ALIGN-MLM: Word Embedding Alignment is Crucial for Multilingual Pre-training

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Abstract
Multilingual pre-trained models exhibit zero-shot cross-lingual transfer, where a model fine-tuned on a source language achieves surprisingly good performance on a target language. While studies have attempted to understand transfer, they focus only on MLM, and the large number of differences between natural languages makes it hard to disentangle the importance of different properties. In this work, we specifically highlight the importance of word embedding alignment by proposing a pre-training objective (ALIGN-MLM) whose auxiliary loss guides similar words in different languages to have similar word embeddings. ALIGN-MLM either outperforms or matches three widely adopted objectives (MLM, XLM, DICT-MLM) when we evaluate transfer between pairs of natural languages and their counterparts created by systematically modifying specific properties like the script. In particular, ALIGN-MLM outperforms XLM and MLM by 35 and 30 F1 points on POS-tagging for transfer between languages that differ both in their script and word order (left-to-right v.s. right-to-left). We also show a strong correlation between alignment and transfer for all objectives (e.g., $\rho_s = 0.727$ for XNLI), which together with ALIGN-MLM’s strong performance calls for explicitly aligning word embeddings for multilingual models.\footnote{Code available at: https://github.com/princeton-nlp/align-mlm}  

1 Introduction
Multilingual pre-trained models like Multilingual-BERT (Devlin, 2019) and XLM (Conneau and Lample, 2019) have shown impressive zero-shot cross-lingual transfer (hereon, transfer). However, predicting the factors required for good transfer between languages is challenging, given the large number of linguistic factors which can vary between them (e.g., script, syntax, and vocabulary size). Recent works have alleviated this issue (Deshpande et al., 2021; K et al., 2020) by considering transfer between natural languages and counterparts constructed by modifying specific aspects (e.g., word order, transliteration). However, they analyze only the masked language-modeling (MLM) pre-training objective, even though newer objectives like XLM (Conneau and Lample, 2019) have been proposed and widely adopted. Furthermore, while they highlight weaknesses of MLM, they do not propose improvements.

In this paper, we address both these issues by proposing a multilingual pre-training objective called ALIGN-MLM which highlights the importance of word embedding alignment. ALIGN-MLM incorporates alignment across languages by increasing the cosine similarity of embeddings corresponding to words in different languages with the same meaning (left). These words are chosen from a small bilingual dictionary (here, two word pairs denoted by orange arrows). Effectiveness of transfer is measured by the difference between supervised performance and zero-shot transfer ($\Delta$), with lower values being better. ALIGN-MLM (yellow) outperforms or matches other multilingual pre-training objectives (here by $> 30$ F1 points on POS).
MLM always outperforms or performs on par with three widely used objectives: MLM (Devlin et al., 2019), XLM (uses parallel sentences) (Conneau and Lample, 2019) and DICT-MLM (uses a dictionary) (Chaudhary et al., 2020). For example, ALIGN-MLM outperforms XLM and MLM by 30 and 35 F1 points on part-of-speech tagging for a language pair which differ in their script and have inverted word orders. ALIGN-MLM’s strong performance displays the importance of word embedding alignment for multilingual pre-training.

Furthermore, we show that even for other pre-training objectives (MLM, XLM, DICT-MLM), there exists a strong and positive correlation between word embedding alignment and zero-shot transfer ($\rho_s = 0.727$ for XNLI). This provides evidence that word embedding alignment is crucial for transfer, and its absence leads to poor transfer even for widely adopted objectives like XLM. ALIGN-MLM offers evidence that existing pre-training objectives can be improved by incorporating word alignment.

