Unsupervised Cross-lingual Adaptation for Sequence Tagging and Beyond

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Abstract

Cross-lingual adaptation with multilingual pre-trained language models (mPTLMs) mainly consists of two lines of works: zero-shot approach and translation-based approach, which have been studied extensively on the sequence-level tasks. We further verify the efficacy of these cross-lingual adaptation approaches by evaluating their performance on more fine-grained sequence tagging tasks. After re-examining their strengths and drawbacks, we propose a novel “warmup-then-adaptation” framework to better exploit the translated training sets while inheriting the cross-lingual capability of the mPTLMs. Instead of simply augmenting the source-language training data with the machine-translated data, we tailor-make a warmup mechanism to distill multilingual task-specific knowledge from the translated data in each language and inject them into the model. Then, an adaptation approach is applied to the refined model parameters and the cross-lingual transfer is performed in a warm-start way. The experimental results on nine target languages over three diverse sequence tagging tasks demonstrate that our method is beneficial to the cross-lingual adaptation with mPTLMs.

1 Introduction

The emergence of multilingual pre-trained language models (mPTLMs)\textsuperscript{1} (Devlin et al., 2019; Mulcaire et al., 2019; Conneau and Lample, 2019; Conneau et al., 2020) has led to significant performance gains on a variety of cross-lingual natural language understanding (XLU) tasks (Lewis et al., 2019; Conneau et al., 2018; Hu et al., 2020). Similar to the monolingual scenario (Radford et al., 2018; Peters et al., 2018; Yang et al., 2019b; Liu et al., 2019b), exploiting mPTLMs for cross-lingual transfer\textsuperscript{2} usually involves two phases: 1) pre-train mPTLMs on a large multilingual corpus, and 2) adapt the pre-trained mPTLMs and task-specific layers to the target language. Intuitively, advancing either pre-training technique or adaptation approach is useful for improving the XLU performance. However, due to the prohibitive computational cost of pre-training on a large-scale corpus, designing a better adaptation framework is more practical to the NLP community.

Among the research efforts on cross-lingual adaptation, the most widely-used approach is zero-shot adaptation (Pires et al., 2019; Wu and Dredze, 2019; Keung et al., 2019), where the model with a mPTLM backbone is solely fine-tuned on the labeled data from the source language (typically English). Then, with the help of the multilingual pre-training, the fine-tuned model is applied seamlessly on the testing data of the target language. Another line of works belongs to translation-based adaptation (Conneau et al., 2020; Artetxe and Schwenk, 2019; Yang et al., 2019a; Eisenschlos et al., 2019; Huang et al., 2019; Cao et al., 2020), whose core idea is to borrow machine translation techniques to translate the source-language training set into the target language (Banea et al., 2008; Duh et al., 2011; Tiedemann et al., 2014). The cross-lingual adaptation is achieved via supervised training on the translated data.

Despite the superiority of translation-based adaptation to zero-shot adaptation on text classification (Prettenhofer and Stein, 2010; Schwenk and Li, 2018) and text pair classification (Conneau et al., 2018; Liu et al., 2019a; Yang et al., 2019a), it still remains unknown which one is better on more fine-grained XLU tasks, such as named entity recognition. One reason is that most of the existing translation-based approaches, built on top of off-

\textsuperscript{1}We abbreviate “pre-trained language models” as “PTLMs” rather than “PLMs” to differentiate it with “probabilistic language models” (Kneser and Ney, 1995; Bengio et al., 2003).

\textsuperscript{2}Without specification, “cross-lingual transfer/adaptation” in this paper refers to unsupervised transfer where neither labeled data in target language nor parallel corpus is available.
the-shelf translators, do not have access to token-level alignment for building pseudo-labeled data in the target language. Therefore, they fail to be applied to more fine-grained XLU tasks. Although some findings from existing works suggest that the translation-based approach outperforms the zero-shot approach by a large margin on the NER task (Mayhew et al., 2017), such result cannot fully reflect the truth due to the fact that the adopted zero-shot baselines (Täckström et al., 2012; Bharadwaj et al., 2016) are too weak — they did not introduce multilingual representations from mPTLMs but only used delexicalized features to reduce the language discrepancy.

In order to faithfully reveal the capabilities of different cross-lingual adaptation approaches, we survey a variety of existing translation-based approaches and systematically compare them with zero-shot approach on three sequence tagging tasks, namely, Named Entity Recognition (NER), Semantic Role Labeling (SRL) and Aspect-Based Sentiment Analysis (ABSA). Note that translation-based approaches for cross-lingual sequence tagging require word-level pseudo labels in the target language, we tailor-make a span-to-span mapping component to support assigning pseudo labels for the translated corpus, which aggregates word-based alignment to span-based alignment and propagates labels via aligned spans rather than aligned words (§ 2.2). Contrary to the previous findings, we show that, even armed with the proposed span-to-span mapping, the translation-based approaches are still inferior to the zero-shot approach in most cases.

