SParse: Koç University Graph-Based Parsing System for the CoNLL 2018 Shared Task

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Abstract

We present SParse, our Graph-Based Parsing model submitted for the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies (Zeaman et al., 2018). Our model extends the state-of-the-art biaffine parser (Dozat and Manning, 2016) with a structural meta-learning module, SMeta, that combines local and global label predictions. Our parser has been trained and run on Universal Dependencies datasets (Nivre et al., 2016, 2018) and has 87.48% LAS, 78.63% MLAS, 78.69% BLEX and 81.76% CLAS (Nivre and Fang, 2017) score on the Italian-ISDT dataset and has 72.78% LAS, 59.10% MLAS, 61.38% BLEX and 61.72% CLAS score on the Japanese-GSD dataset in our official submission. All other corpora are evaluated after the submission deadline, for whom we present our unofficial test results.

1 Introduction

End-to-end learning with neural networks has proven to be effective in parsing natural language (Kiperwasser and Goldberg, 2016). Graph-based dependency parsers (McDonald et al., 2005) represent dependency scores between words as a matrix representing a weighted fully connected graph, from which a spanning tree algorithm extracts the best parse tree. This setting is very compatible with neural network models that are good at producing matrices of continuous numbers.

Compared to transition-based parsing (Kirnap et al., 2017; Kiperwasser and Goldberg, 2016), which was the basis of our university’s last year entry, graph-based parsers have the disadvantage of producing $n^2$ entries for parsing an $n$-word sentence. Furthermore, algorithms used to parse these entries can be even more complex than $O(n^2)$. However, graph-based parsers allow easy-to-parallelize static architectures rather than sequential decision mechanisms and are able to parse non-projective sentences. Non-projective graph-based parsing is the core of last year’s winning entry (Dozat et al., 2017).

Neural graph-based parsers can be divided into two components: encoder and decoder. The encoder is responsible for representing the sentence as a sequence of continuous feature vectors. The decoder receives this sequence and produces the parse tree, by first creating a graph representation and then extracting the maximum spanning tree (MST).

We use a bidirectional RNN (bi-RNN) to produce a contextual vector for each word in a sentence. Use of bi-RNNs is the de facto standard in dependency parsing, as it allows representing each word conditioned on the whole sentence. Our main contribution in the encoder part is to word embeddings feeding the bi-RNN. We use word vectors coming from a language model pre-trained on very large language corpora, similar to Kirnap et al. (2017). We extend word embeddings with learnable embeddings for UPOS tags, XPOS tags and FEATs where applicable.

Our decoder can be viewed as a more structured version of the state-of-the-art biaffine decoder of Dozat et al. (2017), where we attempt to condition the label-seeking units to a parse-tree instead of simple local predictions. We propose a meta-learning module that allows structured and unstructured predictions to be combined as a weighted sum. This additional computational complexity is paid off by our simple word-level model in the encoder part. We call it that we call structured meta-biaffine decoder or shortly SMeta.

We implemented our model using Knet deep
learning framework (Yuret, 2016) in Julia language (Bezanson et al., 2017). Our code will be made available publicly.

We could only get official results for two corpora due to an unexpected software bug. Therefore, we present unofficial results obtained after the submission deadline as well.

2 Related work

Kiperwasser and Goldberg (2016) use trainable BiLSTMs to represent features of each word, instead of defining the features manually. They formulated the structured prediction using hinge loss based on the gold parse tree and parsed scores.

Dozat and Manning (2016) propose deep bi-affine attention combined with the parsing model of Kiperwasser and Goldberg (2016), which simplifies the architecture by allowing implementation with a single layer instead of two linear layers.

Stanford’s Graph-based Neural Dependency Parser (Dozat et al., 2017) at the CoNLL 2017 Shared Task (Zeman et al., 2017) is implemented with four ReLU layers, two layers for finding heads and dependents of each word, and two layers for finding the dependency relations for each head-dependent pair. The outputs are then fed into two biaffine layers, one for determining the head of the word, and another for determining the dependency relation of head-dependent pair.

