PAPER

TongSACOM: A TongYiCiCiLin and Sequence Alignment-Based Ontology Mapping Model for Chinese Linked Open Data

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SUMMARY Linked Open Data (LOD) at Schema-Level and knowledge described in Chinese is an important part of the LOD project. Previous work generally ignored the rules of word-order sensitivity and polysemy in Chinese or could not deal with the out-of-vocabulary (OOV) mapping task. There is still no efficient system for large-scale Chinese ontology mapping. In order to solve the problem, this study proposes a novel TongYiCiCiLin (TYCCL) and Sequence Alignment-based Chinese Ontology Mapping model, which is called TongSACOM, to evaluate Chinese concept similarity in LOD environment. Firstly, an improved TYCCL-based similarity algorithm is proposed to compute the similarity between atomic Chinese concepts that have been included in TYCCL. Secondly, a global sequence-alignment and improved TYCCL-based combined algorithm is proposed to evaluate the similarity between Chinese OOV. Finally, comparing the TongSACOM to other typical similarity computing algorithms, and the results prove that it has higher overall performance and usability. This study may have important practical significance for promoting Chinese knowledge sharing, reusing, interoperability and it can be widely applied in the related area of Chinese information processing.

key words: *Semantic Web, linked open data, ontology mapping, similarity computing, TongYiCiCiLin*

1. Introduction

The vision of the Semantic Web is to establish a web of data that would allow machines to understand semantic information on the Internet [1]. Ontology, as the core factor of the Semantic Web, is considered as a formalization and normalization method that describes the shared concepts of specific domains [2]. It is the foundation for realizing knowledge sharing and semantic interoperability. Currently, research on linked open data (LOD) [3] is primarily centered on the levels of instances [4], [5], but studies on linked data at the schema level are equally important [6]. As a typical scenario of linking open data on schema-level, ontology alignment has been widely researched.

Melnik et al. [7] proposed a structural level ontology mapping algorithm called “similarity flooding” that uses the

concept of ontology to build a similarity propagation map and then spreads and corrects any similarities between the concepts. Cohen et al. [8] listed some typical similarity computing algorithms on the element-level based on Edit-Distance and Token, and then evaluated their performance. Giunchiglia et al. [9] proposed that semantic relationships should be discovered based on linguistic method by introducing shared knowledge dictionary (e.g., WordNet [10]). Isaac et al. [11] proposed an Instance-Level ontology mapping algorithm that would measure the similarities between the concepts according to the number of similar instance of ontology concepts. Based on the Workflow technique, Nikolov et al. [12] proposed a linked data framework: KnoFuss, which make use of the hierarchy between concepts in order to pick up the most suitable mapping parameter and approach. Zhong et al. [13] developed the RiMOM system, which is a multi-strategy mapping system based on ontology instance, concept name, ontology structure and other characteristics, and applied it for large-scale ontology mapping by introducing universal field theory. Based on bootstrapping and taking Wikipedia classification tree as the knowledge base for semantic similarity computing, Jain et al. proposed the BLOOMS system [6], which can efficiently build the Schema-Level interlinking, that is ontology mapping, in LOD environment. But all the researches mentioned above are limited to the schema matching between datasets described in the English language only.

However, due to the cultural background, a large-scale ontology alignment system for Chinese language has not yet to be developed. In recent years, more researches have been conducted in association with large-scale Chinese ontology and linked data. Li et al. [14] proposed a similarity computing method on the element-level based on HowNet [15] and established a Chinese ontology mapping system, which is called ELOMC; unfortunately, it ignored the rules of word-order sensitive and polysemy in Chinese language proposed by Chinese linguists Lu [16]; therefore, its practicability and effectiveness still need to be verified while facing the large-scale ontology mapping task. Based on TongYiCiCiLin (TYCCL), a Chinese synonym thesaurus, Tian et al. [17] proposed an algorithm for computing the similarity between atomic Chinese concepts, but whose method do not apply to the LOD environment and could not deal with the out-of-vocabulary (OOV).

In addition, there are also some typical systems, which should be mentioned, establishing the interlinking between LOD datasets mainly at the instance level. Silk [18], [19]

Manuscript received July 15, 2016.

Manuscript revised February 2, 2017.

Manuscript publicized March 15, 2017.

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DOI: 10.1587/transinf.2016EDP7307

is a framework for building the interlinking between different datasets, by a declarative language, users can configure the linking strategy, such as the type, conditions etc., and it also supports the remote interlinking. Hassanzadeh et al. [20] proposed a common and extensible system: LinQL, which has integrated some existed link discovery method. The purpose of this system is for helping users to select the most suitable method to interlink their own dataset. Meanwhile, it also support publishing RDF triples from Relational Data Base (RDB) by using D2RQ [21] and Virtuoso. In order to achieve the sharing, reusing, and interoperation of knowledge bases in LOD environment, it is necessary to link ontologies described in different languages. Wang et al. [22] proposed a method for cross-linguistic interlinking establishing in LOD. Firstly, by using the concept annotation method, with the help of a small amount of cross-language and internal links seed to enrich the internal links, secondly, a regression model is used to predict the potential cross-language links between Chinese and English Wiki. Wang et al. [5] proposed extracting the hierarchical relationships between concepts and the concept property contained in Infobox based on the DMOZs (a kind of open classification project) of Chinese Wiki; furthermore, based on a simple keyword-matching method, eventually building a BaiduBaiké and Hudong-based ontology and establishing the co-reference relationships between instances with DBpedia [23]. Niu et al. [4] conducted semantic integrations of Baidu Baiké[†], Hudong^{††}, and DBpedia^{†††}, and developed a Chinese linked data application system, Zhishi.me, at the instance-level. But all the researches mentioned above are limited to the instance-level matching between datasets and establishing of interlinking at schema-level of them is still insufficient.

