Ranking Ontologies Based on Formal Concept Analysis

Jianghua Li*[1, 2]
1 School of Information and Engineering, Jiangxi University of Science and Technology, Ganzhou, Jiangxi, China
Email: jxsimil@hotmail.com

Peng Shi[2]
2 National Center for Materials Service Safety, University of Science and Technology Beijing, Beijing, China
Email: pshi@ustb.edu.cn

Mingzhi Cheng[3, 4]
3 College of Information Engineering, Beijing Institute of Graphic Communication, Beijing, China
4 National Engineering Laboratory for Disaster Backup and Recovery, Beijing, China
Email: chengmz@bigc.edu.cn

***Abstract*—Ontology ranking is one of the important functions of ontology search engine and plays an important role for ontology reuse. It facilitates effectively user to choose the reusable ontologies from the search results returned by ontology search engine. The current ontology ranking methods can not satisfy user because of various defects. On the basis of analyzing the existing ontology ranking methods, we think both the correlation among the ontologies and the matches between the query and ontologies should fully be considered on ranking ontologies. An ontology ranking method is proposed based on Formal Concept Analysis in this paper. The experimental results show that the proposed method is better than that of hyperlink analysis and content analysis. Ontology search engines will get benefit from our method because if can also help user to choose efficiently suitable ontologies to reuse.**

***Index Terms*—ontology ranking, Formal Concept Analysis, correlation, concept lattice**

I. INTRODUCTION

Ontology is a formal explicit specification of shared conceptualization [1]. The definition means that ontology is conceptualized, explicit, formalized and shared. Its aim is to provide a common understanding of domain knowledge. This is realized by specifying shared vocabulary and taxonomy which models a domain with the definition of objects/concepts, as well as their attributes and relations. Since ontology was put forward, it has been widely and successfully used in knowledge sharing, software reuse, digital library, information retrieval, data integration and other fields. Ontology has been proved to be the backbone of domain knowledge description and the Semantic Web [2].

More and more applications need ontology to realize knowledge sharing and reusing to improve the abilities of system communication, interoperability and automatic processing. The traditional artificial construction of ontology is a time-consuming labor process, at the same time, more and more ontologies have been published on the Internet. Obviously, it is an efficient solution to search suitable ontology from the Web and reuse it by extending, refining and pruning according to specific application demands. For this purpose, several ontology libraries [3-8] and ontology search engines [7-15] have been developed by some researchers and organizations, as well as some prototype systems [16-19]. Nevertheless, ontology search is encountering the same problem as Web document search, namely ontology ranking. Generally, when a query is submitted to an ontology search engine, the result returned is a set of ontologies meeting the query. To facilitate users choosing desirable ontologies, the ontology search engine should have the function to rank ontologies. But what kind of strategy and method should be applied to ontology ranking is a problem to be solved.

The rest of the paper is organized as follows. Section 2 is dedicated to the related work of ontology ranking, as well as the challenges of ontology ranking method and our motivation. Section 3 introduces the basic principle on FCA and elaborates the proposed ontology ranking method. The experiments and evaluation are presented in Section 4. Finally, Section 5 gives some conclusions and future work.

II. RELATED WORK

At present, several methods to rank ontologies have been proposed, which can be classified roughly as follows.

Ranking method based on link analysis is proposed in Swoogle [7], OntoKhoj [8] and [19]. Three kinds of link relations between ontologies are discussed as follows in Swoogle. One is extension relation held between two ontologies when one defines a term using terms defined by another. The other is use-term relation held between two ontologies when one uses a term defined by another. The third is import relation held when one ontology imports directly or transitively another. With the ontology ranking method similar to PageRank, an ontology is

doi:10.4304/jcp.9.1.215-221

thought more important than another if the ontology has more inlink and outlink with other ontologies than another. Compared to Swoogle, the link relations in OntoKhoj are much simpler, and the ranking algorithm proposed in [19] is based on HITS.

Ranking method based on content analysis is proposed in [20] by Jones. It is done according to how many of the concept labels in those ontologies match the terms in the query. The matched concept labels include classes, literals, and comments in ontology.

