# ProMap: <br> Effective Bilingual Lexicon Induction via Language Model Prompting 

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#### Abstract

Bilingual Lexicon Induction (BLI), where words are translated between two languages, is an important NLP task. While noticeable progress on BLI in rich resource languages using static word embeddings has been achieved. The word translation performance can be further improved by incorporating information from contextualized word embeddings. In this paper, we introduce ProMap, a novel approach for BLI that leverages the power of prompting pretrained multilingual and multidialectal language models to address these challenges. To overcome the employment of subword tokens in these models, ProMap relies on an effective padded prompting of language models with a seed dictionary that achieves good performance when used independently. We also demonstrate the effectiveness of ProMap in re-ranking results from other BLI methods such as with aligned static word embeddings. When evaluated on both rich-resource and low-resource languages, ProMap consistently achieves state-of-the-art results. Furthermore, ProMap enables strong performance in few-shot scenarios (even with less than 10 training examples), making it a valuable tool for low-resource language translation. Overall, we believe our method offers both exciting and promising direction for BLI in general and low-resource languages in particular. ProMap code and data are available at https://github.com/4mekki4/promap.


## 1 Introduction

Bilingual Lexicon Induction (BLI) is the task of automatically constructing a bilingual lexicon or a list of word translations between two different languages (Mikolov et al., 2013; Artetxe et al., 2018b; Lample et al., 2018; Patra et al., 2019; Shi et al., 2021). BLI has a wide range of uses, including in Natural Language Processing (NLP) tasks such

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Figure 1: Overview of ProMap, depicting the workflow for translating the word "draws" from English to French. The figure illustrates the use of $\operatorname{ProMap}_{G}$ for generating the translation sub-tokens and ProMap ${ }_{S}$ for re-ranking Contrastive Vecamp predictions
as machine translation, and multilingual information retrieval, as well as in language learning and serious games. It is also vital in building systems for low-resource languages. The majority of recent BLI research focuses on using linear (Mikolov et al., 2013; Xing et al., 2015; Artetxe et al., 2016; Smith et al., 2017) and non-linear (Mohiuddin et al., 2020) mapping-based methods to align between two languages. The standard inputs to these methods are: 1) static word embeddings (WEs) of a source language $L 1$ and a target language $L 2$ and 2) a seed dictionary that covers a few thousand translation pairs.

Traditionally, static WEs are used to achieve state-of-the-art results in BLI. These embeddings are generated by training a language model on large amounts of monolingual texts and representing vocabulary words as points in a continuous vector space. For good BLI performance, the monolingual texts used to train these embeddings should have similar distributions and come from the same domain across the source and target languages. To
force this constraint, recent BLI research (Artetxe et al., 2018b; Glavaš et al., 2019; Karan et al., 2020) exploits Wikipedia dumps to train static WEs for these languages.

Regardless, ensuring good performance in NLP tasks when resources are limited is still a known challenge. This is especially true for BLI where researchers have been criticized for studying this task using down-sampled corpora of high-resource languages (Artetxe et al., 2020) that may not be representative of real low-resource languages. For example, real low-resource languages are characterized by scripting differences, domain shifts, and a lack of sufficient bitext, resulting in less isomorphic embedding spaces and thus a decrease in BLI performance (Søgaard et al., 2018; Nakashole and Flauger, 2018; Ormazabal et al., 2019; Glavaš et al., 2019; Vulić et al., 2019; Patra et al., 2019; Marchisio et al., 2020). Arabic, a collection of diverse languages and dialect varieties, is a case in point where it is hard to find resources to build good embeddings for mapping-based BLI methods. This makes BLI even more challenging, especially for Arabic dialects.

Recently, BLI performance has been improved by using contextualized word embeddings (Zhang et al., 2021; Li et al., 2022), generated from multilingual Pretrained Language Models (mPLMs), like mBERT (Devlin et al., 2019) and XLM-R (Lample and Conneau, 2019). Furthermore, advancements in multilingual language modeling have led to the development of multi-dialectal models (Abdul-Mageed et al., 2021; Inoue et al., 2021), which are designed to handle multiple dialects within a single Arabic language model. However, finetuning these PLMs on low-resource tasks can suffer from overfitting. To address this issue, prompt-based PLMs finetuning has been applied to enable few-shot learning (Gao et al., 2021).

In this paper, we introduce ProMap, a new approach of BLI that incorporates multilingual and multdialectal PLMs using padded prompt-based finetuning. ProMap boosts the performance of word translation tasks and comes in two variants:
(i) $\operatorname{ProMap}_{G}$ (G for Generation): This variant is particularly applicable when working with low-resource languages where it is difficult to acquire isomorphic static WEs. It directly generates the translation of a source word, assuming the availability of a Pretrained Language Model (PLM) that can handle both the
source and target languages. This variant shows promising results in few-shot scenarios even with less than 10 training pairs.
(ii) $\operatorname{ProMap}_{S}$ (S for Selection): This variant leverages an existing static WEs mapping method such as Vecamp (Artetxe et al., 2018a), to select the correct translation from $K$ candidate translations proposed by this mapping.

The main contributions of this paper can thus be summarized as follows:

1. Introduction of ProMap, a novel approach for BLI leveraging the power of pretrained multilingual and multidialectal language models. To the best of our knowledge, no prior work has tackled the BLI task using prompt-based finetuning of mPLMs.
2. Extensive evaluation of ProMap through: (i) Word translation on a standard multilingual BLI benchmark (Glavaš et al., 2019), (ii) Multilingual word translation using few-shot learning, and (iii) Word translation for lowresource languages. We evaluate word translation between Arabic dialects using four Arabic dialectal pairs following Erdmann et al. (2018) and from ten Arabic dialects to Modern Standard Arabic (MSA) exploiting a lexicon from Bouamor et al. (2018). We show that ProMap outperforms state-of-the-art methods in the majority of experiments.

The rest of the paper is organized as follows: Section 2 presents related work. In Section 3, we introduce our method ProMap. In Section 4, we present our experiments and results. Section 5 is a discussion of our results. In Section 6, we conclude the paper and draw the limitations of our work.

## 2 Related Work

Bilingual Language Modeling. In recent years, there has been a significant increase in research on BLI with a variety of solutions proposed (e.g. Artetxe et al., 2016; Zhang et al., 2017a,b; Søgaard et al., 2018; Patra et al., 2019; Jawanpuria et al., 2019; Glavaš and Vulić, 2020). On the one hand, some of these solutions, such as Procrustes-based methods, assume that the embedding spaces are roughly isomorphic. However, other researchers have argued that this assumption may not hold true
(Patra et al., 2019; Mohiuddin et al., 2020), particularly for low-resource languages where it may be difficult to obtain sufficient data to construct isomorphic word embeddings (Feng et al., 2022; Marchisio et al., 2022). On the other hand, other studies have attempted to use BLI for translation between Arabic variants (Erdmann et al., 2018; El Mekki et al., 2021), which are considered to be very low-resource and non-standard languages (Salloum and Habash, 2014; Habash et al., 2018). Nevertheless, many approaches have focused solely on high-resource languages for evaluation, which may limit advancements in the field (Artetxe et al., 2020). Recently, there has been a trend towards combining contextualized and static word embeddings to improve alignment and boost BLI performance (Zhang et al., 2021; Li et al., 2022).

Prompting Pretrained Language Models. In the recent past, more and more research has focused on the use of prompt-based finetuning methods for language models. These studies primarily focus on identifying the most effective prompting templates (Schick et al., 2020; Shin et al., 2020) and investigating the use of prompting to address fewshot learning tasks (Schick and Schütze, 2021a,b; Gao et al., 2021). Our work in this paper continues in this vein, but with particular emphasis on the task of BLI with minimal to large supervision.

## 3 Method

In this paper, we assume the availability of an mPLM trained on multiple languages or dialects. Although some languages or dialects may be lowresource in terms of non-noisy and task-specific data, we presume the availability of unlabeled data from various resources, such as social networks (e.g., Facebook, Twitter). An example of this approach is seen in MARBERT (Abdul-Mageed et al., 2021), which was primarily trained on 1B Arabic tweets (covering more than 20 Arab countries).

The intuitive idea of our approach for the BLI task is to finetune an mPLM by prompting it to translate a source word $w_{s}$ of the language $L 1$ to a target word $w_{t}$ of the language $L 2$. Although mPLMs are known for their smaller vocabulary size compared to static WEs, they tokenize words into sub-tokens. This leads to the issue of the pairs $w_{s}$ and $w_{t}$ being represented by multiple sub-tokens. To solve this problem, we introduce a padded prompting-based finetuning approach of mPLMs for word mapping/translation, namely

ProMap. In summary, ProMap can be used in two variants:
(i) $\operatorname{ProMap}_{G}$ : This variant is effective when there is no access to comparable static WEs while there is access to an mPLM with a reasonable vocabulary coverage. In this case, it translates $w_{s}$ to $w_{t}$ using solely the promptbased finetuned mPLM to generate the subtokens that form the translation word.
(ii) $\operatorname{ProMap}_{S}$ : This variant assumes the availability of both comparable static WEs and an mPLM. It uses the mPLM to re-rank the top $K$ predictions from an already existing robust alignment method between the comparable static WEs.

Figure 1 summarizes an example of the use of ProMap for the translation from the word "draws" in English to the word "dessine" in French. The figure presents uses of both of our method's variants. In the remainder of this paper, we will refer to our method using three notations: ProMap, $\operatorname{ProMap}_{G}$ and $\operatorname{ProMap}_{S}$. We will also assume access to a training dictionary, denoted as $D_{\text {train }}$, and a testing dictionary denoted as $D_{\text {test }}$, respectively. These encompass the training and testing word pairs, respectively.

### 3.1 ProMap

The basic idea of ProMap is to perform a promptbased finetuning of the PLM, where we model the BLI task as a natural language template (more details about the prompt-based finetuning are presented in Appendix A).

