ERNIE-M: Enhanced Multilingual Representation by Aligning Cross-lingual Semantics with Monolingual Corpora

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Abstract
Recent studies have demonstrated that pre-trained cross-lingual models achieve impressive performance on downstream cross-lingual tasks. This improvement stems from the learning of a large amount of monolingual and parallel corpora. While it is generally acknowledged that parallel corpora are critical for improving the model performance, existing methods are often constrained by the size of parallel corpora, especially for the low-resource languages. In this paper, we propose ERNIE-M, a new training method that encourages the model to align the representation of multiple languages with monolingual corpora, to break the constraint of parallel corpus size on the model performance. Our key insight is to integrate the idea of back translation in the pre-training process. We generate pseudo-parallel sentences pairs on a monolingual corpus to enable the learning of semantic alignment between different languages, which enhances the semantic modeling of cross-lingual models. Experimental results show that ERNIE-M outperforms existing cross-lingual models and delivers new state-of-the-art results on various cross-lingual downstream tasks. The codes and pre-trained models will be made publicly available.

1 Introduction
Recent studies have demonstrated that the pre-training of cross-lingual language models can significantly improve their performance in cross-lingual NLP tasks (Devlin et al., 2018; Lample and Conneau, 2019; Conneau et al., 2019; Liu et al., 2020). Existing pre-training methods include multilingual masked language modeling (MMLM; Devlin et al. 2018) and translation language modeling (TLM; Lample and Conneau 2019), of which the key point is to learn a shared language-invariant feature space among multiple languages. MMLM implicitly models the semantic representation of each language in an unified feature space by learning them separately. TLM is an extension of MMLM that is trained with parallel corpus and captures semantic alignment by learning a pair of parallel sentences simultaneously. This work show that the use of parallel corpora can significantly improve the performance on downstream cross-lingual understanding and generation tasks. However, the sizes of parallel corpora are rather limited (Tran et al., 2020), restricting the performance of the cross-lingual language model.

To break the constraint of parallel corpus size on the model performance, we propose ERNIE-M, a novel cross-lingual pre-training method to learn semantic alignment among multiple languages on monolingual corpora. Specifically, we propose cross-attention masked language modeling (CAMLM) to improve the cross-lingual transferability of the model on parallel corpora, which trains the model to predict the tokens of one language by using only another language. Then, we utilize the transferability learned from parallel corpora to enhance the multilingual representation. We propose back-translation masked language modeling (BTMLM) to train the model, which helps the model to learn sentence alignment from monolingual corpora. In BTMLM, a part of the tokens in the input monolingual sentences are predicted into the tokens of another language. We then concatenate the predicted tokens and the input sentences as pseudo parallel sentences to train the model. In this way, the model can learn the sentence alignment with monolingual corpora only, which breaks the constraint of parallel corpus size and improves the model performance.

ERNIE-M is conducted on the basis of XLM-R (Conneau et al., 2019) and we evaluate its performance on five widely used cross-lingual benchmarks: XNLI (Conneau et al., 2018) for cross-lingual Natural Language Inference, MLQA
(Lewis et al., 2019) for cross-lingual Question Answering, CoNLL (Sang and De Meulder, 2003) for Named Entity Recognition, PAWS-X (Hu et al., 2020) for cross-lingual paraphrase identification, and Tatoeba (Hu et al., 2020) for cross-lingual retrieval. Experimental results demonstrate ERNIE-M outperforms existing cross-lingual models and delivers new state-of-the-art results.

2 Related Work

2.1 Multilingual Language Models

Existing multilingual language models mainly can be classified into two categories: (1) discriminative models, and (2) generative models.

In the first category, Multilingual BERT (mBERT; Devlin et al. 2018) is pre-trained with multilingual masked language modeling (MMLM) on a monolingual corpus, which learns a shared language-invariant feature space among multiple languages. Evaluation results show that mBERT achieves significant performance on downstream tasks (Wu and Dredze, 2019). XLM (Lample and Conneau, 2019) is extended on the basis of mBERT and proposes translation language modeling (TLM), which enables the model to learn cross-lingual token alignment from parallel corpora. XLM-R (Conneau et al., 2019) studies the effects of models when trained on a large scale corpus. It used 2.5T data extracted from Common Crawl (Wenzek et al., 2019) that involves 100 languages for MMLM training. Results show that a large scale training corpus can significantly improve the performance of the cross-lingual model. Unicoder (Huang et al., 2019) achieves gains on downstream tasks with a multi-task learning framework to learn cross-lingual semantic representation with monolingual and parallel corpus. ALM (Yang et al., 2020) improves the model’s transferability by enabling model to learn cross-lingual code-switch sentences. INFOXLM (Chi et al., 2020b) adds a comparative learning task for cross-lingual model training. HICTL (Wei et al., 2020) learns the cross-lingual semantic representation from multiple facets (at word-levels and sentence-levels) to improve the performance of the cross-lingual models. VECO (Luo et al., 2020) presents a variable encoder-decoder framework to unify understanding task and generation task and achieves significant improvement on both downstream tasks.