Unless the ontological knowledge described in Chinese is addressed, it will be impossible to collect semantic data described by Chinese ontology. Therefore, mapping Chinese ontology as well as the ontology described with other languages is integral to sharing and interoperation among ontologies. Moreover, the researches on Chinese linked data on the web are still in the early stage; the approaches for linked the Schema-Level data in Chinese are very insufficient.

Based on the above, this study proposes a novel linked open data model (TongSACOM) for large-scale Chinese ontology mapping in LOD environment and experiments have shown that TongSACOM has more advantages and rationality than those traditional methods while facing the Chinese ontology schema matching task.

2. Definition of the Problem

In Chinese ontology mapping, simple lexical units and

OOV words correspond to the ontology concepts to be mapped. Therefore, the simple lexical unit is termed as the atomic concept (AC) and the concept that corresponding to the OOV word is termed as the compound concept (CC). TongSACOM defines that all CC_s comprise a linear array and a combination of multiple atomic concepts [14]. Firstly, the formal descriptions of the problems faced are given.

Definition 1: Ontology mapping: There are two ontologies for mapping, namely, O_s and O_t . For each concept C_s in O_s , finding a corresponding concept C_t in O_t that has the same or similar semantic meaning as it. Define the mapping function map: $O_s \rightarrow O_t$:

For $C_s \in O_s$, $C_t \in O_t$, if $\text{sim}(C_s, C_t) > t$; $\text{map}(C_s) = C_t$
 t is a threshold value indicates that, when the semantic similarity between C_s and C_t is greater than t , $\langle C_s, C_t \rangle$ will be considered as the discovered concept mapping pair.

Definition 2: For the TYCCL semantic knowledge base (SKB), the set SKB_{TYCCL} comprises the atomic concepts. In other words, $SKB_{TYCCL} = \{AC_1, AC_2, \dots, AC_N\}$, in which an element AC_i is an atomic concept in the set SKB_{TYCCL} and N is the number of lexical units contained in the knowledge base.

Definition 3: The compound concept CC_i comprises an ordered combination of atomic concepts. In other words, for $\forall AC_i \in SKB_{TYCCL}$, introduce two-dimensional indices i and j , and then there is an ordered sequence $CC_i = [AC_{i1}, AC_{i2}, \dots, AC_{ij}]$, where $j \geq 1$ and $CC_i \notin SKB_{TYCCL}$; j is the position of atomic concept AC_i in the ordered sequence CC_i ; in particular, for all atomic concepts AC_i , $AC_i = [AC_i]$.

Definition 4: As with C_s and C_t in O_s and O_t , the ontology concepts for mapping are $C_s = CC_s = [AC_{s1}, AC_{s2}, \dots, AC_{sm}]$ and $C_t = CC_t = [AC_{t1}, AC_{t2}, \dots, AC_{tn}]$, where m and n are the length of the ordered sequences CC_s and CC_t , which correspond to C_s and C_t , respectively, and then $m, n \geq 1$.

3. A TongYiCiCiLin and Sequence Alignment-Based Chinese Ontology Mapping Model (TongSACOM)

On the basis of formal descriptions and definitions of the problems given above, the TongSACOM model is proposed and each situation of the problem will be discussed. The architecture of the model is shown in Fig. 1.

The TongSACOM model is mainly consisted of the following modules: Ontology Pre-Processing, Improved TYCCL Similarity Computing, Splitting Compound Concept, Building Scoring Matrix, Compound Concept Similarity, and Sequence Alignment Processing.

While mapping any two concepts C_s and C_t in O_s and O_t will result in one of the following three cases:

(1) C_s and C_t are both the atomic concepts, i.e., $C_s \in SKB_{TYCCL}$ and $C_t \in SKB_{TYCCL}$.

(2) One of the two concepts (C_s or C_t) is an atomic concept, but another one is a compound concept, i.e., $C_s \notin SKB_{TYCCL}$ xor $C_t \notin SKB_{TYCCL}$.

(3) C_s and C_t are both compound concepts, i.e., $C_s \notin$

[†]See <http://baike.baidu.com/>

^{††}See <http://www.hudong.com/>

^{†††}See <http://wiki.dbpedia.org/>

Fig. 1 The architecture of TongSACOM.

Table 1 An example of a TYCCL code

Code Bit	1	2	3	4	5	6	7	8
Sub-Code	B	a	0	1	A	0	2	= or # or @
Meaning	Broad heading	Middle heading	Small heading	Word group	Atomic word group			synonym/unequal /isolated
Level	Level 1	Level 2	Level 3	Level 4	Level 5			

SKB_{TYCCL} and $C_t \notin SKB_{TYCCL}$.

For Case (1), it is implemented by the “*Improved TYCCL Similarity Computing*” module as shown in Fig. 1, and the improved TYCCL-based similarity algorithm is proposed to evaluate the semantic similarity between the two atomic concepts; the specific discussion about it is in the following Sect. 3.1. Furthermore, the solutions for Cases (2) and (3) are implemented by the “*Compound Concept Similarity*” module in which a sequence alignment and improved TYCCL-based combined algorithm is proposed to evaluate the similarity between compound concepts, the input of this module is the two unmapped sequences corresponding to the compound concepts and the scoring matrix, both of them are generated by the previous “*Splitting Compound Concept*” and “*Building Scoring Matrix*” modules respectively. The detail of this module is in the following Sect. 3.2.

