English Light Verb Construction Identification Using Lexical Knowledge

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Abstract

This research describes the development of a supervised classifier of English light verb constructions, for example, *take a walk* and *make a speech*. This classifier relies on features from dependency parses, OntoNotes sense tags, WordNet hypernyms and WordNet lexical file information. Evaluation shows that this system achieves an 89% $F_1$ score (four points above the state of the art) on the BNC test set used by Tu & Roth (2011), and an $F_1$ score of 80.68 on the OntoNotes test set, which is significantly more challenging. We attribute the superior $F_1$ score to the use of our rich linguistic features, including the use of WordNet synset and hypernym relations for the detection of previously unattested light verb constructions. We describe the classifier and its features, as well as the characteristics of the OntoNotes light verb construction test set, which relies on linguistically motivated PropBank annotation.

1 Introduction

As one construction in which the relational semantics of verbs can be extended in novel ways, English light verb constructions (LVCs) represent a powerfully expressive resource of English. These constructions, such as *make an offer* and *give a groan*, are thought to consist of a semantically general verb and a noun that denotes an event or state. However, an exact definition of an LVC, which would precisely delimit these constructions from either idiomatic expressions or compositional, ‘heavy’ usages of the same verbs (e.g. *She made a dress; He gave me a present;* etc.) remains under debate. As a result, it is no surprise that the automatic detection of English LVCs also remains challenging, especially given the semi-productive nature of LVCs, which allows for novel LVCs to enter the language. Novel LVCs are particularly difficult to detect, yet it is key for Natural Language Processing (NLP) systems to identify and interpret LVCs correctly by recognizing, for example, that *She made an offer to buy the house for $1.5 million* is an offering event, rather than a *making* or *creation* event.

This research describes a system for the automatic detection of LVCs. Related work is given in Section 2, and relevant linguistic resources are described in Section 3. A comparison of the OntoNotes LVC annotations to the British National Corpus\(^1\) LVC annotations, used by Tu and Roth (2011), is given in Section 4. The description of our system is presented in Section 5, and our experiments and results in 6, followed by concluding remarks and future work.

2 Related Work

There are two main approaches for the automatic identification of LVCs: contextually-based and statistically-based. Contextually-based approaches detect the surrounding tokens and decide whether the verb, noun pair with these context words should be considered an LVC. Vincze et al. (2003) propose a contextually-based model, with a conditional random fields machine learning method, for detecting English and Hungarian LVCs. Evaluation showed that their model performs well in various domains of LVCs and performs well in detecting low-frequency LVCs. On the other hand, the statistically-based approach finds LVCs among verb, noun pairs from a well-defined set of verbs and eventive nouns (nouns denoting events, like *declaration*), then a classifier function decides if a pair is an LVC or not. Van de Cruys and Moirn (2007) propose a statistically and semantically-based method for recognizing verb-preposition-noun dependency relation combinations of LVCs. Furthermore, Gurruñagá and Alegria (2012) detect idiomatic and light verb-noun pairs from Basque, using statistical methods.

To compare these two approaches, Tu and Roth (2011) proposed a Support Vector Machine (SVM) based classifier to identify LVCs. They developed their system using both contextual and statistical features and analyzed the deep interaction between them. They concluded that local contextual features perform better than statistical features on ambiguous examples, and combining them did not give better performance. We also focus on contextual features and find additional features that improve performance.

3 Resources

This research uses several resources: PropBank (PB) (Palmer, Guildea, and Kingsbury 2005), the OntoNotes (ON) sense groupings (Pradhan et al. 2007), WordNet (WN)\(^2\) http://www.natcorp.ox.ac.uk/XMLEdition/
3.1 PropBank

The primary goal of PB was the development of an annotated corpus to be used as training data for supervised machine learning systems. The first PB release consists of 1M words of the Wall Street Journal portion of the Penn Treebank II (Marcus, Santorini, and Marcinkiewicz 1994), annotated with predicate-argument structures for verbs, using semantic role labels for each verb argument. Although the semantic role labels are purposely chosen to be quite generic and theory neutral, Arg0, Arg1, etc., they are still intended to consistently annotate the same semantic role across syntactic variations (Arg0 and Arg1 do consistently correspond to Dowty’s (1991) concepts of Proto-Agent and Proto-Patient respectively). For example, the Arg1 or Patient in John broke the window is the same window that is annotated as the Arg1 in The window broke, even though it is the syntactic subject in one sentence and the syntactic object in the other. Thus, the main goal of PB is to supply consistent, simple, general purpose labeling of semantic roles for a large quantity of coherent text to support the training of automatic semantic role labelers, as the Penn Treebank has supported the training of statistical syntactic parsers.