The second category includes MASS (Song et al., 2019), mBART (Liu et al., 2020), and XNLG (Chi et al., 2020a). MASS is a transformer-based model (Vaswani et al., 2017) in which successive token fragments are masked and the training object is to restore the input sentences. Similar to MASS, mBART pre-trains a denoised sequence-to-sequence model and uses an auto-regressive task to train the model. XNLG focuses on multilingual question generation and abstractive summarization, and updates the parameters of encoder and decoder through auto-regressive and auto-encoding tasks.

2.2 Back Translation

Back translation (BT) is an effective neural-network-based machine translation method proposed by Sennrich et al. (2015). It can significantly improve the performance of both supervised and unsupervised machine translation in a self-training manner (Lample et al., 2017). It can also improve the speed of machine translation by predicting the token of the target language in one batch for the non-autoregressive machine translation (NAT; Gu et al. 2017; Wang et al. 2019). Our work is inspired by NAT and BT. We generate the tokens of another language in batches, which are then used in pre-training to help sentence alignment learning.

3 Methodology

In this section, we first introduce the general workflow of ERNIE-M, and then present the details of model training.

3.1 Cross-lingual Semantic Alignment

The key idea of ERNIE-M is to utilize the transferability learned from parallel corpora to enhance the model’s learning of large-scale monolingual corpora, and thus enhance the multilingual semantic representation. Based on it, we design ERNIE-M that consists of two stages.

The first stage aligns the cross-lingual semantic representation using cross-attention masked language modeling (CAMLM) on parallel corpora. Then, the transferability learned from parallel corpora is utilized to enhance the multilingual representation in the second stage. Specifically, we propose back-translation masked language modeling (BTMLM) to train the model, which enables the model to align multiple languages semantic from monolingual corpora and improve the multilingual representation of the model. In the following sections, we will introduce the details of each stage of training.
Cross-attention Masked Language Modeling.

To learn the alignment of cross-lingual semantic representations on parallel corpora, we propose a new pre-training object CAMLM. We denote a parallel sentence pair as \(<source\text{ sentence}, target\text{ sentence}>\). In CAMLM, we learn the multilingual semantic representation by restoring the MASK token in the input sentences. When the model restores the \(\text{MASK}\) token in the source sentence, the model can only rely on the semantics of the target sentence, which means that the model has to learn how to represent the source language with the semantics of the target sentence, and thus align the semantics of multiple languages.

Figure 1 (b) and (c) show the differences between TLM and CAMLM. TLM learns the semantic alignment between languages with both the source and target sentences while CAMLM only relies on one side of the sentence to restore the \(\text{MASK}\) token. The self-attention matrix of the example in Figure 1 is shown in Figure 2. For TLM, the prediction of the \(\text{MASK}\) token relies on the input sentence pair, while when the model learns CAMLM, the model can only predict the \(\text{MASK}\) token based on the sentence of its corresponding parallel sentence and the \(\text{MASK}\) symbol of this sentence which provides the position and language information. Thus, the probability of the \(\text{MASK}\) token \(M_2\) is \(p(x_2|M_2, y_1, y_5, y_6, y_7)\), \(p(y_6|x_1, x_2, x_3, M_5, M_6)\) for \(M_5\), and \(p(y_6|x_1, x_2, x_3, M_5, M_6)\) for \(M_6\) in CAMLM.

Given the input in a bilingual corpus \(X_{\text{src}} = \{x_1, x_2, \cdots, x_s\}\), and its corresponding \(\text{MASK}\) position \(M_{\text{src}} = \{m_1, m_2, \cdots, m_s\}\), the target sentence is \(X_{\text{tgt}} = \{x_{s+1}, x_{s+2}, \cdots, x_{s+t}\}\), and its corresponding \(\text{MASK}\) position is \(M_{\text{tgt}} = \{m_{s+1}, m_{s+2}, \cdots, m_{s+t}\}\). In TLM, the model can attend to the tokens in the source sentence and target sentence, so the probability of masked tokens is \(\prod_{m \in M} p(x_m|x/M)\) where \(M = M_{\text{src}} \cup M_{\text{tgt}}\). In CAMLM, the probability of the \(\text{MASK}\) token in the source sentence is \(\prod_{m \in M_{\text{src}}} p(x_m|x/M_{\text{src}} \cup X_{\text{src}})\), which means that when predicting the \(\text{MASK}\) tokens in the source sentence, we only focus on the target sentence. As for the target sentence, the probability of the \(\text{MASK}\) token is \(\prod_{m \in M_{\text{tgt}}} p(x_m|x/M_{\text{tgt}} \cup X_{\text{tgt}})\), which means that the \(\text{MASK}\) tokens in the target sentence will be predicted based only on the source sentence. Therefore, the model must learn to use the corresponding sentence to prediction and learns the alignment across multiple languages.

