Construction of an English Dependency Corpus incorporating Compound Function Words

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Abstract
The recognition of multiword expressions (MWEs) in a sentence is important for such linguistic analyses as syntactic and semantic parsing, because it is known that combining an MWE into a single token improves accuracy for various NLP tasks, such as dependency parsing and constituency parsing. However, MWEs are not annotated in Penn Treebank. Furthermore, when converting word-based dependency to MWE-aware dependency directly, one could combine nodes in an MWE into a single node. Nevertheless, this method often leads to the following problem: A node derived from an MWE could have multiple heads and the whole dependency structure including MWE might be cyclic. Therefore we converted a phrase structure to a dependency structure after establishing an MWE as a single subtree. This approach can avoid an occurrence of multiple heads and/or cycles. In this way, we constructed an English dependency corpus taking into account compound function words, which are one type of MWEs that serve as functional expressions. In addition, we report experimental results of dependency parsing using a constructed corpus.

Keywords: MultiWord Expressions, Dependency Parsing

1. Introduction
Multiword expressions (MWEs) consist of groups of tokens, which should be treated as a single syntactic or semantic unit. MWEs are also known as "idiomatic interpretations that cross word boundaries" (Sag et al., 2002). The recognition of MWEs in a sentence is important for such linguistic analyses as syntactic and semantic parsing, because it is known that combining an MWE into a single token improves accuracy for various NLP tasks, such as dependency parsing (Green et al., 2004), and constituency parsing (Arun and Keller, 2005).

For syntactic parsing that takes in MWEs, it is preferable that the information of an MWE (e.g., part of speech and span of tokens) be integrated into a corpus, such as a phrase or dependency treebank, because an MWE should be a syntactic unit. Actually, an MWE is grouped under “subtree” in French Treebank (Abeillé et al., 2003), which is often used in research focusing on both MWE recognition and syntactic parsing (Green et al., 2011; Candito and Constant, 2014). However, MWEs are not annotated in Penn Treebank, the standard corpus of English syntactic parsing.

In dependency structure that takes MWEs into consideration (i.e., MWE-aware dependency), each MWE becomes a single node. Therefore, to convert word-based dependency to MWE-aware dependency directly, one could combine nodes in an MWE into a single node. Nevertheless, this method often leads to the following problem: A node derived from an MWE could have multiple heads and the whole dependency structure including MWE might be cyclic (Figure 1). This is mainly because Penn Treebank style annotation does not give the special treatment for MWEs. We discuss this problem further in Section 3.

In order to tackle the above problem, we propose a 3-step conversion method for making MWE-aware dependency structures. First, we establish an MWE as a single subtree in a phrase structure belonging to Penn Treebank (Figure 3a → Figure 3b). Second, we replace the subtree corresponding to the MWE by a preterminal with its leaf node as a child (Figure 4). The preterminal has the same part of speech as that of the MWE. Its child node is made by joining all components of the MWE with underscores. As a final step, we convert the phrase structure to Stanford Dependency (de Marneffe and Manning, 2008). In this way, we can avoid an occurrence of multiple heads and/or cycles in an MWE-aware dependency tree, because an MWE constitutes a single node in this dependency. We applied this conversion method to Ontonotes corpus (Pradhan et al., 2007) in order to construct a dependency corpus that takes into consideration MWEs. In this work, we focused on compound function words, which are one type of MWEs that serve as functional expressions. This is because compound function words have a variety of functionalities that may affect language analyses such as parsing and POS tagging. To reduce the cost of annotation in constituting each MWE as a subtree, we classified patterns of MWEs as seen in phrase structure in terms of ease of conversion. We manually annotated only instances including MWEs which were difficult to convert automatically.

Furthermore, we evaluated the performance of the first order MST Parser (McDonald et al., 2005) on the constructed MWE-aware dependency corpus. We got an unlabeled attachment score (UAS) comparable to that obtained on the original Ontonotes corpus. Moreover, we qualitatively analyzed some test instances in which the MWE-aware dependency parser and the original dependency parser inferred the different outputs on the head of an MWE (Section 4).