2 Related Work

Analysis of multilingual models Multilingual pre-trained models (Devlin, 2019; Conneau and Lample, 2019; Conneau et al., 2020a; Xue et al., 2021; Khanuja et al., 2021) exhibit zero-shot cross-lingual transfer, but crucial properties required for transfer between pairs of languages is still unclear. Several analysis studies have put forth inconsistent conclusions about factors like subword overlap and typological similarity (Pires et al., 2019; Conneau et al., 2020b; Wu and Dredze, 2019; Hsu et al., 2019; Lin et al., 2019). Some recent studies (Deshpande et al., 2021; Wu et al., 2022; Dufter and Schütze, 2020; K et al., 2020) consider transfer in controlled settings, between natural languages and derived counterparts created by modifying specific linguistic aspects like script and word order. However, these methods only investigate the masked language-modeling (MLM) objective (Devlin et al., 2019), whereas we additionally analyze newer pre-training methods like XLM (Conneau and Lample, 2019) and DICT-MLM (Chaudhary et al., 2020).

Embedding alignment The ALIGN-MLM objective is inspired by our own analysis in this work and insight from previous studies that have explored word embedding alignment (Cao et al., 2019; Wang et al., 2019; Schuster et al., 2019; Ruder et al., 2019; Yang et al., 2021; Chaudhary et al., 2020; Khemchandani et al., 2021; Dou and Neubig, 2021). ALIGN-MLM differs from these studies by (1) using bilingual dictionaries instead parallel sentences, (2) applying our objective during pre-training, and (3) explicitly aligning the embedding spaces.

3 Approach

We analyze multilingual models pre-trained on two languages ($L_1$, $L_2$) and describe the components.

Multilingual pre-training We consider three existing multilingual pre-training objectives. (1) Masked language-modeling (MLM) (Devlin et al., 2019) involves pre-training a Transformer (Vaswani et al., 2017) simultaneously on both languages. (2) Cross-lingual language models (XLM) (Conneau and Lample, 2019) additionally use translation language-modeling (TLM) which performs MLM on a corpus of parallel sentence pairs. Formally $C_1, C_2$ are the corpora for $L_1$ and $L_2$ respectively, and $C_{1-2}$ contains the parallel sentences. (3) DICT-MLM (Chaudhary et al., 2020) uses MLM, but it randomly translates tokens in masked positions to the other language with the help of a bilingual dictionary, thus creating code-switched data ($\tilde{C}_1$) (Newman, 1951).

$$L_{\text{MLM}} := L_{\text{MLM}}(C_1) + L_{\text{MLM}}(C_2)$$
$$L_{\text{XLM}} := L_{\text{MLM}}(C_1) + L_{\text{MLM}}(C_2) + L_{\text{TLM}}(C_{1-2})$$
$$L_{\text{DICT-MLM}} := L_{\text{MLM}}(\tilde{C}_1) + L_{\text{MLM}}(\tilde{C}_2)$$

Incorporating alignment during pre-training We propose ALIGN-MLM which incorporates word embedding alignment by explicitly encouraging it during pre-training through an auxiliary loss, and compare it with the aforementioned objectives. ALIGN-MLM uses a bilingual dictionary to guide word embeddings of translations to be similar by increasing their cosine similarity. Formally, let $B$ be a bilingual dictionary with $B_{ij}$ and $B_{i2}$, belonging to $L_1$ and $L_2$, corresponding to the tokens in the $i$th entry. Further, let $\mathcal{E}[B_{ij}]$ be the embedding of token $B_{ij}$. $\alpha$ is a hyperparameter which controls the relative importance of the alignment loss.

$$L_{\text{ALIGN}} := -\frac{1}{|B|} \sum_{i=1}^{|B|} \cos \text{sim}(\mathcal{E}[B_{i1}], \mathcal{E}[B_{i2}])$$