Ranking method based on concept structure is proposed in AKTIVERANK [15]. The number of the matched classes and their position structure characteristics in ontology is thought to be able to represent its importance. AKTiveRank applies four types of assessments for each ontology to measure the rankings. They are Class Match Measure (CMM), Density Measure (DEM), Semantic Similarity Measure (SSM) and Betweenness Measure (BEM). Each ontology is examined separately. Once those measures are all calculated for ontology, the resulting values will be merged to produce the total rank for the ontology. The similar ontology ranking method is proposed in OntoFetcher [10].

Ranking method based on schema metrics and instance metrics is proposed in OntoQA [11]. The schema metrics address the design of the ontology. It includes relationship richness metrics and Attribute Richness metrics, which indicate the richness, width, depth, and inheritance of an ontology schema. And in instance metrics, the way data is placed within ontology is thought a very important measure of ontology quality. The placement of instance data and distribution of the data can indicate the effectiveness of an ontology design and the amount of knowledge represented by the ontology. This metrics includes knowledgebase metrics and Class Metrics. The former is comprised of class richness, average population, cohesion, and the latter is comprised of importance, fullness, inheritance richness, relationship richness, connectivity, and readability.

In addition, V.Ravi Sankar [21] defined ontoweight measure and developed a methodology to rank ontologies. The method examines each ontology by considering the OWL language constructs which build that particular ontology. Xu dezhi [22] ranked ontologies by computing the topic similarity and the context relatedness about the matched concepts in the ontology. The former is about the keywords in a query and the topic words extracted from the ontology’s conceptual model. The methods proposed by Kou yange [23], Yu wei [24], Mirco Speretta [25] treat ontology and a query as a bag of words based on vector space model respectively. The weight of each word is computed using the method tf/idf. Then the ontologies are ranked according to the included angle cosine of two vectors. Yang kete [26] proposed a special area oriented ontology ranking algorithm, which combines the method in [23] with the method based on link analysis. Wei Yu [27, 28], K.Samantha [29], Zhiguo Ding [30] and Zhang zhiqiang [31] combined the method in Swoogle with the method in AKTiveRank to rank ontologies. Martínez-Romero1 [32] proposed an approach for the automatic recommendation of ontologies using content-based analysis and link-based analysis.

In fact, the existing ontology ranking methods cannot satisfy users because of some inherent defects. There is no doubt that Swoogle analyzes fully the link relations among ontologies, but the irrevocable reality is that the overwhelming majority of the ontologies on the Internet are mutually independent, and there is no link relation each other or only a little. Another problem is that the ranking method in Swoogle ignores fully the matches between query and ontology. These make the ranking results by Swoogle are greatly discounted. Harith Alani [33] has proved through experiments that the Pearson Correlation Coefficient is a negative value between the Swoogle’s ranking results and the artificial ranking results. It means that the Swoogle’s ranking result is almost opposite to the fact. In the ranking method based on concept structure, an ontology is thought more important than another if the matched classes in the ontology is more close to the center of the ontology and the path between them is more short. We think it is just one-sided because of the reality that the matched classes in the query input by a user can be at any position in ontology. And the method doesn’t measure property information which indicates how well the matched classes are described in ontology. The Content-based Ontology Ranking method only computes the number of the matched words between query and ontology without relation metrics. In the ranking method based on schema metrics and instance metrics, the ontology schema metrics is too simple to reflect the real quality of ontology. On the other hand, the ontology schema is thought more important when ontology is developed or reused. Namely, users usually are more interested in the definitions about classes, taxonomy hierarchy and attributes in ontology. There is a little ontology on the Internet which has been populated complete instances. So the ranking method based on instance metrics cannot meet the needs of users.

Following on from the above, in the absence of a recognized standard there is no uniform measure method for ontology ranking. The existing methods rank ontologies from different aspects, and compute separately the score of every ontology without considering the latent relations among the same domain ontologies. Besides the ranking method based on link analysis in Swoogle, all the above ranking methods are depend on the keywords in the query submitted to ontology search engine by user. They are usually few in number, and they cannot reflect exactly user's query intention. Apparently it is not enough and reasonable if ranking algorithm is totally dependent on the keywords. We think there is some inherent correlation among the same domain ontologies, and the correlation can reflect the associated relationship and some inclusion relations among ontologies. Ontologies can be ranked according to the correlation among ontologies and the matches between query and ontology. On this basis, Formal Concept Analysis is introduced and an ontology ranking method base on FCA is proposed in the paper.

