WECHSEL: Effective initialization of subword embeddings for cross-lingual transfer of monolingual language models

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Abstract

Recently, large pretrained language models (LMs) have gained popularity. Training these models requires ever more computational resources and most of the existing models are trained on English text only. It is exceedingly expensive to train these models in other languages. To alleviate this problem, we introduce a method – called WECHSEL – to transfer English models to new languages. We exchange the tokenizer of the English model with a tokenizer in the target language and initialize token embeddings such that they are close to semantically similar English tokens by utilizing multilingual static word embeddings covering English and the target language. We use WECHSEL to transfer GPT-2 and RoBERTa models to 4 other languages (French, German, Chinese and Swahili). WECHSEL improves over a previously proposed method for cross-lingual parameter transfer and outperforms models of comparable size trained from scratch in the target language with up to 64x less training effort. Our method makes training large language models in non-English languages more accessible and less damaging to the environment. We make our code and models publicly available.

1 Introduction

Large LMs based on the Transformer architecture (Vaswani et al., 2017) have become increasingly popular since GPT (Radford et al., 2018) and BERT (Devlin et al., 2019) were introduced, prompting the creation of many large LMs pretrained on English text (Yang et al., 2019; Clark et al., 2020; Lewis et al., 2020; Joshi et al., 2020; Ram et al., 2021). There is a tendency towards training larger and larger models (Brown et al., 2020; Fedus et al., 2021) while restricting focus to the English language. Recent work has called attention to the costs associated with training increasingly large LMs, including environmental cost and financial cost (Bender et al., 2021). If training large LMs for English is already costly, it is prohibitively expensive to train new, similarly powerful models to cover all other relevant languages.

One approach to address this issue is creating massively multilingual models (Devlin et al., 2019; Conneau et al., 2020; Xue et al., 2021) which are trained on a concatenation of text in many different languages. These models exhibit natural language understanding capabilities in a wide variety of languages, but suffer from what Conneau et al. (2020) call the curse of multilinguality: beyond a certain number of languages in the training data, overall performance decreases on monolingual as well as cross-lingual tasks. Consistent with this finding, Nozza et al. (2020) observe that monolingual LMs often outperform massively multilingual models. It is thus desirable to train monolingual models in more languages. Training monolingual models in non-English languages is commonly done by training a new model with randomly initialized parameters (Antoun et al., 2020; Louis, 2020; Chan et al., 2020; Martin et al., 2020). But to train a model with capabilities comparable to that of an English model in this way, presumably a similar amount of compute to what was used to train the English model would be required.

To address this issue, we introduce WECHSEL\textsuperscript{1}, a novel method to transfer monolingual language models to a new language. WECHSEL uses multilingual static word embeddings between the source language and the target language to initialize model parameters. We copy all inner (non-embedding) parameters of the English model, exchange the tokenizer with a tokenizer for the target language and instead of randomly initializing the token embeddings as done in prior work (de Vries and Nissim, 2021), we initialize token embeddings in the target language such that they are close to semantically

\textsuperscript{1}Word Embeddings Can Help initialize Subword Embeddings in a new Language.
similar English tokens by mapping multilingual static word embeddings to subword embeddings. Embeddings take up roughly 31% of the parameters of RoBERTa (Liu et al., 2019) and roughly 33% of the parameters of GPT2 (Radford et al., 2019). Intuitively, semantically transferring embeddings instead of randomly initializing one third of the model should result in improved performance. Our parameter transfer aims to provide an effective initialization in the target language, requiring significantly fewer training steps to reach high performance. As multilingual static word embeddings are available for many languages (Bojanowski et al., 2017), WECHSEL is widely applicable.

We evaluate our method by transferring English RoBERTa and GPT-2 – as representative models of encoder and decoder language models respectively – to 4 new languages (French, German, Chinese and Swahili). We evaluate our RoBERTa models by fine-tuning on Neural Entity Recognition (NER) and Natural Language Inference (NLI) tasks in the respective languages. Our GPT-2 models are evaluated by computing Language Modelling Perplexity (PPL) on a held-out set. We compare WECHSEL initialization with randomly initialized models (denoted as FullRand) as well as a recently proposed method which only transfers the inner (non-embedding) parameters (denoted as TransInner, de Vries and Nissim (2021)) under the same training conditions (around 4 days on a TPUv3-8). We also compare our model with models of comparable size trained from scratch under significantly larger training regimes, in particular CamemBERT (Martin et al., 2020) (French), GBERT\_Base (Chan et al., 2020) (German), and BERT\_Base-Chinese (Devlin et al., 2019) (Chinese). These models are trained on 6.4, 3.9, and 2 times more tokens, respectively. Results show that RoBERTa models initialized with WECHSEL outperform randomly initialized models by an average of 6.28% accuracy on NLI and 1.3% micro F1 score on NER, and models initialized with TransInner by an average of 1% accuracy and 0.46% micro F1 score on NLI and NER, respectively. GPT-2 models initialized with WECHSEL outperform randomly initialized models by an average of 0.76 PPL and models initialized with TransInner by an average 1.43 PPL. Our models already outperform GBERT\_Base and CamemBERT on average on downstream tasks after 10% of training steps. Our contribution is summarized as follows.