The pre-training loss of CAMLM in the source/target sentence are:

\[
\mathcal{L}_{\text{CAMLM}}(\text{src}) = - \sum_{x \in D_B} \log \prod_{m \in M_{\text{src}}} p(x_m|x/M_{\text{src}} \cup X_{\text{src}})
\]

\[
\mathcal{L}_{\text{CAMLM}}(\text{tgt}) = - \sum_{x \in D_B} \log \prod_{m \in M_{\text{tgt}}} p(x_m|x/M_{\text{tgt}} \cup X_{\text{tgt}})
\]

where \(D_B\) is the bilingual training corpus. The CAMLM loss is:

\[
\mathcal{L}_{\text{CAMLM}} = \mathcal{L}_{\text{CAMLM}}(\text{src}) + \mathcal{L}_{\text{CAMLM}}(\text{tgt})
\]
Back-translation Masked Language Modeling.

To break the constraint of parallel corpus size on the model performance, we propose a novel pre-training object inspired by non-autoregressive machine translation (NAT; Gu et al. 2017; Wang et al. 2019) and back translation (BT) methods called BTMLM to align cross-lingual semantics with the monolingual corpus. We use BTMLM to train our model, which builds on the transferability learned through CAMLM, generating pseudo-parallel sentences from the monolingual sentences and the generated pseudo-parallel sentences are then used as the input of the model to align the cross-lingual semantics, thus enhance the multilingual representation. The training process for BTMLM is shown in Figure 3.

![Figure 3: Overview of BTMLM training, the left figure represents the first stage of BTMLM, predicting the pseudo-tokens. The right figure represents the second stage of the BTMLM, making predictions from the predicted pseudo-tokens and the original sentences.](image)

The learning process for the BTMLM is divided into two stages, with the first stage being the generation of pseudo-parallel tokens from monolingual corpora. Specifically, we fill in several placeholder MASK at the end of the monolingual sentence to indicate the location and the language we want to predict. The probability of the mask token \( M_5 \) is \( p(y_5|x_1, x_2, x_3, x_4, M_5) \), \( p(y_6|x_1, x_2, x_3, x_4, M_6) \) for \( M_6 \) and \( p(y_7|x_1, x_2, x_3, x_4, M_7) \) for \( M_7 \).

Stage 2 uses the pseudo-tokens generated in stage 1 to learn cross-lingual semantics alignment, and the process in stage 2 is shown in the right-hand diagram of Figure 3. In the training process of stage 2, the input of the model is the concatenation of input sentences and the generated pseudo-parallel tokens, and the learning object is to restore the MASK tokens based on the original sentences and the generated pseudo-parallel tokens. Since the model can rely not only the input monolingual sentence but also the generated pseudo-tokens in the process of inference MASK tokens, the model can explicitly learn the alignment of the cross-lingual semantics representation from the monolingual sentences.

The learning process of BTMLM can be interpreted as following. Given the input in monolingual corpora \( X = \{x_1, x_2, \cdots, x_s\} \), the positions of masked tokens \( M = \{m_1, m_2, \cdots, m_M\} \) and the position of the pseudo-token to be predicted \( M_{\text{pseudo}} = \{m_{s+1}, m_{s+2}, \cdots, m_{s+p}\} \), we first generate pseudo-tokens \( P = \{p_{s+1}, p_{s+2}, \cdots, p_{s+p}\} \) as described above, we then concatenate the generated pseudo-token with the original monolingual sentence as a new parallel sentence pair and use it to train our model. Thus the probability of the masked tokens in BTMLM is \( \prod_{m \in M} p(x_m|x/M, P) \), \( x/M \) means all input tokens in \( X \) except \( x \) in \( M \). The pre-training loss of BTMLM is

\[
\mathcal{L}_{\text{BTMLM}} = - \sum_{x \in D_M} \log \prod_{m \in M} p(x_m|x/M, P)
\]

where \( D_M \) is the monolingual training corpus.

3.2 Training Algorithm

To speed up the convergence of the model, we use XLM-R (Conneau et al., 2019) model to initialize the parameters of ERNIE-M, the MMLM and
4 Experimental

We consider five cross-lingual evaluation benchmarks: XNLI for cross-lingual natural language inference, MLQA for cross-lingual question answering, CoNLL for cross-lingual named entity recognition, PAWS-X for cross-lingual paraphrase identification, and Tatoeba for cross-lingual retrieval. We will describe our pre-training details and the performance of ERNIE-M.