III. An Ontology Ranking Method Based on FCA

A. FCA

FCA (Formal Concept Analysis) is a kind of concept hierarchical structure, and also called concept lattice proposed by R.Will [34, 35]. It is an effective tool for data analysis and rule extraction. Every node in concept lattice is named a concept which is composed of objects and attributes. Concept lattice essentially describes the relationship between objects and attributes, indicating the relation of generalization and specialization among concepts. And its hasse diagram is used to realize data visualization. For the convenience of description, some definitions are given as follows at first [36].

Definition 1 A formal context is a triple (D,T,R), where D is a set of objects, T is a set of attributes, and R is a set of binary relations. For $d \in D, t \in T$, dRt means the object d has the attribute t.

Definition 2 Let (D,T,R) is a formal context, for $X \subseteq D, Y \subseteq T$, define:

$$X' = \{t \in T \mid (\forall d \in X)\ dRt\}$$
$$Y' = \{d \in D \mid (\forall t \in Y)\ dRt\}$$

X' is the set of attributes common to all objects in X, and Y' is the set of objects possessing all the attributes in Y. If $X' = Y$ and $Y' = X$ are true, the pair (X,Y) is called a concept, where X and Y are called the extent and the intent of the concept, respectively.

Definition 3 Let $C(D,T,R)$ is the set of concepts of the formal context (D,T,R) and let $(X_1,Y_1),(X_2,Y_2 \in C(D,T,R)$, if $(X_1,Y_1) \le (X_2,Y_2) \Leftrightarrow X_1 \subseteq X_2$, "$\le$"is defined as a partially ordered relation on $C(D,T,R)$, vice versa. The partially ordered set $(C(D,T,R);\le)$ of all the concepts in $C(D,T,R)$ is denoted as $L(D,T,R)$, named concept lattice.

Definition 4 For $\forall a,b \in L(D,T,R)$, if $a < b$ and $a \le z < b$ are true, $a = z$ is true, or if $b < a$ and $b < z \le a$ are true, $a = z$ is true, a is a nearest neighbor of b. It is denoted as $a >-< b$.

Definition 5 Let $C(D,T,R;>-<)$ is the set of concepts of the formal context (D,T,R) together with the nearest neighbor relation. For $\forall a,b \in L(D,T,R)$, Then the transitive closure $>-<*$, of $>-<$ is defined by $a >-<* b$ if and only if $(\exists n \in N)\exists z_0, z_1, ..., z_n \in L(D,T,R)$ is true, such that $a = z_0 >-< z_1 >-< z_2 >-< ... >-< z_n = b$ is true.

B. Proposed Method

From the definition 5, it should be noted that the transitive closure identifies a sequence of minimal refinements or enlargements by which to derive one concept from another. For a given set of ontologies O, its formal context (O,T,R) can be built according to the definition 1, where T is the set of terms including classes, properties and literals defined in O, and R is the set of binary relations about O and T. For $o \subseteq O, t \subseteq T$, $oRt = 1$ means the ontology o has the attribute t, or $oRt = 0$ means the ontology o has not the attribute t. The concept lattice $L(O,T,R)$ about the formal context (O,T,R) can be constructed according to the definition 2 and the definition 3, where every node is a concept. Provided that o_i* is the set of terms included in the ontology o_i (i.e. o_i* is the intent of the object o_i), we observe that (o_i, o_i*) is also a concept in the concept lattice $L(O,T,R)$ according the definition 2. The intent o_i* of every concept (o_i, o_i*) in the concept lattice shows the correlation among the concepts. The shortest path between two concepts in the concept lattice can be computed according to the definition 4 and the definition 5 by the nearest neighbor relations.

We also observe that in special cases, some $T' \subset T$ can be seen as a pseudo-ontology, then T' is possible to be a concept in the concept lattice. In ontology search, user usually inputs some keywords as a query q submitted to the search engine. We can see the query q as a pseudo-ontology, which is also a concept (q, q*) according to the definition 2. IF the concept (q, q*) is mapped into the concept lattice, the distances between it and other concepts can be obtained. Distances between the query concept (q, q*) and other concepts reflect the strength of the correlation between them. According to this principle, the concepts in the concept lattice are ranked.