3.1 The Improved TYCCL Similarity Computing

TYCCL is a Chinese synonym thesaurus in which each word is encoded and organized in a hierarchical tree and each node (lexical unit) represents a concept [24]. In TongSACOM model, an extended version of TYCCL that was published by HIT[†] will be used as a common semantic knowledge base (SKB_{TYCCL}) to acquire the equivalent relationships between concepts.

Improved TYCCL Similarity Computing: In experiment process, two concepts in different hierarchy of TYCCL are represented as <subclass of> relationship, and the purpose of ontology mapping is to find the equivalent relationship between concepts but not the <subclass of> relationship. While Tian et al. emphasizes too much on the semantic correlation between concepts [17], which will cause greater errors that a lot of <subclass of> relationship will appear in result but not the equivalent relationship of

concepts while carrying out the ontology mapping task. Therefore, an improved TYCCL algorithm is proposed by taking into account the influence of hierarchy in TYCCL on concept similarity and involving the semantic correlation factor λ . Finally through the concept similarity weight coefficient: $\lambda \times (L_i/|L|)$ to quantify it so that it can be applied to the ontology mapping task in LOD environment.

Based on the structural characteristics of TYCCL, the TYCCL concept codes for mapping are analyzed first. Extract the sub-codes of Level 1 to Level 5 and then start comparing with the code from the first sublevel. If one sub-code is different, the similarity weight of the mapping pair is determined by the sub-code’s level. The deeper the sub-code’s level, the higher the similarity weight, and vice versa. Meanwhile, the number of branch nodes of each layer also affects the similarity.

Taking the lexical unit “物质 (material)” as an example (TYCCL code: Ba01A02=), its TYCCL code format as indicated in Table 1. The improved TYCCL-based similarity is computed by Eq. (1) as follows:

$$SIM_T(C_s, C_t) = \lambda \times \frac{L_i}{|L|} \times \cos\left(N_T \times \frac{\pi}{180}\right) \times \left(\frac{N_T - D + 1}{N_T}\right) \quad (1)$$

Because ontology mapping is more concerned with the semantic similarity between concepts, the adjustable parameters will be introduced into the model, specifically, semantic correlation factor λ , which is used to adjust the semantic relevance and similarity relationships between the different levels of concepts and to control the degree of similarity between lexical units at different branch levels. Clearly, $\lambda \in (0, 1)$. The greater value of λ , the greater possibility similar or equivalent of lexical units on different levels will be. The influence of the semantic correlation on the final concept similarity will be greater and vice versa. However, the value of λ in TongSACOM should not be set very high. The

[†]http://ir.hit.edu.cn/demo/ltip/Sharing_Plan.htm

reasons are: (i) the “subclass-of” relationship between every two atomic concepts in different levels of the TYCCL will seriously interfere with accumulation of the “equivalentClass” relationship between every two atomic concepts in the Chinese ontology mapping process; and (ii) in the TongSACOM model, we set the threshold value (t) of the “equivalentClass” relationship judgment between every two concepts to $t \geq 0.9$; therefore, if the λ -value is taken too high, it will increase the similarity value of all the mapping results, resulting in a large number of error mapping results output by SIM_T algorithm (because the similarity of some error mapping results will be greater than 0.9 and result in the “subclass-of” relationship between every two atomic concepts in different levels of the TYCCL will be wrongly identified as the “equivalentClass” relationship) and finally reduce the performance of TongSACOM. Therefore, through contrasting several preliminary experiments, an essential conclusion is drew that: While the λ is set to be a random number of $\lambda \in [0.4, 0.5]$, TongSACOM can achieve the best overall performance.

$L = \{1, 2, 3, 4, 5\}$. For $\forall L_i \in L$, L_i represents the level number of Level i . $|L|$ represents the number of elements in the set L . In this system, $|L|$ is constant and equal to 5. The concept similarity weight coefficient is $\lambda \times (L_i / |L|)$. N_T is the total number of nodes of the different sub-codes that appear in Level branch i between C_s and C_t . D is the code distance between C_s and C_t . In particular, when the codes of the five levels correspond to the concepts to be mapped and the last code bit of the TYCCL code is “=”, the returned value of the similarity function SIM_T is 1.0. Clearly, the range of the function SIM_T is $(0, 1]$.

3.2 Sequence Alignment-Based Mapping for Chinese Compound Concept Similarity Computing

Regarding the similarity in computing Chinese compound concepts, scholars have proposed their own solutions. For example, Li *et al.* proposed a Hownet-based concept similarity computing method on element-level and implemented a Chinese ontology mapping system (ELOMC) [14]. In particular, when they calculated the similarity between OOV, two compound concepts A and B to be mapped are expressed in the form of matrix; by *definition 3* and the Chinese Segmentation Tool, they are both split into a group of atomic concepts and consist of two sequences respectively. The matrix is composed of the two sequences of compound concept A and B ; furthermore, Sequences A and B consist of the row and column of this similarity matrix respectively. Finding the relative highest similarity value of atomic mapping pair by traversing between the two sequences in matrix and then it could ultimately obtain the similarity values for the two compound concepts. The algorithm is as follow:

$$Sim(A, B) = \frac{\sum_{i=1}^{\max(m,n)} \max_i(M_{xy})}{\max(m, n)} \quad (2)$$

Fig. 2 The wrong mapping result.

where M_{xy} represents a similarity value of a pair of mapping atomic concepts in the $m \times n$ matrix. m and n is the length of sequence A and B respectively. The $\max_i(M_{xy})$ represents the ranked i -th similarity value in the matrix, and then computes Top $\max(m, n)$ similarity value. Some similar approaches have also been used in Refs. [25]–[27].