Another observation is that performance gains are obtained by performing cross-lingual learning on the combination of the labeled data in the source language and the translated pseudo-labeled data in the target languages for both token-level (Fei et al., 2020a) and sentence-level tasks (Huang et al., 2019; Conneau et al., 2020). This observation indicates that even equipping the cross-lingual model with the simplest “combination” strategy is beneficial. Presumably, there exists some room for developing more advanced strategies to exploit the multilingual pseudo-parallel data so as to further improve the adaptation performance.

Starting from this postulation, we develop Multilingual Warm-Start adaptation (MTL-WS), a novel “warmup-then-adaptation” framework, to optimize the usage of the translated pseudo-labeled data when training the cross-lingual model based on mPTLMs. Concretely, instead of training the cross-lingual model on the entire translated data, we propose to utilize a small number (i.e. warmup steps × batch size) of pseudo-labeled samples from each translated training set to distill the task-specific knowledge in different target languages. The obtained knowledge are then aggregated and injected into the cross-lingual model as the multilingual “warmup”, in order to improve its generalization capability on target languages. With the warm-started cross-lingual model, an existing adaptation approach, e.g., zero-shot approach and target-only translation-based approach, can be further applied to perform the cross-lingual adaptation.

We further evaluate the effectiveness of the proposed MTL-WS framework on the aforementioned three sequence tagging tasks, varying the backbone mPTLMs from multilingual BERT (Devlin et al., 2019) to XLM-RoBERTa (Conneau et al., 2020). The experimental results suggest that our approach surpasses translation-based and zero-shot approaches on almost all language pairs.

2 Preliminary

In this section, we first describe the model architecture shared across different adaptation strategies. Then, we present the component supporting the building of pseudo-labeled training set in the target languages, dubbed as “label projection”.

2.1 Shared Architecture

Backbone We regard multilingual pre-trained language models (mPTLMs), usually a deep Transformer (Vaswani et al., 2017) or deep LSTM architecture (Hochreiter and Schmidhuber, 1997; Peters et al., 2018) pre-trained on large-scale multilingual corpus, as the backbone network to calculate multilingual token representations. Thanks to mPTLMs, learning cross-lingual word embeddings (Mikolov et al., 2013; Faruqui and Dyer, 2014; Smith et al., 2017) is no longer prerequisite for cross-lingual transfer.

Task-specific Layer We adopt a simple feed-forward network with softmax activation, instead of complicated architecture (Akbik et al., 2018), as the sequence tagger, following that in (Devlin et al., 2019) and (Conneau et al., 2020).

3 We use “label projection” to avoid confusion with “annotation projection” (Yarowsky et al., 2001; Das and Petrov, 2011; Akbik et al., 2015), which generates pseudo-labeled data by utilizing pre-trained model to make automatic annotations and projections on the additional parallel corpus.
Given the input token sequence \( \mathbf{x} = \{x_1, \ldots, x_T\} \) of length \( T \) (language identifier is ignored for simplicity), we first employ the backbone mPTLM to produce context-aware token representations \( \mathbf{H} = \{h_1, \ldots, h_T\} \in \mathbb{R}^{T \times \text{dim}_h} \), where \( \text{dim}_h \) denotes the dimension of hidden representations. Then, the token representations are sent to the task layer to perform predictions. Specifically, the probability distribution \( p_\theta(y_t|x_t) \in \mathbb{R}^{\mathcal{Y}} \) (parametrized by \( \theta \)) over the task-dependent tag set \( \mathcal{Y} \) at the \( t \)-th time step is calculated as follows:

\[
p_\theta(y_t|x_t) = \text{softmax}(W h_t + b)
\]

where \( W \in \mathbb{R}^{\mathcal{Y} \times \text{dim}_h} \) and \( b \in \mathbb{R}^{\mathcal{Y}} \) are the trainable parameters of the feed-forward network and \( \text{softmax}(\cdot) \) refers to the softmax activation function.

### 2.2 Label Projection for Sequence Tagging

Label projection is to propagate the gold standard labels of the source-language training sentences to their translations in the target languages. Since the source sentence is naturally aligned to the translated sentence at sentence-level, label projection for sentence classification or sentence pair classification task is straightforward. When it comes to the sequence tagging task requiring token-level supervision signals, an additional alignment model (Och and Ney, 2003; Dyer et al., 2013) is needed to produce more fine-grained alignment information.

