 20, and IE Web browser is recommended). There are two dimensions on the screen. The vertical one is to control the semantic level and the horizontal one is to control the time stamp. The nodes have been selected by humans at each level, because all the nodes cannot be shown in the screen, especially the third level (TidbitLN) in which there are around 1000 nodes. Furthermore, there is no need to exhibit all the keywords, because they will only confuse people rather than enlighten them. So, at the second and third levels, we select a limited number of nodes from the corresponding layer KALN to show the semantic uncertainty.

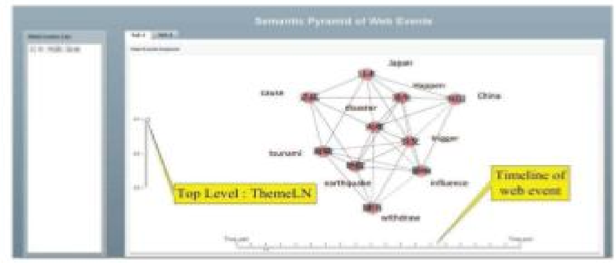


Fig. 9. Mined SP of Web event on ThemeLN (event: Japan earthquake). This level is the most stable one and will not change much with time (slider bar of time at the bottom of the figure).

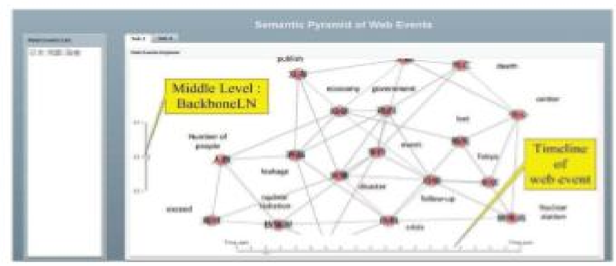


Fig. 10. Mined SP of Web event on BackboneLN (event: Japan earthquake). This level is the medium one.

of those levels and to assist people to understand the semantic uncertainty of a Web event. The analyzed Web event in this Web service is Japan earthquake, from March 9, 2011 to March 29, 2011. With the help of this demo, people can form a general and hierarchical to understand about this web event.

VII. CONCLUSION

A Web event has different levels of semantic uncertainty. If we know about these levels, we can provide different levels of information to people with different requirements. In this paper, we have proposed a content-based Web event representation (KALN) for preserving the semantics of Web events as much as possible. As opposed to the traditional representation methods, the KALN has considered not only the keywords of Web events, but also the more important association relations between them, which can preserve more of the semantics of Web events. We have also proposed three strategies, including the volume property (DF), local structural information (ND), and global structural information (PLC), to identify the different levels of semantic uncertainty. We have found that the strategy that considers both the DF of a keyword and the global network structure of KALN has the best ability to identify the semantic uncertainty levels. Experimental results show that the identified different levels of the semantics display different behaviors over time, so the mined SP can well exhibit the different level semantic uncertainty of Web events. Finally, the demo shows the possible usage of this paper.

There are several interesting research points for further study based on this paper. First, the dynamics between two consecutive time stamps can be measured through complex network metrics. Second, the patterns of different Web events may be different, and these can be mined based on our existing work. Third, challenging prediction work can be done. Finally, server supports may also be considered [37]–[39]. Through semantic analyzing and tracking a Web event,the maximum possible status of this event.

REFERENCES

[1] T. Brants, F. Chen, and A. Farahat, "A system for new event detection," in Proc. 26th Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, Toronto, ON, Canada, 2003, pp. 330–337.

[2] F. Can et al., "New event detection and topic tracking in Turkish," J. Amer. Soc. Inf. Sci. Technol., vol. 61, no. 4, pp. 802–819, Apr. 2010.

[3] M. Gomez Rodriguez, J. Leskovec, and A. Krause, "Inferring networks of diffusion and influence," in Proc. 16th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min., Washington, DC, USA, 2010, pp. 1019–1028.

[4] G. Kumaran and J. Allan, "Text classification and named entities for new event detection," in Proc. 27th Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, Sheffield, U.K., 2004, pp. 297–304.

[5] J. Leskovec, L. Backstrom, and J. Kleinberg, "Meme-tracking and the dynamics of the news cycle," in Proc. 15th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min., Paris, France, 2009, pp. 497–506.

[6] T. Iwata, T. Yamada, Y. Sakurai, and N. Ueda, "Sequential modeling of topic dynamics with multiple timescales," ACM Trans. Knowl. Disc. Data, vol. 5, no. 4, Feb. 2012, Art. ID 19.

[7] Q. Mei and C. Zhai, "Discovering evolutionary theme patterns from text: An exploration of temporal text mining," in Proc. 11th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min., Chicago, IL, USA, 2005, pp. 198–207.

[8] S. Morinaga and K. Yamanishi, "Tracking dynamics of topic trends using a finite mixture model," in Proc. 10th ACM SIGKDD Int. Conf. Knowl. Disc. Data Min., Seattle, WA, USA, 2004, pp. 811–816.

[9] M. G. Morgan and M. Small, Uncertainty: A Guide to Dealing With Uncertainty in Quantitative Risk and Policy Analysis. New York, NY, USA: Cambridge Univ. Press, 1992.

[10] K. Hayes, "Uncertainty and uncertainty analysis methods," Aust. Centre Excellence Risk Assess. (ACERA) Project A 705, Tech Rep. EP102467, 2011.

<u>AUTHOR'S PROFILE:-</u>

B.VISWANATH, received Bachelor of Science (computers) Degree From Sri Srinivasa Degree College Affiliated to Sri venkateswara University, Tirupati in the year of 2012-2015. Pursuing Master of Computer Applications from Sri Venkateswara University, Tirupati in the year of 2015-2018. Research interest in the field of Computer Science in the area of cloud computing ,Data Mining, Neural Networks and Artificial intelligence.

Email:vishwavissu95@gmail.com

Dr. M. Sreedevi M.C.A, M.Phil, Ph.D., is working as a Assistant Professor, Department of Computer science, Sri Venkateswara Univesity College of Commerce Management and Computer Science, Tirupati , A.P. , INDIA. She is presented papers and attended international conferences in India and around Asia. Her areas of interest are Ecommerce, Network security, cloud computing and data mining.

Email: msreedevisvdc@gmail.com