Unsupervised Discovery of Unaccusative and Unergative Verbs

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Abstract

We present an unsupervised method to detect English unergative and unaccusative verbs. These categories allow us to identify verbs participating in the causative-inchoative alternation without knowing the semantic roles of the verb. The method is based on the generation of intransitive sentence variants of candidate verbs and probing a language model. We obtained results on par with similar approaches, with the added benefit of not relying on annotated resources.

1 Introduction

As NLP systems push towards Natural Language Understanding, their ability to grasp verb meaning is central. In this paper we present an unsupervised method to detect English unergative and unaccusative verbs. Within the wider category of intransitive verbs, these subgroups show differences in their behaviour, such as (in different languages) auxiliary selection, passivisation, cliticisation and causative-inchoative alternation. These differences are due to the different semantic roles of the subject of unergative verbs, which shares its agentivity with subjects in transitive frames, and that of unaccusative verbs, more similar to the stereotypically patient- or theme-like objects in transitive frames.

Moreover, these categories relate to the causative-inchoative alternation (Haspelmath, 1993) in which unaccusative verbs can express a same event with either agent and patient (1-a) or with a patient only (1-b), corresponding respectively to a causative and inchoative interpretation of the event:

\begin{itemize}
  \item [1-a.] Hannah popped the balloon.
  \item [1-b.] The balloon popped.
\end{itemize}

The main property of the causative-inchoative alternation is the ability of the patient to be promoted from object to subject, and most theoretical accounts focus on this transitive to intransitive frame change. Once the event is in its intransitive form, however, it is syntactically indistinguishable from any other intransitive verb construction, and in order to categorize the verb one must know the specific semantic roles of its arguments.

This phenomenon is particularly hard to mine because the different realisations are not disambiguated by the context but by the arguments of the verb, and the frequency of the constructions themselves is not an indication of their acceptability. Furthermore, the meaning of the sentence remains virtually the same.\textsuperscript{1} However, picking up this categorisation is important not only for reasons involving the appropriateness of different types of subjects for each verb, but also because it has been shown to influence coreference patterns (Loáiciga et al., 2018). Nevertheless, efforts to discover verbs participating in the alternation using automatic methods are very limited.

Here we focus on the unaccusative vs unergative distinction as it allows us to disambiguate the verbs based on their intransitive frames. While the subjects of unaccusatives are patients (1-b), subjects of unergatives are agents (2-a). The assumption is that alternating verbs belong to the unaccusative category and we can discover them by separating them from the unergative category.\textsuperscript{2}

\begin{itemize}
  \item [2-a.] Hannah slept.
\end{itemize}

\textsuperscript{1}To the point where in the intransitive version of the alternation, an agent can be surmised as implicit, rather than simply not existing.

\textsuperscript{2}Note that this assumption does not exclude the exceptional cases of unaccusatives that do not alternate, e.g., to die, in The cactus died a slow death. Examples of this kind include an internal (or cognate) object, a noun that can be used as the object of an ordinarily intransitive verb by virtue of their semantic similarity.
The key in using these categories is that, without knowing the semantic roles of the verb, we can measure how well a noun fits the subjective position using a large corpus. Our method relies on language modeling to do just this. We investigate the effect of different language models on the task of identifying unaccusatives vs unergatives by testing the intransitive frames of a large quantity of verbs.

2 Related Work

Levin’s (1993) seminal work on verb alternations remains the most comprehensive collection of alternating verbs for English. Other collections, for instance Framenet (Baker et al., 1998) also specify if a verb allows the alternation based on Levin. Typological work for other languages exists in the linguistics literature (Haspelmath, 1993; Schäfer, 2009), but large collections are practically nonexistent.3

Building on Haspelmath’s theory, Samardžić (2014) estimates a Spontaneity score based on the ratio of a verb’s transitive to intransitive occurrence. In this scale, verbs are ranked according to the degree to which they are non-agentive. In other words, verbs without an explicit agent causing the event are more likely to participate in the causative alternation. Samardžić and Merlo (2018) report between 61% and 85% agreement between their model and theoretical classifications.

