Neural networks for cross-lingual negation scope detection

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Abstract

Negation scope has been annotated in several English and Chinese corpora, and highly accurate models for this task in these languages have been learned from these annotations. Unfortunately, annotations are not available in other languages. Could a model that detects negation scope be applied to a language that it hasn’t been trained on? We develop neural models that learn from cross-lingual word embeddings or universal dependencies in English, and test them on Chinese, showing that they work surprisingly well. We find that modeling syntax is helpful even in monolingual settings and that cross-lingual word embeddings help relatively little, and we analyze cases that are still difficult for this task.

1 Introduction

Negation scope is the set of words whose meaning is affected by a word or morpheme expressing negation. For example, in (1), the words ‘you’ and ‘drive’ are in the scope of the negation cue ‘not’.

(1) You must not drive because it is dangerous.

Detecting negation scope is important for many applications, including biomedical information retrieval (e.g. Morante and Daelemans, 2009), sentiment analysis (e.g. Councill et al., 2010), and machine translation (e.g. Fancellu and Webber, 2014). Its importance has prompted the development of several annotated corpora and classifiers that detect negation scope with high accuracy.

Most of this work is confined to English. Supervised machine learning systems require annotated data, and annotating data for negation scope requires substantial effort, both to adapt annotation guidelines to new languages (Altuna et al., 2017), and for the annotation itself. As a consequence, there are only a handful of annotated datasets for languages other than English, such as the Chinese Negation and Speculation corpus (CNeSp, Zou et al., 2016). We ask: Can we learn a model that detects negation scope in English and use it in a language where annotations are not available?

To answer this question, we develop models on English using language agnostic features only and apply them to Chinese; though annotations are available for Chinese we use them only for testing to simulate our zero-resource setting. Our initial model is the state-of-the-art bidirectional LSTM (BiLSTM) of Fancellu et al. (2016), initialized with cross-lingual word embeddings and universal part-of-speech (PoS) tags. But BiLSTMs are sensitive to word order, so we also experiment with a cross-lingual input representation that abstracts from word order—syntax in the form of universal dependencies (UD, de Marneffe et al., 2014)—since we expect that for examples like that in Fig. 1, this will give our model a more consistent view of the input across languages. To condition our model on UD syntax, we consider two different encodings: a Bidirectional DependencyLSTM (D-LSTM below, modeled after the treeLSTM of Tai et al., 2015) and a Graph Convolutional Network (GCN below, Marcheggiani and Titov, 2017).

Our results show it is indeed possible to build models for cross-lingual negation scope detection with performance approaching that of a monolingual oracle. Modeling syntax in addition to surface word order is helpful, as shown by an ensemble of BiLSTM and D-LSTM models outperforming either model alone. Our results also show that cross-lingual word embeddings are not really necessary, suggesting that the model mainly relies on PoS, syntax, and punctuation boundaries—with the latter result reinforcing previous findings (Fancellu et al., 2017).

Finally, error analysis show that our best model performs better when the cue is in the same depen-
You must not drive because it is dangerous

Figure 1: Example dependency parse for the sentence ‘You must not drive because it is dangerous’ and its Chinese translation. While the word order differs in translation, each word in the negation scope stands in the same relation to the cue.

dependency substructure as its scope (as it is in Fig 1) and fails to capture phenomena related to negation scope, such as neg-raising, where lexical information is required.

2 The task

Our input is a sentence with a negation cue, which can be a word (e.g. ‘not’) or a multi-word unit (e.g. ‘by no means’) inherently expressing negation. Our task is to identify the set of words in the scope of the cue; we use gold cues and do not perform automatic cue detection. For example, writing 

**cues in bold red** and underlining scopes:

(2)  

i I must not go

ii I don't think he should come.

iii I didn’t miss the concert because I was sick but because I was busy.

Detecting negation scope is challenging because it often interacts with other semantic phenomena. To resolve (2.i), the system needs to know that ‘must’ scopes over negation but other modals (e.g. ‘should’) do not. Likewise for neg-raising, as in (2.ii), the presence of certain verbs like ‘think’ or ‘believe’ requires the negation scope to span the object clause (i.e. ‘I think he should not come’). Finally, in (2.iii), the causal clause is in the scope despite the marker directly preceding the verb ‘miss’.

Similar interactions are attested in Chinese. However, the lack of markers for certain syntactic environments may pose different challenges, since scope boundaries are not defined explicitly. This is the case of clausal complements and descriptive clauses in the following examples which lack explicit markers (‘to’ and ‘that’ in English).

