Exploring Fine-tuning Techniques for Pre-trained Cross-lingual Models via Continual Learning
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Abstract
Recently, fine-tuning pre-trained cross-lingual models (e.g., multilingual BERT) to downstream cross-lingual tasks has shown promising results. However, the fine-tuning process inevitably changes the parameters of the pre-trained model and weakens its cross-lingual ability, which could lead to sub-optimal performances. To alleviate this issue, we leverage the idea of continual learning to preserve the original cross-lingual ability of the pre-trained model when we fine-tune it to downstream cross-lingual tasks. The experiment on the cross-lingual sentence retrieval task shows that our fine-tuning approach can better preserve the cross-lingual ability of the pre-trained model. In addition, our method achieves better performance than other fine-tuning baselines on zero-shot cross-lingual part-of-speech tagging and named entity recognition tasks.

1 Introduction
Recently, cross-lingual language models (Devlin et al., 2019; Conneau and Lample, 2019), pre-trained on extensive monolingual or bilingual resources across numerous languages, have been shown to have surprising cross-lingual adaptation abilities, and fine-tuning them to downstream cross-lingual tasks has achieved promising results (Pires et al., 2019; Wu and Dredze, 2019). To improve the cross-lingual performance, one line of research is to obtain better pre-trained language models, such as utilizing larger amounts of pre-trained data and a larger size of pre-trained models (Conneau et al., 2019; Liang et al., 2020), and leveraging more tasks in the pre-training stage (Huang et al., 2019).

However, as shown in Figure 1, the cross-lingual language model (multilingual BERT (mBERT)) forgets its original masked language model (MLM) task and partially loses the quality of the cross-lingual alignment (from the cross-lingual sentence retrieval (XSR) experiment) after being fine-tuned to the downstream task in English, which could result in sub-optimal cross-lingual performance to target languages.

Therefore, in this paper, we consider another line of research to improve the cross-lingual performance, which is to preserve the cross-lingual ability of pre-trained cross-lingual language models in the fine-tuning stage. Motivated by the continual learning (Ring, 1994) that aims to learn a new task without forgetting the previous learned tasks, we leverage the idea of continual learning to preserve the original cross-lingual ability of the pre-trained model when we fine-tune it to downstream cross-lingual tasks. The experiment on the cross-lingual sentence retrieval task shows that our fine-tuning approach can better preserve the cross-lingual ability of the pre-trained model. In addition, our method achieves better performance than other fine-tuning baselines on zero-shot cross-lingual part-of-speech tagging and named entity recognition tasks.

Figure 1: Masked language model (MLM) perplexity (top) and cross-lingual sentence retrieval (XSR) accuracy (bottom) before and after fine-tuning mBERT to the English part-of-speech tagging task.

1 This task is to find the correct translation sentence from the target corpus given a source language sentence.
we adopt a continual learning framework to constrain the parameter learning in the cross-lingual pre-trained model when we fine-tune it to downstream tasks in the source language. Specifically, based on the results in Figure 1, we try to maintain the cross-lingual ability of mBERT by utilizing an additional task (MLM or XSR) to constrain the parameter learning in the fine-tuning stage.

The experiments show that mBERT fine-tuned based on continual learning has better cross-lingual ability than other fine-tuning baselines. In addition, our approach surpasses other fine-tuning baselines on zero-shot cross-lingual part-of-speech tagging (POS) and named entity recognition (NER) tasks.

2 Related Work

Cross-lingual models alleviate the need for obtaining annotated data in target languages (Bel et al., 2003; Wan, 2009), which copes with the data scarcity problem (Lample et al., 2018; Winata et al., 2020; Liu et al., 2020). Recently, cross-lingual methods have been applied to multiple NLP tasks, such as task-oriented dialogue systems (Liu et al., 2019a,b), part-of-speech tagging (Wisniewski et al., 2014; Zhang et al., 2016; Kim et al., 2017), named entity recognition (Ni et al., 2017; Xie et al., 2018), abstractive summarization (Duan et al., 2019; Zhu et al., 2019), dependency parsing (Schuster et al., 2019; Ahmad et al., 2019), and personalized dialogue agents (Lin et al., 2020).

