Read, Tag, and Parse All at Once, or Fully-neural Dependency Parsing

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Abstract

We present a dependency parser implemented as a single deep neural network that reads orthographic representations of words and directly generates dependencies and their labels. Unlike typical approaches to parsing, the model doesn’t require part-of-speech (POS) tagging of the sentences. With proper regularization and additional supervision achieved with multitask learning we reach state-of-the-art performance on Slavic languages from the Universal Dependencies treebank: with no linguistic features other than characters, our parser is as accurate as a transition-based system trained on perfect (manually provided) POS tags.

1. Introduction

The ability to communicate using natural language is one of the long-term goals of artificial intelligence. Moreover, due to the huge amount of natural language texts there is a growing need to develop effective algorithms to handle them in a satisfactory manner. In the last decades one could observe a shift of focus from linguistics to statistical text analysis and more recently to machine learning systems and neural networks.

Deep learning methods have led to many breakthrough in NLP tasks, such as language modeling (Mikolov et al., 2010), machine translation (Bahdanau et al., 2014; Sutskever et al., 2014), caption generation (Xu et al., 2015), question answering (Sukhbaatar et al., 2015), speech recognition, POS-taggers and so on.

Finding the syntactical structure of sentences is one of the essential needs in natural language text analysis. Parsing is a key component required for automated natural language understanding. Virtually all NLP task could benefit from having a good quality parse tree for analyzed sentence.

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In this contribution we build a deep learning dependency parser that operates directly on characters. The parser brings together many recent ideas. On the one hand, following (Kiperwasser & Goldberg, 2016; Zhang et al., 2016; Dozat & Manning, 2016) we replace the traditional stack-based parser architecture with a deep recurrent neural encoder followed by a scoring network tasked with selecting the root words. However, similarly to (Kim et al., 2015; Ballesteros et al., 2015) we also remove the dependency on handcrafted word annotations, such as part-of-speech (POS) tags, using instead only raw characters. Despite this lack of feature engineering, our parser achieves good performance on morphologically rich Slavic languages. Furthermore, we show how proper regularization and multi-task learning can greatly reduce overfitting and make our model competitive even on languages with limited training resources.

Our implementation is available at http://github.com/mzapotoczny/dependency-parser.

2. Description of the Model

A dependency parser reads a sentence and finds a set of dependencies, that are triples composed of a head word, a dependent word, and a label describing the dependency type. Each word has exactly one head, with one word in the sentence (typically the verb) having an artificial <ROOT> token attached as its head. Therefore the set of dependencies can be interpreted as an oriented tree linking words of the sentence. Please see Figure 1 for an exemplary dependency tree.

Our dependency parser is implemented as a single neural network with three parts, as depicted in Figure 2. First, the reader subnetwork finds word embeddings based on their orthographic representations using convolutional and highway layers (Kim et al., 2015; Srivastava et al., 2015). Second, a bidirectional recurrent tagger subnetwork puts the individual words into their contexts (Schuster & Paliwal, 1997). Finally, the parser subnetwork uses the soft-attention mechanism to point each word to its head (Vinyals et al., 2015; Bahdanau et al., 2014). Once the head is found, it is used to compute the dependency label.
2.1. Reader subnetwork

The reader subnetwork is tasked with finding embeddings of words given their orthographic representations. For many languages the spelling of a word is a strong indicator of its grammatical function. Following Kim et al. (2015), we use a convolutional filterbank optionally followed by a few layers of nonlinear transformations. Each word \( w \) is represented by a sequence of its characters, fenced with special beginning-of-word and end-of-word markers. We find low-dimensional embeddings of characters and concatenate them to form a matrix \( C_w \).

Next, the matrix \( C_w \) is reduced to a vector of filter responses \( R_w \in \mathbb{R}^{nf} \), where \( nf \) denotes the number of filters. Each filter response is computed as:

\[
R_{i}^{w} = \max(C_{w} \ast F_{i}),
\]

where \( F^{i} \) is the \( i \)-th filter and \( \ast \) denotes convolution over the length of the word. Intuitively, the convolutions act like pattern matches that react to specific parts of the word. Furthermore, the filters can differentiate between prefixes, suffixes and infixes by reacting to the beginning- and end-of-word markers that are added to each word.

Finally, the reader applies a nonlinear transformation to filter responses \( R^w \). First, a linear transformation is used to reduce the dimensionality of the representation. Then a stack of highway layers (Srivastava et al., 2015) is applied to obtain the final word embeddings \( E^w \).

