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HDSKG: Harvesting Domain Specific Knowledge Graph from Content of Webpages

Xuejiao Zhao\textsuperscript{1,2,3}, Zhenchang Xing\textsuperscript{4}, Muhammad Ashad Kabir\textsuperscript{5}, Naoya Sawada\textsuperscript{6}, Jing Li\textsuperscript{3}, Shang-Wei Lin\textsuperscript{1,3}

\textsuperscript{1}Rolls-Royce@NTU Corporate Lab, Nanyang Technological University (NTU), Singapore
\textsuperscript{2}Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly (LILY), NTU, Singapore
\textsuperscript{3}School of Computer Science and Engineering, NTU, Singapore
\textsuperscript{4}Research School of Computer Science, Australian National University, Australia
\textsuperscript{5}School of Computing and Mathematics, Charles Stuart University, Bathurst, NSW, Australia
\textsuperscript{6}Cloud Service Division, NTT Communications Corporation, Japan

\{xjzhao, shang-wei.lin, jli030\}@ntu.edu.sg; zhenchang.xing@anu.edu.au; akabir@csu.edu.au; naoya.sawada@ntt.com

Abstract—Knowledge graph is useful for many different domains like search result ranking, recommendation, exploratory search, etc. It integrates structural information of concepts across multiple information sources, and links these concepts together. The extraction of domain specific relation triples (subject, verb phrase, object) is one of the important techniques for domain specific knowledge graph construction. In this research, an automatic method named HDSKG is proposed to discover domain specific concepts and their relation triples from the content of webpages. We incorporate the dependency parser with rule-based method to chunk the relations triple candidates, then we extract advanced features of these candidate relation triples to estimate the domain relevance by a machine learning algorithm. For the evaluation of our method, we apply HDSKG to Stack Overflow (a Q&A website about computer programming). As a result, we construct a knowledge graph of software engineering domain with 35279 relation triples, 44800 concepts, and 9660 unique verb phrases. The experimental results show that both the precision and recall of HDSKG (0.78 and 0.7 respectively) is much higher than the openIE (0.11 and 0.6 respectively). The performance is particularly efficient in the case of complex sentences. Furthermore, with the self-training technique we used in the classifier, HDSKG can be applied to other domain easily with less training data.

Index Terms—Knowledge Graph, Structural Information Extraction, openIE, Stack Overflow, Dependency Parse

I. INTRODUCTION

Recently, the trends and development of information retrieval and mining have transferred from the document-centric to the entity-centric [1]. So knowledge graph which integrates the structural information of concepts across multiple information sources, and links these concepts together [2] is useful for many different domains, such as search result ranking, recommendation, exploratory search etc [3], [4], [5], [6]. The webpages such as Wikipedia, Quora are potential repositories for building up knowledge graph. Thus, automatic knowledge graph construction techniques for the content of webpages become a widely research topic. [4], [7], [8].

Open information extraction refers to the extraction of relation triples without specifying the fixed relation schema, typically the relation is a triple with (subject, verb phrase, object) structure [9], [10] (Subjects and objects are collectively called concepts). The relation triples are one of the important components of the knowledge graph [11]. There are many researches on open information extraction including NELL [12], OpenIE [13], and Google [14]. The key challenge in construction of the knowledge graph is the extraction of relation triples with high precision and recall.

Knowledge Graph is also popularly used in software engineering domain [6], [15], [16], [17] to solve various problems such as software requirements analysis and design [18], coding support, documentation [6], maintenance and testing [19]. But there are few studies focus on structural knowledge-base construction in software engineering domain. Large scale knowledge-base construction (KBC) in other domains were studied intensely over the last decade [12], [20], [21], [22], [23], [24], [25]. Such as relational database which allow users to semantically query relationships and properties of natural language resources, including links to other related datasets [7]. It can be used to straightforward search engine algorithms or other search operations and improve the accuracy of information retrieval. Even though there are some research focusing on ontology construction in software engineering domain [26], [27]. They only use the domain key words as the concepts and explore the taxonomic relations of the key words. However, there are still many domain concepts indicating richer semantic and more useful relations between the concepts needed to be mined.

Stack Overflow is the most popular Q&A website about computer programming [27], [28], every question requires the asker to give 1-5 tags. The tagWiki is the content used to describe the definition and some related resource of every tag in Stack Overflow. Such a knowledge repository contains huge number of sentences with affluent concepts and concepts relations descriptions of software engineer domain. These relations are essential for construction of software engineer domain knowledge graph. There are a substantial amount of work that explore the knowledge of tagWiki [1], [29], but none of them focus on extraction of the relation triples.

In this paper, an automatic method named HDSKG (Harvesting Domain Specific Knowledge Graph) is proposed to discover domain specific concepts and their relation triples from the domain specific webpages. We incorporate the depen-
dency parser with the rule-based method to chunk the relations triple candidates, then extract novel features of those triples to estimate domain relevance by self-training SVM (Support Vector Machine) classifier.