$$L_{\text{ALIGN-MLM}} := L_{\text{MLM}} + \alpha \cdot L_{\text{ALIGN}}$$

Unlike XLM, ALIGN-MLM uses a bilingual dictionary instead of parallel sentences, but only a bilingual dictionary which is easy to obtain and also used by DICT-MLM.
We consider three language pairs with English as source language (\(L_{\text{NL}}\)) and create a derived language \(L_{\text{deriv}}\): (1) transliteration – \(T_{\text{trans}}\) (changes the script of the language), (2) inversion – \(T_{\text{inv}}\) (inverts the order of tokens in the sentence), and (3) syntax – \(T_{\text{syn}}\) (modifies the syntactic properties, namely the subject-verb-object and noun-adjective order). The transformations are applied both at pre-training and fine-tuning time to create corresponding derived language datasets, and we present the procedure and examples in Appendix F. We pre-train a separate model for every natural-derived language pair. For each pair, we measure zero-shot transfer (ZS) by fine-tuning the model on a downstream task in \(L_{\text{NL}}\) and testing on \(L_{\text{deriv}}\). We also compute the supervised performance (SUP) by both fine-tuning and testing on \(L_{\text{deriv}}\). Since SUP serves as a plausible upper-bound on ZS, a smaller difference (\(\Delta = \text{SUP} - \text{ZS}\)) characterizes better transfer.

### 4 Experimental setup

We consider three language pairs with English as source language \(L_{\text{NL}}\). \(L_{\text{deriv}}\) is created by applying the transformations (1) \(T_{\text{trans}}\), (2) \(T_{\text{trans}} \circ T_{\text{inv}}\), and (3) \(T_{\text{trans}} \circ T_{\text{syn}}\), where \(T_{1} \circ T_{2}\) represents applying transformation \(T_{2}\) followed by \(T_{1}\). Thus, \(T_{\text{trans}} \circ T_{\text{inv}}\) creates a language which differs from English both in its script and syntax. We evaluate on three tasks from XTREME (Hu et al., 2020) – natural language inference (Conneau et al., 2018), named-entity recognition (Pan et al., 2017), and part-of-speech tagging (Nivre et al., 2018), with accuracy for NLI and F1 for NER and POS as the metrics. We compare MLM, XLM, DICT-MLM, and ALIGN-MLM on all language pairs and tasks, and defer pre-training and other details to Appendices G, H.

### 5 Results

**ALIGN-MLM outperforms MLM, XLM, and DICT-MLM**

ALIGN-MLM’s strong performance highlights the importance of word embedding alignment (Figure 2). All objectives transfer well between language pairs which differ only in their script (\(T_{\text{trans}}\)), as substantiated by \(\Delta \approx 0\) (first plot, Fig 2). However, MLM, XLM, and DICT-MLM perform poorly on language pairs which differ in their script and have inverted word orders (\(T_{\text{trans}} \circ T_{\text{inv}}\), second plot—Fig 2), with ALIGN-MLM outperforming or matching them. For example, ALIGN-MLM is better than both XLM and DICT-MLM by over 1.5 and 3.5 points on XNLI and NER. The difference is even more significant for POS tagging, with ALIGN-MLM outperforming XLM by over 30 points. ALIGN-MLM’s zero-shot score (ZS) is 92.0, as opposed to XLM’s 61.8 and DICT-MLM’s 76.0. For \(T_{\text{trans}} \circ T_{\text{syn}}\), which makes local syntax changes when compared to \(T_{\text{trans}} \circ T_{\text{inv}}\), we observe that all objectives outperform MLM (third plot, Fig 2) with ALIGN-MLM beating MLM by over 6 points on NER. ALIGN-MLM’s strong performance when compared to prior widely adopted objectives underlines the importance of alignment.

**Does more parallel data help XLM?**

Results in Figure 2 show that ALIGN-MLM outperforms XLM even though the former does not use parallel data. We now vary the amount of parallel sentences used by XLM relative to the number of sentences used for standard MLM pre-training. For example, if the...
0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5
0 20 40 60 80 100
Alignment
Spearman’s ρ = 0.727, p < .01
Align-MLM
XLM
DICT-MLM
MLM
trans
trans inv
trans syn

Figure 3: Alignment vs Δ for XNLI. We see that better transfer (lower Δ) is strongly correlated with better alignment (ρs = 0.73). For example, for Ttrans ◦ Tinv, ALIGN-MLM has both the best transfer and alignment.