2.2. Tagging subnetwork

The tagging subnetwork works on sequences of representations of words \( E^w \) produced by the reader. It uses bidirectional recurrent layers (BiRNN) to put them into a broader context (Schuster & Paliwal, 1997). Specifically, we use GRU recurrent units (Cho et al., 2014) to scan the sequence forward and backward. The hidden representations are combined using addition, and passed to another layer of recurrent units.

The tagger can be trained based solely on the gradient signal flowing into it from the parsing subnetwork. However, it is also possible to branch off the signal from one of the BiRNN layers and use it to predict part of speech (POS) tags of individual words. This additional supervision typically helps to prevent overfitting of the parser. In the experimental results section we present the impact of explicit POS-tag training.

2.3. Parsing subnetwork

The parsing subnetwork has two objectives: first, to match dependent words to their heads and second, to label each pair of matched words with the proper dependency type.

We have chosen to use the pointer network (Vinyals et al., 2015) approach to find head words. For each sentence the parser obtains a sequence \( H_1, H_2, \ldots, H_n \) of vectors of word annotations produced by the tagger. We prepend to this sequence a special vector \( H_0 \) denoting the root word. This guarantees, that each word of the original sentence has exactly one head word. To train the pointer network we construct a probability distribution over possible head word locations \( l \in 0, 1, \ldots, n \).

First, for each word \( w \in 1, 2, \ldots n \) we compute a score over all possible locations \( l \):

\[
s(w, l) = f(H_w, H_l),
\]

Where the scorer \( f(\cdot, \cdot) \) is implemented as a small feed-forward neural network.

The scores are normalized over locations using the SoftMax function to \( p(w, l) \), which are interpreted as the probabilities that the head of word \( w \) is at location \( l \):

\[
p(w, l) = \frac{s(w, l)}{\sum_{l'=0}^{n} s(w, l')}
\]

Finally, the dependency label is computed by a small Max-out network (Goodfellow et al., 2013) using the annotations
We have briefly experimented with adding a recurrent hidden state to the computation of scores \( s \). The recurrent state was updated after processing each word of the sequence. However, experiments have show little benefits of this additional computation.

2.4. Training criterion

The network receives training signal from three sources:

1. The negative log-likelihood loss on predicting dependency labels \( L_l \). With the soft attention labeler this loss is backpropagated through the entire network and theoretically could be used to train the entire network. With the hard attention labeler this error is not backpropagated to the scorer.

2. The negative log-likelihood loss on finding proper head words \( L_s \) by the scorer. This loss is backpropagated through the reader and tagger subnetworks, but not through the labeler.

3. The optional POS-tagging negative log-likelihood loss \( L_t \). This loss is backpropagated only thorough a few layers of the tagger and through the reader.

The final loss is computed as a linear combination of the individual losses:

\[
L = \alpha_l L_l + \alpha_s L_s + \alpha_t L_t \tag{3}
\]

2.5. Parsing algorithm

At its core, the network produces, for each pair of words, scores that reflect the probability that the words form a dependency. These scores can be used to construct a parse tree by finding a set of dependencies that satisfy some constraints (exactly one word is dependent on the root token, there are no cycles, the tree is projective).

However, we have found that at the end of training the scores computed by eq. (2) typically lead to a very peaked probability distribution that is concentrated on just a single location. Therefore good results are obtained with a greedy parsing strategy that for each word simply chooses the best scoring parent. Only approximately 0.5% of the parses obtained by this procedure have cycles, so using Chu-Liu-Edmonds (Edmonds, 1966) maximum spanning arborescence algorithm (which deletes cycles) gives only a subtle improvement and is not presented in the Table 2.
3. Related work

There are two basic views on syntactic structure of the sentence:

- constituent based, where words are organized in nested constituents
- dependency based, where words are connected by dependency relation

This work focuses on the dependency parsing. We believe that currently two approaches are the most important ones: transition and graph based. A transition based parser aims to predict the best parser action (such as moving the word to stack or add a dependency between current word and the word on a stack) looking at some features (Nivre, 2008). A graph based parser finds the structure which maximizes a global score while preserving some constraints (i.e. forces the output to be well formed tree). Recently, deep neural networks were used with a great success in dependency parsing, both transition (Chen & Manning, 2014; Dyer et al., 2015; Kiperwasser & Goldberg, 2016; Andor et al., 2016; Ballesteros et al., 2015) and graph (Pei et al., 2015) based. Our parser is most similar to the graph-based variant of (Kiperwasser & Goldberg, 2016). However, similarly to (Ballesteros et al., 2015) we replace the word embeddings and POS tags with our reader subnetwork thus reducing the need for feature engineering, which is an important aspect of parser construction which requires knowledge of linguistics. Powerful learning techniques reduce the burden of this somewhat language-specific work.