For the evaluation, we conduct a case study which extracts the knowledge graph from Stack Overflow. Our experimental results show that both the precision and recall of HDSKG (0.78 and 0.7 respectively) is much higher than the openIE (0.11 and 0.6 respectively) – the state of the art tool for relation triples extraction. Furthermore, self-training SVM classifier makes HDSKG easy to be applied to other domains with less training data.

This paper makes following four major contributions:

• We propose HDSKG that extracts the dependencies of the NP (Noun Phrases) and VP (Verb Phrases) from sentences to generate relation triples by incorporating the dependency parser with rule-based chunking.
• We extract advanced features from the relation triples, then leverage a self training SVM classifier and domain lexicon to estimate the domain relevance of the relation triples with a small number of training data.
• We apply HDSKG to Stack Overflow tagWiki, and harvest a knowledge graph of software engineering domain with 44800 concepts, 9660 unique verb phrase and 35279 relation triples, and it is available online 1.

II. RELATED WORK

Automatic knowledge graph construction is a popular research topic. According to the relations property, we divide them into 3 categories.

The first category extract fixed relations using information extraction techniques to construct knowledge graphs. The typical techniques such as CiteSeerX [30], DIG [31], Pujara et al. [32], and NELL [12], etc. focus on small-scale fixed relations extraction with high precision. Deepdive [3] extract relations by Markov Logic Networks (MLNs) and improve the extraction by the bootstrapping system [33]. Bootstrapping technique is similar to self-training in our system.

The second category uses open information extraction technique. It doesn’t need to appoint some fixed relation in advance. Representative technique are proposed by Prismatic [5], Schmitz Michael et al. [34], and Fader et al. [35]. Abebe and Tonella et al. [36] presented a semi-automated approach to construct domain concept ontology from source code identifiers. Our system belongs to this category and we further add the function for domain relevance estimation.

The third category leverage structured data sources to build up the knowledge graph. YAGO [4] and YAGO2s [37] is a structured knowledge base which automatically extracted from Wikipedia with the data e.g., categories, redirects, infoboxes, etc. The knowledge graph of YAGO [4] and YAGO2s [37] is built by defining entity classes from the conceptual Wikipedia categories. As of 2012, YAGO2s has more than 10 million entities and 120 million relations about these entities, the accuracy is above 95% which is checked manually.

Knowledge graph is also widely researched in software engineering domain. Padhye et al. [6] propose a technique to extract the profiles of the usage of API to connect people, projects and libraries in a network. Subramanian et al. [17] link source code examples to API documentation by extraction of entity linking. To the best of our knowledge, our work is the first attempt for mining knowledge graphs which contain relation description for each entity from Q&A website.

III. THE APPROACH

In this section, we describe the approach of HDSKG to show how HDSKG harvest domain specific knowledge graph from content of webpages. In particular, we present how HDSKG works on natural language texts sources to extract relation triples of domain specific knowledge graph.

A. Architecture of HDSKG

Fig. 1 is the framework of HDSKG. The input of HDSKG is the natural language text materials from content of webpages (e.g., healthcare webpages, computer programming webpages, etc.). The output of HDSKG is the knowledge graph of target domain.

The HDSKG contains two main parts as shown in Fig. 1 named HDSKG Chunking and HDSKG Domain Relevance Estimation. HDSKG Chunking incorporates the rule-based method with dependency parser to chunk candidate relation triples. This part comprises five main steps, namely pre-process text, split sentences, add NLP (Natural Language Processing) makeup, chunk NP and VP, and chunk relation triples. The second part is used to estimate domain relevance of the candidate relation triples, which comprises two main components, namely extract features of candidate relation triples, estimate domain relevance of each relation triples by self-training SVM classifier.

B. Pre-process Text

In this step, we extract all the text content from the html files of webpages and filter some useless information which don’t contain concepts and relations like hyperlink lists, code snippets, etc. Then we split the text content into sentences.

After that, we enrich the sentences by two steps:

• Recording the source information for every sentence, e.g., the title of the source webpage from which the sentence are extracted, and the sequence of sentence in the source webpage.
• Making the sentences readable without the context: replacing the pronouns at beginning of the sentences (e.g., it, she, he) with the title of source webpage [9].

Take the sentence “It is written in C++, and is ultimately derived from the Borland InterBase 6.0 source code.” for example. It is the third sentence in the tagWiki of Firebird, so we record the title of the source webpage – Firebird and the sentence sequence – three. Then we replace the “it” to “Firebird”, so the sentence become “Firebird-3, Firebird is

1http://neo4j.tuntunkun.org/xuejiao/
written in C++, and is ultimately derived from the Borland InterBase 6.0 source code.”

C. Add NLP Makeup

NLP is widely used for natural language pre-processing and semantic analysis [38], [39], [40]. The NLP makeup component in HDSKG system adopts the tool named coreNLP of Stanford for Tokenization, POS (Part of Speech) Tagging, Dependency Parsing and Lemmatization [41], [42], [43], [44].

Tokenization is used to break the text into words, phrases, or symbols.

The POS is the category of words (or, more generally, of lexical items) which has similar grammatical properties. e.g., NNP:Proper noun, singular, VBZ:Verb, third person singular present, RB:Adverb. Fig. 2 shows the POS tagging result of definition sentence of Firebird generated by coreNLP.

