A Challenge Set and Methods for Noun-Verb Ambiguity

Ali Elkahky, Kellie Webster, Daniel Andor, and Emily Pitler
Google AI Language
{alielkahky, websterk, andor, epitler}@google.com

Abstract

English part-of-speech taggers regularly make egregious errors related to noun-verb ambiguity, despite having achieved 97%+ accuracy on the WSJ Penn Treebank since 2002. These mistakes have been difficult to quantify and make taggers less useful to downstream tasks such as translation and text-to-speech synthesis. This paper creates a new dataset of over 30,000 naturally-occurring non-trivial examples of noun-verb ambiguity. Taggers within 1% of each other when measured on the WSJ have accuracies ranging from 57% to 75% accuracy on this challenge set. Enhancing the strongest existing tagger with contextual word embeddings and targeted training data improves its accuracy to 89%, a 14% absolute (52% relative) improvement. Downstream, using just this enhanced tagger yields a 28% reduction in error over the prior best learned model for homograph disambiguation for text-to-speech synthesis.

1 Introduction

Whether a word is functioning as a noun or a verb in a particular linguistic context critically affects the output of tasks including translation and text-to-speech synthesis. The English word close may be translated as either nahn (adjective/non-verb) or schließen (verb) (example from Sennrich and Haddow (2016)). In text-to-speech, the homograph lives is pronounced /lairvz/ (noun) or /lvz/ (verb; example from Sproat et al. (1992)).

While downstream applications require taggers to be sensitive to non-local linguistic context, it is difficult to measure such sensitivity with current tagging evaluation. In the past 15 years since Collins (2002), many models have accuracy exceeding 97% when measured on the WSJ Penn Treebank, which is within the level of human inter-annotator agreement for the corpus. Incorporating non-local context via sentence-based representations (Collobert et al., 2011) or state-of-the-art contextual representations of tokens (ELMo, Peters et al. (2018)) yields the same tagging accuracy as Collobert et al.’s limited window-based representation (97.3%). However, existing local models “regularly make egregious errors” (Manning, 2011), notably on imperative detection. That is, the applicability of the part-of-speech labeling task is limited by its standard evaluation not reflecting difficult cases which require contextual reasoning to resolve ambiguity.

In this paper, we address this mismatch by creating a targeted intrinsic evaluation: a challenge dataset of over 30,000 naturally-occurring non-trivial examples of noun-verb ambiguity spanning multiple domains and containing many imperatives that non-expert humans can annotate with high agreement (Section 2). We will publicly release both the training and evaluation data.

We further contribute a series of modeling experiments on this data. We first show that state-of-the-art taggers perform poorly on this challenge (Table 1) and then investigate two simple and orthogonal approaches to enhancing a state-of-the-art tagger: incorporating generic contextual embeddings trained on billions of words, and incorporating thousands of examples of training data targeted for this task. Both of these approaches yield large and complementary improvements: the combined methods give an accuracy of 89.1%, a 14% absolute improvement over a state-of-the-art tagger and a 31% absolute improvement over the widely used Stanford tagger. Section 3 provides an overview of the investigated taggers, experiments, and results.

1 In experiments with recipe data in Kiddon et al. (2015), an unsupervised system had an F1 score over 20% higher in absolute terms than supervised taggers.

2 http://goo.gl/language/noun-verb
Table 1: Empirical Results. All investigated new and existing taggers are within 1% of each other when measured on the WSJ test set. When evaluated on the Noun-Verb dataset, however, existing taggers range from 57% to 74%. Adding enhancements to the Bohnet et al. (2018) tagger gives over 14% absolute improvement. Best results and results insignificantly different from the best are bolded (two-tailed $t$-test).

Finally, we demonstrate that these tagging improvements make a positive impact on the downstream task of homograph disambiguation for text-to-speech (Section 4).

2 Noun-Verb Dataset

Consider the ambiguous examples below:

1. Certain insects can damage plumerias, such as mites, **flies**, or aphids. **NOUN**
2. **Mark** which area you want to distress. **VERB**

All tested existing part-of-speech taggers (Table 1) mistag both of these examples, tagging **flies** as a verb and **Mark** as a noun. Looking at only the WSJ Penn Treebank, all occurrences of **Mark** are nouns, so a part-of-speech tagger that ignores context completely could appear to do quite well on this word type. Similarly, all occurrences of the word type **share** in the WSJ development set are noun instances.

