Cross-lingual Dependency Parsing as Domain Adaptation

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Abstract

In natural language processing (NLP), cross-lingual transfer learning is as essential as in-domain learning due to the unavailability of annotated resources for low-resource languages. In this paper, we use the ability of a pre-training task that extracts universal features without supervision. We add two pre-training tasks as the auxiliary task into dependency parsing as multi-tasking, which improves the performance of the model in both in-domain and cross-lingual aspects. Moreover, inspired by the usefulness of self-training in cross-domain learning, we combine the traditional self-training and the two pre-training tasks. In this way, we can continuously extract universal features not only in training corpus but also in extra unannotated data and gain further improvement.

1 Introduction

Dependency parsing is a fundamental task for language processing that aims to establish syntactic relations between words in a sentence. It consists of two parts: an encoder that transforms input text sequences into contextual representations and a decoder that generates the corresponding parse tree. Graph-based models (McDonald et al., 2005; Koo and Collins, 2010; Dozat et al., 2017) and transition-based models (Nivre, 2008) are the most successful solutions to the challenge. In this paper, we use a graph-based model which scores parse components of a sentence and then finds the highest scoring tree through inference.

Dependency syntax is an artificially defined language structure; making high-quality labeled data relies on human analysis, and it is very time-consuming and painful. Therefore, although there is relatively sufficient labeled data in some languages such as English, and most dependency parsers demonstrate very good performance in those languages (Ji et al., 2019a; Zhang et al., 2020), there are still many languages that lack manually annotated data.

Cross-lingual transferring, which transfers models across languages, is useful to reducing the requirement of annotated data for a target language especially when the target language is lack of resources. It is challenging as it requires adapting differences of morphology, syntax, and semantics of different languages. The essence of it is to learn general features that can be strictly transferred across a wide variety of languages. Prior works on unsupervised cross-lingual dependency parsing mainly focused on sharing word-level information by using multilingual word embeddings (Guo et al., 2015). Moreover, to carry more generic contextual information rather than language-specific properties, some recent works fine-tuned the structure of encoder, and others utilized unlabeled data for training encoder (Täckström et al., 2012; Ahmad et al., 2018).

In this paper, we consider how to improve the performance of dependency parsing in both in-domain and cross-lingual by making full use of training corpus and extra unlabeled data. With recent advances in transfer learning of NLP, there are two typical approaches that have shown to be very effective: pre-trained language model and self-training. Suggestively, we closely combine those two methods in our approach.

Pre-training is a kind of unsupervised learning task trained by a large amount of unlabeled data in order to learn rich generic language information, which improves the performance of many downstream tasks. We consider that multi-tasking train-
ing of dependency parsing and several pre-training tasks, which means using those pre-training tasks as the auxiliary task of the original parsing model, can help to inspire the model to achieve better results on dependency parsing. In this paper, we use Word Ordering (WO) (Nishida and Nakayama, 2017) and Mask Language Model (MLM) as the auxiliary task for the biaffine dependency parsing (Dozat and Manning, 2017) which gains a great improvement on a number of datasets.

Self-training aims to pick up some high-quality auto-labeled training instances from unlabeled data through a number of iterations. Because pre-training tasks are good at exploring generic language information in unlabeled data. With self-training being combined to our work, the pre-training tasks can increasingly benefit dependency parsing, especially in cross-lingual transfer learning.

Above all, our contribution can be summarized as below:

• We build a multi-task framework that consists of dependency parsing and two pre-training tasks (WO and MLM) and gain a great improvement on a number of datasets by only using the original parsing training corpus.

• We closely combine pre-training and self-training by tri-training algorithm with our multi-task model which make full use of the extra unlabeled data and get a further improvement in cross-lingual dependency parsing task.

