A WordNet Expansion-based Approach for Question Targets Identification and Classification

Tianyong Hao[1,2], Wenxiu Xie[2], and Feifei Xu[3]

[1] Key Lab of Language Engineering and Computing of Guangdong Province, Guangdong University of Foreign Studies, Guangzhou, China
[2] Cisco School of Informatics, Guangdong University of Foreign Studies, Guangzhou, China
[3] College of Computer Science and Technology, Shanghai University of Electric Power, Shanghai, China
haoty@126.com,981555724@qq.com,xufeifei1983@hotmail.com

Abstract. Question target identification and classification is a fundamental and essential research for finding suitable target answer type in a question answering system, aiming for improving question answering performance by filtering out irrelevant candidate answers. This paper presents a new automated approach for question target classification based on WordNet expansion. Our approach identifies question target words using dependency relations and answer type rules through the investigation of sample questions. Leveraging semantic relations, e.g., hyponymy, we expanse the question target words as features and apply a widely used classifier LibSVM to achieve question target classification. Our experiment datasets are the standard UIUC 5500 annotated questions and TREC 10 question dataset. The performance presents that our approach can achieve an accuracy of 87.9% with fine gained classification on UIUC dataset and 86.8% on TREC 10 dataset, demonstrating its effectiveness.

Keywords: Question target classification ·question target words ·WordNet

1 Introduction

Question Answering (QA) has become a hot research area in recent years targeting for providing concise answers rather than a long list of documents [1]. Generally, Question Target Classification (QTC) is the first step in a QA system. A correct and meaningful classification of the question target can benefit the system on efficient and accurate answer extraction. From existing research, incorrect QTC has been addressed as one of the major factors for the poor performance of the Question Answering Systems [2]. Moldovan et al. [3] reported that 36.4% of answering failures caused by incorrect question analysis.

The correct identification of question target is the vital task. Different from question topic, question target (QT) is a representation of users' intention of desirable answer type thus it directly helps in detecting answer relevance. For instance, as for the question "*Who is the largest producer of laptop computers in the world*?", the

adfa, p. 1, 2011.
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question target (answer type) is “*organization*” rather than “*person*”. It helps to classify the question to the correct target category, which directly enhances the answer filtering performance, as filtering out answers in “*person*” category in the example.

In this paper, we propose an automated approach based on dependency relation analysis to identify question target words and extract target semantic features by WordNet expansion. These semantic features are further calculated with QTC taxonomy for acquiring best category labels. Parts of features are used to train LibSVM classifier to obtain correct question target categories. Our datasets are two standard publicly available datasets: UIUC 5500 annotated QA dataset and TREC 10 QA dataset. Applying on a two-layered classification taxonomy proposed by Li and Roth [4], our approach achieved an accuracy of 87.9% with fine gained classification on UIUC dataset and 86.8% on TREC 10 dataset, significantly improved the baseline SVM classifier, demonstrating the effectiveness in improving question target categorization.

The organization of this paper is as follows: Section 2 describes the related work and section 3 presents the detailed information of our approach, particularly the QTW extraction. Section 4 shows our experiments and results on two open datasets. Finally, section 5 summarizes the paper.

2 Related Work

Regardless of the characteristics of question target (answer type), question target classification can be treated as a question classification problem. There are many different methods to resolve the question classification problem. Most of the approaches can be divided into two categories: pattern-based classifiers using patterns and heuristic rules [5] and supervised classifiers using machine learning methods.