A baseline of selecting the most frequent tag per word type (ignoring all context) achieves 93.0% accuracy on the ambiguous tokens in the WSJ (WSJ:NV), but would fare much worse on the Noun-Verb dataset.

2.1 Collection Methodology

Our goal is to build a resource which captures a wide range of challenges that a part-of-speech tagger needs to handle in the wild. To produce this resource, we find large sources of naturally occurring examples with a diversity of challenges, identify noun-verb ambiguity, find the non-trivial examples, and finally acquire high-precision labels from humans.

2.1.1 Naturally Occurring Sources

All examples come from naturally occurring English web text from three distinct genres. Typical examples from each are shown in Table 3. These genres present a diverse range of challenges: genre 1 has long well-edited sentences, genre 2 makes heavy use of imperative verbs, and genre 3 contains largely headline style short sentences.

2.1.2 Ambiguous Token Detection

We used an online dictionary to identify ambiguous word types (such as **play**) that can be either a noun or a verb. To find ambiguous instances of these types, we ran a CRF-based tagger similar to Toutanova et al. (2003) over the input sen-

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3The enhanced tagger that uses both contextual word embeddings and data augmentation (+ELMo+NV Data in Table 1) gets both Example (1) and Example (2) correct.

4We exclude a short stop list (**do**, **name**, **state**); the final list contains 24,170 word types.
Representative Examples  

| Genre 1 | Label |
|---------|-------|
| “Man With a Vision” peaked at #91 in the UK, spending two weeks on the chart. 40.7% of the population benefit from public assistance as of 2004, up from 23.0% in 2000. | NOUN VERB |

| Genre 2 | Label |
|---------|-------|
| Your doctor may recommend a diet or exercise routine. Use within 3 days of cooking. | NOUN VERB |

| Genre 3 | Label |
|---------|-------|
| Safeguard Infrastructure From Electrical Surges & Limit Downtime. Stop in Today Or Shop Online! | NOUN VERB |

Table 3: Noun and Verb examples from each genre. All examples are taken from the development set.

2.1.3 Filtering Trivial Examples

Part-of-speech tagging is already a well-established task with plenty of existing labeled examples. Adding more examples similar to John watched a play would not affect the output predictions of taggers, which already tend to correctly label tokens as nouns if they follow determiners. Inspired by work on active learning (Tomanek and Hahn, 2009; Small and Roth, 2010), we focused our data collection efforts on difficult examples. To remove easy contexts, we excluded tokens preceded by a determiner or modal verb. Tokens were additionally restricted to be neither adjectival modifiers nor components of noun-compounds.

2.1.4 Diversification

Noun-verb disambiguation is a challenge for modern POS taggers both because words can look simultaneously noun- and verb-like to a model, but also because verbs (nouns) can falsely present as nouns (verbs). Our extraction methodology is well-designed to identify the former. To identify tokens on which models are falsely confident, we manually reviewed a sample of tokens discarded in extraction. We found that sentence-initial imperative verbs were very likely to be confidently tagged as nouns. To ensure that this important class of ambiguous tokens was included in our dataset, we made it a special extraction case and did not apply the above filters for trivial examples.

2.1.5 Crowdsourced Annotation

We presented annotators with the extracted tokens in their full sentence context. Annotators were asked to select whether the target word was a “Noun”, a “Verb”, “Ambiguous”, or “Neither” (a noun or a verb). Full annotation guidelines will accompany the dataset release. Each example was annotated by at least three annotators for quality assurance. For batches with larger than average proportions of non-unanimous annotations, the non-unanimous examples were sent to an additional two annotators for a total of five annotations. Table 4 shows that annotators generally had a high level of agreement with each other, with unanimous agreement on 71.4% of the examples and majority agreement on 98.7% of the examples. Annotators achieved an average pace of 40 seconds per sentence.

| Agreement Type | #     | %     |
|----------------|-------|-------|
| Unanimous      | 23,908| 71.4% |
| Majority       | 9,122 | 27.3% |
| Disagreement   | 432   | 1.3%  |

Table 4: Inter-annotator agreement rates. Unanimous examples had 3/3 agreement, while majority examples had 2/3, 3/5, or 4/5 in agreement.