We propose a dependency parsing model based on the graph-based parser by Dozat and Manning (2016). We are adding a meta-biaffine decoder layer, similar to the tagging model proposed by Bohnet et al. (2018), for computing the arc labels based on the full tree constructed from the unlabelled arc scores instead of computing them independently.

Our parsing model uses pretrained word embeddings from Kirnap et al. (2017). Our parser uses the same language model with Kirnap et al. (2017), in which graph based-parsing algorithms are applied. However, a transition-based parsing model is given in Kirnap et al. (2017). Therefore, some adaptations are made on the features proposed by Kirnap et al. (2017) in order to use them in a graph based parsing model. We did not use contextual features coming from the language model or features related to words in stack and buffer. Instead, we trained a three-layer BiLSTM from scratch to encode contextual features.

3 Model

In this section, we depict important aspects of our architecture which is shown in Figure 1. We discuss encoder and decoder separately and then give the model hyper-parameters used.

3.1 Encoder

Word Model

We used four main features to represent each word in a sentence: a pre-trained word embedding, UPOS tag embedding, XPOS tag embedding and FEAT embedding.

Pre-trained words come from the language model in Kirnap et al. (2017). This model represents each word using a character-level LSTM, which is a suitable setting for morphologically rich languages, as shown in Dozat et al. (2017). We use the word vectors without further training.

UPOS and XPOS tag embeddings are represented by vectors randomly initialized using unit Gaussian distribution.

Morphological features, also called FEATs, are different in the sense that there are zero or more FEATs for each word. We follow a simple strategy: we represent each FEAT using a randomly initialized vector and add all FEAT embeddings for each word. We simply used zero for word vectors without any morphological features.

For practical reasons, we also needed to represent ROOT word of a sentence. We do so by randomly initializing a word embedding and setting all other embeddings to zero.

At test time, we used tags and morphological features produced by MorphNet (Dayanık et al., 2018). For languages where this model is not available, we directly used UDPipe results (Straka et al., 2016).

Sentence Model

We used a three-layer bidirectional LSTM to represent a sentence. We used the hidden size of 200 for both forward and backward LSTMs. Dropout (Srivastava et al., 2014) is performed at the input of each LSTM layer, including the first layer. Our LSTM simply use nth hidden state for nth word, different from the language model in Kirnap et al. (2017).

The language model discussed in the previous section also provides context embeddings. We performed experiments for combining our own contextual representation with this representation
using various concatenation and addition strategies, but we observed poorer performance in terms of generalization. Also, using the language model directly as a feature extractor led to unsatisfactory performance, different from last years’ transition-based entry of our institution (Kırnap et al., 2017).

3.2 Decoder

Structured Meta-Biaffine Decoder (SMeta)

Deep biaffine decoder (Dozat and Manning, 2016) is the core of last year’s winning entry (Dozat et al., 2017), so we used this module as our starting point. Biaffine architecture is computationally efficient and can be used with easy-to-train softmax objective, different from harder-to-optimize hinge loss objectives as in Kiperwasser and Goldberg (2016).

Similar to (Dozat et al., 2017), we produce four different hidden vectors, two for arcs and two for relations (or labels). Formally

\[ h_i^{(arc-head)} = \text{MLP}^{(arc-head)}(h_i) \]  \hspace{1cm} (2)

\[ h_i^{(rel-dep)} = \text{MLP}^{(rel-dep)}(h_i) \]  \hspace{1cm} (3)

\[ h_i^{(rel-head)} = \text{MLP}^{(rel-head)}(h_i) \]  \hspace{1cm} (4)

where \( h_i \) represents \( i \)th hidden state of the bi-LSTM embedding. The vectors correspond to arcs seeking their dependents, arcs seeking their heads, and corresponding relations. MLP can be any neural network module. Here, we simply use dense layers followed by ReLU activations, as in (Dozat et al., 2017).