2. Related Work
Shigeto et al. (2013) created a dictionary of English compound function words, and annotated those appearing in Penn Treebank. In their corpus, each MWE has its part of
3. Construction of an MWE-aware Dependency Corpus

We built an MWE-aware dependency corpus on the basis of a corpus by Shigeto et al. (2013). In their corpus, an entire MWE is assigned a single part of speech. In that case, it is preferable that an MWE be a single node in an MWE-aware dependency structure. On the other hand, each word is treated as a node in conventional dependency structure.

If we try to directly convert word-based dependency to MWE-aware dependency, we need to combine nodes in an MWE into a single node. However, this naïve approach often leads to the following problem: A node derived from an MWE could have multiple heads and the whole dependency structure including MWE might be cyclic. In Figure 1 for instance, “a number of” has multiple heads (“cities” and “have”), and a cycle occurs because of the following edges: “a number of” → “cities” and “cities” → “a number of” (Figure 1b). Therefore we need to remove one of the edges in order to get a dependency tree. Another problem that arises is the following: The syntactic head of “a number of cities” is “cities” in an MWE-aware dependency structure (Figure 1c), because “a number of” is a determiner. Nevertheless, we cannot get the correct dependent of “have” (i.e., “cities”) by the above direct method. Similarly, if we combine words of the MWE into a single node in Figure 2, “about to” has multiple heads (“is” and “slip”), and a cycle occurs between “about to” and “slip”.

In order to solve these problems, we adopted the following approach: First we establish an MWE in a phrase structure tree as a single subtree. After that, we convert phrase structure to dependency structure. With this method, we can avoid cycles and/or multiple heads.

Concretely, we built a corpus of dependency structures considering compound function words according to the following method:

1. Find an MWE in a phrase structure tree of Ontonotes
and establish it as a single subtree (Figure 3a → Figure 3b)\(^1\)

(2) Replace the above subtree by a preterminal with its leaf node as a child. The preterminal has the same part of speech as that of the MWE. Its child node is made by joining all components of the MWE with underscores, as in Figure 4.

(3) Convert phrase structure to Stanford Dependency (de Marneffe and Manning, 2008)\(^2\)

In Step (1), we convert an MWE into a single subtree in the phrase structure tree. For example, “even though” in Figure 3a is annotated as an MWE in Shigeto et al. (2013). We convert it as in Figure 3b. If we can convert the span of an MWE into a single subtree without influencing the structures of other subtrees, we call this instance “Simple”. Otherwise the instance is “Complex”. When grouping MWE, we focus on the LCA-tree, which is the subtree rooted in the Least Common Ancestor (LCA) of the components of the MWE. In Figure 3a, the tree rooted in the LCA of “even” and “though” (LCA here being SBAR) is the LCA-tree.

The method we described above relates to Finkel and Manning (2009). For joint parsing and named entity recognition, they classified named entities which do not correspond to a phrase in the constituency tree to the following two categories. A named entity belonging to the first category is contiguous multiple children of some nonterminal. This category corresponds to the above “Simple” case. On the other hand, A span of each named entity belonging to the second category crosses brackets in the parse tree. It corresponds to the above “Complex” case.

3.1. Simple Case

In the “Simple” case, we insert a new internal node under the LCA (Figure 3a → Figure 3b). This internal node covers precisely the span of the MWE.

3.2. Complex Case

In the “Complex” case, if we convert the MWE into a subtree (e.g. Figure 5a → Figure 5b), the structures of other subtrees need to be changed. For example, it is reasonable to remove the right child of LCA (PP) in Figure 5a at the time of the conversion as in Figure 5b.

Further, we classified “Complex” into “Complex-Normal” and “Complex-Abnormal” based on the extent to which the LCA-tree is changed by the conversion.

3.2.1. Complex-Normal Case

In this case, we can convert an MWE into a single subtree without influencing subtrees which cover words outside the MWE. In Figure 5a for instance, the span of the right subtree (from “to” to “Wednesday”) partially overlaps the span of the MWE (“according to”), but there is an internal node which covers the entire span to the right of the MWE (see the grandchild of the LCA (NP)).

We define the subtree covering the span to the left of the MWE as \(T_{\text{pre}}\), the subtree covering the MWE as \(T_{\text{mwe}}\), and the subtree covering the span to the right of the MWE as \(T_{\text{post}}\). In Figure 5a, the subtree surrounded by a triangle is \(T_{\text{post}}\).

We converted the tree so that the LCA has \(T_{\text{pre}}, T_{\text{mwe}}, T_{\text{post}}\) as children (Figure 5a → Figure 5b).

