On the Importance of Word Order Information in Cross-lingual Sequence Labeling

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Abstract

Word order variances generally exist in different languages. In this paper, we hypothesize that cross-lingual models that fit into the word order of the source language might fail to handle target languages. To verify this hypothesis, we investigate whether making models insensitive to the word order of the source language can improve the adaptation performance in target languages. To do so, we reduce the source language word order information fitted to sequence encoders and observe the performance changes. addition, based on this hypothesis, we propose a new method for fine-tuning multilingual BERT in downstream cross-lingual sequence labeling tasks. Experimental results on dialogue natural language understanding, partof-speech tagging, and named entity recognition tasks show that reducing word order information fitted to the model can achieve better zero-shot cross-lingual performance. Furthermore, our proposed methods can also be applied to strong cross-lingual baselines, and improve their performances.

1 Introduction

Neural-based data-driven supervised approaches have achieved remarkable performance in sequence labeling tasks (e.g., named entity recognition) (Lample et al., 2016; Devlin et al., 2019). Nevertheless, these methods are not applicable to low-resource languages where extensive training data are absent. Recently, numerous cross-lingual adaptation methods have been 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, the word order differences across languages is a less studied problem of the cross-lingual task. For cross-lingual models, sequence encoders that are based on LSTM (Hochreiter and Schmidhuber, 1997) or Transformer (Vaswani et al., 2017) inevitably model the word order information in the source language (Xie et al., 2018; Liu et al., 2019b). We characterize this as the *order-sensitive* property (Ahmad et al., 2018). Since different languages have different word orders, models that fit into the source language word order could hurt the performance in the target languages due to the word order differences.

In this paper, we investigate whether making models insensitive to or not fit into the source language word order can boost the cross-lingual performance. Concretely, we choose order-sensitive sequence encoders, such as LSTM and the Transformer encoder, as our baseline models. Then, we propose three approaches to construct orderinsensitive models, and we compare them with the baseline models. First, we remove the positional embeddings from the Transformer encoder, and utilize one-dimensional convolutional networks (Conv1d) as a feed-forward layer to encode partial order information, so that the model becomes less dependent on word order. Second, we add perturbations to the word order in the training samples, and the baseline models trained with them become insensitive to the word order. Third, we hypothesize that the positional embeddings in multilingual BERT (mBERT) (Devlin et al., 2019) are orderagnostic given the surprising cross-lingual ability that it has (Pires et al., 2019; Wu and Dredze, 2019). Hence, we take the positional embeddings from mBERT to initialize the positional embeddings in the Transformer encoder, and we freeze them in the training phase to make the model order-agnostic.

Additionally, we propose to freeze the positional embeddings when we fine-tune mBERT to downstream cross-lingual tasks, which makes the model avoid fitting into the source language word order.

We conduct experiments on zero-shot cross-

lingual sequence labeling tasks, namely, part-ofspeech tagging (POS), named entity recognition (NER) and dialogue natural language understanding (NLU). From the experimental results, we summarize our insights as follows:

- Order-insensitive models are robust to word order shuffled sequences and consistently outperform order-sensitive models, including the state-of-the-art model.
- Retaining the order-agnostic property of mBERT positional embeddings gives a better generalization ability to target languages.
- Encoding partial word order information is necessary for cross-lingual tasks. Models that do not encode any word order information (i.e., most insensitive to word order) perform badly on both source and target languages.

2 Related Work

2.1 Cross-lingual Adaptation

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). Chen et al. (2019) proposed mixture-ofexperts models to exploit the similarity between the target language and each individual source language, which achieve promising results on the cross-lingual NER task. Liu et al. (2019a,b) utilized task-related keywords to build robust crosslingual dialogue NLU systems. Taking this further, cross-lingual language models (Pires et al., 2019; Lample and Conneau, 2019; Conneau et al., 2019) pre-trained based on large amounts of monolingual or bilingual resources achieved the state-of-theart performance in many cross-lingual adaptation tasks, such as NER and POS.