Now, we perform the biaffine transformation to compute the score matrix representing the graph,

\[ s_i^{(arc)} = H^{(arc-head)} \mathbf{W}^{(arc)} h_i + H^{(arc-head)} \mathbf{b}^{T}^{(arc)} \]  \hspace{1cm} (5)

where \( H^{(arc-head)} \) represents matrix of \( h_i^{(arc-head)} \) vectors, \( \mathbf{W}^{(arc)} \) and \( \mathbf{b}^{(arc)} \) are learnable weights.
Up to this point, our decoder is identical to the one in (Dozat et al., 2017). The difference is in the computation of predicted arcs. We compute two different predictions:

\[ y_i^{\prime (arc)} = \arg \max_j s_j^{(arc)} \]  \hfill (6)

\[ \mathbf{p} = \text{parse} (S^{(arc)}) \]  \hfill (7)

\[ y_i^{s(arc)} = p_i \]  \hfill (8)

Here \( S^{(arc)} \) is the matrix of arc scores and \( \text{parse} \) is a spanning tree algorithm that computes the indices of the predicted arcs. Now, we compute label scores using these two predictions. First, we compute coefficient vector \( \mathbf{k} \) using the bi-RNN encodings,

\[ \mathbf{h}' = \frac{\sum_{i=1}^{n} \mathbf{h}_i}{n} \]  \hfill (9)

\[ \mathbf{k} = \mathbf{W}^{(meta)} \mathbf{h}' + \mathbf{b}^{(meta)} \]  \hfill (10)

where \( n \) is the number of words in the sentence, \( \mathbf{W} \) and \( \mathbf{b} \) are learned parameters. Averaging over time is inspired by the global average pooling operator in the vision literature (Lin et al., 2013), transforming temporal representation to a global one.

We now compute the weighted sum of label predictions using coefficient vector \( \mathbf{k} \).

\[ s_i^{l(red)} = \mathbf{h}_i^{y_i^{l(arc)}} \mathbf{U}^{(rel-head)} \mathbf{h}_i^{(rel-dep)} \]

\[ s_i^{l(red)} = \mathbf{h}_i^{y_i^{l(arc)}} \mathbf{U}^{(rel-head)} \mathbf{h}_i^{(rel-dep)} \]

\[ s_i^{s(red)} = \mathbf{h}_i^{y_i^{s(arc)}} \mathbf{U}^{(rel-head)} \mathbf{h}_i^{(rel-dep)} \]

\[ s_i^{s(red)} = \mathbf{h}_i^{y_i^{s(arc)}} \mathbf{U}^{(rel-head)} \mathbf{h}_i^{(rel-dep)} \]

\[ s_i^{(rel)} = k_1 s_i^{l(red)} + k_2 s_i^{s(red)} \]  \hfill (13)

\[ y_i^{l(red)} = \arg \max_j s_j^{(rel)} \]  \hfill (14)

where \( \mathbf{U}^{(rel)}, \mathbf{W}^{(red)} \) and \( \mathbf{b}^{(red)} \) are learned parameters.

Our model is trained using sum of softmax losses similar to (Dozat et al., 2017).

### Parsing algorithms

In our parsing model, Chu-Liu-Edmonds algorithm (Chu, 1965; Edmonds, 1967) and Eisner (1996)’s algorithm are used interchangeably, during both the training of parser models and parsing phase of test datasets. On the languages whose training dataset consists of more than 250,000 words, Chu-Liu-Edmonds algorithm is used for parsing since it has a complexity of \( O(n^3) \), where \( n \) is the number of words.

This approach allows us to train our models on relatively larger datasets in less amount of time, compared to the Eisner’s algorithm whose time complexity is \( O(n^5) \).

