Preserving Cross-Linguality of Pre-trained Models via Continual Learning

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Abstract

Recently, fine-tuning pre-trained language 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 leads to sub-optimal performance. To alleviate this problem, we leverage continual learning to preserve the original cross-lingual ability of the pre-trained model when we fine-tune it to downstream tasks. The experimental result shows that our fine-tuning methods can better preserve the cross-lingual ability of the pre-trained model in a sentence retrieval task. Our methods also achieve better performance than other fine-tuning baselines on the zero-shot cross-lingual part-of-speech tagging and named entity recognition tasks.

1 Introduction

Recently, multilingual 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 enjoy 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). Taking this further, better pre-trained language models have been proposed to improve the cross-lingual performance, such as using larger amounts of pre-trained data with larger pre-trained models (Conneau et al., 2019; Liang et al., 2020), and utilizing more tasks in the pre-training stage (Huang et al., 2019).

However, we observe that multilingual BERT (mBERT) (Devlin et al., 2019), a pre-trained language model, forgets the masked language model (MLM) task that has been learned and partially loses the cross-lingual ability (from a cross-lingual sentence retrieval (XSR)\(^1\) experiment) after being fine-tuned to the downstream task in English, as shown in Figure 1, which results in sub-optimal cross-lingual performance to target languages.

In this paper, we consider a new direction to improve the cross-lingual performance, which is to preserve the cross-lingual ability of pre-trained multilingual models in the fine-tuning stage. Motivated by the continual learning (Ring, 1994; Rebuffi et al., 2017; Kirkpatrick et al., 2017; Lopez-Paz and Ranzato, 2017) that aims to learn a new task without forgetting the previous learned tasks, we adopt a continual learning framework to constrain the parameter learning in the pre-trained multilingual model when we fine-tune it to downstream targets.

\(^1\)This task is to find the correct translation sentence from the target corpus given a source language sentence.
tasks in the source language. Specifically, based on the results in Figure 1, we aim to maintain the cross-linguality of pre-trained multilingual models by utilizing MLM and XSR tasks to constrain the parameter learning in the fine-tuning stage.

Experiments show that our methods help pre-trained models better preserve the cross-lingual ability. Additionally, our methods surpass other fine-tuning baselines on the strong multilingual model mBERT and XLMR (Conneau et al., 2019) on zero-shot cross-lingual part-of-speech tagging (POS) and named entity recognition (NER) tasks.

2 Related Work

Cross-lingual methods, which alleviate the need for obtaining large amounts of annotated data in target languages, have been applied to multiple NLP tasks, such as task-oriented dialogue systems (Chen et al., 2018; Liu et al., 2019), part-of-speech tagging (Wisniewski et al., 2014; Zhang et al., 2016; Kim et al., 2017), named entity recognition (Mayhew et al., 2017; Ni et al., 2017; Xie et al., 2018; Liu et al., 2021), abstractive summarization (Duan et al., 2019; Zhu et al., 2019), and dependency parsing (Schuster et al., 2019; Ahmad et al., 2019). Recently, multilingual language models (Devlin et al., 2019; Conneau and Lample, 2019; Huang et al., 2019; Conneau et al., 2019), pre-trained on a large-scale data corpus across a great many languages, have significantly improved the cross-lingual performance. However, the corresponding fine-tuning techniques have been less studied. Wu and Dredze (2019) investigated the effectiveness of fine-tuning mBERT by freezing its partial bottom layers, and Muller et al. (2021) further analyzed the fine-tuning of mBERT.

3 Methodology

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

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

(1)

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 utilizes the losses for the previous $n - 1$ tasks in Eq. (1) as inequality constraints, avoiding their increase but allowing their decrease. Concretely, when observing the training samples $(x, y)$ from the $n$-th task, GEM solves the following problem:

$$\text{minimize}_{\theta} \mathcal{L}(f_{\theta}(x, n), y)$$

subject to

$$\mathcal{L}(f_{\theta}, \mathcal{M}_k) \leq \mathcal{L}(f_{\theta}^{n-1}, \mathcal{M}_k) \text{ for all } k < n,$$

(2)

where $f_{\theta}^{n-1}$ is the model before learning task $n$.