Let \( \mathbf{x}^{\text{src}} = \{x_i^{\text{src}}\}_{i=1}^{T_{\text{src}}} \) and \( \mathbf{x}^{\text{tgt}} = \{x_j^{\text{tgt}}\}_{j=1}^{T_{\text{tgt}}} \) be the source sentence and the translated sentence in target language respectively. The paired sentences are then sent to the word alignment toolkit to generate word alignment links \( \mathbf{a} = \{a_i\}_{i=1}^{T_{\text{src}}} \), where \( a_i \in [1, T_{\text{tgt}}] \cup \{\text{NULL}\} \) indicates which target word (or NULL) is the translation of the \( i \)-th source word. Directly aligning word-level labels (Mayhew et al., 2017; Xie et al., 2018; Fei et al., 2020a) provides a simple solution for token-level label projection, however, it is fragile to the change of word order and the alignment missing issue, as depicted in Figure 1a. Instead, to improve the alignment quality, we propose “span-to-span mapping” strategy to transform word-based alignment to span-based alignment and propagate the source labels via the aligned spans. For each gold standard span \( \mathbf{x}_{i:j}^{\text{src}} \) from the \( i \)-th source word to the \( n \)-th source word \( (n \geq i) \), we locate the aligned span \( \mathbf{x}_{j:m}^{\text{tgt}} \) in the target language as follows:

\[
j = \min a_{i:n}
m = \max a_{i:n}
\]

where \( a_{i:n} \) denotes the alignment links of all source words in \( \mathbf{x}_{i:j}^{\text{src}} \). Then, we copy the source span label, e.g., PER or LOC in the NER task, to the aligned span and re-generate the boundary label. With this strategy, the post-processing efforts for the potential change of word order are saved and the alignment missing issue is largely alleviated. Note that span-to-span mapping is equivalent to word-by-word mapping when the source and target spans have the same length and word order.

### 3 Zero-shot Adaptation

Zero-shot adaptation (ZERO-SHOT) only fine-tunes model on the source labeled data. The reason that ZERO-SHOT approach works without explicit guidance in the target language may come from two aspects: 1) the shared tokens across languages serve as the anchors for multilingual generalization (Pires et al., 2019); 2) the deep architecture of mPTLMs can capture some language-independent semantic abstractions (Artetxe et al., 2019; K et al., 2020). The training objective \( \mathcal{J}(\theta) \) is as follows:

\[
\mathcal{J}(\theta) = \frac{1}{|\mathcal{D}^{\text{src}}|} \sum_{(\mathbf{x}, \mathbf{y}) \in \mathcal{D}^{\text{src}}} \mathcal{L}_\theta(\mathbf{x}, \mathbf{y}),
\]

\[
\mathcal{L}_\theta(\mathbf{x}, \mathbf{y}) = -\frac{1}{T} \sum_{t=1}^{T} y^\theta_t \circ \log p_\theta(y_t|x_t)
\]

where \( (\mathbf{x}, \mathbf{y}) \in \mathcal{D}^{\text{src}} \) denotes a gold standard training sample in the source language and \( y^\theta_t \in \mathbb{R}^{\mathcal{Y}} \) corresponds to the \( t \)-th tag (with one-hot encoding) of \( y \). \( \circ \) is inner product operation.

### 4 Translation-based Adaptation

Translation-based adaptation is a group of adaptation approaches exploiting the usage of machine-translated pseudo-labeled data in the target language. First of all, the source training corpus

\footnote{There are two modes of translation-based adaptation, namely, Translate-Train and Translate-Test. The former one guides the learning in the target languages by training on the translated pseudo-labeled data (Banea et al., 2008; Duh et al., 2011). While the Translate-Test fine-tunes the cross-lingual model on the source labeled data and then performs inference on the text translated from the target language to the source language (Lambert, 2015; Conneau et al., 2018). In this paper, we mainly discuss the approaches under Translate-Train mode.}
is translated into the target language. Then, the label projection component armed with the proposed span-to-span mapping (see Sec. 2.2) is employed to propagate labels from the source text to the paired target text along the aligned text segments.

**Target-Only** As the simplest translation-based approach, Target-Only (TO) exclusively fine-tunes the model on the translated training set from the specified target language, as done in (Banea et al., 2008; Duh et al., 2011). Let \( D^{tgt} \) be the translated corpus, the goal of TO is to optimize the following objective:

\[
\mathcal{J}^{TO}(\theta) = \frac{1}{|D^{tgt}|} \sum_{(x, \hat{y}) \in D^{tgt}} \mathcal{L}_\theta(x, \hat{y}),
\]

where \( \hat{y} \) denotes the pseudo-labels produced by label projection.

**Bilingual** Since machine translation can be regarded as the process of paraphrasing the source text in the target language, Bilingual adaptation approach (BILINGUAL) (Zhang et al., 2019) is developed following the idea of paraphrase-based data augmentation (Yu et al., 2018; Xie et al., 2019). Concretely, BILINGUAL augments the source-language training set with the translated training set in target language. Then, the cross-lingual model is fine-tuned on the augmented bilingual training set. Note that the examples from different languages are not differentiated but treated equally during training. The computational process for optimization is as follows:

\[
\mathcal{J}^{BILINGUAL}(\theta) = \frac{1}{|D^{src} \cup D^{tgt}|} \sum_{(x, \hat{y}) \in D^{src} \cup D^{tgt}} \mathcal{L}_\theta(x, \hat{y}),
\]

Here, \( \hat{y} \) is either the ground truth from the source corpus or the pseudo labels from the target corpus.