PB provides a lexical entry for each broad meaning of every annotated verb, including the possible arguments of the predicate and their labels (its ‘roleset’) and all possible syntactic realizations. This lexical resource is used as a set of verb-specific guidelines for annotation. In addition to numbered roles, PB defines several more general (ArgM, ‘Argument Modifier’) roles that can apply to any verb, such as LOCation, TeMPoral, and DIRection, etc.

In the past, PB annotation had been restricted to verb relations, but recent work has extended coverage to noun relations and complex relations like LVCs. In current practices, annotators identify light verbs and the main noun predicate in an initial verb pass of annotation. In a second pass, annotation is completed for the full span of the complex predicate, using the roleset of the noun. Consider the example, Yesterday-ARGM-TEMPORAL, John-ARG0 made-REL an offer-REL [to buy the house]-ARG1 [for $350,000]-ARG2, which uses the offer roleset:

- **Arg0**: entity offering
- **Arg1**: commodity, thing offered
- **Arg2**: price
- **Arg3**: benefactive or entity offered

PB ensures that the complete argument structure of the complex predicate receives annotation, regardless of whether the argument is within the domain of locality of the noun or verb, and ensures that the roles assigned reflect the event semantics of the noun.

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### Table 1: WordNet lexical file information types of interest for eventive and stative nouns

<table>
<thead>
<tr>
<th>Name</th>
<th>Nouns denoting...</th>
</tr>
</thead>
<tbody>
<tr>
<td>noun.act</td>
<td>acts or actions</td>
</tr>
<tr>
<td>noun.cognition</td>
<td>cognitive process</td>
</tr>
<tr>
<td>noun.communication</td>
<td>communicative process</td>
</tr>
<tr>
<td>noun.event</td>
<td>natural events</td>
</tr>
<tr>
<td>noun.feeling</td>
<td>feelings and emotions</td>
</tr>
<tr>
<td>noun.location</td>
<td>spatial position</td>
</tr>
<tr>
<td>noun.motive</td>
<td>goals</td>
</tr>
<tr>
<td>noun.phenomenon</td>
<td>natural phenomena</td>
</tr>
<tr>
<td>noun.possession</td>
<td>possession and transfer</td>
</tr>
<tr>
<td>noun.process</td>
<td>natural processes</td>
</tr>
<tr>
<td>noun.relation</td>
<td>relations between things</td>
</tr>
<tr>
<td>noun.state</td>
<td>stable states of affairs</td>
</tr>
</tbody>
</table>

3.2 WordNet

WN is a large electronic database of English words, which was in part inspired by work in psycholinguistics investigating how and what type of information is stored in the human mental lexicon (Miller 1995). WN is divided firstly into syntactic categories: nouns, verbs, adjectives and adverbs, and secondly by semantic relations. The semantic relations that organize WN are: synonymy (given in the form of ‘synsets’), antonymy, hyponymy (e.g. a Maple is a tree; therefore, tree is a hypernym of Maple), and meronymy (part-whole relations). These relations make up a complex network of associations that is both useful for computational linguistics and NLP, and also informative in situating a word’s meaning with respect to others.

Of particular interest for this research are the synsets, the hyponymic relations of nouns in WN, and the noun’s ‘type,’ as indicated by the lexical file information. For each noun in WN, lexicographers have coded the noun with one primary superordinate, or lexical file, given forty-five numbered options. In our research, nouns that can possibly denote events or states are the focus, because it is these nouns that can theoretically combine with a light verb to form an LVC. The type designations that may denote eventive and stative nouns are listed in Table 1. The use of synset, hyponym and lexical file information (or noun ‘type,’) is described in Section 5.2.

