Do We Need Word Order Information for Cross-lingual Sequence Labeling

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Abstract

Most of the recent work in cross-lingual adaptation does not consider the word order variances in different languages. We hypothesize that cross-lingual models that fit into the source language word order might fail to handle target languages whose word orders are different. To test our conjecture, we build an order-agnostic model for cross-lingual sequence labeling tasks. Our model does not encode the word order information of the input sequences, and the predictions for each token are based on the attention on the whole sequence. Experimental results on dialogue natural language understanding, part-of-speech tagging, and named entity recognition tasks show that getting rid of word order information is able to achieve better zero-shot cross-lingual performance than baseline models.

1 Introduction

Recently, neural-based supervised approaches have achieved remarkable performance in sequence labeling tasks (e.g., named entity recognition). Nevertheless, these methods are not applicable to low-resource languages where extensive training data is absent. Lately, numerous cross-lingual adaptation methods are applied to this data-scarcity scenario where zero or very few target language training samples are utilized (Wisniewski et al., 2014; Schuster et al., 2019b; Artetxe and Schwenk, 2019; Liu et al., 2019a).

However, most of the cross-lingual research work ignores the word order differences across languages and utilizes sequence encoders that are based on LSTM (Hochreiter and Schmidhuber, 1997) or Transformer (Vaswani et al., 2017) which inevitably models the word order information in the source language (Xie et al., 2018; Liu et al., 2019b). Since different languages are likely to have different word orders, models that fit into the source language word order could impede the performance in the target languages due to the word order differences. Therefore, in this paper, we investigate whether taking away source language word order information can improve the adaptation performance in target languages.

To cope with word order variances across languages, Ahmad et al. (2018) proposed to utilize relative positional encoder. However, their model still contains partial word order information in the source language. In this paper, instead, we try to get rid of all the possible source language word order information and conduct experiments on zero-shot cross-lingual sequence labeling tasks. We build our sequence encoding model based on the encoder of Transformer (Vaswani et al., 2017) and remove the positional encoding to make the model order-agnostic. In addition, in sequence labeling, conditional random field (CRF) which models the conditional probability of label sequences could also implicitly model the source language word order in the training. Hence, we study whether removing the CRF layer helps improve cross-lingual performance. Moreover, we propose to enhance Transformer’s cross-lingual ability by replacing multi-head attention with single head attention.

We conduct experiments based on cross-lingual word embeddings RCSLS (Joulin et al., 2018) and multilingual BERT (Devlin et al., 2019). Results show that getting rid of word order information is able to outperform the models that contain or partially contain word order information for zero-shot cross-lingual sequence labeling tasks.

2 Related Work

Coping with the scenario where zero or very few training samples are available is always an interesting and challenging research topic (Gu et al.,...
2018; Lee et al., 2019; Liu et al., 2019c). Recently, cross-lingual sequence labeling approaches that circumvent the need for extensive training data in target languages have achieved remarkable performance (Kim et al., 2017; Ni et al., 2017; Liu et al., 2019a). Cross-lingual language models pre-trained based on large amounts of monolingual or bilingual resources achieve state-of-the-art performance in many cross-lingual adaptation tasks (Pires et al., 2019; Lample and Conneau, 2019; Conneau et al., 2019).

Word order differences across languages have been considered in cross-lingual dependency parsing (Tiedemann and Agic, 2016; Zhang et al., 2019) by using Treebank translation. For the same task, on the other hand, Ahmad et al. (2018) leverage relative positional self-attention encoder (Shaw et al., 2018) to reduce the word order differences. Compared to previous approaches, our work studies getting rid of all the possible word order information for cross-lingual sequence labeling tasks, and our model does not require any external library like Treebank.

3 Methodology

This section can be separated into three parts. First, we introduce how we remove word order information based on the Transformer encoder (Vaswani et al., 2017). Second, we discuss the conditional random field (CRF). Third, we propose to replace multi-head attention in Transformer with single head attention to enhance the cross-lingual ability.

3.1 Removing Positional Encoding

For the encoder of Transformer, positional encoding is the only module to model the word order for the input sequences. Hence, we remove the positional encoding of the Transformer encoder to create an order-agnostic model. In the training phase, each token learns to attend to other related tokens in the input sequence so that the predictions do not depend on the order information, which makes the cross-lingual adaptation more robust.