- We propose WECHSEL, a novel method for transferring monolingual language models to a new language by utilizing multilingual static word embeddings between the source and the target language.
- We show effective transfer of RoBERTa and GPT-2 using WECHSEL to 4 different languages and high performance after minimal training effort.
- We train more effective GPT-2 and RoBERTa models for German, French, Chinese and Swahili than previously published models under a more efficient training setting. Our code and models are publicly available at github.com/cpjku/wechsel.

In the following, we review related work in Section 2. We then introduce the WECHSEL method in Section 3, followed by explaining the experiment setup in Section 4. We show and discuss results in Section 5.

2 Related Work

Large Language Models. Training Language Models is usually done in a self-supervised manner i.e. deriving labels from the training text instead of needing explicit annotations. One widely-used optimization objective is Masked Language Modelling (Devlin et al., 2019, MLM), where random tokens in the input are masked (replaced by a special \[\text{[MASK]}\] token), and the task is to predict the original tokens. Another common objective is Causal Language Modelling (CLM), where the task is to predict the next token. These two objectives highlight a fundamental distinction between language models: models can be trained as encoders (e.g. with MLM) or as decoders (e.g. with CLM).

Instead of words, the vocabulary of language models usually consists of subwords. A subword is a combination of characters below or at word-level. Many recently proposed language models use subword tokenization (Clark et al., 2020; Liu et al., 2019; Devlin et al., 2019). WECHSEL can be used for any model which (1) uses subword-based tokenization and (2) learns an embedding for each token.

Multilingual representations. There has been a significant amount of work in creating multilingual static word embeddings. Multilingual static word embeddings can be created by learning static word
embeddings from scratch using data in multiple languages (Luong et al., 2015; Duong et al., 2016). Alternatively, multilinguality can be achieved by aligning existing monolingual word embeddings using a bilingual dictionary, so that the resulting embeddings share the same semantic space (Xing et al., 2015; Joulin et al., 2018). Recent studies improve this by reducing the need for bilingual data (or even requiring no bilingual data at all) (Artetxe et al., 2017, 2018; Lample et al., 2018).

Besides multilingual static word embeddings, multilinguality is also relevant to contextualized representations. Multilingual contextualized representations can be learned through training a model on a concatenation of corpora in different languages. Among such models are mBERT (Devlin et al., 2019), XLM-R (Conneau et al., 2020) and mT5 (Xue et al., 2021), which are trained on text in 104, 100 and 101 languages, respectively. As shown by Pires et al. (2019), a multilingual model such as mBERT can enable cross-lingual transfer by using task-specific annotations in one language to fine-tune the model for evaluation in another language. However, recent studies outline a number of problems with massively multilingual models. Wu and Dredze (2020) empirically show that in mBERT “the 30% languages with least pretraining resources perform worse than using no pretrained language model at all”. Conneau et al. (2020) report that beyond a certain number of languages in the training data, the overall performance decreases both on monolingual as well as cross-lingual tasks. These studies motivate our work on creating monolingual LMs for more languages.

Cross-lingual transfer of monolingual LMs. Studies related to the cross-lingual transfer of monolingual language models can be divided into two categories:

- **Bilingualization of a monolingual LM** is concerned with transferring a model to a new language while preserving capabilities in the original language. Artetxe et al. (2020) achieve this goal by replacing the tokenizer and relearning the token embeddings, while freezing other parameters. Such a model becomes bilingual, since the initial tokenizer and embeddings can be used for tasks in the source language while the new tokenizer and embeddings can be used for tasks in the target language. Thus, a model can be finetuned on annotated task data in the source language, then zero-shot transferred to the target language. Tran (2020) follow a similar approach, while instead of randomly initializing embeddings, they utilize static word embeddings to initialize embeddings in the target language close to semantically similar English tokens. They then continue training the model on an English text corpus as well as on the target language in order to preserve model capabilities in English.

