Explicit Alignment Objectives for Multilingual Bidirectional Encoders

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Abstract

Pre-trained cross-lingual encoders such as mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) have proven to be impressively effective at enabling transfer-learning of NLP systems from high-resource languages to low-resource languages. This success comes despite the fact that there is no explicit objective to align the contextual embeddings of words/sentences with similar meanings across languages together in the same space. In this paper, we present a new method for learning multilingual encoders, AMBER (Aligned Multilingual Bidirectional Encoder). AMBER is trained on additional parallel data using two explicit alignment objectives that align the multilingual representations at different granularities. We conduct experiments on zero-shot cross-lingual transfer learning for different tasks including sequence tagging, sentence retrieval and sentence classification. Experimental results show that AMBER obtains gains of up to 1.1 average F1 score on sequence tagging and up to 27.3 average accuracy on retrieval over the XLM-R-large model which has 4.6x the parameters of AMBER.

1 Introduction

Cross-lingual embeddings, both traditional non-contextualized word embeddings (Faruqui and Dyer, 2014) and the more recent contextualized word embeddings (Devlin et al., 2019), are an essential tool for cross-lingual transfer in downstream applications. In particular, multilingual contextualized word representations have proven effective in reducing the amount of supervision needed in a variety of cross-lingual NLP tasks such as sequence labeling (Pires et al., 2019), question answering (Artetxe et al., 2020), parsing (Wang et al., 2019), sentence classification (Wu and Dredze, 2019) and retrieval (Yang et al., 2019a).

Some attempts at training multilingual representations (Devlin et al., 2019; Conneau et al., 2020) simply train a (masked) language model on monolingual data from many languages. These methods can only implicitly learn which words and structures correspond to each-other across languages in an entirely unsupervised fashion, but are nonetheless quite effective empirically (Wu et al., 2020; K et al., 2020). On the other hand, some methods directly leverage multilingual parallel corpora (McCann et al., 2017; Eriguchi et al., 2018; Conneau and Lample, 2019; Huang et al., 2019), which gives some degree of supervision implicitly aligning the words in the two languages. However, the pressure on the model to learn clear correspondences between the contextualized representations in the two languages is still implicit and somewhat weak. Because of this, several follow-up works (Schuster et al., 2019; Wang et al., 2020; Cao et al., 2020) have proposed methods that use word alignments from parallel corpora as the supervision signals to align multilingual contextualized representations, albeit in a post-hoc fashion.

In this work, we propose a training regimen for learning contextualized word representations that encourages symmetry at both the word and sentence levels at training time. Our word-level alignment objective is inspired by work in machine translation that defines objectives encouraging consistency between the source-to-target and target-to-source attention matrices (Cohn et al., 2016). Our sentence-level alignment objective encourages prediction of the correct translations within a mini-batch for a given source sentence, which is inspired by work on learning multilingual sentence representations (Yang et al., 2019a; Wieting et al., 2019). In experiments, we evaluate the zero-shot cross-lingual transfer performance of AMBER on three
different NLP tasks including part-of-speech (POS) tagging, paraphrase classification, and sentence retrieval. We show that AMBER obtains gains by up to 1.1 average F1 score on cross-lingual POS tagging, up to 27.3 average accuracy score on sentence retrieval, and achieves competitive accuracy in paraphrase classification when compared with the XLM-R-large model. This is despite the fact that XLM-R-large is trained on 23.8x as large\footnote{AMBER is trained on 26GB parallel data and 80GB monolingual Wikipedia data, while XLM-R-large is trained on 2.5TB monolingual CommonCrawl data.} and has 4.6x parameters of AMBER. This shows that compared to large amounts of monolingual data, even a small amount of parallel data leads to significantly better cross-lingual transfer learning.

2 Cross-lingual Alignment

This section shows three objectives for training contextualized representations. We denote the monolingual and parallel data as $\mathcal{M}$ and $\mathcal{P}$ respectively.

**Masked Language Modeling (MLM)** A masked language modeling objective takes a pair of sentences $x, y$, and optimizes the prediction of randomly masked tokens in the concatenation of the sentence pair as follows:

$$
\ell_{\text{MLM}}(x, y) = - \mathbb{E}_{z \sim |z|} \log P(z_s | z \setminus s),
$$

where $z$ is the concatenation of the sentence pair $z = [x; y]$, $z_s$ are the masked tokens randomly sampled from $z$, and $z \setminus s$ are all the other tokens except the masked ones.