3.2 Removing CRF Layer

Combining sequence encoder such as BiLSTM (Hochreiter and Schmidhuber, 1997) with conditional random field (CRF) has become a commonly used architecture for monolingual (Lample et al., 2016; Winata et al., 2019) as well as cross-lingual sequence labeling tasks (Xie et al., 2018; Schuster et al., 2019a; Liu et al., 2019b). Since different languages have different word order patterns, the pattern for label sequences might be different as well. However, the CRF layer models the conditional probability of label sequences, which implicitly contains the word order information. Therefore, we try to remove the CRF layer, and the word-level predictions are obtained by a linear layer with softmax.

3.3 Single Head Attention

As illustrated in Vaswani et al. (2017), Transformer with multi-head attention outperforms single head attention in the machine translation task. This is because multi-head jointly attends to information from different representation subspaces, hence it works better than single head attention for a sophisticated task like machine translation. However, the feature space for sequence labeling tasks is not as large as the machine translation task, and conducting multi-head attention needs to split the representations, which might break the alignment of cross-lingual embeddings. Therefore, we propose to revise multi-head attention in Transformer encoder to single head attention to enhance the cross-lingual ability of Transformer.

4 Experiments

4.1 Experimental Settings

We test our methods on three sequence labeling tasks in the zero-shot cross-lingual setting, namely dialogue natural language understanding (NLU), part-of-speech tagging (POS), and named entity recognition (NER). For evaluating the NLU task, we use the multilingual NLU dataset proposed by Schuster et al. (2019a), which contains English, Spanish and Thai across weather, alarm and reminder domains. For the POS task, we utilize Universal Dependencies 2.0 (Nivre et al., 2017) and choose English, French, Spanish, Portuguese, Greek and Russian to evaluate our approaches. And we evaluate the NER task on CoNLL 2002 and CoNLL 2003 datasets (Tjong Kim Sang, 2002; Sang and De Meulder, 2003), which contain English, German, Spanish and Dutch.

For all the tasks, we use English as the source language and other languages as target languages. For the zero-shot scenario, we do not use any data sample in target languages, and we select our fi-
Table 1: Zero-shot cross-lingual accuracies on the POS tagging task (results are averaged over three runs).

| Model / Embeddings          | es  | fr  | pt  | ru  | el  | AVG  |
|-----------------------------|-----|-----|-----|-----|-----|------|
| RCSLS Cross-lingual Embeddings |    |     |     |     |     |      |
| Ahmad et al. (2018)         | 39.87 | 38.39 | 23.61 | 39.37 | 28.76 | 34.00 |
| BiLSTM+CRF                  | 33.94 | 26.50 | 17.91 | 31.73 | 22.30 | 26.48 |
| TRS+Linear                  | 39.38 | 37.33 | 24.52 | 33.41 | 30.58 | 33.04 |
| TRS+CRF                     | 38.41 | 37.31 | 23.34 | 32.61 | 27.63 | 31.86 |
| OATRS+Linear                | 41.56 | 40.99 | 28.41 | 37.56 | 32.50 | 36.20 |
| OATRS+CRF                   | 39.39 | 38.22 | 27.13 | 33.44 | 32.03 | 34.07 |
| SHTRS+Linear                | 39.38 | 37.33 | 24.52 | 33.41 | 30.58 | 33.04 |
| SHTRS+CRF                   | 37.43 | 37.25 | 23.41 | 31.92 | 27.15 | 31.43 |
| SHOA+Linear                 | 39.64 | 40.22 | 32.13 | 40.20 | 35.40 | 37.52 |
| SHOA+CRF                    | 45.33 | 46.06 | 34.22 | 45.47 | 35.42 | 41.30 |
| mBERT Cross-lingual Embeddings (Freeze mBERT) |    |     |     |     |     |      |
| Ahmad et al. (2018)         | 71.85 | 80.54 | 32.57 | 77.52 | 74.43 | 67.38 |
| BiLSTM+Linear               | 70.22 | 77.74 | 29.28 | 77.36 | 72.64 | 65.45 |
| TRS+Linear                  | 72.08 | 79.03 | 32.65 | 78.06 | 72.75 | 66.91 |
| OATRS+Linear                | 72.70 | 80.16 | 33.05 | 78.64 | 75.01 | 67.91 |
| SHTRS+Linear                | 72.21 | 78.43 | 32.81 | 77.82 | 75.48 | 67.35 |
| SHOA+Linear                 | 72.65 | 80.99 | 35.84 | 76.70 | 75.69 | 68.37 |
| mBERT+Linear (Fine-tune mBERT) |    |     |     |     |     |      |
| w/ word order               | 84.31 | 80.54 | 54.30 | 84.19 | 84.35 | 79.24 |
| w/o word order              | 84.73 | 89.18 | 54.56 | 86.17 | 85.66 | 80.06 |

4.2 Results

Zero-shot cross-lingual performances for the POS, NER and NLU tasks are illustrated in Table 1, Table 2 and Table 3, respectively. We denote Transformer encoder as *TRS*, order-agnostic Transformer encoder as *OATRS*, single head Transformer encoder as *SHTRS*, single head order-agnostic Transformer encoder as *SHOA+TR*. The number of heads for the *TRS* and *OATRS* is eight.