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5 Nouns and verbs were identified by mapping the fine-grained part-of-speech tag to its coarse-grained category (Petrov et al., 2012): https://github.com/slavpetrov/universal-pos-tags/blob/master/en-ptb.map

6 We excluded VBN from the set of verb tags, as it often functions more similarly to non-verbs.

7 Specifically, non-sentence initial tokens.

8 Labeled as amod according to a dependency parser.

9 Labeled as nn according to a dependency parser.
2.2 Final Dataset

To compile the final dataset, we rejected examples in which there was no majority agreement or in which the majority label was “Ambiguous” or “Neither”. This excluded 808 sentences and yielded a final dataset size of 32,654. We divided this into training, development, and test sets. Table 5 shows the dataset sizes and genre distributions. The genre distribution of the training set is intentionally different from that of the development and test sets, as realistically one will often have different distributions at training and test time, and future work may want to model this difference (Donmez et al., 2010; Steinhardt and Liang, 2016).

We asked a professional linguist to independently label 200 examples and adjudicate any differences from the crowd-sourced labels with other professional linguists. The linguists found only 7 actual mistakes (3.5% of examples). Of the remaining 96.5% plausible annotations, the linguist agreed with the crowd in 167 cases (83.5%), and found 26 disparities between PTB-style guidelines and plausible intuitive judgments (13%). All but one of the disparities involved a word ending in “ing” inside a noun phrase, such as “Manufacturing defects”). Also, all but two of the disparities were cases which the crowd source annotators labeled as nouns while the PTB-style guidelines labeled as verbs.

While humans can do well on these instances, Table 2 shows that baseline taggers that use little or no context have high error rates on this dataset, in contrast to the WSJ.

3 Empirical Evaluation of Taggers

In this section, we demonstrate empirically the limitations of several existing taggers on the new challenge dataset. We then take the most accurate, Bohnet et al. (2018), and investigate how it can be enhanced to be much more discriminative in ambiguous contexts. We finish with some error analysis to inspire future work.

3.1 Experimental Setup

Training All experiments used the standard splits of the WSJ Penn Treebank and the new Noun-Verb dataset. Specifically, WSJ Sections 2-21 were used to train all models; where indicated, this was augmented with the training portion of the Noun-Verb dataset. Neural models (Dozat et al. (2017), Bohnet et al. (2018), and extensions) used WSJ Section 22 for early stopping, and were run with $n = 10$ random restarts to compute standard deviations.

Evaluation Models are evaluated on the Noun-Verb test set. The development set was used for developing the proposed enhancements, as well as to do error analysis. To verify performance on the standard task, we also evaluate accuracy on WSJ Section 23, cf. Table 1 first column.

Our evaluation metric is VERB/NON-VERB classification accuracy over tokens which have gold annotations. To evaluate the taggers we map the fine-grained tag output using Petrov et al. (2012): tags with a coarse-grained VERB category map to the VERB label, and all other tags to the NON-VERB label.

3.2 Existing Taggers

We evaluated four commonly used and/or state-of-the-art taggers on our task. The first investigated tagger is the Stanford POS tagger\(^{10}\) (Toutanova et al., 2003), part of the Stanford CoreNLP Toolkit (Manning et al., 2014) and widely used. This pre-trained model is a log-linear model with features over the surrounding words and tags in a local window around the focus word.

The second investigated tagger is the publicly available NLP4J, a pre-trained tagging model (Choi, 2016)\(^{11}\). It used feature induction to expand the feature set during training by adding combinations of low-dimensional features. The approach achieved 97.64% on WSJ evaluation. It is worth noting that this model used a large automatically tagged corpus to get ambiguity classes for each word and Choi (2016) showed that this extra piece of information was responsible for the largest part of the improvement.