In the standard monolingual corpus, $x, y$ are two contiguous sentences in a monolingual corpus. In Conneau and Lample (2019), $x, y$ are two sentences in different languages from a parallel corpus, an objective we will refer to as Translation Language Modeling (TLM).

**Sentence Alignment** Our first proposed objective encourages cross-lingual alignment of sentence representations. For a source-target sentence pair $(x, y)$ in the parallel corpus, we separately calculate sentence embeddings denoted as $c_x, c_y$ by averaging the embeddings in the final layer as the sentence embeddings.\footnote{In comparison, mBERT encodes a sentence pair jointly, then uses the CLS token embedding to perform its next sentence prediction task.} We then encourage the model to predict the correct translation $y$ given a source sentence $x$. To do so, we model the conditional probability of a candidate sentence $y$ being the correct translation of a source sentence $x$ as:

$$
P(y|x) = \frac{e^{c_x^T c_y}}{\sum_{y' \in \mathcal{M} \cup \mathcal{P}} e^{c_x^T c_{y'}}},
$$

where $y'$ can be any sentence in any language. Since the normalization term in Eq. (2) is intractable, we approximate $P(y|x)$ by sampling $y'$ within a mini-batch $\mathcal{B}$ rather than $\mathcal{M} \cup \mathcal{P}$. We then define the sentence alignment loss as the average negative log-likelihood of the above probability:

$$
\ell_{\text{SA}}(x, y) = - \log P(y|x).
$$

**Bidirectional Word Alignment** Our second proposed objective encourages alignment of word embeddings by leveraging the attention mechanism in the Transformer model. Motivated by the work on encouraging the consistency between the source-to-target and target-to-source translations (Cohn et al., 2016; He et al., 2016), we create two different attention masks as the inputs to the Transformer model, and obtain two attention matrices in the top layer of the Transformer model. We compute the target-to-source attention matrix $A_{y \rightarrow x}$ as follows:

$$
g_{y \rightarrow x}^l = \text{Attn}(Q = g_{y \rightarrow x}^{l-1}, KV = g_{y \rightarrow x}^{l-1} \cdot W^{l}),
$$

$$
g_{x \rightarrow y}^l = \text{Attn}(Q = g_{x \rightarrow y}^{l-1}, KV = g_{x \rightarrow y}^{l-1} \cdot W^{l}),
$$

$$
\text{Attn}(QKV; W) = \text{softmax}(QW^\top(KW^\top)^\top V)\cdot W^v
$$

$$
A_{y \rightarrow x}[i, j] = g_{y \rightarrow x}^l[i, j].
$$

Figure 1: (a-b) show the computation of the target-to-source attention matrix used for the word alignment objective: (a) Masked attention for source/target (blue/green) sentences on the $l$-th layer; (b) Attention from $y$ to $x$ on the top layer. (c) shows the separate encoding of source/target sentences for the sentence alignment objective.
Table 1: Details of baseline and state-of-the-art models.

| Model     | Data          | Langs | Vocab size | Layers | Parameters | Ratio |
|-----------|---------------|-------|------------|--------|------------|-------|
| AMBER     | Wiki & MT     | 104   | 120K       | 12     | 179M       | 1.0   |
| mBERT     | Wiki          | 104   | 120K       | 12     | 179M       | 1.0   |
| XLM-15    | Wiki & MT     | 15    | 95K        | 12     | 346M       | 1.9a  |
| XLM-100   | Wiki          | 100   | 200K       | 12     | 828M       | 4.6a  |
| XLM-R-base| CommonCrawl   | 100   | 250K       | 12     | 470M       | 2.6x  |
| XLM-R-large| CommonCrawl  | 100   | 250K       | 24     | 816M       | 4.6x  |

where $g^y_{y}$ is the embedding of the $t$-th word in $y$ on the $t$-th layer, $A_{y\rightarrow x}[i, j]$ is the $(i, j)$-th value in the attention matrix from $y$ to $x$, and $W = \{W^q, W^k, W^v\}$ are the linear projection weights for $Q, K, V$ respectively. The source-to-target matrix $A_{x\rightarrow y}$ is computed similarly by switching $x$ and $y$ in Appendix A.2.