2 Related Work

Nowadays, many works on in-domain dependency parsing have been coming with very high precision. Wang and Tu (2020) proposed a second-order graph-based dependency parsing using message passing and end-to-end neural networks. Li et al. (2020) introduced a novel parsing order objective considering both global feature extraction and time complexity. Zhou et al. (2019b) presented LIMIT-BERT for learning language representations across multiple linguistics tasks, including dependency parsing with multi-task learning. Zhou et al. (2019a) proposed a joint model of syntactic and semantic parsing on both span and dependency representations. Similarly, Zhou and Zhao (2019) attempted to formulate a simplified HPSG by integrating constituent and dependency formal representations into a head-driven phrase structure.

Unsupervised Cross-lingual Parsing. Unsupervised cross-lingual transfer for dependency parsing has been studied over the past few years.

Some works trained only on the source language and directly transferred the model to the target languages. These monolingual parsers are often abstract and are in a way fair for each target language. Typical approaches include removing all lexical features from the source treebank (Zeman and Resnik, 2008; McDonald et al., 2013), selecting the underlying feature model from the Universal POS Tagset (Petrov et al., 2011) and fine-tuning the model in order to ignore some language-unique features such as word order (Ahmad et al., 2018).

Another pool of prior work focus on adapting the model to better fit the target languages includes choosing the source language data points suitable for the target language (Segaard, 2011; Täckström et al., 2013), transferring from multiple sources (McDonald et al., 2011; Guo et al., 2016; Täckström et al., 2013), using cross-lingual word clusters (Täckström et al., 2012), lexicon mapping (Xiao and Guo, 2014; Guo et al., 2015) and allowing unlabeled data from one or more auxiliary (helper) languages other than the source language to train the model (Ahmad et al., 2019).

Multilingual Representation Learning. The basic of the unsupervised cross-lingual parsing is that we can align the representations of different languages into the same space, at least at the word level. The main idea is that we can train a model on top of the source language embeddings, which are aligned to the same space as the target language embeddings, and thus all the model parameters can be directly shared across languages. In our work, we use Fasttext as our multilingual word embedding. This idea is further extended to learn multilingual contextualized word representations, for example, multilingual BERT (Devlin et al., 2019). In this work, we show that further improvements can be achieved when the encoders are trained on top of multilingual BERT because our pre-train tasks in multi-tasking are more inclined to the target language.

Word Ordering Model. WO has been widely applied in pre-training (Nishida and Nakayama, 2017; Wang et al., 2018). The main task is to restore the disordered sentences to the original ones. Many of the existing WO models can be helpful to
our task.

3 Methodology

This section introduces the structures of Biaffine dependency parser and two extra language modeling pre-training task we adopted. Then we present how to combine them as a multi-task training framework and show how to apply a self-training algorithm to this multi-task model subsequently.

3.1 Biaffine dependency parser

Our approach is based on the state-of-the-art graph-based deep biaffine dependency parser (Dozat and Manning, 2017).

For encoder, the biaffine parser applies multi-layer bidirectional LSTMs (BiLSTM) to encode the input sentence \([x_1, x_2, ..., x_l]\). Each word-level representation \(x_i\) is the concatenation of word/char/postag embeddings, i.e., \(x_i = \theta_1 e_{wi} \oplus \theta_2 e_c \oplus \theta_3 e_p\). The character-level information \([e_{c_1}, e_{c_2}, ..., e_{c_l}]\) is learned by convolutional neural networks (CNNs) to better handle out-of-vocabulary words. The outputs of encoder is a sequence of context-dependent representations \([h_1, h_2, ..., h_l]\).

\[
h_i = \text{BiLSTM} ([w_i; c_i; p_i])
\]

In order to distinguish the representation of words between head and dependent, we feed \(h_i\) into two separate MLPs to get two lower-dimensional representation of the word, as a head and a dependent respectively.

\[
r_{i}^{m} = \text{ReLU}(\text{MLP}^{m}(h_i)), m \in \{\text{head, dep}\}
\]

The scores of all possible head-dependent pairs are computed via the Variable-class biaffine classifier (Dozat and Manning, 2017):

\[
R_m = [r_{i}^{1}; r_{i}^{2}; ..., r_{i}^{l}], m \in \{\text{head, dep}\}
\]

\[
S_{arc} = R_{head}^{T}U_{1}R_{dep} + u_{2}^{T}R_{head} + u_{3}^{T}R_{dep} + b
\]

Similarly, the parser uses the other two MLPs to get the representation of head and dependent for computing label scores through the Fixed-class biaffine classifier.