Taking this further, pre-trained on large-scale monolingual or bilingual resources across a great many languages, cross-lingual language models (Devlin et al., 2019; Conneau and Lample, 2019; Huang et al., 2019) have significantly improved the cross-lingual performance upon the cross-lingual word embeddings (Conneau et al., 2017; Artetxe et al., 2018) based models (Wu and Dredze, 2019).

In the meantime, Conneau et al. (2019); Liang et al. (2020) constructed a better pre-trained model to improve the cross-lingual performance by enlarging the amount of pre-trained data and the size of the pre-trained model. In this paper, we study another line of research, which is to find a better way to fine-tune the pre-trained cross-lingual language model to downstream cross-lingual tasks.

3 Methodology

In this section, we first describe the gradient episodic memory (GEM) (Lopez-Paz and Ranzato, 2017), a continual learning framework, that we adopt to constrain the fine-tuning process. Then, we introduce how we fine-tune the cross-lingual pre-trained model with GEM.

3.1 Gradient Episodic Memory (GEM)

We consider a scenario where the model has already learned \( n - 1 \) tasks and needs to learn the \( n \)-th task. The main feature of GEM is an episodic memory \( \mathcal{M}_k \) that stores a subset of the observed examples from task \( k \) (\( k \in [1, n] \)). The loss at the memories from the \( k \)-th task can be defined as

\[
\mathcal{L}(f_\theta, \mathcal{M}_k) = \frac{1}{|\mathcal{M}_k|} \sum_{(x_i,k,y_i) \in \mathcal{M}_k} \mathcal{L}(f_\theta(x_i,k), y_i),
\]

where the model \( f_\theta \) is parameterized by \( \theta \).

In order to maintain the performance of the model in the previous \( n - 1 \) tasks while learning the \( n \)-th task, GEM utilized the losses for the previous \( n - 1 \) tasks in Eq. (1) as inequality constraints, avoiding their increase but allowing their decrease. More specifically, when observing the training samples \((x, y)\) from the \( n \)-th task, GEM solves the following problem:

\[
\begin{align*}
\text{minimize}_\theta & \quad \mathcal{L}(f_\theta(x, n), y) \\
\text{subject to} & \quad \mathcal{L}(f_\theta, \mathcal{M}_k) \leq \mathcal{L}(f_\theta^{n-1}, \mathcal{M}_k) \quad \text{for all } k < n,
\end{align*}
\]

where \( f_\theta^{n-1} \) is the model state at the end of learning of the task \( n - 1 \).

3.2 Fine-tuning with GEM

GEM can also be considered as a method to constrain a model by making the losses of previous learned tasks not increase when it starts to learn a new task. In our experiments, we leverage mBERT as the cross-lingual pre-trained model, and we utilize GEM to constrain the fine-tuning process of mBERT. In this paper, we propose two approaches for the fine-tuning constraint.

**Constraint based on the MLM task** We consider two tasks (\( n = 2 \)) in total by applying GEM to fine-tune mBERT. The first task is MLM, which is the original task for training mBERT. The second task is the fine-tuning task to the target downstream task in the source language. We follow Eq. (2) when we fine-tune mBERT, and we specify the process as follows:

\[
\begin{align*}
\text{minimize}_\theta & \quad \mathcal{L}(f_\theta(x, \mathcal{T}_n), y) \\
\text{subject to} & \quad \mathcal{L}(f_\theta, \mathcal{T}_{\text{mlm}}) \leq \mathcal{L}(f_\theta^{\text{mlm}}, \mathcal{T}_{\text{mlm}}),
\end{align*}
\]
where $T_{ft}$ and $T_{mlm}$ denote the fine-tuning task and the MLM task, respectively, and $f^\theta_{mlm}$ represents the original mBERT after finishing the MLM task.