- **Creating a new monolingual LM in the target language** is, in contrast, concerned with creating a model in the target language without the necessity to preserve its capabilities in the source language. Zoph et al. (2016) and Nguyen and Chiang (2017) show that cross-lingually transferring a machine translation model can improve performance, especially for low-resource languages. They replace the model tokenizer with a tokenizer for the target language. Zoph et al. (2016) then use embeddings of random tokens in the original vocabulary to initialize token embeddings in the new vocabulary, while Nguyen and Chiang (2017) improve on this by utilizing vocabulary overlap between the source and target language. More recently, de Vries and Nissim (2021) follow a similar approach to the one of Artetxe et al. (2020) by transferring a GPT-2 model to a new language. de Vries and Nissim (2021) add an additional step, where they train the entire model for some amount of steps to allow adapting to the target language beyond the lexical level. We refer to the method of de Vries and Nissim (2021) as TransInner and consider it as a baseline in our experiments.

Our WECHSEL method belongs to the second category. WECHSEL is an extension to the method proposed by Tran (2020) with the goal of creating a new monolingual LM instead of bilingualizing the LM. This allows removing the constraints imposed by the need to preserve capabilities in the source language. In addition, we generalize the semantic subword mapping done by Tran (2020) to consider an arbitrary number of semantically similar subword with an arbitrary temperature. We are the first to show that a cross-lingually transferred model can outperform monolingual models which have been trained extensively from scratch in the target language, while requiring substantially less computational resources.
3 Methodology

Given the tokenizer $T^s$ in the source language (with vocabulary $\mathcal{U}^s$), the corresponding token embeddings $E^s$ and a tokenizer $T^t$ in the target language (with vocabulary $\mathcal{U}^t$), our goal is to find a good initialization of the embeddings $E^t$ by using $E^s$. To this end, we use existing bilingual word embeddings enriched with subword information (Bojanowski et al., 2017), containing a set of words and subword n-grams in the source and target language and their aligned vectors. We denote the set of words and n-grams in the source and target language as $\mathcal{V}^s$ and $\mathcal{V}^t$ respectively, and the aligned static embeddings as $W^s$ and $W^t$.

First, independently for both languages, we compute static subword embeddings for tokens in the tokenizer vocabulary in the same semantic space as the static word embeddings (Section 3.1). This results in subword embeddings $U^s$ and $U^t$ for the source and target language, respectively. Next, we use $U^s$ and $U^t$ to compute semantic similarity of every subword in $\mathcal{U}^s$ to every subword in $\mathcal{U}^t$. Using these semantic similarities, we initialize the embeddings in $E^t$ through an affine combination of embeddings in $E^s$ (Section 3.2). By applying WECHSEL, the vectors of $E^t$ are in the same semantic space as $E^s$, where a subword in the target language is semantically similar to its counterpart(s) in the source language. These steps are summarized in Figure 1 and explained in detail in the following.

3.1 Subword Embedding Computation

The process of mapping word embeddings to subword embeddings is done separately for source and target languages. Given a tokenizer $T$ (with vocabulary $\mathcal{U}$) and embeddings $W$, the goal is to find subword embeddings $U$ for subwords in $\mathcal{U}$ in the same semantic space as $W$. To this end, we decompose subwords in $U$ into n-grams and compute the embedding by taking the sum of the embeddings of all occurring n-grams, equivalent to how embeddings for out-of-vocabulary words are computed in fastText (Bojanowski et al., 2017).

$$u_x = \sum_{g \in \mathcal{G}^{(x)}} w_g$$

where $\mathcal{G}^{(x)}$ is the set of n-grams occurring in the subword $x$ and $w_g$ is the embedding of the n-gram $g$. Subwords in which no known n-gram occurs are initialized to zero.

3.2 Subword similarity-based Transfer

Applying the previous step to both source and target language results in the subword embeddings $U^s$ and $U^t$ over the subword vocabularies $\mathcal{U}^s$ and $\mathcal{U}^t$, respectively. Our aim is now to use these embeddings to find an effective transformation from $E^s$ to $E^t$. We first compute the cosine similarity of every subword $x \in \mathcal{U}^t$ to every subword $y \in \mathcal{U}^s$, denoted as $s_{x,y}$.

$$s_{x,y} = \frac{u_x^T u_y}{\|u_x\| \|u_y\|}$$

We now exploit these similarities to initialize embeddings in $E^t$ by an affine combination of embeddings in $E^s$. Each subword embedding in $E^t$ is defined as the weighted mean of the $k$ nearest embeddings in $E^s$ according to the similarity values. The weighting is done by a softmax of the similarities with temperature $\tau$.

$$e_x^t = \sum_{y \in \mathcal{J}_x} \exp \frac{s_{x,y}}{\tau} \cdot e_y^s$$

where $\mathcal{J}_x$ is the set of $k$ neighbouring subwords in the source language. Subword embeddings for which $U^t$ is zero are initialized from a random normal distribution $\mathcal{N}(\mathbb{E}[E^s], \text{Var}[E^s])$. The inner (non-embedding) parameters are simply copied from the source model.
4 Experiment Design