3.2 Fine-tuning with GEM

We consider two tasks ($n = 2$) in total by applying GEM to the fine-tuning of pre-trained multilingual models, namely, mBERT and XLMR. The first task is either what the pre-trained models have already learned (MLM) or the ability that they already possess (XSR), and the second task is the fine-tuning task. We follow Eq. (2) when we fine-tune the pre-trained models:

$$\text{minimize}_{\theta} \mathcal{L}(f_{\theta}(x, T_2), y)$$

subject to

$$\mathcal{L}(f_{\theta}, T_1) \leq \mathcal{L}(f_{\theta}^1, T_1),$$

(3)

where $T_1$ and $T_2$ denote the first and second tasks, respectively, and $f_{\theta}^1$ represents the original pre-trained model. When the MLM task is considered as the first task, we constrain the fine-tuning process of the pre-trained model by preventing it from forgetting its original task after fine-tuning so as to better preserve the original cross-lingual ability. When the XSR task is considered as the first task, on the other hand, we prevent the pre-trained model from losing its cross-lingual ability after fine-tuning. We also consider incorporating both MLM and XSR as the first task.

4 Experiments

4.1 Dataset

For the POS task, we use Universal Dependencies 2.0 (Nivre et al., 2017) and select English (en), French (fr), Spanish (es), Greek (el) and Russian (ru) to evaluate our methods. For the NER task,
Table 1: Experiments on MLM and XSR tasks based on mBERT. Models other than mBERT are fine-tuned to the English POS task. The underlined numbers in the MLM task denote that the performance is close to mBERT’s. The bold numbers in the XSR task denote the best performance after fine-tuning without using the XSR supervision.

| Model                  | MLM (en) | MLM (es) | MLM (fr) | MLM (el) | MLM (ru) | XSR (Spanish to English) | XSR (Italian to English) |
|------------------------|----------|----------|----------|----------|----------|---------------------------|--------------------------|
|                        | P@1      | P@5      | P@10     | P@1      | P@5      | P@10                      | P@10                     |
| mBERT                  | 10.68    | 3.51     | 8.63     | 2.08     | 7.02     | 56.26                     | 68.80                    |
| Naive Fine-tune        | 216.80   | 16.72    | 40.54    | 5.62     | 8.61     | 87.26                     | 68.12                    |
| w/ frozen layers       | 95.17    | 9.33     | 30.04    | 3.44     | 5.34     | 83.26                     | 53.92                    |

Multi-Task Learning

|                        | P@1      | P@5      | P@10     | P@1      | P@5      | P@10                      |
|------------------------|----------|----------|----------|----------|----------|---------------------------|
| MTF w/ MLM             | 9.50     | 5.10     | 6.25     | 2.56     | 3.47     | 35.93                     | 50.41                    |
| MTF w/ XSR             | 121.50   | 100.10   | 96.50    | 77.00    | 180.80   | 180.80                    | 75.40                    |
| MTF w/ Both            | 9.89     | 9.45     | 11.30    | 3.80     | 4.16     | 77.84                     | 82.57                    |

Continual Learning

|                        | P@1      | P@5      | P@10     | P@1      | P@5      | P@10                      |
|------------------------|----------|----------|----------|----------|----------|---------------------------|
| GEM w/ MLM             | 12.99    | 6.62     | 11.39    | 2.87     | 4.22     | 42.90                     | 57.26                    |
| GEM w/ XSR             | 252.9    | 26.73    | 55.95    | 11.84    | 16.46    | 63.65                     | 75.45                    |
| GEM w/ Both            | 12.16    | 6.40     | 10.62    | 3.40     | 4.30     | 64.34                     | 76.23                    |

5 Results & Analysis

Does GEM preserve the cross-lingual ability? From Table 1, 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 subword embeddings are fine-tuned, which makes mBERT lose more MLM task information in English. Naive fine-tuning also makes the XSR performance of mBERT drop significantly. We observe that fine-tuning with partial layers frozen is able to somewhat prevent the MLM performance from getting worse, while fine-tuning with GEM based on that 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 still preserves the task-related parameters that are useful for other languages. Correspondingly, we can see that GEM w/ MLM achieves better XSR performance than Naive Fine-tune w/ frozen layers, which shows that GEM helps better preserve the cross-lingual ability of mBERT.

In addition, although GEM w/ XSR aggravates the catastrophic forgetting in the MLM task, it is able to significantly improve the XSR performance due to the usage of the XSR supervision. Furthermore, incorporating both the MLM and XSR tasks can better preserve the performance in both tasks.

Does GEM improve the cross-lingual performance? From Table 2, we can see that our methods consistently surpass the fine-tuning baselines on all target languages in the POS and NER tasks. In terms of the average performance, our methods outperform the baselines by an around or more
We conjecture that the effectiveness of both methods is similar, although they come from different angles. When the information of both tasks is utilized, GEM is able to slightly improve the performance. We find that the experimental results on XLMR are consistent with mBERT.