The intuition for this approach is that we make mBERT not forget its original task after fine-tuning so that the original cross-lingual ability can be better preserved.

**Constraint based on the XSR task**  We follow the same process as the first approach except replacing the first task MLM with XSR. We consider that mBERT has already learned the XSR task given the surprising cross-lingual ability it has. Then the fine-tuning process can be described as

$$\min_{\theta} \mathcal{L}(f_\theta(x, T_{ft}), y)$$

subject to  \( \mathcal{L}(f_\theta, T_{xsr}) \leq \mathcal{L}(f^\theta_{mlm}, T_{xsr}) \), \hspace{1cm} (4)

where the $T_{xsr}$ represents the XSR task.

The intuition for this approach is that we make mBERT not lose its cross-lingual ability after fine-tuning by constraining it on XSR, which is directly related to this ability.

## 4 Experiments

### 4.1 Dataset

For the cross-lingual POS task, we utilize Universal Dependencies 2.0 (Nivre et al., 2017) and choose English (en), French (fr), Spanish (es), Greek (el) and Russian (ru) to evaluate our approaches. For the cross-lingual NER task, we utilize CoNLL 2002 (Tjong Kim Sang, 2002) and CoNLL 2003 (Sang and De Meulder, 2003), which contain English (en), German (de), Spanish (es) and Dutch (nl) to evaluate our approaches. For both tasks, we consider English as the source language and other languages as target languages.

### 4.2 Baselines

**Naive Fine-tune**  We follow the same fine-tuning method as Pires et al. (2019) and Wu and Dredze (2019), which is to add one linear layer on top of mBERT while fine-tuning the whole model to POS and NER tasks.

**Fine-tune with Partial Layers Frozen**  Wu and Dredze (2019) improved the mBERT fine-tuning performance by freezing partial bottom layers of mBERT.

**Multi-Task Fine-tune (MTF)**  Since our approaches utilize training data from an additional task (either the MLM task or the XSR task), we add a multi-task fine-tuning baseline, which conducts the training of both the fine-tuning task and the MLM task (or XSR task) for fair comparison.

### 4.3 Training Details

We follow the implementation details in Wu and Dredze (2019) for fine-tuning mBERT. For fine-tuning mBERT constrained on the MLM task, we utilize the Wikipedia corpus. We conduct the MLM constraint with two settings. First, we only utilize the English Wikipedia corpus for the MLM task. Second, we utilize both the source and target languages Wikipedia corpus. Note that we do not use all the pre-trained languages in mBERT for the MLM constraint because it would make the fine-tuning process very time-consuming.

For fine-tuning mBERT constrained on the XSR task, we leverage the Europarl parallel cor-

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**Table 1:** Zero-shot cross-lingual POS results (evaluated using accuracy). Our fine-tuning approaches (GEM w/ MLM and GEM w/ XSR) are based on the Naive approach. We utilize only the English Wikipedia corpus for the MLM task, while the other setting for the MLM task is in the ablation study. “avg” denotes the average performance over the target languages (English is excluded). † indicates that the results are statistically significant compared to all the baselines with $p < 0.01$ by t-test.

|                | en  | es  | fr  | el  | ru  | avg |
|----------------|-----|-----|-----|-----|-----|-----|
| Naive Fine-tune| 96.23 | 82.95 | 89.12 | 84.21 | 85.45 | 85.43 |
| w/ frozen layers | 96.07 | 83.41 | 89.41 | 85.54 | 85.17 | 85.88 |
| Multi-task Learning | | | | | | |
| MTF w/ MLM | 94.47 | 83.01 | 88.08 | 84.48 | 80.46 | 84.01 |
| MTF w/ XSR | 96.39 | 82.41 | 87.05 | 72.51 | 86.09 | 82.01 |
| Continual Learning | | | | | | |
| GEM w/ MLM | 97.79 | 84.65 | 89.74 | 86.04 | 86.93 | 86.84† |
| GEM w/ XSR | 96.97 | 84.53 | 89.83 | 86.53 | 86.36 | 86.81† |