In the train phase, the parser aims to optimize the following probability:

\[
P_{\theta}(Y|X) = \prod_{i=1}^{l} P_{\theta}(y_{i}^{\text{label}}|x_i) P_{\theta}(y_{i}^{\text{arc}}|x_i)\prod_{i=1}^{l} P_{\theta}(y_{i}^{\text{arc}}|x_i)
\]

where \(Y\) is a dependency tree, \(X\) is the given sentence, \(\theta\) denotes the learnable parameters and \(y_{i}^{\text{arc}}, y_{i}^{\text{label}}\) denote the highest-scoring head and dependency relation for word \(x_i\). The training objective for parser is the cross-entropy loss, which minimizes the negative log-likelihood:

\[
L_{\text{parse}} = L_{\text{arc}} + L_{\text{label}}
\]

\[
L_{\text{arc}} = -\sum_{i=1}^{l} \log P_{\theta}(y_{i}^{\text{arc}}|x_i)
\]

\[
L_{\text{label}} = -\sum_{i=1}^{l} \log P_{\theta}(y_{i}^{\text{label}}|x_i)\]

Denote \(T\) as the set of dependency label. In the inference phase, the graph-based dependency parser uses a max spanning tree (MST) decoder to find the highest-scoring tree relying on all \(p_{i,j}^{\text{arc}}\), the probability that \(x_j\) is the head of \(x_i\) and \(p_{i,j}^{\text{label}}\), the probability that \(\text{tag}_i\) is the label of \((x_i, x_j)\) if \((x_i, x_j)\) is an arc. \((i, j \in \{1, 2, ..., l\}, t_r \in T)\).

3.2 Word Ordering as Training Objective

Word Ordering (WO) has become a common pre-training task, and today it has been structured in a variety of ways. WO randomly changes the order of some words in the sentence, and restores the sentence to its original order by neural networks. In this paper, We built our WO model referring to Nishida and Nakayama (2017).

We first apply a learnable linear function to the input sentence \([x_1, x_2, ..., x_l]\) for transforming word-level representations to low-dimensional continuous vector.

\[
w_{i}^{es} = U^{T}x_i + b
\]

Then we use multi-layer BiLSTM with a soft attention mechanism to encode the input sentence. The BiLSTM’s t-th hidden state \(h_t\) and memory cells \(c_t\) are computed by the following function:

\[
h_t, c_t = \begin{cases} 
MLP(\pi), & (t = 0) \\
F_{\text{LSTM}}(x_{i=t-1}, h_{t-1}, c_{t-1}), & (1 \leq t \leq l)
\end{cases}
\]

where \(h_0\) is obtained by feeding the average of all the word representations into a MLP. The function \(F_{\text{LSTM}}\) is the state-update function of BiLSTM and \(i_{t-1} \in \{1, ..., l\}\) represents the index of word
We train the above two language modeling objectives and dependency parsing with a multi-task diagram. We randomly mask a number of words of the sentence and feed the masked sentence into multiple layers BiLSTM encoder in MLM training. Then map the output of the encoder into word alphabet dimension for predicting those masked words. Since we only used this model during the training phase, we did not need to consider the influence of Mask on the model as BERT did. The loss function for MLM is also cross-entropy loss.

\[
L_{mlm} = -\sum_{t=1}^{l} \log p_{t,i_t}
\]

\[
p_{t,i_t} = P_{\theta}(x_{i_t}|x_{i_1}, x_{i_2}, \ldots, x_{i_{t-1}})
\]

### 3.3 Multi-task Learning

We train the above two language modeling objectives and dependency parsing with a multi-task diagram. We randomly mask a number of words of the sentence and feed the masked sentence into multiple layers BiLSTM encoder in MLM training. Then map the output of the encoder into word alphabet dimension for predicting those masked words. Since we only used this model during the training phase, we did not need to consider the influence of Mask on the model as BERT did. The loss function for MLM is also cross-entropy loss.