Definition 6 Let q is a user query, the formal context (O_q,T_q,R_q) derives (O,T,R) with q, and $>-<$ is the nearest neighbor relation defined on the concept lattice $L(O_q,T_q,R_q)$. For $\forall o_1, o_2 \in O, \forall a_1, a_2 \in L(D_q,T_q,R_q)$, the intents of the a_1 and a_2 are o_1* and o_2* respectively, if and only if $n_1 < n_2$ is true, $r(o_1) > r(o_2)$ is true, where $n_i = min\{ n \in N \mid q >-<^* o_i \}$, and $r(o_i)$ is the order of the ontology o_i, and vice versa. It means the ontology o_1 should be ranked ahead of the ontology o_2. Otherwise $r(o_1) > r(o_2)$ is true, if and only if $|o_1^*|>|o_2^*|$, is true, where $|o_i^*|$ is the number of terms defined in the ontology o_i.

In the definition 6, if two concepts have the same shortest path along with the nearest neighbor relation, we think the concept with more terms is more important than the other, because the more terms defined imply the more completely the domain knowledge is described by the ontology.

The algorithm for the ontology ranking is given in Table 1. To construct the concept lattice in our algorithm, we use the tool GALOIS, which is described in detail in [37], as well as its space and time complexity, and not in the scope of the paper. A complete ranked ontology list can be obtained by arranging all the ontologies in the increasing order of minimal transformations that are necessary to derive each ontology from the query. The longer the radius, the lower the ontology scores.

From the above definitions and algorithm, the conclusion can be obtained as follows. If an ontology $o_1 \in O$ is ranked ahead of an ontology $o_2 \in O$ for a user query q, according to Definition 6, the set of terms contained in o_1 can be derived from the set of terms contained in q by a smaller number of admissible minimal transformations, with respect to the concept lattice, than the set of terms contained in o_2.

TABLE I.
THE PROPOSED ONTOLOGY RANKING ALGORITHM

```
Input: the set of ontologies O={o1,o2,……,on},
    the query Q={kw1,kw2,……,kwm}
Output: a complete ranked ontology list
for i=1 to n
{ att=f_get_property(oi)
 T=T ∪att }
(O,T,R)=f_construct_formal_context(O, T)
con=f_get_concept(O,T,R)
L(O,T,R)=f_constuct_concetp_lattice(con)
q=f_get_ pseudo_concept(Q)
L(Oq,Tq,Rq)= L(O,T,R).addconcept(q)
for i=1 to n
r(oi)=f_get_nearest_neighbor_path(oi, q)
list_temp=f_get_ascendind_oder(r)
// get ascending order of the distances
list_ranking=f_get_ontology_oder(list_temp)
// rank ontologies according list_temp
for i=1 to n-1
{for j=i+1 to n
if r(oi)==r(oj) and |oi*|>|oj*| then
list_ranking=f_ajust(list_ranking) }
//rank oi ahead of oj in list_ranking
return list_ranking
```

C. An Example

To illustrate the ontology ranking method we have proposed, an example is elaborated as follows. Let $O= \{o_1, o_2, o_3, o_4, o_5, o_6, o_7\}$ is the set of ontologies, $T= \{t_1, t_2, t_3, t_4, t_5, t_6, t_7\}$ is the set of terms defined in O, and Q= $\{t_1, t_4\}$ is the query. Let R is a set of binary relations defined on O and T, for $o \in O, t \in T$, oRt means the ontology o has the term t. The formal context about O is shown in Table 2. The concept lattice built from the formal context (O, T, R) and from the query Q treated as a pseudo-ontology q is illustrated in Figure 1 by a Hassle diagram.

TABLE II.
THE FORMAL CONTEXT (O, T, R) ABOUT O

$O \backslash T$	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8
o_1	1	0	0	1	1	1	0	0
o_2	1	0	0	0	0	1	1	0
o_3	1	0	0	0	1	1	0	0
o_4	0	1	1	1	0	0	0	0
o_5	0	1	1	0	0	0	0	0
o_6	0	1	0	0	0	1	0	1
o_7	1	1	1	1	0	0	0	0

The hasse diagram shows the set of concepts along with the nearest neighbor relation in Definition 4, implying that there is an edge between two nodes if and only if they represent comparable concepts and there is no other intermediate concept in the lattice.