The goal of lemmatization is to reduce inflectional forms and derivational related forms of a word to a common base form.

D. Chunk Candidate Relations Triples

There are twice chunking to get the candidate relation triples. Firstly, HDSKG Chunking chunks the tokens in the sentence to NP and VP according to the POS, then utilizes the dependency of the tokens to chunk the VP and NP to relation triples.

1) Chunk NP and VP by Rule-Based Chunking: In this step, we adopt a fulltext parsing techniques called “rule-based chunking” to extract NP and VP [45], [46].

In our system, the NP and VP are identified by the regular expressions as shown in Tab. I. Where (MD) is modal; (VB.) stands for different categories of verb such as VB - verb base form, VBG - verb gerund or present participle, VBN - verb past participle, VBP - verb non-3rd person singular present, VBZ - verb 3rd person singular present. (NN.*) stands for different categories of noun such as NN - singular or mass noun, NNS - plural noun, NNP - singular proper noun, NNPS - plural proper noun. (JJ) represents an adjective; (RB) is adverb; (DT) presents an article; and (IN*) means any preposition or subordinating conjunction. The “VVP” is the VP with open clausal complement.

In the regular expressions, “?” stands for whether or not there is such a determinant; “*” means zero or more determinant; “+” means must have such a determinant; “-” means continue to next row.

Using the rule-based chunking, we chunk the tokens of sentence to VP and NP. For example, the sentence “PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.”, we chunk VP “is built on” and “using”; NP “PyTables”, “HDF5 library”, “Python language”, and “NumPy package” as shown in Fig. 3.

2) Dependency Parsing: Dependency Parsing extracts the grammatical structure of the sentence, then derive relationships
Firebird is written in C++, and is ultimately derived from the Borland InterBase 6.0 source code.

Fig. 2. POS tagging results of the definition sentence of the Firebird

Fig. 3. Result of NP and VP Chunking

Fig. 4. Graphical representation of the Dependencies for the sentence: “PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.”

between “head” words (also known as Governor) and words which modify the heads (also known as dependent). Fig. 4 shows a directed graph representation of the dependencies for the sentence: “PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.”. The nodes of Fig. 4 are the words of the sentence, and the edges in Fig. 4 are grammatical relations.

Tab. II presents some important dependencies of sentence “PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.” used in our system.

As Tab. II shows, “nsubjpass” is a NP and the syntactic subject of a passive clause [47]. For our illustrative sentence, nsubjpass(PyTables-1, built-3) means that “PyTables-1” is the syntactic subject of the verb “built-3”.

The “nmod” used between two content words, as the preposition of one content word is now viewed as a case depending on its complement. In general, the “nmod” indicates some further adjunct relation specified by the case [48]. The nmod (library-9, built-3) means that “built-3” is nominal modifiers of “library-9”. The “library-9” expresses further “on top of” relation to “built-3”. Notice that some times there will appear a preposition after “nmod” like “nmod:at”. This “at” means the complement use the preposition “at” to modify the Dependent.

The “xcomp” means open clausal complement of a verb or an adjective. These complements are always non-finite rather than adjuncts/modifiers. It is a predicative or clausal complement without its own subject. So the “xcomp” always expresses a new meaning or new relation. The xcomp means that “using-11” is open clausal complement of “built-3”.

The “dobj” is the direct object of a VP, and is also a NP which is the accusative object of the verb.

3) Chunk Relation Triples: After the VP and NP chunking, we can chunk semantic relation like (concept, relation verb phrase, concept). Traditional rule-based chunking detects the chunk with morphological structure like (NP, VP, NP). This method not only misses many information, but also adds noise to the relation triples. For example, from sentence “Firebird is written in C++, and is ultimately derived from the Borland InterBase 6.0 source code.”, traditional rule-based chunking can only extract relation triple (Firebird; is_written_in; C++). From sentence Eclipse on your system can be used as a Java editor and a C++ editor, relation triple (system; can_be_used_as; Java_editor) are extracted by traditional rule-based chunking using the morphological structure (NP, VP, NP). However, it is semantically wrong.

To tackle the above problems, we propose a method which incorporates the dependency parser with rule-based chunking. By analyzing the dependency generated by the dependency parse technique, the real subject of the verb in a complex sentence is determined. We assuming having a sentence $S$. Firstly we use the rule-based chunking to get all the VP and NP as below:

$$S = (NP_1, VP_2, ..., NP_i, ..., VP_j, ..., VP_m, VP_1, VP_2, ..., VP_j, ..., VP_n)$$

Where $NP_i$ is the $i$th NP in $S$, $VP_j$ is the $j$th VP in $S$, there are $m$ NP and $n$ VP in $S$.

$$NP_j = (n_{j1}, n_{j2}, ..., n_{jr}, ..., n_{jg})$$

$$VP_i = (v_{i1}, v_{i2}, ..., v_{ik}, ..., v_{ip})$$

Where $n_{jr}$ is the $r$th term of $NP_j$, $v_{ik}$ is the $k$th term of $VP_i$, we assume that $NP_j$ contains $q$ terms and $VP_i$ contains $p$ terms.