3.3 OntoNotes

The ON corpus integrates several layers of different annotation types in a single corpus, making it ideal training data for semantic analysis (Pradhan et al. 2007). The five layers of annotation include: 1) the syntactic parse from the Penn Treebank, 2) proposition structure from PB, 3) coarse-grained word senses from the ON sense grouping inventory, 4) named entity types, and 5) anaphoric coreference. The latest release, ON 4.99 (Weischedel et al. 2011), contains 2.6 million English words. In this research, the PB and word sense layers are of primary interest, the latter is described next.

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2The PB lexicon of rolesets can be found here: http://verbs.colorado.edu/propbank/framesets-english/

3http://wordnet.princeton.edu/wordnet/
The ON sense groupings can be thought of as a more coarse-grained view of WN senses because these sense groupings were based on WN senses, which were successively merged into more coarse-grained senses, based on the results of inter-annotator agreement (Duffield et al. 2007). Essentially, where two annotators were consistently able to distinguish between two senses, the distinction was kept. Where annotators were not able to consistently distinguish between two senses, the senses were reorganized and tagged again. It was found that sense distinctions with this level of granularity can be detected automatically at 87-89% accuracy, making them effective for NLP applications (Dligach and Palmer 2011). This sense inventory was used to annotate ON verbs and nouns with more than three WN senses. Unfortunately, the sense tagging is not complete for all of the ON corpus: there are about one million verbs and nouns in ON 4.99, but only 288,217 of these have sense tags (although many are surely monosemous), including 120,400 nouns with sense tags. Each ON sense also lists which WN senses it includes, providing a mapping between ON annotations and WN senses.

4 Comparison of Light Verb Construction Resources

The existing state of the art system for LVC recognition is arguably that of Tu and Roth (2011), who achieve 86.3% accuracy. To best compare our work to the state of the art, a detailed comparison was made of the resources used by Tu and Roth and the PB LVC data set used in the present work. Tu and Roth construct a dataset of 2,162 English sentences with LVCs drawn from the British National Corpus (BNC). Their approach in constructing this data set differs from that of PB in several ways, and therefore results in resources containing some overlapping and some distinct constructions. Firstly, the authors restrict their annotations to LVCs involving the six most frequent light verbs: do, get, give, have, make, take. In the PB annotation process, it is possible for annotators to mark any verb as a light verb, resulting in a corpus that contains seven LVC types with verbs not included in the Tu and Roth data, such as textstring charges against... and conduct repairs. Secondly, Tu and Roth filter their data set by including only LVCs with nouns that are zero-derived nominals (e.g. offer), or derivationally related to a verb (e.g. destruction). The PB corpus includes an additional 25 LVC types (not found in the Tu and Roth data), which involve nouns that have no etymologically related verb counterpart, such as take a trip. Although the PB procedure allows for more variety, this has not resulted in a broader data set with more unique LVC types overall. The comparison shows that there are 115 LVC types that appear in both data sets, 245 LVC types that appear only in the BNC, and 218 LVC types that appear only in ON.

Although the majority of these different types simply arise from the differing sources and genres, there are notably more instances of LVCs involving get and give in the BNC data set. PB has previously treated many of these usages as ‘semi-light,’ and opted to annotate both the argument structure of the verb and that of the noun in distinct annotation passes instead of marking these as LVCs. As a result, the BNC data set includes 83 additional types with get and give. The PB practice has led to some inconsistencies; for example, give a speech (to the audience) has been treated as semi-light (since the audience can be seen as either the Recipient of the give event or the speaking event), while make a speech has been treated as an LVC (since there is no similar overlap in the noun and verb relations’ roles). To remedy such inconsistencies, PB will be loosening the annotation requirements and including such semi-light usages in the LVC annotations. Table 2 gives an overview of the number of positive LVC types and tokens, and the number of non-LVC tokens and non-LVC verb+noun types involving several common light verbs in the ON corpus. The ‘overlap’ portion indicates the number and percentage of nouns that appear in both positive and negative examples. Notably, this overlap is highest for have, indicating that it involves a high number of surface-identical LVC and non-LVC usages.

In summary, the two LVC lexical resources differ in ways that likely provide an advantage for the Tu and Roth system: the BNC data has less variety in the types of nouns that can be involved in LVCs, and it embraces a more general definition of LVCs since it has not distinguished light and semi-light usages.