Representative researches include Li and Roth [4]. They developed a machine learning approach utilizing SNoW (Sparse Network of Winnows) learning architecture for question classification. They also built a UIUC question target category taxonomy, which has been extensively used around the world. In their approach, a set of syntactic features as well as semantic features using WordNet[1] [6] were used to identify class-specific related words. Using the features, they reported question classification accuracy as high as 98.8% for coarse gained classification. Huang et al. [7] presented two methods to obtain augment semantic features of defined head words based on WordNet. The results demonstrated that the WordNet-based approach significantly increased the accuracy. Their linear SVM (Support Vector Machine) and ME (Maximum Entropy) models achieved accuracy of 89.2% and 89.0%, respectively. Bakhtyar et al. [8] proposed a new hierarchy for processing questions that belong to the class “Other” and presented an automatic hierarchy creation method to add new class nodes using WordNet and noun-phrase parsing.

[1] http://wordnet.princeton.edu/

Particularly, we investigated a number of recent question classification techniques mainly about two aspects: the machine learning-based method SVM (Support Vector Machine) and WordNet-based question classification techniques during 2013 – 2015 as follows:

Machine learning-based methods [9, 10, 11, 12, 13] have been applied to various domains and languages [14] and have achieved results comparable to previous rule-based QA systems. The SVM is one of the most successful classification algorithms from them. An advantage of the SVM is that, once non-support vectors (non-SVs) that do not have any influence on classifier are identified, the vectors can be thrown away in the next test phase [15]. Recently, Yen et al. [16] employed TREC-QA tracks and question classification benchmarks to evaluate the machine learning-based method. Their experimental results showed that the question classifier achieved 85.60% accuracy without any additional semantic or syntactic taggers, and reached 88.60% after they employed a term expansion technique and a predefined related-word set. Hardy et al. [17] used Extreme Learning Machine (ELM) for question classification based on semantic features to improve both training and testing speeds compared with benchmark Support Vector Machine (SVM) classifier. Improvements have also been presented on the head word extraction and word sense disambiguation processes. Their results reached a higher accuracy (an increase of 0.2%) for the classification of coarse gained classes compared to the benchmark.

WordNet corpus is also popular in leveraging semantic in question feature identification. In 2013, Jeong et al. [18] applied WordNet and demonstrated that unit feature dependency information and deep-level WordNet hypernyms are useful for event recognition and type classification. Their experimental results showed that the method outperformed an accuracy of 83.8%. Later, Gao et al. [19] presented a new approach for semantic similarity measuring based on edge-counting and information content theory and resulted in a better distribution characteristics of the coefficient. Eduard et al. [20] used three widely used linguistic resources for taxonomic and non-taxonomic relation extraction: WordNet, general corpora acquired from the Web, and Wikipedia.

These work motivated us to conduct research on question target classification by refereeing the existing ideas of WordNet usage and machine learning methods from question classification area even though they have significant differences task by task.

3 The WordNet-based Expansion Approach

As defined by Li and Roth [4], question target classification is a task that, given a question, maps it to one of the predefined *k* classes, which indicates a semantic constraint on the sought-after answer. To identify the question target, we need to obtain question target representations and prune out irrelevant information which may mislead the classification process. Therefore we propose to use Question Target Words (QTWs) which is a group of words (existing or not existing in the question) as the target representations for specifying the answer type that the question seeks.

Our method contains three main steps: the QTW Extraction, WordNet expansion, and SVM classification. The processing workflow is shown in Fig. 1. The first step is to obtain QTWs utilizing a principle-based English parser MiniPar[2] [21]. Afterwards, the QTWs are expanded with hyponymy features using WordNet to acquire their categories according to depth and distance-based semantic relevance calculation. Finally, the features are sent to a trained LibSVM classifier to obtain their question target (answer type) categories.