Correlation between word embedding alignment and transfer There exists a one-to-one correspondence between the vocabularies of LNL and Lderiv when transliteration (Ttrans) is used (even if other transformations are used in addition). Following Deshpande et al. (2021), the alignment score of a token in the vocabulary of LNL can be defined as 100% if its cosine similarity with the corresponding token in the Lderiv is highest among Lderiv’s vocabulary, else it is 0%. We denote the average alignment for all tokens in the LNL to be “alignment”. Figure 3 shows that higher alignment is correlated with better transfer (smaller Δ) on XNLI. For example, across pre-training methods, for language pairs constructed using Ttrans ◦ Tinv, better alignment implies better transfer (red triangles). Better alignment is strongly correlated with better transfer as measured by Spearman correlation (ρs = 0.73, p (2-tailed) < .01), and this is also true for other tasks (Appendix E). This highlights the importance of alignment for all pre-training methods.

6 Conclusion
ALIGN-MLM highlights the importance of word embedding alignment during pre-training. It matches or even outperforms several objectives from prior work (MLM, XLM, DICT-MLM). We also show that alignment is strongly correlated with better transfer performance for all objectives. Taken together, our results call for improvements in multilingual pre-training objectives, and we recommend doing so by explicitly incorporating alignment, rather than relying on its emergence.
7 Limitations

Our focus for this paper is on creating a controlled study because previous studies have failed to conclude anything significant while using natural languages (refer to discussion in (§ 2)). Our experiments are done on language pairs which have controlled differences, because natural languages can have multiple differences which makes it hard to pinpoint crucial properties for transfer. While we are comprehensive in creating these language pairs and use ones in literature (Deshpande et al., 2021), future studies can consider more properties while creating language pairs. Further, we need large scale compute and use TPUs for our analysis because of the scale of our experiments.

Acknowledgement

This work was funded through a grant from the Chadha Center for Global India at Princeton University. We thank the Google Cloud Research program for computational support.

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Appendix

A Comparing different pre-training objectives

We add an extended version of Figure 2 which compares different pre-training objectives in Table 3.

B DICT-MLM vs ALIGN-MLM

We compare DICT-MLM and ALIGN-MLM while varying the size of the bilingual dictionary relative to the vocabulary size of $L_{NL}$ and report the results in tables 4 and 5 for $T_{trans} \circ T_{inv}$ and $T_{trans} \circ T_{syn}$ respectively. We observe that in all but one case ALIGN-MLM outperforms DICT-MLM by making better utilization of the bilingual dictionary.

C Varying the amount of parallel data for XLM

We vary the amount of parallel data used by XLM relative to the amount of unsupervised data used by MLM and report the results in Table 6. We notice that as we increase the amount of parallel sentences, performance improves for XNLI and NER, but does not change or decreases for POS. Regardless of the task, transfer can be poor even when a large number of parallel sentences are used (such as 100%), as measured by $\Delta$.

D Vocabulary overlap

We measure the performance of XLM when $L_{NL}$ and $L_{deriv}$ share a percentage of the vocabulary for $T_{trans} \circ T_{inv}$. Instead of $T_{trans}$ changing the script of all the tokens in $L_{NL}$, it changes only a percentage of tokens. We present the results in Table 7, where we notice that as $L_{NL}$ and $L_{deriv}$ share more sub-words, transfer improves, as expected.

E Analyzing word embedding alignment and zero-shot transfer

From our results in Table 8, we observe that better word embedding alignment is strongly correlated with better transfer as measured by spearman correlation ($\rho_s = 0.727$, $p$ (2-tailed) < .01), and this is true for other tasks as well (NER – $\rho_s = 0.781$, $p < .01$ and POS – $\rho_s = 0.734$, $p < .01$).