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The third tagger is Dozat et al. (2017), which won the UPOS portion of the CoNLL 2017 Shared Task on Universal Dependencies (Zeman et al.,

\(^{10}\)https://nlp.stanford.edu/software/tagger.shtml
\(^{11}\)https://github.com/emorynlp/nlp4j
2017) by a wide margin. It represents each word by a sum of its pretrained word embedding (glove Pennington et al. (2014)), trained word embedding, and the output from an LSTM runs over word’s characters. Those representations are supplied to a deep BiLSTM followed by a Multi-Layer Perceptron (MLP) layer. The output from the MLP layer is multiplied by a learned embedding for tags and the tag with the highest score is selected as the output.

Finally the fourth existing tagger is the Meta-BiLSTM (Bohnet et al., 2018) which is the current state of the art on both WSJ and CoNLL 2017 POS tagging evaluation. This model consists of three components, all of which run over the entire input sentence: a word-BiLSTM that takes a sum of pretrained (GloVe (Pennington et al., 2014)) and trained word embeddings, a char-BiLSTM that consumes trained characters embedding and a Meta component that takes a concatenation of word and character representations (at word boundaries) and feeds it to a Bi-LSTM followed by a MLP layer. The final output is computed using softmax over the Meta-MLP representation but a multi-loss is also optimized at the char and word representations level.

For Dozat et al. (2017) and Bohnet et al. (2018), we trained the model on WSJ PTB training data to get comparable models to the two previous systems. For Dozat et al. (2017) we used the default hyperparameters. For Bohnet et al. (2018), the hyperparameters used are almost identical to the original paper.\footnote{Two hyperparameter differences: we used two layers instead of three for the word component and a learning rate decay of 0.999994 instead of 0.999994. These were fixed early on and not tuned.}

The first two taggers are linear models (with feature combinations) while the second two are neural models. Both Dozat et al. (2017) and Bohnet et al. (2018) take non-local context into account through BiLSTMs over the full sentence. However, these models might not use this modeling power when trained on the WSJ, since local context is usually sufficient (Table 2).

3.3 Enhancements

We take the best existing tagger (Bohnet et al., 2018) as our starting point to investigate the efficacy of two simple enhancements and their combination for improving noun-verb disambiguation.

The first enhancement is to add generic, contex-
tual word embeddings trained on a billion words of language modeling data (Peters et al., 2018). The second enhancement is to add task-specific targeted training data, with thousands of examples derived from the Noun-Verb training set.

**Contextual Word Embeddings (ELMo)** The statistics of the new dataset, shown in Table 2, suggest that this dataset might benefit from more contextual modeling. Although the basic Meta-BiLSTM model is already contextual, one can suspect based on the first row in Table 2 that WSJ training might lead the model to ignore wider context. One way to make the model use more contextual information is to replace the word embedding layer with a contextual embedding. We used ELMo embeddings (Peters et al., 2018), which are generated by training a bi-directional language model on a large corpus of unlabeled data. The aim of using ELMo here is that we expect to get different embeddings for a word like “play” when it is used as a verb, as in “I will come and play”, versus when it is used as a noun, as in “I liked the two-act play”.

We replaced the word embedding layer in the Word component with ELMo.\footnote{We used the “Original” model from https://allennlp.org/elmo.} As in Peters et al. (2018), we trained a task specific weighting of the three ELMo layers:

\[
u^{(\text{word})}_i = \gamma \sum_{j=0}^{2} s_j h_{i,j}^{\text{ELMo}},
\]

where \(h_{i,j}^{\text{ELMo}}\) is the \(j\)-th layer ELMo embedding of word \(i\), \(s_j\) are softmax-normalized weights over the layers, and \(\gamma\) is a scalar parameter. We trained this model on the WSJ training data only.