**Multilingual** Introduced by Yang et al. (2019a); Huang et al. (2019); Conneau et al. (2020), Multilingual adaptation approach (MTL) is a multilingual extension of BILINGUAL adaptation, where the model is fine-tuned on the union set of source-language training data and its translations in all of the target languages. Given the task-specific language set \( L \) including the source language and the target languages, the adaptation objective is given below:

\[
\mathcal{J}^{MTL}(\theta) = \frac{1}{\bigcup_{\ell \in L} D^{\ell}} \sum_{(x, \hat{y}) \in \bigcup_{\ell \in L} D^{\ell}} \mathcal{L}_\theta(x, \hat{y}),
\]

Similar to BILINGUAL, the multilingual training examples in MTL contribute equally to the fine-tuning. One important property of MTL approach is “once for all”—performing one-time adaptation for all target languages, greatly reducing the maintenance cost.

## 5 Multilingual Warm-Start Adaptation

The aforementioned MTL exploits the translated data by training the model on the union set of the data from source language and the machine-translated data in target languages. According to the results in Fei et al. (2020a), such simple “combination” already gives considerable improvement, plausibly, designing advanced strategies for incorporating the translated data can further boost the performance. With this motivation, we propose Multilingual Warm-Start adaptation (MTL-WS), a “warmup-then-adaptation” framework, to optimize the usage of the translated data while inheriting the cross-lingual capability of mPTLMs.

### 5.1 Multilingual Warmup

The first step of our MTL-WS is to warm up the model parameters, including the parameters of mPTLMs and those of the task-specific component, with the translated data. Given a subset of translated data in each target language, we perform \( Z \) epochs of warmup operation. As observed in Snyder et al. (2009); Ammar et al. (2016); Ahmad et al. (2019), the model trained on multiple languages can produce representations that are more suitable for the downstream task or further adaptation, therefore we do warmup on all of the target languages.
Specifically, for the $z$-th epoch, let $\theta_z$ denote the model parameters after warmup, which is calculated from $\theta_{z-1}$ and $|L|-1$ copies of language-specific model parameters $\theta_{z}^{l}$:

$$\theta_{z} = \theta_{z-1} + \frac{\gamma}{|L|-1} \sum_{\ell \in L_{\{src\}}} (\theta_{z}^{\ell} - \theta_{z-1}),$$  \hspace{1cm} (7)

where $\gamma$ denotes the step size of the warmup. Each $\theta_{z}^{\ell}$ is calculated from $K$ steps of updates by only using the translated data $\mathbb{D}^{\ell}$ of $\ell$:

$$\theta_{z,k}^{\ell} = \theta_{z,k-1}^{\ell} - \beta \nabla L_{\theta_{z,k-1}^{\ell}}(x^{\ell}, y^{\ell}),$$  \hspace{1cm} (8)

where $(x^{\ell}, y^{\ell}) \in \mathbb{D}^{\ell}$ and $\theta_{z,0}^{\ell} \leftarrow \theta_{z-1}$. Since the warmup is performed on the task-specific pseudo-labeled data, the task information and the lexical features in the target languages can be naturally introduced via gradient-based learning on such data. In MTL-Ws, we do not directly train the model but separately estimate the task-specific gradients with a small number of gradient update steps on the pseudo-labeled data. The reason why we average the task-specific gradients is that we want to enable the generalizability of the obtained the language-independent task-specific gradients to all of the target languages.

5.2 Adaptation

After the warmup encoding of task-specific and language-specific features from the target languages, the approaches mentioned in Sec. 3 and 4 can be applied to further adapt the warm-started model $\theta_{z}$. The multilingual approach, namely MTL, stands out for its effectiveness and “once-for-all” property. However, its training cost is $|L|-1$ times higher than ZERO-SHOT, which is computationally prohibitive as the $|L|$ increases. Moreover, our experiments show that even equipped with the span-to-span mapping, these translation-based adaptation approaches are still less effective than ZERO-SHOT in most cases. Considering these issues, we employ ZERO-SHOT approach instead of the multilingual ones to preserve the “once-for-all” property while not introducing additional training cost. At the same time, the proposed multilingual warmup mechanism compensates the deficiency that ZERO-SHOT does not exploit the translated data. Similar to Eq. 3, the objective of the adaptation is to minimize the training loss on the source-language data with gold-standard annotations:

$$J_{\text{MTL-Ws}}(\theta_{Z}) = \frac{1}{|D_{\text{src}}|} \sum_{(x,y) \in D_{\text{src}}} L_{\theta_{Z}}(x, y).$$  \hspace{1cm} (9)

6 Experiments

We evaluate the effectiveness of zero-shot approach, translation-based approaches and our Multilingual Warm-Start adaptation approach.