2.2 Coping with Order Differences

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) leveraged a relative positional self-attention encoder (Shaw

et al., 2018) to make the sequence encoder less sensitive to word orders and increase the adaptation robustness for target languages that are topologically different from the source language. Compared to the previous approaches, we conduct extensive experiments to illustrate the effectiveness of order-insensitive models for cross-lingual sequence labeling tasks, and our model does not require an external library, such as Treebank.

3 Methodology

In this section, we introduce the proposed approaches to reduce the word order of source language fitted to order-sensitive sequence labeling models.

3.1 Removing Positional Embeddings

Given that Transformer (Vaswani et al., 2017) relies on positional embeddings to encode word order information, we propose to remove them from the Transformer encoder to build an order-insensitive encoder. Note that given a linear feed-forward layer for the Transformer encoder, as in Vaswani et al. (2017), removing the positional embeddings module means getting rid of all the word order information, which would have the cost of a large performance drop in the source language and lead to low performance for the cross-lingual transfer. To cope with this issue, we utilize one-dimensional convolutional networks (Conv1d) (Kim, 2014) as the feedforward layer to extract the n-gram features from the Multi-Head Attention features. Specifically, we formulate the encoding process as follows:

$$g[1:n] = MultiHead(E(X[1:n])), (1)$$

where X[1:n] represents the n tokens input sequence, E denotes the embedding layer, and $g[1:n] \in R^{n \times d}$ represents the sequence features generated by Multi-Head Attention, where d is the hidden size of the Transformer encoder. After that, a feature c_i is generated from the window of features g[i:i+h-1] by

$$c_i = \text{Conv1d}(g[i:i+h-1]),$$
 (2)

where h is the kernel size of Conv1d and the dimension of c_i equals the number of output channels in Conv1d. We add padding for this convolution process to ensure the output feature length is the same as the length of the input tokens. Finally, the output feature sequences from the Conv1d is the concatenation of c_i , where $i \in [1, n]$.

In this way, we fit the model with less word order information since the model only encodes the local order information and the prediction for each token is made based only on the token itself and its neighbor tokens.

3.2 Order-Agnostic Positional Embeddings

Instead of removing positional embeddings, an alternative method is to make positional embeddings order-agnostic so that the models can still encode less order information. In light of mBERT's astonishing cross-lingual performance (Pires et al., 2019; Wu and Dredze, 2019), we speculate that the positional embeddings in mBERT are order-agnostic. Hence, we leverage mBERT's positional embeddings to initialize the positional embeddings for the Transformer encoder, and we freeze them in the training phase to prevent them from fitting into the source language word order.

In the experiments, we leverage mBERT to tokenize sequences and generate cross-lingual embeddings since mBERT positional embeddings follow the mBERT subword tokenization. Then, the Transformer encoder is added on top of the mBERT embeddings. We freeze the parameters of mBERT in the training phase to ensure the cross-lingual embeddings from mBERT do not fit into the source language word order.

3.3 Shuffle Word Order

To fit models with less word order information and make them robust to the order differences across languages, we propose to add perturbations to the word order of input sequences in the source language training samples, while we keep the order of tokens in each entity the same and consider them as one "word" to make sure we don't break entities in the sequences.

We follow Lample et al. (2018) to generate permutations similar to the noise observed with word-by-word translation (i.e., word order differences across languages). Concretely, we apply a random permutation σ to the input sequence, verifying the condition $\forall i \in \{1,n\}, |\sigma(i)-i| \leq k$, where n is the length of the input sentence and k is a tunable parameter. We utilize the order-shuffled training samples to train our sequence encoders to build order-insensitive models.