We might design our mPLM prompting template for a pair $\left(w_{s}, w_{t}\right)$ as follows:

$$
\begin{equation*}
x_{p}=[C L S] \text { The translation of the word } w_{s} \text { is }[\text { MASK }] \tag{1}
\end{equation*}
$$

The masked token $[M A S K]$ can be predicted using the MLM classification head of the PLM. The probability that the word $w_{t}$ from the PLM vocabulary $V$ will be predicted as a translation to the word $w_{s}$ using the template $x_{p}$ is:

$$
\begin{aligned}
p\left(w_{t} \mid w_{s}\right) & =p\left([\text { MASK }]=w_{t} \mid x_{p}\right) \\
& =\operatorname{softmax}\left(W_{w_{t}} \cdot h_{[M A S K]}\right) \\
& =\frac{\exp \left(W_{w_{t}} \cdot h_{[M A S K]}\right)}{\sum_{w_{i} \in V} \exp \left(W_{w_{i}} \cdot h_{[M A S K]}\right)}
\end{aligned}
$$

Where $W_{w_{*}}$ and $h_{[M A S K]}$ refer to the hidden vectors of the target word $w_{t}$ and the $[M A S K]$, respectively. The prompt-based finetuning utilizes the mPLM pretrained weights without adding any additional parameters, making it more efficient than standard finetuning. Thus, we can train the system by feeding all the pairs $\left(w_{s_{i}}, w_{t_{i}}\right) \in D_{\text {train }}$ to the mPLM model using the template $x_{p}$ of equation (1), and then optimizing the cross-entropy loss between the predicted $[M A S K]$ value and the ground truth $w_{t_{i}}$.

One challenge, however, is that in $x_{p}$ we assume that the majority of words $w_{s_{i}}$ and $w_{t_{i}}$ are represented by a single sub-token. This assumption can be valid for PLMs that cover one (e.g. English variant of BERT) or two (e.g. GigaBERT (Lan et al., 2020) that covers MSA and English) languages, but for PLMs that encode a large number of languages (mPLMs) (e.g. mBERT, XLM, XLM-R), the maximum vocabulary size does not cover all words from all languages as individual sub-token each. To tackle this issue, we adapt our method to non-autoregressively predict multiple sub-tokens using padded MLM.

Padded Prompting. A PLM model in its original form only considers one token to be masked and infilled when using the $[M A S K]$ token. To predict a span of sub-tokens of a fixed-length $n$ instead of a single token, we follow the approach of (Mallinson et al., 2020; Malmi et al., 2020) in using a nonautoregressive padded MLM. This approach masks a fixed-length span of $n$ tokens within a sentence and the PLM is trained to predict them while also predicting a $[P A D]$ token for masked positions that should not be infilled. In ProMap, we first design BLI training data for this model by converting all words $w_{s}$ and $w_{t}$ in our dictionaries $D_{\text {train }}$ and $D_{\text {test }}$ into spans of $n$ sub-tokens, padded with the token $P A D$ for words that have less than $n$ subtokens (the source words are also padded to unify the structure of the template over all the training examples). Then, we model our new prompt template based on the template in equation (1). For example, if $n=4$ and for the translation pair $\left(w_{s}, w_{t}\right)$, where the sub-tokens of $w_{s}$ are $\left\{w_{s_{0}}, w_{s_{1}}, w_{s_{2}}, w_{s_{3}}\right\}$, the prompt is modeled as follows:

$$
\begin{gathered}
x_{p}=[C L S] \text { The translation of the word } \\
w_{s_{0}} w_{s_{1}} w_{s_{2}} w_{s_{3}} i s[M A S K] \\
\\
{[M A S K][M A S K][M A S K]}
\end{gathered}
$$

The targets to be predicted for the 4 [MASK] tokens are the sub-tokens of the target word $w_{t}$ padded with $[P A D]$ to match the fixed length $n=4$. For the training step, we follow Malmi et al. (2020) in computing the pseudo-likelihood of the original sub-tokens of $w_{t}$ denoted as $W_{i: j}=$ $w_{t_{0}}, w_{t_{1}}, w_{t_{2}}, w_{t_{3}}$ as follows:

$$
\mathcal{L}\left(W_{i: j} \mid x_{p} ; \Theta\right)=\prod_{c=i}^{j} P_{\mathrm{MLM}}\left(w_{c} \mid x_{p} ; \Theta\right)
$$

Where $i$ and $j$ denote the range of the masked sub-tokens in $x_{p}, P_{\mathrm{MLM}}\left(w_{c} \mid x_{p} ; \Theta\right)$ refers to the probability that the $c$-th token in $x_{p}$ takes the value $w_{c}$ (even a word sub-token or $[P A D]$ ) and $\Theta$ denotes the training data. The training of the model proceeds by finetuning the mPLM with the above formula.

### 3.2 ProMap $_{G}$ : Generation of Translation Sub-Tokens

The first variant of ProMap, namely ProMap ${ }_{G}$, predicts the translation of the source word $w_{s}$ based only on the mPLM model. It uses ProMap to independently generate the sub-tokens that form the predicted translation. To get the translation of an input word $w_{s}$, we first pass the word through the template in equation (2), then we decode the nonautoregressively predicted sub-tokens and concatenate them to form the prediction word.

### 3.3 ProMap : Selection from $K$ Candidates

The second variant ProMap $_{S}$ relies on re-ranking the predictions extracted from an existing static WEs alignment method. It uses the same finetuned ProMap model defined in section 3.1.

### 3.3.1 Static WEs Alignment

The objective of this step is to align the static WEs of languages $L 1$ and $L 2$. This is achieved by mapping both WEs into a shared embedding space through the use of dual linear mapping. This operation involves the use of two linear transformation matrices. As reported in Artetxe et al. (2018a), a self-training process is conducted after each mapping iteration such that the training dictionary is expanded and the mapping performance is improved. In ProMap ${ }_{S}$, we follow the method outlined in Li et al. (2022), namely CLC1, which involves utilizing contrastive learning (CL) optimization in conjunction with self-training at each mapping iteration.

From the shared embedding space and for every source word $w_{s}$, we extract the top $K$ word translation candidates $P=\left[p_{1}, p_{2}, \ldots, p_{k}\right]$ and their corresponding similarity scores * $S=\left[s_{1}, s_{2}, \ldots, s_{k}\right]$ between every word vector $p_{i} \in P$ and $x_{s}$ (the static word vector of the $w_{s}$ ).

### 3.3.2 Re-ranking $K$ Candidates

In this step, we use the set of candidates $P$ and the finetuned ProMap model from Section 3.1 to re-rank and select the correct translation of a source word $w_{s}$. First, we convert the cosine similarity score vector $S$ to probability weights using softmax with a standard temperature T, as follows:

$$
S W_{i}=\operatorname{softmax}\left(s_{i}\right)=\frac{e^{s_{i} / T}}{\sum_{j=1}^{k} e^{s_{j} / T}}
$$

Where $S W_{i}$ denotes the softmax score for each cosine similarity score $s_{i}$. Then, we compute the loss of $x_{s}$ as $L_{P L M}=\left[l_{p l m_{1}}, l_{p l m_{2}}, \ldots, l_{p l m_{k}}\right]$, such as $l_{p l m_{i}}$ denotes the average cross-entropy loss ( $L_{c e}$ ) when the word $p_{i}$ is fed to the ProMap as translation of $x_{s}$. It is expressed as:

$$
l_{p l m_{i}}=\frac{1}{m} \sum_{j=0}^{m} L_{c e}\left(p t_{j}, t_{j}\right)
$$

Where:

- $m$ is the number of valid sub-tokens in $p_{i}$ (subtokens different from $[P A D]$ ).
- $p t_{j}$ and $t_{j}$ represent the $j$-th sub-token predicted by the MLM classifier and the $j$-th subtoken from the word $p_{i}$, respectively.
Then, we compute $S_{P L M}{ }^{\dagger}$

$$
S_{P L M}=\left[s_{p l m_{1}}, s_{p l m_{2}}, \ldots, s_{p l m_{K}}\right]
$$

where:

$$
s_{p l m_{i}}=S W_{i} \cdot \frac{1}{\log \left(1+l_{p l m_{i}}\right)}
$$

The selected translation is $p_{c} \in P$ where:

$$
c=\underset{i}{\arg \max }\left(s_{p l m_{i}}\right)
$$

This score refers to the best token in $P$ chosen by ProMap $_{S}$.

[^1]
## 4 Experiments

We evaluate the performance of ProMap variants on two different scenarios: 1) language pairs that have access to both static WEs and mPLM, and 2) language pairs that only have access to mPLM. We use $\mathrm{P} @ 1$ to compare our results with the baselines.

### 4.1 Data

In the first scenario, we adopt the same BLI setup from previous studies, specifically those described in Artetxe et al. (2018b); Glavaš et al. (2019); Karan et al. (2020). We utilize the dataset and monolingual static WEs proposed by Glavaš et al. (2019) which comprise both closely related and distant languages. In addition, we use the XLM-17 (Lample and Conneau, 2019) mPLM which covers 17 languages with a vocabulary covering 200 K tokens. However, as XLM-17 does not cover all the language pairs in the described dataset, our evaluation is performed on 15 language pairs covered by this mPLM, including English (EN), French (FR), German (DE), Turkish (TR), Italian (IT), and Russian (RU). For the translation pairs, we use 5 K training pairs for every language pair, and 2 K pairs for testing.

In the second scenario, we evaluate the word translation between Arabic variants using $\operatorname{ProMap}_{G}$ in two cases. The first case involves translation between Arabic dialects, for which we adopt the methodology of Erdmann et al. (2018); El Mekki et al. (2021) by utilizing four Arabic dialects, namely, Maghrebin (MAG), Egyptian (EGY), Gulf (GLF), and Levantine (LEV). We utilize the dictionaries proposed by Erdmann et al. (2018) in this case. In the second case, we evaluate word translation between Arabic dialects and Modern Standard Arabic (MSA). To achieve this, we construct 10 new dictionaries between Arabic dialects and MSA utilizing the MADAR Lexicon (Bouamor et al., 2018) which covers 10 Arabic variants. We split these dictionaries into Train and Test sets. The sizes of these splits are reported in table 8 in Appendix 2.1.4. We employ MARBERT (Abdul-Mageed et al., 2021) as an mPLM since it has been shown to achieve SOTA results on many NLU tasks for Arabic dialects. Also, it has a sizeable vocabulary of 100 K tokens.

### 4.2 Baseline Systems

For the first scenario, we compare ProMap variants to 6 strong baselines, namely, RCSLS (Joulin et al.,
2018), Vecmap (Artetxe et al., 2018a), LNMap (Mohiuddin et al., 2020), FIPP (Sachidananda et al., 2021), CLC1 (Li et al., 2022) and CLC2 (Li et al., 2022). The first 5 approaches only deal with static WEs, while the last one combines static WEs with contextualized WEs. For the second scenario ${ }^{\ddagger}$, we compare our results to 4 competitive approaches that have performed BLI work on Arabic dialects. These approaches are all based on Vecmap with several enhancements using orthographic features. A summary of each baseline system is reported in Appendix 2.2.