6.1 Tasks andDatasets

We conduct experiments on three sequence tagging tasks, namely, Named Entity Recognition (NER), dependency-based Semantic Role Labeling (SRL) and unified Aspect-based Sentiment Analysis (ABSA).

NER We use datasets from CoNLL-02 and CoNLL-03 NER shared tasks, containing English (en), Spanish (es), German (de) and Dutch (nl) (Tjong Kim Sang, 2002; Tjong Kim Sang and De Meulder, 2003) to run NER experiments.

SRL We follow the settings of Dependency-based SRL (Roth and Lapata, 2016; Marcheggiani et al., 2017), whose aim is to identify the syntactic heads of arguments with respect to the given predicate. As done by Fei et al. (2020b), we use datasets from Universal Proposition Bank (UPB) (Akbik et al., 2015)\(^5\), containing English (en), French (fr), Spanish (es), German (de), Italian (it), Portuguese (pt), Finnish (fi), to run SRL experiments.

ABSA We follow the settings of Unified Aspect-based Sentiment Analysis (Mitchell et al., 2013; Zhang et al., 2015), which jointly detects the aspect terms mentioned in the reviews and the associated sentiment labels using a single sequence tagging model. We use dataset from SemEval ABSA challenge (Pontiki et al., 2016), containing English (en), French (fr), Spanish (es), Turkish (tr), Dutch (nl) and Russian (ru), to run ABSA experiments.

Pre-processing details and dataset statistics are sketched in Appendix.

6.2 Experimental Settings

Our cross-lingual models are based on two different mPTLMs, namely, multilingual BERT (mBERT)

\(^5\)https://github.com/System-T/UniversalPropositions. UPB is built upon Universal Dependency Treebank (Nivre et al., 2016) and Proposition Bank (Palmer et al., 2005).
Table 1: Experimental results on NER task (%). **Avg.** refers to the averaged F1 score over all of the target languages. We bold the best result in each group.

| Model       | es   | de   | nl   | F1     | P1    | R1    | Avg. |
|-------------|------|------|------|--------|-------|-------|------|
| mBERT       | 76.14| 67.92| 77.10| 73.72  | 46.64 | 51.04 | 49.34 |
| To          | 69.17| 63.46| 70.90| 67.84  | 42.13 | 46.43 | 44.28 |
| BILINGUAL   | 71.09| 67.14| 71.43| 69.89  | 47.63 | 52.11 | 49.87 |
| MTL         | 72.32| 68.06| 72.68| 71.02  | 51.73 | 56.18 | 53.95 |
| MTL-WS (OURS) | 75.67| 71.69| 78.31| 75.22  | 56.07 | 60.10 | 58.09 |
| XLM-R       | 77.47| 68.69| 78.38| 74.85  | 53.35 | 58.09 | 55.67 |
| To          | 74.67| 70.51| 73.25| 72.81  | 48.13 | 52.63 | 50.37 |
| BILINGUAL   | 75.29| 71.35| 73.77| 74.47  | 52.83 | 57.53 | 55.18 |
| MTL         | 75.38| 72.10| 74.60| 74.03  | 53.93 | 58.63 | 56.23 |
| MTL-WS (OURS) | 76.73| 74.92| 78.62| 76.76  | 57.03 | 61.73 | 60.85 |

Table 2: Experimental results on SRL task (%). We bold the best result in each group.

| Model       | fr   | es   | de   | it   | nl   | F1     | P1    | R1    | Avg. |
|-------------|------|------|------|------|------|--------|-------|-------|------|
| mBERT       | 42.27| 45.74| 48.89| 51.07| 47.52| 41.74  | 46.20 | 49.06 | 46.64 |
| To          | 44.99| 47.22| 53.90| 52.17| 48.42| 41.43  | 48.02 | 49.87 | 46.37 |
| BILINGUAL   | 44.74| 47.88| 54.22| 51.25| 49.48| 41.44  | 48.51 | 49.87 | 46.37 |
| MTL         | 44.34| 45.82| 51.71| 50.47| 47.69| 40.38  | 46.73 | 49.06 | 46.37 |
| MTL-WS (OURS) | 45.36| 48.21| 52.31| 50.47| 50.47| 41.95  | 48.94 | 50.18 | 46.64 |
| XLM-R       | 45.74| 49.76| 54.01| 53.00| 50.59| 50.73  | 50.85 | 50.73 | 49.87 |
| To          | 44.19| 46.64| 54.92| 51.79| 49.13| 44.18  | 48.48 | 49.13 | 44.18 |
| BILINGUAL   | 45.06| 48.75| 56.20| 51.03| 51.35| 46.67  | 50.18 | 50.18 | 46.64 |
| MTL         | 44.19| 46.64| 54.92| 51.79| 49.13| 44.18  | 48.48 | 49.13 | 44.18 |
| MTL-WS (OURS) | 45.74| 49.76| 54.01| 53.00| 50.59| 50.73  | 50.85 | 50.73 | 49.87 |

Table 3: Experimental results on ABSA task (%). We bold the best result in each group.

and XLM-RoBERTa (XLM-R). We use the pre-trained checkpoints from Huggingface Transformer (Wolf et al., 2019) to initialize the backbone mPTLMs. We regard English as the source language and the others as target languages.