However, important information is often arranged in the second half rather than the first half of a sentence in Chinese [16], [28]; thus, this approach above will inevitably lead to semantic similarity computing errors because it ignored the rules of word-order sensitivity and polysemy in Chinese. For example, there are two compound ontology concepts to be mapped in Hudong-DBpedia sub-mapping task: history, namely, “历史理论 (history theory)” and “思想史 (history of thought).” After they are split, two ordered atomic concept sequences are obtained: [历史, 理论] ([history, theory]) and [思想, 史] ([thought, history]). Based on the OOV word processing method that was presented in Eq. (2), the mapping result is shown in Fig. 2. Computing the semantic similarity of each pair of atomic concepts to be mapped based on Eq. (1), and then comprehensively compute the similarity using Eq. (2), given in Refs. [14]. The resulting similarity value of the concept is 1.0. It appears that the compound concept mappings and similarity results are not reasonable at all, which primarily because this approach ignores a word-order sensitivity and polysemy that is prevalent in Chinese mentioned before.

Thus, a novel method for improving the similarity computing between compound concepts is proposed. Specifically, while calculating the element-level similarity between the concepts, semantic similarity is computed by introducing a bioinformatics-based global dual-sequence alignment algorithm.

3.2.1 Overview of the Sequence Alignment Algorithm

In bioinformatics, dual-sequence alignment refers to two DNA or protein sequences that are arranged together to indicate their similarities; a space characters (-) can be inserted to have the same or similar symbols arranged in the same sequences. By comparing the similar fragments and conserved sites of two sequences, we can search for possible molecular evolutionary relationships [29].

3.2.2 Building a Dynamic Programming Scoring Matrix

A sequence refers to a string consisting of a series of words based on certain rules of arrangement.

Splitting the Compound Concept: Specifically, when computing similarity in ontology concepts, TongSACOM model considers the compound concept to be a sequence

Algorithm 1: *CompoundConceptSimilarity*(CC_s, CC_t)

Input: Scoring matrix $M_{(i)j}$ corresponding to compound concepts CC_s and CC_t

Output: The matrix $M'_{(i)j}$ including the optimal alignment path

1. $p \leftarrow -0.05$ //Define the constant p as the penalty factor of algorithm, and it equals to -0.05
 2. for each $i \leftarrow 1, 2, \dots, m+1; j \leftarrow 1, 2, \dots, n+1$ //Initialize the dynamic programming matrix
 3. $M_{(i)(n+1)} \leftarrow p \times (m-i+1)$
 4. $M_{(m+1)j} \leftarrow p \times (n-j+1)$
 5. end for
 6. for each $i \leftarrow m, m-1, \dots, 1$
 7. for each $j \leftarrow n, n-1, \dots, 1$
 8. $M_{(i)j} \leftarrow \max(M_{(i+1)j+1} + \text{SIM}_T(AC_{si}, AC_{tj}), M_{(i)j+1} + p, M_{(i+1)j} + p)$
//Recursively compute the value of each element in the matrix
 9. end for
 10. end for
 11. Get the matrix $M'_{(i)j}$ //including the optimal alignment path of sequence through recurrence
 12. return $M'_{(i)j}$
-

Fig. 3 The processing of getting the optimal alignment path between compound concepts.

of word strings in which each element is an atomic concept. First, splitting a compound concept into a list of simple lexical units and obtain its word string sequence which is generated by the “Splitting Compound Concept” module as shown in Fig. 1. In large-scale Chinese ontology mapping, the ICTCLAS50 software[†], developed by the Institute of Computing, Chinese Academy of Sciences, is used as the word segmentation tool. The alphabet is defined as the “Semantic Knowledge Base” of TYCCL (SKB_{TYCCL}).

TongSACOM abstracts the computation of similarity between ontology concepts into a process of aligning two sequences. The gap penalty function is used to determine the location for inserting space characters in the sequences to give them the same length, and a mapping relationship will be built between two atomic concepts or between an atomic concept and a space character in the aligning sequences. The sequence alignment algorithm essentially aims to find the global optimization alignment result between two sequences by using a scoring strategy.

Building the Scoring Matrix: In TongSACOM model, the two sequences to be aligned are expressed in the form of a scoring matrix firstly and then are treated as the two dimensions in the dynamic programming matrix: M .

For C_s and C_t in O_s and O_t , Row i in the scoring matrix M corresponds to the atomic concept AC_{si} in the sequence CC_s . Column j corresponds to the atomic concept AC_{tj} in the sequence CC_t , where $i \leq m$ and $j \leq n$. The element in Row i and Column j of the dynamic programming matrix M is called M_{ij} . Following the principles of dynamic programming, the model expresses the two sequences in rows and columns.

Assuming that sequence CC_s has length m and that sequence CC_t has length n , we can obtain a two-dimensional

matrix with CC_s as the row and CC_t of $(m+1) \times (n+1)$ as the column.