Secondly we use dependency parsing to get the dependency of all terms $v$ and $n$. Due to the dynamic of natural language, there are too many different expressions for the same meaning. After we analyzing the dataset deeply, we propose many scenarios to deal with the sentences. We choose six scenarios in our system to show how HDSKG Chunking chunks the candidate relation triples.

Scenario 1: If we extract the nsubjpass $(n_{12}, v_{13})$, dobj$(v_{13}, n_{22})$ from $S$ by dependency parsing, we can chunk $(NP_1, VP_1, NP_2)$ as a relation triple. For example, in the sentence “OpenRPT provides WYSIWYG editor”, the “openRPT” is $NP_1$ and $n_{11}$, the “WYSIWYG editor” is $NP_2$ and “editor” is $n_{22}$, the “provides” is $VP_1$ and $v_{11}$. From dependency parsing we
get nsubjpass (openRPT-1, provides-2) and dobj (provides-2, editor-4), so we can chunk relation triple (OpenRPT; provides; WYSIWYG_editor).

Scenario 2: If we extract the dependency like nsubjpass \((v_{11}, v_{12})\), nmod \((v_{12}, v_{23})\) in sentence “**HSQLDB is developed by many Java frameworks.**”, where \(v_{11}\) is “HSQLDB”, \(v_{12}\) is “supported”, \(v_{23}\) is “frameworks”. We should chunk relation triple (HSQLDB; is supported by; many_Java_frameworks). Here we assume adjective “many” can’t be ignored like DT (article), because “many Java frameworks” is not equal to “all Java frameworks”.

Scenario 3: In some cases, for example “webkit is developed by Intel at the Intel Open Source Technology Center.”, we get dependency like nsubjpass(webkit-1, developed-3), nmod:agent(developed-3, Intel-5) and nmod:at(developed-3, Center-12), we chunk two relation triples (webkit; is_developed_by; Intel) and (webkit; is_developed_at; Intel_Open_Source_Technology_Center). Notice that with the preposition of dependency “nmod:at”, the preposition of VP1 “is_developed_by” can be changed to “at” while chunking the second relation triples.

Scenario 4: If there is an “and” between two NPs, we will chunk 2 relation triples with different subjects or objects. For example, from sentence “flashcanvas renders shapes and images.”, we will chunk relation triples as:

- (flashcanvas; renders; shapes)
- (flashcanvas; renders; images)

Scenario 5: If there is a dependency “xcomp” extracted from \(S\), we will give an additional dependency “nsubjpass” to the dependencies of the sentence. For example, the sentence “**PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.**” as shown in section. III-D, we extract two dependencies – xcomp(using-11, built-3) and nsubjpass(PyTables-1, built-3) from this sentence, we will add an additional dependency nsubjpass(PyTables-1, using-11) to this sentence. It because that as a open clausal complement of a verb or an adjective, the “xcomp” always expresses a new meaning or new relation. Thereby we can chunk relation triples as:

- (PyTables; is_built_on_top_of; HDF5_library)
- (PyTables; using; Python_language)
- (PyTables; using; NumPy_package)

Scenarios 6: If \(S\) contains VVP as mentioned in section. III-D1, we don’t chunk two relation triples like Scenarios 5 even there is a “xcomp” extracted from \(S\). This is because the two verbs of VVP share the same object. Instead, we chunk only one relation triple and leave the two verbs together in VVP as the relation verb of the relation triple. For example “Joone is used to build neural networks.”, we will chunk relation triple as:

- (Joone; is_used_to_build; neural_networks)

By the above method, from “Firebird is written in C++, and is ultimately derived from the Borland InterBase 6.0 source code.”, we can get dependency nsubjpass(Firebird-1, derived-10), so we will chunk relation triples as:

- (Firebird; is_ultimatelyderived_from; Borland_InterBase_6.0_source_code)
- (Firebird; iswritten_in; C++)

From sentence “**Eclipse on your system can be used as a Java editor.**” we can get nsubjpass(Eclipse-1, used-7). Thus we can chunk relation triples as:

- (Eclipse; canbe_used_as; Java_editor)
- (Eclipse; canbe_used_as; C++_editor)

E. Domain Relevance Estimation of Candidate Relations Tri-}

From **HDSKG Chunking** we present in section. III-D, we harvest many candidate relation triples (subject, verb phrase, object). But some of the relation triples are not related to our target domain. For example, the relation triple (Values; may be enclosed in; quotes), this is a correct chunking but meaningless for the software engineering domain. In this section, we use a machine learning method with advanced features to estimate the domain relevance of the candidate relation triples generated by **HDSKG Chunking**.

1) Feature Engineering: There are many properties beyond simple term statistics which can be extracted from the candidate relation triples to estimate the domain relevance of them. We use the features list in Tab. III to represent each candidate relation triples.

For the complex features we provide a brief description below.