We employ Google Translate (Wu et al., 2016; Johnson et al., 2017)\(^6\) to translate the English training sentences into target languages and Fast Align (Dyer et al., 2013)\(^7\) to generate alignments between the source texts and the translated texts.

As with tagging schemes, we adopt BIO/ES for NER, IOI for SRL and BIO/ES for ABSA\(^8\), as done in (Lample et al., 2016), (Marcheggiani et al., 2017)

\(^6\) bert-base-multilingual-cased for mBERT and xlm-roberta-base for XLM-R.

\(^7\) https://translate.google.com/.

\(^8\) https://github.com/clab/fast_align.

\(^9\) Please refer to (Tjong et al., 1999) for more details about these tagging schemes.

Since our aim is not to build a new state-of-the-art model but investigate effective strategies for exploiting the translated pseudo-labeled data, thus, we do not compare with the previous best models (Wu et al., 2019; Wang et al., 2020; Fei et al., 2020b; Saiful Bari et al., 2020) on cross-lingual NER or cross-lingual SRL tasks. In principle, our **MTL-WS**, a model-agnostic framework, can be packed with such mPTLM-based models to further improve the adaptation performance, which is a worthwhile direction to explore.

Concrete details with respect to the experiment are presented in Appendix. Note that, for fair comparison, we keep the parameter settings and the model selection strategies of the proposed **MTL-WS** identical to those of the compared adaptation approaches.

### 6.3 Result Discussions

Table 1, Table 2 and Table 3 present the experimental results for NER, SRL and ABSA respectively.

#### 6.3.1 Main Results

As shown in Tables 1-3, the proposed **MTL-WS** approach achieves the best averaged F1 scores on different multilingual pre-trained language models (mPTLMs), demonstrating its effectiveness on cross-lingual sequence tagging. Comparing with the best translation-based approaches, namely, **MTL**, our **MTL-WS**, which injects the language- & task-specific knowledge into the cross-lingual model via the warmup mechanism, makes better use of the multilingual training set and brings in 4.2%, 2.2% and 3.2% absolute gains for the mBERT-based NER model, SRL model and ABSA model, respectively.

**MTL-WS** can be seen as applying **ZERO-SHOT** approach on the warm-started model parameters. By exploiting the source labeled data as well as the multilingual pseudo-labeled data, the cross-lingual model is better adapted to the target languages, especially on the ABSA task, the tailor-made multi-

\(^10\) Output is correct if and only if it exactly matches the span boundaries and span label.
lingual warmup boosts the averaged score by ∼10% with mBERT as backbone.

We also observe that changing the backbone from mBERT to XLM-R drastically advances the F1 score of *MTL-Ws* on ABSA (45.9⇒58.6). It is presumably because XLM-R pre-trained on much larger corpus is capable of capturing rich lexical variation and handling potential spelling errors from the informal texts. Meanwhile, the performance gain on NER (75.2⇒76.8), where the data is built upon the more formal Reuters news corpus, is not that significant, suggesting that mBERT is still a promising choice when handling the formal textual input such as news articles.

### 6.3.2 Zero-shot or Using Translation?

According to the results on the NER and ABSA tasks, **ZERO-SHOT** without any guidance in the target language outperforms **TO** on the majority of language pairs. Compared to **MTL**, **ZERO-SHOT** obtains comparable or even better averaged F1 score. Such findings are contrary to those from cross-lingual sequence (or sequence pair) classification tasks. We attribute this to the lower tolerance of NER model and ABSA model to the translation errors. More specifically, the issues of under-translation and mis-translation have the tendency to lose the expected translations of the aspect/entity mention, which will hinder the label projection for these two tasks requiring the token-level labels. While the yielding side-effect on the sequence-level tasks is less severe. Besides, the translation-based approaches on sequence tagging rely on unsupervised aligners to produce alignment links, which may introduce additional noises, even using our proposed span-to-span projection.

It is notable that the translation-based **TO** and **MTL** are still superior to **ZERO-SHOT** on the SRL task. The probable reason is that the lexical transfer in **ZERO-SHOT** is insufficient for discovering the internal structure of sentence. At the same time, the translation-based counterparts can implicitly generate the predicate-argument dependencies in the translated text via the projection of semantic role labels, which directly helps the learning of semantic roles in the target language.