3.2.3 Needleman-Wunsch Algorithm

The Needleman-Wunsch (NW) algorithm is a typical global alignment and dynamic programming algorithm for comparing the similarity between the two sequences [30]. The optimal alignment path in matrix M can be recursively solved based on the idea of dynamic programming.

In TongSACOM model, a sequence-alignment and improved TYCCL-based combined algorithm is proposed to evaluate the similarity between Chinese OOV.

Sequence Alignment Processing: Firstly, let the penalty factor of sequence alignment algorithm be $p = -0.05$ and initialize Row $m+1$ and Column $n+1$ in the matrix. Secondly, evaluating all the pair of atomic concepts similarity based on the improved TYCCL similarity function SIM_T (Eq. (1)) and the remaining $m \times n$ elements value will be computed recursively in the matrix. The definition of the scoring function f is shown in Eq. (3):

$$f(AC_{si}, AC_{tj}) = \begin{cases} \text{SIM}_T(AC_{si}, AC_{tj}) & \text{if } AC_{si} \neq \text{“-”} \text{ and } AC_{tj} \neq \text{“-”} \\ f(AC_{si}, -) = p = -0.05 & \text{if } AC_{tj} = \text{“-”} \\ f(-, AC_{tj}) = p = -0.05 & \text{if } AC_{si} = \text{“-”} \end{cases} \quad (3)$$

Considering the feature of “back loading” that is prevalent in Chinese concepts [16], [28], we choose the end of two compound concepts, that is the element M_{mn} , as the starting point of the recursive algorithm in the scoring matrix. Please see Eq. (1) for the description of SIM_T . The recursive rule is as described in Eq. (4).

[†]<http://ictclas.org/>

$$M_{ij} = \max \begin{cases} M_{(i+1)(j+1)} + f(AC_{si}, AC_{tj}) \\ M_{(i)(j+1)} + p \\ M_{(i+1)(j)} + p \end{cases} \quad (4)$$

Thirdly, starting from M_{mn} in the matrix, backtracking M_{11} and it will be possible to obtain the optimal alignment path-contained matrix: $M'_{(i)(j)}$, returned by Algorithm 1. It should be noted that, if there is more than one optimal alignment path, only one should be chosen. Here, a space character (“-”) was inserted, as there were sequences of the two compound concepts for mapping that were equal in length, called CC'_{si} and CC'_{ti} . The length of the two sequences is defined as L . The Algorithm 1 shows the details of getting the optimal alignment path processing between compound concepts based on the NW algorithm.

Finally, we obtain Eq. (5) to compute the similarity between compound concepts based on alignment results and scoring function f :

$$SIM_{NW}(CC'_{si}, CC'_{ti}) = \sum_{i=1}^{|L|} \frac{f(AC_{si}, AC_{ti})}{|L|} \quad (5)$$

4. Experimental Results and Analysis

This study used online Chinese encyclopedia knowledge bases as sources of the experimental data. In addition to the DBpedia (Chinese version) [23], we used a crawler toolkit, HTMLParser, to crawl and analyze the classification tree of Baidu Baike and Hudong. We did not only analyze the classification systems in Chinese open-source encyclopedia knowledge bases, but also extracted and analyzed the structured Infobox information included in all of the entry pages and organized them in the form of Chinese triples. All concepts for mapping are on the classification tree of Chinese online encyclopedias.

Eventually, the three large-scale ontologies for mapping are formed, as Shown in Table 2. The strategy for building ontology for Baidu Baike and Hudong Baike was based on the methods reported in Refs. [5], [31].

4.1 Sequence Alignment Result Analysis

For example, splitting a pair of compound concepts to

be mapped in Baidu-DBpedia sub-mapping task: history, namely, “第二次工业革命 (the second industrial revolution)” and “第二次世界大战人物 (people of the second world war),” we can obtain two word sequences: [第二, 次, 工业革命] ([second, (measure word), industrial revolution]) and [第二, 次, 世界大战, 人物] ([second, (measure word), world war, people]). Based on the idea of dynamic programming, the two word-sequences are expressed in rows and columns which consist of the scoring matrix: $M_{(i)(j)}$.

Similarly using the example of combining the concepts: “第二次工业革命 (the second industrial revolution)” and “第二次世界大战人物 (people of the second world war),” matrix $M'_{(i)(j)}$, which includes the optimal alignment path—which is resolved using Algorithm 1. The scoring matrix outputted by Algorithm 1 is shown in Fig. 4. The bold arrow indicates the optimal alignment path that is obtained. The bold diagonal arrow indicates that two atomic concepts at the end are mapped. The bold horizontal arrows indicate a space character “-” should be inserted in front of the atomic concept on the row where the sequence CC_s is located. A bold vertical arrow indicates a space character “-” should be inserted in front of the atomic concept on the column where the sequence CC_t is located.

The optimal alignment results of sequence [第二, 次, 工业革命] and [第二, 次, 世界大战, 人物] are shown in Fig. 5.

Fig. 4 The scoring matrix for Example 2.

Fig. 5 The correct sequence alignment result for Example 2.

Table 2 Information on chinese encyclopedia knowledge bases

	Items	Baidu Baike	Hudong	DBpedia
Concept	Top Categories	13	13	23
	Number of Concepts	1,336	29,276	106,023
	Chinese Literal Triples	1,323	29,263	106,000
Infobox	Number of Infoboxes	214,732	257,215	204,822
	Number of Properties	21,152	1,061	18,206
	Chinese Literal Triples	1,698,149	2,161,616	4,077,898
Individual	Infobox Percentage	2.30%	10.10%	19.74%
	Chinese Literal Triples	9,346,184	2,545,447	1,037,557

Fig. 6 The correct sequence alignment result for Example 1.