We evaluate our method by transferring the English RoBERTa model (Liu et al., 2019) and the English GPT-2 model (Radford et al., 2019) to a subset of the 7 languages proposed in Conneau et al. (2020) (French, German, Chinese and Swahili). Chinese allows evaluation of cross-lingual transfer to a strongly dissimilar language. Swahili serves to evaluate our method on a low-resource language. We use the pretrained models RoBERTa\textsubscript{Base} with 125M parameters, and the small GPT-2 variant with 117M parameters provided by HuggingFace’s Transformers (Wolf et al., 2020) in all experiments. To ensure our method does not depend on excessive amounts of data in the target language we restrict the amount of training data to subsets of 4GiB from the OSCAR corpus (Ortiz Suárez et al., 2019) for all experiments except Swahili. For Swahili, we use the 1.6GiB Swahili subset of the CC-100 corpus (Conneau et al., 2020). To obtain aligned word embeddings between the source and the target language we use monolingual fastText word embeddings\textsuperscript{2} (Bojanowski et al., 2017) and align them using the Orthogonal Procrustes method (Schönemann, 1966; Artetxe et al., 2016) with bilingual dictionaries from MUSE\textsuperscript{3} (Conneau et al., 2017) for French, German and Chinese and a bilingual dictionary from FreeDict\textsuperscript{4} (Bański and Wójtowicz, 2009) for Swahili. We choose temperature $\tau = 0.1$ and neighbors $k = 10$ for WECHSEL by conducting a grid search over initializations with varying $k$ and $\tau$ using linear probes (Appendix A). We train tokenizers in the target languages using a vocabulary size of 50k tokens and byte-level BPE (Radford et al., 2019). After applying WECHSEL, we continue training RoBERTa on the MLM objective and GPT-2 on the CLM objective. We compare against two baseline methods.

- Randomly initializing $E'$ while transferring all other parameters from the English model as in de Vries and Niissim (2021). After training only embeddings for a fixed amount of steps while freezing other parameters, the entire model is trained for the remaining steps. We refer to this method as TransInner.

- Training from scratch in the target language, as is commonly done when training BERT-like or GPT-like models in a new language (Antoun et al., 2020; Louis, 2020; Chan et al., 2020; Martin et al., 2020). We refer to this method as FullRand.

All models are trained for 250k steps with the same hyperparameters across all languages (reported in Appendix B). Training one model takes around 4 days on a TPUv3-8. For WECHSEL and FullRand we use a learning rate (LR) schedule with linear warmup from zero to peak LR for the first 10% of steps, then linear decay to zero. For TransInner we perform two warmup phases from zero to peak LR, once for the first 10% of steps for training embeddings only, then again for the remaining steps while training the entire models.

5 Results

We show results for RoBERTa on two downstream tasks (NLI, NER) and for GPT-2 (CLM). The performance of our models throughout training is shown in Figure 2.

5.1 Transferring RoBERTa

We evaluate WECHSEL-RoBERTa by fine-tuning on XNLI (Conneau et al., 2018), and on the balanced train-dev-test split of WikiANN (Rahimi et al., 2019; Pan et al., 2017) to evaluate NLI and NER performance, respectively. The hyperparameters used for fine-tuning are reported in Appendix B.

Table 1 reports the evaluation results on RoBERTa. As shown, models initialized with WECHSEL outperform models trained from scratch and models initialized with TransInner across all languages. Surprisingly, close relatedness of the source and target language is not necessary to achieve effective transfer, as e.g. on NLI WECHSEL improves by 7.15%, 6.31%, 6.94% and 4.71% absolute accuracy over models trained from scratch for French, German, Chinese and Swahili, respectively.

Next, we compare WECHSEL-RoBERTa to monolingual models CamemBERT (Martin et al., 2020) (French), GBERT\textsubscript{Base} (Chan et al., 2020) (German), and BERT\textsubscript{Base}-Chinese (Devlin et al., 2019) (Chinese), and to fine-tuning XLM-R\textsubscript{Base} (Artetxe et al., 2020) in the target language. To the best of our knowledge there is no monolingual model available for Swahili. We observe a