### 6.3.3 Further Discussions on mPTLMs

As discussed in Sec. 6.3.1, the performance gap between mBERT and XLM-R is exceptionally large on the cross-lingual ABSA task. Here, we attempt to empirically track the sources that may contribute to this situation. We first conduct monolingual experiments on English with results shown in Table 4. As can be seen, the F1 scores between mBERT and XLM-R are very close when applied to the formal NER/SRL texts, while on the ABSA task, the former is far behind the latter, suggesting that handling informal texts with rich morphology changes is challenging for mBERT even in the most resource-rich language, i.e. EN. We also evaluate the monolingual performances of mPTLMs on two low-resource languages: Turkish (tr) and Finnish (fi)

|                   | English | Low-Resource Languages |
|-------------------|---------|-------------------------|
|                   | NER     | SRL | ABSA | NER (fi) | SRL (fi) | ABSA (tr) |
| mBERT             | 91.35   | 82.37 | 66.67 | 71.77    | 43.66    |
| XLM-R             | 91.46   | 84.03 | 73.74 | 76.70    | 65.73    |
| ∆                 | 0.09    | 1.66 | 7.07  | 4.93     | 22.07    |

Table 4: Monolingual performances (F₁).

![Figure 2: Effects of warmup mechanism on convergence.](image-url)
Table 5: Performances of TO on NER with different label projection strategies.

| Backbone | span-to-span | word-to-word | $\Delta_{LP}$ |
|----------|--------------|--------------|---------------|
| mBERT    | 69.17        | 58.46        | -10.71        |
| XLM-R    | 74.67        | 61.70        | -12.97        |

As shown in Fig. 2, after introducing the warmup mechanism, both mBERT and XLM-R converge faster at the first few epochs. Such property is especially useful when the training data is large and the computational power is limited.

6.5 Effects of Span-to-Span Mapping

As mentioned in Sec. 2.2, the proposed span-to-span mapping is more robust than the label projection via aligned words. Here, we assess this property on NER. We fix the target language as Spanish and compare the downstream adaptation performances of TO with different label projection strategies. As shown in Table 5, replacing our span-to-span strategy with the word-to-word strategy leads to remarkable decline of $F_1$ scores, suggesting that the quality of the pseudo-labeled data is unacceptable without considering the potential change of word order and missing alignment. The experimental results also demonstrate that our span-to-span mapping, a simple heuristic strategy, can alleviate the problem to some extent.

7 Related Work

Unsupervised Multilingual Pre-training With the help of deep neural architectures (Vaswani et al., 2017; Peters et al., 2018) and unsupervised representation learning techniques, multilingual Pre-trained Language Models (mPTLMs) (Che et al., 2018; Devlin et al., 2019; Conneau and Lample, 2019; Mulcaire et al., 2019; Conneau et al., 2020) greatly advances the state-of-the-art for a series of zero-shot cross-lingual natural language understanding tasks (Prettenhofer and Stein, 2010; Schwenk and Li, 2018; Conneau et al., 2018; Zeman et al., 2018; Liu et al., 2019a). Exploiting mPTLMs for cross-lingual learning usually involves two phases: general-purpose pre-training on multilingual corpus and task-specific adaptation. Since the cost of improving the former is not affordable to the majority of the NLP community, the researchers turn to explore more effective adaptation approaches for better performances.

Cross-lingual Adaptation The existing studies of mPTLM-based cross-lingual adaptation can be categorized into two lines: 1) zero-shot approach; and 2) translation-based approach. The zero-shot approach (Pires et al., 2019; Wu and Dredze, 2019; Keung et al., 2019) solely fine-tunes the cross-lingual model on the source labeled data and there is no explicit lexical transfer except the shared tokens across different languages. Instead, the translation-based approach borrows machine translation system to perform explicit transfer and tailor-makes some strategies to make use of the translated training set in target languages. Some ideas such as paraphrase-based data augmentation (Yu et al., 2018; Xie et al., 2019) and multi-task learning (Caruana, 1997; Ruder, 2017) have been adopted in translation-based approaches and achieve encouraging results on cross-lingual adaptation (Artetxe and Schwenk, 2019; Yang et al., 2019a; Huang et al., 2019; Conneau et al., 2020; Cao et al., 2020). The Multilingual Warm-Start adaptation (MTL-WS) proposed in this paper can be viewed as a hybrid of the zero-shot approach and the translation-based approach.

8 Conclusions

In this paper, we re-examine the effectiveness of the existing cross-lingual adaptation approaches for multilingual pre-trained language model (mPTLMs) on sequence tagging tasks. We show how to perform label projection for enabling the translation-based approaches in sequence tagging task, and develop a span-to-span mapping strategy to handle the potential change of word order and alignment missing issue. Moreover, we propose Multilingual Warm-Start (MTL-WS) adaptation to further enhance the cross-lingual transfer. Specifically, we tailor-make a warmup mechanism to distill the knowledge from the translated training sets and inject the obtained knowledge into the cross-lingual model. As the multilingual warmup is able to compensate the deficiency of not exploiting the translated data, Zero-Shot approach is then applied to preserve the “once for all” property while not increasing the training cost. Through the comprehensive experiments over nine languages from three sequence tagging tasks, we demonstrate that the proposed MTL-WS works well across different languages without any task-specific design for the downstream model. We also demonstrate that the superiority of our approach to other adaptation approaches is generally consistent across different mPTLMs.
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A Settings

