GreenPLM: Cross-lingual pre-trained language models conversion with (almost) no cost

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Abstract
While large pre-trained models have transformed the field of natural language processing (NLP), the high training cost and low cross-lingual availability of such models prevent the new advances from being equally shared by users across all languages, especially the less spoken ones. To promote equal opportunities for all language speakers in NLP research and to reduce energy consumption for sustainability, this study proposes an effective and energy-efficient framework Green-PLM that uses bilingual lexicons to directly translate language models of one language into other languages at (almost) no additional cost. We validate this approach in 18 languages and show that this framework is comparable to, if not better than, other heuristics trained with high cost. In addition, when given a low computational cost (2.5%), the framework outperforms the original monolingual language models in six out of seven tested languages. We release language models in 50 languages translated from English and the source code here.

Keywords: Natural Language Processing, Pre-trained Language Models, Green AI, Language Equality

1 Introduction
In recent years, natural language processing (NLP) has welcomed great advances and significant progress in deep learning. Pre-trained language models (PLMs) based on deep learning have significantly improved various NLP tasks, such as text classification, sequence labeling, and machine translation, bringing NLP with new research paradigms, including "pre-training and fine-tuning" and "prompt-based learning" [1]. These paradigms have shown the high capability, and efficiency in various NLP tasks [2, 3]. However, despite PLMs’ extraordinary performance, they all highly rely on substantive computational power and training data. The former has raised public concern about substantial energy consumption, and environmental damage [4], while the latter inevitably polarizes unequal opportunities for NLP research in different languages.

According to estimates [5], computation costs of deep learning architectures expanded 300,000 times from 2012 to 2018, going against green AI principles [5]. Figure 1 shows a comparison of PLMs from BERT-base [6] to PaLM [7] (mainstreaming models with significant performance boosts) in terms of model sizes, computational costs, economic costs, and environmental costs, from which we observe ever-increasing trends [8] and [5] calculated CO₂ emissions and financial requirements to pre-train popular PLMs. For example, pre-training a BERT-base model needs $3,751 to $12,571 in cloud computing, which is unaffordable for personal use and most researchers in developing countries. As for carbon emissions during pre-training, BERT, T5 [9], PaLM, Gopher [10], and GPT-3 [11] emitted 0.65, 46.7, 271.43, 380, and 552.1 tons
Fig. 1 Trends of Complexity and Training Cost in Mainstream PLMs with Significant Performance Boosts

of CO₂, respectively. Since carbon neutrality is a crucial and urgent goal in sustainable development [12], this trend strongly suggests the need for green and sustainable NLP research.

For equal language research opportunities, the limited amount of monolingual texts impedes the usage of large PLMs in low-resource languages. Languages with a more significant number of speakers have a larger corpus available for PLMs training. This leaves only a tiny fraction of the approximately 7000 languages [13] worldwide with their monolingual PLMs. Table 1 lists the amount of training materials for monolingual BERT for several languages, which shows a significant inequality in monolingual materials. English has 45 TB of monolingual material when training GPT-3, equivalent to 4,608 times the Hindi BERT pre-training corpus. In addition, inequality is also caused by many social and financial factors, such as internet infrastructure, education, and computational resources. Self-supervised pre-training exaggerates the disparity between high- and low-resource languages, making the development of modern NLP particularly difficult to be equally shared among all language speakers.

To address the above issues, we propose a generalizable framework, GreenPLM, to translate monolingual PLMs to new languages at almost no additional cost. Since human languages have universals [14], we hypothesize that the linguistic logic learned by monolingual PLMs on large monolingual corpora is transferable to low-resource languages through knowledge transfer. In addition, many NLP tasks [15, 16] have experimented with using bilingual lexicons as prior knowledge or enhancements. Their results demonstrate the wide availability and high scalability of bilingual lexicons. As shown in Figure 2, Therefore, GreenPLM utilizes bilingual lexicons to bridge cross-lingual semantic space
and keeps the well-trained parameters of PLMs fixed. The experimental results show that zero-cost GreenPLM’s performance is comparable to or better than current heuristics in 18 tested languages. In addition, with only 1% computational cost compared to pre-training a BERT model from scratch, continued pre-trained GreenPLMs could outperform monolingual PLMs’ performances. To sum up, we contribute to NLP research in the following ways:

1) proposed a green way of PLMs’ translation which used low (almost no) computational cost, which will significantly reduce the carbon emission for PLMs training
2) reduced constant language disparity in PLMs in terms of language resources
3) proposed a new pipeline to build a more powerful PLM in target languages with very limited computational cost (1%)