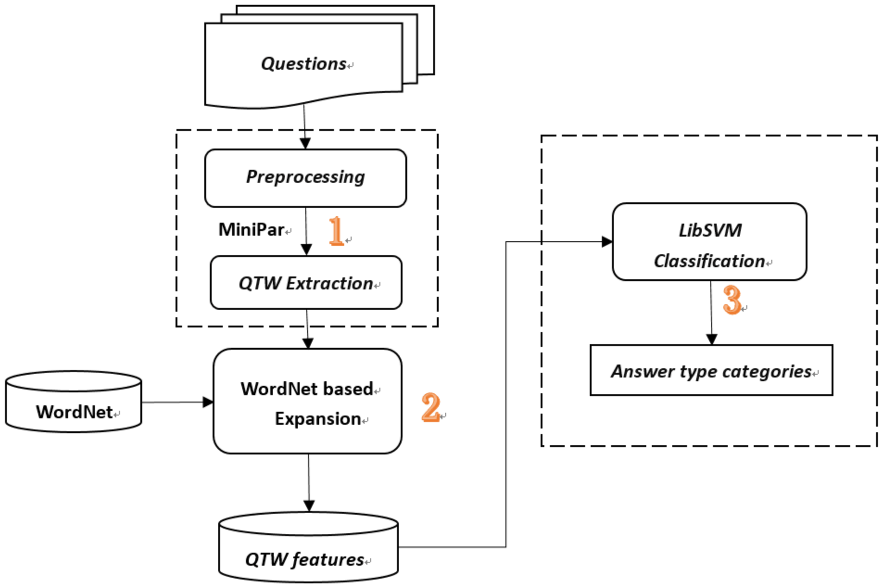

Fig. 1. The workflow of our question target classification approach using WordNet-based expansion and LibSVM classifier

3.1 Question Target Word Extraction

As the accuracy of QTW Extraction directly affects the overall classification performance, we concern a lot on this step and have tried several strategies to ensure the extraction quality. In this process, we apply a principle-based English parser MiniPar to generate a dependency tree for a given question. A dependency relation is a binary relation between two words with one marked as a head word and another marked as a dependent using $\boxed{\text{pos : relation : pos}}$ between them. For instance, the dependency relations of the question "*where can I buy a Guitar in Guangzhou?*" analyzed by MiniPar are shown as Fig. 2. According to the dependency tree, we can extract the main verb-relation : buy ← $\boxed{\text{V:obj:N}}$ → guitar ← $\boxed{\text{N:mod:Prep}}$ → in ←

[2] Available at http://www.cs.ualberta.ca/~lindek/minipar.htm

N:pcomp-n:N → Guangzhou. Therefore, we can extract needed information from it, e.g., "*buy a guitar*" in the example as main event.

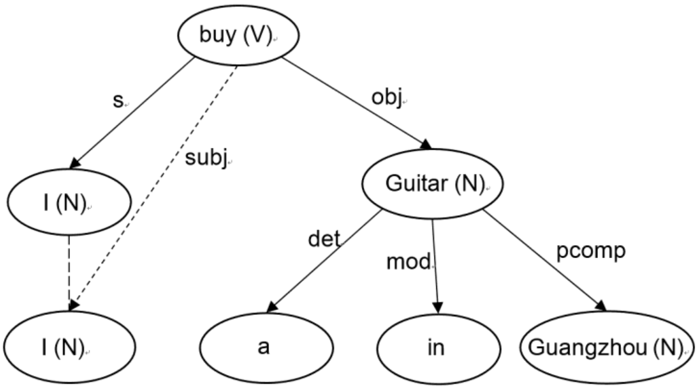

Fig. 2. The dependency relations of the question "*where can I buy a Guitar in Guangzhou?*" analyzed using MiniPar

Therefore, the essential work is to detect useful relations to extract needed QTWs. Due to the manner of question asking and the variety of interrogative words, the syntactic structures of different questions may be much different. After analyzing hundreds both questions dependency relations and syntactic structures between the manually identified QTWs and other (irrelevant) parts of the questions, three situations are identified and analyzed with each of them having a specific processing strategy. Please note the strategies are applied sequentially starting from *Strategy 1*.

Strategy 1: extract QTWs by locating interrogative words

The first strategy is to extract QTWs by directly referring the interrogative words of a question when the question is in formal representation. It is the most common situation for question target word extraction.