It should be noted that both the intents of the lattice top node (i.e. the common terms of all the ontologies) and the extents of the bottom concept (i.e. the common ontologies of all the terms) are empty set. So the two nodes will be excluded on ranking the ontologies. As stated in Definition 2, not every term subset is a lattice concept. For instance, in the lattice relative to the context in Table 1 there is not any concept having an intent equal to t_3. But we observe that all ontologies having t_3 have also t_2. The completeness constraint limits the number of admissible concepts by favoring maximally specific descriptions of the extent's ontologies. In other terms, it is thought that if one term always appears jointly with other terms, the single term cannot be a distinct concept while their tuple does convey a useful meaning. In a sense, every complete set of co-occurrences determines a concept specific to the formal context. So the terms t_5 cannot be a concept in the lattice because it always appears jointly with the term t_6.

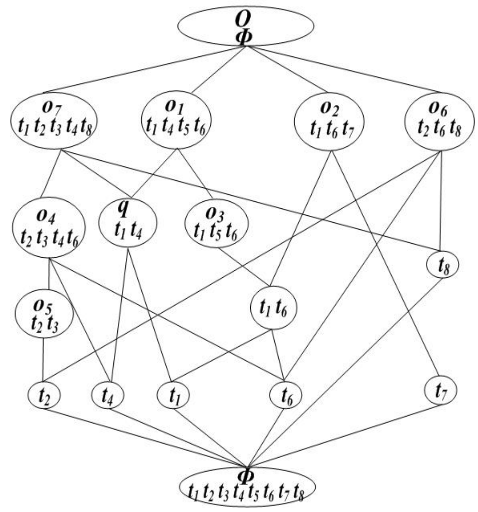

Figure 1. The concept lattice associated with the formal context in Table Ⅱ and with the query Q.

It can be seen from Figure 1 that there is a different path from the query node q to any other nodes in the hasse diagram along with its transitive closures according to the definition 5. Now let us see how the ranked list for the given ontologies and query is produced. The nodes that are closest to the query q are t_1, t_4, t_1-t_2-t_3-t_4, and t_1-t_4-t_5-t_6. The relevant ontologies are o_1 and o_7. The closer nodes contain t_1 -t_6, t_2-t_3-t_4 *and* t_1-t_5-t_6, which yield the ontologies o_3 and o_4, and so on. The list of the ontologies is the following according to their distance from the query node: o_1 (1), o_7 (1), o_3 (2), o_4 (2), o_2 (3), o_5 (3), and o_6 (4). Then the complete ranked list of the ontologies is {o7, o1, o_4, o_3, o_2, o_5, o_6}.

Ⅳ. EXPERIMENTS AND EVALUATION

To evaluate the performance of the proposed ontology ranking method, the following experiment is conducted. At present, because of the absence of the test benchmark and the data set in the field of ontology ranking, for the purpose of comparison, the same query and the same set of ontologies coming from [20] is used in our experiments. The keywords as the query is shown in Table 3, which are the synonyms, hyponyms and hypernyms of the term cancer obtained from WordNet for expanding the disease sense of the word cancer. The set of OWL ontologies about cancer to be ranked in the experiments appear in Table 4, which are selected from the returned ontologies by Google with the query.

TABLE III.
THE GOOGLE QUERY FOR ONTOLOGY SEARCH

The keywords in the query
Cancer, cell, tumor, patient, document, risk, carcinoma, lymphoma, disease, access, skin, liver, treatment, leukemia, breast, genetic, gene, tobacco, thymoma, malignant, clinical, neoplasm, pancreatic, Tissue, therapy, lesion, blood, study, thyroid, smoking, polyp, human, health, exposure, studies, ovarian, related, information, research, drug, oral, associated, bone, neoplastic, chemotherapy, body, lung, oncology, growth, medical

TABLE IV.
THE ONTOLOGIES TO BE RANKED

ID	Ontology URL
1	http://semweb.mcdonaldbradley.com/OWL/Cyc/FreeToGov/60704/FreeToGovCyc.owl
2	http://www.inf.fu-berlin.de/inst/agnbi/research/swpatho/owldata/swpatho1.owl
3	http://www.mindswap.org/2003/CancerOntology/nciOncology.owl
4	http://sweet.jpl.nasa.gov/ontology/data_center.owl
5	http://compbio.uchsc.edu/Hunter_lab/McGoldrick/DataFed_OWL.owl
6	http://www.cs.umbc.edu/~aks1/ontosem.owl
7	http://homepages.cs.ncl.ac.uk/phillip.lord/download/knowledge/ontologyontology.owl
8	http://www.daml.org/2004/05/unspsc/unspsc.owl
9	http://envgen.nox.ac.uk/miame/MGEDOntology_env_final.owl
10	http://www.fruitfly.org/%7Ecjm/obo-download/obo-all/mesh/mesh.owl