When both \(T_{\text{pre}}\) and \(T_{\text{post}}\) were present, we manually determined which of the following choices is preferable: LCA having \(T_{\text{pre}}, T_{\text{mwe}}, T_{\text{post}}\) as flat children, or LCA having a new internal node (covering \(T_{\text{mwe}}\) and \(T_{\text{pre}}\) or \(T_{\text{post}}\)) as a child.

\(^1\)We utilized MWE information (position in sentence and part of speech) provided by Shigeto et al. (2013).

\(^2\)We designated “-conllx -basic -makeCopulaHead -keepPunct” as an option for the conversion command.
3.2.2. Complex-Abnormal Case

In this case, we cannot avoid influencing subtrees outside the MWE when converting the MWE into a single subtree (Figure 6a → Figure 6b). The span of the right subtree of LCA (from “with” to “Boat”) partially overlaps the span of the MWE (“along with”), and there is no internal node which covers precisely a span to the left or right of the MWE. Thus we manually determined how to combine a subtree covering the MWE with subtrees covering spans excluding the MWE.

Regarding “Simple” case and “Complex-normal” case, we decided a symbol of an LCA as follows:

$$\arg \max_{X_{LCA}} (P(A \rightarrow B_1 \ldots X_{LCA} \ldots B_m) \times P(X_{LCA} \rightarrow C_1 \ldots C_n))$$

We show the numbers of instances and types of MWEs for each case in our corpus (Section 00-24 of Wall Street Journal in Ontonotes) in Table 1.

| Case                  | No. of instances | Types of MWEs |
|-----------------------|------------------|----------------|
| Simple                | 5129             | 427            |
| Complex-Normal        | 1742             | 117            |
| Complex-Abnormal      | 57               | 27             |

Table 1: Gross corpus statistics of an MWE-aware Dependency Corpus.

4. MWE-aware Dependency Parsing

In this section, we report dependency parsing based on the corpus we built according to the method described in Section 3.

4.1. Experimental Setting

We trained and tested an original dependency parser and an MWE-aware dependency parser independently. The evaluation measure we adopted was UAS (unlabeled attachment score). We used the first-order MST Parser (McDonald et al., 2005) and the standard split for Ontonotes (Wall Street Journal): Sections 02-21 for training, 23 for testing. We also used gold part-of-speech tags both in training and testing.

4.2. Experimental Results

We show the experimental results in Table 2. Because the original and the MWE-aware dependency structures are different, we cannot directly compare the results of these dependency parsers, however, we got comparable UAS results for the two parsers on both whole sentences (in a test set of 1640 sentences) and sentences including MWEs (266 sentences).

In the following, we describe the qualitative analysis. First, we show an instance for which the original dependency parser inferred an incorrect output and the MWE-aware dependency parser returned a correct output.

The full sentence is “Mrs. Hills’ remarks did raise questions, at least among some U.S. officials, about what exactly her stance is on U.S. access to the Japanese semiconductor market.”
In this instance, by recognizing the MWE before parsing, the MWE-aware dependency parser avoids an incorrect inference originating from the part-of-speech tag of a component of the MWE. This is consistent with the error analysis by Nivre and Nilsson (2004) for Swedish dependency parsing involving compound function words.

Next, we show an instance for which the original dependency parser inferred a correct output, but the MWE-aware dependency parser inferred an incorrect output. In Figures 8a and 8b, the original dependency parser infers “costs” correctly as the head of “because”. However, the MWE-aware dependency parser infers “707s” as the head of MWE (“because of”).

In fact, this MWE and almost all MWEs in the test set (286 out of 289) also appear in the training set. Therefore, to make a correct inference for the above instance, we need to explore MWE-specific features (the word form and the part-of-speech tag of each component of the MWE) and/or higher order features for the dependency parser rather than dealing with unseen MWEs.

5. Conclusion

We created an English dependency corpus incorporating compound function words and conducted dependency parsing using the constructed corpus. Our corpus is available at: https://github.com/naist-cl-parsing/mwe-aware-dependency. In the future, we plan to design features for MWE-aware dependency parsing, and to integrate MWE recognition and dependency parsing. We also plan to explore a linguistic analysis in which MWE-aware dependency is preferable to word-based dependency.

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