To encourage the model to align source and target words in both directions, we aim to minimize the distance between the forward and backward attention matrices. Similarly to Cohn et al. (2016), we aim to maximize the trace of two attention matrices, i.e., $\text{tr} (A_{y\rightarrow x}^T A_{x\rightarrow y})$. Since the attention scores are normalized in $[0, 1]$, the trace of two attention matrices is upper bounded by $\min(|x|, |y|)$, and the maximum value is obtained when the two matrices are identical. Since the Transformer generates multiple attention heads, we average the trace of the bidirectional attention matrices generated by all the heads denoted by the superscript $h$

$$\ell_{WA}(x, y) = 1 - \frac{1}{H} \sum_{h=1}^{H} \frac{\text{tr} (A_{y\rightarrow x}^h A_{x\rightarrow y}^h)}{\min(|x|, |y|)}.$$  \hspace{1cm} (8)

Notably, in the target-to-source attention in Eq (4), with attention masking we enforce that the $t$-th token in $y$ can only perform the attention over its preceding tokens $y_{<t}$ and the source tokens in $x$. This is particularly useful to control the information access of the query token $y_t$, in a manner similar to that of the decoding stage of NMT. Without attention masking, the standard Transformer performs self-attention over all tokens, i.e., $Q = K = g^h$, and minimizing the distance between the two attention matrices by Eq. (8) might lead to a trivial solution where $W^q \approx W^k$.

**Combined Objective** Finally we combine the masked language modeling objective with the alignment objectives and obtain the total loss in Eq. (9).

Notice that in each iteration, we sample a mini-batch of sentence pairs from $M \cup P$.

$$L = E_{(x,y) \in M \cup P} \ell_{MLM}(x, y) + E_{(x,y) \in P} [\ell_{SA}(x, y) + \ell_{WA}(x, y)].$$  \hspace{1cm} (9)

3 Experiments

3.1 Training setup

Following the setting of Hu et al. (2020), we focus on zero-shot cross-lingual transfer where we fine-tune models on English annotations and apply the models to predict on non-English data. Table 1 shows details of models in comparison. Notice that we adopt the exact same architecture as mBERT for AMBER, and first train the model on the Wikipedia data for 1M steps with a larger batch of 8,192 sentence pairs, as these practices have been shown effective in Liu et al. (2019). Starting from our mBERT model, we continue training the model by our objectives for another 1M steps with a batch of 2,048 sentence pairs from Wikipedia corpus and parallel corpus which is used to train XLM-15 (Conneau and Lample, 2019). Notice that AMBER and XLM-15 are both trained on the additional parallel data, while the other models are trained only on monolingual data. Notably, XLM-R-base/large models have 2.6x/4.8x the parameters of AMBER and are trained on the much larger CommonCrawl corpus. More details are in Appendix A.1.

3.2 Result Analysis

**Cross-lingual Part-Of-Speech (POS)** We use the POS tagging data in 13 languages from the Universal Dependency v2.3 (Nivre et al., 2018). Table 2 shows the F1 scores of the zero-shot POS tag predictions by all the models. First, we find that our re-trained mBERT (AMBER with MLM) performs better than the publicly available mBERT, which confirms that pre-training BERT models on a larger parallel data, while the other models are trained only on monolingual data. Notably, XLM-R-base/large models have 2.6x/4.8x the parameters of AMBER and are trained on the much larger CommonCrawl corpus. More details are in Appendix A.1.

**PAWS-X** The Cross-lingual Paraphrase Adversaries from Word Scrambling (Yang et al., 2019b) dataset requires to predict whether two sentences in the same language are paraphrases. We train models on the PAWS training data in English (Zhang et al., 2019), and evaluate the prediction accuracy on the test set translated into 4 other languages.

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^3XLM-R’s Chinese predictions are very poor. A further analysis showed that the sentencepiece tokenizer used by XLM-R introduces many extra “---” (U+2581) tokens as Chinese is written without spaces, and XLM-R usually misclassifies a span with those tokens as PUNCT.
We find that our re-trained mBERT model (AMBER with MLM) obtains substantial improvements in all languages. We use the Tatoeba dataset (Artetxe and Schwenk, 2019), which includes up to 1,000 English-aligned sentence pairs covering 122 languages. We select the 14 non-English languages covered by our parallel data, and follow the setup in (Hu et al., 2020) to retrieve the English translation for a given non-English sentence without fine-tuning models on any extra data. Specifically, we find the nearest neighbour using cosine similarity and calculate the prediction accuracy. In Table 3, we find that XLM-15 that is trained on additional parallel data outperforms the other existing models trained only on monolingual data. We also find that using additional parallel data, AMBER with MLM and TLM objectives significantly improves over AMBER with the MLM objective by 15.6 average accuracy score, while combining our word-level alignment objective yields a marginal improvement over AMBER with MLM and TLM objectives. However, adding the sentence-level alignment objective, AMBER trained by the combined objective can further improve AMBER with the MLM and word-level alignment objectives by 19.1 average accuracy score. This confirms our intuition that the explicit sentence-level objective can effectively leverage the alignment supervision in the parallel corpus, and encourage contextualized sentence representations of aligned pairs to be close by the cosine similarity metric.