Our parsing network brings together ideas from many recent contributions. Ling et al. (2015) successfully applied character-based word embeddings computed with small BiRNNs (another possible implementation of our “reading” subnetwork) to POS-tagging and language modeling with recurrent networks. A similar mechanism was employed in (Ballesteros et al., 2015) in a character-based shift-reduce dependency parser. The character-based word embeddings that we have used were described by Kim et al. (2015). They were extensively analyzed and compared against ones computed with BiRNNs by Jojefowicz et al. (2016) in a large language-modeling study.

A purely neural constituency parser was shown by Socher et al. (2011). It built a parse tree by repeatedly joining words or subtrees using a recursive network. Later, Vinyals et al. (2014) have shown that good constituency parsers can be created by learning to “translate” between a given sentence and the linearization of its parse tree. The parser accessed the source sentence through word embeddings, which were initialized with Word2Vec (Mikolov et al., 2013) and adapted during parser training. We build on their work by directly using the attention matrix as pointers into the source sentence locations that correspond head words. This change greatly simplifies the parser: there is no recurrent generator and no need for an approximate search during evaluation.

Our parser is unique in the fact that it requires virtually no data engineering and the employed training criterion mimics the definition of dependency parsing: it is trained to simply point head-words. The model also has new and intriguing properties. Notably it is confident enough in its predictions to allow for greedy creation of parse trees.

4. Experimental Setup

We have evaluated our parser on three languages, English, Czech, and Polish from the Universal Dependencies (UD) v. 1.2 dataset (Nivre et al., 2015). We have chosen this dataset because of its wide availability and because in the future we want to investigate the possibility of cross-lingual training. While the English treebank used in UD is rather small and non-standard, treebanks for other languages are often the typical and standard ones. In particular, we evaluate on Polish for which the UD project uses the only polish treebank “Składnica” (Świdziński & Wolniński, 2010) and on Czech for which UD uses the large and standard “Prague Treebank” (Bejček et al., 2013). Properties of the dataset are gathered in Table 1.

**Model selection** We have conducted a hyperparameter search on the Polish treebank, which is the smallest one. We have used the Spearmint system to choose network layer sizes and regularization hyperparameters (Snoek et al., 2012). Based on the experiments on Polish we have chosen three network configurations that we have used for Czech and English. On all languages we have trained the networks on the provided training splits and performed model selection and early stopping on the development split.

The best overall network used 1050 filters in the reader subnetwork (50 · k filters of length k for k = 1, 2, . . . , 6) whose outputs were projected into 512 dimensions and transformed by 3 Highway layers. The tagging network consisted of 2 BiRNN layers each composed of 548 GRU units whose hidden states were aggregated using addition. Head words

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1Unfortunately we couldn’t access the more typically used CoNLL ’09 shared task data because the licensing webpage was not operational during the preparation of this manuscript.
We have used the AdaDelta (Zeiler, 2012) learning rule with a projection layer between filters and highway units in the reader to speed the computations: we have discovered that generally increasing the number of filters is beneficial, however with a large number of filters the highway layers became a bottleneck (they are twice more expensive to evaluate than standard fully connected layers). Likewise, we have used a large dropout fraction in the BiRNN encoder and we have decided to add, rather than concatenate the hidden activations to reduce the input into the next recurrent layers.

**Training procedure** All non-recurrent weights were initialized from a normal Gaussian distribution with standard deviation set to 0.01, while the recurrent weights were orthogonalized. Initial states of recurrent layers were learned. We have used the AdaDelta (Zeiler, 2012) learning rule with parameters $\epsilon = 10^{-8}$ and $\rho = 0.95$. We have routinely used an adaptive gradient clipping mechanism (Chorowski et al., 2014). All runs were early stopped based on the Unlabeled Attachment Score (UAS).

The primary training criterion was a linear combination of negative log-likelihoods of proper head word detection (taken with a weight of $\alpha_p = 0.6$) and dependency label prediction (taken with a weight of $\alpha_l = 0.4$). In experiments in which POS tags were used as auxiliary training targets we have split the POS tags into individual attributes and added their negative log-likelihood costs with a weight $\alpha_t = 1$.