Kann et al. (2019) rely on Levin’s work to create synthetic data and build classifiers able to discriminate between several alternations. Their data sets are built using proper names as subjects and common nouns as objects, and they focus on the transitive to intransitive construction case. In this paper we rely on intransitive constructions exclusively, as will be explained below in Section 3. In addition, we use their FAVA data set for evaluation in Section 4.

Our method is most similar to the RNN-based method reported by Seyffarth (2019). Contrary to our work which queries language models with inflected sentences, Seyffarth uses an RNN to score artificially created transitive and intransitive argument sequences of the type invite-Pat-Kim vs invite-Pat. Using Framenet as gold standard, they report an accuracy of 66% on all verbs.

3 Generating Probing Sentences

To generate probing sentences, we start by extracting transitive verb frames from a corpus. We start with a version of Europarl (Koehn, 2005) with dependency annotations automatically generated with the Stanza parser (Qi et al., 2020) trained on Universal Dependencies v2.5. In these parses, we extract lemmas of transitive verbs with the head nouns of their subject and object noun phrases. In particular, we search for words tagged with a VERB part-of-speech tag having a dependent in an obj relation, its direct object. We find the subject of these verbs either as their nsubj children, or, if they are the head of a relative clause, as their head, to which they are linked with an act:relel dependency arc. We extract an example, consisting of a triplet of (subject, verb, object) lemmas, if both the subject and the object are nouns. We assume that the subjects of transitive verbs are typically in an agent-like relation with the predicate, so we treat them as agent candidates, whereas the objects are more likely to be in a patient-like relation and are used as patient candidates.

In a next step, we expand the set of agent and patient nouns by using it to seed the lookup of semantically related words in a non-contextual word embedding space generated by Pennington et al. (2014). We start with the pretrained 300-dimensional glove-wiki-gigaword-300 model from the gensim library (Rehurek and Sojka, 2010). First, we filter the vocabulary of the GloVe model so that it only contains nouns. Then, we expand the word sets according to the following procedure:

1. Let \( V \) be the original vocabulary of the embeddings space, and \( S \) and \( O \) be the sets of words observed in subject and object position of transitive verb frames, respectively.
2. Disjoint sets of seed words are created as \( S' = V \setminus S \setminus O \) and \( O' = V \setminus O \setminus S \).
3. We proceed as follows to create expanded sets \( S^+ \) and \( O^+ \) from \( S' \) and \( O' \), respectively:
   (a) We draw 20 samples of 10 items from the seed word list, \( S' \) or \( O' \).
   (b) For each sample, we find the 50 nearest neighbours in the embedding space using the 3CosMUL similarity metric of Levy and Goldberg (2014). The union of these 20 sets of nearest neighbours forms the expansion candidates.
   (c) Disjoint sets \( S^+ \) and \( O^+ \) are created by

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3The World Atlas of Transitivity Pairs (WATP, 2014), for instance, includes many languages but only a few verbs.
taking the 30 highest-scoring expansion candidates generated from \(S'\) and \(O'\) respectively, but ignoring items that occur in the subject and object expansion candidates of the same verb.

Probing sentences are generated by inserting the items of the agent-like and patient-like expanded sets into templates of the form

\(<s> \text{The noun verbs}. </s>\)

These sentences are then scored with the language model, resulting in a probability for each \text{noun-verb} pair. Finally, we sum up the probability of the agent-like and patient-like nouns separately. We classify a verb as unaccusative if the total probability of the sentences with patient-like fillers exceeds that of the sentence with agent-like fillers, and as unergative otherwise.