### 4.3 Implementation Details

In this work, we used Pytorch as the primary framework for building and training our models. We utilized the Huggingface library to load the pretrained models with no modifications. Since the ProMap training requires a validation set to choose the best number of epochs, and the best hyper-parameters, we could not find a validation set for our BLI approach since the used BLI datasets lack such a set. To tackle this issue, we randomly used the language pair (EN, FR) to learn the best hyper-parameters and used them for all other language pair experiments. We conducted experiments with different learning rates ranging from $1 e-4$ to $5 e-6$ and found that a learning rate of $2 e-5$ provides the best results. The batch size was fixed to 64 for all experiments and the models were trained for 5 epochs. For the first scenario, we set the maximum length for the padded MLM to $n=4$, the number of selected translation candidates from static WEs BLI in all experiments to $K=10$, and the temperature $T$ to 0.1 . For the second scenario, we choose $n=1$. This indicates that the PLM will predict the translation word directly rather than multiple sub-tokens.

Table 6 in the appendix 2.1 .1 presents the number of trainable parameters for each mPLM used in our paper.

### 4.4 Main Results

Table 1 summarizes the main results of the multilingual experiments. For the majority of language pairs, ProMap achieves significant improvements compared to the previous SOTA methods. ProMap ${ }_{S}$ outperforms the best static-based WEs BLI method (CLC1) by an average of 3.7 P@1 points while outperforming the SOTA method that

[^2]combines static and contextualized WEs (CLC2) by an average of $1.12 \mathrm{P} @ 1$ points. It is worth mentioning that $\mathrm{ProMap}_{S}$ improves the overall performance for both the same script (e.g. DE-FR) and different script (e.g. EN-RU) language pairs. The CLC2 baseline performs slightly better than ProMap $_{S}$ in the (DE-IT), (IT-FR), and (DE-TR) language pairs, but ProMap ${ }_{S}$ still performs competitively in these cases. Also, ProMap ${ }_{G}$ predicts accurate translations with the non-autoregressive generation of sub-tokens that form a whole word. It achieves $41.51 \mathrm{P} @ 1$ between Italian and French words. Despite ProMap ${ }_{G}$ demonstrating suboptimal performance relative to the baseline models within this context, the empirical results nonetheless indicate its effectiveness in specific applications. In particular, ProMap $_{G}$ exhibits proficient functionality during re-ranking processes, as demonstrated by ProMap . $^{\text {. }}$

### 4.5 Analyses

### 4.5.1 ProMap $_{G}$ vs. Static WEs Mapping

To demonstrate the effectiveness of $\operatorname{ProMap}_{G}$, we conduct a fair comparison with other static WEs mapping approaches. To ensure the fairness of the experiments, we use the same dictionaries for training and evaluation for both $\operatorname{ProMap}_{G}$ and the other approaches. Specifically, we only select word pairs that were covered by both the multilingual PLM vocabulary and the static WEs (both ProMap ${ }_{G}$ and the baselines are trained on the same training pairs). The new sizes of the Train and Test dictionaries after this selection are reported in Table 2. The results, presented in Table 2, show that $\operatorname{ProMap}_{G}$ significantly outperforms the other static WEs approaches across all 15 language pairs with an average improvement of $10.55 \mathrm{P} @ 1$ points. This is achieved for both close language pairs such as English-German, where $\operatorname{ProMap}_{G}$ outperforms the best static WEs alignment method, namely CLC1, by $14.01 \mathrm{P} @ 1$ points. Additionally, for distant language pairs, ProMap ${ }_{G}$ shows large performance gains. This is true even for language pairs that do not share the same script, such as the TurkishRussian pair where the performance increases from 24.66 P@1 using the CLC1 approach to $32.88 \mathrm{P} @ 1$ using ProMap ${ }_{G}$, with a gain of $8.22 \mathrm{P} @ 1$ points.

The impact of $\operatorname{ProMap}_{G}$ on an mPLM is illustrated in in Appendix 3.6. The t-SNE plot (van der Maaten and Hinton, 2008) demonstrates the embeddings generated for each word in the Test sets

| Pairs | Baselines |  |  |  |  |  | Ours |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | RCSLS | VecMap | LNMap | FIPP | CLC1 | CLC2 | ProMap $_{G}$ | ProMap ${ }_{S}$ |
| DE $\rightarrow$ FR | 52.74 | 50.44 | 48.46 | 50.44 | 53.78 | 55.56 | 31.47 | 56.40 |
| DE $\rightarrow$ IT | 52.63 | 50.55 | 47.94 | 49.97 | 52.79 | 54.77 | 28.19 | 54.44 |
| $\mathbf{D E} \rightarrow \mathbf{R U}$ | 42.41 | 34.38 | 37.92 | 37.09 | 44.29 | 46.79 | 15.64 | 48.50 |
| DE $\rightarrow$ TR | 30.99 | 27.18 | 29.16 | 27.65 | 34.69 | 38.86 | 10.67 | 37.36 |
| EN $\rightarrow$ DE | 57.60 | 51.00 | 47.95 | 51.85 | 54.9 | 57.75 | 24.28 | 59.89 |
| EN $\rightarrow$ FR | 66.55 | 63.10 | 62.10 | 63.25 | 65.05 | 67.20 | 46.42 | 69.38 |
| EN $\rightarrow$ IT | 64.05 | 60.40 | 59.05 | 59.75 | 63.45 | 65.60 | 41.79 | 68.42 |
| $\mathbf{E N} \rightarrow$ RU | 49.40 | 39.65 | 41.10 | 42.00 | 49.15 | 50.50 | 19.57 | 54.98 |
| EN $\rightarrow$ TR | 39.05 | 32.05 | 32.85 | 32.40 | 41.35 | 44.75 | 12.67 | 45.21 |
| IT $\rightarrow$ FR | 66.51 | 65.89 | 64.60 | 65.32 | 66.51 | 67.86 | 41.51 | 67.13 |
| $\mathbf{R U} \rightarrow \mathbf{F R}$ | 47.67 | 47.51 | 43.64 | 47.15 | 50.55 | 52.70 | 30.70 | 54.06 |
| $\mathbf{R U} \rightarrow$ IT | 46.57 | 46.78 | 43.74 | 45.89 | 49.66 | 51.96 | 26.89 | 53.02 |
| TR $\rightarrow$ FR | 36.10 | 36.58 | 34.08 | 34.40 | 40.63 | 43.88 | 21.23 | 43.91 |
| TR $\rightarrow$ IT | 34.56 | 34.24 | 32.00 | 33.44 | 38.98 | 42.17 | 19.31 | 43.49 |
| $\mathbf{T R} \rightarrow$ RU | 28.06 | 26.20 | 26.20 | 26.36 | 32.00 | 36.16 | 11.27 | 37.17 |
| Avg. | 47.66 | 44.40 | 43.39 | 44.46 | 49.19 | 51.77 | 25.44 | 52.89 |

Table 1: P@1 scores on the multilingual BLI benchmark using 5K translation pairs. The highest scores among all approaches are highlighted in bold.


Figure 2: Scatter plot of cross-lingual word embeddings for Test sets generated by the multilingual XLM model. The embeddings are represented in two dimensions using t-SNE (van der Maaten and Hinton, 2008) and depict the difference in performance before and after promptbased finetuning.
before and after $\operatorname{ProMap}_{G}$. Before finetuning, the plot shows a clear separation of the language subspaces by the mPLM, which explains why it is challenging to directly extract translations without finetuning. After $\operatorname{ProMap}_{G}$, the shapes of the sub-spaces shift towards a shared sub-space where every token translation in the source language is projected towards its corresponding translation in the target language.

### 4.5.2 Few-shot BLI with ProMap ${ }_{G}$

Prompt-based finetuning of PLMs has been found effective in few-shot learning tasks. In the following experiments, we train $\operatorname{ProMap}_{G}$ with different

| Pairs | Data Size (Train/Test) | VecMap | CLC1 | ProMap $_{G}$ |
| :--- | :---: | :---: | :---: | :---: |
| $\mathbf{D E} \rightarrow \mathbf{F R}$ | $2,189 / 385$ | 51.08 | 57.53 | $\mathbf{6 0 . 7 5}$ |
| $\mathbf{D E} \rightarrow \mathbf{I T}$ | $2,084 / 368$ | 46.18 | 50.99 | $\mathbf{5 7 . 5 1}$ |
| $\mathbf{D E} \rightarrow \mathbf{R U}$ | $1,256 / 172$ | 35.37 | 37.20 | $\mathbf{5 0 . 0 0}$ |
| $\mathbf{D E} \rightarrow \mathbf{T R}$ | $1,458 / 248$ | 27.50 | 37.50 | $\mathbf{5 4 . 1 7}$ |
| $\mathbf{E N} \rightarrow \mathbf{D E}$ | $2,180 / 257$ | 58.75 | 63.42 | $\mathbf{7 7 . 4 3}$ |
| $\mathbf{E N} \rightarrow \mathbf{F R}$ | $2,984 / 361$ | 64.82 | 66.20 | $\mathbf{7 8 . 6 7}$ |
| $\mathbf{E N} \rightarrow \mathbf{I T}$ | $2,797 / 327$ | 61.47 | 63.61 | $\mathbf{7 9 . 8 2}$ |
| $\mathbf{E N} \rightarrow \mathbf{R U}$ | $1,561 / 131$ | 24.43 | 35.88 | $\mathbf{5 3 . 4 4}$ |
| $\mathbf{E N} \rightarrow \mathbf{T R}$ | $1,871 / 210$ | 36.67 | 46.67 | $\mathbf{5 9 . 0 5}$ |
| $\mathbf{I T} \rightarrow \mathbf{F R}$ | $2,993 / 586$ | 67.08 | 68.31 | $\mathbf{7 2 . 5 4}$ |
| $\mathbf{R U} \rightarrow \mathbf{F R}$ | $1,651 / 242$ | 41.18 | 46.64 | $\mathbf{5 4 . 2 0}$ |
| $\mathbf{R U} \rightarrow \mathbf{I T}$ | $1,584 / 231$ | 37.84 | 40.54 | $\mathbf{5 0 . 0 0}$ |
| $\mathbf{T R} \rightarrow \mathbf{F R}$ | $1,894 / 319$ | 27.52 | 36.58 | $\mathbf{4 5 . 3 0}$ |
| $\mathbf{T R} \rightarrow \mathbf{I T}$ | $1,819 / 311$ | 29.45 | 35.62 | $\mathbf{4 3 . 8 4}$ |
| $\mathbf{T R} \rightarrow \mathbf{R U}$ | $1,086 / 151$ | 19.86 | 24.66 | $\mathbf{3 2 . 8 8}$ |
| $\mathbf{A v g}$. | - | 41.95 | 47.42 | $\mathbf{5 7 . 9 7}$ |