**Targeted Data Augmentation (NV Data)** Our Noun-Verb training data comes with gold binary labels (“Noun” or “Verb”). To add them to our current model, we took a simple approach to map the Noun-Verb labels into the fine-grained POS tagset used in the WSJ dataset. To do that, we ran the baseline tagger used to extract the annotated examples in §2.1 over the Noun-Verb training data, and extracted all possible tags for the annotated words, sorted by their score. We then assigned to that word the highest scoring tag consistent with the coarse-grained tags. This resulted in a silver training dataset containing partially labeled sentences, each with one word tagged by its
Table 6: Development set accuracies on sentence initial (SI) tokens compared with non-sentence-initial (¬SI) tokens.

| Model                              | SI     | ¬SI    |
|------------------------------------|--------|--------|
| Majority class per word type using Noun-Verb training set | 74.6   | 69.3   |
| Existing Taggers                   |        |        |
| Toutanova et al. (2003)            | 47.4   | 59.6   |
| Choi (2016)                        | 67.8   | 71.0   |
| Dozat et al. (2017)                | 68.3   | 70.7   |
| Bohnet et al. (2018)               | 68.4±4.0 | 74.4±0.9 |
| Enhancements                       |        |        |
| +ELMo                              | 73.4±2.2 | 82.1±1.0 |
| +NV Data                           | 89.3±0.5 | 85.4±0.5 |
| +ELMo+NV Data                      | 90.0±0.8 | 87.6±0.6 |

3.4 Results

Table 1 shows the main results of both existing taggers and the enhanced models on both WSJ and the Noun-Verb Challenge Set.

Existing Taggers While all four selected taggers achieve accuracies above 97% on WSJ, they all struggle on our noun-verb challenge (Table 1). The widely used tagger of Toutanova et al. (2003) has an accuracy of just 57.6%, below the 70.1% accuracy of a per-word type majority class baseline (Table 2). The best performing tagger (Bohnet et al., 2018) was 3.9% above the next best model. However it still has an error rate of 25%.

The ranking of the four taggers stays the same whether one uses the WSJ or the Noun-Verb Challenge Set for evaluation. However, the magnitude of differences changes drastically. For example, on the WSJ test set, the differences between Dozat et al. (2017) and Toutanova et al. (2003) appear insignificant: Dozat et al. (2017) improves over Toutanova et al. (2003) by 0.09% absolute (3% relative reduction in error). When measured on the Noun-Verb Challenge Set, the differences are stark: the tagger of Dozat et al. (2017) is 12.8% absolute more accurate, which is a 30% relative reduction in error.

Enhancements Experimental results in Table 1 show that ELMo gave 7.2% absolute improvement and did not significantly affect the WSJ results\(^{14}\). This is further evidence that WSJ evaluation does not model ambiguities in cases where context matters. Adding the silver Noun-Verb data to the baseline model gave 10% absolute improvement over the baseline. This is significant given that the model capacity remained unchanged. By contrast, hooking up ELMo added a very large multi-layer BiLSTM language model to the parameters.

The best model was the model which used both ELMo embeddings and data augmentation. It achieved 13.1% absolute improvement over the state-of-the-art baseline of Bohnet et al. (2018), equivalent to over a 52% error reduction. This demonstrates that the improvement from ELMo is complementary to that from the additional Noun-Verb data.

Sentence-Initial Examples The trend in Table 1 is magnified in Table 6, which shows development set accuracies separately for tokens that are sentence-initial (SI), which are often imperatives, and for tokens that are not SI.

On SI accuracy, none of the WSJ-trained baselines could beat the most-frequent-tag baseline from the Noun-Verb training data. This shows that these sorts of examples, which are mostly imperatives, are underrepresented in the WSJ corpus. ELMo embeddings were able to improve both SI and non-SI accuracies by roughly the same amount, but again, not as much as adding the Noun-Verb data, which gave a 21.7% boost to SI accuracy. The efficacy of the Noun-Verb data in this case shows that directed training examples can

\(^{14}\)We also ran the experiment using the “Original (5.5B)” ELMo model, trained on a larger and more diverse corpus. We did not find any significant difference between the two.
Table 7: Effect of using different tuning sets. As usual with early stopping, the best tuning set performance was used to evaluate the test set. Here, we evaluated the same experimental runs at two points: when the performance was best on the WSJ development set, and again when the performance was best on the Noun-Verb development set. The increase in Noun-Verb results is significant at the $p < 0.001$ (†) and $p < 0.01$ (‡) levels.