**Text Features:** This feature type regards the basic text properties of the cr (candidate relation triples) at the term level. The POS fraction features capture the distribution of POS tags in the cr and uses following definition:

- **noun:** the tokens which POS tags are NN, NNS, NNP, or NNPS.
When subject occurs, the confidence to be relevant to target domain with higher potential. The concepts, if extracted from source webpages many times, this will appear to be relevant to target domain with higher potential. The occurrence when object occurs. And the support indicates the percentage that subject and object occur simultaneously in the corpus. These association rule features present relation between the subject and object. If these two concepts can be found frequently from the content, these two concepts are high potential relevant to target domain.

Concept Features: These features regard the quality of the concepts. TF-IDF is a numerical statistic approach which can determine the words relevance in a corpus of documents [49],[50]. TF (Term Frequency) means the raw frequency of a term in a document. IDF (Inverse document frequency) is the logarithmically scaled inverse frequency of the documents that contain the word, obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient. Here is the formula for unnormalized weight of term_i in document_j in a corpus of D (documents):

$$TF-IDF_{weight_{ij}} = frequency_{ij} * log_{2}(\frac{|D|}{document_{freq}})$$  (4)

Thus the features subj_tfidf, obj_tfidf, sum_tfidf and average_tfidf can indicate the domain relevance of subjects and objects. If most of the terms in a subject are very general like “values”, “process”, etc., the value of the subj_tfidf will be very low. Otherwise if the subject contains unique and distinctive terms like “c++ library”, “MySQL relational database”, the subj_tfidf value will be high.

We also prepare the domain lexicon which contains the specialized vocabularies of the target domain for estimating the domain relevance of the candidate relation triples. Obviously the candidate relation triples which contain more specialized vocabularies of the target domain show higher domain relevance [51].

Source Features: Here, we refer to features of the cr depended on the stm (source text material) and ss (source sentence) [52]. For the cr_position and ss_position, these two features mean that the cr extracted from the front part of the stm and the front part of the ss is high relevance to target domain. The position refer to the sequence of a cr in the stm or the ss. On the other hand, if a cr is extracted from the webpage in which the topic contains the terms of concepts, it shows high domain relevance. For the long sentence, cr_position, start_index_cr and end_index_cr.
we select the best single classifier – SVM classifier with a HDSKG system process for acquiring the domain specific
To reduce the labor force and improve the prediction accuracy,
Tab. IV shows a example about how to label the positive and
classify the relation triples, but also provide a confidence level
get the labels (or classes) of them. The classifier not only
the unlabel relation triples to the trained SVM classifier and
first iteration, we use the expert labeled relation triples as the
self learning structure to do the classification [27]. In the
labeling new training data is the most labor consuming part.
the applicability and the portability of a system. Obviously,
4 experts are involved in our ground truth. Finally we get 96
relation triples from the webpages of the 47 tagWikis. The four
experts have the background in software engineering and three
of them have ever published knowledge graph or ontology
construction related papers. To ensure the precision, we give
the hyperlinks to the experts rather than the pre-processed
documents. Only the relation triples which extract by at least
5 of them due to their source sentences from webpages are
different from the source sentences from data dump. We use
the rest 91 relation triples as the ground truth to evaluate the
performance of HDSKG.

3) Semi-Supervised SVM Classifier Learning: The workload while using a system to a new domain determines
the applicability and the portability of a system. Obviously, labeling new training data is the most labor consuming part.
To reduce the labor force and improve the prediction accuracy,
we select the best single classifier – SVM classifier with a self learning structure to do the classification [27]. In the
first iteration, we use the expert labeled relation triples as the training data and get a trained SVM classifier. Then, we input
the unlabel relation triples to the trained SVM classifier and
get the labels (or classes) of them. The classifier not only classify the relation triples, but also provide a confidence level
every classified relation triple to show the probability of current classification. From the second iteration, self-training
enrich training data with the labeled relation triples which confidence > 0.9 or confidence < 0.1 to train a new
classifier for the next iteration. The iteration will terminate if
the difference of accuracy lower than a threshold or achieved
the preset iteration time. Then we use the trained SVM classifier at the end of the iterations to classify all the unlabeled
relation triples, and use the relation triples in the positive
classes to construct the knowledge graph of target domain.

Source Text Materials Acquisition: We use the tagWiki of
Stack Overflow provided in a html format as our source text
materials and delete some content which contain few relation
triples such as “frequent question”, “Useful links”, etc. Like
the tagWiki of tag “Firebird”, the input is the html file of the
webpage of “Firebird”\(^2\). As a result, we acquire 20534
documents and split 97454 sentences from the documents.

**Domain Lexicon:** We use the tags of Stack Overflow as the domain lexicon. Finally, 27620 tags is acquired, these
tags cover the popular programming languages(e.g., java, python, php), frameworks(e.g., GWTP, Pallet, AnyEvent), li-

**Ground Truth of the Relation Triples:** From the tagWiki of Stack Overflow, we choose 47 tagWikis by random as our
evaluation materials. Four experts are asked to extract the
relation triples from the webpages of the 47 tagWikis. The four
experts have the background in software engineering and three
of them have ever published knowledge graph or ontology
construction related papers. To ensure the precision, we give
the hyperlinks to the experts rather than the pre-processed
documents. Only the relation triples which extract by at least
2 experts are involved in our ground truth. Finally we get 96
relation triples from the webpages of tagWiki, but we ignore
5 of them due to their source sentences from webpages are
different from the source sentences from data dump. We use
the rest 91 relation triples as the ground truth to evaluate the
performance of HDSKG.