(3)  

i. 他说 不 要 等

He say not need to go

“He says not to wait”

ii. 我 有 衣 服 不 要 洗

I have clothes not need wash

“I have clothes that do not need to be washed”

3 Related work

Automatically detecting negation scope at the string level has been tackled by a variety of classifiers (e.g. Lapponi et al., 2012; Packard et al., 2014) exclusively in English or Chinese monolingual settings using language-specific heuristics or resources (e.g. DeepBank Flickinger et al., 2012). Corpora also reflect this limitation, with only one available in a language other than English.

Recently, Fancellu et al. (2016) proposed a BiLSTM model that can be easily repurposed to a new dataset without feature engineering, since it requires only word and universal PoS tags embeddings. Its performance is state-of-the-art in both English and Chinese, but to train it on another language we would still need annotations in that language.

In the absence of annotated data in a target language, many work have underlined the usefulness of Universal Dependencies, a cross-lingually consistent syntactic annotation framework. Tiedemann (2015) and Ammar et al. (2016) explore the problem of parsing across the languages annotated for UD, while Reddy et al. (2017) have converted UD
4 The models

4.1 BiLSTM

Our BiLSTM model follows Fancellu et al. (2016), to which we refer the reader for further detail. Given a sentence \( w = w_1...w_n \), we encode \( w_i \) as \( d \)-dimensional embedding vector, \( w_i \in \mathbb{R}^d_w \). Alongside \( w_i \), we also encode information 1) about whether a word \( w_i \) is a cue or not, encoded in a cue-embedding vector \( c_i \in \mathbb{R}^d_c \) and 2) about the universal PoS tag of \( w_i \), represented as a PoS embedding vector \( p_i \in \mathbb{R}^d_p \). We then concatenate these vectors to yield the input \( x_i \) as follows:

\[
x_i = [w_i; c_i; p_i]
\] (1)

Our goal is to predict the negation scope \( s \in \{1, 0\}^{|w|} \), where \( s_i = 1 \) if a token is part of the scope and 0 otherwise.

4.2 Bidirectional Dependency LSTM (D-LSTM)

We now turn to the encoding of a dependency tree, considering the example in Figure 1. We can traverse the tree bottom-up, from leaves to root, or top-down, from root to leaves. A top-down pass seems insufficient, since negation since cues are usually leaves as in the example. On the other hand, a bottom-up pass would fully encode the subtree rooted at the parent of the cue (in Fig. 1, ‘drive’) but would not be able to encode information about the subordinate being out of scope. Hence we need a bi-directional model that can encode the tree bottom-up and top-down. But this is still insufficient unless the passes communicate: that is, if the bottom-up pass first collects information about the children of ‘drive’, then the top-down pass can pick up that information and pass it downward, hence communicating information about ‘not’ to its sibling nodes in scope.

The model accepts as input dependency trees. A dependency tree \( g \) is a tuple \((V, E)\), where \( V_g \) is the set of word-nodes and \( E_g \) the set of dependency edges. Each \( e \in E \) is assigned a dependency label \( l \). We define as \( p(v) \) the parent of node \( v \) and \( C(v) \) the set of its children. \( r \) is the root node.

We represent each word-node \( v \in V \) as shown in Eq.2. The input vector differs from the one used in the BiLSTM model in that we add an an extra embedding \( l \) representing the dependency label of the word in \( v \) and a linear transformation to allow multiple layers to be stacked together, as \( x_v \) can be replaced with the hidden state from a previous layer.

\[
x_v = W[x_v; c_v; p_v; l_v] + b \tag{2}
\]

The computation of the bottom-up pass is the same as in Tai et al. (2015). This pass returns the state \( s^\uparrow_v = (h^\uparrow_v, c^\uparrow_v) \), where \( h^\uparrow_v \) and \( c^\uparrow_v \) are the hidden state and the memory cell of node \( v \).

To address the lack of bi-directionality in the original child-sum TreeLSTM of Tai et al. (2015), we add a second top-down pass where we feed the states computed during the bottom-up pass; in this our model is very similar to the one of Chen et al. (2017).