\textsuperscript{2}https://fasttext.cc
\textsuperscript{3}https://github.com/facebookresearch/MUSE
\textsuperscript{4}https://freedict.org
Table 1: Results from fine-tuning RoBERTa models. We report accuracy for NLI on XNLI and micro F1 score for NER on WikiANN. Results are averaged over 3 runs. We report scores before training (Score@0), after 10% of steps (Score@25k) and after training (Score@250k). We also report results from fine-tuning prior monolingual models and XLM–R (Score (more training)) which are trained on more tokens than our models (c.f. Section 5.3). For each language, the best results in every column are indicated with underlines. The overall best results, including the comparison with prior monolingual models of comparable size, are shown in bold.

| Lang   | Model            | Score@0 | Score@25k | Score@250k | Score (more training) |
|--------|------------------|---------|-----------|------------|-----------------------|
|        |                  | NLI    | NER    | Avg | NLI    | NER    | Avg | NLI    | NER    | Avg |
|        |                  | Score@0 | Score@25k | Score@250k | Score (more training) |
|        |                  | NLI    | NER    | Avg | NLI    | NER    | Avg | NLI    | NER    | Avg |
| French | TransInner-RoBERTa | 78.25  | 86.93  | 82.59 | 81.63  | 90.26  | 85.95 | 82.43  | 90.88  | 86.65 |
| German | FullRand-RoBERTa  | 55.71  | 70.79  | 63.25 | 69.02  | 84.24  | 76.63 | 75.28  | 89.30  | 82.29 |
|        | CamemBERT        | -      | -      | -    | -      | -      | -    | -      | -      | -    |
|        | XLM–RBase        | -      | -      | -    | -      | -      | -    | -      | -      | -    |
|        |                  | -      | -      | -    | -      | -      | -    | -      | -      | -    |
| French | TransInner-RoBERTa | 73.64  | 84.53  | 80.08 | 81.11  | 89.05  | 85.08 | 81.79  | 89.72  | 85.76 |
| German | FullRand-RoBERTa  | 54.82  | 66.84  | 60.83 | 68.02  | 81.53  | 74.77 | 75.48  | 88.36  | 81.92 |
|        | GBERTBase        | -      | -      | -    | -      | -      | -    | -      | -      | -    |
|        | XLM–RBase        | -      | -      | -    | -      | -      | -    | -      | -      | -    |
| Chinese| TransInner-RoBERTa | 63.23  | 72.79  | 68.01 | 77.19  | 79.07  | 78.13 | 78.32  | 80.55  | 79.44 |
| German | FullRand-RoBERTa  | 44.24  | 57.95  | 51.09 | 58.34  | 64.84  | 61.59 | 71.38  | 78.35  | 74.86 |
|        | GBERTBase-Chinese| -      | -      | -    | -      | -      | -    | -      | -      | -    |
|        | XLM–RBase        | -      | -      | -    | -      | -      | -    | -      | -      | -    |
| Chinese| TransInner-RoBERTa | 54.67  | 64.46  | 59.56 | 58.85  | 80.27  | 69.56 | 74.10  | 78.05  | 72.79 |
| Swahili | FullRand-RoBERTa | 50.59  | 62.35  | 56.47 | 63.79  | 83.49  | 73.64 | 70.34  | 87.34  | 78.84 |
|        | XLM–RBase        | -      | -      | -    | -      | -      | -    | -      | -      | -    |

5.2 Transferring GPT-2

GPT-2 is evaluated by Perplexity (PPL) on a held-out set from the same corpus on which the model was trained on (OSCAR for French, German and Chinese; CC-100 for Swahili). Results are shown in Table 2. Consistent with results for WECHSEL-RoBERTa, the GPT-2 models trained with WECHSEL outperform the models trained from scratch and the models trained with TransInner across all languages.

For the language modeling task, we observe a strong dependence on similarity of the source to the target language than for downstream tasks such as NLI or NER. For French and German, WECHSEL is consistently better than TransInner and Full-Rand throughout the entire training. For Chinese, a decrease in perplexity towards the end of training causes WECHSEL to surpass training from scratch.

Table 2: Results of training GPT2 models. We report Perplexity before training (PPL@0), after 10% of steps (PPL@25k) and after training (PPL@250k).

| Lang   | Model             | PPL@0 | PPL@25k | PPL@250k |
|--------|-------------------|-------|---------|----------|
| French | TransInner-GPT2   | 1.7e+3| 23.47   | 19.71    |
|        | FullRand-GPT2     | 5.9e+4| 25.99   | 20.47    |
| German | TransInner-GPT2   | 3.7e+3| 34.35   | 26.80    |
|        | FullRand-GPT2     | 8.6e+4| 37.29   | 27.63    |
| Chinese| TransInner-GPT2   | 1.5e+5| 71.02   | 51.97    |
|        | FullRand-GPT2     | 5.8e+4| 69.29   | 52.98    |
| Swahili| TransInner-GPT2   | 1.4e+5| 13.02   | 10.14    |
|        | FullRand-GPT2     | 5.8e+4| 13.22   | 10.58    |