2 Related Work

Cost Reduction in PLMs Training Cost reduction can be broadly summarized into two directions: reducing computational costs and reducing data requirements. Many studies have been devoted to efficient PLM pre-training
for reducing computational costs. For example, [17] introduced the disentangled attention mechanism to separate token and position embeddings, reducing over 60% costs of pre-training from scratch with optimized implementation; [18] proposed a task-driven language modeling framework to pre-train task-specific PLMs with around 2% original computational costs. Besides training from scratch, [19] and [20] leveraged a small “teacher PLM” to pre-train a large ”student PLM” at a low computational cost. Reducing data requirement remains less studied compared to the former, and [21] for the first time introduced unlabeled text to low-resource scenarios. To bridge the study gaps, this work focuses on simultaneously reducing computational costs and data requirements.

Language Disparity in PLMs Researchers have devoted numerous efforts to equalize human languages in PLMs. Rather, the democratization of language technology [22] still remains a major challenge. Multilingual BERT is a preliminary attempt to adapt PLMs to multiple languages. It is pre-trained on the corpora concatenation from different languages [2]. However, cross-lingual PLMs only cover a limited number of languages. For example, multilingual BERT and XLM-R [23] cover 104 and 100 languages, respectively, only about 1.5% of human languages. In addition, pre-training multilingual PLMs is also unexpectedly costly. Meanwhile, model performances in specific languages are reported to be highly dependent on pre-training corpus sizes. In summary, the fundamental inequities in PLMs lie in the availability of monolingual texts.

Language Transfer After multilingual BERT showed impressively better performance in zero-shot cross-language transfer settings [24], substantial attempts have been made in adapting monolingual or multilingual PLMs to other languages. These efforts mainly focused on modifying multilingual PLMs. This section will briefly review efforts made in language transferring regarding multilingual and monolingual PLMs.

In adapting multilingual PLMs, [25] examined the performance of multilingual BERT in human languages and reported that the model performs well in high-resource languages but not low-resource languages. Nonetheless, in low-resource settings, multilingual BERT performs better than monolingual BERT. This attribute validates Multilingual BERT’s cross-language generalizability. [26] explored multilingual BERT’s performance in never-before-seen languages. They found that multilingual BERT has unstable performance across languages, depending on the training data. [13] used the New Testament, which is available in most languages, to adapt multilingual PLMs to more than 1600 languages using continual pre-training, vocabulary extension, and adapter transformers. [27] explored how bilingual lexicons can enhance the multilingual language coverage of PLMs. Since Bilingual lexicons are available in 70% of human languages, while the Bible is present in only 23%. Their results had consistent improvement across sequence labeling and dependency parsing tasks in 19 low-resource languages.
Table 1 Chosen Languages in This Study and Corresponding Information

| Languages | Language Families | Language Settings according to [32] | Monolingual PLMs’ Corpus Size |
|-----------|-------------------|------------------------------------|------------------------------|
| Spanish   | Indo-European     | 5 - The Winners                    | 2998.01 million words        |
| Indonesian| Austronesian      | 3 - The Rising Stars               | 220 million words            |
| Turkish   | Turkic            | 4 - The Underdogs                  | 440.50 million words         |
| Tagalog   | Austronesian      | 3 - The Rising Stars               | 39 million words             |
| Italian   | Indo-European     | 4 - The Underdogs                  | 2050 million words           |
| Romanian  | Indo-European     | 3 - The Rising Stars               | 2421.3 million words         |
| Persian   | Indo-European     | 4 - The Underdogs                  | 1300 million words           |
| Malay     | Austronesian      | 2 - The Hopefuls                   | -                            |
| Maltese   | Afro-Asiatic      | 2 - The Hopefuls                   | -                            |
| Maori     | Austronesian      | 1 - The Scraping-Bys               | -                            |
| Wolof     | Niger–Congo       | 2 - The Hopefuls                   | -                            |
| Luganda   | Niger–Congo       | 1 - The Scraping-Bys               | -                            |
| Ilokano   | Austronesian      | 1 - The Scraping-Bys               | -                            |
| Hausa     | Afro-Asiatic      | 2 - The Hopefuls                   | -                            |
| Bulgarian | Indo-European     | 3 - The Rising Stars               | -                            |
| Latvian   | Indo-European     | 3 - The Rising Stars               | -                            |
| Ancient Greek | Indo-European | - | -|
| Norwegian | Indo-European     | 1 - The Scraping-Bys               | -                            |
| Danish    | Indo-European     | 3 - The Rising Stars               | -                            |