3.4 Fine-tuning mBERT

The original fine-tuning of mBERT to the downstream cross-lingual tasks is done by adding a linear layer on top of mBERT and fine-tuning all the parameters of the model to the source language task (Pires et al., 2019; Wu and Dredze, 2019), which inescapably fits the model with the source language word order. To circumvent this issue, we freeze the positional embeddings in mBERT in the fine-tuning stage. By doing so, the positional embeddings can still provide order information for mBERT to encode input sequences, and the model avoids fitting the source language word order.

4 Experiments

4.1 Dataset

We test our methods on three sequence labeling tasks in the cross-lingual setting, namely, dialogue natural language understanding (NLU), part-ofspeech 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 (en), Spanish (es) and Thai (th) across weather, alarm and reminder domains. For the POS task, we utilize Universal Dependencies 2.0 (Nivre et al., 2017) and choose English (en), French (fr), Spanish (es), Portuguese (pt), Greek (el) and Russian (ru) 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 (en), German (de), Spanish (es) and Dutch (nl).

4.2 Experimental Setting

Our Models and Baselines All our models and baseline models consist of a sequence encoder to produce features for input sequences and a conditional random field (CRF) layer (Lample et al., 2016) to make predictions based on the sequence features. For the sequence encoder, we utilize Bidirectional LSTM (BiLSTM) (Hochreiter and Schmidhuber, 1997), the Transformer **Enc**oder (**TrsEnc**) using sinusoidal functions as positional embeddings (Vaswani et al., 2017), or the positional-embeddings-removed Order-Insensitive Transformer Encoder (OIT). In addition, we compare our approaches to the Relative positional Transformer Encoder (RelaTrsEnc) proposed in Ahmad et al. (2018). The Transformerbased encoders all use Conv1d as the feed-forward

¹They utilize relative positional embeddings to build orderinsensitive models. Originally, the method was applied to the cross-lingual dependency parsing task.

	en	es	fr	pt	ru	el	de	nl	th	AVG
Part-of-speech Taggi	ng Task									<u> </u>
BiLSTM	93.60	40.30	39.26	27.94	37.16	31.23	-	-	-	35.18
w/ shuffled data	88.57	33.15	34.89	28.12	32.32	26.63	-	-	-	31.02
TrsEnc	93.55	49.06	52.52	35.14	47.10	38.27	-	-	-	44.42
w/ shuffled data	88.24	46.91	49.45	33.56	43.87	37.29	-	-	-	42.22
Ahmad et al. (2018)	93.21	53.19	50.47	35.84	49.76	40.07	-	-	-	45.87
OIT	93.32	53.26	56.79	37.64	52.02	45.46	-	-	-	49.03
Named Entity Recogn	nition To	ask								
BiLSTM	87.99	33.71	-	-	-	-	15.28	25.28	-	24.76
w/ shuffled data	83.85	30.09	-	-	-	-	13.22	22.87	-	22.06
TrsEnc	88.67	30.76	-	-	-	-	18.53	30.54	-	26.61
w/ shuffled data	82.75	28.54	-	-	-	-	16.17	28.43	-	24.38
Ahmad et al. (2018)	87.86	32.49	-	-	-	-	19.24	31.83	-	27.85
OIT	88.41	34.33	-	-	-	-	24.12	33.54	-	30.66
Natural Language U	nderstar	nding Ta	sk							
BiLSTM	94.87	59.51	-	-	-	-	-	-	20.63	40.07
w/ shuffled data	93.57	62.02	-	-	-	-	-	-	21.43	41.73
TrsEnc	94.78	62.67	-	-	-	-	-	-	22.33	42.50
w/ shuffled data	92.07	63.86	-	-	-	-	-	-	24.17	44.02
Ahmad et al. (2018)	94.23	62.07	-	-	-	-	-	-	23.14	42.61
OIT	94.50	66.84	-	-	-	-	-	-	25.53	46.19

Table 1: Zero-shot cross-lingual results on POS, NER and NLU tasks (averaged over three runs). Results for the NLU task are the slot F1-scores. "-" denotes that this target language does not exist in the dataset we use. We use w/ and w/o shuffled data to denote the models trained with and without word order shuffled source language training samples, respectively. AVG represents the average performance over the target languages (English is excluded).

layer for fair comparison.