Table 3: Accuracy of zero-shot cross-lingual classification on PAWS-X. Bold numbers highlight the highest scores across languages on the existing models (upper part) and AMBER variants (bottom part).

| Model                  | de | en | es | fr | zh | Avg |
|------------------------|----|----|----|----|----|-----|
| mBERT (public)         | 85.7| 94.0| 87.4| 87.0| 77.0| 86.2|
| XLM-15                 | 88.5| 94.7| 89.3| 89.6| 78.1| 88.0|
| XLM-100                | 85.9| 94.0| 88.3| 87.4| 76.5| 86.4|
| XLM-R-base             | 87.0| 94.2| 88.6| 88.7| 78.5| 87.4|
| XLM-R-large            | 89.7| 94.7| 90.1| 90.4| 82.3| 89.4|
| AMBER (MLM, our mBERT) | 87.3| 93.9| 87.5| 87.8| 78.8| 87.1|
| AMBER (MLM+TLM)        | 87.6| 95.8| 87.4| 88.9| 78.7| 87.7|
| AMBER (MLM+TLM+WA)     | 88.9| 95.5| 88.9| 90.7| 81.1| 89.0|
| AMBER (MLM+TLM+WA+SA)  | 89.4| 95.6| 89.2| 90.7| 80.9| 89.2|

Table 4: Accuracy of Part-of-Speech tag predictions from the Universal Dependency v2.3. Bold numbers highlight the highest scores across languages on the existing models (upper part) and AMBER variants (bottom part).

| Method                  | ar | bg | de | el | en | es | fr | hi | ru | tr | ur | vi | zh | Avg |
|-------------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|
| mBERT (public)          | 14.9| 85.2| 89.3| 82.8| 95.3| 85.7| 84.1| 65.1| 86.0| 67.5| 57.4| 18.5| 58.9| 68.5|
| XLM-15                  | 17.5| 86.1| 89.3| 85.4| 95.7| 85.9| 84.9| 63.9| 86.8| 69.3| 55.1| 18.0| 57.2| 68.8|
| XLM-100                 | 17.1| 85.8| 89.3| 85.7| 95.4| 85.3| 84.3| 67.0| 87.1| 65.0| 62.0| 19.2| 60.2| 69.5|
| XLM-R-base              | 17.6| 88.5| 91.1| 88.2| 95.8| 87.2| 85.7| 70.1| 88.9| 72.7| 61.6| 19.2| 27.9| 68.8|
| XLM-R-large             | 18.1| 87.4| 91.9| 87.9| 96.3| 87.8| 87.3| 76.1| 89.9| 74.3| 67.6| 19.5| 26.5| 70.0|

Table 2: F1 scores of Part-of-Speech tag predictions from the Universal Dependency v2.3. Bold numbers highlight the highest scores across languages on the existing models (upper part) and AMBER variants (bottom part).

| Method                  | ar | bg | de | el | en | es | fr | hi | ru | tr | ur | vi | zh | Avg |
|-------------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|
| mBERT (public)          | 15.4| 86.6| 90.1| 84.3| 95.5| 86.5| 84.6| 68.2| 86.8| 69.0| 59.2| 18.7| 62.1| 69.8|
| XLM-15                  | 16.0| 87.2| 91.5| 86.4| 95.7| 86.9| 85.2| 67.7| 87.9| 72.9| 57.9| 19.1| 62.1| 70.5|
| XLM-100                 | 14.8| 86.9| 90.4| 84.9| 95.6| 86.7| 84.8| 72.5| 87.8| 73.9| 63.8| 19.5| 62.3| 71.1|
| XLM-R-base              | 14.6| 87.1| 90.6| 85.9| 95.5| 87.0| 86.0| 68.6| 87.4| 73.4| 60.2| 18.8| 61.8| 70.5|
| XLM-R-large             | 14.6| 87.1| 90.6| 85.9| 95.5| 87.0| 86.0| 68.6| 87.4| 73.4| 60.2| 18.8| 61.8| 70.5|