5 Light Verb Construction Recognition

Our LVC identifier determines what combinations of potential light verbs and eventive nouns should be labeled as LVCs. For a given dependency tree T, the system first checks if T meets certain criteria in order to decide if T should be put into the candidate set (these criteria are described in Section 5.1). Next, the light (or ‘Support’) verb V and eventive noun NE pair is submitted to an LVC binary classifier, which labels the VS-NE pair as an LVC or not an LVC. This supervised classifier is trained with the LibLinear (Fan et al. 2008) algorithm.

5.1 Candidate Identification

The first step for LVC recognition is to select the candidate dependency trees for the training of the classifier. Here, the PB layer of the ON 4.99 corpus is used as a starting point. For this research, we chose to exploit LVCs that are composed of a limited set of the six most frequent light verbs in the data, since these cover 99.26% of the VS-NE pairs. In the future, we plan to expand our verb set.

<table>
<thead>
<tr>
<th>Type</th>
<th>Count</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>have</td>
<td>221</td>
<td>52.4%</td>
</tr>
<tr>
<td>do</td>
<td>1,781</td>
<td>75.8%</td>
</tr>
<tr>
<td>make</td>
<td>671</td>
<td>58.7%</td>
</tr>
<tr>
<td>take</td>
<td>317</td>
<td>58.7%</td>
</tr>
</tbody>
</table>

Table 2: Token and type frequency of positive LVC and non-LVC examples, and the number of overlapping verb+noun types that can be either positive or negative examples in ON.
Table 3: Distribution of Dependency Relation Type of LVCs in ON 4.99 data

<table>
<thead>
<tr>
<th>Relation Type</th>
<th>Numbers</th>
<th>Portion</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Direct Child</td>
<td>1,546</td>
<td>87.44%</td>
</tr>
<tr>
<td>II. Quantity</td>
<td>16</td>
<td>0.90%</td>
</tr>
<tr>
<td>III. Head of the clause</td>
<td>178</td>
<td>10.07%</td>
</tr>
<tr>
<td>Sub-Total</td>
<td>1,740</td>
<td>98.42%</td>
</tr>
<tr>
<td>Other Type</td>
<td>28</td>
<td>1.58%</td>
</tr>
<tr>
<td>Total</td>
<td>1,768</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Table 4: Basic Features (W^{−1/+1} refer to the left word / right word of W, and W^h refers to the head word of W), often very high, but the training sample size is small. LibLinear performs only logistic regression without using a kernel. Results show that LibLinear reduces both training and decoding times, while maintaining the accuracy of the prediction.

Several features are used by the classifier, categorized into 3 different types: Basic Features, ON Word Sense Features, and WN Features.

### Basic Features
Basic features include the lexicon, part of speech (POS) tag, and the dependency relation of VS and NE. The paths of the dependency relation and POS are included as well. Additionally, the subcategorization frame which concatenates the dependency labels of VS and NE is adopted. These features are used either individually or jointly (e.g., POS of VS and lemma of NE make another new feature). The basic features are listed in Table 4.

### OntoNotes Word Sense Features
Word sense plays an important role in recognizing LVCs. For example, consider the following two sentences:

1. We are going to take a look at the trials and tribulations of Martha Stewart.
2. Barbie gets a makeover to give her a more youthful look.

In sentence (1) above, take a look is an LVC, while give her a more youthful look in sentence (2) is not. The difference in LVC status is reflected in the two different senses of look: the meaning of the first look is “act of looking,” and the second usage of look is closer to the meaning “perceived appearance or feel.” Although it is difficult to discover the lexical and dependency differences between these two VS-NE pairs, the word sense gives a useful clue for our classifier to identify the LVC.

In the ON 4.99 corpus, a word sense tag is annotated on the verbs with three or more senses and many nouns. The coarse-grained sense inventory, described in Section 3.3, gives a definition for each word sense. Ideally, for the data to be the most effective for LVC detection, all verbs and nouns would have sense tags. Unfortunately, not all of the subcorpora of the ON corpus are sense tagged. In the first step
of our ON data experiment (in Section 6.2), the verbs and nouns in the automatically generated dependency trees don’t contain any of the word sense tags. Hence, a Word Sense Disambiguation (WSD) model is necessary. In Lee (2002), a SVM-based WSD model that integrates the lemma, POS tag, and collocation information from near-by words is proposed. We apply this model to the WSD task with the ON word senses labels and implement our WSD classifier with the LibLinear algorithm with L2-regularization and L1-loss support vector classification. This algorithm uses a linear classifier to maximize the margin, instead of using a kernel. For the target word, we select ±3 words as the window size, while we adopt the same feature list that was used in Lee (2002).