For instance, as for the question "*What's the abbreviation for trinitrotoluene?*", the dependency relation of the question by MiniPar is shown below. The relation between *abbreviation* and *trinitrotoluene* is therefore represented as: *what* ←N:subj:N→ *abbreviation* ←N:mod:Prep → *for*←Prep:pcomp-n:N→ *trinitrotoluene* . Through the representation, we can extract the target of the question as *abbreviation* which leads to the answer type "ABBR:abbreviation".

fin	C:whn:N	*what*
fin	C:i:VBE	*be*
be	VBE:pred:N	*abbreviation*
abbreviation	N:subj:N	*what*
abbreviation	N:det:Det	*the*
abbreviation	N:mod:Prep	*for*
for	Prep:pcomp-n:N	*trinitrotoluene*

The defined dependency relations with interrogative words as rules include "C:whn:N", "C:wha:A", "Q:whn:N", "N:det:Det", "N:subj:N", "N:nn:N", and "N:gen:N". These relations help locate interrogative words and the question target being asked. Moreover, the relation rules can also be applied to questions without interrogative words, e.g., the question "*Name a tiger that is extinct*" to extract the correct target word "*tiger*".

Strategy 2: extract QTWs by using interrogative words with extra relations

The second situation is more complicated as interrogative words cannot ensure the correct question target identification thus additional rules of relations, e.g., "Prep:pcomp-n:N", are needed. For example, as for the dependency relation of the question "*What kind of animal is Babar*?", the interrogative words "*What*" cannot be simply used to identify QT through relation analysis. Otherwise, the word of "*kind*" is extracted as QT rather than the needed word "*animal*", as shown below.

fin	C:whn:N	*kind*
kind	N:det:Det	*what*
kind	N:comp1:Prep	*of*
of	Prep:pcomp-n:N	*animal*
fin	C:i:VBE	*be*
be	VBE:pred:N	*Babar*
Babar	N:subj:N	*kind*

In the dependency relation of the question example, a new relation link: *what* ← N:det:Det → *kind* ← N:comp1:Prep → *of* ← Prep:pcomp-n:N → *animal* can be identified to solve this kind of problems. According our investigation, a list of relation rules are summarized as as "C:whn:N", "Q:whn:N", "N:det:Det", "N:subj:N", "N:nn:N", "Prep:pcomp-n:N", "N:gen:N" for solving the situation.

Strategy 3: extract QTWs by using verb-centered relations

The third situation is the most complex one. The interrogative word and above relations as well as related rules sometimes could not extract correct target words. The reason is that these questions contain at least one verb and generated dependency tree is verb-rooted, causing incorrect relation link analysis. For instance, the question "*What garment was named for Bradley, Voorhees and Day*". The dependency relation is as below:

fin	C:whn:N	*what*
fin	C:i:V	*name*
name	V:s:N	*garment*
name	V:be:be	*be*
name	V:obj2:N	*what*
name	V:obj1:N	*garment*
name	V:mod:Prep	*for*
for	Prep:pcomp-n:N	*Bradley*

A new relation link is observed as *fin* → $\boxed{\text{C:i:V}}$ → *name* ← $\boxed{\text{V:s:N}}$ → *garment* without interrogative words and pcomp relations. The main relation is linked by a verb "*name*". Looking inside the relations, we define a list of relation rules as "C:whn:N", "C:i:V", "YNQ:head:V", "V:subj:N", "V:obj:N", "V:obj1:N", "V:obj2:N", and "V:s:N" as the strategy to deal with such kind of questions.

3.2 WordNet-based Feature Expansion

With regarding to the weakness of WordNet in dealing with verbs and interrogative words, the previous step is to identify QT words with obvious relations. The obtained QTWs can be further expanded by WordNet to acquire expected answer types. In WordNet, senses are organized into hierarchies with hyponyms relationships, i.e., *A* is a kind of *B*, providing a way to augment hyponyms feature for the QTWs. For instance, the QTW of the question "*What kind of flowers does detective Nero Wolfe raise*" is "*flower*". The hierarchy for the noun sense of "*flower*" is as: "*flower* → *flowering plant* → *seed plant* → *vascular plant* → *plant* → *organism* → *living thing* → *object* → *physical entity* → *entity*", where " *A* → *B*" representing that *B* is the hyponyms of *A*.