The top-down pass is similar to the bottom-up one but traverses the vertices in a topological order. To create a dependency between passes, we made the states computed during the bottom-up pass, \( s^\uparrow_v \), available in the form of additional weighted feature during the top-down pass. We start by computing the representation of the root node \( r \) as follows:

\[
s^\downarrow_r = LSTM(x_r, s^\uparrow_r) \tag{3}
\]

When computing the state of a node top-down, we use the parent state the same we did for the children states in the bottom-up pass. The hidden representation of the remaining nodes \( v, s^\downarrow_v \), is computed as follows:

\[
s^\downarrow_v = LSTM(x_v, s^\uparrow_v, s^\downarrow_{p(v)}) \tag{4}
\]

After both passes are computed, we pass the hidden states obtained at the end of the top-down pass to the softmax layer to compute the probability of a given node to be inside or outside the scope of negation.

\[
p(y|v) = softmax(W h^\downarrow_v + b) \tag{5}
\]

A summary of the architecture is shown in Fig. 2.
4.3 Graph convolutional networks

Our GCN is based on (Marcheggiani and Titov, 2017), to which we refer the reader for details. The intuition behind a GCN is that the hidden representation for each node in the tree is a function that aggregates information from its immediate neighbors. To communicate information between nodes that are not immediate neighbors, this process is iterated a fixed number of times, where each iteration corresponds to a neural network layer. GCNs do not assume that their input directed, so they have no notion of bottom-up or top-down traversal and do not distinguish between parent or child nodes; directionality is encoded explicitly into the neighborhood function.

The input to the model is a vector $[w_n; c_n; p_n] \in \mathbb{R}^d$, which is passed through a non-linearity or through a bi-LSTM before being fed to the GCN.

The computation for the hidden state of a given node $v$ takes into account: the hidden state of a neighbor node $n$; the directionality of the edge between $v$ and $n$ and the dependency label with its directionality specified. For each directionality a different weight matrix $W^{(K)}_{dir(u,v)}$ is used. Unlike the D-LSTM, information regarding the dependency label is not encoded in the input but in the bias vector $b^{(u,v)}$. This yields the following equation:

$$h_v^{(K+1)} = \text{ReLU}(\sum_{u \in \mathcal{N}(v)} g_{v,u}^{(K)}(W^{(K)}_{dir(u,v)} h_v + W^{(K)}_{l}(u,v) + b)))$$

(6)

where $g_{(v,u)}$ is an edge-wise scalar gate to help weighing the importance of an edge-node pair amongst several neighbors and $K$ the current layer. However, whereas the original formulation of the GCN encodes information about the dependency labels in the bias term, we weight it alongside other input features. In this way, our GCN resembles the input of the D-LSTM. Our modification results in Eq 7

$$h_v^{(K+1)} = \text{ReLU}(\sum_{u \in \mathcal{N}(v)} g_{v,u}^{(K)}(W^{(K)}_{dir(u,v)} h_v + W^{(K)}_{l}(u,v) + b) + b))$$

(7)

A summary of the architecture is shown in Fig. 3.

4.4 Ensemble

Finally, we experiment with two different ensemble models, where we join together the BiLSTM
with either the D-LSTM and GCN. We ensemble together our sequential classifier with each of the structured models, to see whether syntactic information can benefit from sequential information and vice versa. We experimented with three different ensemble techniques: a) jointly train the two systems and concatenate the output states of each word before softmax; b) feed the input through a BiLSTM layer (as shown in Eq. 1) before passing it through either the D-LSTM or the GCN (same to what Marcheggiani and Titov (2017) have done to improve the performance of the GCN model) and c) voting. We found voting to achieve the best performance. We also experimented with different kind of voting and we opted for ‘confidence’ voting, where for each word we choose the system where the absolute difference between probability of token being inside and outside the scope is larger. The results in the next section will be based on this last ensemble model.

5 Data and experiment settings

We experiment with NEGPAR (Liu et al., 2018), a parallel English-Chinese corpus of four Sherlock Holmes stories annotated for negation. Although the English side of NEGPAR leverages pre-existing annotations (ConanDoyleNeg Morante and Daelemans, 2012), most of it has been reannotated to better capture semantic phenomena related to negation scope like modality and neg-raising. Note that the Chinese translation often converts positive English statements to negative—for example, ‘This dress is cheap’ becomes 这件衣服不贵 (‘This dress is not expensive’). Hence the Chinese contains more negation instances (Table 1).

We obtain PoS tags and dependency parses using the Stanford Parser (Chen and Manning, 2014). In preliminary experiments, we compared UD version 1 and version 2. We observed that UD1 performs consistently better, so all experiments reported below are based on version 1. PoS tags are converted into universal PoS tags.\(^2\) The word segmentation the Chinese side of NEGPAR is based on also leverages Stanford toolkits (Chang et al., 2008). When testing across language, we remove language-specific dependency tags (e.g. conj:and→ conj).