We train and test our model on the ON data for out-of-genre experiments (See Section 6 for the details of the data preparation). Our WSD model reaches a 76.16 Precision, 71.32 Recall, and 73.66 F1 score. Although the overall performance of our WSD model is not ideal, the predicted word sense tag is only used in the automated generated dependency trees as one feature that supports the improvement of our LVC recognition.

**WordNet Features** WordNet contains rich word sense information and relational information between words. In our model, several pieces of WN information are used as features:

- **WordNet Sense**: The fine-grained WN sense inventory provides word sense information for each verb and noun. As mentioned previously, the ON data is annotated with the ON sense inventory tag only. However, the ON sense inventory provides a mapping between each coarser-grained ON sense and the WN senses that it comprises. Thus, the WN sense tag can be extracted via the ON sense tag. Since the WN sense inventory is more fine-grained than the ON sense inventory, one ON sense may map to multiple WN senses. We opted to extract 1) The highest-frequency sense (with the lowest WN sense label number) as the WN Sense feature, and 2) The set of WN senses mapped to the ON sense. These two features are applied to both VS and NE.

- **WordNet Noun Type (Lexical File Information)**: For each of the noun senses in WN, the manually assigned lexical file information is given. These can be thought of as the word’s supertype, and in this research, twelve basic types that indicate the noun could be eventive or stative are selected (discussed in Section 3.2). This base type is a more generalized property for each noun, and provides more common patterns for discovering previously unattested LVCs.

- **WordNet Hyponymy**: Each word sense in WN contains the hyponym derived by the knowledge structure. The hyponym of the NE provides a more generalized feature than the WN sense itself, but more fine-grained information than the base noun type.

## 6 Experiments and Results

For our experiments, we used two target corpora, the BNC LVC data provided by Tu and Roth (2011) and the ON 4.99 data. The BNC data is a balanced data set, including 1,039 positive LVC examples and 1,123 negative examples. We randomly sample 90% of the instances for training and the rest for testing. We also experiment with the ON 4.99 data. In order to evaluate the accuracy of our model for the different genres, we split our training and testing sets by randomly selecting different parts of subcorpora in each genre of ON. Portions of the following six corpora are used for the testing set: the MSNBC broadcast conversation, the CNN broadcast news, the Sinorama news magazine, the WSJ newswire, the CallHome telephone conversation, and the GALE web-text. In all of the ON data, 1,768 LVCs are annotated (in Table 3). Among all these LVCs in ON, 1,588 LVCs are listed in the training data set, and 180 LVCs are in the testing data set.

We also present an experiment investigating how to discover low-frequency LVCs using the WN synsets of nouns found in high-frequency LVCs (Section 6.3).

### 6.1 BNC Data

We first train and evaluate our model with the BNC data using automatic parsers produced by ClearNLP (Choi and McCallum 2013). Table 5 shows the performance of Tu & Roth’s model (2011) and our classifier on the BNC data set at each step: precision, recall, and F1-measure. Our baseline model involves the basic features only. Our All features model, which includes the three WN features, gains around 3 to 4% improvement for positive and negative examples, with respect to Tu and Roth’s contextual features and statistical features. In all we have added several beneficial features in comparison to the system of Tu & Roth: the dependency tree relation, the POS path between light verb and eventive noun, the subcategorization set, and the distance between light verb and eventive noun as new features. We discuss the the contribution of each individual feature in the next section.