Table 2: Comparison of P@1 scores between our approach for generating word translation and static word embeddings-based alignment approaches. All models are trained on the shared pairs by the static word embeddings and the mPLM vocabularies. The highest scores among all approaches are highlighted in bold.
sizes of training data between 1 and 512 samples. We use the same data as in Section 4.5.1. For each experiment, we randomly sample $N$ pairs from $D_{\text {train }}$ and use them to train ProMap ${ }_{G}$. We then report the result achieved on the Test dictionary. Table 3 presents a subset of the results (the full results are in Table 15 in Appendix 3.5). The results show that the BLI performance using $\operatorname{ProMap}_{G}$ in-

| Pairs | DE $\rightarrow \mathbf{I T}$ | EN $\rightarrow \mathbf{F R}$ | EN $\rightarrow \mathbf{T R}$ | IT $\rightarrow \mathbf{F R}$ | RU $\rightarrow \mathbf{I T}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| $\mathbf{N}=\mathbf{1}$ | $5.34(2.86)$ | $20.67(15.58)$ | $8.09(7.05)$ | $13.05(10.88)$ | $9.70(7.99)$ |
| $\mathbf{N}=\mathbf{3}$ | $14.99(6.27)$ | $39.89(8.92)$ | $16.80(9.14)$ | $38.87(7.81)$ | $22.40(1.93)$ |
| $\mathbf{N}=\mathbf{5}$ | $29.40(4.33)$ | $48.08(16.50)$ | $22.48(6.71)$ | $48.24(8.64)$ | $25.29(2.37)$ |
| $\mathbf{N}=\mathbf{1 0}$ | $25.27(13.35)$ | $66.03(6.50)$ | $28.55(11.40)$ | $52.25(4.36)$ | $30.93(0.94)$ |
| $\mathbf{N}=\mathbf{1 6}$ | $18.74(6.69)$ | $65.40(5.96)$ | $34.60(7.35)$ | $39.57(11.49)$ | $33.10(1.85)$ |
| $\mathbf{N}=\mathbf{3 2}$ | $34.01(1.37)$ | $59.45(9.21)$ | $37.68(5.81)$ | $46.11(6.37)$ | $36.29(0.61)$ |
| $\mathbf{N}=\mathbf{6 4}$ | $38.34(4.35)$ | $59.80(10.21)$ | $41.40(11.40)$ | $55.57(6.67)$ | $38.40(2.42)$ |
| $\mathbf{N}=\mathbf{1 2 8}$ | $45.95(2.13)$ | $70.44(3.48)$ | $42.85(4.34)$ | $59.06(9.14)$ | $42.81(2.25)$ |
| $\mathbf{N}=\mathbf{2 5 6}$ | $50.82(2.44)$ | $74.37(1.98)$ | $48.94(2.62)$ | $68.74(2.25)$ | $45.37(2.11)$ |
| $\mathbf{N}=\mathbf{5 1 2}$ | $51.33(6.86)$ | $74.21(4.48)$ | $57.17(7.06)$ | $66.11(8.81)$ | $47.20(2.21)$ |

Table 3: Comparison of P@1 Scores of ProMap $_{G}$ Using N -Shot training example pairs. Every value in the table presents the average (and standard deviation) of 25 runs (corresponding to 5 random samples x 5 random seeds). The full results table, Table 15, is in Appendix 3.5.
creases with the number of training samples. Additionally, $\operatorname{ProMap}_{G}$ demonstrates promising results for word translation with minimal training examples for both closely and distantly related language pairs (such as EN-FR and RU-IT, respectively). For instance, when using only $N=1$ training example, ProMap ${ }_{G}$ attains a P@ 1 score of 20.67 for the EN-FR pair, and a score of 9.70 for the RU-IT pair. Furthermore, with only 10 training examples, the P@1 score for the EN-FR pair increases to 66.03 . In our experiments employing VecMap, we found that the performance was consistently $0.0 \mathrm{P} @ 1$ for all few-shot scenarios where N is less than 256 training examples. This suggests that while mPLMs effectively align words with their corresponding translations across languages, even when presented with a minimal number of training examples, static word embedding alignment methods such as VecMap train their embeddings independently and require substantial data to achieve comparable accuracy.

### 4.6 Evaluation on Arabic Variants

We test the effectiveness of ProMap ${ }_{G}$ on Arabic variants which are considered low-resource languages. With the limited availability of lexicons and mPLMs that cover these variants, it is hard to afford static WEs for every country-level Arabic variant. Table 4 presents the results achieved for the word translation between Arabic variants. The results show that ProMap ${ }_{G}$ largely outperforms the baseline models by 6.90 $\mathrm{P} @ 1$ points on average. It is worth highlighting that we only rely on the translations directly generated using $\operatorname{ProMap}_{G}$ without involving any static WEs. Also, our model outperforms the results achieved by (Riley and Gildea, 2018; El Mekki et al., 2021) which takes the orthographic similarities between Arabic variants into
consideration when predicting the translation word.
Furthermore, for the case of word translation between Arabic dialects and MSA (both directions), Table 5 displays a subset of the results (full results are in Table 13, Appendix 3.4). The Table presents the $\mathrm{P} @ 1, \mathrm{P} @ 5, \mathrm{P} @ 10$, and $\mathrm{P} @ 50$ scores achieved for the different pairs. On average, the performance of word translation from Arabic dialects to MSA is 58.99 and 77.69 for $\mathrm{P} @ 1$ and P@5, respectively. This indicates a potential for increased transfer learning between dialects and MSA. However, the performance of word translation from MSA to dialects is lower: it has an average P@1 and P@5 scores of 40.32 and 60.27 , respectively. This discrepancy can be attributed to the wide diversity in the dialects as the model branches out to $N$ dialects while attempting to map an MSA word to a dialectal word from the wide selection. That is, while this seems to be a one-to-one mapping between a word from MSA and a dialectal word, the model seems to be trying to learn a dialect path (from many) while selecting the target word.

|  | Baselines |  |  |  | Ours |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  | M1 | M2 | M3 | M4 | ProMap $_{G}$ |
| EGY $\rightarrow$ GULF | 48.30 | 52.34 | 53.56 | 55.27 | $\mathbf{6 4 . 4 0}$ |
| MAG $\rightarrow$ GULF | 40.00 | 44.92 | 45.27 | 47.87 | $\mathbf{5 5 . 3 6}$ |
| LEV $\rightarrow$ GULF | 41.70 | 46.85 | 46.03 | 48.49 | $\mathbf{6 0 . 1 4}$ |
| LEV $\rightarrow$ EGY | 37.70 | 42.48 | 42.52 | 45.67 | $\mathbf{5 7 . 3 3}$ |
| MAG $\rightarrow$ EGY | 36.60 | 41.13 | 41.96 | 44.48 | $\mathbf{5 5 . 1 1}$ |
| MAG $\rightarrow$ LEV | 54.00 | 62.70 | 57.01 | $\mathbf{6 4 . 5 3}$ | 55.33 |
| Avg. | 43.05 | 48.40 | 47.73 | 51.05 | $\mathbf{5 7 . 9 5}$ |

Table 4: P@1 scores on the BLI benchmark between Arabic Regions dialects following the datasets proposed by Erdmann et al. (2018). ProMap $_{G}$ is compared to 4 others methods namely, M1 (Erdmann et al. (2018)), M2 (Artetxe et al. (2018a)), M3 (Riley and Gildea (2018)), and M4 (El Mekki et al. (2021)). Bold scores denote the highest scores among all approaches.

|  | MAR-MSA |  | LEV-MSA |  | EGY-MSA |  | YEM-MSA |  | IRQ-MSA |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ |
| P@1 | 52.98 | 39.55 | 60.37 | 40.91 | 61.95 | 41.63 | 56.72 | 38.75 | 67.33 | 49.08 |
| P@5 | 64.90 | 54.80 | 80.65 | 64.46 | 80.49 | 67.81 | 81.72 | 59.41 | 85.64 | 70.18 |
| P@10 | 70.86 | 59.89 | 83.41 | 73.14 | 84.39 | 74.68 | 86.19 | 68.63 | 88.61 | 75.69 |
| P@50 | 83.44 | 72.32 | 94.93 | 87.60 | 92.68 | 85.41 | 91.79 | 82.29 | 93.07 | 84.86 |

Table 5: Subset of results of ProMap $_{G}$ for word translation between Arabic dialects and MSA using MARBERT on the MADAR Lexicon. In the table, one country from every Arab region was selected. Table 13 in Appendix 3.4 presents the full results.

## 5 Discussion

Our experimental results indicate that ProMap outperforms previous BLI approaches and can generate high-quality translation pairs using both richand low-resource languages in both the generation and selection settings. By utilizing only the pairs covered by both the static WEs vocabulary and the mPLM vocabulary, $\operatorname{ProMap}_{G}$ is able to generate largely superior results without the need to make use of, or depend on, any other approach. In our analysis, we find that variations in the prompting template do not have a significant effect on BLI performance (Appendix 3.3), although slightly better results are achieved when using a template written in the source language. Also, we find that injecting the source and target language information in the template does not affect the performance. Additionally, experiments show that $\operatorname{ProMap}_{G}$ can learn word translation with only one training example. In addition, promising results are possible across some pairs with just ten examples.

Furthermore, regarding the diminished performance of $\operatorname{ProMap}_{G}$, it is more pronounced in scenarios with multiple sub-tokens (when $n>1$ ). We identify two primary reasons for this. First, the multiple sub-tokens scenario can be likened to a multi-label classification task where the model is tasked with assigning multiple tags to different segments of the output. For an accurate translation in our context, all these decisions must be precise. Second, the complexity of the multiple sub-tokens scenario is exacerbated by the morphological richness of certain languages (e.g., Arabic), leading to significant variation in sub-token choices, For instance, if $\operatorname{ProMap}_{G}$ employs CAMELBERT to generate the word "عالسـلاعـة", it must predict three sub-tokens: "عال", "سـلام", and "ةار". Similarly, for the word "امبـارح", the model must to predict "بار", " "ام", and "حارح". A mistake in predicting even a single sub-token can compromise the entire target translation. To mitigate this challenge, we have considered expanding the vocabulary of mPLMs by incorporating non-covered words and initializing their embedding weights by averaging the weights of their sub-token embeddings. Nevertheless, this method produced a performance inferior to that of generating multiple sub-tokens with ProMap ${ }_{G}$.