Monolingual adaptation remains relatively under-explored compared to multilingual. It follows two general directions: extending monolingual PLMs to bilingual and adapting a source language PLM to monolingual PLMs. In the first direction, [28] continually pre-trained English PLMs on data in target languages with the transformer frozen and fine-tuned the PLMs on labeled English data. Their results confirmed generalizability of monolingual PLMs across languages. [29] transferred PLMs by initializing foreign language embeddings in the English vector space and jointly fine-tuning both models. For the second direction, [30], and [31] used word embeddings as the bridge to adapt monolingual models to other languages with continual pre-training. Motivated by these works, we leverage more widely available and less computationally expensive resources other than word embeddings to generalize PLMs.

3 Materials and Evaluation

3.1 Language and Model Choices

English was chosen to be the source language due to its largest pre-training corpus size and extensive literature. For target languages, we included 18 languages from five language families (Table 1) since we aimed to cover as many language families as possible. According to [32], the chosen languages fall under several various language resources’ levels from the extremely low-resource level “1 - The Scraping-Bys” to the high-resource level “5 - The Winners”.

To demonstrate the generalizability of GreenPLM, the first PLM model, bert-base-uncased model of English was chosen as the source PLM, as it has the broadest coverage in academic and industrial usage. The model’s light-weight allows extensive experiments on various NLP tasks across languages, even with limited computation resources. The GreenPLM framework is independent of the structure of PLM networks and hence benefits from the evolution of large-scale PLMs.
3.2 Experimental Settings

3.2.1 Data and Evaluation

**Bilingual Lexicons** The bilingual lexicons are built upon multiple resources to be made comprehensive. [33] is used as the primary source and complete lexicon sources are listed in supplementary materials. For low-resource languages, we adopted lexicons from [27].

**Evaluation** New language models were evaluated by performance comparison with previous PLMs. We used the F1 score for noted sequence labeling tasks, and accuracy otherwise. We re-scaled and took the average of model performance to fit a 0 to 100 scale for a fair comparison. Further details are included in supplementary materials.

Since most chosen languages have available benchmark datasets for performance comparison. For example, [34] as the Spanish benchmark; IndoLEM in [35] for Indonesian; [36], [37–39], [40], [41] and [42] for Turkish, Tagalog, Italian, Romanian, and Persian, respectively. For benchmark datasets with multiple tasks, we divided the tasks into two main categories: sequence labeling and language understanding, and randomly drew two tasks from each category for performance evaluation.

3.2.2 Baseline Methods

This study compared the proposed framework with four baselines: (1) a randomly initialized BERT model to check if the proposed framework can enhance random models; (2) deep learning models implemented with NCRF++ [43] for examining the performance of GreenPLMs at zero training cost, including long short-term memory (LSTM), and convolutional neural networks (CNNs); (3) multilingual BERT [2]; and (4) available monolingual BERT models. We compared the GreenPLMs continually trained with additional costs to multilingual and monolingual BERT models pre-trained at high costs. Only uncased models were used in this study because most bilingual lexicons are uncased.

4 Results

Table 2 shows the experiment results. The first part of this section discusses the performance of each model in the chosen target languages. The second part further presents model performance after continuous pre-training of the best GreenPLMs given step-wise additional costs.

4.1 GreenPLMs without Pre-training Cost

As shown in Table 2, under the no pre-training cost condition, GreenPLMs already have better or comparable performance than most baselines. In Tagalog, the GreenPLM wins over all baselines and shows a large improvement over the monolingual BERT. This may imply that the original Tagalog BERT was
not pre-trained with sufficient data. In Maltese and Ilokano, the GreenPLMs also outperform all existing baselines.

For Indonesian, Maltese, and Ilokano, corresponding GreenPLMs outperform the three baselines. In Indonesian, the GreenPLM even shows more than 5% performance improvements on three baselines. For Spanish, Turkish, Romanian, Persian, Luganda, Hausa, Bulgarian, Latvian, and Ancient Greek, the GreenPLMs perform better than the two baselines. For example, in Spanish, Turkish, Romanian, Persian, Hausa, Bulgarian, Latvian, Norwegian, Danish, and Ancient Greek, GreenPLMs outperform random BERT and other non-BERT deep learning models. For Luganda, the GreenPLM outperforms random BERT and multilingual BERT. We observe that GreenPLMs perform much better than random BERT in 14 out of 18 languages, except for a few sequence labeling tasks in 4 languages. This validates the effectiveness of GreenPLM in cross-linguistic knowledge transfer and provides a new perspective on rapid language adaptation. However, we observe a slight disadvantage of GreenPLMs, when pre-trained at no cost, to multilingual BERT. We future discuss this in the following section.