Applying Order-Insensitive Models to Competitive Models We apply the order-insensitive model, OIT, to two competitive cross-lingual models for zero-shot cross-lingual NLU (Liu et al., 2019a) and NER (Chen et al., 2019), and both of them are based on BiLSTM as the sequence encoder which is order-sensitive. To ensure fair comparison, we keep all the settings as in the original papers except that we replace the sequence encoder models. For the NLU model in Liu et al. (2019a), we replace the BiLSTM encoder with our proposed OIT. And for the NER model in Chen et al. (2019), we replace the BiLSTM encoder in the shared feature extractor module with OIT.

4.3 Implementation Details

We leverage cross-lingual embeddings RC-SLS (Joulin et al., 2018) for the POS and NER tasks, and we use the refined cross-lingual embeddings in Liu et al. (2019a) for the NLU task due to the better cross-lingual alignment quality for this task. We fine-tune mBERT by adding a linear layer on top of it, and we compare two different fine-tuning mBERT approaches (with and without freezing the positional embeddings). We set the

kernel size as 3 for the feed-forward layer Conv1d in the Transformer encoder. For the word order shuffled data, we generate ten different word order shuffled samples with $k = \infty$ (can generate any permutation) for each source language training sample. For all the tasks, we use English as the source language and other languages as target languages. In the zero-shot scenario, we do not use any data samples in the target languages, while in the few-shot setting, we utilize a few training samples in the target languages. In this paper, we mainly focus on the effectiveness of our approaches on zero-shot adaptation, and we also explore the performance changes over different numbers of target language training samples. We use the standard BIO-based F1-score to evaluate the NER and NLU tasks as in Lample et al. (2016), and accuracy score for evaluating the POS task as in Kim et al. (2017). And for the NLU task, we only take the slot filling task for the investigation of sequence labeling and remove the intent detection task.

5 Results & Discussion

5.1 Zero-shot Adaptation

In this section, we follow several questions to analyze the zero-shot adaptation results.

	en	es	fr	pt	ru	el	de	nl	th	AVG	
Part-of-speech Taggi	Part-of-speech Tagging Task										
mBERT fine-tuning	97.22	83.31	88.92	53.47	84.84	85.26	-	-	-	79.16	
w/ freezed PE	97.20	84.13	88.96	53.79	86.60	85.30	-	-	-	79.76	
Named Entity Recog	nition T	ask									
mBERT fine-tuning	91.95	74.49	-	-	-	-	69.13	77.32	-	73.65	
w/ freezed PE	91.87	74.98	-	-	-	-	70.22	77.63	-	74.28	
Natural Language U	Natural Language Understanding Task										
mBERT fine-tuning	95.97	69.41	-	-	-	-	-	-	10.45	39.93	
w/ freezed PE	95.90	70.30	-	-	-	-	-	-	12.53	41.42	

Table 2: Zero-shot cross-lingual results by fine-tuning mBERT on POS, NER and NLU tasks. Results for the NLU task are the slot F1-scores. PE represents the positional embeddings in mBERT.

5.1.1 Do Order-Insensitive Models Improve Cross-lingual Performance?

Removing Positional Embeddings As we can see from Table 1, removing positional embeddings from TrsEnc (OIT) only makes the performance in the source language (English) drop slightly (around 0.5%). This indicates that leveraging only local order information can perform sequence labeling tasks well. In other words, relying just on the information from the neighboring words (how many neighboring words depends on the kernel size in Conv1d) can ensure good performance for sequence labeling tasks.

On the other hand, in terms of zero-shot adaptation to target languages, OIT achieves consistently better performance than the other ordersensitive encoders (i.e., BiLSTM and TrsEnc) as well as the competitive order-insensitive encoder RelaTrsEnc (Ahmad et al., 2018). For example, in the NLU task, in terms of the average performance (AVG), OIT outperforms BiLSTM, TrsEnc and RelaTrsEnc by 6.12%, 3.69% and 3.58% on the F1-score, respectively.