On training datasets having at most 250,000 words, Eisner’s algorithm is used during both training and parsing phase. Eisner’s algorithm produces only projective trees and Chu-Liu-Edmonds algorithm produces both projective and non-projective trees. This means the number of possible trees Eisner’s algorithm can generate is fewer compared to Chu-Liu-Edmonds algorithm, so even though Eisner’s algorithm has higher time complexity than Chu-Liu-Edmonds algorithm, parsing models are trained faster when Eisner’s algorithm is used.

### 3.3 Hyperparameters

We used a 150-dimensional tag and feature embeddings and 350-dimensional word embeddings for the word model. Bi-RNN sentence model has the hidden size of 200 for both forward and backward RNNs, producing 400-dimensional feature context vectors. We used the hidden size of 400 for arc MLPs and 100 for relation MLPs.

### 4 Training

We used Adam optimizer (Kingma and Ba, 2014) with its standard parameters. Based on dataset size, we trained the model for 25 to 100 epochs and selected the model based on its validation labeled attachment accuracy.

We sampled sentences with identical number of words in a minibatch. In training corpora that are sufficiently large, we sampled minibatches so that approximately 500 tokens exist in a single mini-batch. We reduced this size to 250 for relatively small corpora. For very small corpora, we simply sample a constant number of sentences as a mini-batch.
| Dataset       | LAS  | MLAS | BLEX | Dataset       | LAS  | MLAS  | BLEX |
|--------------|------|------|------|---------------|------|-------|------|
| ar_padt      | 67.57% | 56.22% | 58.84% | hu_szedeg     | 73.84% | 56.03% | 63.31% |
| bg_ancora    | 85.85% | 76.28% | 74.73% | id_gsd        | 76.88% | 65.34% | 64.89% |
| ca_ancora    | 87.60% | 79.05% | 79.49% | it_isdt       | 87.51% | 78.81% | 78.75% |
| cs_cac       | 86.05% | 73.54% | 80.14% | it_postwita   | 69.48% | 56.20% | 56.73% |
| cs_fictree   | 84.21% | 71%    | 76.86% | ja_proiel     | 22.91% | 8.47%  | 9.73% |
| cs_pdt       | 86.07% | 76.54% | 81.39% | ko_gsd        | 75.52% | 69.15% | 63.18% |
| cs_pud       | 81.80% | 68.19% | 75.10% | ko_kaist      | 81.64% | 74.46% | 68.86% |
| cu_proiel    | 67.80% | 56.51% | 60.93% | la_ittb       | 77.66% | 68.09% | 73.91% |
| da_dtt       | 77.90% | 68.14% | 68.64% | la_perseus    | 47.45% | 29.99% | 32.47% |
| de_gsd       | 70.65% | 34.50% | 60.40% | la_proiel     | 64.29% | 51.80% | 58.05% |
| el_gdt       | 83.65% | 66.76% | 70.14% | lv_lvbt       | 71.52% | 57.26% | 60.20% |
| en_ewt       | 77.87% | 68.57% | 70.83% | nl_alpino     | 78.28% | 63.38% | 66.08% |
| en_gum       | 75.51% | 63.95% | 63.52% | nl_lassysmall | 78.10% | 65.73% | 66.77% |
| en_lines     | 73.97% | 65.15% | 66.06% | pl_lfg        | 88.21% | 75.40% | 79.25% |
| en_pud       | 81.31% | 69.85% | 73.18% | pl_sz         | 83.01% | 65.10% | 73.34% |
| es_ancora    | 86.94% | 79.14% | 79.58% | pt_bosque     | 84.32% | 70.27% | 75.29% |
| et_edt       | 77.45% | 69.58% | 66.05% | ro_rrt        | 82.74% | 74.19% | 74.60% |
| eu_bdt       | 73.84% | 60.49% | 66.38% | ru_syntagrus  | 88.22% | 80.16% | 81.05% |
| fa_seraji    | 81.74% | 75.15% | 71.93% | ru_taiga      | 40.01% | 23.92% | 25.44% |
| fi_ftb       | 76.62% | 66.28% | 62.88% | sk_snk        | 77.81% | 56.11% | 62.23% |
| fi_idt       | 79.30% | 71.07% | 64.37% | sl_ssj        | 78.46% | 64.93% | 70.50% |
| fr_gsd       | 82.32% | 72.91% | 74.97% | sl_sst        | 43.63% | 31.14% | 35.41% |
| fr_sequioa   | 82.60% | 73.07% | 76.07% | sv_lines      | 74.87% | 59.32% | 67.25% |
| fr_spoken    | 64.62% | 53.15% | 54.18% | sv_pud        | 71.66% | 43.65% | 55.60% |
| ga_idt       | 35.84% | 13.07% | 16.77% | sv_talbanken  | 79.06% | 70.55% | 71.16% |
| gl_ctg       | 80.31% | 67.77% | 70.72% | tr_imst       | 60.19% | 49.57% | 51.02% |
| got_proiel   | 62.40% | 49.19% | 55.13% | ug_udt        | 58.48% | 38.18% | 45.94% |
| grc_perseus  | 61.82% | 34.17% | 41.16% | uk_ie         | 75.93% | 57.81% | 64.84% |
| grc_proiel   | 68.03% | 49.40% | 55.62% | ur_udtb       | 78.41% | 51.28% | 64.94% |
| he_hdtb      | 60.09% | 46.32% | 49.19% | vi_vtb        | 41.27% | 34.73% | 36.95% |
| hi_hdtb      | 87.66% | 70%    | 80.47% | zh_gsd        | 59.51% | 49.33% | 54.33% |
| hr_set       | 80.86% | 60.65% | 72.36% |                |      |       |      |