## 6 Conclusion

In this work, we introduced a new method dubbed ProMap for translating words between languages
using multilingual pretrained language models. ProMap demonstrates strong performance in both rich-resource and low-resource languages. It is also able to achieve good results even with limited amounts of training data. Overall, we believe ProMap comprises an exciting advancement in bilingual lexicon induction and holds promise for improving translation in low-resource languages.

## Limitations

While the proposed ProMap model has demonstrated promising performance, it is important to highlight the following potential limitations:

- The ProMap ${ }_{G}$ model struggles to generate words of multiple sub-tokens, particularly when $n>1$. This limitation is primarily due to the complexity of word combinations that can be generated from multiple masked tokens. In cases of languages with rich morphology such as Arabic, this situation is even more challenging due to the vast number of possible combinations a word can have.
- The performance of ProMap $_{S}$ heavily depends on the $\mathbf{P} @ \mathbf{K}$ performance achieved by the static WEs alignment method, and therefore, in the case of the few-shot learning, it is hard to achieve better results using this variant.
- Finetuning large PLMs is a time-consuming process, making the task of finding optimal hyperparameters labor-intensive. Additionally, finetuning large PLMs poses a significant challenge in reproducing results, requiring multiple runs to achieve consistent results.
- We evaluate our approach for multilingual scenarios using the XLM-17 mPLM, which currently supports 17 languages. However, it should be noted that not all languages in the dictionaries dataset we used are covered by XLM-17. It is also worth experimenting with language models with larger vocabularies and fewer languages as a way to alleviate challenges compounded by the curse of multilinguality caused by mPLMs where per-language performance drops as with the increase of languages in the mPLM (Conneau et al., 2020).


## Ethics Statement

This research aims to improve language technology for under-resourced languages by addressing
lexical disparities between languages, groups, and cultures. The focus is on bilingual lexicon induction, a vital aspect in cross-lingual NLP with implications for machine translation and other tasks. The study includes various language families and all Arabic dialects, which are spoken by $\sim 450 \mathrm{M}$ people. The goal is to expand NLP methods to lower-resource and under-represented languages using few-shot techniques. Ultimately, our work seeks to increase access to technology by serving diverse populations.

The data used in our work, word translation pairs, is publicly accessible and in our view poses no risks. For any real-world use, we strongly suggest extensive evaluations and analyses be made before deployment. We also encourage use of our work in pro-social contexts such as health and language education.

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## Appendices

We provide an overview of the Appendix below.

## I Method (Appendix A).

This section provides more details about the prompting-based finetuning of BERT-like PLMs.

## II Experiment Settings (Appendix 2.1).

This section gives additional information about the considered experiment environments.

- We provide implementation details in Appendix 2.1.1.
- We describe the computing infrastructure in Appendix 2.1.2.
- We show the average runtimes of the competitive approaches in Appendix 2.1.3.
- We give more insights about the MADAR lexicon in Appendix 2.1.4.
- We provide the links of the used datasets in 2.1.5.


## III Baseline Systems (Appendix 2.2).

This section presents the various baseline systems against which we compared our results.

## IV Analyses (Appendix C).

Finally, we provide additional experiments and results, including:

- Examples of word translations by ProMap in 3.1.
- Comparison between the performance of ProMap $_{G}$ on Dialectal Arabic using two competitive PLMs in Appendix 3.2.
- Comparison of the performance achieved by different prompt templates in Appendix 3.3.
- The full results on all the Arabic pairs covered by the Madar Lexicon in Appendix 3.4.
- The full results of the few-shot experiments on the multilingual scenario in Appendix 3.5 .
- Various t-SNE visualizations of the WEs before and after finetuning in Appendix 3.6.


## A Prompt-based Finetuning Method

Prompt-based finetuning involves using natural language templates to represent input statements and treating text classification tasks as cloze-style tasks. For example, in sentence classification, if we need to classify the sentence "The Moroccan team made it to the world cup semi-final" as either $y_{1}=$ POLITICS or $y_{2}=$ SPORT, the template might look like this:

$$
x_{p}=[\mathrm{CLS}] x, \mathrm{a}[\mathrm{MASK}] \text { topic }
$$

With $x=\left\{x_{1}, \ldots, x_{l}\right\}$ is the input sentence of $l$ tokens. Using masked language modeling as the finetuning task, the $[M A S K]$ token in $x_{p}$ will have a predicted token $v_{p} \in V=\left\{v_{1}, \ldots, v_{r}\right\}$ where $V$ is the vocabulary covered by the PLM with size $r$. Then, the value $v_{p}$ should be mapped to the final label (i.e. POLITICS or SPORT for the example of sentence $x$ ). The objective is to extract the token $v_{p}$ from $V$ that can have the maximal probability to be filled in $[M A S K]$. It can be noted as $p\left([\mathrm{MASK}]=v_{p} \in V \mid x_{p}\right)$. To finetune a PLM using this prompt-based method for a classification task, all input sentences should first be designed as a unique template (such as $x_{p}$ ) when the ground truth label is replaced by the masked token [MASK], and then train the model to infill the masked token with the class-token.

## B Experiments

### 2.1 Settings

### 2.1.1 Implementation Details

Table 6 presents the number of trainable parameters for each mPLM used in our paper.

| Model | \# of trainable parameters |
| :--- | :---: |
| XLM-MLM-17-1280 | $571,696,960$ |
| MARBERT | $162,942,880$ |

Table 6: The number of trainable parameters for each mPLM used for ProMap.

### 2.1.2 Computing Infrastructure

We conducted our experiments utilizing a workstation equipped with an $\operatorname{Intel}(\mathrm{R}) \operatorname{Xeon}(\mathrm{R})$ Silver 4216 CPU operating at 2.10 GHz and a single Nvidia Tesla V100 GPU with 32GB of RAM.

| Method | Average runtime |
| :--- | :--- |
| CLC1 | 21 m 38 s |
| ProMap $_{G}$ | 6 m 46 s |
| ProMap $_{S}$ | 8 m 36 s |

Table 7: Average training runtime of the ProMap and CLC1 methods. The runtime of $\mathrm{ProMap}_{S}$ includes both the finetuning of ProMap and the re-ranking.

### 2.1.3 Average Runtimes

### 2.1.4 Insights about the Dialectal Arabic to MSA Data

To construct the dictionaries for word translation between Dialectal Arabic and MSA experiments, we utilized the MADAR lexicon, which encompasses 25 Arab cities. This lexicon provides an MSA translation for every Dialectal Arabic word. We grouped the words from cities within the same country to create a country-level dictionary. This resulted in dictionaries of 10 Arab countries. We then performed a random split to divide the data into training and testing sets. Table 8 presents the train and test sizes for each country-level Arabic dialect to MSA dictionary.

| Arabic variants pairs | \# of training pairs | \# of testing pairs |
| :--- | :---: | :---: |
| Moroccan (MAR) $\rightarrow$ MSA | 740 | 193 |
| Algerian (ALG) $\rightarrow$ MSA | 638 | 161 |
| Tunisian (TUN) $\rightarrow$ MSA | 844 | 209 |
| Libyan $($ LBY $\rightarrow$ MSA | 879 | 217 |
| Egyptian $($ EGY) $\rightarrow$ MSA | 1,077 | 282 |
| Sudanese $\rightarrow$ MSA | 1,322 | 341 |
| Leventine (LEV) $\rightarrow$ MSA | 1,111 | 298 |
| Iraqi $($ IRQ) $\rightarrow$ MSA | 1,027 | 255 |
| Gulf $(G L F) \rightarrow$ MSA | 2,051 | 526 |
| Yemeni $(Y E M) \rightarrow$ MSA | 1,466 | 350 |

Table 8: Sizes of train and test datasets constructed from the MADAR lexicon for the case of country-level dialectal Arabic to MSA word translation.

### 2.1.5 Datasets Links

## Multilingual Scenario:

- XLING bilingual dictionaries


## Multi-dialectal Scenario:

- MADAR lexicon
- Arabic dialect to Arabic dialect lexicon


### 2.2 Baseline Systems

In the first scenario, when evaluating the multilingual setting, we compare the performance of ProMap variants to the following baseline systems:

- RCSLS (Joulin et al., 2018) optimizes a convex relaxation of CSLS loss during training, and therefore it learns a non-orthogonal mapping and improves the supervised BLI performance.
- Vecmap (Artetxe et al., 2018a) follows multiple steps to perform word translation between two languages. The steps are whitening, orthogonal mapping, re-weighting, dewhitening, and dimensionality reduction.
- LNMap (Mohiuddin et al., 2020) uses nonlinear autoencoders to learn a non-linear mapping of the static WEs of two languages into two latent spaces. It then uses these latent spaces to learn another non-linear mapping between them.
- FIPP (Sachidananda et al., 2021) finds the common geometric structure between both languages' embeddings, then using the common structure, it aligns the Gram matrices of these embeddings.
- CLC1 (Li et al., 2022) refines the linear Vecmap framework via CL objective iterations.
- CLC2 (Li et al., 2022) combines the embeddings generated by CL1 and a multilingual PLM (optimized using a contrastive learning objective on the seed dictionary) aligned to the CLC1 embeddings.

For the word translation between Arabic variants, we compare our results to the following approaches that have demonstrated good performance on the same task:

- Erdmann et al. (2018) presents the first version of the Vecamp framework, which uses a linear mapping to align the static word embeddings (WEs) of two languages, $L 1$ and $L 2$. This method employs the orthogonal Procrustes problem to learn the mapping.
- Artetxe et al. (2016) uses the same Vecmap version as (Erdmann et al., 2018) to align the static WEs of $L 1$ and $L 2$. In addition, it uses self-training iterations to allow the model to learn from a larger dictionary at each iteration.
- Riley and Gildea (2018) extends the static WEs of $L 1$ and $L 2$ by incorporating orthographic features of the covered words. The

Vecmap mapping is then applied to these extended WEs.

- El Mekki et al. (2021) uses Canonical Correlation Analysis (CCA) to align the orthographic features in a shared space before extending the static WEs, as in (Riley and Gildea, 2018).


## C Analyses

### 3.1 Examples of Translations by ProMap

Table 9 presents examples of translations predicted by ProMap variants and CLC1 for various language pairs. The table illustrates both instances when ProMap variants accurately predict translations and instances when it fails. Additionally, the table displays the sub-tokens generated by the $\operatorname{ProMap}_{G}$ variant. As demonstrated by the provided examples, ProMap variants are capable to predict correct translations, even for distant languages such as Turkish-Italian, where both ProMap variants were able to correctly predict translations while the CLC1 model failed. Additionally, there are cases where only $\operatorname{ProMap}_{G}$ predicts the correct translations even if it contains more than one subtoken. This indicates that the non-autoregressive word translation method for the mPLM can independently generate correct sub-tokens that form the correct word translation. Furthermore, ProMap ${ }_{S}$ demonstrated in some cases to be the only successful model, highlighting the power of the re-ranking mechanism implemented in our approach.