With the hyponym hierarchy, the hyponym labels as the super semantic layers can be calculated with our QTC taxonomy to obtain best category labels. To achieve that, we firstly design a QTC taxonomy, as shown in Table 1, by following Li & Roth in the research of UIUC QA category [4].

Table 1. The QTC taxonomy defining two-level categories following Li & Roth [4]

Coarse	Fine grained	Count
ABBR	abbreviation, expansion	2
DESC	definition, description, manner, reason	4
ENTY	animal, body, color, creation, currency, disease/medical, event, food, instrument, language, letter, other, plant, product, religion, sport, substance, symbol, technique, term, vehicle, word	22
HUM	description, group, individual, title	4
LOC	city, country, mountain, other, state	5
NUM	code, count, date, distance, money, order, other, percent, period, speed, temperature, size, weight	13

Though the hyponym hierarchy in WordNet is commonly used, e.g. [7], we calculate the conceptual similarity differently, as relevance, between each hyponym label of a QTW and each category label defined in the taxonomy. By referring the similarity matrix proposed in [22], we define a new relevance calculation measure utilizing both depth and distance information in WordNet, as shown in Equation (1).

The higher the relevance, the higher possibility of a category label is chosen as the candidate QTC.

$$Relevance_{QTC} = \frac{(Depth_{label_i} + Depth_{label_j})}{2 \times Max(Depth_{label_i}, Depth_{label_j})} \times \frac{1}{Log(Distance(label_i, label_j)) + 1} \qquad (1)$$

$Relevance_{QTC}$ denotes the relevance of a hyponym label $label_i$ of a QTC word with a category label $label_i$. $Depth_{label}$ denotes the number of levels of the label $label_i$ from the root node in WordNet; *Max* is to obtain the maximum depth for normalization; *Distance* is the minimum length of all ancestral paths between the two labels. Thus the minimum length between any two labels is 1. The relevance value is finally normalized into [0, 1].

The WordNet-based expansion is able to identify QTC alone. However, according to our observation on a large number of questions, certain types of questions are difficult for the method to achieve high performance, e.g., "Entity/other", as shown in Table 2 in next section. We therefore employ both Wordnet-based expansion and a standard LibSVM classifier for improving classification performance. The used features are all the words in a question. As LibSVM is a widely used classification tool, it will not be described repeatedly in the paper.

4 Experiments and Results

Two publicly available standard datasets are used to test the effectiveness of our approach: 1) Dataset A: 5500 questions with manually annotated question target labels from University of Illinois at Urbana-champaign (UIUC) [3]; 2) Dataset B: 500 TREC 10 (Text Retrieval Conference) questions with manually annotated question target labels from UIUC [4]. Both the two dataset were mapped to 6 coarse grained classes and 50 fine grained classes, where the classess are shown in Table 1. Based on them, we split dataset A and B into training and testing datasets for three experiments. Our measurement is the commonly used accuracy defined as the total number of questions with correctly labeled QTC divided by the total number of questions in experiment dataset.