**Table 2:** Zero-shot cross-lingual NER results (evaluated using F1-score). We utilize only the English Wikipedia corpus for the MLM task. † indicates that the results are statistically significant compared to all baselines with $p < 0.01$ by t-test.

|                | en  | es  | de  | nl  | avg |
|----------------|-----|-----|-----|-----|-----|
| Naive Fine-tune| 91.97 | 74.96 | 69.56 | 77.57 | 74.03 |
| w/ frozen layers | 91.90 | 75.90 | 70.40 | 78.10 | 74.80 |
| Multi-task Learning | | | | | |
| MTF w/ MLM | 91.82 | 71.47 | 67.90 | 74.91 | 71.43 |
| MTF w/ XSR | 91.85 | 74.02 | 68.55 | 75.67 | 72.75 |
| Continual Learning | | | | | |
| GEM w/ MLM | 91.93 | 76.76 | 71.59 | 79.54 | 75.96† |
| GEM w/ XSR | 91.89 | 76.43 | 71.89 | 79.72 | 76.01† |
Table 3: Perplexities on the masked language model (MLM). * denotes the original mBERT without any fine-tuning, and other models are fine-tuned to the English POS task. We only utilize English in the MLM task. Bold numbers denote the best perplexity performance among all the listed models.

Table 4: Cross-lingual sentence retrieval (XSR) results. P@$k$ ($k=1,5,10$) accounts for the fraction of pairs for which the correct translation of the source language sentence is in the $k$-th nearest neighbors. Listed models except mBERT are fine-tuned to the English POS task. Bold numbers denote the best performance after fine-tuning without using the XSR supervision.

5 Results

5.1 Cross-lingual POS & NER Tasks

From Table 1, we can see that in the POS task, our approaches surpass other fine-tuning baselines consistently on all target languages. In terms of the average performance, our methods outperform others by an around or more than 1% accuracy score with the statistically significant test. Also, we observe a similar improvement in the NER task from Table 2. This is because fine-tuning mBERT with GEM is able to better preserve mBERT’s cross-lingual ability, which leads to better cross-lingual performance. In addition, constraining mBERT fine-tuning on the MLM task performs similar to constraining it on the XSR task. We conjecture that the effectiveness of both approaches are similar although they are from different angles.

On the other hand, fine-tuning mBERT with an additional task (MTF) decreases the performance. We speculate that the cross-lingual ability of mBERT becomes worse when one more task is added to the fine-tuning process.

5.2 MLM & XSR Tasks

From Table 3, we can see that naive fine-tuning mBERT significantly decreases the MLM performance especially in English. Since mBERT is fine-tuned to the English task, the English embeddings are fine-tuned, which makes mBERT lose more MLM task information in English. In the meantime, from Table 4, Naive Fine-tune also makes the XSR performance of mBERT significantly drop. From Table 3, we observe that fine-tuning with partial layers frozen is able to partly prevent the MLM performance from getting worse, while fine-tuning with GEM based on the MLM task almost preserves the original MLM performance of mBERT. Although we only use English data in the MLM task, using GEM based on the MLM task can still preserve the task-related parameters that are useful for other languages. Additionally, from Table 4, we can see that GEM w/ MLM achieves better XSR performance than Naive Fine-tune w/ frozen layers, which illustrates the effectiveness of fine-tuning with GEM.

We notice that using the MLM task, MTF achieves better perplexity than GEM since MTF directly trains mBERT on the MLM task. However, from Table 1 and Table 4, we can see that fine-tuning mBERT on the MLM task would have negative effects on the cross-lingual performance. We conjecture that it requires the same amount of corpus data in more than 100 languages as pre-training mBERT to preserve the cross-lingual ability for MTF, which could make the fine-tuning process very time-consuming. Since the data we use for the MLM task is limited, MTF just learns the MLM task information, while it makes the cross-lingual ability of mBERT decrease.