In the same vein, Table 10 presents examples of predictions generated ProMap ${ }_{G}$ applied on MARBERT. These examples demonstrate the ability of this model to handle word translation between different Arabic dialects and MSA. Also, the table illustrates that in most cases, the correct predictions can be found within the top-5 predictions. However, the model appears to have difficulties in translating from MSA to dialectal Arabic in some instances, in contrast to the translation from dialectal Arabic to MSA which is accurate in the majority of examples.

### 3.2 Comparison Between Dialectal Arabic PLMs

We evaluate the performance of $\operatorname{ProMap}_{G}$ for word translation between different Arabic dialects and MSA using two dialectal Arabic PLMs: MARBERT and CAMELBERT (the mix variant). The re-
sults, summarized in Table 11, indicate that MARBERT outperformed CAMELBERT in the majority of experiments. Additionally, it is worth noting that CAMELBERT has a vocabulary of 30k tokens, while MARBERT has a vocabulary of 100k tokens. These factors led us to adopt MARBERT for our results in the paper.

It should also be noted that the results presented in Table 2 in the paper differ from those in Table 11 because the latter table evaluates the overlapped dictionary pairs between the two PLMs vocabularies, while the results reported in the paper were based on pairs covered by MARBERT vocabulary only.

### 3.3 The Effect of the Prompt Template

One of the challenges in prompt-based finetuning is constructing the template, particularly in the context of a cross-lingual task. We had to choose whether the template should be in the source language, the target language, a random language, or include special tokens. To address this question, we conduct several experiments where we apply prompt-based finetuning to all language pairs using four different templates: a template written in the source language, a template written in the target language, a template written in English, a template composed of random tokens from various languages, and a template made from special tokens added to the PLM vocabulary. The results presented in table 12 show that the performance gap between the different templates is not significant, but the templates expressed in the source and target languages yielded the best and most stable results.

### 3.4 Results of ProMap ${ }_{G}$ on the MADAR Lexicon

Table 13 presents the results achieved on the different Arabic variants covered by the MADAR lexicon (11 pairs). P@1, P@5, P@10 and P@50 scores are reported.

### 3.5 ProMap Few-shot Results $_{G}$

Tables 15 and 16 show the results of few-shot experiments on $\operatorname{ProMap}_{G}$ for 15 different language pairs. The scores reported are the average of 25 runs with 5 different random samplings of $N$ examples and 5 random seeds. The standard deviation is also reported and it is observed that it is large for many experiments. This is likely due to the choice of training samples for the ProMap ${ }_{G}$ model.

| Pair | Source Word | True Translation | CLC1 | ProMap ${ }_{G}$ sub-tokens | ProMap $_{G}$ | ProMap $S_{S}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| DE-FR | animationen | animations | animées | anim, ations, [PAD], [PAD] | animations | animations |
| DE-FR | infinitesimalrechnung | calcul | infinitésimal | calcul, [PAD], [PAD], [PAD] | calcul | infinitésimal |
| DE-FR | erniedrigung | humiliation | privation | humili, ation, [PAD], [PAD] | humiliation | humiliation |
| EN-IT | grille | griglia | calandra | gr, iglia, [PAD], [PAD] | griglia | calandra |
| EN-IT | selector | selettore | selezionatore | selet, tore, [PAD], [PAD] | selettore | selettore |
| EN-IT | consulate | consolato | ambasciata | consul, ato, [PAD], [PAD] | consulato | consolato |
| TR-IT | hatırlatır | ricorda | rammenta | ricorda, [PAD], [PAD], [PAD] | ricorda | ricorda |
| TR-IT | gezi | escursione | passeggiata | escur, aggio, [PAD], [PAD] | escuraggio | escursione |
| TR-IT | fosforilasyon | fosforilazione | pathway | fosfor, dazione, [PAD], [PAD] | fosfordazione | fosforilazione |
| TR-IT | aldatma | inganno | inganno | donazione, [PAD], [PAD], [PAD] | donazione | seduzione |
| EN-FR | abbreviation | abréviation | abréviation | sigle, [PAD], [PAD], [PAD] | sigle | sigle |
| EN-FR | presumed | présumé | présumé | sup, posé, [PAD], [PAD] | supposé | supposé |
| TR-FR | acımasızlık | cruauté | cruauté | mé, ence, [PAD], [PAD] | méence | cruauté |
| DE-IT | abkürzungen | abbreviazioni | abbreviazioni | abbrevi, zioni, [PAD], [PAD] | abbrevizioni | abbreviazioni |
| DE-IT | antibiotika | antibiotici | antibiotici | antibi, oti, ici, [PAD] | antibiotiici | antibiotici |
| DE-IT | bruderschaft | fratellanza | confraternita | confratern, fratern, fratern, | confraternfraternfratern. | confraternita |

Table 9: Translation Examples in the Multilingual Setting. The table displays the language pairs, source words, corresponding target words, and translations predicted by the CLC1, ProMap ${ }_{G}$, and ProMap ${ }_{S}$ models, as well as the sub-tokens generated by the ProMap ${ }_{G}$ model. A green background indicates a correct prediction, while a red background indicates an incorrect prediction.

To further investigate this, Table 14 presents examples of training samples for the one-shot scenario (where $N=1$ ) and shows how the chosen sample can greatly impact the performance on the test set. For example, when using the sample "jurisdiction" - "juridiction" for the English-French language pair, the $\mathrm{P} @ 1$ score is 52.35 , while the sample "ideal" - "idéal" results in a P@1 score of 8.59 . In some cases, the chosen training sample can prevent the model from converging at all. This can be seen in the Turkish-Italian pair, where the sample "mineral" - "minerale" results in a P@1 score of 0.00, while the sample "olasılık" - "possibilità" results in a P@1 score of 6.51 . It is also observed that when the chosen example is exclusive to the language pair, the performance is better than when the example is shared with other language pairs.

### 3.6 Visualisations of the Word Embeddings generated by the mPLM Before and After Finetuning

Figures (3-15) present the t-SNE visualizations of the XLM-17 embeddings generated for the word pairs available in the test sets for the different language pairs before and after the prompt-based finetuning using ProMap $_{G}$.

| Language pair | Source Word | Ground Truth Translation | Top 5 Predictions |
| :---: | :---: | :---: | :---: |
| MOR-MSA | جاي | قادم | انی, قادم, جاء, جاي, سياتي |
| MOR-MSA | عيان | مريض | مريض, كصـاب, طبيب, عبان, |
| MOR-MSA | كورة | كرة | كرة, كورة, لعبة, رياضة, مبار ان |
| MOR-MSA | تلفون | هاتف | هاتف, جوال, تلفون, جهاز , برا بطارية |
| MOR-MSA | شاف | شاهد | شاها, سمع, رای, ڤرا |
| MOR-MSA | فلوس | نقود | فود, مبلغ, امو ال, دو دلا لار , فلوس |
| EGY-MSA | شال | حمل | حمل, وضع, ترك, نسي, سقط |
| EGY-MSA | جدع | رجل | صديق, طيب, كريّ, كر, رجل, شهم |
| EGY-MSA | ايوه | نعم | نعم, اذن, حسنا, لا, ایضا |
| EGY-MSA | عيشة | حياة | حياة, طعام, عيش, عيشة, نوم |
| EGY-MSA | امبارح | امس | غدا, البارحة, غد, امس, اليوم |
| GLF-MSA | شنطة | حقيبة | حقيبة, متاع, شنطب, محفظّ, حقايب |
| GLF-MSA | تيشبرت | قيص | قميص, فستان, حذاء, معطف, سترة |
| GLF-MSA | زفت | سيء | سيء, سيي, جيد, قبيح, خطير |
| YEM-MSA | خلص | انتهى | انتهى, بدا, توقف, , اغلق, قضى |
| YEM-MSA | فوت | طعام | نقود, طعام, خبز, فوت, ساعد |
| LEV-MSA | لازم | لابد | ممكن, يجب, لابد, لازع, ضاروري |
| LEV-MSA | بعدين | لاحقا | الان, لاحقا, بعدين, حالا, قادم |
| MSA-MOR | انتم | نتوما | هوما, حنا, انتّ, نـنوما, انتا |
| MSA-MOR | للى | عند | عند, عندا, كاين, عندي, بين |
| MSA-MOR | كيف | كيفان | كيف, علاش, كيفاش, مزيان, شنو |
| MSA-EGY | لماذا | ليه | ايه, ليه, عشان, فين, ازل الي |
| MSA-IRQ | داخل | جو | داخل, جوات, جوة, جوا, برة |
| MSA-LBY | سقط | ط | طاح, وقع, طيح, فعد, سقط |

Table 10: Examples of word translations between Arabic dialects and MSA generated by ProMap ${ }_{G}$ with MARBERT. The table presents several Arabic variant pairs and the top 5 predictions for each query. The top 5 predictions are presented from right to left direction.