4.1 Data and Model

ERNIE-M is trained with monolingual and parallel corpora that involved 96 languages. For the monolingual corpus, we extracted it from CC-100 according to Wenzek et al. (2019); Conneau et al. (2019). For bilingual corpus, we use the same corpus as INFOXLM (Chi et al., 2020b), including MultiUN (Ziemski et al., 2016), IIT Bombay (Kunchukuttan et al., 2017), OPUS (Tiedemann, 2012) and WikiMatrix (Schwenk et al., 2019). In order to balance the size of data for high-resource and low-resource languages, both monolingual and parallel corpora were sampled with parameter alpha of 0.1 referred to the method of (Lample and Conneau, 2019). Details can be found in the appendix.

We use Transformer-encoder (Vaswani et al., 2017) as the backbone of the model. For ERNIE-M_{BASE} model, we adopt a 12 layers, 768 hidden units, 12 heads structure. For ERNIE-M_{LARGE} model, we adopt a 24 layers, 1024 hidden units, 16 heads structure, and the activation function is GeLU (Hendrycks and Gimpel, 2016). To speed up the pre-training process, we use XLM-R model to initialize ERNIE-M. We use Adam optimizer (Kingma and Ba, 2014) to train ERNIE-M, the learning rate is scheduled with a linear decay with 10K warm-up steps, and the peak learning rate is $2e^{-4}$ for base model and $1e^{-4}$ for large model. We run the pre-training experiments with 64 Nvidia V100-32GB GPUs with the 2048 batch size and 512 max lengths. The pre-training parameter details can be found in the appendix.

4.2 Experimental Evaluation

Cross-lingual Natural Language Inference. The cross-lingual natural language inference (XNLI; Conneau et al. 2018) task is a multilingual language inference task. The goal of XNLI is to determine the relationship between the two input sentences. We evaluate ERNIE-M in (1) cross-lingual transfer (Conneau et al., 2018) setting: fine-tune the model with English training set and evaluate on foreign language XNLI test and (2) translate-train-all (Huang et al., 2019) setting: fine-tune the model on the concatenation of all other languages and evaluate on each language test set.

Table 1 shows the results of ERNIE-M in XNLI task. The result shows that ERNIE-M outperforms all baseline models including XLM (Lample and Conneau, 2019), Unicoder (Huang et al., 2019), XLM-R (Conneau et al., 2019), INFOXLM (Chi et al., 2020b) and VECO (Luo et al., 2020) on both two evaluation setting on XNLI. The final score on the testset are averaged over five runs with difference random seeds. On cross-lingual transfer setting, ERNIE-M achieves 77.3 average accuracy, which outperforming INFOXLM by 1.1. ERNIE-M also has outstanding performance in low-resource languages, including 69.5 in Swahili (sw) and 68.8 in Urdu (ur). In case of translate-train-all, ERNIE-MBASE improves performance and reaches 80.6 accuracy, a new state-of-the-art for XNLI outperforming INFOXLM 0.9. To more accurately evaluate the performance of ERNIE-M, we trained the ERNIE-M-15 model in only 15 languages on the XNLI task, the evaluation detail in XNLI for 15 languages models can be found in the appendix.

Named Entity Recognition. For named entity recognition task (NER), we evaluate ERNIE-M on CoNLL-2002 and CoNLL-2003 datasets (Sang and De Meulder, 2003), which is a cross-lingual NER task including English, Dutch, Spanish and German. We consider ERNIE-M in the following setting: (1) fine-tune on English dataset and evaluate on each cross-lingual dataset to evaluate cross-lingual transfer and (2) fine-tune on all training datasets to evaluate cross-lingual learning. For each setting, we reported the F1 score in each languages.

Table 2 shows the results of ERNIE-M, XLM-R and mBERT on CoNLL-2002 and CoNLL-2003.
| MODEL     | en  | fr  | es  | de  | el  | bg  | ru  | tr  | ar  | vi  | th  | zh  | hi  | sw  | ur  | Avg |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Fine-tune cross-lingual model on English training set (Cross-lingual Transfer) |
| XLM       | 85.0| 78.7| 78.9| 77.8| 76.6| 77.4| 75.3| 72.5| 73.1| 76.1| 73.2| 76.5| 69.6| 68.4| 67.3| 75.1|
| Unicoder  | 85.1| 79.0| 79.4| 77.8| 77.2| 77.2| 76.3| 72.8| 73.5| 76.4| 73.6| 76.2| 69.4| 69.7| 66.7| 75.4|
| XLM-R     | 85.8| 79.7| 80.7| 78.7| 77.5| 79.6| 81.7| 74.2| 73.8| 76.5| 74.6| 76.7| 72.4| 66.5| 68.3| 76.2|
| InfoXLM   | 86.4| 80.6| 80.8| 78.9| 79.4| 79.9| 77.9| 77.6| 75.6| 74.0| 77.0| 73.7| 76.7| 72.0| 66.4| 67.1| 76.2|
| ERNIE-M   | 85.5| 80.1| 81.2| 79.2| 79.1| 80.4| 78.1| 76.8| 76.3| 78.3| 75.8| 77.4| 73.9| 69.5| 68.8| 77.3|
| XLM-R\_LARGE | 89.1| 84.1| 85.1| 83.9| 82.9| 84.0| 81.2| 79.6| 79.8| 80.8| 78.1| 80.2| 76.9| 73.9| 73.8| 80.9|
| InfoXLM\_LARGE | 89.7| 84.5| 85.5| 84.1| 83.4| 84.2| 81.3| 80.9| 80.4| 80.8| 78.9| 80.9| 77.9| 74.8| 73.7| 81.4|
| VECO\_LARGE | 88.2| 79.2| 83.1| 82.9| 81.2| 84.2| 82.8| 76.2| 76.3| 74.3| 77.0| 78.4| 71.3| 80.4| 79.1| 79.9|
| ERNIE-M\_LARGE | 89.3| 85.1| 85.7| 84.4| 83.7| 84.5| 82.0| 81.2| 81.2| 81.9| 79.2| 81.0| 78.6| 76.2| 75.4| 82.0|