### 4.2 Continual Pre-training on GreenPLM

As a further enhancement to the GreenPLMs, we applied continuous pre-training to the best GreenPLMs for the seven languages mentioned above (Figure 3 (b) provides a visualized comparison). In the continuous pre-training column of Table 2, we list the performance of the enhanced GreenPLMs (GreenPLMs+) when they outperform multilingual BERT or monolingual BERT for the first time. We also note in brackets the percentage of costs compared to pre-training a PLM from scratch. We observe that the GreenPLMs+ outperform all monolingual BERT at a relatively low cost, except in Spanish. For example, GreenPLM+ outperforms the original PLM with only 0.68% of the pre-training cost for Indonesian. For Spanish, GreenPLM+ outperforms multilingual BERT and achieves comparable performance over the monolingual BERT when given 1% of the pre-training cost.

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**Table 2** Experimental Results under Six Settings

| Language     | Scratch | Pre-BERT | mBERT | monolingual BERT | Ours     | Continual pre-training |
|--------------|---------|----------|-------|------------------|----------|------------------------|
| Spanish      | 67.38   | 81.68    | 88.04 | 89.37            | 85.37    | 88.58 (0.7%)           |
| Indonesian   | 63.67   | 75.17    | 80.65 | 84.56            | 81.08    | 84.57 (0.68%)          |
| Turkish      | 70.38   | 90.41    | 92.97 | 93.07            | 90.70    | 93.09 (2.5%)           |
| Tagalog      | 77.41   | 77.44    | 89.43 | 85.77            | 89.59    | 89.59 (0%)             |
| Italian      | 83.47   | 96.39    | 97.44 | 97.38            | 95.98    | 97.63 (0.5%)           |
| Romanian     | 87.08   | 82.26    | 86.5  | 85.77            | 89.59    | 88.79 (1.2%)           |
| Persian      | 84.9    | 90.52    | 91.96 | 93.59            | 91.05    | 93.60 (0.8%)           |
| Maltese      | 40.47   | 70.79    | 73.30 | -                | 76.93    | -                      |
| Māori        | 53.33   | 89.44    | 81.97 | -                | 79.21    | -                      |
| Wolof        | 48.45   | 72.99    | 72.72 | -                | 72.71    | -                      |
| Luganda      | 30.39   | 74.65    | 74.19 | -                | 74.48    | -                      |
| Ilokano      | 29.65   | 64.58    | 67.44 | -                | 67.98    | -                      |
| Hausa        | 50.66   | 82.38    | 85.58 | -                | 84.97    | -                      |
| Bulgarian    | 92.16   | 97.93    | 99.06 | -                | 97.96    | -                      |
| Latvian      | 89.53   | 94.48    | 96.33 | -                | 94.59    | -                      |
| Ancient Greek| 89.42   | 95.00    | 96.00 | -                | 95.08    | -                      |
| Norwegian    | 92.82   | 96.50    | 97.61 | -                | 96.75    | -                      |
| Danish       | 82.37   | 94.50    | 97.80 | -                | 95.90    | -                      |
Fig. 3 Performance comparison of GreenPLM under different settings.
(a) Results by NER, POS and Classification task types
(b) Experimental results in six continual pre-training languages
(c) Comparison between continual pre-training GreenPLM versus multilingual BERT in Persian
(d) A linear relationship between language distance and error reduction rate