These three models share the same multi-layer BiLSTM encoder. In this way, the overfitting of the encoder on the training set can be avoided to a certain extent, and the context information that is more universal and helpful to the test set can be learned. To further enhance the word-level representations, we joint a fine-tuned representation \(e_{lm}\) from pre-trained ELMo (Peters et al., 2018) or BERT (Devlin et al., 2019) model.

\[
h_t^m = BiLSTM([e_{w_i}^m, e_i^m, e^m_{p}, e^m_{lm}])
\]

Since the training set for parsing is much smaller than for traditional pre-train model, it is very difficult for our WO and MLM models to fully converge. So we add two weights \(\gamma_{wo}\) and \(\gamma_{mlm}\) to the loss of these two models, in order to avoid heavy influence of them on the encoder which would harm its ability in parsing. The train loss of the multitask is calculated by weighting the losses of three tasks together.

\[
L = L_{parse} + \gamma_{wo}L_{wo} + \gamma_{mlm}L_{mlm}
\]

We only uses the dependency parsing in the inference phase, which is as same as the one we introduced in Section 3.1.

### Algorithm 1: Self-training

**Input:** original training corpus \(D = (X_{original}, Y_{original}, Confidences = 1)\), testing corpus \(D_1 = (X_{test}, Y_{dev});\) extra corpus \(D = (X_{extra})\)

**Output:** the ensemble model of round \(n\)

1. teacher-model \(\leftarrow\) None;
2. for \(i \leftarrow 1\) to \(n\) do
   3. if not teacher-model then
      4. set different random seed to train \(m\) student models \(M_i = \{m_1, ..., m_{im}\}\) on \(D;\)
   5. else
      6. \(\hat{Y}_{dev}^i, \alpha\) \(\leftarrow\) teacher-model(\(X_{dev}\));
      7. \(Confidences_i\) \(\leftarrow\) evaluate correctness of \(\hat{Y}_{dev}^i\) against \(Y_{dev};\)
      8. \(\hat{Y}_{extra}^i\) \(\leftarrow\) teacher-model(\(X_{extra}\));
      9. \(\hat{D}_i = D \cup (X_{extra}, \hat{Y}_{extra}^i, Confidences_i);\)
     10. set different random seed to train \(m\) student models \(M_i = \{m_1, ..., m_{im}\}\) on \(\hat{D}_i;\)
11. teacher-model \(\leftarrow\) ensemble models in \(M_i;\)
12. return teacher-model;

### 3.4 Self-training

By setting up different random seeds, we can train several models whose performance is different but all of which are improved compared to the baseline. During inference, we can take the weighted average of the distributions predicted by these models to get further improvement. Suppose we have \(n\) models \(\theta_{1:n}\) and the \(m\)-th model predicts the distribution \(p_{arc}^m\) and \(p_{label}^m\), then the ensemble of \(n\) models predicts the distribution \(e\) as follows:

\[
e_{arc}^i = \sum_{m=1}^{n} \alpha_m p_{arc}^m(x_j|x_i, \theta)
\]

\[
e_{label}^i = \sum_{m=1}^{n} \alpha_m p_{label}^m(l_r|x_i, x_j, \theta)
\]

The models can be ensemble as long as they have the same decoding strategy (MST). So we do not
need each model to have the same structure. We can use other pre-training models instead of WO and MLM. In this paper, we replaced the WO in some models with the Pointer Network-based (Vinyals et al., 2015) Word Ordering model, which can achieve better results when ensembling these models with different structures.

Knowledge distillation (Hinton et al., 2015) describes a method for training a smaller student network to perform better by learning from a larger teacher network. In this work, the teacher network refers to the ensemble model and the student network refers to a single model.