The first experiment evaluated the effects of different size training datasets and testing datasets to question target classification performance. The purpose was to view the stablibility of our apporach by using different sizes of datasets. We firstly randomly selected 1000 questions from Dataset A as testing dataset UIUC 1000 and randomly selected 1000 to 3500 questions from the same Dataset A as training datasets. For each training dataset, accuracy was calculated. Similarly, 2000 questions from Dataset A were randomly selected from Dataset A as UIUC 2000 and the training datasets were also the data from 1000 to 35000. The accurracy calculation results are shown as Fig. 3. From the result, the size of training dataset contributes

[3] http://cogcomp.cs.illinois.edu/Data/QA/QC/train_5500.label
[4] http://cogcomp.cs.illinois.edu/Data/QA/QC/TREC_10.label

accuracy much when the training dataset size is below 1500. After that, the accuracies on both UIUC 1000 and 2000 tend to be stable and the accuracies are very close when the training dataset size ranges from 3000 to 3500. The experiment results indicate that the performance of our approach is not affected by training dataset size much. This is meaningful since our approach enables achieving stable performance using a relatively small training dataset, which is helpful in large dataset processing.

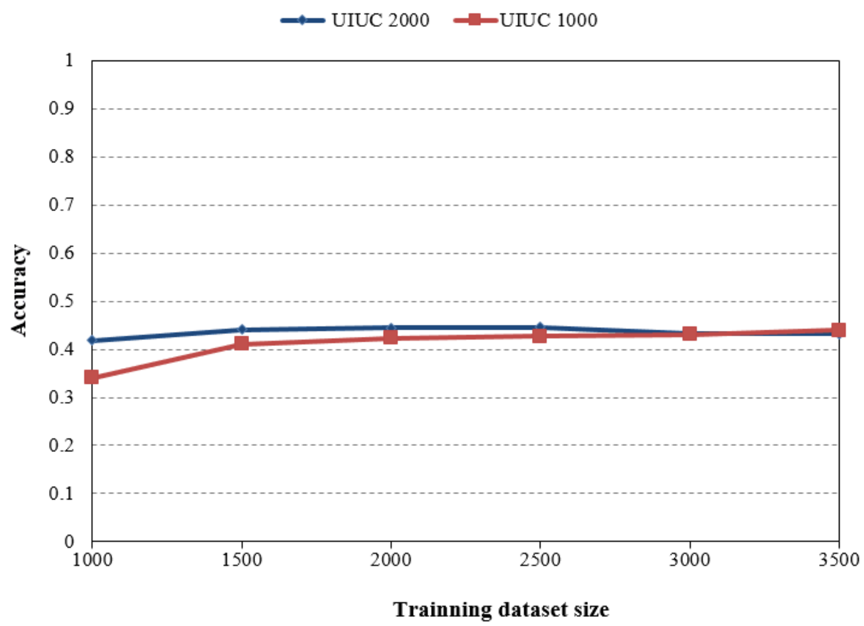

Fig. 3. Number of training dataset vs. classification accuracy on UIUC 1000 and 2000 testing questions

The second experiment conducted a comparison between the contribution of WordNet-based expansion (as WordNet) and SVM-based classification (as LibSVM) on every detailed fine grained category. The purpose was to view the strength and weakness of the two approaches on different categories. The training dataset was randomly selected 3500 questions from Dataset A and the other 2000 were used as testing dataset. The result, as shown in Table 2, presented that these two classifiers were complementary to each other on certain categories. WordNet achieved much higher accuracy on “ENTY:religion”, “ENTY:letter”, “ENTY:plant”, “ENTY:veh”, and “NUM:volsize” while LibSVM achieved much higher accuracy on “DESC:def”, “ENTY:symbol”, “NUM:temp”, etc. For “ENTY:color”, “ENTY:currency”, “NUM:ord”, and “NUM:period ”, both the two methods obtained excellent performance. However, both the methods obtained bad performance on “NUM:code” and “ENTY:techmeth”, indicating big space for improvement on these categories.