**Involved Tools:** The Stanford CoreNLP is used to do the
NLP make up and dependency parse [53]. The tf-idf library
of Gensim is used to compute tf-idf [54]. The nltk is used to
do the VP, NP chunking [55]. neo4j is used to store the finally
relation triples for supporting the knowledge graph searching
and result visualization [56].

**B. Comparison Method openIE**

We leverage the popular open information extraction tool - open IE of Stanford as the comparison method [10], [13] due
to it is close to HDSKG.

But there are also some differences between our tool and
openIE. First is the method to extract relation triples from stm.
openIE only focus on extraction of relation triples, but ignore
the subject and object should be entities. For example, from
sentence “Born in a small town, she took the midnight train
going anywhere.”, openIE will extract relation triple (she; took;
midnight_train). Here “she” is not an entity. HDSKG identifies the
pronouns in a sentence and replace by suitable nouns.
If some pronouns can’t be replaced, we will not extract the corresponding relations, because the relation triples between
the pronouns and the nouns is useless to knowledge graph.
The other difference is that openIE only extract the relation
triples but can’t estimate the domain reverence of them. So
there are many redundancy relation triples will be extracted
by openIE.

1https://archive.org/details.stackexchange

2http://stackoverflow.com/tags/firebird/info

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<th>TABLE IV</th>
<th>EXAMPLE OF RELATION TRIPLES LABEL</th>
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<tr>
<td>Candidate Relation Triples</td>
<td>Label</td>
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<tr>
<td>(Java; supports; features)</td>
<td>False</td>
</tr>
<tr>
<td>(row; is_represented_as; list)</td>
<td>False</td>
</tr>
<tr>
<td>(Values; may_be_enclosed_in; quotes)</td>
<td>False</td>
</tr>
<tr>
<td>(Java; was_originally_developed_by; James_Gosling)</td>
<td>True</td>
</tr>
<tr>
<td>(Java; was_originally_developed_at; Sun_Microsystems)</td>
<td>True</td>
</tr>
<tr>
<td>(Eclipse; is; open-source_ide_platform)</td>
<td>True</td>
</tr>
</tbody>
</table>

indicate that the cr extracted from the front part of a long ss
shows high domain relevance.

2) Label Data: We design the estimation of domain relevance as a binary-class classification problem to solve. The supervised learning of classification requires the labeled data
for training. We manually mark candidate relation triples by
domain experts as training data to boost the learning process.
Tab. IV shows a example about how to label the positive and
negative relation triples.

3) Semi-Supervised SVM Classifier Learning: The workload while using a system to a new domain determines
the applicability and the portability of a system. Obviously, labeling new training data is the most labor consuming part.
To reduce the labor force and improve the prediction accuracy,
we select the best single classifier – SVM classifier with a self learning structure to do the classification [27]. In the
first iteration, we use the expert labeled relation triples as the training data and get a trained SVM classifier. Then, we input
the unlabel relation triples to the trained SVM classifier and
get the labels (or classes) of them. The classifier not only classify the relation triples, but also provide a confidence level
every classified relation triple to show the probability of current classification. From the second iteration, self-training
enrich training data with the labeled relation triples which confidence > 0.9 or confidence < 0.1 to train a new
classifier for the next iteration. The iteration will terminate if
the difference of accuracy lower than a threshold or achieved
the preset iteration time. Then we use the trained SVM classifier at the end of the iterations to classify all the unlabeled
relation triples, and use the relation triples in the positive
classes to construct the knowledge graph of target domain.

IV. EXPERIMENT

In this section, a case study is proposed to illustrate the
HDSKG system process for acquiring the domain specific relation triples and constructing a knowledge graph. tagWiki of Stack Overflow is used to extract the knowledge graph and some tagWiki documents are chose to evaluate our system.

A. Experiment Setup

1) Data Acquisition: We download the data dump of Stack Overflow until Mar, 2015 from Stack Overflow official data
dump\(^1\).

\(^1\)https://archive.org/details/stackexchange
C. Evaluation and Results Analysis

1) Classifier Comparison and Accuracy Evaluation of Iterations: We do 10-folder cross-validation to evaluate the accuracy in each iteration. The 1000 labeled data (contain 467 positive data and 523 negative data) are separated in two parts, 900 of them are used as training data and 100 of them are used as testing data. In every cross-validation, the prediction confidences of every prediction data are recorded. After 10 times cross-validation, only the prediction data which confidence > 0.9 or confidence < 0.1 in all the 10 times cross-validation are chose to append to training data for the next iteration. Fig.5 is the accuracy of different classifiers in each iteration. It shows the performance of the DNN is the most sensitive classifier to the number of training data, so if we can get large number of training data, the best classifier should be DNN. SVM linear classifier achieves the highest accuracy with the 6 times self-training iterations. The accuracy increase from 0.71 to 0.76, which better than random forest (estimators number = 500) and 4 layers DNN with the hidden_units = [200, 400, 100, 50].