Denote $T$ as the label set, $X$ as the given sentence and $Y$ as a dependency tree. Instead of minimizing the cross-entropy with the observed data, knowledge distillation uses the teacher distribution $e^{arc}$ and $e^{label}$ as target and minimizes the loss:

$$L_{KD}^{parse} = - \sum_{i=1}^{l} \sum_{j=1}^{l} e^{arc}(x_j | x_i) \times \log P_b(x_j | x_i)$$

$$- \sum_{i=1}^{l} \sum_{j=1}^{l} \sum_{r=1}^{T} e^{label}(l_r | x_i, x_j) \times \log P_b(l_r | x_i, x_j)$$

Rewrite the function to the sequence-level:

$$L_{KD}^{parse} = - \sum_{i=1}^{l} e(Y | X) \times \log P_b(Y | X)$$

Due to the exponential large search space of $Y$, we make an approximation of the loss function by replacing the teacher distribution $e$ by a one-hot distribution, which has the probability 1 on the parsing result $\hat{Y}$ of the teacher model.

$$L_{KD}^{parse} \approx - \log P_b(\hat{Y} | X)$$

In self-training, we iteratively train multiple rounds of models. Suppose we train $n$ rounds and in each round we train $m$ models. $\{m_{1,1}, ..., m_{1,m}\}; ...; \{m_{n,1}, ..., m_{n,m}\}$. We take the ensemble of $m$ models in round $i - 1$ as the teacher model of round $i$. In addition to the original training set, we parse the extra unannotated data of target domain/languages with teacher model, and add these data into the training set for the next round of training. Since the data parsed by teacher model is not completely correct, we give a confidence hyperparameter for each word according to the accuracy rate of the teacher model in the test set. We use cross-entropy loss for the original training data and use the loss of knowledge distillation for extra data. The final loss function can be applied as follows:

$$L = L_{KD}^{parse}(X_{original}) + \sum_{i \in X_{extra}} \alpha_i L_{KD}^{parse}(x_i)$$

$$+ \gamma_{wo} L_{WO}^{wo}(X_{all}) + \gamma_{mlm} L_{mlm}^{mlm}(X_{all})$$

4 Experiment

We evaluate the in-domain performance of our model on the English Penn Treebank (PTB), the Chinese Penn Treebank (CTB) and 12 treebanks from the Universal Dependency (UD) Treebanks: Bulgarian (bg), Catalan (ca), Czech (cs), Dutch (nl), English (en), French (fr), German (de), Italian (it), Norwegian (no), Romanian (ro), Russian (ru) and Spanish (es). We evaluate the cross-lingual performance of our model on UD by using en as the training corpus and de, fr, no as the target cropus.

We use GloVe (Pennington et al., 2014) and BERT-Large-Uncased model for PTB, and FastText (Bojanowski et al., 2017) and BERT-Base-Chinese model for CTB. For UD, we also use FastText embedding and use BERT-Base-Multilingual-Cased model for cross-lingual learning.

We use unlabeled attachment scores (UAS) and labeled attachment scores (LAS) as the metrics. Punctuation is ignored as in previous work (Dozat and Manning, 2017).

4.1 Implementation Details

Hyper-parameters. In the character CNN, the convolutions have a window size of 3 and consist of 50 filters. We use 3 bidirectional LSTMs with 512-dimensional hidden states as the encoder. In parser, the outputs of the BiLSTM employ a 512-dimensional MLP layer for the arc scorer and a 128-dimensional MLP layer for the label scorer with all using ReLU as the activation function. In WO, the learnable linear function map the embedding into 512-dimensions. In Pointer Network-based WO, we use 1 layer BiLSTM with 512-dimensional hidden state as the decoder.

Training. Parameter optimization is performed with the Adam optimizer with $\beta_1 = \beta_2 = 0.9$. We choose an initial learning rate of $\eta_0 = 0.001$. The learning rate $\eta$ is annealed by multiplying a fixed decay rate $\rho = 0.999995$ when parsing performance stops increasing on validation sets. To reduce the effects of an exploding gradient, we use a gradient clipping of 5.0. For the BiLSTM
in encoder and decoder, we use recurrent dropout with a drop rate of 0.33 between hidden states and 0.33 between layers. Following Dozat and Manning (2017), we also use embedding dropout with a rate of 0.33 on all word, character, and POS tag embeddings. The weights for the losses of WO and MLM are 0.2 and 0.15. In self-training, we trained 3 models with seed = 42, 144, 216 for each round.