Table 2. Accuracy comparison using WordNet and LibSVM on 50 fine grained categories

Category/accuracy	WordNet	LibSVM	Category/accuracy	WordNet	LibSVM
ABBR:abb	0.688	1	ABBR:exp	0.774	0.667
DESC:def	0.042	0.911	DESC:desc	0.696	0.704
DESC:manner	0.99	0.959	DESC:reason	0.906	0.923
ENTY:animal	0.848	0.484	ENTY:currency	1	1
ENTY:body	0.222	0.333	ENTY:dismed	0.854	0.833
ENTY:color	1	1	ENTY:event	0.68	0.333
ENTY:cremat	0	0.589	ENTY:food	0.67	0.471
ENTY:instru	0.7	1	ENTY:religion	0.75	0
ENTY:lang	0.875	0.78	ENTY:sport	0.706	0.75
ENTY:letter	0.78	0	ENTY:substance	0.75	0.571
ENTY:other	0	0.442	ENTY:symbol	0.25	1
ENTY:plant	0.77	0	ENTY:techmeth	0	0.143
ENTY:product	0.738	0.222	ENTY:termeq	0.111	0.786
ENTY:word	0.77	0.60	ENTY:veh	0.929	0
HUM:desc	0.979	0.857	HUM:ind	0.874	0.88
HUM:gr	0.406	0.485	HUM:title	0	0.20
LOC:city	0.845	0.962	LOC:country	0.9	0.964
LOC:mount	0.905	0.625	LOC:other	0	0.848
LOC:state	1	0.929	NUM:code	0	0
NUM:count	0.967	0.984	NUM:date	0.156	0.958
NUM:dist	0.571	0.50	NUM:money	0.765	0.90
NUM:ord	1	1	NUM:other	0	1
NUM:perc	0.857	0.25	NUM:period	1	1
NUM:speed	1	0.667	NUM:temp	0	1
NUM:volsize	0.923	0	NUM:weight	0	0.25

The third experiment evaluated the performance improvement of our approach (as WordNet+LibSVM) compared with WordNet-based expansion and LibSVM classification. In the WordNet-based expansion, we further separated it into WordNet-based expansion on identified categories by removing categories that WordNet-based expansion preformed 0 accuracy according to the analysis of the second experiment as WordNet-concise and WordNet-based expansion on all categories as WordNet. The first testing dataset was 2000 questions randomly selected from Dataset A (other 3500 questions are used as training dataset) as UIUC(2000). The second dataset was all the 500 questions from Dataset B (the same training dataset as the first one) as TREC_10(500). Table 3 shows the results of the comparison. WordNet-concise has a relatively high accuracy compared with WordNet, indicating our WordNet-based expansion is effective to some extent regardless of the QTC categories that the method cannot process. WordNet achieved 74.2% accuracy on UIUC(2000) but only 33% on TREC_10(500). This is reasonable as the training questions are from UIUC rather than TREC_10. LibSVM obtained better results than WordNet. However, as analyzed in the previous experiment, WordNet has obvious advantages in processing of certain categories. Our method WordNet+LibSVM achieved the best performance with an accuracy of 87.9% on UIUC(2000) and 86.8% on TREC_10(500), presenting significant improvement compared with both LibSVM and WordNet.

Table 3. Accuracy comparison among our approach WordNet+LibSVM and other classification strategies on the two datasets

	UIUC(2000)	TREC_10(500)
WordNet-concise	91%	77%
WordNet	74.2%	33%
LibSVM	78%	79%
WordNet + LibSVM	87.9%	86.8%

6. Conclusions

Targeting at question target identification and classification for answer type filtering, this paper proposed a method based on dependency tree analysis for question target word identification. Afterwards, a compact but effective WordNet-based hyponymy expansion strategy was proposed to classify the identification question target words into question target categories. Based on two standard fully annotated datasets: UIUC dataset and TREC 10 dataset, we conducted three experiments to evaluate the effectiveness of our approach through the comparison with other methods. The results presented that our approach achieved the best performance from the comparison, demonstrating its capability in question target classification task.