In addition, both the GEM and MTF approaches that are based on XSR make the MLM performance worse. This is because XSR is a totally different task compared to MLM, and constraining or training models based on the losses of XSR makes the catastrophic forgetting worse. While, as seen in Table 4, MTF w/ XSR and GEM w/ XSR improve the
XSR performance of mBERT since both of them utilize the supervision from this task. We observe that although MTF achieves the best performance in the XSR task since it directly fine-tunes mBERT on XSR task, we can see from Table 1 and Table 2, that GEM w/ XSR boosts the cross-lingual performance of downstream tasks, while MTF w/ XSR causes the opposite effect. We speculate that brutally fine-tuning mBERT on XSR task (MTF w/ XSR) just makes mBERT learn the XSR task, while using GEM to constrain the fine-tuning on the XSR task is able to preserve the cross-lingual ability of mBERT.

### 5.3 Ablation Study

The ablation study on leveraging the MLM task in the fine-tuning stage is conducted with the results from the MLM and POS tasks illustrated in Table 5. We can see that using GEM to constrain fine-tuning on MLM with all languages (GEM w/ MLM (all)) achieves better performance than it does with only English (GEM w/ MLM (en)) on the MLM task since more MLM supervision signals are provided, while their performances in the POS task are comparable. Intuitively, since GEM w/ MLM is able to improve the cross-lingual performance, constraining on more languages should have better performance. We conjecture that the constraint with all languages could be too harsh, and then mBERT might tend to learn the MLM task information in all languages instead of preserving its original cross-lingual ability. We leave the explorations on this issue for future work.

In addition, MTF w/ MLM (all) achieves better results than MTF w/ MLM (en) on the MLM task, while the results are opposite on the POS task.

This is because mBERT is required to learn the MLM task in more languages in MTF w/ MLM (all), which further weakens mBERT’s cross-lingual ability.

### 6 Conclusion

In this paper, we propose to preserve the cross-lingual ability of pre-trained cross-lingual language models in the fine-tuning stage. We adopt a continual learning framework, GEM, to constrain the parameter learning in mBERT based on MLM or XSR tasks when we fine-tune it to downstream tasks in the source language. Experimental results show that our approaches achieve better performance than other fine-tuning baselines on zero-shot cross-lingual POS and NER tasks. Additionally, further analysis on MLM and XSR tasks illustrates that our approaches have the capability to preserve the cross-lingual ability of mBERT.

### References

Wasi Ahmad, Zhisong Zhang, Xuezhe Ma, Eduard Hovy, Kai-Wei Chang, and Nanyun Peng. 2019. On difficulties of cross-lingual transfer with order differences: A case study on dependency parsing. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2440–2452.

Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. A robust self-learning method for fully unsupervised cross-lingual mappings of word embeddings. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 789–798.

Nuria Bel, Cornelis HA Koster, and Marta Villegas. 2003. Cross-lingual text categorization. In International Conference on Theory and Practice of Digital Libraries, pages 126–139. Springer.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116.

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems 32, pages 7059–7069. Curran Associates, Inc.

Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2017. Word translation without parallel data. arXiv preprint arXiv:1710.04087.
Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186.

Xiangyu Duan, Mingming Yin, Min Zhang, Bojing Chen, and Weihua Luo. 2019. Zero-shot cross-lingual abstractive sentence summarization through teaching generation and attention. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3162–3172.

Haoyang Huang, Yaobo Liang, Nan Duan, Ming Gong, Linjun Shou, Daxin Jiang, and Ming Zhou. 2019. Unicoder: A universal language encoder by pre-training with multiple cross-lingual tasks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2485–2494.

Joo-Kyung Kim, Young-Bum Kim, Ruhi Sarikaya, and Erik Fosler-Lussier. 2017. Cross-lingual transfer learning for pos tagging without cross-lingual resources. In Proceedings of the 2017 conference on empirical methods in natural language processing, pages 2832–2838.

Philipp Koehn. 2005. Europarl: A parallel corpus for statistical machine translation. Citeseer.

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. 2018. Unsupervised machine translation using monolingual corpora only. In International Conference on Learning Representations (ICLR).