We experimented with three different cross-lingual word embeddings: a) embeddings pre-trained on Wikipedia data \(^3\) where a linear transformation has mapped Chinese and English embeddings into a common space (Smith et al., 2017); b) average cross-lingual word-embeddings (Guo et al., 2016), where the embedding vector of a Chinese word is an average of the embedding vectors of its English translations and c) where we take as the embedding vector of a Chinese word the one of the English word with the highest translation probability. We found that c) consistently outperforms the other methods and that’s what we are going to use in our experiments. We observed that method a) in particular suffers from a coverage problem since the embeddings cover only 64% of the training vocabulary. We obtain translation probabilities from approximately 2 million sentences of the UN corpus (Rafalovitch et al., 2009) using fast_align (Dyer et al., 2013).

Hyperparameter tuning was performed separately for each system. Both the D-LSTM and the GCN are optimized using Adam (Kingma and Ba, 2014), with an initial learning rate of 0.005. We found 4 layers to yield the best performance for the GCN models. We use a dropout as regularizer; in the D-LSTM, dropout is performed on the output layer, whereas in the GCN we follow Marcheggiani and Titov (2017) in performing dropout on the neighbors \(N(v)\).

We evaluate our models using precision, recall, and \(F_1\) over the number of scope tokens; and using the percentage of full scopes spans we correctly detect (PCS below). We evaluate our model cross-lingually by training in English and testing in Chinese (English→Chinese); and for comparison we test models that are trained and test monolingually, on only English or Chinese.

|          | English | Chinese |
|----------|---------|---------|
| train    | 981     | 1206    |
| dev      | 174     | 230     |
| test     | 263     | 341     |

Table 1: Number of negation instances in the train, dev and test set in the English and Chinese sides of NEGPAR.

\(^2\)Mapping available at https://github.com/slavpetrov/universal-pos-tags

\(^3\)Available at https://github.com/Babylonpartners/fastText_multilingual
Table 2: (P)recision, (R)ecall, F\textsubscript{1}, and percentage of correct Scope (PCS) for each model English, where the model has been trained and tested in English; Chinese, where the model has been trained and tested in Chinese; and English→Chinese, where the model has been trained in English and tested in Chinese.

| Model          | English P | English R | English F\textsubscript{1} | PCS | English→Chinese P | English→Chinese R | English→Chinese F\textsubscript{1} | PCS | Chinese P | Chinese R | Chinese F\textsubscript{1} | PCS |
|---------------|-----------|-----------|------------------|-----|------------------|------------------|------------------|-----|---------|---------|------------------|-----|
| BiLSTM        | 85.29     | 89.76     | 87.47            | 55.89 | 70.45            | 69.94            | 18.64            | 77.71 | 79.35   | 78.52   | 33.14            |     |
| D-LSTM        | 81.30     | 85.37     | 83.28            | 52.47 | 68.60            | 65.97            | 15.67            | 76.70 | 71.91   | 74.23   | 29.59            |     |
| GCN           | 81.78     | 81.09     | 81.43            | 46.18 | 59.71            | 65.53            | 17.46            | 72.09 | 75.19   | 73.61   | 23.69            |     |
| BiLSTM+D-LSTM | 87.86     | 89.77     | 88.80            | 61.98 | 72.03            | 72.46            | 21.01            | 81.47 | 77.89   | 79.64   | 40.53            |     |
| BiLSTM+GCN    | 88.19     | 87.34     | 87.77            | 59.54 | 74.62            | 71.92            | 23.65            | 78.02 | 78.89   | 78.95   | 37.28            |     |

6 Results and Discussion

We summarize the results in Table 2 as follows:

1. **Modeling syntax is useful, though not on its own.** The ensembles that incorporate syntax outperform other models on both F\textsubscript{1} and PCS in both the monolingual and cross-lingual settings, showing that syntax is indeed beneficial—not that they outperform the state-of-the-art BiLSTM of Fancellu et al. (2016, 2017).\(^4\) The D-LSTM outperforms the GCN in the monolingual settings but the latter performs better in terms of full scope spans detected in the when training in English and testing in Chinese.

2. **The BiLSTM model on its own outperforms either syntactic model on its own by a large margin.** Perhaps surprisingly, the BiLSTM performs on par with the D-LSTM in the cross-lingual setting as well, despite relying solely on surface word order. We investigate this in more detail below.

3. **It is indeed possible to build a cross-lingual model of negation**, with performance that approaches that of a monolingual Chinese system.

We also address the following questions:

*Do all features contribute in the same way?* We perform feature ablation on our BiLSTM+D-LSTM ensemble by either removing the cross-lingual word embedding feature (-w) or the universal PoS embedding feature (-p) from either or both model in the ensemble (Table 3). Results for the BiLSTM+GCN ensemble are similar.

