Abstract

While pretrained language models (PLMs) primarily serve as general purpose text encoders that can be fine-tuned for a wide variety of downstream tasks, recent work has shown that they can also be rewired to produce high-quality word representations (i.e., static word embeddings) and yield good performance in type-level lexical tasks. While existing work primarily focused on lexical specialization of PLMs in monolingual and bilingual settings, in this work we expose massively multilingual transformers (MMTs, e.g., mBERT or XLMT) to multilingual lexical knowledge at scale, leveraging BabelNet as the readily available rich source of multilingual and cross-lingual type-level lexical knowledge. Concretely, we leverage BabelNet’s multilingual synsets to create synonym pairs across 50 languages and then subject the MMTs (mBERT and XLMT) to a lexical specialization procedure guided by a contrastive objective. We show that such massively multilingual lexical specialization brings massive gains in two standard cross-lingual lexical tasks, bilingual lexicon induction and cross-lingual word similarity, as well as in cross-lingual sentence retrieval. Crucially, we observe gains for languages unseen in specialization, indicating that the multilingual lexical specialization enables generalization to languages with no lexical constraints. In a series of subsequent controlled experiments, we demonstrate that the pretraining quality of word representations in the MMT for languages involved in specialization has a much larger effect on performance than the linguistic diversity of the set of constraints. Encouragingly, this suggests that lexical tasks involving low-resource languages benefit the most from lexical knowledge of resource-rich languages, generally much more available.

1 Introduction

Massively multilingual transformers (MMTs) such as mBERT (Devlin et al., 2019) and XLM-R (Con-
first specializes monolingual PLMs with monolingual lexical constraints and then aligns the obtained monolingual type-level word representations using cross-lingual word pairs.

Further, with the aim of pinpointing the exact factors that drive the downstream lexical performance of the specialized models, we perform a series of diagnostic experiments in which we control for (i) the size of the specialization dataset, i.e., the number of synonym pairs from BabelNet used in contrastive training and (ii) the linguistic diversity of the language represented in the specialization dataset. The results of our diagnostic experiments strongly suggest that the MMT’s initial representation quality for the languages of BabelNet constraints used in specialization (i.e., the specialization languages) defines the downstream performance much more than the linguistic diversity of the specialization dataset. These findings for multilingual specialization for (type-level) lexical tasks contrast the observations for higher-level tasks, requiring the modeling of sentence or sentence-pair semantics, in which both multi-source specialization/fine-tuning on diverse languages (Chen et al., 2019; Ansell et al., 2021) and linguistic proximity between training and evaluation languages (Lin et al., 2019; Lauscher et al., 2020a) have been shown to strongly affect the transfer performance. At the same time, these results suggest that, unlike in higher-level semantic tasks, we can successfully improve the MMT’s lexical representations of low-resource languages by leveraging the abundant external lexical knowledge of high-resource languages. We make our code available at https://github.com/umanlp/babelbert.

2 Related Work

External lexical knowledge from lexico-semantic resources (e.g., WordNet, ConceptNet) has been extensively leveraged for improving distributional representations of words – a process commonly referred to as semantic specialization. Earlier work on semantic specialization of word embeddings can roughly be divided into (i) joint specialization approaches (Yu and Dredze, 2014; Xu et al., 2014; Bian et al., 2014; Kiela et al., 2015; Liu et al., 2015; Ono et al., 2015, inter alia), which integrate the external lexical constraints in the word embedding (pre)training and (ii) retrofitting or postprocessing techniques that post-hoc modify the pretrained embeddings, conforming them to external lexical constraints (Faruqui et al., 2015; Wieting et al., 2015; Mrkšić et al., 2017; Vulić et al., 2018; Glavaš and Vulić, 2018; Ponti et al., 2018).

External lexical knowledge has also been used to enrich (primarily monolingual) PLMs (Lauscher et al., 2020b; Levine et al., 2020). Both Lauscher et al. (2020b) and Levine et al. (2020) couple the masked language modeling with an auxiliary pre-training objective: the former predicts whether pairs of words stand in synonymy or direct hypernymy relation in WordNet, whereas the latter predicts the WordNet supersynset of the masked words. It is important, however, that neither of the two aims to produce better type-level word representations, but rather to enrich the Transformer with additional knowledge to be exploited in various downstream tasks.

In multilingual settings, semantic specialization simultaneously (a) improves the semantic representations of words from all involved languages and, through that, (b) better semantically aligns the word representations across languages. To this end, several paradigms for obtaining semantically improved multilingual representation spaces have been proposed for static word embeddings: (i) align-and-specialize (Mrkšić et al., 2017) starts from mutually unaligned monolingual embedding spaces and both aligns them and semantically specializes for semantic similarity (as opposed to other types of semantic relatedness) by means of both multilingual (i.e., monolingual constraints for multiple languages) and cross-lingual lexical constraints; (ii) in cross-lingual specialization transfer (Vulić et al., 2018; Glavaš and Vulić, 2018) the embedding space of target languages is first projected into the (unspecialized) space of the rich source language (typically English) using a limited amount of cross-lingual source-target lexical constraints and then specializes the cross-lingual space with the (abundant) lexical constraints in the resource-rich source language; (3) constraint transfer (Ponti et al., 2019) noisily translates the (abundant) source language constraints into target languages and uses those to specialize the monolingual embedding spaces of target languages.