Table 1: Our unofficial F1 scores. Tests are done in TIRA (Potthast et al., 2014) machine allocated for the task.
We saved best models with corresponding configurations, scores and optimization states during training for recovery. We then re-create the model files for the best models of each corpus by removing the optimization states.

MorphNet is the morphological analysis and disambiguation tool proposed by Dayanık et al. (2018), which we used while training our parsing model. During training of the parser, CoNLL-U formatted training dataset files, which are produced by UDPipe (Straka et al., 2016), are given to MorphNet as input. Then, MorphNet applies its own morphological analysis and disambiguation, and new CoNLL-U formatted files produced by MorphNet are used by our parser.

Even though we used lemmatized and tagged outputs generated by MorphNet while training our parser, we run our parser on outputs generated by UDPipe, due to time constrains during parsing.

5 Results and Discussion

Short after the testing period ended, our parser obtained results on 64 treebank test sets out of 82, which are shown in Table 1. According to the results announced including the unofficial runs, we had an average LAS score of 57% on the 64 test sets on which our model is run and ranked 24th among the best runs of 27 teams. The MLAS score of our model is 46.40% and our model is ranked 22nd out of the submissions of 27 models. And, the BLEX score of our model is 49.17% and our model is ranked 21st out of the best BLEX results of all 27 models including unofficial runs.¹

According to the results, our model performs better at datasets with comparably larger training data. For instance, our model has around 90% LAS score on Catalan, Indian, Italian, Polish and Russian languages which have higher number of tokens in training data. Furthermore, our model performs relatively well in some low-resource languages like Turkish and Hungarian. However, on the datasets with very small or no training data, such as Japanese Modern, Russian Taiga and Irish IDT, we get lower scores. Hence, our model benefits from large amount of data during training process, but prediction with low resources remains as an issue for our model.

6 Contributions

In this work, we proposed a new decoding mechanism, called SMeta, for graph-based neural dependency parsing. This architecture attempts to combine structured and unstructured prediction methods using meta-learning. We coupled this architecture with custom training methods and algorithms to evaluate its performance.

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