### 4 Evaluation

We test our method on three data sets. The first is a small set with manually constructed examples containing 10 verbs of each category. The second is the subset of causative-inchoative alternating verbs from the FAVA data set. This means that it only contains verbs of the unaccusative class. The FAVA data set includes both the transitive and intransitive variants of each verb. However, since each sentence uses a proper name as subject and we do not consider proper names in our pattern, “\(<s> \text{The noun verbs}. </s>\)”, we just retain the verbs. The third evaluation data set is composed of the subset of FrameNet verbs annotated as unaccusative or unergative verbs. We randomly sample 50% of the verbs each time we query the language models. For the first two data sets, we present results both with the manually curated sentences and with generated sentences (according to Section 3). Since we do not have manually curated sentences for the FrameNet data set, we only provide results with generated sentences.

In terms of language models, we experiment with two \(n\)-gram models and the neural model GPT-2 (Radford et al., 2019). The first two are \(5\)-grams models with modified Kneser-Ney smoothing (Chen and Goodman, 1998; Kneser and Ney, 1995) trained using KenLM (Heafield et al., 2013). They have different sizes: the small one is trained on the News Commentary portion of the shared-task training data for the Conference on Machine Translation (WMT) 2016 (Bojar et al., 2016), while the large one is trained using the entirety of the monolingual English training data of the WMT 2016 news translation shared task.

For the neural model, we normalised the sentence log probabilities produced by GPT-2 by sentence length and lexical frequency following Lau et al. (2015). Since some of the verb variants risked to be infrequent but grammatical, we expected the normalisation to provide a better estimate of the suitability of each query. We estimated an unigram language model on Europarl for the normalisation.

### 5 Results

The difference between the \(n\)-gram models confirms that it is possible to differentiate between the classes using intransitive frames only and that a larger model produces better predictions. The results of the neural model, on the other hand, seem to contradict this last statement.

We know that the \(n\)-gram model may do hard back-offs when not recognising a \(3\)-gram “\(<\text{noun}\) <\text{verb}>.””, causing the final score to depend only on the prior frequency of the subject. However, it is hard to diagnose what it is that the neural model is reacting to.

The neural model has a maximal precision of 0.69 in the Constructed set and a precision of 0.60 in the FrameNet set. The comparison of the evaluation on the Constructed set using simple sentences (Table 1) with the expanded sentences generated

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Table 1: Precision, recall and F-scores using a manually curated data set. We present results using the present tense.

|               | n-gram small |           | n-gram large |           | GPT-2       |           |
|---------------|--------------|-----------|--------------|-----------|-------------|-----------|
|               | Unacc. P     | R         | F1           | Unacc. P  | R         | F1         | Unacc. P  | R         | F1         | Unacc. P  | R         | F1         |
|               |              |           |              | Unacc. P  | R         | F1         | Unacc. P  | R         | F1         | Unacc. P  | R         | F1         |
| Constructed   | 20           | 0.20      | 0.25         | 0.22      | 0.40      | 0.33       | 0.36       | 0.80      | 0.61       | 0.69       | 0.50       | 0.50       | 0.59       |

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\(4\)The normalisation LP-div is defined as

\[
- \log P_m(\xi) - \log P_u(\xi),
\]

while the SLOR (syntactic log-odds ratio) is defined as

\[
\log \frac{P_m(\xi)}{P_u(\xi)},
\]

where \(P_m(\xi)\) is the probability of the sentence given by the model and \(P_u(\xi)\) is the unigram probability of the sentence.
Table 2: Precision, recall and F-scores for the GPT-2 model on the different evaluation sets. We present results using the present tense. Notation: Expanded_EP refers to probing sentences generated with any word tagged as NOUN in English Europarl; Expanded_Lefff refers to probing sentences generated with all nouns listed in the English dictionary Lefff.

6 Conclusions

We proposed a method to detect unaccusative vs unergative verbs based on the generation of intransitive sentence frames of candidate verbs. The results with a large language model show moderate success, highlighting that the causative-inchoative alternation is a challenging meaning distinction to detect automatically. Since the method relies primarily on parsed data and language models, it has the potential to be extended to languages where verbal annotated resources are scarce.

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