More recently, Vulić et al. (2020c) showed that pretrained transformers encode a wealth of lexical knowledge in their parameters and that it is possible to obtain from them type-level (i.e., static, out-of-context) word representations that outperform representations obtained with word embed-
We first describe the process of acquisition of lexical constraints for a given selection of languages and then provide details of contrastive multilingual lexical specialization training.

3 Multilingual Lexical Specialization

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3.1 Constraint Mining

In line with most work on lexical specialization for semantic similarity, we exploit the lexico-semantic relation of synonymy to obtain the specialization constraints. The multilingual synsets of BabelNet¹ allow us to simultaneously obtain both monolingual and cross-lingual synonym pairs. Let \( \mathcal{L} = \{L_1, L_2, \ldots, L_n\} \) be the predefined set of languages for which we mine the constraints. We iterate over the most frequent words in English Wikipedia (excluding stopwords) in decreasing order of their frequency and fire them as queries against BabelNet: for each word, we obtain all BabelNet synsets containing that word, discarding synsets that represent named entities. We then iterate over the fetched synsets, creating all possible (monolingual and cross-lingual) synonym pairs: since the synsets generally contain more senses for higher-resource languages – and aiming to create a linguistically diverse set of constraints – we limit the number of synonym pairs for a language pair (e.g., monolingual EN-EN or cross-lingual EN-FR) obtained for one query word to \( n_q \). We also discard words that are flagged as automatic translations or Wikipedia redirections. The construction of the synonym pair dataset finishes once it contains at least \( \min_l \) distinct words for each of the \( |\mathcal{L}| \) languages.

3.2 Specializing for Semantic Similarity

Our lexical semantic specialization is based on a Bi-Encoder architecture² and a contrastive training objective.

Type-Level Word Representations. Following the best-practice observations from related work (Vulić et al., 2020b; Bommasani et al., 2020; Vulić et al., 2021a), we obtain type-level word representations from a PLM independently for each word from the synonym pair: we tokenize each word into its constituent subwords \( sw_1 \ldots sw_m \) and feed the sequence \([SPEC_1][sw_1] \ldots [sw_m][SPEC_2]\) into the MMT, with \([SPEC_1]\) and \([SPEC_2]\) denoting the special sequence start and sequence end tokens of the MMT (e.g., \([CLS]\) and \([SEP]\), respectively, for BERT). We get the final representation \( e_w \) by mean pooling the representations of its subwords (without the special tokens) from the last layer of the Transformer encoder.

¹The latest 5.0 version of BabelNet covers 500 languages.
²Often also referred to as Dual-Encoder or Siamese architecture.
Contrastive Objective. We train in batches $B = \{(w_1^{(i)}, w_2^{(i)}, \text{syn}_{id}^{(i)}), n_B\}$ of synonym pairs, with $\text{syn}_{id}^{(i)}$ denoting the BabelNet synset from which the synonym pair $(w_1^{(i)}, w_2^{(i)})$ originated. In a single batch, there might be more than one pair belonging to the same synset, thus we form all possible ordered positive pairs in a set $P$, i.e., pairs of words with same $\text{syn}_{id}$. We train by minimizing a variant of the popular InfoNCE (van den Oord et al., 2018) contrastive loss:

$$
L_{\text{InfoNCE}}^B = -\frac{1}{|P|} \sum_{(w_1^{(i)}, w_2^{(i)}) \in P} \log \left( \text{sim}(e_{w_1}^{(i)}, e_{w_2}^{(j)}) \right)
- \log \left( \text{sim}(e_{w_1}^{(i)}, e_{w_2}^{(j)}) - \sum_{n \in \Lambda^{(i)}} \text{sim}(e_{w_1}^{(i)}, e_n) \right)
$$

where $\text{sim}(e_{w_1}^{(i)}, e_{w_2}^{(j)}) = \exp(\cos(e_{w_1}^{(i)}, e_{w_2}^{(j)})/\tau)$, with $\tau$ as the temperature hyperparameter and $\Lambda^{(i)}$ as the set of in-batch negatives, i.e., words from the other pairs in the batch that come from a BabelNet synset other than $\text{syn}_{id}^{(i)}$.

