Semantic Structure Analysis of Noun Phrases using Abstract Meaning Representation

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Abstract

We propose a method for semantic structure analysis of noun phrases using Abstract Meaning Representation (AMR). AMR is a graph representation for the meaning of a sentence, in which noun phrases (NPs) are manually annotated with internal structure and semantic relations. We extract NPs from the AMR corpus and construct a data set of NP semantic structures. We also propose a transition-based algorithm which jointly identifies both the nodes in a semantic structure tree and semantic relations between them. Compared to the baseline, our method improves the performance of NP semantic structure analysis by 2.7 points, while further incorporating external dictionary boosts the performance by 7.1 points.

1 Introduction

Semantic structure analysis of noun phrases (NPs) is an important research topic, which is beneficial for various NLP tasks, such as machine translation and question answering (Nakov and Hearst, 2013; Nakov, 2013). Among the previous works on NP analysis are internal NP structure analysis (Vadas and Curran, 2007; Vadas and Curran, 2008), noun-noun relation analysis of noun compounds (Girju et al., 2005; Tratz and Hovy, 2010; Kim and Baldwin, 2013), and predicate-argument analysis of noun compounds (Lapata, 2002).

The goal of internal NP structure analysis is to assign bracket information inside an NP (e.g., (lung cancer) deaths indicates that the phrase lung cancer modifies the head deaths). In noun-noun relation analysis, the goal is to assign one of the predefined semantic relations to a noun compound consisting of two nouns (e.g., assigning a relation purpose to a noun compound cooking pot, meaning that pot is used for cooking). On the other hand, in predicate-argument analysis, the goal is to decide whether the modifier noun is the subject or the object of the head noun (e.g., car is the object of love in car lover, while child is the subject of behave in child behavior).

Previous NP researches have mainly focused on these different subproblems of NP analysis using different data sets, rather than targeting general NPs simultaneously. However, these subproblems of NP analysis tend to be highly intertwined when processing texts. For the purpose of tackling the task of combined NP analysis, we make use of the Abstract Meaning Representation (AMR) corpus.

AMR is a formalism of sentence semantic structure by directed, acyclic, and rooted graphs, in which semantic relations such as predicate-argument relations and noun-noun relations are expressed. In this paper, we extract substructures corresponding to NPs (shown in Figure 1) from the AMR Bank\(^1\), and create a data set of NP semantic structures. In general, AMR substructures are graphs. However, since we found out that NPs mostly form trees rather than graphs in the AMR Bank, we can assume that AMR substructures corresponding to NPs are trees. Thus, we define our task as predicting the AMR tree structure, given a sequence of words in an NP.

\(^1\)http://amr.isi.edu/
two-step approach: first identifying distinct concepts (nodes) in the AMR graph, then defining the dependency relations between those concepts (Flanigan et al., 2014). In the concept identification step, unlike POS tagging, one word is sometimes assigned with more than one concept, and the number of possible concepts is far more than the number of possible parts-of-speech. As the concept identification accuracy remains low, such a pipeline method suffers from error propagation, thus resulting in a suboptimal AMR parsing performance.

To solve this problem, we extend a transition-based dependency parsing algorithm, and propose a novel algorithm which jointly identifies the concepts and the relations in AMR trees. Compared to the baseline, our method improves the performance of AMR analysis of NP semantic structures by 2.7 points, and using an external dictionary further boosts the performance by 7.1 points.

2 Abstract Meaning Representation

2.1 Extraction of NPs

We extract substructures (subtrees) corresponding to NPs from the AMR Bank (LDC2014T12). In the AMR Bank, there is no alignment between the words and the concepts (nodes) in the AMR graphs. We obtain this alignment by using the rule-based alignment tool by Flanigan et al. (2014). Then, we use the Stanford Parser (Klein and Manning, 2003) to obtain constituency trees, and extract NPs that contain more than one noun and are not included by another NP. We exclude NPs that contain named entities, because they would require various kinds of manually crafted rules for each type of named entity. We also exclude NPs that contain possessive pronouns or conjunctions, which prove problematic for the alignment tool. Table 1 shows the statistics of the extracted NP data.