Compared to the order-sensitive models, OIT fits the word order of the source language less, which increases its adaptation robustness to target languages. As for the reason why OIT outperforms the order-insensitive baseline (Ahmad et al., 2018), we conjecture that RelaTrsEnc still keeps the relative word distances. Although it reduces the order information that the model encodes, it might not be suitable for some target languages that do not have similar relative word distance patterns to English. While, OIT removes all the order information in positional embeddings, which makes it more robust to the order differences.

Shuffle Word Order From Table 1, we can see that the models trained with word order shuffled

data lead to a visible performance drop in English. For target languages, however, we observe that the performance improves in the NLU task by using such data. In this task, using the order shuffled data to train TrsEnc improves the performance by 1.52% on the averaged F1-score. For cross-lingual adaptation, performance loss in the source language has a negative impact on the performance in target languages. Therefore, for the NLU task, the improvement on target languages means that the benefits from being order-insensitive are greater than the performance losses in English.

On the other hand, for the NER and POS tasks, using order shuffled data makes the performance in target languages worse. For example, for the POS task, the average accuracy drops 2.2% for TrsEnc trained with the order shuffled data compared to the one trained without such data. We observe large performance drops for the NER and POS tasks caused by using the order shuffled data (For example, for the POS task, the drop is around 5%), since the models for these tasks are more vulnerable to the shuffled word order. In this case, the performance losses in English are larger than the benefits from being order-insensitive.

Order-Agnostic Positional Embeddings As we can see from Table 3, compared to TrsEnc trained without mBERT PE, we observe that TrsEnc trained with mBERT PE only results in a slight performance drop in English, while it generally brings better zero-shot adaptation performance to target languages. For example, in the POS task, TrsEnc with mBERT PE achieves 1.59% higher accuracy in Spanish (es) and 1.83% higher accuracy in Greek (el) than the one without mBERT PE.

Since mBERT is trained using more than 100 languages, positional embeddings in mBERT are fitted with different word orders across various lan-

	en	es	de	nl	el				
Part-of-speech Taggi	ng Task								
TrsEnc	93.92	72.08	-	-	72.75				
w/ mBERT PE	93.78	73.67	-	-	74.58				
Ahmad et al. (2018)	93.35	71.85	-	-	74.13				
OIT	93.70	72.75	-	-	74.97				
Named Entity Recognition Task									
TrsEnc	89.53	58.93	46.28	63.15	-				
w/ mBERT PE	88.44	58.27	47.63	64.12	-				
Ahmad et al. (2018)	89.96	60.55	45.43	61.58	-				
OIT	89.46	58.35	45.95	66.31	-				
Natural Language U	Natural Language Understanding Task								
TrsEnc	94.93	46.75	-	-	-				
w/ mBERT PE	94.53	47.23	-	-	-				
Ahmad et al. (2018)	94.38	47.80	-	-	-				
OIT	94.55	48.42	-	-	-				

Table 3: Zero-shot cross-lingual results on POS, NER and NLU tasks using freezed mBERT embeddings. (Results for all languages are in the appendix.) We use w/ and w/o mBERT PE to denote the model initialized with and without the freezed mBERT positional embeddings, respectively.

guages and become order-agnostic. The freezed mBERT positional embeddings still provide order information in the training phase so that the model maintains similar performance in English. And since the pre-trained positional embeddings are freezed, their order-agnostic property is retained, which brings more robust adaptation to target languages.

Fine-tuning mBERT As shown in Table 2, we observe that the results in the source language, English, are similar for both approaches to fine-tune mBERT (less than 0.1% differences), while freezing the positional embeddings when fine-tuning mBERT generally achieves better zero-shot performance in target languages than the original finetuning approach. Although positional embeddings are freezed, they can still provide order information for the model to encode sequences, which ensures the performance in English does not greatly drop. In the meantime, the positional embeddings are not affected by the English word order, and the order-agnostic trait of the positional embeddings is preserved, which improves the generalization ability to target languages.