Table 1: Evaluation results on XNLI cross-lingual natural language inference. We report the accuracy on each language testset with five runs average.

Results of XLM-R and mBERT are reported from Conneau et al. (2019). ERNIE-M model get state-of-the-art on both setting and outperforms XLM-R by 0.45 F1 when trained on English, and 0.70 F1 when trained on all languages in the base model. Similar to the performance in the XNLI task, ERNIE-M has better performance on low-resource languages. For large models and fine-tune in all languages setting, we are 2.21 F1 higher than SoTA in Dutch (nl) and 1.6 F1 higher than SoTA in German (de).

Cross-lingual Question Answering. For question answering task, we use multilingual question answering (MLQA) dataset to evaluate ERNIE-M. MLQA has the same format as SQuAD v1.1 (Rajpurkar et al., 2016) and it’s a multilingual language question answering task which composed of seven languages. We fine-tune ERNIE-M by training on English data and evaluating on seven cross-lingual datasets. The fine-tune method is the same as Lewis et al. (2019) that concatenates the question-passage pair as the input.

Table 2 compares ERNIE-M with several baseline models on MLQA, we report F1 score and extract match (EM) scores with five runs average. The performance of ERNIE-M in MLQA is significantly better than the previous models and has achieved a state-of-the-art score. We outperformed InfoXLM 0.8 in F1 and 0.5 in EM.

Cross-lingual Paraphrase Identification. For cross-lingual paraphrase identification task, we use cross-lingual Paraphrase Adversaries from Word Scrambling (PAWS-X) (Hu et al., 2020) dataset to evaluate our model, the goal of PAWS-X is to determine whether two sentences are paraphrases, we evaluate ERNIE-M on both cross-lingual transfer setting and translate-train-all setting.

Table 3 compares ERNIE-M with various baseline model on PAWS-X, we report the accuracy score on each language testset with five runs average. The results show that ERNIE-M outperform all baselines model on most language and achieved a new SoTA.
### Cross-lingual Sentence Retrieval

The goal for the cross-lingual sentence retrieval task is to extract parallel sentences from bilingual corpora. We use a subset of Tatoeba (Hu et al., 2020) dataset that contains 36 language pairs to evaluate ERNIE-M. Following Luo et al. 2020, we use the averaged representation in the middle layer of the best XNLI model to evaluate the retrieval task.

Table 5 shows the results of ERNIE-M in retrieval task. XLM-R results is from Luo et al. 2020, ERNIE-M achieving a score of 87.9 in Tatoeba dataset, outperforming VECO 1.0 and delivers new state-of-the-art results. The details of each language’s accuracy in Tatoeba can be found in the appendix.

| Model       | en  | de  | es  | fr  | ja  | lo  | zh  | Avg |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|
| mBERT       | 94.0| 85.7| 87.4| 87.0| 73.0| 69.6| 77.0| 81.9|
| XLM         | 94.0| 85.9| 88.3| 87.4| 69.3| 64.8| 76.5| 80.9|
| MMTE        | 93.1| 85.1| 87.2| 86.9| 72.0| 69.2| 75.9| 81.3|
| XLM-R       | 94.7| 89.7| 90.1| 90.4| 78.7| 79.0| 82.3| 86.4|
| VECO-LARGE  | 96.2| 91.3| 91.4| 92.0| 81.8| 82.9| 85.1| 88.7|
| ERNIE-M_LARGE | 96.0| 91.9| 91.4| 92.2| 83.9| 84.5| 86.9| 90.5|

Table 5: Evaluation results on Tatoeba.