![Accuracy of Classifiers in each Iteration](image)

2) Features Contribution Analysis: For exploration the effect of different features set, we train 5 SVM classifiers using different features groups. Each classifier only uses text features, corpus features, concept features, source features and all features respectively. As shown in Fig.5, the classifier with all features performs best. From Fig.5 we also can infer that all these features we design are useful in estimation the domain relevance of relation triples.

![Accuracy of Classifiers with Different Features](image)

3) Performance Comparison: We further explore the performance of HDSKG. Tab. V shows the extractions of traditional Rule Based Chunking, openIE, HDSKG Chunking and HDSKG Domain Relevance Estimation. This example indicates that compare with traditional Rule Based Chunking, HDSKG Chunking can get more relation triples which can’t extract by simple morphology matching. The traditional Rule Based Chunking can only chunk the relation triples (PyTables; is_built_on_top_of; HDF5_library) from sentence “PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.”. but can’t chunk (PyTables; using; NumPy_package) because the morphology of this relation triple is not continuous (NP,VP,NP). With the using of dependency parsing, we can get the xcomp (using-11, built-3), dobj (using-11, language-14), and dobj (using-11, package-18). These dependencies mean that “using-11” is open clausal complement of “built-3”, and the object of “using-1” is “language-14” and “package-18”. From scenario 5 of HDSKG Chunking, we can chunk (PyTables; using; NumPy_package) and (PyTables; using; Python_language). openIE derives the latent relation triple (PyTables; using; Python_language), but ignores the paralleled relation triple (PyTables; using; NumPy_package). But this relation triple captures by HDSKG accurately by the scenario 4 designed in our system. In addition to above shortcoming, openIE also generates many redundant relation triples like (PyTables; is; built). HDSKG doesn’t make this mistake due to our VP and NP chunking can identify the verb phrase “is built on top of”.

For the sentence “Jansi is a small java library that allows you to use ANSI escape codes to format your console output which works even on windows.”, all the above tree methods extract the wrong relation triple (ANSI; escape; codes). Then we can use the HDSKG Domain Relevance Estimation to filter this irrelevant relation triple. From the Tab. V we can see the HDSKG Domain Relevance Estimation can reserve the correct relation triples and filter out the irrelevant relation triples accurately.

Compare with the above 2 methods, HDSKG Chunking extracts both apparent and latent relation triples, and the domain relevance estimation of HDSKG filters the relation triples which less relevant to the target domain.

Precision, recall and f-measure are used as evaluation metrics of the extractions of HDSKG. Precision is the ratio of the correct relation triples to all extractions, this metric is seen as a measure of quality. Recall is the ratio of the correct relation triples to all ground truth relation triples, which is a measure of completeness. F-measure is computed by:

$$F = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

Fig. 7 shows the performance of different extracting methods, compare with openIE, HDSKG domain relevance estimation achieves the highest precision 0.77 and HDSKG Chunking get the highest recall 0.74.

According to the result, even we lose 0.04 recall by estimation of domain relevance, the precision is be improved 0.25.
TABLE V
RELATION TRIPLES EXTRACTED FROM DIFFERENT EXTRACTION METHODS

<table>
<thead>
<tr>
<th>Extraction Method</th>
<th>Content of Sentence</th>
<th>Jansi is a small java library that allows you to use ANSI escape codes to format your console output which works even on windows.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule Based Chunking Extraction</td>
<td>PyTables is built on top of the HDF5 library, using the Python language and the NumPy package.</td>
<td></td>
</tr>
<tr>
<td>openIE Extraction</td>
<td>(PyTables; is_built_on_top_of; HDF5_library)</td>
<td>(Jansi; is; small_java_library) (ANSI; escape; codes)</td>
</tr>
<tr>
<td>HDSKG Chunking Extraction</td>
<td>(PyTables; using; Python_language) (PyTables; is; built) (PyTables; is_built_on_top_of; HDF5_library)</td>
<td>(Jansi; is; small_java_library) (ANSI; escape; codes)</td>
</tr>
<tr>
<td>HDSKG Domain Relevance Estimation Extraction</td>
<td>(PyTables; using; Python_language) (PyTables; using; NumPy_package) (PyTables; is_built_on_top_of; HDF5_library)</td>
<td>(Jansi; is; small_java_library)</td>
</tr>
<tr>
<td>Ground Truth</td>
<td>(PyTables; using; Python_language) (PyTables; using; NumPy_package) (PyTables; is_built_on_top_of; HDF5_library)</td>
<td>(Jansi; is; small_java_library)</td>
</tr>
</tbody>
</table>

Fig. 7. Performance of different Extraction Methods

The recall performance of the openIE is 0.6, which is close to the recall of HDSKG Domain Relevance Estimation, but this recall of openIE is at the expense of reduction of the precision by generating more irrelevance relation triples.