Fig. 7 The scoring matrix for Example 1.

Here, we reexamined the two examples of computing similarity that were mentioned before.

Example 1: $CC_s = [\text{思想}, \text{史}]$ ([thought, history]), $CC_t = [\text{历史}, \text{理论}]$ ([history, theory]).

The similarity value of the component concept that is obtained using Eq. (2) is:

$$\text{Sim}(CC_s, CC_t) = (1.0 + 1.0)/2 = 1.0$$

Moreover, the alignment effect on the two compound concept sequences that returned by the sequence alignment algorithm is shown in Fig. 6.

The corresponding scoring matrix is shown in Fig. 7.

The final similarity between the compound concepts should be:

$$\text{SIM}_{NW}(CC_{si}, CC_{ti}) = (-0.05 + 1.0 - 0.05)/3 = 0.3$$

Example 2: $CC_s = [\text{第二}, \text{次}, \text{工业革命}]$ ([second, (measure word), industrial revolution]), $CC_t = [\text{第二}, \text{次}, \text{世界大战}, \text{人物}]$ ([second, (measure word), world war, people]).

The component concept similarity value that is obtained using Eq. (2) is $\text{Sim}(CC_s, CC_t) = 1.0$. This is because atomic concept “次” has a phenomenon of “polysemy”. Specifically, the lexical unit “次” has multiple items of TYCCL (extended version) code, among which the code “Dn04B03=” determines that two atomic lexical units, “第二” and “次”, are equivalent. Thus, according to Eq. (2) given by Refs. [14], there are four cases in which the mapping result of the atomic concept is 1.0: $\langle \text{第二}, \text{次} \rangle = 1.0$; $\langle \text{第二}, \text{第二} \rangle = 1.0$; $\langle \text{次}, \text{第二} \rangle = 1.0$; and $\langle \text{次}, \text{次} \rangle = 1.0$. Put these in Eq. (2), and

$$\text{Sim}(CC_s, CC_t) = (1.0 + 1.0 + 1.0 + 1.0)/4 = 1.0$$

The final compound concept similarity value, which is computed based on Algorithm 1, should be:

$$\text{SIM}_{NW}(CC_{si}, CC_{ti}) = (1.0 + 1.0 + 0.18 - 0.05)/4 = 0.5325$$

Its sequence matching results are shown in Fig. 5.

It can be seen that there are no equivalent relationship between the two compound concepts in Example 1

Table 3 Statistics on standard reference mapping pairs of Baidu – Hudong mapping task

Mapping Task	Top Category	Number of Concepts in Baidu-Baiku	Number of Concepts in Hudong	Reference Mapping Pairs
Baidu-Hudong	Person	120	1497	57
	Science	157	2323	62
	Society	102	3937	60
	History	118	2093	54
	Art	84	1506	55
	Nature	104	5688	71
	Sports	165	258	59
	Geography	133	3632	97

and Example 2 at all. The wrong conclusion is given by the traditional method that their similarity values are 1.0, which is extremely high. Conversely, the similarity values that are obtained using Algorithm 1 are more reasonable. Thus, when the features of Chinese, such as word order-sensitive and polysemy are considered, using the global alignment algorithm based on the Needleman-Wunsch algorithm can effectively avoid the incorrect mapping that the traditional method represented by Eq. (2) may cause. Meanwhile, when mapping compound concepts, if the semantic orders of atomic concepts in word sequences are essentially the same, then Algorithm 1 is consistent with the traditional method.

In summary, the method for computing similarity in element-level concepts based on global sequence alignment is more advantageous and reasonable than the traditional method for open-domain and large-scale Chinese ontology mapping tasks.

4.2 Evaluation Indicators

In this study, the Precision, Recall, and F-measure (F1) were used as the final evaluation criteria.

Precision (P) = Correct mapping pairs / total output mapping pairs $\times 100\%$

Recall (R) = Correct mapping pairs / total reference mapping pairs $\times 100\%$

$$\text{F-measure (F1)} = 2 \times P \times R / (P + R) \times 100\%$$

We invite four Chinese senior grade students from Capital University of Economics and Business to use the manual identification and manual annotation-based method for annotating the equivalence relationships between concepts existing in the top classification tree of DBpedia, BaiduBaiku and Hudong. The annotation results are treated as the reference mapping pairs for the Chinese ontology mapping task. The number of reference mapping pairs in the three mapping tasks is shown in Tables 3, 4 and 5:

4.3 Evaluation of the Chinese Ontology Mapping Results

This study used four different algorithms to evaluate the

results of large-scale Chinese ontology mapping in LOD environment. The first one is the Edit-Distance based algorithm, which can be commonly used in different languages [32]. The second one is the traditional TYCCL-based algorithm (TYCCL algorithm) that computes the similarity between Chinese atomic concepts [17]. The third one is the ELOMC system proposed by Li et al. [14]. The fourth one is the TongSACOM proposed in this study.

To ensure fairness, the similarity threshold value will be set to $t = 0.9$, which is used to determine the equivalent relationships between concepts in each algorithm. The evaluation results for the three mapping tasks are shown in Tables 6, 7 and 8.