### 4.3 Ablation Study

To understand the effect of aligning multiple languages semantic representation in the training process of ERNIE-M, we conduct an ablation study as reported in Table 6. We train (1) only MMLM on the monolingual corpus, (2) MMLM on the monolingual corpus and TLM on the bilingual corpus, (3) MMLM on the monolingual corpus and CAMLM on the bilingual corpus, and (4) MMLM and BTMLM on the monolingual corpus and CAMLM on the bilingual corpus. We use the base model structure for our experiments, and to speed up the experiments, we use the XLM-R_{BASE} model to initialize the model parameters, all of these experiments ran 50,000 steps with the same hyperparameters with batch size 2048, the score reported on downstream task is the average score of five runs.

| Model       | MLQA | XNLI | CoNLL | Average |
|-------------|------|------|-------|---------|
| mBERT       | 23.3 | 16.9 | 20.1  |
| XLM-R       | 17.6 | 10.4 | 14.0  |
| INFOXLM     | 15.7 | 10.9 | 13.3  |
| ERNIE-M     | 15.0 | 8.8  | 11.9  |

Table 7: Cross-lingual transfer gap score, smaller gap indicates better transferability.

Compared with \(exp_2\) \(exp_3\) \(exp_4\) and \(exp_1\), we find that the learning of cross-lingual semantic alignment on parallel corpora is helpful for the performance of the model. Experiments that used bilingual corpus for training showed significant improvements in XNLI. Compared with \(exp_2\) and \(exp_4\), we find that our proposed BTMLM and CAMLM are better for learning alignment of cross-lingual semantic. The training model with CAMLM and BTMLM brings a 0.3 improvement on XNLI and a 1.3 improvement on CoNLL com-
pared to the training model with TLM. Comparing \(exp_3\) with \(exp_4\), there is a 0.5 improvement in XNLI and 0.1 improvement after adding BTMLM for training. This demonstrates that our proposed BTMLM can learn cross-lingual semantic alignment and improve the performance of our model.

Table 7 shows the gap scores for English and other languages on downstream task, this gap score is the difference between the English testset and the average performance on the testset in other languages. So a smaller gap score represents a better transferability of the model. We can notice that the gap scores of ERNIE-M are smaller compared to XLM-R and INFOXLM in both XNLI task and MLQA task which indicate a better transferability of ERNIE-M.

In addition, we explore the effect of the number of pseudo-tokens generated on BTMLM. Specifically, we investigate the effect of generating 5%, 10%, 15% and 20% pseudo-tokens on the convergence of the model. As shown in Figure 5, we can observe that as the proportion of generated pseudo-tokens increases, the PPL (Perplexity) of the BTMLM gradually decreases because the more pseudo-tokens are generated. The richer the token information in another language is provided to the model, thus better helping the model to converge.

![PPL in each mask prob](image)

Figure 5: PPL in BTMLM training with different mask prob

## 5 Conclusion

In this paper, we propose a new cross-lingual model ERNIE-M, which is trained with both monolingual and parallel corpora. The training process of ERNIE-M consists of two stages. The first stage is to enhance the multilingual representation on parallel corpora by cross-attention masked language modeling (CAMLM), and the second stage is to encourage the model to align cross-lingual semantic representations from a monolingual corpus by back-translation masked language modeling (BTMLM). Experiments show that ERNIE-M achieves the state-of-the-art results on various cross-lingual downstream tasks with the XNLI, MLQA, CoNLL, PAWS-X, and Tatoeba datasets.

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A Pre-training Data

We follow (Wenzek et al., 2019) to reconstruct CC-100 data for ERNIE-M training. The monolingual training corpus contains 96 languages as shown in Table 8. Notice that several languages have same the ISO code, e.g., zh represents both Simplified Chinese and Traditional Chinese, ur represents both Urdu and Urdu Romanized. Table 9 shows the statistics of the parallel data in each language.