### 4.2 Result

Table 1 shows the UAS and LAS of our approach as well as the reported scores of previous state-of-the-art approaches on PTB and CTB. It can be seen that without BERT, our approach achieves state-of-the-art performance on CTB and gains almost the same performance as the very recent work of Zhou and Zhao (2019) on PTB. With fixed BERT embeddings, our approach greatly outperforms baseline according to Li et al. (2020) on PTB and has the best accuracy on CTB. By fine-tuning BERT, our model can gain further improvement.

In Table 2, we report results of our approach on the test sets of 12 different languages from the UD treebanks along with the biaffine baseline according to Ma et al. (2018) and the size of training corpus assessed by the number of sentences. It shows that our approach achieves state-of-the-art results in most languages for both UAS and LAS. Our approach tends to improve more in language whose training corpus is larger (es, ru). Moreover, our approach tends to improve more in language which is in the IE.Romance Family (es, ca, fr, it, ro) and improve less or even lower performance in language which is in the IE.Germanic Family (en, de, nl, no). This result indicates that the word order of languages in the IE.Romance Family has stronger characteristics, while the word order of languages in the German family is very unstable, so that the features learned by WO task are limited.

For cross-lingual transfer learning, we take English as the source language and de, fr as target languages. We applied self-training to our multi-task model. In the first round, we only use the training set of en to train the model, which means no additional unlabeled data has been added. Starting from the second round, we first obtained a model with better performance on the target language development set using the three model we gained from the last round, then we use this model to annotate the unlabeled data and add it to the training set. In each round, we use the same 1.5w extra unlabeled target language data.

Table 3 shows the result of our approach in the first round and the ninth round together with the baseline we obtained using the original biaffine parsing model referring to Dozat and Manning (2017). We also show the RNN-Graph result in Ahmad et al. (2018). It can be seen that our approach can gain an improvement by only use source language training. With self-training, our approach can get a big promotion which achieve comparable result to the model using Multilingual BERT. Figure 1 shows the growth curve of the accuracy of our model during self-training.

### 4.3 Ablation

Table 4 shows the ablation result on PTB and CTB. When only WO or MLM is used as the auxiliary
| Language | Baseline UAS | Ahmad et al. (2018) UAS | Ours\textsuperscript{1st} UAS | Ours\textsuperscript{MLM} UAS |
|----------|--------------|-------------------------|---------------------|---------------------|
| de       | 70.23        | 69.49                   | 71.16               | 76.20               |
| fr       | 78.50        | 78.35                   | 79.01               | 77.43               |
| de + BERT|              |                         |                     |                     |

Table 3: Zero-shot cross-lingual results on the test sets of UD.

Figure 1: The accuracy curve of cross-lingual learning on DE test set during self-training.

| Systems       | PTB UAS | PTB LAS | CTB UAS | CTB LAS |
|---------------|---------|---------|---------|---------|
| Ours          | 96.05   | 94.43   | 91.22   | 90.05   |
| Ours w/o WO   | 95.95   | 94.26   | 91.04   | 89.87   |
| Ours w/o MLM  | 95.92   | 94.29   | 90.97   | 89.85   |
| Ours w/o WO & MLM | 95.83 | 94.19   | 90.32   | 89.07   |

Table 4: Ablation results on PTB and CTB.

task, the performance of the dependency parsing model is improved compared with that of the original model, while the model performs best when those two tasks are both added at the same time. It can be seen that our proposed method is effective.

5 Conclusion

In this work, we use two pre-training tasks including WO and MLM as the auxiliary task of dependency parsing to build a multi-task. Our approach gains a great improvement on PTB dataset and gets the stat-of-the-art result on CTB and UD dataset by only using original parsing training corpus. Moreover, we closely combine pre-training tasks and self-training by tri-training our multi-task model which make full use of the extra unlabeled data and get a further improvement in cross-lingual transfer learning which is comparable to the model using Multilingual BERT. Our experimental analysis shows that the effects of our approach vary across different families of languages.

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