Both ensembles show the same trend in that removing the cross-lingual word embedding or the universal PoS embedding feature from the structured models helps with both recall and F\textsubscript{1}. This shows that both the D-LSTM and the GCN leverage the dependency structure as main feature for cross-lingual negation scope detection, with little impact from the other two features. Results also show that for both ensembles, results are worse when removing the PoS embedding feature from the BiLSTM model, suggesting that the BiLSTM relies on PoS to model word order.

\(^4\)Our results are not directly comparable to those of Fancellu et al. (2016, 2017) since the annotation of the English data is different.
sidering that the sequential nature of the BiLSTM does not adapt well with difference in word ordering that language can exhibit. This might be an artifact of the two languages used in the experiment, since English and Chinese have similar word order. However, this also could be explained by a striking observation by Fancellu et al. (2017), who showed that recurrent classifiers are very accurate when negation scope is delimited by punctuation and sentence boundaries but inaccurate otherwise. For example, they would correctly predict the scope in Ex. (4.i), which we refer to as an easy case, but not the one in Ex. (4.ii), a hard case.

(4) i. ‘She is not a princess’, said the queen.
ii. I eat pizza but do not drink beer.

To assess whether BiLSTM learns that punctuation is informative also in a cross-linguistic setting, we carry out two additional experiments.

First, we replicate the experiments Fancellu et al. (2017) and divide the development instances into two groups, the easy instances, predictable by punctuation alone and the hard instances where scope cannot be predicted by punctuation alone. If the predictions of the BiLSTM are guided by punctuation we would expect easy instances to be predicted correctly more often than hard ones. Results in Table 4 seems to confirm our prediction where the sequential model learns to use punctuation to detect negation scope. As for the hard cases we also noticed that in 47.6% of the cases prediction begins or ends at a punctuation token.

| condition | P  | R  | F₁  | PCS |
|-----------|----|----|-----|-----|
| with punctuation | 66.2 | 71.0 | 68.5 | 13.8 |
| without   | 57.7 | 59.8 | 58.4 | 8.6 |

Table 5: Comparison between two BiLSTM models in the cross-lingual task on the development set, one with (punct) and one without (no punct.) punctuation tokens.

| label      | Chinese F₁ | PCS | English→Chinese F₁ | PCS |
|-----------|------------|-----|-------------------|-----|
| root      | 76.4       | 41.1| 70.5              | 22.9|
| conj      | 81.6       | 32  | 81.7              | 25.8|
| ccomp     | 77.5       | 43  | 66.5              | 10.7|
| nsubj     | 77.3       | 25  | 65.4              | 3.2 |
| dep       | 79.8       | 44  | 78.0              | 30.2|
| dobj      | 70.8       | 6   | 63.2              | 9.3 |
| nmod:prep | 68.9       | 0   | –                 | –   |
| nmod      | –          | –   | 55.9              | 5.2 |
| advmod    | 52.9       | 0   | 61                | 0   |

Table 6: Analysis of the syntactic environment around the scope where the dependency label represents the parent of the least common ancestor of all the nodes in the scope. Labels are ordered from most to least frequent.

7 Error Analysis

What is our model learning? To analyze the performance of our best ensemble model, the BiLSTM+D-LSTM, we look at the syntactic environment scope appears in. We approximate this by looking at the least common ancestor for all the nodes in the scope and by taking the label its parent edge; if the scope is discontinuous, we take into consideration the labels on top of all spans. For each of the most frequent dependency labels, we report token-level F₁, as well as the percentage of correct scope spans we recover (PCS).

Results are shown in Table 6 for both English→Chinese and Chinese settings. In the former, we notice that there is usually a substantial loss in performance in terms of PCS but not in terms of F₁, meaning that although the scope is not exactly captured the model is still able to correctly detect approximately the same proportion of tokens.

In general, high performance is related to whether the cue is in the same dependency substructure as its scope. This happens when negation scope spans the entire sentence (‘root’) or when it
8 Conclusion

Let us go back to our initial research question: when detecting negation scope in a language other than English, can we train a system to detect negation scope in English using language agnostic features and apply it to a language where no annotations are available? Although not quite as accurate as an oracle monolingual model, we show that this is indeed possible by an ensemble of neural networks, where syntactic and surface word order complement each other. More interestingly, we show that the contribution of other cross-lingual features, such as bilingual word embeddings is minor compared to the information extracted from syntax. We also found that this applies to recurrent models as well, where structural information is extracted in the form of punctuation boundaries around a negated scope.

However, some phenomena related to negation scope, especially those requiring lexical information, are still missed by our system fail. We also suggest that future work could apply this method to languages where negation is realized in divergent ways from that of English, like those displaying double and morphological negation.

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