|  |  | MAR-MSA |  | ALG-MSA |  | TUN-MSA |  | LBY-MSA |  | EGY-MSA |  | SDN-MSA |  | LEV-MSA |  | IRQ-MSA |  | GLF-MSA |  | YEM-MSA |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ | $\rightarrow$ | $\leftarrow$ |
| CAMELBERT | P@1 | 60.71 | 50.36 | 65.06 | 54.08 | 63.03 | 56.43 | 68.99 | 56.49 | 62.34 | 51.40 | 57.71 | 44.17 | 58.33 | 50.24 | 73.01 | 61.58 | 50.85 | 32.71 | 60.21 | 52.22 |
|  | P@5 | 70.54 | 61.31 | 77.11 | 65.31 | 73.95 | 65.00 | 83.72 | 75.32 | 80.52 | 69.83 | 82.86 | 60.19 | 76.04 | 65.88 | 85.28 | 75.71 | 70.94 | 51.88 | 81.15 | 68.97 |
|  | P@10 | 76.79 | 65.69 | 80.72 | 69.39 | 78.15 | 68.57 | 88.37 | 79.87 | 84.42 | 75.42 | 85.71 | 65.53 | 81.25 | 73.93 | 87.73 | 79.66 | 79.91 | 57.14 | 83.25 | 74.38 |
|  | P@50 | 83.04 | 73.72 | 89.16 | 78.57 | 85.71 | 77.86 | 92.25 | 85.71 | 91.56 | 85.47 | 91.43 | 79.61 | 91.15 | 81.52 | 92.64 | 86.44 | 88.46 | 77.44 | 88.48 | 85.71 |
| MARBERT | P@1 | 59.82 | 50.36 | 65.06 | 53.06 | 65.55 | 54.29 | 72.09 | 58.44 | 66.88 | 51.40 | 65.14 | 47.09 | 62.50 | 45.97 | 79.14 | 51.41 | 61.54 | 30.45 | 63.35 | 49.75 |
|  | P@5 | 69.64 | 61.31 | 78.31 | 67.35 | 78.15 | 66.43 | 86.82 | 74.68 | 81.17 | 68.16 | 84.57 | 61.65 | 82.29 | 67.77 | 87.73 | 61.02 | 80.77 | 49.62 | 84.29 | 67.49 |
|  | P@10 | 76.79 | 62.77 | 79.52 | 69.39 | 81.51 | 70.71 | 87.60 | 79.87 | 85.71 | 73.74 | 87.43 | 67.48 | 84.90 | 72.51 | 91.41 | 63.28 | 85.04 | 58.27 | 88.48 | 75.37 |
|  | P@50 | 85.71 | 69.34 | 87.95 | 75.51 | 88.24 | 78.57 | 93.02 | 87.01 | 92.86 | 87.15 | 94.86 | 85.92 | 91.67 | 84.83 | 93.87 | 70.62 | 93.16 | 74.06 | 93.19 | 84.24 |

Table 11: A comparison of $\mathrm{P} @ 1$ for ProMap $_{G}$ using CAMELBERT and MARBERT as Arabic PLMs between Arabic dialects and MSA.

| Pairs | English template | Source language template | Target language template | Random language template | Special Tokens |
| :---: | :---: | :---: | :---: | :---: | :---: |
| DE $\rightarrow$ FR | 58.07 (1.37) | 59.08 (1.02) | 59.14 (1.22) | 57.47 (0.58) | 58.98 (1.48) |
| DE $\rightarrow$ IT | 55.67 (0.29) | 56.94 (0.85) | 56.30 (1.14) | 56.83 (0.47) | 55.75 (2.38) |
| DE $\rightarrow$ RU | 44.82 (3.47) | 45.73 (6.05) | 48.90 (1.32) | 48.17 (1.49) | 48.29 (1.80) |
| DE $\rightarrow$ TR | 51.25 (1.41) | 53.42 (1.12) | 53.92 (1.83) | 52.17 (0.75) | 52.92 (2.48) |
| EN $\rightarrow$ DE | - | 74.55 (2.25) | 72.06 (2.16) | 73.31 (2.25) | 73.62 (1.01) |
| EN $\rightarrow$ FR | - | 79.83 (0.91) | 80.44 (1.28) | 80.17 (0.58) | 79.67 (0.89) |
| EN $\rightarrow$ IT | - | 77.61 (1.36) | 76.70 (1.13) | 72.54 (7.97) | 75.41 (0.71) |
| EN $\rightarrow$ RU | - | 55.73 (5.78) | 59.16 (2.53) | 57.25 (3.70) | 56.79 (2.98) |
| EN $\rightarrow$ TR | - | 58.93 (2.65) | 57.33 (1.74) | 58.00 (0.85) | 57.33 (1.92) |
| IT $\rightarrow$ FR | 72.47 (1.78) | 73.55 (1.45) | 72.54 (2.30) | 72.50 (2.48) | 72.96 (1.18) |
| RU $\rightarrow$ FR | 49.66 (3.58) | 51.26 (2.12) | 52.18 (1.13) | 52.94 (1.22) | 52.44 (1.50) |
| RU $\rightarrow$ IT | 48.20 (3.01) | 50.36 (1.81) | 48.11 (4.30) | 52.25 (1.01) | 51.91 (2.28) |
| TR $\rightarrow$ FR | 46.11 (1.25) | 49.87 (0.70) | 47.32 (1.36) | 48.15 (2.98) | 48.52 (0.90) |
| TR $\rightarrow$ IT | 46.92 (1.88) | 51.44 (1.54) | 46.78 (0.79) | 49.04 (2.60) | 48.08 (1.62) |
| TR $\rightarrow$ RU | 30.31 (2.59) | 37.95 (2.30) | 34.52 (1.50) | 32.88 (2.17) | 35.62 (3.40) |

Table 12: Comparison of P@1 Scores of ProMap $_{G}$ using different prompting templates. Every value in the table presents the average (and standard deviation) of 5 runs, corresponding to 5 random seeds.


Figure 3: A t-SNE visualization of word embeddings generated from the mPLM for words in the DEFR pair test set, before and after the prompt-based finetuning.


Figure 5: A t-SNE visualization of word embeddings generated from the mPLM for words in the DETR pair test set, before and after the prompt-based finetuning.


Figure 4: A t-SNE visualization of word embeddings generated from the mPLM for words in the DEIT pair test set, before and after the prompt-based finetuning.


Figure 6: At-SNE visualization of word embeddings generated from the mPLM for words in the ENFR pair test set, before and after the prompt-based finetuning.


Figure 7: A t-SNE visualization of word embeddings generated from the mPLM for words in the EN-IT pair test set, before and after the prompt-based finetuning.


Figure 10: A t-SNE visualization of word embeddings generated from the mPLM for words in the IT-FR pair test set, before and after the prompt-based finetuning.


Figure 13: A t-SNE visualization of word embeddings generated from the mPLM for words in the TR-FR pair test set, before and after the prompt-based finetuning.


Figure 8: A t-SNE visualization of word embeddings generated from the mPLM for words in the ENRU pair test set, before and after the prompt-based finetuning.


Figure 11: A t-SNE visualization of word embeddings generated from the mPLM for words in the RU-FR pair test set, before and after the prompt-based finetuning.


Figure 14: A t-SNE visualization of word embeddings generated from the mPLM for words in the TR-IT pair test set, before and after the prompt-based finetuning.


Figure 9: A t-SNE visualization of word embeddings generated from the mPLM for words in the ENTR pair test set, before and after the prompt-based finetuning.


Figure 12: A t-SNE visualization of word embeddings generated from the mPLM for words in the RU-IT pair test set, before and after the prompt-based finetuning.


Figure 15: A t-SNE visualization of word embeddings generated from the mPLM for words in the TR-RU pair test set, before and after the prompt-based finetuning.

| Pair | P@1 | P@5 | P@ $\mathbf{1 0}$ | P@ $\mathbf{5 0}$ |
| :--- | :---: | :---: | :---: | :---: |
| $\mathbf{M A R ~} \rightarrow$ MSA | 52.98 | 64.90 | 70.86 | 83.44 |
| MSA $\rightarrow$ MAR | 39.55 | 54.80 | 59.89 | 72.32 |
| ALG $\rightarrow$ MSA | 50.81 | 68.55 | 75.00 | 79.84 |
| MSA $\rightarrow$ ALG | 37.32 | 51.41 | 63.38 | 71.13 |
| TUN $\rightarrow$ MSA | 51.55 | 73.29 | 80.12 | 85.09 |
| MSA $\rightarrow$ TUN | 43.62 | 59.57 | 63.30 | 72.34 |
| LBY $\rightarrow$ MSA | 66.67 | 81.55 | 84.52 | 91.67 |
| MSA $\rightarrow$ LBY | 52.02 | 69.70 | 76.26 | 86.36 |
| EGY $\rightarrow$ MSA | 61.95 | 80.49 | 84.39 | 92.68 |
| MSA $\rightarrow$ EGY | 41.63 | 67.81 | 74.68 | 85.41 |
| SDN $\rightarrow$ MSA | 61.32 | 79.01 | 86.01 | 93.00 |
| MSA $\rightarrow$ SDN | 34.57 | 56.13 | 62.08 | 82.53 |
| LEV $\rightarrow$ MSA | 60.37 | 80.65 | 83.41 | 94.93 |
| MSA $\rightarrow$ LEV | 40.91 | 64.46 | 73.14 | 87.60 |
| IRQ $\rightarrow$ MSA | 67.33 | 85.64 | 88.61 | 93.07 |
| MSA $\rightarrow$ IRQ | 49.08 | 70.18 | 75.69 | 84.86 |
| GLF $\rightarrow$ MSA | 60.17 | 81.10 | 86.05 | 93.02 |
| MSA $\rightarrow$ GLF | 25.75 | 49.32 | 56.44 | 76.71 |
| YEM $\rightarrow$ MSA | 56.72 | 81.72 | 86.19 | 91.79 |
| MSA $\rightarrow$ YEM | 38.75 | 59.41 | 68.63 | 82.29 |
| Avg. |  |  |  |  |
| $* \rightarrow$ MSA | 58.99 | 77.69 | 82.52 | 89.85 |
| MSA $\rightarrow *$ | 40.32 | 60.27 | 67.35 | 80.15 |

Table 13: Results of $\operatorname{ProMap}_{G}$ for word translation between Arabic dialects and MSA using MARBERT on the MADAR Lexicon.

| Pair | Training example | P@ $\mathbf{1}$ |
| :--- | :--- | :--- |
| DE-FR | zahlung - paiement | 15.05 |
|  | system - système | 2.15 |
| DE-IT | expedition - spedizione | 2.55 |
|  | fenster - finestra | 4.88 |
| EN-FR | jurisdiction - juridiction | 52.35 |
|  | ideal - idéal | 8.59 |
|  | orientation - orientation | 0.83 |
| EN-IT | weight - peso | 15.90 |
|  | rice - riso | 1.53 |
| EN-TR | league - lig | 31.90 |
|  | agreement - anlaşma | 3.81 |
|  | influence - etki | 0.00 |
| TR-IT | olasilı - possibilità | 6.51 |
|  | mineral - minerale | 0.00 |

Table 14: The effect on the selected training example for the few-shot scenario when $N=1$. The table shows examples of the selected training example for several pairs and the corresponding P@1 score of ProMap $_{G}$ on the test set.