### GEM vs. MTF

From Table 1, we notice that using the MLM task, MTF achieves lower perplexity than GEM since it aggressively trains mBERT on this task. However, we observe that MTF w/ MLM makes the performance of the XSR, POS and NER tasks worse than Naive Fine-tune, and we speculate that MTF pushes mBERT to be overfit to the monolingual MLM task, instead of preserving its cross-lingual ability. Meanwhile, we can see that GEM regularizes the loss of the training on the MLM task to avoid catastrophic forgetting of previously trained languages, and conserve the cross-linguuality of the pre-trained multilingual models.

In addition, we observe that adding XSR objectives to the training cause the MLM performance worse. Although MTF achieves the best performance in the XSR task since it directly fine-tunes mBERT on that task, we can see from Table 2 that GEM w/ XSR boosts the cross-lingual performance of downstream tasks, while MTF w/ XSR has the opposite effect. We speculate that brutally fine-tuning mBERT on the XSR task (MTF w/ XSR) just makes mBERT learn the XSR task, while using GEM to constrain the fine-tuning on the XSR task can preserve its cross-lingual ability of mBERT. Incorporating both the MLM and XSR tasks further improves the performance for GEM, while MTF still performs worse than Naive Fine-tune.

### Ablation Study

From Table 3, 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 similar. Intuitively, since GEM w/ MLM is able to improve the cross-lingual performance, constraining on more languages should give better performance. We conjecture, however, that the constraint with all languages could be too aggressive, so mBERT might tend to be overfit to the monolingual MLM task in all languages instead of preserving its original cross-linguual ability. In addition, we observe that fine-tuning mBERT on the MLM task (MTF) would get worse when more languages are utilized.

### Conclusion

In this paper, we propose to preserve the cross-linguuality of pre-trained language models in the fine-tuning stage. To do so, we adopt a continual...
learning framework, GEM, to constrain the parameter learning in pre-trained multilingual models based on the MLM and XSR tasks when we fine-tune them to downstream tasks. Experiments on the MLM and XSR tasks illustrate that our methods can better preserve the cross-lingual ability of pre-trained models. Furthermore, our methods achieve better performance than fine-tuning baselines for the strong multilingual models mBERT and XLMR on the zero-shot cross-lingual POS and NER tasks.

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A Training Details

We utilize the Wikipedia corpus for the MLM task. Given that using all the Wikipedia corpus will greatly lower the training speed, we randomly sample 1M sentences for each language for the training of MTF w/ MLM and GEM w/ MLM, and we use another 100K sentences for each language to evaluate the model performance on the MLM task. We take the English-Spanish (en-es), English-Italian (en-it), English-French (en-fr), English-Greek (en-el), English-German (en-de), and English-Dutch (en-nl) parallel datasets from the Europarl parallel corpus. We randomly select 90% of them for the training of GEM w/ MLM and GEM W/ XSR, and the rest 10% of them are used for evaluating the model performance on the XSR task. We use accuracy for evaluating the POS task, BIO-based F1-score for evaluating the NER task, perplexity for evaluating the MLM task, and P@k for evaluating the XSR task. Concretely, 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. We use an early stop strategy which is based on the average performance over the target languages to select the model. We use the Adam optimizer with a learning of 1e-5. We use batch size 16 for the all tasks, namely, POS, NER, MLM and XSR. In each iteration, we use GEM to constrain the fine-tuning on a batch of data samples from the MLM and XSR tasks. Our models are trained on V100. The number of parameters for the mBERT-based model is around 178.6 million and for the XLMR-based model is around 278.9 million.

| # samples | en  | es  | de  | nl  |
|-----------|-----|-----|-----|-----|
| Train     | 14,040 | 8,319 | 12,152 | 15,802 |
| Validation| 3,249  | 1,914 | 2,867 | 2,895 |
| Test      | 3,452  | 1,516 | 3,005 | 5,194 |

Table 4: Number of samples for each language in the CoNLL 2002 and CoNLL 2003 NER datasets.

| # samples | en | es | fr | el | ru |
|-----------|----|----|----|----|----|
| Train     | 12,543 | 14,187 | 14,450 | 1,662 | 3,850 |
| Validation| 2,002  | 1,400 | 1,476 | 403  | 579 |
| Test      | 2,007  | 426  | 416  | 456  | 601 |

Table 5: Number of samples for each language in the Universal Dependencies 2.0 dataset for the POS task.