2.2 Previous Method for AMR Analysis

We adopt the method proposed by Flanigan et al. (2014) as our baseline, which is a two-step pipeline method of concept identification step and relation identification step. Their method is designed for parsing sentences into AMR, but here, we use this method for parsing NPs.

In their method, concept identification is formulated as a sequence labeling problem (Janssen and Limnios, 1999) and solved by the Viterbi algorithm. Spans of words in the input sentence are labeled with concept subgraphs. Figure 2 illustrates the concept identification step for an NP a retired plant worker.

After the concepts have been identified, these concepts are fixed, and the dependency relations between them are identified by an algorithm that finds the maximum spanning connected subgraph (Chu and Liu, 1965), which is similar to the maximum spanning tree (MST) algorithm used for dependency parsing (McDonald et al., 2005).

They report that using gold concepts yields much better performance, implying that joint identification of concepts and relations can be helpful.

3 Proposed Method

In this paper, we propose a novel approach for mapping the word sequence in an NP to an AMR tree, where the concepts (nodes) corresponding to the words and the dependency relations between those concepts must be identified. We extend the arc-standard algorithm by Nivre (2004) for AMR parsing, and propose a transition-based algorithm which jointly identifies concepts and dependency relations.
relations. Our algorithm is similar to (Hatori et al., 2011), in which they perform POS tagging and dependency parsing jointly by assigning a POS tag to a word when performing SHIFT, but differs in that, unlike POS tagging, one word is sometimes assigned with more than one concept. In our algorithm, the input words are stored in the buffer and the identified concepts are stored in the stack. SHIFT identifies a concept subtree associated with the top word in the buffer. REDUCE identifies the dependency relation between the top two concept subtrees in the stack. Figure 3 illustrates the process of deriving an AMR tree for a retired plant worker, and Figure 4 shows the resulting AMR tree.

Table 2 shows the definition of each action and state transition. A state is a triple \((σ, β, R)\), where \(σ\) is a stack of identified concept subtrees, \(β\) is a buffer of words, and \(R\) is a set of identified relations. SHIFT\((c(w_i))\) extracts the top word \(w_i\) from the buffer, generates a concept subtree \(c(w_i)\) from \(w_i\), and pushes \(c(w_i)\) onto the stack. The concept subtree \(c(w_i)\) is generated from \(w_i\) by using one of the rules defined in Table 3. LEFT-REDUCE\((r, n)\) pops the top two subtrees \(c_i, c_j\) from the stack, identifies the relation \(r\) between the root \(n_{\text{root}}(c_i)\) of \(c_i\) and the node \(n(c_j)\) in \(c_j\), adds \(r\) to \(R\), and pushes \(c_j\) back onto the stack. Here, \(n\) denotes a mapping from a subtree to its specific node, which allows for attachment to an arbitrary concept in a subtree. Since the sizes of the subtrees were at most two in our data set, \(n \in \{n_{\text{root}}, n_{\text{child}}\}\), where \(n_{\text{root}}\) is a mapping from a subtree to its root, and \(n_{\text{child}}\) is a mapping from a subtree to the direct child of its root. RIGHT-REDUCE\((r, n)\) is defined in the same manner. EMPTY-REDUCE removes an empty subtree \(∅\) at the top of the stack. EMPTY-REDUCE is always performed immediately after SHIFT(∅) generates an empty subtree ∅. In the initial state, the stack \(σ\) is empty, the buffer \(β\) contains all the words in the NP, and the set of the identified relations \(R\) is empty. In the terminal state, the buffer \(β\) is empty and the stack \(σ\) contains only one subtree. The resulting AMR tree is obtained by connecting all the subtrees generated by the SHIFT actions with all the relations in \(R\).

The previous method could not generate unseen concepts in the training data, leading to low recall in concept identification. In contrast, our method defines five rules (Table 3), three of which
(LEMMa, DICTPREd, and DICTNOuN) allow for generation of unseen concepts from any word.

3.1 Features

The feature set $\phi(s, a)$ for the current state $s$ and the next action $a$ is the direct product (all-vs-all combinations from each set) of the feature set $\phi_{state}(s)$ for the current state and the feature set $\phi_{action}(s, a)$ for the next action.

$$\phi(s, a) = \phi_{state}(s) \times \phi_{action}(s, a)$$

$\phi_{state}(s)$ is the union of the feature sets defined in Table 4, where $w(c)$ denotes the word from which the subtree $c$ was generated.