5 Discussion

Impact on Sustainable Development The high requirements of computational resources for pre-training PLMs or even deep learning have been a headache for researchers. Even a slight boost in the model performance often comes at the cost of rapidly growing model complexity. GreenPLM successfully outperforms pre-BERT deep learning models at zero pre-training costs and generates monolingual BERT for medium-level and low-level resource languages at extremely low pre-training costs, in both economic costs and CO2 emissions. Although [18] used similar computational costs to generate high-resource language PLMs, the GreenPLM framework is task-agnostic and helps to promote equality in worldwide languages. All translation work in GreenPLM experiments can be done on a personal computer within 10 seconds. Specifically, continued pre-training in Indonesian, Romanian, and Persian will only cost 10% of original language resources in less than 8 hours on 8 RTX3090. As a result, the consistent difficulty in data scarcity and expensive training is alleviated.
**Impacts on Language Equality** Unequal language resources have been preventing recent advances in PLMs from being equally shared by all language speakers. GreenPLM proposes a method to translate PLMs from one language to another language with a widely available language resource – bilingual lexicons at the expense of extremely low pre-training costs. It can serve as a platform to share resources from different languages and reduce both language and economic disparities of using PLMs in different languages and socioeconomic backgrounds. Experimental results show that GreenPLMs+ perform the best in languages with the most petite pre-training corpus sizes, such as Indonesian, Turkish, and Tagalog. This suggests that translating PLMs to new languages is more effective and, therefore, more beneficial to low-resource languages. We also compare the performance of GreenPLMs+ with multilingual BERTs in languages with relatively low language resources, such as Romanian and Persian. Experimental results show that multilingual BERT only performs better than the GreenPLM+ at the beginning stage. The GreenPLMs+ quickly catch up after pre-trained with the same number of steps. This proves that GreenPLMs have more potential than multilingual BERT with average-sized language resources. Besides, results also show that for languages with corpora of less than 440 million words, GreenPLMs are likely to outperform multilingual BERT. Given that these languages are medium-level rich in resources according to [32], the GreenPLM framework is comparable to, if not better than, multilingual BERT in most languages.

**Applicability for Downstream Tasks** Potential downstream tasks of this work can be categorized into three parts: part-of-speech tagging (POS), named entity recognition (NER), and classification tasks corresponding to word-level, span-level, and sentence-level understanding. Results in Figure 3 (a) show that the GreenPLMs, compared to random BERT models, have the most remarkable improvement on POS tasks, followed by NER and classification tasks. However, compared to multilingual BERTs, GreenPLMs fall short in POS, followed by NER and classification tasks. This suggests that GreenPLMs transfer sentence-level understanding the best in downstream tasks, possibly because embedding-based strategies focus mainly on semantic information and ignore the variability of syntactic information in natural languages.

**Language Distance** In addition, we use a language distance calculator from eLinguistics [44] as a reference and quantify the performance by the error reduction rate (ERR) metric because languages are classified according to their diachronic relatedness in linguistic typology. Corresponding results in Figure 3 (d) indicate that the closer the selected language is to English, the better its GreenPLM will perform. This suggests that linguistic distance is likely to be a crucial evaluation metric in cross-lingual knowledge transfer.

**GreenPLM Extension** GreenPLM can be further extended to several other levels and models. For example, this paper uses English to be the source language and starts from an English PLM to generate target language PLMs,
which is a one-to-one translation. We expect to merge PLMs in multiple languages for cross-enhancement to generate a target language PLM. In addition, GreenPLM can be extended to multi-modal and multi-domain settings where bilingual dictionaries can facilitate information exchange. Finally, it would be interesting to investigate how GreenPLM performs in higher-level BERT-class PLMs such as RoBERTa and XLNet[45], and if it works well for PLMs of different architectures such as BART[46].

Limitations GreenPLM has two main limitations. First, it only covers uncased PLMs at the current stage because most bilingual lexicons are uncased. Capitalizing words will affect model performance, according to some preliminary experiments. Second, there is no mechanism to rank the importance of single entries in bilingual lexicons. Therefore, newly generated models generally have a more extensive vocabulary than the original PLM.

6 Conclusion

This paper proposes a bilingual lexicon-based framework that “translates” a monolingual PLM to language at no additional cost. We verify the effectiveness in 17 languages and further pre-train the GreenPLMs to validate their performance when given minimal training cost. We prove that the GreenPLMs+ outperform monolingual BERT at much lower computational costs than current frameworks, such as fine-tuning multilingual BERT. This framework is easy to incorporate and can be adapted to various languages, given the wide availability of bilingual lexicons. It promotes green AI and equality across world languages.

7 Methodology

7.1 Overall Architecture

The overview of GreenPLM is shown in Figure 2. GreenPLM framework mainly includes four modules: (1) Bilingual lexicon pairs are collected together. (2) Specific PLMs were selected as the source language PLM. (3) PLM translation module utilized four strategies, lexicon walk mapping, vocabulary expansion, vocabulary one-on-one mapping, and vocabulary translation mapping to adapt embeddings from the source language to target languages. (4) GreenPLM in target languages will be evaluated and continually pre-trained. This framework will generate a local corpus enhanced GreenPLM as the final output.