| Code | Size (GB) | Code | Size (GB) | Code | Size (GB) |
|------|-----------|------|-----------|------|-----------|
| af   | 0.1       | hi   | 4.2       | or  | 0.3       |
| am   | 0.3       | hr   | 1.0       | pa  | 0.6       |
| ar   | 12.5      | hu   | 6.9       | pl  | 20.2      |
| as   | 0.1       | hy   | 0.6       | ps  | 0.3       |
| az   | 0.6       | id   | 11.7      | pt  | 27.4      |
| be   | 0.4       | is   | 0.4       | ro  | 7.5       |
| bg   | 5.6       | it   | 32.9      | ru  | 215.6     |
| bn   | 4.6       | ja   | 78.1      | sa  | 0.1       |
| br   | 0.0       | jv   | 0.0       | sd  | 0.1       |
| bs   | 0.0       | ka   | 0.9       | si  | 1.1       |
| ca   | 2.1       | kk   | 0.5       | sk  | 9.5       |
| cs   | 10.5      | km   | 0.2       | sl  | 4.3       |
| cy   | 0.3       | kn   | 0.2       | so  | 0.0       |
| da   | 4.8       | ko   | 29.4      | sq  | 2.0       |
| de   | 71.0      | ku   | 0.1       | sr  | 5.5       |
| el   | 10.5      | ky   | 0.4       | su  | 0.0       |
| en   | 512.5     | la   | 0.2       | sv  | 42.1      |
| eo   | 0.4       | lo   | 0.2       | sw  | 0.2       |
| es   | 62.6      | lt   | 1.7       | ta  | 6.9       |
| et   | 1.0       | lv   | 0.9       | te  | 2.0       |
| eu   | 0.7       | mg   | 0.0       | th  | 29.1      |
| fa   | 14.8      | mk   | 0.5       | tl  | 0.8       |
| fi   | 4.3       | ml   | 1.2       | tr  | 43.3      |
| fr   | 61.5      | mn   | 0.3       | ug  | 0.1       |
| fy   | 0.1       | mr   | 0.4       | uk  | 11.1      |
| ga   | 0.2       | ms   | 0.5       | ur  | 2.2       |
| gd   | 0.0       | my   | 0.4       | uz  | 0.1       |
| gl   | 1.0       | ne   | 0.5       | vi  | 52.0      |
| gu   | 0.2       | nl   | 17.8      | yi  | 0.2       |
| hi   | 3.3       | no   | 3.8       | zh  | 96.0      |

Table 8: The statistics of CC-100 used for ERNIE-M pre-training.

| ISO Code | Size (GB) | ISO Code | Size (GB) |
|----------|-----------|----------|-----------|
| ar       | 9.8       | ru       | 8.3       |
| bg       | 2.2       | sw       | 0.1       |
| de       | 10.7      | th       | 3.3       |
| el       | 4.0       | tr       | 1.1       |
| es       | 8.8       | ur       | 0.7       |
| fr       | 13.7      | vi       | 0.8       |
| hi       | 0.3       | zh       | 5.0       |

Table 9: The statistics of parallel data used for ERNIE-M pre-training.

B Hyperparameters for Pre-training

Table 10 shows the hyperparameters for pre-training. We use XLM-R model to initialize the parameters of ERNIE-M and the vocab is the same as XLM-R.

| Hyperparameters | BASE | LARGE |
|-----------------|------|-------|
| Layers          | 12   | 24    |
| Hidden size     | 768  | 1024  |
| FFN inner hidden size | 3,072 | 4,096 |
| FFN dropout     | 0.1  | 0.1   |
| Attention heads | 12   | 16    |
| Attention dropout | 0.1  | 0.1   |
| Embedding size  | 768  | 1024  |
| Training steps  | 150K | 200K  |
| Batch size      | 2,048| 2,048 |
| Learning rate   | 2e-4 | 1e-4  |
| Learning rate schedule | Linear | Linear |
| Adam β1         | 0.98 | 0.98  |
| Adam β2         | 0.999| 0.999 |
| Weight decay    | 0.01 | 0.01  |
| Warmup steps    | 10,000| 10,000|

Table 10: Hyperparameters used for ERNIE-M pre-training.

C Hyperparameters for Fine-tuning

Table 11 and Table 12 show the fine-tuning parameters on XNLI, MLQA, CoNLL and PAWS-X. For each task, we select the model with the best performance on the validation set and the testset score is the average of five runs with different random seeds.

D Evaluation results for 15 languages model

To better evaluate the performance of ERNIE-M, we trained the ERNIE-M-15 model for 15 languages and evaluated it on the XNLI dataset. ERNIE-M-15 model outperformed the current best 15-language cross-lingual model on the XNLI task, achieving a score of 77.5 in the cross-lingual transfer setting, outperforming HICTL 0.2 and 80.7 in translate-train-all setting, outperforming HICTL 0.7. ERNIE-M Achieves SoTA results on XNLI task.

E Evaluation results for Cross-lingual Retrieval

Table 14 shows the details of each language accuracy in cross-lingual retrieval task. ERNIE-M outperform VECO in most languages and achieves SoTA results on Tatoeba.
| Hyperparameters | XNLI | XNLI | MLQA | CoNLL | CoNLL |
|-----------------|------|------|------|-------|-------|
| Batch size      | 32   | 128  | 32   | 8     | 8     |
| Learning rate   | 5e-5 | 5e-5 | 8e-5 | 4e-4  | 3e-4  |
| Layerwise LR decay | 0.8  | 0.8  | 0.8  | 0.8   | 0.8   |
| LR schedule     | Linear | Linear | Linear | Linear | Linear |
| Warmup faction  | 10%  | 10%  | 10%  | 10%   | 10%   |
| Weight decay    | 0    | 0    | 0    | 0.01  | 0.01  |
| Epoch           | 5    | 2    | 2    | 10    | 10    |