Table 5 shows the feature set $\phi_{action}((\sigma, [w_i, \beta], R), a)$ for each action $a$, where $\text{rule}(w_i, c)$ is a function that returns the rule which generated the subtree $c$ from the top word $w_i$ in the buffer. In order to allow different SHIFT actions and different LEFT-RIGHT/REDUCE actions to partially share features, Table 5 defines features of different granularities for each action. For example, although \text{SHIFT}((\text{run-01})) and \text{SHIFT}((\text{sleep-01})) are different actions, they share the features \{"S", \text{"S"} \circ \text{DICTPREd}" because they share the generation rule DICTPREd.

4 Experiments

We conduct an experiment using our NP data set (Table 1). We use the implementation of (Flanigan et al., 2014) as our baseline. For the baseline, we use the features of the default settings.

The method by Flanigan et al. (2014) can only generate the concepts that appear in the training data. On the other hand, our method can generate concepts that do not appear in the training data using the concept generation rules LEMMa, DICTPREd, and DICTNOuN in Table 3. For a fair comparison, first, we only use the rules EMPTY and KNOWN. Then, we add the rule LEMMa, which can generate a concept of the lemma of the word. Finally, we add the rules DICTPREd and DICTNOuN. These two rules need conversion from nouns and adjectives to their verb and noun forms. For this conversion, we use CatVar v2.1 (Habash and Dorr, 2003), which lists categorial variations of words (such as verb run for noun runner). We also use definitions of the predicates from PropBank (Palmer et al., 2005), which AMR tries to reuse as much as possible, and impose constraints that the defined predicates can only have semantic relations consistent with the definition.

During the training, we use the max-violation perceptron (Huang et al., 2012) with beam size 8 and average the parameters. During the testing, we also perform beam search with beam size 8.

Table 6 shows the overall performance on NP semantic structure analysis. We evaluate the performance using the Smatch score (Cai and Knight,
### Table 6: Performance on NP semantic structure analysis

| Method                                           | P     | R     | F1    |
|--------------------------------------------------|-------|-------|-------|
| (Flanigan et al., 2014)                          | 75.5  | 61.1  | 67.5  |
| Our method (EMPTY/KNOWN)                         | 78.0  | 63.8  | 70.2  |
| Our method+LEMMA                                 | 75.7  | 75.2  | 75.4  |
| Our method+LEMMA/DICT                            | 77.3  | 77.3  | 77.3  |

### Table 7: Performance on concept identification

| Method                                           | P     | R     | F1    |
|--------------------------------------------------|-------|-------|-------|
| (Flanigan et al., 2014)                          | 88.4  | 71.4  | 79.0  |
| Our method (EMPTY/KNOWN)                         | 88.9  | 72.2  | 79.7  |
| Our method+LEMMA                                 | 84.8  | 84.2  | 84.5  |
| Our method+LEMMA/DICT                            | 85.8  | 85.6  | 85.7  |

2013), which reports precision, recall, and F1-score for overlaps of nodes, edges, and roots in semantic structure graphs. Compared to the baseline, our method improves both the precision and recall, resulting in an increasing of F1-score by 2.7 points. When we add the LEMMA rule, the recall increases by 11.4 points because the LEMMA rule can generate concepts that do not appear in the training data, resulting in a further increase of F1-score by 5.2 points. Finally, when we add the DICT rules, the F1-score improves further by 1.9 points.

Table 7 shows the performance on concept identification. We report precision, recall, and F1-score against the correct set of concepts. For each condition, we observe the same tendency in performance increases as Table 6. Thus, we conclude that our method improves both the concept identification and relation identification performances.

### 5 Conclusion

In this paper, we used Abstract Meaning Representation (AMR) for semantic structure analysis of noun compounds (NPs). We extracted substruc- tures corresponding to NPs from the AMR Bank, and created a data set of NP semantic structures. Then, we proposed a novel method which jointly identifies concepts (nodes) and dependency relations in AMR trees. We confirmed that our method improves the performance on NP semantic structure analysis, and that incorporating an external dictionary further boosts the performance.

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