F Transformations and their examples

We present examples of transformations in Table 9, borrowed from Deshpande et al. (2021). We follow Deshpande et al. (2021) for all the transformations.
Table 3: Results for all four pre-training methods considered in the paper. All four pre-training methods use their default setup.

| Pre-training method | Transformation | XNLI | NER | POS |
|---------------------|----------------|------|-----|-----|
|                     |                | SUP | ZS  | ∆   | SUP | ZS  | ∆   |
| MLM                 | Trans          | 76.4| 74.9| 1.5 | 80.6| 78.0| 2.6 |
|                     | Trans + Inv    | 73.9| 56.7| 17.2| 79.2| 35.9| 43.3|
|                     | Trans + Syn    | 73.5| 69.0| 4.5 | 71.3| 52.3| 19.0|
| XLM                 | Trans          | 77.3| 77.5| -0.2| 80.8| 79.7| 1.1 |
|                     | Trans + Inv    | 75.4| 67.2| 8.2 | 80.0| 60.7| 19.4|
|                     | Trans + Syn    | 76.1| 74.1| 1.9 | 71.5| 59.6| 11.9|
| DICT-MLM            | Trans          | 77.0| 75.9| 1.1 | 79.3| 78.3| 1.1 |
|                     | Trans + Inv    | 74.5| 65.3| 9.2 | 79.1| 59.8| 19.3|
|                     | Trans + Syn    | 74.3| 72.2| 2.2 | 71.4| 57.6| 13.8|
| ALIGN-MLM           | Trans          | 75.1| 75.5| -0.5| 79.4| 78.6| 0.8 |
|                     | Trans + Inv    | 75.5| 68.8| 6.7 | 80.0| 64.5| 15.5|
|                     | Trans + Syn    | 74.7| 71.1| 3.6 | 71.3| 58.3| 13.1|

Table 4: Results for $T_{trans} \circ T_{inv}$

| % tokens in dictionary | XNLI (Δ) | NER (Δ) | POS (Δ) |
|------------------------|----------|---------|---------|
|                        | DICT    | ALIGN   | DICT    | ALIGN   | DICT    | ALIGN   |
| 25%                    | 9.2     | 6.7     | 19.3    | 15.5    | 19.0    | 3.0     |
| 50%                    | 6.0     | 5.7     | 15.9    | 14.0    | 3.4     | 1.5     |

Table 5: Results for $T_{trans} \circ T_{syn}$

| % tokens in dictionary | XNLI (Δ) | NER (Δ) | POS (Δ) |
|------------------------|----------|---------|---------|
|                        | DICT    | ALIGN   | DICT    | ALIGN   | DICT    | ALIGN   |
| 25%                    | 2.2     | 3.6     | 13.8    | 13.1    | 1.0     | 0.8     |
| 50%                    | 2.9     | 1.6     | 13.4    | 11.5    | 0.9     | 0.7     |

Transliteration We create a copy of the vocabulary for all the tokens in $L_{NL}$ other than the special tokens like [CLS].

Inversion We invert the order of tokens in a sentence. We use the period token to decide sentence boundaries both during pre-training and fine-tuning.

Syntax We modify the syntax of the English sentence to match that of French by using Wang and Eisner (2016) which stochastically re-orders the dependents of nouns and verbs in the dependency parse.

G Implementation Details

G.1 Data Generation

Our base English training corpus is the Wikitext-103 training corpus (Merity et al., 2017), the same as the one used by Deshpande et al. (2021). Let this pre-training corpus be denoted as $C_{L_{NL}}$. To generate the synthetic corpus, we perform the transformation on each sentence individually to generate a new corpus, which we will denote as $C_{L_{deriv}}$. For the syntax transformation ($T_{syn}$), we follow Deshpande et al. (2021) and use galactic dependencies (Wang and Eisner, 2016) to stochastically permute the nodes in the dependency parse from $L_{NL}$’s syntax (here, English) to that of French.

The procedure for generating the finetuning corpora is the same. We perform the desired transformation on the input sentences, as well as any other corresponding labels. In XNLI, we also transform the second sentence. In NER and POS, we transform the tags of each word by moving them to the corresponding location where the actual word has been moved to. In NER, we do additional transformations on sequences of B and O tags to ensure B always comes before O, which is a requirement of the NER task.