Applying OIT to Competitive Models As shown in Table 4 and Table 5, we leverage OIT to replace the order-sensitive encoders (BiLSTM) in the competitive zero-shot cross-lingual sequence labeling models proposed in Liu et al. (2019a) and Chen et al. (2019). The zero-shot cross-lingual

	Spa	nish	Thai		
	intent	slot	intent	slot	
Liu et al. (2019a)	90.20	65.79	73.43	32.24	
using TrsEnc		69.52			
using OIT	91.46	71.36	75.02	34.61	

Table 4: Zero-shot results for the intent accuracy and slot F1-score on the NLU task.

	es	de	nl	AVG
Chen et al. (2019)	56.0		72.40	
using TrsEnc	56.89		72.22	
using OIT	58.97	74.65	72.56	68.73

Table 5: Zero-shot results on the NER task.

NLU model proposed in Liu et al. (2019a) is the current state-of-the-art for the multilingual NLU dataset (Schuster et al., 2019a), and the model in Chen et al. (2019) achieves competitive results in the zero-shot cross-lingual NER task. Nevertheless, replacing the order-sensitive encoders in their models with OIT can still boost the performance. We conjecture that since there are always cross-lingual performance drops caused by word order differences, making models order-insensitive to the source language is able to improve the performance.

In addition, we observe that the performance stays similar when we replace BiLSTM with TrsEnc, which illustrates that the performance improvement made by OIT does not come from the Transformer encoder but from the model's insensitivity to word order.

5.1.2 How Do Performance Improvements Relate to Language Distance?

As we can see from Table 1 and 3, our proposed order-insensitive models (e.g., OIT and TrsEnc w/ mBERT PE) are generally better compared to the baseline models in all languages, including Spanish (es) and French (fr), that have a close language distance to English, and Greek (el) and Thai (th), which are lexically and syntactically different from English. This is because although different languages naturally have different word orders, they are more likely to have the same word orders in some local areas, such as the entity names. Hence, OIT which only encodes local word order information generally improves performance when transferring to close and distant target languages compared to other baselines. As for TrsEnc with freezed mBERT positional embeddings, it can also gen-

	k = 0	k = 1	k=2
BiLSTM TrsEnc	94.87	85.16	83.68
TrsEnc	94.78	84.56	83.06
Ahmad et al. (2018)	94.23	84.93	83.86
OIT	94.50	87.87	86.95

Table 6: Slot F1-scores on different noisy NLU test sets in English. k = 0 denotes the original English test set.

erally boost performance on different target languages given the generalization ability of the orderagnostic positional embeddings.

5.1.3 How Order-Insensitive Is Our Order-Insensitive Model?

To test how order-insensitive our proposed OIT is, we follow the order shuffled methods in Section 3.3, and set k=1 and k=2 to slightly shuffle the word order of the sequences and create a noisy English test set. As we can see from Table 6,² OIT achieves better results than BiLSTM, TrsEnc and RelaTrsEnc (Ahmad et al., 2018) on the noisy NLU test set, which further illustrates that OIT is more insensible and resistant to word order differences than the baseline encoders. This property improves the generalization ability of OIT to target language word orders.