Table 11: Hyperparameters used for ERNIE-M\textsubscript{BASE} fine-tuning, parameters with "*" are Translate-Train-All setting, without "*" are Cross-lingual setting.

| Hyperparameters | XNLI | XNLI | MLQA | CoNLL | CoNLL |
|-----------------|------|------|------|-------|-------|
| Batch size      | 32   | 128  | 32   | 8     | 8     |
| Learning rate   | 5e-5 | 5e-5 | 8e-5 | 4e-4  | 3e-4  |
| Layerwise LR decay | 0.8  | 0.8  | 0.9  | 0.8   | 0.9   |
| LR schedule     | Linear | Linear | Linear | Linear | Linear |
| Warmup faction  | 10%  | 10%  | 10%  | 10%   | 10%   |
| Weight decay    | 0    | 0    | 0    | 0.01  | 0.01  |
| Epoch           | 5    | 1    | 2    | 10    | 10    |

Table 12: Hyperparameters used for ERNIE-M\textsubscript{LARGE} fine-tuning, parameters with "*" are Translate-Train-All setting, without "*" are Cross-lingual setting.

| MODEL | en | fr | es | de | el | bg | ru | tr | ar | vi | th | zh | hi | sw | ur | Avg |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|
| Fine-tune cross-lingual model on English training set (Cross-lingual Transfer) |
| XLM   | 85.0 | 78.7 | 78.9 | 77.8 | 76.6 | 77.4 | 75.3 | 72.5 | 73.1 | 76.1 | 73.2 | 76.5 | 69.6 | 68.4 | 67.3 | 75.1 |
| HICTL | 86.3 | 80.5 | 81.3 | 79.5 | 78.9 | 80.6 | 79.0 | 75.4 | 74.8 | 77.4 | 75.7 | 77.6 | 73.1 | 69.9 | 69.7 | 77.3 |
| ERNIE-M-15 | 85.9 | 80.5 | 81.3 | 79.8 | 79.3 | 80.7 | 78.7 | 76.8 | 76.8 | 78.0 | 76.1 | 77.4 | 72.9 | 68.9 | 68.9 | 77.5 |

| MODEL | af | ar | bg | bn | de | el | es | et | eu | fa | fi | fr | he | hi | hu | id | it | ja |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| Fine-tune cross-lingual model on all training sets (Translate-Train-all) |
| XLM   | 85.0 | 80.8 | 81.3 | 80.3 | 79.1 | 80.9 | 78.3 | 75.6 | 77.6 | 78.5 | 76.0 | 79.5 | 72.9 | 72.8 | 68.5 | 77.8 |
| HICTL | 86.5 | 82.3 | 83.2 | 80.8 | 81.6 | 82.2 | 81.3 | 80.5 | 78.1 | 80.4 | 78.6 | 80.7 | 76.7 | 73.8 | 73.9 | 80.0 |
| ERNIE-M-15 | 86.4 | 82.4 | 83.5 | 82.7 | 83.1 | 83.2 | 81.0 | 80.6 | 80.5 | 80.9 | 79.2 | 80.6 | 77.7 | 75.8 | 72.8 | 80.7 |

Table 13: Evaluation results on XNLI cross-lingual natural language inference in 15 languages model.

| MODEL | af | ar | bg | bn | de | el | es | et | eu | fa | fl | fr | he | hi | hu | id | it | ja |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| VECOLARGE | 80.9 | 85.1 | 91.3 | 78.1 | 98.5 | 89.5 | 97.4 | 94.8 | 97.8 | 93.1 | 95.4 | 93.7 | 85.8 | 94.2 | 93.8 | 93.0 | 92.2 | 92.8 |
| ERNIE-M\textsubscript{LARGE} | 88.6 | 88.9 | 92.2 | 84.8 | 98.8 | 92.4 | 96.3 | 82.4 | 78.8 | 92.5 | 92.2 | 94.0 | 86.2 | 95.4 | 88.7 | 91.5 | 90.3 | 86.7 |
| MODEL | jv | ka | kk | ko | ml | mr | nl | pt | ru | sw | ta | te | th | tl | tr | ur | vi | zh |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| VECOLARGE | 51.5 | 83.0 | 74.1 | 88.7 | 94.8 | 82.5 | 95.9 | 94.6 | 92.2 | 69.7 | 82.4 | 91.0 | 94.7 | 73.0 | 95.2 | 63.8 | 95.1 | 93.9 |
| ERNIE-M\textsubscript{LARGE} | 48.0 | 84.2 | 78.2 | 85.3 | 95.2 | 87.6 | 96.1 | 92.6 | 93.1 | 59.4 | 86.9 | 94.0 | 95.6 | 75.4 | 96.3 | 90.8 | 94.5 | 91.7 |

Table 14: Tatoeba results for each language.