Our vocabulary of size 40,000 is generated using the same approach as Deshpande et al. (2021); we use the shared-byte-pair-encoding tokenizer described in (Sennrich et al., 2015). Bilingual dictionaries are generated using two sets of tokens created using transliteration, one for the original-language and one for the derived-language, with a 1-to-1 mapping between them. In particular, the mapping represents the translation between the words of the dictionary.
| # parallel sent relative to MLM | XNLI | NER | POS |
|---------------------------------|------|-----|-----|
|                                 | SUP  | ZS  | ∆   |
| 1%                              | 75.9 | 59.8| 16.1|
| 10%                             | 75.3 | 65.8| 9.5 |
| 25%                             | 75.4 | 67.2| 8.2 |
| 100%                            | 75.0 | 65.2| 9.8 |

Table 6: XLM results when varying the amount of parallel sentences for \( T_{\text{trans}} \circ T_{\text{inv}} \).

| % vocabulary overlap | XNLI | NER | POS |
|----------------------|------|-----|-----|
|                      | SUP  | ZS  | ∆   |
| 0%                   | 75.4 | 67.2| 8.2 |
| 25%                  | 76.6 | 71.3| 5.2 |
| 50%                  | 75.0 | 72.2| 2.8 |

Table 7: XLM results when varying the percentage of vocabulary overlap between \( L_1 \) and \( L_2 \), for the transformation \( T_{\text{trans}} \circ T_{\text{inv}} \).

### G.2 MLM

Our approach for MLM follows the same structure as Deshpande et al. (2021). The only difference is that we perform syntax and inversion transformations on a word level, instead of on a token level. Their approach involved tokenizing the words, then performing the transformation on the tokens, whereas our approach involves first performing the transformation on the words of a sentence to generate \( C_{\text{deriv}} \), before passing it into the MLM model. For more information, see G.1.

### G.3 XLM

Let us define the set of sentences in the original dataset as \( s_{1:N}^{L_{\text{NL}}} \), where \( N \) is the number of sentences in \( C_{\text{NL}} \). Similarly, the sentences in our synthetic language will be denoted as \( s_{1:N}^{L_{\text{deriv}}} \). Both are individually tokenized into \( N \) sentences of word tokens, which we’ll denote \( x_{1:N}^{L_{\text{NL}}} \) and \( x_{1:N}^{L_{\text{deriv}}} \). We keep concatenating these sentences of tokens together until including any more would exceed the max tokens per instance limit of \( H = 512 \), where an instance represents a single vector of data being fed to the model (equivalently the coresponding data for a batch size of 1). Therefore, each instance is of the form \( v_i^L = [x_{\alpha_{L},i:a_{L},i+1}, \text{pad}_{L}^i] \), where \( L \in \{ L_{\text{NL}}, L_{\text{deriv}} \} \), \( x_{\alpha_{L},i:a_{L},i+1} \) is the concatenation of the token sentences in \( L \) from \( a_{L},i \) to \( a_{L},i+1 \) inclusive, and \( \text{pad}_{L}^i \) is a sequence of padding tokens to ensure \( v_i^L \) is of length 512. Simultaneously, as in all RoBERTa models, we generate corresponding position tokens for every input token in \( v_i^L \). We also assign a language ID token for every input token in \( v_i^L \), to indicate if the input token is from \( L_{\text{NL}} \) or \( L_{\text{deriv}} \). The position and language ID tokens corresponding to padding word tokens are also changed to padding tokens.

Denote each combined instance of word, position, and language ID tokens as \( w_i^L \). Applying the above steps generates data of the form \( D = \{ u_{1:M_1}^{L_{\text{NL}}}, w_{1:M_2}^{L_{\text{deriv}}} \} \), which we will denote as MLM data since each instance is monolingual. It isn’t necessarily the case that \( M_1 = M_2 \), since the number of tokens in the original and synthetic text, even when parallel, can be different.