Table 3: Sentence retrieval accuracy on the Tatoeba dataset. Bold numbers highlight the highest scores across languages on the existing models (upper part) and AMBER variants (bottom part).
Table 5: Accuracy of zero-shot crosslingual classification on the XNLI dataset. Bold numbers highlight the highest scores across languages on the existing models (upper part) and AMBER variants (bottom part).

| Models                  | en  | zh  | es  | de  | ar  | ur  | ru  | bg  | el  | fr  | hi  | sw  | th  | tr  | vi  | avg |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| mBERT (public)          | 80.8| 67.8| 73.5| 70.0| 64.3| 57.2| 67.8| 68.0| 65.3| 73.4| 58.9| 49.7| 54.1| 60.9| 69.3| 65.4|
| XLM-15                  | 84.1| 68.8| 77.8| 75.7| 70.4| 62.2| 75.0| 75.7| 73.3| 78.0| 67.3| 67.5| 70.5| 70.0| 73.0| 72.6|
| XLM-100                 | 82.8| 70.2| 75.5| 72.7| 66.0| 59.8| 69.9| 71.9| 70.4| 74.3| 62.5| 58.1| 65.5| 66.4| 70.7| 69.1|
| XLM-R-base              | 83.9| 73.6| 78.3| 75.2| 71.9| 65.4| 75.1| 76.7| 75.4| 77.4| 69.1| 62.2| 72.0| 70.9| 74.0| 73.4|
| XLM-R-large             | 88.7| 78.2| 83.7| 82.5| 77.2| 71.7| 79.1| 83.0| 80.8| 82.2| 75.6| 75.6| 71.2| 71.2| 77.4| 78.0| 79.3| 79.2|
| AMBER (MLM, our mBERT)  | 82.1| 71.0| 75.3| 72.7| 66.2| 60.1| 70.4| 71.3| 67.9| 74.4| 63.6| 50.1| 55.0| 64.2| 71.6| 67.7|
| AMBER (MLM+TLM)         | 84.3| 71.6| 77.2| 73.9| 69.1| 59.6| 72.5| 73.6| 70.9| 78.0| 64.7| 57.4| 65.0| 72.2| 73.1| 70.9|
| AMBER (MLM+TLM+WA)      | 84.1| 72.1| 76.6| 74.7| 69.3| 61.5| 72.9| 73.9| 71.6| 77.7| 65.7| 58.6| 65.3| 72.7| 73.4| 71.3|
| AMBER (MLM+TLM+WA+SA)   | 84.7| 71.6| 76.9| 74.2| 70.2| 61.0| 73.3| 74.3| 72.5| 76.6| 66.2| 59.9| 65.7| 73.2| 73.4| 71.6|

proves the public mBERT model by 2.3 average accuracy score. Additionally, AMBER trained by our explicit alignment objectives obtains a large gain of 3.9 average accuracy score than AMBER trained with only the MLM objective. Compared with existing XLM/XLM-R models with much more parameters, AMBER trained with only MLM objective falls short of some low-resourced and morphologically rich languages such as Swahili, Thai, and Turkish. However, AMBER trained with our alignment objectives significantly narrows the gap of classification accuracy on these languages with respect to the XLM/XLM-R models.

5 Conclusion

This paper examined the problem of aligning contextualized representations of multilingual encoders by two explicit alignment objectives. Our zero-shot cross-lingual transfer experiments show that multilingual models trained by our alignment objectives on even a small amount of parallel data obtain significantly better cross-lingual generalization, when compared to much larger models trained on large amounts of monolingual data. In particular, this finding indicates that a compact multilingual model can be trained more efficiently on parallel data, which reduces the heavy reliance on computational resources. Nonetheless, several challenging and promising directions can be considered in the future. First, most existing multilingual models tokenize words into subword units, which makes the alignment less interpretable. How to align a span of subword units with meaningful semantics at the phrase level deserves further investigation. Second, several studies (Ghader and Monz, 2017; Li et al., 2019) have shown that attention may fail to capture word alignment for some language pairs, and Legrand et al. (2016); Alkhouli et al. (2018) proposed neural word alignment to improve the word alignment quality. Incorporating such recent advances into the alignment objective is one future direction. Third, how to fine-tune a well-aligned multilingual model on English annotations without the catastrophic forgetting of the alignment information is a potential way to improve cross-lingual generalization on the downstream applications.