A conclusion can be get from Baidu-Hudong mapping

Table 4 Statistics on standard reference mapping pairs of Hudong – DBpedia mapping task

Mapping Task	Top Category	Number of Concepts in Hudong	Number of Concepts in DBpedia	Reference Mapping Pairs
Hudong-DBpedia	Person	1497	4737	380
	Science	2323	156	33
	Society	3937	10676	303
	History	2093	5648	524
	Art	1506	1908	193

Table 5 Statistics on standard reference mapping pairs of Baidu – DBpedia mapping task

Mapping Task	Top Category	Number of Concepts in Baidu-Baike	Number of Concepts in DBpedia	Reference Mapping Pairs
Baidu-DBpedia	Person	120	4737	26
	Society	102	10676	28
	History	118	5648	11
	Art	84	1908	25
	Geography	133	37936	95

result as shown in Table 6. The Precision of TongSACOM was, on average, approx. 38% and 36% higher than that for TYCCL algorithm and ELOMC, respectively. Its Recall was, on average, approx. 14% and 3% higher than the Edit-Distance and TYCCL algorithm but is roughly equal to ELOMC. Its average overall performance (F-measure) values were 7%, 22% and 20% higher than the Edit-Distance, TYCCL algorithm and the ELOMC system respectively.

Hudong-DBpedia mapping result presented in Table 7 shows that the Precision of TongSACOM was, on average, approx. 1%, 10% and 11% higher than that for Edit-Distance, TYCCL algorithm and ELOMC, respectively. Its Recall was, on average, approx. 6% and 1% higher than that for Edit-Distance and TYCCL algorithm respectively, and is essentially equal to ELOMC. The average F1 values of TongSACOM were 3%, 6% and 6% higher than the other three algorithms respectively.

Table 8 has shown us that, while facing the Baidu-DBpedia mapping task, the Precision of TongSACOM is, on average, approx. 39% and 43% higher than that for TYCCL algorithm and ELOMC. Its Recall was, on average, approx. 17%, 6% and 3% higher than that for Edit-Distance, TYCCL algorithm and ELOMC respectively. The average F1 values were 8%, 26% and 30% higher than the other three algorithms respectively.

In addition, under the conditions of 4 levels of Algorithm factor (Edit-Distance, TYCCL algorithm, ELOMC and TongSACOM) and 72 samples, this study assumes that samples are independent of each other and follow normal distribution for conducting a Significance Test (One-Way ANOVA). We observe that, under 0.05 of the significance level, Precision of the four algorithms is significantly different affected by the Between Groups ($F_{0.05}(3, 68) < 27.496$, $p = 0.000 < 0.05$); Recall of the four algorithms is significantly different affected by the Between Groups ($F_{0.05}(3, 68) < 5.194$, $p = 0.003 < 0.05$); and the overall performance (F-measure) of the four algorithms is also significantly different affected by the Between Groups ($F_{0.05}(3, 68) < 9.474$, $p = 0.000 < 0.05$).

Table 6 Results and evaluation of four typical similarity algorithms of Baidu – Hudong mapping task

Mapping Task	Top Category	Edit-Distance Algorithm[32]			Original TYCCL-Based Algorithm[17]			ELOMC[14]			TongSACOM		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
Baidu-Hudong	Person	1.000	0.526	0.690	0.657	0.772	0.710	0.943	0.877	0.909	0.980	0.877	0.926
	Science	1.000	0.742	0.852	0.422	0.790	0.551	0.387	0.774	0.516	0.982	0.774	0.866
	Society	1.000	0.567	0.723	0.640	0.800	0.711	0.622	0.850	0.718	0.662	0.817	0.731
	History	1.000	0.611	0.759	0.607	0.630	0.618	0.607	0.685	0.643	1.000	0.685	0.813
	Art	1.000	0.727	0.842	0.769	0.909	0.833	0.729	0.927	0.816	1.000	0.927	0.962
	Nature	1.000	0.704	0.826	0.369	0.775	0.500	0.364	0.775	0.495	0.965	0.775	0.859
	Sports	1.000	0.763	0.865	0.554	0.780	0.648	0.516	0.814	0.632	0.980	0.814	0.889
	Geography	1.000	0.691	0.817	0.470	0.804	0.593	0.491	0.845	0.621	0.988	0.835	0.905
	Average	1.000	0.666	0.797	0.561	0.782	0.645	0.582	0.818	0.669	0.945	0.813	0.869

Table 7 Results and evaluation of four typical similarity algorithms of Hudong – DBpedia mapping task

Mapping Task	Top Category	Edit-Distance Algorithm[32]			Original TYCCL-Based Algorithm[17]			ELOMC[14]			TongSACOM		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
Hudong-DBpedia	Person	0.973	0.861	0.913	0.955	0.889	0.921	0.949	0.924	0.936	0.956	0.924	0.940
	Science	0.939	0.939	0.939	0.838	0.939	0.886	0.886	0.939	0.912	1.000	0.939	0.969
	Society	0.964	0.894	0.928	0.793	0.983	0.878	0.794	0.993	0.883	0.990	0.993	0.992
	History	0.987	0.987	0.987	0.992	0.989	0.990	0.979	0.992	0.986	0.994	0.992	0.993
	Art	0.984	0.938	0.960	0.823	0.990	0.899	0.740	0.995	0.849	0.989	1.000	0.994
	Average	0.969	0.924	0.946	0.880	0.958	0.915	0.870	0.969	0.913	0.986	0.970	0.978