5.3 Effect of training effort

To highlight the improvement in training efficiency of WECHSEL as opposed to prior monolingual models, we consider the total number of tokens...
the model has encountered in the target language, computed as the product of batch size $\times$ sequence length $\times$ train steps (shown in Table 3). We expect FullRand-RoBERTa to approach performance of the respective prior monolingual models when trained on the same amount of tokens. This allows quantifying the difference in training effort required to achieve good performance with WECHSEL as opposed to training from scratch. For French, WECHSEL-RoBERTa outperforms CamemBERT after 10% of training, reducing training effort by 64x. For German, WECHSEL-RoBERTa outperforms GBERT Base after 10% of training steps, reducing training effort by 39x. For Chinese, WECHSEL-RoBERTa outperforms BERT Base-Chinese on NLI, but does not outperform BERT Base-Chinese on NER.

### 5.4 Additional Analyses

To qualitatively assess how well subword tokens can be mapped between the source and the target language, we show a random sample of tokens in the target language and their most similar English tokens (according to WECHSEL) for each language (Appendix C). We also consider an alternative way to map word to subword embeddings if no subword n-gram information is available (Appendix D).

#### 5.4.1 Relearning embeddings

To quantitatively evaluate the mapping resulting from WECHSEL we conduct an additional experiment where we keep all non-embedding parameters frozen and only train the embeddings. The better the initialization, the less improvement would be

| Model               | Tokens trained on | Factor |
|---------------------|-------------------|--------|
| WECHSEL-RoBERTa     | 65.5B             | 1.0x   |
| TransInner-RoBERTa  | 65.5B             | 1.0x   |
| FullRand-RoBERTa    | 65.5B             | 1.0x   |
| CamemBERT           | 419.4B            | 6.4x   |
| GBERT Base-Chinese  | 255.6B            | 3.9x   |
| BERT Base-Chinese   | 131.1B            | 2.0x   |

Table 3: Tokens trained on in the target language between our models and previous monolingual models.
possible with more training. We conduct this experiment for French as most similar language to English and Chinese as most dissimilar language and train GPT-2 models. Hyperparameters match the ones of our main experiments, except that we train for 75k steps only. We observe a strong decrease in Perplexity from training, indicating that our mapping is far from optimal. Especially early merges in the BPE vocabulary (i.e. common tokens) change compared to their initial value. Future work could investigate improving the mapping done by WECHSEL under this metric. Additional information is shown in Appendix E.

5.4.2 Is freezing necessary?

Previous work using the TransInner method freezes non-embedding parameters for a fixed amount of steps before training the entire model (de Vries and Nissim, 2021). This is done to prevent catastrophic forgetting at the beginning of training. To evaluate if freezing non-embedding parameters is still necessary with our method, we conduct an additional experiment. We train a model with WECHSEL and a model with TransInner without freezing any parameters, and the same models with freezing of non-embedding parameters for the first 10% of steps. We again match hyperparameters of the main experiments but train for 75k steps only. We train a German GPT-2 model and conjecture that the same result will hold for other languages and model types. Results are shown in Figure 3. We conclude that freezing is necessary when using TransInner, but there is no need for freezing when using WECHSEL (in fact, freezing slightly decreases performance).

6 Conclusion

We introduce WECHSEL, an effective method to transfer monolingual language models to new languages. WECHSEL exploits multilingual static word embeddings to compute an effective initialization of subword embeddings in the target language. Experiments on transferring representative transformers-based encoder and decoder language models from English to French, German, Chinese and Swahili show that the transferred RoBERTa and GPT-2 models are more efficient than strong baselines, and outperform prior monolingual models that have been trained for a significantly longer time. WECHSEL facilitates the creation of effective monolingual LMs in new languages in low resource and computationally-limited settings. Our work provides further evidence towards the hypothesis by Artetxe et al. (2020) that deep monolingual language models learn some abstractions that generalize across languages.

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A Grid search over $k$ and $\tau$

To choose number of neighbors $k$ and temperature $\tau$ for WECHSEL we conduct a grid search over linear probes of models with different initialization shown in Table 7. For RoBERTa, we compute scores on NLI (using XNLI) and POS tagging (using the French, German and Chinese GSD corpora in Universal Dependencies) using linear probes of the last hidden state. We probe on NLI by taking a concatenation of the mean of all token representations in the premise with the mean of all token representations in the hypothesis. We probe on POS tagging by taking the mean of all token representations belonging to each word. For GPT2, we compute language modelling Perplexity on the hold-out set also used to evaluate performance of the trained models.