The next step is to generate TLM data. Unlike the original implementation in Lample and Conneau (2019), the architecture we’re using has a fixed maximum sequence length. Therefore, we decided to always divide an instance into (at most) 256 tokens of the original language followed by (at most) 256 instances of the synthetic language. The remaining space in both the first and second half is filled up with post-padding tokens. In every instance, we keep sampling until adding another parallel sentence of both original and synthetic data would cause the tokens in the
| Pre-training method | Transformation | Alignment | XNLI ∆ (1) |
|---------------------|----------------|-----------|------------|
| MLM                 | Trans          | 90.0      | 1.5        |
|                     | Trans + Inv    | 0.3       | 17.2       |
|                     | Trans + Syn    | 57.3      | 4.5        |
| XLM                 | Trans          | 97.7      | 0.2        |
|                     | Trans + Inv    | 85.6      | 8.2        |
|                     | Trans + Syn    | 98.6      | 1.9        |
| DICT-MLM            | Trans          | 95.7      | 1.1        |
|                     | Trans + Inv    | 64.2      | 9.2        |
|                     | Trans + Syn    | 93.7      | 2.2        |
| ALIGN-MLM           | Trans          | 98.4      | -0.5       |
|                     | Trans + Inv    | 95.2      | 6.7        |
|                     | Trans + Syn    | 98.2      | 3.6        |

Table 8: Word embedding alignment scores for all pre-training methods considered. All four pretraining-methods use their default setup.

| Transformation | Instance (s) | Transformed instance (T(s)) |
|---------------|--------------|-----------------------------|
| Inversion ($T_{inv}$) | Welcome to ACL | ACL to Welcome |
| Transliteration ($T_{trans}$) | I am Sam . I am | ♣(i) ♦(am) ◊(Sam) ♣(i) ♦(am) |
| Syntax ($T_{syn}$) | Sara (S) ate (V) apples (O) | Sara (S) apples (O) ate (V) |
|                 | Une table (N) ronde (A) | Une ronde (A) table (N) |

Table 9: Examples of our transformations applied to different sentences (without sub-word tokenization). Inversion inverts the tokens, Permutation samples a random reordering, and Transliteration changes the script. We use symbols (♣) to denote words in the new script and mention the corresponding original word in brackets. Syntax stochastically modifies the syntactic structure. In the first example for Syntax, the sentence in Subject-Verb-Object (SVO) order gets transformed to SOV order, and in the second, the sentence in Noun-Adjective (NA) order gets transformed to the AN order. The examples are high probability re-orderings and other ones might be sampled too.

original sentences or synthetic sentences to exceed 256 tokens. We then populate the instance with padding tokens as described above, before continuing with the next set of sentences. This results in $M_3$ TLM instances of the form $w_{1:M_1}^{L_{MLM}} = [x_{a_{L_{NL}}, i}; a_{L_{NL}, i+1}, \text{pad}_{1, i}^{L_{MLM}}, x_{a_{L_{Deriv}}, i}; a_{L_{Deriv}, i+1}, \text{pad}_{2, i}^{L_{MLM}}]$. Finally, the MLM and TLM data are combined yielding our final dataset $\{w_{1:M_1}^{L_{NL}}, w_{1:M_2}^{L_{Deriv}}, w_{1:M_3}^{L_{MLM}}\}$.

In our XLM model, for both MLM and TLM data, all sentences that exceed 512 or 256 tokens respectively are thrown out. Most sentences are significantly shorter than this, so few were actually thrown out. We decided this was a reasonable tradeoff to avoid the complications that arise from splitting a translated pair of sentences into multiple instances, while trying to ensure each resulting instance pair is still a translation of the other. Finally, note that for finetuning, we do not need to generate TLM data.

We ran a number of ablation studies on XLM by varying the amount of TLM data relative to MLM, and by varying the percentage of vocabulary overlap between $L_{NL}$ and $L_{Deriv}$. The results of these studies can be found in Appendix C and D. The default setup for XLM uses 25% TLM data relative to MLM, and no word overlap. This most closely resembles the ratio of TLM and MLM used in the original implementation of XLM (Lample and Conneau, 2019).