**Regularization** Polish and English treebanks are rather small and proper regularization was crucial to achieve optimum performance. We have obtained best results with Dropout (Srivastava et al., 2014). We have applied 20% Dropout just after the Reader subnetwork, 70% after every BiRNN layer in the tagger subnetwork (Pham et al., 2013) and 50% in the labeler. In contrast to Vinyals et al. (2014) we have not used data augmentations techniques.

5. Results

Our parser has reached competitive performance with transition-based dependency parsers, as demonstrated in Table 2. For all datasets we report: the percentage of correctly labeled dependencies (LA), the percentage of correctly attached heads (Unlabeled Attachment Score, UAS), and the percentage of both correctly attached heads and labels (Labeled attachment Score, LAS) measured on the test set for the model that achieved the highest performance on the development set. The results were computed using the MaltEval tool.

We compare the performance of parsers in two regimes: first, to obtain baselines we consider operation when the ground-truth (gold) POS tags are given during inference. Second, we report results when the gold POS tags are not available during inference and they either have to be predicted using a separate tagger, or as in the case of our network, the parser can directly refer to the spelling of words to infer their grammatical function. The neural parser is competitive in both cases.

5.1. Baseline Models

We have used MaltParser v. 1.8.1 tuned with MaltOptimizer (Nivre et al., 2005; Ballesteros & Nivre, 2012) on all information available in UD treebanks (gold POS). This gave us an optimistic baseline, since during normal use POS tags will contain errors due to the tagger. This error has been analyzed on UD v. 1.0 by Tiedemann (2015). As an additional optimized baseline we include also results from Straka et al. (2015) that were reported on the same version of UD treebanks that we use.

5.2. Neural Parser with Golden Tags During Inference

To compare our parser with the optimistic baseline, we have trained it on gold POS tags. We have observed that best results were obtained when the POS attributes were split and given to the network as several categorical inputs. On Czech and Polish the neural network improves the optimistic baseline error rates, while on English the results are comparable.

5.3. Neural Parser without POS Tags During Inference

In the next experiment we have evaluated the network without POS tag information during inference. When trained on individual words treated as discrete entities, the performance of the parsing network has dropped significantly, which can be seen in Table 2. One solution, outlined by Vinyals et al. (2014) involves pre-training word embeddings on a large corpus and using them in the input look-up tables. However, we wanted to use the information present in the spelling of each word and decided to use the character-based embedder by Kim et al. (2015). Intuitively, in morphologically rich languages such as Czech or Polish the spelling of a word conveys many hints about its grammatical function.

We have tested four variants of the networks: with and without an auxiliary training objective consisting of predicting POS tags and with the hard and soft attention in labelers (c.f. Section 2.3). We have established that on Polish for which has the smallest treebank multitask learning increased the UAS score when the POS tag prediction used hidden states
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Table 2. Model performance on selected languages

|                | Czech | English | Polish |
|----------------|-------|---------|--------|
|                | LA    | UAS     | LAS    | LA    | UAS     | LAS    | LA    | UAS     | LAS    |
| MaltParser     | 91.6  | 86      | 83     | 92.0  | 87.0    | 84.0   | 92.0  | 89.1    | 85.8   |
| (Straka et al., 2015) | -     | 87.7    | 84.7   | -     | 88.2    | 84.8   | -     | 89.8    | 85.5   |
| (Tiedemann, 2015) | -     | -       | 85.7   | -     | -       | 85.7   | -     | -       | -      |
| NN (this work)  | 93.8  | 91.7    | 88     | 92.3  | 88.6    | 85.1   | 93.9  | 93.4    | 89.3   |

Gold POS tags used during inference

|                | Predicted POS tags used during inference |
|----------------|----------------------------------------|
|                | No POS tags used during inference       |
| NN words       | 82.4 82.4 72.1 85 81.9 74.7 73.8 74.6 61.6 |
| NN chars, soft att. | 92.1 90.1 85.7 90 86.5 82.1 88.7 89.1 82.5 |
| NN chars, tags, soft att. | 89.5 89.6 82.8 89.2 86.2 81.3 89.3 90.4 83.9 |
| NN chars, tags, hard att. | **92.6 90.1 86.7 90.4 87.6 83.6 90.9 91.3 86** |

Note: MaltParser results on Czech are sub-optimal because due to lack of computational resources we had to use a small dataset for parser optimization.

of the penultimate BiRNN layer. On the larger datasets available on Czech and English the extra supervision added by predicting POS tags slightly decreases the results. However, on all languages the best setup involved multitask learning and soft attention.