In [20] two medical students were asked to rank each of the selected ontologies according to how well the ontologies cover the concept of cancer. As a result the Pearson Correlation Coefficient (PCC) between the two sequences of the two experts was 0.92, which indicated that the two human ranks were relatively consistent. In our experiments, we compared our ontology ranking method and the human, as well as the content-based ontology ranking method in [20].These comparisons are shown in Table 5, where CBR Rank is the sequence by the method in [20], and CLR Rank is ours.

It can be seen from the Table 5, the ontology 1 and the ontology 8 is ranked the third and the fourth respectively by CBR, which implies they have more matches with the query. But they are ranked the sixth and the eighth respectively by human. The ontology 10 is ranked the fifth by CBR, which means it have relatively less matches with the query. But it is ranked the second by human. This is possibly due to the fact that the more properties are defined in the ontology 10, which are just ignored by CBR. These indicate that it is unreliable to rank ontologies just according to the matches between query and ontology. In our method, the ontology 10 is ranked the third, which is possible due to its strong correlation with the ontology 3 and the ontology 6. From the overall view, the PCC between the CLR Rank and Human Rank is 0.875, so the comparison shows the proposed method is better than CBR.

TABLE V.
COMPARISON OF RANKS WITH HUMAN AND CBR

Ontology ID	Human Rank	CBR Rank	CLR Rank
3	1	1	1
10	2	5	4
6	3	2	2
2	4	6	3
5	5	7	6
1	6.5	3	8
9	6.5	8	5
8	8	4	10
7	9	10	7
4	10	9	9
PCC		0.693	0.875

VI. CONCLUSION AND FUTURE WORK

Ontology ranking is one of the important functions of the ontology search engine, and provides user a reference to choose the reusable ontologies. At present, although ontology can be evaluated and ranked by many ways from different aspects, there is no recognized method satisfying user. Here we proposed an ontology ranking method based on FCA ranking ontologies according to the inherent correlation among the same domain ontologies and the matches between query and ontology, but incompletely depending on the keywords input by user. Experimental results show our method is better than content-based ontology ranking.

All the above ontology ranking methods are designed for users, but not for applications. For a given application, how to evaluate how well an ontology fits it automatically[38] ? It will involve in the following questions. How to describe formally and quantitatively the ontology need of an application? And how to construct systematically ontology evaluation index system and ontology evaluation standard? These are our future work, as well as the real-time of the ontology ranking algorithm.

ACKNOWLEDGMENT

The work in this paper is supported mainly by National Program on Key Basic Research Project (973 Program) under Grant No.2013CB329606, the Scientific Research Found of Jiangxi Provincial Education

Department of China under Grant No.GJJ13411 and the Jiangxi Provincial Ministry of Education Research Fund under Grant No.12770. And the work is also partly supported by the Key Science-Technology Plan of the National 'Twelfth Five-Year-Plan' of China under Grant No.2011BAK08B04, the Fundamental Research Funds for the Central Universities under Grant No.FRF-TP-12-162A, Beijing Natural Science Foundation under Grant No. 4122026 and Scientific Research Common Program of Beijing Municipal Commission of Education under Grant No. KM201210015007, KM201210015006.

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Jianghua Li was born in Henan Province, China, in 1976. He received the BS degree and MS degree in computer science from Jiangxi University of Science and Technology in 2000 and 2005 respectively. From 2010 to date, he works as a Ph.D. candidate in the National Center for Materials Service Safety, University of Science and Technology Beijing, China, and an associate professor in the School of Information and Engineering, Jiangxi University of Science and Technology, China. His research interests include Semantic Web, domain data engineering, software engineering and digital watermark.

Peng Shi is an associate professor in the National Center for Materials Service Safety, University of Science and Technology Beijing, China. He received his Ph.D. in the Institute of Computing Technology, Chinese Academy of Science in 2007. His research interests include data and knowledge engineering, cloud computing and Semantic Web.

Mingzhi Cheng(1974-), male, Hu Bei, Xiang Ning. He is a lecturer in Beijing Institute of Graphic Communication, doctor degree. His current research interests include packaging anti-counterfeiting and Digital Content Security.