B Hyperparameters

Hyperparameters used to fine-tune RoBERTa on downstream tasks are shown in Table 4. Hyperparameters used to train models in our main experiments are shown in Table 5.

C Qualitative subword correspondence

We show a small random sample of tokens in the target language and their closest English token (according to WECHSEL) in Table 6.

| Parameter | RoBERTa | GPT2 |
|-----------|---------|------|
| peak learning rate | 2e-5 | 2e-5 |
| batch size | 128 | 32 |
| sequence length | 128 | 128 |
| Adam $\epsilon$ | 1e-8 | 1e-8 |
| Adam $\beta_1$ | 0.9 | 0.9 |
| Adam $\beta_2$ | 0.999 | 0.999 |
| train epochs | 2 | 10 |
| warmup | 10% of steps | 10% of steps |
| warmup schedule | linear | linear |
| LR decay | linear to zero | linear to zero |

Table 4: Hyperparameters used to fine-tune RoBERTa models on NLI (XNLI) and NER (WikiANN).

| Parameter | RoBERTa | GPT2 |
|-----------|---------|------|
| peak learning rate | 1e-4 | 5e-4 |
| batch size | 512 | 512 |
| sequence length | 512 | 512 |
| weight decay | 0.01 | 0.01 |
| Adam $\epsilon$ | 1e-6 | 1e-6 |
| Adam $\beta_1$ | 0.9 | 0.9 |
| Adam $\beta_2$ | 0.98 | 0.98 |
| train steps | 250k | 250k |

Table 5: Hyperparameters of the models transferred from RoBERTa and GPT2.

D Using Word Embeddings without subword information

As an alternative to n-gram decomposition, we introduce a method for mapping word embeddings to subword embeddings without using any subword information (shown in Figure 4). For this method, we require word frequency information in addition to the word embeddings. We apply the tokenizer $T$ to every word $v$ in $\mathcal{V}$ resulting in a set of subwords for each word. For GPT2, we compute language modelling Perplexity on the hold-out set also used to evaluate performance of the trained models.

We show a small random sample of tokens in the target language and their closest English token (according to WECHSEL) in Table 6.

We find that performance is roughly
E Relearning embeddings

We show performance throughout training of GPT-2 models in French and Chinese where all non-embedding parameters are frozen in Figure 5.

| Lang  | Target Token | Closest English Token |
|-------|--------------|-----------------------|
| French| héritage      | legacy                |
|       | tremp        | soaked                |
|       | épiscop      | bishop                |
|       | scandaleux   | udicrous              |
|       | vertig       | astonishing           |
|       | enregistrer  | rec                   |
|       | sucrés       | sweets                |
|       | Emmanuel     | Emmanuel              |
|       | encourager    | condif                |
|       | secrétariat  | ariat                 |
| German| machen       | ize                   |
|       | mit          | with                  |
|       | Sprichwort   | proverb               |
|       | erischen     | Austrian              |
|       | minuten      | utes                  |
|       | Haustechnik  | umbing                |
|       | dringen      | urgent                |
|       | verfeinern   | refine                |
|       | umgebung     | vironments            |
|       | ternehmen    | irms                  |
| Chinese| 到处         | everywhere            |
|       | 巧合         | coinc                 |
|       | 第三         | third                 |
|       | 杂交         | recomb                |
|       | 刺来         | chnology              |
|       | 政务         | stone                 |
|       | 石           | sing                  |
|       | 喊麦         | iterranean            |
|       | 中海         | defendant             |
| Swahili| Shirikische  | Marriage              |
|       | Harusi       | ery                   |
|       | pesile       | graduate              |
|       | tihani       | ool                   |
|       | changi       | ingestion             |
|       | kuugua       | acclaim                |
|       | kuzidi       | Trouble               |
|       | vipigo       | conscience             |
|       | dhamirini    | Slowly                |
|       | aliposituma  |                       |

Table 6: Samples of tokens in each language and the corresponding closest tokens from the English vocabulary according to WECHSEL.
Figure 5: Perplexity over training steps from training French and Chinese GPT-2 models. We train models initialized with WECHSEL and with TransInner for 75k steps and freeze all non-embedding parameters for the entirety of training.