7.2 Lexicon Walk Mapping Strategy

We proposed a Lexicon Walk Mapping (LWM) pipeline to map the semantic space between the source language and target language. The first step of LWM is to collect bilingual lexicons in the source-target language order from
various resources. In lexicons retrieved from [33], some word pairs are mappings of the same language, and even the same word, for example, “apple - apple”. This framework removes such pairs and merges different sources for lexicons of the same languages. Then, bilingual lexicons are used as the bridge to transfer the embedding knowledge. Given a bilingual lexicon $L = \{x_i, y_i\}$ where $x_i$ is a word or phrase in the source language (English, in our settings) and $y_i$ is $x_i$’s translation in target languages and a source language’s PLM $S$ with its vocabulary $S_{vocab}$ and token embeddings $S_{embedding}$, our pipeline walks through the lexicon, first tokenize $x_i$ into a set of tokens $T = \{t_1, t_2, \ldots, t_n \mid t_i \in S_{vocab}\}$, then map $T$ in the token embedding layer of $S$ to get a set of embeddings $E = \{e_1, e_2, \ldots, e_i, \ldots, e_n \mid e_i \in S_{embedding}\}$. $E$ is averaged along the dimension and the new embedding $e_{average}$ serves as $y_i$’s token embedding in the GreenPLM. If $y_i$ repeats in the lexicon, the GreenPLM framework accumulates several $e_{average}$ and uses the averaged embedding as the final token embedding.

For words, tokenized word pieces, and special characters in $S_{vocab}$, this framework keeps their corresponding token embeddings in the GreenPLM. As a result, our pipeline expands the vocab length to a certain extent according to the size of bilingual lexicons. For example, in Spanish, the GreenPLM has a vocabulary size of 119,999 words, while the corresponding monolingual BERT only has 31,002. Naturally, bilingual lexicons act as an adjustable component for GreenPLMs and can vary along with different tasks. In this work, the aim is to cover as many tasks as possible to build general-purpose PLMs through knowledge transfer. Details of the framework are illustrated in Figure 2. Several other strategies have also extensively attempted to utilize bilingual lexicons, as summarized in the supplementary materials.

### 7.3 Continual Pre-training

Continuous pre-training has long been validated as one of the most effective strategies to enhance PLM. There are several strategies in continuous pre-training, such as masked language modeling (MLM) [2] and translation language modeling (TLM) [47]. In addition, some special techniques, such as contrastive learning, can be combined with pre-training tasks. MLM is used as the basic pre-training task in the current continuous pre-training setup. For each language, GreenPLM is further pre-trained with a batch size of 1024 and a sequence length of 128 symbols. Each GreenPLM was pre-trained for 5 epochs and every 10,000 pre-training steps were saved.

Current experiments only implemented GreenPLMs+ in seven languages: Spanish, Indonesian, Tagalog, Turkish, Italian, Romanian, and Persian because they are the only languages with a moderate amount of language resources. The attempt to further pre-train GreenPLM for Maltese fails because the available resources (17 MB in OSCAR corpus) are too scarce to maintain training stability.
7.4 Preliminary Attempts before the LWM Strategy

In this study, the GreenPLM framework ends up using LWM. But before LWM, several other methods, such as Vocabulary Expansion, Vocabulary One-on-one Mapping, and Vocabulary Translation Mapping have been tested.

**Vocabulary Expansion (VE)** refers to expanding the vocabulary based on the vocabulary of the source language PLM. Given a bilingual lexicon \( \text{lexicon} = \{x_i, y_i\} \) and the PLM \( S \) of the source language with a vocabulary of \( S_{\text{vocab}} = \{w_1, w_2, ..., w_i, ..., w_n\} \) and token embeddings \( S_{\text{embedding}} \), VE will walk through \( S_{\text{vocab}} \) if multiple lexical entries exist, VE will find their corresponding translations by \( S_{\text{vocab}} \) and \( W_i \). If no matching entries exist, this strategy will keep the original tokens. Then, VE will merge and remove all \( W_t \) as the lexicon of the new model, where average embeddings are used for the newly extended lexicon.

**Vocabulary One-on-one Mapping (VOM)** adopts a similar methodology to VE but only uses one translation for multiple entries. While both LWM and VE increase the vocabulary sizes, introducing more parameters, VOM yields GreenPLMs with the same vocabulary sizes.

**Vocabulary Translation Mapping (VTM)** is the most basic strategy being tested. It cuts sentences according to space delimitation and uses bilingual lexicons to directly transfer the tokens into another language. Then, the newly generated sentences are directly fed to the GreenPLM for downstream tasks.

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