### 6.2 OntoNotes Gold Data Evaluation

We first train and evaluate our model with automatic parse trees. The overall results are lower than on the BNC test set, in part due to errors in the automatic trees, but also because the data exhibits more variety with respect to the nouns found in the data, as discussed in Section 4. We achieved Precision of 54.94%, Recall of 77.22% and an F1 score of

<table>
<thead>
<tr>
<th>Model</th>
<th>P</th>
<th>R</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>TR-C</td>
<td>86.49</td>
<td>84.21</td>
<td>85.33</td>
</tr>
<tr>
<td>TR-S</td>
<td>86.15</td>
<td>88.19</td>
<td>87.16</td>
</tr>
<tr>
<td>Basic</td>
<td>86.48</td>
<td>85.09</td>
<td>86.46</td>
</tr>
<tr>
<td>All Features</td>
<td>88.89</td>
<td>87.40</td>
<td>87.06</td>
</tr>
<tr>
<td></td>
<td>81.13</td>
<td>86.00</td>
<td>83.50</td>
</tr>
<tr>
<td></td>
<td>88.93</td>
<td>84.50</td>
<td>86.82</td>
</tr>
<tr>
<td></td>
<td>85.32</td>
<td>93.00</td>
<td>89.00</td>
</tr>
<tr>
<td></td>
<td>94.31</td>
<td>97.88</td>
<td>92.90</td>
</tr>
</tbody>
</table>

Table 5: Model Comparison for BNC data. TR-C is Tu & Roth’s contextual feature model; TR-S refers is their statistical feature model. Basic model is our classifier with basic features only; compared to an All Features model. The ‘+’ refers to performance in detecting LVCs, while the ‘-’ refers to performance in detecting non-LVCs.
6.3 Using WordNet Relations

Although the above model could capture the majority of the LVCs in the corpus, those that are detected are relatively high-frequency LVCs. This led to the question of whether or not there is a better way to detect previously unattested LVCs. One idea is to leverage some general information that would allow the classifier to detect other possible LVCs. In the previous section, the results show that WN features provide positive contributions to our model. In this section, we analyze a small set of data from the ON corpus and corresponding WN features to explore the following possibility: if there is a high-frequency, attested light verb + noun combination, then any other eventive or stative noun sharing a synset or hypernym with this noun may also combine with that light verb to form an LVC.

To explore this, we first calculate the frequency of all the gold LVC pairs in the ON 4.99 data. Then we extract the top 10 highest-frequency $V_S-N_E$ pairs. In order to generate candidate LVC pairs, we fix the verb found in the high-frequency, attested LVC, and combine this with nouns that either share a synset or a hypernym with the noun from the same high-frequency LVC. This replacement of the eventive noun with its synonyms could allow for the discovery of promising LVC candidates. For example, the derived LVCs make attempt, make effort, and make endeavor are obtained by examining the synset and hypernym relations of the high-frequency LVC make contribution.

Using this process, we find a total of 91 tokens of potential LVCs in the ON corpus. When we compare this to our existing annotations, we see that 49 of these are already annotated as LVCs. Table 9 displays the numbers of gold true LVCs and candidate $V_S-N_E$ pairs. The probability that combinations generated from the synonyms are true LVCs is twice the baseline probability that any $V_S-N_E$ pair is an LVC. Thus, we can assume that WN synsets could play an important role in discovering low-frequency and previously unattested LVCs.

Notably, of the 91 potential LVC tokens that this process generated, there were 22 unique light verb + noun types. Of these 22 potential LVC types, four were attested in the corpus and already annotated as LVCs, including the high-frequency types make effort and make commitment. This is not to say...
that the other candidate LVC combinations are not LVCs, but they are either not attested or not annotated as LVCs in the corpus. Further research is required.

7 Conclusion & Future Work

We have described a system for the recognition of LVCs in English, in which we build a regression classifier for automatically identifying LVCs based on lexical, WN, and ON word sense information. Our evaluations show that the performance of our system achieves an 88.90% $F_1$ score on the BNC data set and 64.20% $F_1$ score on the ON 4.99 data. Using ON Gold Standard parses and sense tags, our $F_1$ score is 80.68%. Evaluation also shows that both the WN and the ON word sense features result in better performance. In addition, we demonstrate that the LVCs derived by WN relations from high-frequency LVCs have a higher probability of true LVC-hood than other combinations of light verb + noun.

In the future, we would like to investigate adding more general information to our model, such as word embeddings and clustering based on verb dependencies. Secondly, we plan to integrate our LVC detection model into SRL processing to further improve the performance of the SRL system. We aim to improve our ON sense inventory and word sense disambiguation accuracy, and then apply it to our model. We will also update the ON 4.99 test set to include more consistent annotation of light usages of give and get.

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