A.1 General Settings

For each task, we only search the best number of warmup iterations $Z$, the best number of gradient updates $k$ within each warmup iteration and the
Table 6: The general experimental settings. **mBERT/XLM-R** here refers to the cross-lingual model with a mBERT/XLM-R backbone.

| Hyper-params | mBERT NER SRL ABSA | XLM-R NER SRL ABSA |
|--------------|----------------------|---------------------|
| Z            | 100 50 100           | 50 100 100          |
| K            | 5 30 20              | 20 30 20            |
| γ            | 5e-5                 | 5e-5                |
| β            | 1e-3                 | 1e-3                |
| learning rate| 5e-5                 | 1e-5                |
| batch size   | 8                    | 4                   |

best learning rate for the adaptation on the English development set. The hyper-parameter ranges are as follows: the number of warmup iterations $Z$ \{50, 75, 100\}; the number of warmup steps $k$ \{5, 10, 20, 30\}; learning rate \{5e-4, 1e-5, 2e-5, 5e-5\}. Batch size for mBERT-based model is set as 8 and that for XLM-R-based model is set as 4, due to the limit of GPU memory. Other hyper-parameters are empirically selected. The step size for warmup, namely $\gamma$, and that for gradient-based training on the target language, namely $\beta$, are set as 5e-5 and 1e-3 respectively. The finalized parameter settings are given in Table 6.

A.2 Task-specific Settings

**NER** Table 7 depicts the statistics for NER datasets. For the NER experiments, we truncate the maximum length of sub-word sequence to 128 and adopt the gold standard train/dev/test split. We train mBERT-based NER model up to 3000 steps and conduct model selection after 2000 steps, where we evaluate the performance on development set every 200 steps. For those based on XLM-R, We train them up to 6,000 steps. Similarly, after training 4000 steps, we test the model performance on development set every 400 steps to select the model for prediction.

**SRL** Table 9 depicts the statistics for SRL datasets. Apart from the text, we also feed the Part-of-speech (POS) tags provided by UPB as the input of the model. We use stanza (Qi et al., 2020)\[^{12}\] to produce POS tags for the translated data. For the model based on mBERT, we train them up to 10000 steps and conduct model selection every 1000 steps. The models based on XLM-R, we train them up to 20000 steps and conduct model selection every 2000 steps.

**ABSA** The dataset statistics are shown in Table 8. Since there is no official development set, we randomly sample 20% training samples and regard them as development data. We do not perform truncation for the sentences in ABSA datasets. Following Li et al. (2019), we train the model up to 1,500 steps and conduct model selection after 1000 steps. For model selection, we evaluate the performance on development set every 100 steps.

\[^{12}\]https://github.com/stanfordnlp/stanza.
| Language | Train | Dev | Test |
|----------|-------|-----|------|
|          | # sent. | # entity | # sent. | # entity | # sent. | # entity |
| en       | 14041   | 23499   | 3250   | 5942    | 3453   | 5648    |
| es       | 8323    | 18798   | 1915   | 4351    | 1517   | 3558    |
| de       | 12152   | 11851   | 2867   | 4833    | 3005   | 3673    |
| nl       | 15806   | 13344   | 2895   | 2616    | 5195   | 3941    |

Table 7: Statistics of NER datasets.

| Language | Train | Test |
|----------|-------|------|
|          | # sent. | # aspect | # sent. | # aspect |
| en       | 2000   | 2507    | 676     | 859     |
| fr       | 1733   | 2530    | 696     | 950     |
| es       | 2070   | 2720    | 881     | 1072    |
| tr       | 1104   | 1535    | 144     | 159     |
| nl       | 1711   | 1860    | 575     | 613     |
| ru       | 3490   | 4022    | 1209    | 1300    |

Table 8: Statistics of ABSA datasets.
| Language | Train | | | Test | | |
| --- | --- | --- | --- | --- | --- | --- |
|  | # sent. | # pred. | # sent. | # pred. | # sent. | # pred. |
| en | 10908 | 40149 | 1632 | 4892 | 1634 | 4700 |
| fr | 14554 | 29263 | 1596 | 3043 | 298 | 635 |
| es | 28492 | 73254 | 3206 | 8274 | 1995 | 5437 |
| de | 14418 | 21261 | 799 | 1180 | 977 | 1317 |
| it | 12837 | 25621 | 489 | 1009 | 489 | 1014 |
| pt | 7494 | 16842 | 938 | 2071 | 936 | 2107 |
| fi | 12217 | 25584 | 716 | 1477 | 648 | 1451 |

Table 9: Statistics of SRL datasets. # pred. refers to the number of predicates.