We use {model}+CRF to represent the model followed by the CRF layer and {model}+Linear to represent the model followed by a linear layer with softmax (i.e., CRF layer is removed). Furthermore, we compare with Transformer with relative positional encoding proposed in Ahmad et al. (2018) \(^1\). All the models have the same or similar model size for the fair comparison.

4.2.1 Does Removing Positional Encoding Help?

In general, order-agnostic models (i.e., Transformer based models without positional encoding) outperform their corresponding vanilla Transformer, Transformer with relative positional encoding (Ahmad et al., 2018) and commonly used BiLSTM+CRF structure (Lample et al., 2016; Schuster et al., 2019a).

As illustrated in Table 1, Table 2 and Table 3, removing positional encoding consistently improves the zero-shot cross-lingual performance. For example, in the POS task, in terms of the average performance over all languages (AVG), with RCSLS cross-lingual embeddings, OATRS+CRF outperforms TRS+CRF by 4.34% accuracy, and SHOA+CRF outperforms SHTRS+CRF by

\(^1\) Originally, the idea is for cross-lingual dependency parsing. In this paper, we combine the Relative Positional Encoding Transformer with CRF for sequence labeling tasks.
around 10% accuracy, and with mBERT cross-lingual embeddings, around 1% accuracy improvements are observed by removing positional encoding. Also, our order-agnostic Transformer outperforms relative positional encoding models that still contain partial word order information. For example, in the NER task with RCSLS cross-lingual embeddings, OA TRS+CRF surpasses Ahmad et al. (2018) by around 4% F1-score. Additionally, for fine-tuning mBERT, we observe that adding positional encoding for the sequence embeddings from mBERT (w/ word order) makes the performance worse.

### 4.2.2 Does Removing CRF Layer Help?

As shown in Table 1, Table 2 and Table 3, removing the CRF layer cannot improve the performance, and instead, it makes the performance worse. For example, in the NER task with RCSLS cross-lingual embeddings, OA TRS+CRF surpasses Ahmad et al. (2018) by around 4% F1-score. Additionally, for fine-tuning mBERT, we observe that adding positional encoding for the sequence embeddings from mBERT (w/ word order) makes the performance worse.

### 4.2.3 Does Single Head Attention Help?

We can see from Table 1, Table 2 and Table 3, Transformer based models with single head attention slightly better the corresponding models with multi-head attention. For example, in the NLU task with refined RCSLS embeddings, SHOA TRS+CRF outperforms OA TRS+CRF in Thai by 1.88% accuracy in intent detection and 0.85% F1-score. Additionally, in the POS task with mBERT embeddings, SHOA TRS+Linear outperforms OA TRS+Linear by 0.46% F1-score.
### 4.2.4 How Order Information Influences the Performance?

Interestingly, getting rid of the positional encoding in Transformer shows improvements in all languages compared to the original Transformer as well as relative positional encoding Transformer, including Spanish and French that have a close language distance to English, and Greek and Thai which are lexically and syntactically different from English. This is because word order differences naturally exist in different languages, and the baseline models contain or partially contain the source language order information. Order-agnostic models are able to learn the task in the source language well enough due to the extensive training data and have a better adaptation ability to target languages since the models do not overfit to the source language word order.

In addition, we observe that TRS+CRF generally achieves better results than BiLSTM+CRF. We conjecture that it is because BiLSTM contains more order information than Transformer since BiLSTM has a memory cell to remember the previous tokens and Transformer only leverage positional encoding for modeling word orders. Hence, BiLSTM might have a more serious overfitting problem to the source language word order.

### 5 Conclusion and future work

Word order differences naturally exist among different languages. To explore this intuition, in this paper, we first hypothesize that getting rid of all the word order information is able to achieve better performance. We conduct experiments by removing the positional encoding of Transformer and the CRF layer for zero-shot cross-lingual sequence labeling tasks. Experimental results show that removing positional encoding helps improve performance while removing the CRF layer makes the performance worse. In the future, we plan to conduct a more comprehensive analysis of why removing positional encoding can work and explore better order-agnostic models.

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