Compare with the openIE, HDSKG Chunking produces less relation triples with higher precision. HDSKG Domain Relevance Estimation estimates the domain relevance with small loss of recall but improves the precision conspicuously. Fig. 8 is part of the knowledge graph generate by HDSKG in the software engineering domain.

V. DISCUSSION

So far, we have extracted a knowledge graph of software engineering domain from the tagWiki of Stack Overflow. In this section, we discuss the implications of our research for knowledge graph extraction, information retrieval of software engineering domain, and knowledge representation.

A. Implications for Knowledge Graph Extraction

As shown in section III-D, HDSKG Chunking incorporates the dependency parser with rule-based method and extracts the candidate relation triples in the natural language materials with high precision and low recall. The 6 scenarios we present in section III-D3 cover most of the occasions in natural language expressions. It ensures the HDSKG can easy to be used in other natural language materials, e.g., healthcare, industrial design, etc.

For the estimation of domain relevance part of HDSKG, the features we designed are efficient to distinguish domain relevant relation triples as shown in section IV-C2. HDSKG just needs to change the domain lexicon to the domain you want and label few training data, with the self-training SVM classifier, HDSKG will construct the knowledge graph of your target domain automatically.

B. Implications for Information Retrieval in Software Engineering Domain

With the knowledge graph of software engineering domain, we can change the traditional information retrieval way.

Firstly, a direct answer search engine can be constructed [57], [58]. As it shown in Fig. 8, there are 2 kinds of relations, they are “is a” and “object property”.”is a” is the taxonomic relations which indicate a containment relation between 2 concepts [59]. For example, the taxonomic relation like “pi-db” -> “relational_database” -> “database” in Fig. 8. “pi-db” is subclass of “relational_database”, and “relational_database” is subclass of “database”. So we can derive if we have a sentence like "The employees’ information is put in firebird", this sentence "The employees’ information is put in database" is also right. The “object property” is the non-taxonomic relations, these relations present some properties of the concepts. So if there is a query like: “Which database can run on Unix and be written in C++” From the query we can extract the VP “run on” and “be written in”, and the concepts “database”, “Unix” and “C++”. Then the “firebird” will be recommended directly. This direct answer search engine can answer many questions which ask about a specific concept and help developers to find available technologies without reading many webpages.

We can also use this knowledge graph to the semantic search engine because it links the concepts across query key words, documents, databases, webpages, etc. via semantic modeling.
For example, the phrase “firebird is written in C++” and the phrase “C++ is microsoft language” are extracted from different webpages. There is no link between the concept “firebird” and the concept “microsoft language”. But in the knowledge graph, these two concepts connect to “C++”. So in the search results, the ranking algorithms should concern the weight to “microsoft language” related webpages when search “firebird”.

C. Implications for Knowledge Representation

Our knowledge graph is also a structural knowledge representation which can be used to do data documentation and enrich search result pages. Actually Stack Overflow paid effort on it already. There is a new online function which is still under beta test named documentation\(^1\). In this part, Stack Overflow organizes the information of each tag structural like “different version”, “important functions” and “useful code snippets”, etc. Compare to the traditional tagWiki, developer can easy to locate the information they want. But this documentation is contributed by the users of Stack Overflow manually, it’s low efficient and subjective. Our knowledge graph can assist to enrich the documentation. Because it is extracted from the materials which is contributed by many developers, with the “corpus features” we used to the classifier in section. III-E1, the subjective relation triples can be removed. And with the result like the 5 “is written in” relations in Fig. 8, we can enrich the documentation of “C++” with the tools or libraries which are written by “C++”.

Our knowledge graph also can be used to enrich the search result. For example, if you search “iso standard”, as the result in Fig. 8, we will recommend “C++” which is standardized by “iso standard”.

VI. CONCLUSION AND FUTURE WORK

Knowledge graph integrates structural information of concepts across multiple information sources, and links these concepts together. It is useful in many domains such as search result ranking, recommendation, exploratory search, etc. In this paper, an automatic method named HDSKG is proposed to discover domain specific concepts and their relation triples from the content of webpages. By incorporation of the dependency parser with rule-based method, we get the candidate relations triple candidates with high precision and recall. And by utilizing the self-training SVM classifier, we can estimate the domain relevance of the candidate relation triples.

However, even we already proposed six different particular scenarios, due to the dynamic of natural language, there are still some scenarios HDSKG can’t deal with very well. For example, the “of” in NP sometimes make the concept very long like “Middleware is a framework of hooks into Django’s request or response processing.”. But if we delete the content after “of”, some mistakes will be caused like “Windows is a family of graphical operating-systems” will extract (Windows; is; family), it is obviously incorrect. There are also some concepts which refer to same meaning but different expressions, like “python” and “python_language”, “operation_system” and “operating_system”, etc). In the future, we plan to do the concepts and verb phrase clustering to unify the expressions and optimize our system to deal with more particular scenarios.

VII. ACKNOWLEDGEMENTS

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\(^1\)http://stackoverflow.com/documentation
ceedings of the 10th International Conference on Language Resources and Evaluation (LREC 2016), 2016.