Using hard attention is also beneficial. We interpret this fact as follows: with hard attention, the labeler always sees the annotations of the correct head and dependent words, while with soft attention the head annotation may refer to possibly many incorrect words chosen by the attention mechanism. With hard attention gradients from the labeler are backpropagated to the correct head word only, which helps training. On the other hand, with soft attention the gradients from the head nodes sometimes are backpropagated to incorrect locations. This adds noise during training, but possibly makes the labeler more robust to errors in localization of head words.

We can make the following observation based on Table 2: on all tested languages we can see that, according to our expectations, we have generally that NN with characters outperforms NN with words. Czech and Polish belong to morphologically reach languages, and on these languages we can observe clear benefit from using POS-tags as a additional learning objective (the greater role of tags in Czech and Polish is also visible, when we look at the difference between versions with and without golden POS tags). Furthermore, when we don’t use golden tags, for Polish and Czech our best algorithm achieves best UAS and LAS (for Polish this remains true even when compared with MaltParser trained on gold POS tags).

While both our neural parser and classical parsers (Tiedemann, 2015) perform better when ground-truth POS tags are given during inference, we observe the neural network suffers a smaller accuracy decrease than a cascade of separately trained tagger and parser. We hypothesize that this is due to the end-to-end trainability of the neural parser. Comparing the scores achieved by our parser when it has only access to word embeddings (row “NN words”) or word spellings (row “NN chars”), we confirm that the reading subnetwork can extract meaningful grammatical features from word’s orthographic representations.

Decoding algorithm The decoding algorithm has little impact on the parser’s performance. We have investigated the attention outputs which show, for each word, probabili-
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itities assigned by the network to the locations of the head word. These probability distributions are very sharp, with virtually no ambiguities. The attention matrix for one sentence is shown in Figure 3. Therefore the greedy head attachment strategy works very well in practice.

On the three languages tested, about 98% of parses produced by the greedy strategy were correct trees, with a single ROOT and no cycles.

6. Conclusions and Future Works

We have presented a dependency parser that is able to operate directly on characters, obviating the need for a traditional NLP pipeline. The parser is trained in an end-to-end manner, and has separate cost terms that pertain to label accuracy, head word localization and optionally POS tagging. On morphologically rich languages the parser is competitive with traditional transition-based solutions that use gold POS tag information, despite the fact that no hand-designed linguistic features are used and all information comes directly from the orthographic form of words.

Our parser uses a distributed representation of words created by the tagging subnetwork. In future work we plan to investigate the possibility of co-training multilingual neural-net based parsers that permit parameter sharing between languages to improve the models on languages with very small corpora, such as Polish or Slovenian. A multilingual shift-reduce parser using a set of unified POS tags was recently proposed by (Ammar et al., 2016) and we are curious whether the benefits of multilingual parsing can be achieved without the manual labor associated with the unification of linguistic features between languages.

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Table 3. Results of parsers trained on UD v1.3 (newer data compared to table 2) Our models use only orthographic representations of tokenized words during inference and work without a separate POS tagger. Ammar et al. (Ammar et al., 2016) uses version 1.2 of UD and uses gold language ids and predicted coarse tags. SyntaxNet(Andor et al., 2016) works on predicted POS tags, while ParseySaurus(Alberti et al., 2017) uses word spellings.

| language     | #sentences | Ours UAS | Ours LAS | SyntaxNet UAS | SyntaxNet LAS | Ammar et al. UAS | Ammar et al. LAS | ParseySaurus UAS | ParseySaurus LAS |
|--------------|------------|----------|----------|---------------|---------------|------------------|------------------|------------------|------------------|
| Czech        | 87,913     | 91.41    | 88.18    | 89.47         | 85.93         | -                | -                | 89.09            | 84.99            |
| Polish       | 8,227      | 90.26    | 85.32    | 88.30         | 82.71         | -                | -                | 91.86            | 87.49            |
| Russian      | 5,030      | 83.29    | 79.22    | 81.75         | 77.71         | -                | -                | 84.27            | 80.65            |
| German       | 15,892     | 82.67    | 76.51    | 79.73         | 74.07         | 71.2             | -                | 84.12            | 79.05            |
| English      | 16,622     | 87.44    | 83.94    | 84.79         | 80.38         | 79.9             | -                | 87.86            | 84.45            |
| French       | 16,448     | 87.25    | 83.50    | 84.79         | 81.05         | 78.5             | -                | 86.61            | 83.1             |
| Ancient Greek| 25,251     | 78.96    | 72.36    | 68.98         | 62.07         | -                | -                | 73.85            | 68.1             |

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