Table 8 Results and evaluation of four typical similarity algorithms of Baidu – DBpedia mapping task

Mapping Task	Top Category	Edit-Distance Algorithm[32]			Original TYCCL-Based Algorithm[17]			ELOMC[14]			TongSACOM		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
Baidu-DBpedia	Person	1.000	0.692	0.818	0.452	0.731	0.559	0.733	0.846	0.786	0.963	1.000	0.981
	Society	1.000	0.679	0.809	0.639	0.821	0.719	0.500	0.821	0.622	0.955	0.750	0.840
	History	1.000	0.727	0.842	0.692	0.818	0.750	0.188	0.818	0.305	0.900	0.818	0.857
	Art	1.000	0.760	0.864	0.639	0.920	0.754	0.821	0.920	0.868	1.000	1.000	1.000
	Geography	1.000	0.853	0.920	0.421	0.979	0.589	0.413	1.000	0.585	0.989	0.989	0.989
	Average	1.000	0.742	0.851	0.569	0.854	0.674	0.531	0.881	0.633	0.961	0.912	0.934

The Precision of TongSACOM is slightly lower than the Edit-Distance algorithm in Baidu-Hudong and Baidu-DBpedia mapping task. It is mainly because a few concepts are controversial or improper classified as a pair of synonym in TYCCL, such as: “作家 (writer)” and “女作家 (female writer)”, “文学家 (litterateurs)” and “散文家 (essayist)”, “民族 (nation)” and “中华民族 (the Chinese nation)”, “刑法 (Criminal laws)” and “刑事 (criminal)”, “辛亥革命 (the Revolution of 1911 (the Chinese bourgeois democratic revolution led by Dr. Sun Yat-sen which overthrew the Qing Dynasty))” and “革命 (revolution)” *etc.* If they appear in the final result, we consider them as the wrong mapping pairs. This situation appears more in the Society sub-mapping task of Baidu-Hudong but rarely appears in others; furthermore, the average Precision of TongSACOM in the three groups of Chinese Encyclopedia mapping tasks are 94.5%, 98.6% and 96.1% respectively, which are still completely within the acceptable range. While the Edit-Distance algorithm can only mechanically compare the concept similarity on the literal similarity level, which totally ignores the semantic similarity between concepts and will inevitably lead to its recall in all mapping tasks were significantly lower than those of the other systems. By comparison, TongSACOM firstly introduces the TYCCL (extended version) as the semantic dictionary and then improves the original TYCCL algorithm in order to adapt it to the large-scale Chinese ontology mapping task; therefore, the Recall of TongSACOM is significantly higher than Edit-Distance algorithm, which

Fig. 8 The example 1 of unreasonable sequence alignment result

Fig. 9 The example 2 of unreasonable sequence alignment result

eventually makes the overall average performance (F-measure) of TongSACOM is higher than Edit-Distance algorithm in all the three groups of Chinese Encyclopedias mapping results.

The specific Recall of Society and Geography in Baidu-Hudong mapping task is slightly lower than the ELOMC. The reason is that there were thought to be correct synonym mapping pairs such as “组织 (organization)” and “组织机构 (organizational structure)”, “地形地貌 (topography)” and “地形 (topography)” in the Society and Geography mapping results, but due to the length of the two sequences to be mapped is 1 and 2 respectively, a differential of 2, which ultimately led to the wrong sequence alignment result. As shown in Figs. 8 and 9. Therefore, while the length of two sequences to be mapped corresponding to the

correct synonym mapping pairs is various, sequence alignment algorithm is easy to cause the unreasonable similarity value. This situation rarely appears in the three groups of Chinese Encyclopedia mapping tasks. Compared to the previous algorithm that completely ignored the rules of word-order sensitivity and polysemy in Chinese, TongSACOM has an obvious advantage in the promotion of Precision, which eventually makes the overall average performance (F-measure) of TongSACOM is obviously higher than the traditional TYCCL algorithm and the ELOMC system in all the three groups of Chinese Encyclopedias mapping results.

In summary, the overall performance (F-measure) of TongSACOM is the best of its kind. Its Precision is obviously higher than traditional TYCCL algorithm and ELOMC. The Recall of the TongSACOM model is higher than Edit-Distance and traditional TYCCL algorithm, and is essentially equal to ELOMC system.

5. Conclusion

Linked Open Data at Schema-Level and knowledge described in Chinese is an important part of the LOD project. Previous work generally ignored the rules of word-order sensitivity and polysemy in Chinese or could not deal with the out-of-vocabulary mapping task. In this paper, the further and systematic research is done at the aspect of how to build Chinese linked open data at Schema-Level, and a novel Chinese ontology mapping prototype (TongSACOM) in LOD scenario is proposed.

Based on the TYCCL and global sequence alignment theory, firstly, for a pair of atomic Chinese concepts, an improved TYCCL-based algorithm is proposed to compute the similarity between two atomic concepts; secondly, for a pair of compound Chinese concepts, based on the semantic features of Chinese, a novel strategy for Chinese ontology alignment is proposed by incorporating sequence alignment from bioinformatics.

This study may have important practical significance for enriching the schema-interlinkings between the Chinese Knowledge Bases in LOD environment and can hasten some new online applications in different areas.

Acknowledgments

This work was supported by BPSSP (15ZHB011), JSPS KAKENHI Grant (No.15K00332) and Capital University of Economics and Business Research Grant.

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