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References

Tamer Alkhouli, Gabriel Bretschner, and Hermann Ney. 2018. On the alignment problem in multi-head attention-based neural machine translation. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 177–185, Brussels, Belgium. Association for Computational Linguistics.

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics.

Mikel Artetxe and Holger Schwenk. 2019. Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond. Transactions of the ACL 2019.

Peter F. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer. 1993. The mathematics of statistical machine translation: Parameter estimation. Computational Linguistics, 19(2):263–311.

Steven Cao, Nikita Kitaev, and Dan Klein. 2020. Multilingual alignment of contextual word representations. In International Conference on Learning Representations.

Trevor Cohn, Cong Duy Vu Hoang, Ekaterina Vymolova, Kaisheng Yao, Chris Dyer, and Gholamreza Haffari. 2016. Incorporating structural alignment biases into an attentional neural translation model. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 876–885, San Diego, California. Association for Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics.

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.

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, Minneapolis, Minnesota. Association for Computational Linguistics.

Akiko Eriyuchi, Melvin Johnson, Orhan Firat, Hideto Kazawa, and Wolfgang Macherey. 2018. Zero-shot cross-lingual classification using multilingual neural machine translation. arXiv preprint arXiv:1809.04686.

Manaal Faruqui and Chris Dyer. 2014. Improving vector space word representations using multilingual correlation. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 462–471, Gothenburg, Sweden. Association for Computational Linguistics.

Hamidreza Ghader and Christof Monz. 2017. What does attention in neural machine translation pay attention to? In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 30–39, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Di He, Yingce Xia, Tao Qin, Liwei Wang, Nenghai Yu, Tie-Yan Liu, and Wei-Ying Ma. 2016. Dual learning for machine translation. In Advances in Neural Information Processing Systems 29, pages 820–828. Curran Associates, Inc.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. In International Conference on Machine Learning (ICML).

Haoyang Huang, Yaobo Liang, Nan Duan, Ming Gong, Linjun Shou, Daxin Jiang, and Ming Zhou. 2019. Unicoder: A universal language encoder by pretraining 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, Hong Kong, China. Association for Computational Linguistics.

Karthikeyan K, Zihan Wang, Stephen Mayhew, and Dan Roth. 2020. Cross-lingual ability of multilingual bert: An empirical study. In International Conference on Learning Representations.

Joël Legrand, Michael Auli, and Ronan Collobert. 2016. Neural network-based word alignment through score aggregation. In Proceedings of the First Conference on Machine Translation: Volume 1, Research Papers, pages 66–73, Berlin, Germany. Association for Computational Linguistics.
Yuan Zhang, Jason Baldridge, and Luheng He. 2019. 
PAWS: Paraphrase adversaries from word scrambling. 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 1298–1308, Minneapolis, Minnesota. Association for Computational Linguistics.
A Appendices

A.1 Training details

Although English is not the best source language for some target languages (Lin et al., 2019), this zero-shot cross-lingual transfer setting is still practical useful as many NLP tasks only have English annotations. To continue training AMBER with additional objectives on parallel data, we use 10k warmup steps with the peak learning rate of 1e-4, and use a linear decay of the learning rate. All models are pre-trained with our proposed objectives on TPU v3, and we use the same hyper-parameter setting for our AMBER variants in the experiments. For fine-tuning the models on the downstream applications, we use the constant learning rate of 2e-5 as suggested in the original paper (Devlin et al., 2019). We fine-tune all the models for 10 epochs on the cross-lingual POS tag prediction task, and 5 epochs on the paraphrase classification task. We use the batch size of 32 for all the models. All models are fine-tuned on 2080Ti GPUs. All the datasets in the downstream applications can be downloaded by the script at https://github.com/google-research/xtreme/blob/master/scripts/download_data.sh. We build our AMBER on top of the original mBERT implementation at https://github.com/google-research/bert, and we will release our pre-trained AMBER models and code.

A.2 Source-to-target attention matrix

We derive the source-to-target attention matrix as follow:

$$g^L_{xj} = \text{Attn}(Q = g^L_{x-1}, KV = g^L_{x}[<j; y]}, W^L),$$

$$g^L_{yj} = \text{Attn}(Q = g^L_{y}, KV = g^L_{y}^{-1}; W^L),$$

$$\text{Attn}(QKV; W) = \text{softmax}(QW^q(KW^k)^T)VV^w$$

$$A_{x \rightarrow y}[j, i] = g^L_{xj} \cdot g^L_{yi},$$