G.4 DICT-MLM

We largely follow the DICT-MLM-50 model introduced in Chaudhary et al. (2020) with two languages. With 50% probability, the label of a masked token is altered according to the normal mBERT implementation. With the remaining 50% probability, the masked token is changed to a cross-lingual synonym. Since we only work with 2 lan-
guages at a time, the latter case always changes the token to its synonym if it is in the bilingual dictionary; otherwise, we leave it as the original token. Finally, we did not include the language conditioning layer since its performance fluctuates compared to the vanilla DICT-MLM (Chaudhary et al., 2020).

Since DICT-MLM requires the use of language IDs, we built this pre-training method on top of our implementation of XLM. The DICT-MLM objectives are applied onto the MLM data, which we generate following Appendix G.3. We do not generate TLM data for DICT-MLM.

Our default setup uses 25% of tokens in the bilingual dictionary. The original implementation of DICT-MLM uses the MUSE dataset, which contain 110 large-scale ground-truth bilingual dictionaries, some of which contain 100,000 token pairs (Conneau et al., 2017; Chaudhary et al., 2020). Since $\mathcal{L}_{NL}$ only has a vocabulary size of 40,000 in our experiments, it’s more than reasonable to have a dictionary capturing at least 25% of the tokens. The effects of the percentage of tokens in the bilingual dictionary can be seen in Appendix B.

### G.5 ALIGN-MLM

Unlike XLM and DICT-MLM, we don’t want to have language ID embeddings in ALIGN-MLM. To see why, observe that in the RoBERTa model, language ID token embeddings would eventually be summed with the word token embeddings, before being passed through the model during finetuning and evaluation. However, the goal of ALIGN-MLM is to explicitly align embeddings between corresponding words in the bilingual dictionary, with no mention of the language ID embeddings. This means it is best not to include language ID tokens at all. Therefore, unlike DICT-MLM, ALIGN-MLM is directly constructed using the MLM model explained in Appendix G.2. The only difference is we additionally apply the objective function explained in Section 3, using an $\alpha$ of 10. $\alpha = 10$ was chosen from a simple grid search on $[1, 10, 100]$. We noticed that the difference in performance was small and chose 10 because it performed marginally better by 2 points on $\mathcal{T}_{\text{trans}} \circ \mathcal{T}_{\text{inv}}$.

We ran ablation studies that varied the percentage of tokens contained in the bilingual dictionary. The default used was 25%, and the full results can be found in Appendix B.

### H Hyperparameters

The model used in our experiments is a modified RoBERTa model (Liu et al., 2019). The parameters used during pretraining can be found in Table 10, while the parameters used during finetuning can be found in Table 11.

| Parameter Name | Parameter Value |
|----------------|-----------------|
| Number of Attention Heads | 8 |
| Number of Hidden Layers | 8 |
| Hidden Dimensionality | 512 |
| Training Steps | 500,000 |
| Batch size | 128 |
| Learning Rate | $10^{-4}$ |
| Linear Warmup | 10,000 |
| $\mathcal{L}_1$ Vocabulary Size | 40,000 |

Table 10: This is the list of pretraining parameters used in our experiments. Any unlisted parameters use the same values as in RoBERTa (Liu et al., 2019).

| Evaluation Benchmark | Parameter | Value |
|----------------------|-----------|-------|
| XNLI                 | Learning Rate | $2 \times 10^{-5}$ |
| NER                  | Learning Rate | $2 \times 10^{-5}$ |
| POS                  | Learning Rate | $2 \times 10^{-5}$ |

Table 11: Finetuning parameters used in our experiments.

### I Training Time

All four methods have similar training times. Using a v3-8 Google TPU on Google’s Cloud platform, pretraining for 500,000 steps on $\mathcal{T}_{\text{trans}} \circ \mathcal{T}_{\text{inv}}$ took 40.7, 40.6, 44.9, and 39.7 hours using MLM, TLM, Align-MLM, and DICT-MLM respectively. These results are consistent across other transformations.