| Pairs | DE $\rightarrow$ FR | DE $\rightarrow$ IT | $\mathrm{DE} \rightarrow \mathrm{RU}$ | DE $\rightarrow$ TR | EN $\rightarrow$ DE | EN $\rightarrow$ FR | EN $\rightarrow$ IT | EN $\rightarrow$ RU | EN $\rightarrow$ TR | $\mathrm{IT} \rightarrow \mathrm{FR}$ | $\mathrm{RU} \rightarrow \mathrm{FR}$ | $\mathrm{RU} \rightarrow \mathbf{I T}$ | TR $\rightarrow$ FR | TR $\rightarrow$ IT | $\mathrm{TR} \rightarrow \mathrm{RU}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{N}=1$ | (1.92) | (2.86) | (0.00) | 4.21 (3.90) | 10.95 (5.46) | 20.67 (15.58) | 11.04 (2.34) | 6.87 (1.53) | 8.09 (7.05) | 13.05 (10.88) | 6.27 (3.19) | 9.70 (7.99) | 2.60 (0.59) | 7.02 (6.72) | 2.74 (0.00) |
| $\mathrm{N}=3$ | 22.03 (8.59) | 14.99 (6.27) | 6.63 (6.82) | 7.45 (3.87) | 24.50 (8.00) | 39.89 (8.92) | 32.39 (17.51) | 12.15 (5.51) | 16.80 (9.14) | 38.87 (7.81) | 17.61 (7.61) | 22.4 (1.93) | 15.40 (2.46) | 10.44 (3.09) | 4.43 (2.68) |
| $\mathrm{N}=5$ | 23.27 (12.13) | 29.40 (4.33) | 13.42 (5.42) | 16.42 (8.44) | 39.52 (7.66) | 48.08 (16.50) | 44.54 (8.78) | 31.08 (2.87) | 22.48 (6.71) | 48.24 (8.64) | 25.81 (8.34) | 25.29 (2.37) | 23.03 (6.54) | 17.73 (7.74) | 7.64 (3.75) |
| $\mathrm{N}=10$ | 31.10 (6.88) | 25.27 (13.35) | 19.88 (5.03) | 26.68 (10.79) | 52.71 (2.93) | 66.03 (6.50) | 52.85 (7.04) | 32.04 (4.15) | 28.55 (11.40) | 52.25 (4.36) | 31.98 (5.46) | 30.93 (0.94) | 33.44 (1.32) | 28.95 (4.71) | 16.87 (3.26) |
| $\mathrm{N}=16$ | 30.46 (9.54) | 18.74 (6.69) | 22.99 (3.32) | 29.43 (7.81) | 45.44 (6.94) | 65.40 (5.96) | 51.17 (7.89) | 35.60 (5.01) | 34.60 (7.35) | 39.57 (11.49) | 35.26 (2.41) | 33.10 (1.85) | 36.50 (0.86) | 34.75 (1.51) | 25.84 (2.15) |
| $\mathrm{N}=32$ | 37.72 (8.9) | 34.01 (1.37) | 27.47 (4.94) | 26.79 (3.44) | 53.63 (4.08) | 59.45 (9.21) | 47.17 (17.87) | 42.26 (4.96) | 37.68 (5.81) | 46.11 (6.37) | 40.35 (2.22) | 36.29 (0.61) | 39.06 (1.64) | 39.47 (2.20) | 28.16 (1.56) |
| $\mathrm{N}=64$ | 36.61 (4.14) | 38.34 (4.35) | 28.16 (4.86) | 30.57 (9.11) | 55.45 (6.49) | 59.8 (10.21) | 52.83 (13.38) | 46.49 (2.50) | 41.40 (11.4) | 55.57 (6.67) | 41.97 (2.61) | 38.40 (2.42) | 41.29 (1.16) | 43.55 (0.64) | 30.66 (1.73) |
| $\mathrm{N}=128$ | 46.85 (3.44) | 45.95 (2.13) | 27.04 (6.06) | 32.77 (8.96) | 54.84 (13.3) | 70.44 (3.48) | 56.22 (11.46) | 31.88 (17.06) | 42.85 (4.34) | 59.06 (9.14) | 39.12 (13.12) | 42.81 (2.25) | 40.96 (0.72) | 44.64 (0.65) | 32.98 (1.50) |
| $\mathrm{N}=256$ | 53.18 (2.63) | 50.82 (2.44) | 37.38 (6.02) | 46.64 (0.95) | 61.69 (6.22) | 74.37 (1.98) | 66.33 (3.35) | 45.44 (7.99) | 48.94 (2.62) | 68.74 (2.25) | 49.78 (1.77) | 45.37 (2.11) | 44.59 (0.91) | 47.00 (1.52) | 33.75 (1.87) |
| $\mathrm{N}=512$ | 53.69 (4.02) | 51.33 (6.86) | 42.14 (4.22) | 48.46 (5.74) | 67.44 (4.21) | 74.21 (4.48) | 65.96 (10.78) | 51.55 (4.65) | 57.17 (7.06) | 66.11 (8.81) | 51.57 (3.35) | 47.2 (2.21) | 46.24 (0.65) | 44.75 (6.61) | 36.20 (0.70) |

Table 15: Comparison of $\mathrm{P} @ 1$ scores of $\mathrm{ProMap}_{G}$ using different sizes of training example pairs. Every value in the table presents the average (and standard deviation) of 25 runs, corresponding to 5 random samplings with 5 random seeds.

| Pairs | DE $\rightarrow$ FR | DE $\rightarrow$ IT | $\mathrm{DE} \rightarrow \mathrm{RU}$ | DE $\rightarrow$ TR | EN $\rightarrow$ DE | EN $\rightarrow$ FR | EN $\rightarrow$ IT | EN $\rightarrow$ RU | EN $\rightarrow$ TR | $\mathrm{IT} \rightarrow \mathrm{FR}$ | $\mathrm{RU} \rightarrow \mathrm{FR}$ | $\mathrm{RU} \rightarrow \mathrm{IT}$ | TR $\rightarrow$ FR | TR $\rightarrow$ IT | TR $\rightarrow$ RU |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{N}=1$ | 10.97 (4.75) | 10.56 (3.71) | 4.41 (2.71) | 11.02 (8.03) | 21.30 (7.82) | 30.77 (13.02) | 24.25 (4.34) | 9.21 (5.77) | 15.22 (5.65) | 30.48 (9.70) | 23.01 (9.65) | 24.36 (12.63) | 9.22 (6.23) | 11.50 (3.65) | 7.27 (1.89) |
| $\mathrm{N}=3$ | 39.30 (9.39) | 26.14 (12.01) | 22.74 (7.01) | 12.85 (7.01) | 33.74 (13.18) | 46.03 (10.55) | 46.46 (25.67) | 24.12 (12.09) | 30.43 (13.26) | 39.84 (9.89) | 37.28 (16.67) | 44.51 (3.38) | 29.19 (8.14) | 22.84 (6.10) | 9.81 (2.64) |
| $\mathrm{N}=5$ | 36.53 (19.20) | 30.27 (16.60) | 30.34 (11.29) | 24.11 (8.97) | 49.02 (16.12) | 60.32 (23.94) | 53.44 (8.22) | 35.29 (19.58) | 38.14 (13.32) | 70.09 (19.96) | 49.61 (11.49) | 48.48 (4.45) | 40.98 (8.18) | 35.07 (9.62) | 16.50 (4.17) |
| $\mathrm{N}=10$ | 37.58 (12.83) | 28.15 (18.80) | $34.84(8.76)$ | 35.76 (16.70) | 75.91 (2.72) | 82.63 (8.08) | 70.59 (8.49) | 53.70 (6.96) | 41.59 (18.41) | 61.19 (10.24) | 57.56 (6.76) | 54.36 (4.27) | 52.63 (2.92) | 49.04 (5.55) | 31.84 (4.54) |
| $\mathrm{N}=16$ | 44.60 (19.01) | 28.35 (11.78) | 38.73 (9.73) | 35.12 (13.23) | 63.83 (9.13) | 69.52 (14.17) | 67.19 (9.46) | 56.16 (7.17) | 53.69 (13.17) | 49.89 (20.10) | 62.56 (3.56) | 56.02 (5.42) | 57.19 (0.77) | 54.98 (1.93) | 42.33 (2.22) |
| $\mathrm{N}=32$ | 49.55 (12.27) | 48.06 (4.82) | 37.04 (12.4) | 38.29 (10.7) | 62.67 (15.82) | 73.97 (11.43) | 56.77 (21.09) | 60.35 (9.55) | 58.03 (10.85) | 56.02 (15.95) | 67.36 (1.23) | 61.13 (1.39) | 60.21 (2.39) | 60.20 (2.55) | 47.26 (2.89) |
| $\mathrm{N}=64$ | 56.86 (6.43) | 60.86 (8.09) | 45.45 (6.48) | 42.28 (14.55) | 73.80 (8.67) | 73.59 (11.51) | 68.17 (19.03) | 57.32 (17.71) | 54.78 (12.92) | 70.02 (12.97) | 70.74 (0.51) | 66.31 (1.34) | 63.62 (1.17) | 66.00 (1.79) | 53.50 (0.72) |
| $\mathrm{N}=128$ | 69.69 (4.81) | 70.54 (4.01) | 46.97 (11.62) | 49.50 (14.17) | 69.60 (18.88) | 78.62 (15.37) | 76.51 (11.56) | 49.67 (21.26) | 50.55 (16.40) | 71.24 (21.90) | 64.23 (17.46) | 61.98 (13.20) | 51.30 (24.37) | 68.24 (0.47) | 55.84 (0.72) |
| $\mathrm{N}=256$ | 76.40 (2.12) | 75.98 (1.60) | 56.96 (11.17) | 69.11 (1.86) | 83.75 (6.13) | 88.94 (2.00) | 85.95 (2.98) | 68.21 (5.48) | 67.94 (6.27) | 85.99 (0.84) | 73.33 (0.51) | 70.52 (1.56) | 66.67 (1.63) | 71.34 (1.3) | 56.41 (1.15) |
| $\mathrm{N}=512$ | 76.36 (3.13) | 76.45 (6.15) | 66.78 (3.27) | 69.68 (6.46) | 87.12 (2.37) | 89.70 (1.71) | 85.19 (9.52) | 71.62 (3.87) | 77.81 (4.63) | 83.52 (5.19) | 73.8 (1.90) | 71.60 (1.55) | 70.21 (0.76) | 69.41 (7.06) | 59.66 (0.45) |

Table 16: Comparison of $\mathrm{P} @ 5$ scores of ProMap $_{G}$ using different sizes of training example pairs. Every value in the table presents the average (and standard deviation) of 25 runs, corresponding to 5 random samplings with 5 random seeds.


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[^1]:    *We use cosine similarity to compute the similarity between word vectors.
    ${ }^{\dagger}$ In order to ensure that the scale and direction of losses are consistent with the softmax probabilities, we apply a logarithmic transformation and inverse function to the losses.

[^2]:    ${ }^{\ddagger}$ In the second case, we did not report any baselines due to unavailability of static WEs for the country-level Arabic variants.