Yaobo Liang, Nan Duan, Yeyun Gong, Ning Wu, Fenhui Guo, Weizhen Qi, Ming Gong, Linjun Shou, Daxin Jiang, Guilin Cao, et al. 2020. Xglue: A new benchmark dataset for cross-lingual pre-training, understanding and generation. arXiv preprint arXiv:2004.01401.

Zhaojiang Lin, Zihan Liu, Genta Indra Winata, Samuel Cahyawijaya, Andrea Madotto, Yejin Bang, Etsuko Ishii, and Pascale Fung. 2020. Xpersona: Evaluating multilingual personalized chatbot. arXiv preprint arXiv:2003.07568.

Zihan Liu, Jamin Shin, Yan Xu, Genta Indra Winata, Peng Xu, Andrea Madotto, and Pascale Fung. 2019a. Zero-shot cross-lingual dialogue systems with transferable latent variables. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1297–1303.

Zihan Liu, Genta Indra Winata, Zhaojiang Lin, Peng Xu, and Pascale Fung. 2019b. Attention-informed mixed-language training for zero-shot cross-lingual task-oriented dialogue systems. arXiv preprint arXiv:1911.09273.

Zihan Liu, Genta Indra Winata, Peng Xu, and Pascale Fung. 2020. Coach: A coarse-to-fine approach for cross-domain slot filling. arXiv preprint arXiv:2004.11727.

David Lopez-Paz and Marc’Aurelio Ranzato. 2017. Gradient episodic memory for continual learning. In Advances in Neural Information Processing Systems, pages 6467–6476.

Jian Ni, Georgiana Dinu, and Radu Florian. 2017. Weakly supervised cross-lingual named entity recognition via effective annotation and representation projection. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1470–1480.

Joakim Nivre, Željko Agić, Lars Ahrenberg, et al. 2017. Universal dependencies 2.0. lindat/clarin digital library at the institute of formal and applied linguistics, charles university, prague.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual bert? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001.

Mark Bishop Ring. 1994. Continual learning in reinforcement environments. Ph.D. thesis, University of Texas at Austin Austin, Texas 78712.

Erik Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the conll-2003 shared task: Language-independent named entity recognition. In Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003, pages 142–147.

Tal Schuster, Ori Ram, Regina Barzilay, and Amir Globerson. 2019. Cross-lingual alignment of contextual word embeddings, with applications to zero-shot dependency parsing. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1599–1613.

Erik F Tjong Kim Sang. 2002. Introduction to the conll-2002 shared task: language-independent named entity recognition. In proceedings of the 6th conference on natural language learning-Volume 20, pages 1–4.

Xiaojun Wan. 2009. Co-training for cross-lingual sentiment classification. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1, volume 1, pages 235–243. Association for Computational Linguistics.
Genta Indra Winata, Samuel Cahyawijaya, Zihan Liu, Zhaojiang Lin, Andrea Madotto, Peng Xu, and Pascale Fung. 2020. Learning fast adaptation on cross-accented speech recognition. arXiv preprint arXiv:2003.01901.

Guillaume Wisniewski, Nicolas Pécheux, Souhir Gabbiche-Braham, and François Yvon. 2014. Cross-lingual part-of-speech tagging through ambiguous learning. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1779–1785.

Shijie Wu and Mark Dredze. 2019. Beto, bentz, becas: The surprising cross-lingual effectiveness of bert. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 833–844.

Jiateng Xie, Zhilin Yang, Graham Neubig, Noah A Smith, and Jaime G Carbonell. 2018. Neural cross-lingual named entity recognition with minimal resources. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 369–379.

Yuan Zhang, David Gaddy, Regina Barzilay, and Tommi Jaakkola. 2016. Ten pairs to tag–multilingual pos tagging via coarse mapping between embeddings. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1307–1317.

Junnan Zhu, Qian Wang, Yining Wang, Yu Zhou, Jiajun Zhang, Shaonan Wang, and Chengqing Zong. 2019. Ncls: Neural cross-lingual summarization. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3045–3055.