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References

1 Phuong, L., Phan, X., Nguyen, T.: Using Dependency Analysis to Improve Question Classification. Knowledge and Systems Engineering. Springer International Publishing, 653-665 (2015)
2 Ray, S.K., Shailendra, S., Bhagwati, P. J.: A semantic approach for question classification using WordNet and Wikipedia. Pattern Recognition Letters 31.13, 1935-1943 (2010)
3 Moldovan, D., Paşca, M., Harabagiu, S., Surdeanu, M.: Performance issues and error analysis in an open-domain question answering system. ACM Transactions on Information Systems (TOIS), 21(2), 133-154 (2003)
4 Li, X., Roth, D.: Learning question classifiers. In Proceedings of COLING (2002)

5 Voorhees, E.M.: Overview of the TREC 2003 Question Answering Track. TREC (2003)
6 Miller, G., Christiane, F.: WorldNet: An electronic lexical database. Cambridge, MA: MIT Press (1998)
7 Huang, Z.H., Thint, M., Qin, Z.C: Question classification using head words and their hypernyms. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP) (2008)
8 Bakhtyar, M., Kawtrakul, A., Baber, J. Doudpota, S. M.: Creating Multi-level Class Hierarchy for Question Classification with NP analysis and WordNet. Journal of Digital Information Management 10.6, 379 (2012)
9 Martin, A.I., Franz, M., Roukos, S.: IBM's Statistical Question Answering System-TREC-10. In Proceedings of the Tenth Text REtrieval Conference (TREC) (2001)
10 Moschitti, A., Quarteroni, S.: Kernels on linguistic structures for answer extraction. In Proceedings of ACL (2008)
11 Quarteroni, S., Moschitti, R., Man, S., Basili, R.: Advanced Structural Representations for Question Classification and Answer Re-ranking. Lecture Notes in Computer Science:234-245 (2007)
12 Ray, S.K., Singh, S., Joshi, B.P.: A semantic approach for question classification using WordNet and Wikipedia. Pattern Recognition Letters 31.13:1935–1943 (2010)
13 Wu, Y.Z., Zhang, R.Q., Hu, X.H., Kashioka, H.: Learning Unsupervised SVM Classifier for Answer Selection in Web Question Answering. In Proceedings of EMNLP-CoNLL, pp.33-41 (2007)
14 Sasaki, Y.: Question Answering as Question-Biased Term Extraction: a New Approach Toward Multilingual. In Proceedings of ACL, pp. 215-222 (2005)
15 Ogawa, K., Takeuchi, I.: Safe Screening of Non-Support Vectors in Pathwise SVM Computation. In Proceedings of International Conference on Machine Learning (ICML) (2013)
16 Yen, S.J., Wu, Y.C., Yang, J.C., Lee, Y.S., Lee, C.J., Liu, J.J.: A support vector machine-based context-ranking model for question answering. Information Sciences, 224.2, 77–87 (2013)
17 Hardy, H., Cheah, Y.N.: Question Classification Using Extreme Learning Machine on Semantic Features. Journal of ICT Research and Applications 7.1: 36-58 (2013)
18 Jeong, Y., Myaeng, S.H.: Using WordNet hypernyms and dependency features for phrasal-level event recognition and type classification. Advances in information retrieval. Springer Berlin Heidelberg, 267-278 (2013)
19 Gao, J.B., Zhang, B.W., Chen, X.H.: A WordNet-based semantic similarity measurement combining edge-counting and information content theory. Engineering Applications of Artificial Intelligence: 80–88 (2015)
20 Barbu, E.: Property type distribution in WordNet, corpora and Wikipedia. Expert Systems with Applications 42.7: 3501-3507 (2015)
21 Berwick, R.C.: Principles of principle-based parsing. Principle-Based Parsing. Springer Netherlands, 1-37 (1992)
22 Hao, T.Y., Xu, F.F., Lei, J.S., Liu, W.Y., Li, Q.: Toward Automatic Answers in User-Interactive Question Answering Systems, International Journal of Software Science and Computational Intelligence, Vol.3, No.4, pp.52-66 (2011)