3.5 Error Analysis

Table 8 shows representative examples that the best baseline run got wrong, along with the predictions from the best runs for each of the different enhancements. While each enhancement reduces all error types, adding Noun-Verb data improves imperatives in particular when compared with adding ELMo. This holds true even when imperatives are not sentence-initial, like the *practice* example in Table 8.

Of the errors made by our best model, roughly a quarter occurred when the focus word was a conjunction. This provides additional evidence for the importance of modeling non-local context in this dataset.

4 Homograph Disambiguation

To show the impact of our best models on a downstream task, we used the text-to-speech homograph disambiguation task described in Gorman et al. (2018). The dataset contains 161 word types, each of which has up to three possible pronunciations. In that work, the authors built a linear model that used lexical features of the focus word and its surrounding words, POS tags, and capitalization, to achieve 95.4% on this task. Here, we want to see the effectiveness of our taggers by using just the POS tag of each word to determine its pronunciation category. To do this, we annotated the homograph disambiguation train and test data with POS tags using each of our taggers. We collected counts from the training corpus of the form `<word, POS tag, word_sense, Count>`. These counts show how many times a given word got assigned to a certain word sense when it has a certain POS tag. We used those counts to select the most frequent pronunciation for each `<word, POS tag>` pair on the test data. Note that this approach will miss some word senses that cannot be determined from the word and POS tag only, like the difference in pronunciation of the word “jesus” between English: /ˈdʒɪzəs/ and Spanish: /ˈheɾes/.s/. Table 9 shows results for the micro and macro accuracies among different word types in the same way (Gorman et al., 2018) reported their results. The overall results show similar trend to what is observed in the Noun-Verb evaluation results. The Choi (2016), and Bohnet et al. (2018) baseline taggers perform close to the full model in Gorman et al. (2018), which uses a wider context and more features. This is probably due to having a stronger POS tagger than the one used in that model. It is also interesting to see the gap between Toutanova et al. (2003) and the rest of baseline taggers which was measured only on the Noun-Verb evaluation and not in WSJ evaluation. The rest of the results show that using either ELMo achieves a 1.3% absolute improvement over the baseline, while adding data augmentation achieves 0.3% absolute improvement over the baseline. Using both ELMo
Will gets his revenge by masquerading as Sue’s hairdresser and forcibly shaving her head bald. Will putting a patch over my eye help to get the object out of it? If you don’t have a table, you can mount the frame on a desk, stand, or other structure that will hold the bike off the ground. For best results, practice hitting one note higher than your standard range. Spirit actually suggests unpacking their smokes by rolling the cigarette between your fingers, filter to end, so that a pinch or so of tobacco comes out. Choose the highest combat level and duel.

Table 8: Development set examples that reflect the types of errors the enhancements address. Base is the tagger of Bohnet et al. (2018), while the remaining columns show the impact of the enhancements. Tags consistent with the gold annotations are in bold and inconsistent are in italics.

| Example                                                                 | Gold | Base | +ELMo | +Data | +ELMo+Data |
|-------------------------------------------------------------------------|------|------|-------|-------|------------|
| Will gets his revenge by masquerading as Sue’s hairdresser and forcibly shaving her head bald. | NOUN | MD   | NNP   | MD    | NNP        |
| Will putting a patch over my eye help to get the object out of it?      | VERB | NN   | VB    | NN    | VB         |
| If you don’t have a table, you can mount the frame on a desk, stand, or other structure that will hold the bike off the ground. | NOUN | VB   | VB    | NN    | NN         |
| For best results, practice hitting one note higher than your standard range. | VERB | NN   | NN    | VB    | VB         |
| Spirit actually suggests unpacking their smokes by rolling the cigarette between your fingers, filter to end, so that a pinch or so of tobacco comes out. | NOUN | VB   | VB    | VB    | NN         |

Table 9: Accuracies of different models on the homograph disambiguation test set. All enhancements’ improvements over (Bohnet et al., 2018) baseline are statistically significant $p < 0.008$. Standard deviations are estimated from $n = 10$ random restarts, and $p$-values were computed using a heteroscedastic two-tailed $t$-test.