5.2 Few-shot Adaptation

Since we do not observe the order information for target languages in the zero-shot scenario, the order-insensitive encoders have more robust adaptation ability. Then, the question we want to ask is whether order-insensitive models can still improve the performance if a few training samples in target languages are available. We test with different numbers of target language training samples for the NLU task, and the results are shown in Figure 1. We observe that as the proportion of target language training samples goes up, the improvement made by OIT goes down. This is because the model is able to learn the target language word order based on the target language training samples, which decreases the advantages of the order-insensitive models. We also observe that RelaTrsEnc generally achieves worse performance

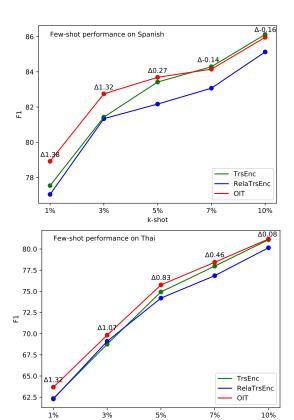


Figure 1: Few-shot F1-scores for the slot filling on the NLU task (Spanish on the top and Thai on the bottom). The x-axis represents the proportion of target language training samples in the training set. The Δ numbers denote how much OIT outperforms TrsEnc.

than TrsEnc, and we conjecture that RelaTrsEnc requires more training samples to learn the relative word order information than TrsEnc, which lowers its generalization ability to the target language in the few-shot scenario.

5.3 Ablation Study

In this section, we explore the model variations in terms of positional embeddings, the feed-forward layer for TrsEnc and OIT, adding different perturbations to the shuffled word order, and whether to use the CRF layer. We test the models' zero-shot performance on the NLU task for this ablation study, and results are illustrated in Table 7.

Positional Embeddings We observe that TrsEnc+CRF using trainable positional embeddings achieves similar performance to using sinusoidal positional embeddings.

Feed-forward Layer We observe that Trs+CRF using linear layers as the feed-forward layer achieves slightly better performance than using Conv1d. We conjecture that Conv1d encodes the

²Note that we do not include the shuffled word order and mBERT based models in the table. It is not fair to compare the other models with those trained with word order shuffled data since the training set has a similar distribution to the test set. Also, the mBERT-based models are pre-trained based on the correct language order. Hence, it is not suitable to feed them with the order-shuffled test set.

	PE	kernel [†]	k	es	th
TrsEnc+CRF	Trainable	linear [‡]	-	62.13	22.68
TrsEnc+CRF	Sinusoid	linear [‡]	-	62.55	21.82
w/ shuffled data	Sinusoid	linear [‡]	∞	58.89	19.27
TrsEnc+Linear	Sinusoid	3	-	55.40	19.33
TrsEnc+CRF	Sinusoid	3	-	62.67	22.33
w/ shuffled data	Sinusoid	3	2	61.12	21.24
w/ shuffled data	Sinusoid	3	3	63.20	23.34
w/ shuffled data	Sinusoid	3	4	63.54	23.59
w/ shuffled data	Sinusoid	3	∞	63.86	24.17
OIT+Linear	-	3	-	61.76	22.44
OIT+CRF	-	3	-	66.84	25.53
OIT+CRF	-	2	-	66.56	24.82
OIT+CRF	-	5	-	66.40	24.41
OIT+CRF	-	linear [‡]	-	58.27	20.35

Table 7: Ablation study on positional embeddings, feed-forward layer, perturbation for word order shuffle, and the CRF layer. Results are the slot filling F1-scores for the zero-shot NLU task. † denotes the kernel size of the Conv1d. ‡ denotes that the model uses linear layer as the feed-forward layer. k represents the tunable parameter for the order shuffle. "-" denotes that the model does not have this module. "+CRF" and "+Linear" denotes using and not using the CRF layer, respectively.

source language order information; hence, using the linear layer encodes less order information. However, when we replace Conv1d with linear layers for the feed-forward layer in OIT, the performance greatly drops ($\sim 8.5\%$ F1-score drops for Spanish and $\sim 5\%$ F1-score drops for Thai). This is because this model does not encode any order information when it uses linear layers as the feed-forward layer, which makes the model perform badly in the source language and then weakens its adaptation ability to target languages.

In addition, we observe that the Conv1d feedforward layer is also important for TrsEnc trained with order-shuffled data. This is because Conv1d encodes the order of tokens in the entity (we do not shuffle the tokens in an entity), which is essential for detecting entities. We also test OIT with different kernel sizes of Conv1d, since different kernel sizes represent different amounts of local order information. Results show that the performance stays similar with different kernel sizes.