Table 7: Grid search over the temperature $\tau$ and number of most similar tokens $k$ parameters of WECHSEL.

| Lang | Model          | $k$ | $\tau$ | Scores NLI  | POS  | LM  |
|------|----------------|-----|--------|------------|------|-----|
| French | WECHSEL@0 | 1   | 1      | 38.4       | 58.2 | 2.5e+5  |
|       |              | 10  | 0.1    | 59.8       | 86.8 | 2.0e+5  |
|       |              | 10  | 1      | 58.3       | 84.4 | 4.8e+5  |
|       |              | 50  | 0.1    | 57.2       | 83.6 | 3.1e+6  |
|       |              | 50  | 1      | 54.0       | 81.6 | 1.8e+7  |
|       | FullRand@0   | -   | -      | 46.3       | 60.6 | 5.7e+6  |
|       | CamemBERT    | -   | -      | 63.5       | 93.6 | -      |
| German | WECHSEL@0 | 1   | 1      | 55.8       | 72.7 | 6e+5    |
|       |              | 10  | 0.1    | 58.9       | 76.0 | 4.2e+5  |
|       |              | 10  | 1      | 57.5       | 75.4 | 8.3e+6  |
|       |              | 50  | 0.1    | 55.4       | 75.4 | 1.0e+7  |
|       |              | 50  | 1      | 53.6       | 69.5 | 5.9e+7  |
|       | FullRand@0   | -   | -      | 44.5       | 49.1 | 6.2e+6  |
|       | GBERTBase    | -   | -      | 63.2       | 81.4 | -      |
| Chinese | WECHSEL@0 | 1   | 1      | 47.4       | 75.4 | 2.7e+6  |
|       |              | 10  | 0.1    | 48.0       | 80.7 | 2.6e+6  |
|       |              | 10  | 1      | 48.3       | 80.3 | 3.1e+6  |
|       |              | 50  | 0.1    | 48.3       | 77.8 | 3.7e+7  |
|       |              | 50  | 1      | 47.9       | 76.5 | 8.6e+7  |
|       | FullRand@0   | -   | -      | 37.5       | 53.7 | 5.8e+6  |
|       | BERTBase-Chinese | - | -     | 61.9       | 91.9 | -      |

Table 8: Results of training WECHSEL TFR GPT2 models. We report Perplexity before training (PPL@0), after 10% of steps (PPL@25k) and after training (PPL@250k).

| Lang | Model       | PPL@0 | PPL@25k | PPL@250k |
|------|-------------|-------|---------|----------|
| French | WECHSEL-GPT2 | 1.7e+3 | 23.47 | 19.71  |
|       | WECHSEL_TFR-GPT2 | 2.3e+3 | 23.45 | 19.70  |
| German | WECHSEL-GPT2 | 3.7e+3 | 34.35 | 26.80  |
|       | WECHSEL_TFR-GPT2 | 5.0e+3 | 34.46 | 26.82  |
| Chinese | WECHSEL-GPT2 | 2.4e+4 | 71.02 | 51.97  |
|       | WECHSEL_TFR-GPT2 | 2.5e+4 | 72.11 | 52.07  |
| Swahili | WECHSEL-GPT2 | 1.4e+5 | 13.02 | 10.14  |
|       | WECHSEL_TFR-GPT2 | 1.5e+5 | 13.03 | 10.06  |
Table 9: Results from fine-tuning WECHSEL-TFR-RoBERTa models. We report results the same way as in Table 1.

| Lang   | Model                   | Score@0   | Score@25k | Score@250k |
|--------|-------------------------|-----------|-----------|------------|
|        |                         | NLI | NER | Avg | NLI | NER | Avg | NLI | NER | Avg |
| French | WECHSEL-RoBERTa         | 78.25 | 86.93 | 82.59 | 81.63 | 90.26 | 85.95 | 82.43 | 90.88 | 86.65 |
|        | WECHSEL-TFR-RoBERTa     | 78.25 | 87.43 | 82.84 | 81.86 | 90.07 | 85.96 | 82.55 | 90.80 | 86.68 |
| German | WECHSEL-RoBERTa         | 75.64 | 84.53 | 80.08 | 81.11 | 89.05 | 85.08 | 81.79 | 89.72 | 85.76 |
|        | WECHSEL-TFR-RoBERTa     | 77.00 | 84.70 | 80.85 | 80.71 | 89.09 | 84.90 | 82.04 | 89.72 | 85.88 |
| Chinese| WECHSEL-RoBERTa         | 63.23 | 72.79 | 68.01 | 77.19 | 79.07 | 78.13 | 78.32 | 80.55 | 79.44 |
|        | WECHSEL-TFR-RoBERTa     | 62.75 | 72.87 | 67.81 | 77.07 | 78.03 | 77.55 | 77.99 | 80.65 | 79.32 |
| Swahili| WECHSEL-RoBERTa         | 60.28 | 74.38 | 67.33 | 73.87 | 87.63 | 80.75 | 75.05 | 87.39 | 81.22 |
|        | WECHSEL-TFR-RoBERTa     | 60.14 | 75.42 | 67.78 | 74.04 | 87.79 | 80.92 | 74.58 | 87.66 | 81.12 |