| Model                      | Micro | Macro |
|----------------------------|-------|-------|
| **Best ML system**         |       |       |
| Gorman et al. (2018)       | 95.4  | 95.1  |
| **Existing Tagger**        |       |       |
| Toutanova et al. (2003)    | 91.1  | 91.5  |
| Choi (2016)                | 95.8  | 95.8  |
| Dozat et al. (2017)        | 94.6  | 94.7  |
| Bohnet et al. (2018)       | 95.9±0.2 | 95.9±0.2 |
| **Enhancements**           |       |       |
| +ELMo                      | 96.7±0.2 | 96.7±0.2 |
| +NV Data                   | 96.2±0.2 | 96.2±0.2 |
| +ELMo+NV Data              | 96.7±0.3 | 96.7±0.3 |

This work filtered out trivial examples via handwritten heuristics targeted towards examples that taggers generally get correct (Section 2.1). One interesting direction for future work would be to eliminate this manual step. One option could be to instead use automatically produced high-precision interpretable rules to filter out these examples, such as the Anchor explanations output by Ribeiro et al. (2018). Table 1 in that paper shows how the system can automatically induce that a part-of-speech tagging system will tag the word *play* as a NOUN in the sentence *I went to a play yesterday* because the previous word is a determiner.

5 Discussion and Related Work

**Dataset Creation** Prior work in crowd-sourcing syntactic annotations and using them in models motivated the dataset creation portion of this work. Jha et al. (2010) showed that non-linguists could reliably do aspects of syntactic annotation, and Hovy et al. (2014) showed that non-experts could annotate universal part-of-speech tags (Petrov et al., 2012) almost as well as experts. He et al. (2016) then showed that incorporating crowd-sourced annotations improves parsing by a noticeable margin on the subset of sentences in which the human judgments affected the parser’s output. Inspired by this result, we focused our efforts on collecting annotations that were likely to change a tagger’s predictions and humans can annotate reliably.

Measurement Manning (2011) performed an error analysis for WSJ and discovered that 19% of the errors fall under “Difficult linguistics” which need non-local context modeling to be able to...
solve them. The negative results of Kiddon et al. (2015) on using existing supervised part-of-speech taggers for imperative detection provided motivation for focusing on noun-verb confusion. However, we are not aware of any prior work on trying to measure part-of-speech-tagging accuracy on hard ambiguities that are easily recognized by human using diverse corpora.

6 Conclusion and Future Work

This paper proposes a challenge set approach to evaluating part-of-speech taggers, and builds a new resource for doing so. We show that a part-of-speech tagger can be trained to be better at noun-verb ambiguity by using extra Noun-Verb targeted training data or by adding contextual word embedding. We also show that our evaluation data can measure improvements in Noun-Verb disambiguation that standard evaluation dataset was not able to capture. Those previously unmeasured improvements in the Noun-Verb disambiguation are shown to lead to improvements in a downstream task. Improvements were especially large on sentence-initial tokens, which are often imperatives. Even with these improvements, there is still a large gap between the noun-verb accuracies and overall WSJ tagging accuracy. We expect that closing this gap will make incorporating syntax more useful across natural language understanding applications.

Future work can include exploring ways to incorporate more context into the tagger, possibly by using information from dependency tree. Also investigating more downstream tasks and explore if this dataset can be used directly in downstream tasks in a way similar to what have been done in Swayamdipta et al. (2017) and (Eriguchi et al., 2017; Niehues and Cho, 2017; Kiperwasser and Ballesteros, 2018) for injecting syntax in semantic role labeling and translation tasks. A third direction for research would be using this dataset to evaluate different contextual modeling approaches and investigate the creation and using such context sensitive dataset to create simpler and smaller models that can capture a lot of contextual word representation.

Future work on dataset creation can include generating similar challenge datasets for different key ambiguities in NLP. A collection of such datasets could be one way to cover hard examples that models do not get right but humans are good at. Such targeted datasets can complement the use of large unsupervised contextual embedding models. This can open an avenue to improve core NLP tasks on hard relevant ambiguities that allows making progress on downstream tasks.

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