Different Perturbations to Shuffle Word Order

We try adding different perturbations (changing the value of k) to the word order to generate order-shuffled data. As we can see, when we slightly shuffle the word order (k=2), the performance becomes worse than not using order-shuffled data. This is because the model fits the slightly shuffled word order, which is not similar to the target lan-

guages. After adding more perturbations, TrsEnc becomes more robust to order differences.

Effectiveness of the CRF Layer For sequence labeling tasks, the CRF layer, which models the conditional probability of label sequences, could also implicitly model the source language word order in the training. Therefore, we conduct an ablation study to test the effectiveness of the CRF layer for the cross-lingual models.

From Table 7, we can see that removing the CRF layer makes the performance worse. We conjecture that although the CRF layer might contain some information on the word order pattern in the source language, which could hurt the performance of the model in target languages. It also models the conditional probability for tokens that belong to the same entity so that it learns when the start or the end of an entity is. This is important for sequence labeling tasks, and the models that have the CRF layer removed might not have this ability. For example, in the NLU task, when the user says "set an alarm for 9 pm", "for 9 pm" belongs to the "DateTime" entity, and the CRF layer learns to model "for" and "pm" as the start and the end of the "DateTime" entity, respectively. Without the CRF layer, models treat the features of these tokens independently.

6 Conclusion

In this paper, we investigate whether making models insensitive to the word order of the source language can improve the cross-lingual sequence labeling performance. We build order-insensitive models by reducing the word order of the source language fitted to sequence encoders, and then compare them with order-sensitive models. Extensive experimental results show that the order-insensitive models are robust to the word order shuffled sequences and consistently outperform order-sensitive models, including the previous state-of-the-art model. In addition, preserving the order-agnostic property for the mBERT positional embeddings gives a better generalization ability to target languages.

Furthermore, we find that we need to weigh the models' insensitivity to word order, and crosslingual sequence labeling models still need to preserve partial sensitivity to word order. Models that do not encode any word order information, in other words, models that are the most insensitive to word order, perform badly in both source and target languages.

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	en	es	fr	pt	ru	el	de	nl	th	AVG
Part-of-speech Tagging	Task									
Ahmad et al. (2018)	93.35	71.85	79.54	42.69	77.22	74.13	-	-	-	69.09
TrsEnc w/o mBERT PE	93.92	72.08	79.03	42.76	78.06	72.75	-	-	-	68.94
TrsEnc w/ mBERT PE	93.78	73.67	80.72	43.85	78.24	74.58	-	-	-	70.21
OIT	93.70	72.75	80.15	43.18	78.71	74.97	-	-	-	69.95
Named Entity Recognition	Named Entity Recognition Task									
Ahmad et al. (2018)	89.96	60.55	-	-	-	-	45.43	61.58	-	55.85
TrsEnc w/o mBERT PE	89.53	58.93	-	-	-	-	46.28	63.15	-	56.12
TrsEnc w/ mBERT PE	88.44	58.27	-	-	-	-	47.63	64.12	-	56.67
OIT	89.46	58.35	-	-	-	-	45.95	66.31	-	56.87
Natural Language Unde	rstandin	g Task								
Ahmad et al. (2018)	94.38	47.80	-	-	-	-	-	-	8.83	28.32
TrsEnc w/o mBERT PE	94.93	46.75	-	-	-	-	-	-	9.76	28.26
TrsEnc w/ mBERT PE	94.53	47.23	-	-	-	-	-	-	10.06	28.65
OIT	94.55	48.42	-	-	-	-	-	-	9.92	29.17

Table 8: Zero-shot cross-lingual results on POS, NER and NLU tasks using freezed mBERT embeddings. We denote w/ and w/o mBERT PE as the model initialized with and without the freezed mBERT positional embeddings, respectively.