B Data Statistics

The data statistics of the NER and POS datasets are shown in Table 4 and Table 5, respectively.

C Results

C.1 XLMR Experiments

Experiments on POS and NER tasks for XLMRbase are illustrated in Table 6 (in the next page). The results on XLMR are consistent with mBERT.

C.2 XSR Experiments

Experiments on more language pairs are illustrated in Table 7 (in the next page). The results on French to English, Greek to English, German to English and Dutch to English are consistent with the XSR results shown in the main paper (i.e., Spanish to English and Italian to English).
### Table 6: Zero-shot results on POS and NER tasks based on XLMR.

| Model                          | POS | NER |
|-------------------------------|-----|-----|
|                               |     |     |
|                               | en  | es  | fr  | el  | ru  | avg† | en  | es  | de  | nl  | avg† |
| Naive Fine-tune               |     |     |     |     |     |       |     |     |     |     |       |
| w/ frozen layers              |     |     |     |     |     |       |     |     |     |     |       |
| **Multi-Task Learning**       |     |     |     |     |     |       |     |     |     |     |       |
| MTF w/ MLM                    |     |     |     |     |     |       |     |     |     |     |       |
| MTF w/ XSR                    |     |     |     |     |     |       |     |     |     |     |       |
| MTF w/ Both                   |     |     |     |     |     |       |     |     |     |     |       |
| **Continual Learning**        |     |     |     |     |     |       |     |     |     |     |       |
| GEM w/ MLM                    |     |     |     |     |     |       |     |     |     |     |       |
| GEM w/ XSR                    |     |     |     |     |     |       |     |     |     |     |       |
| GEM w/ Both                   |     |     |     |     |     |       |     |     |     |     |       |

Table 6: Zero-shot results on POS and NER tasks based on XLMR. †The average scores excluding en.

### Table 7: Experiments on XSR tasks based on mBERT. Models other than mBERT are fine-tuned to the English POS task. The bold numbers in the XSR task denote the best performance after fine-tuning without using the XSR supervision.

| Model                          | XSR (French to English) | XSR (Greek to English) | XSR (German to English) | XSR (Dutch to English) |
|-------------------------------|-------------------------|------------------------|-------------------------|------------------------|
|                               | P@1 | P@5 | P@10 | P@1 | P@5 | P@10 | P@1 | P@5 | P@10 | P@1 | P@5 | P@10 |
| mBERT                         | 53.92 | 65.44 | 72.12 | 35.68 | 59.40 | 65.31 | 52.10 | 64.71 | 69.43 | 54.56 | 66.69 | 72.54 |
| Naive Fine-tune               |     |     |     |     |     |     |     |     |     |     |     |     |
| w/ frozen layers              |     |     |     |     |     |     |     |     |     |     |     |     |
| MTF w/ MLM                    | 32.49 | 48.67 | 56.23 | 14.67 | 32.29 | 40.64 | 32.37 | 47.45 | 55.48 | 32.86 | 50.35 | 56.55 |
| MTF w/ XSR                    | 74.20 | 78.65 | 83.69 | 73.94 | 77.59 | 83.47 | 75.48 | 80.67 | 85.44 | 75.83 | 85.28 | 88.35 |
| MTF w/ Both                   | 75.30 | 79.34 | 84.86 | 74.25 | 78.39 | 84.63 | 77.93 | 82.67 | 87.86 | 74.42 | 83.57 | 86.68 |
| **Continual Learning**        |     |     |     |     |     |     |     |     |     |     |     |     |
| GEM w/ MLM                    | 39.79 | 55.62 | 63.34 | 21.33 | 29.60 | 47.36 | 37.70 | 53.44 | 60.53 | 38.35 | 54.89 | 63.06 |
| GEM w/ XSR                    | 63.11 | 67.81 | 71.92 | 61.79 | 65.37 | 70.43 | 63.14 | 75.52 | 80.85 | 63.90 | 78.33 | 83.46 |
| GEM w/ Both                   | 63.84 | 68.50 | 72.05 | 61.54 | 64.38 | 69.50 | 64.41 | 76.39 | 81.70 | 64.36 | 79.65 | 84.72 |

Table 7: Experiments on XSR tasks based on mBERT. Models other than mBERT are fine-tuned to the English POS task. The bold numbers in the XSR task denote the best performance after fine-tuning without using the XSR supervision.