Adapter-Based Fine-Tuning. By default, we fully fine-tune the MMT’s parameters in our lexical specialization. Depending on the nature of the fine-tuning task and the dataset size, full fine-tuning may be both (a) computationally expensive and (b) lead to forgetting of the distributional knowledge acquired in pretraining. To remedy for these potential problems, we additionally experiment with adapter-based lexical specialization (i.e., adapter-based fine-tuning) (Houlsby et al., 2019). Adapters, shown useful in various sequential and transfer learning scenarios (Pfeiffer et al., 2020b; Rücklé et al., 2020; Lauscher et al., 2021; Hung et al., 2022) are parameter-light modules that are inserted into a PLM’s layers before specialization (i.e., fine-tuning); during specialization, only adapter parameters are tuned, while the PLM’s pretrained parameters are kept fixed. We adopt the adapter architecture of Pfeiffer et al. (2020c), in which one adapter layer is inserted into each Transformer layer. The output of the adapter (sub-)layer – which itself is a two-layer feed-forward network – is computed as follows:

$$
\text{Adapter}(h, r) = W_U \cdot f(W_D \cdot h) + r,
$$

with $h$ and $r$ as the hidden state and residual of the respective transformer layer. Matrices $W_D \in \mathbb{R}^{m \times H}$ and $W_U \in \mathbb{R}^{H \times m}$ are the linear down- and up-projections, respectively (with $H$ as the transformer’s hidden size, and $m$ as the adapter’s “bottleneck” dimension), and $f(\cdot)$ as a non-linear activation function. The residual $r$ is the output of the Transformer’s feed-forward layer and $h$ is the output of the immediately following layer normalization. The down-projection matrix $W_D$ compresses token representations to the adapter size $m \ll H$, and the up-projection matrix $W_U$ projects the activated compressions back to the transformer’s hidden size $H$. The ratio $H/m$ determines how much more adapter-based fine-tuning is computationally efficient than full fine-tuning.

4 Experimental setup

We first describe the set of languages for which we mine the constraints from BabelNet and provide the statistics of the final multilingual dataset of lexical constraints that we use for lexical specialization of MMTs. We then specify the training details and finally describe the evaluation tasks and procedures.

Constraints Mining. Our central experimentation involves the 50 diverse languages from the popular XTREME-R benchmark (Ruder et al., 2021a): af, ar, az, bg, bn, de, el, en, es, et, eu, fa, fi, fr, gu, he, hi, ht, hu, id, it, ja, jv, ka, kk, ko, lt, ml, mr, ms, my, nl, pa, pl, pt, qu, ro, ru, sw, ta, te, th, tl, tr, uk, ur, vi, wo, yo, zh. The sample covers 14 language families (Afro-Asiatic, Austro-Asiatic, Austronesian, Dravidian, Indo-European, Japonic, Kartvelian, Kra-Dai, Niger-Congo, Sino-Tibetan, Turkic, Uralic, Creole, and Quechuan) and additionally contains Basque and Korean as two language isolates.

We collect the constraints from BabelNet with the procedure described in §3.1, using the following values: $n_q = 3$ (we allow at most 3 different word pairs for any language pair for a single query) and $\text{min}_l = 25$ (mining stops when we have at least 25 distinct words from each of the 50 languages within the collected constraints). The final specialization dataset contains in total 4,029,934 constraints.

Evaluation Tasks. We evaluate our approach on two standard cross-lingual word-level tasks, bilingual lexicon induction (BLI) and cross-lingual word similarity (XLSIM). We couple this with an evaluation on unsupervised cross-lingual sentence
Task 1: Bilingual Lexicon Induction. BLI tests the quality of a multilingual (bilingual) representation of the query in the target language ranking by means of type-level word alignment. For a given query word from a source language, words from the vocabulary of a target language are ranked based on their similarity with the query. The position of the correct translation of the query in the target language ranking reflects the quality of the type-level word alignment between the languages. We carry out the evaluation on two established BLI benchmarks: G-BLI (Glavaš et al., 2019) covers 28 language pairs between 8 languages (de, en, fi, fr, hr, it, ru, and tr), whereas PanlexBLI (Vulić et al., 2019) spans 15 diverse languages (bg, ca, eo, et, eu, fi, he, hu, id, ka, ko, lt, no, th, tr) giving a total of 210 language pairs. For both datasets, we evaluate on the designated test portions consisting of 2,000 word pairs per language pair and report the performance in terms of Mean Reciprocal Rank (MRR), as recommended by Glavaš et al. (2019).

Task 2: Cross-Lingual Word Similarity. XLSIM measures the correlation between the similarities of cross-lingual word pairs obtained based on their representations in the multilingual (bilingual) representation. Before the lexical specialization, we remove all constraints that contain any of the words that appear in BLI and XLSIM datasets. The numbers of monolingual and cross-lingual synonymy constraints in the training set for the selection of 50 languages from the XTREME-R benchmark. Most monolingual constraints have been obtained for Chinese (6427) and most cross-lingual constraints between Japanese and Chinese (6740).
representation space and similarity scores assigned by human annotators. We evaluate the performance on 66 language pairs between 12 languages (zh, cy, en, et, fi, fr, he, pl, ru, es, sw, yue) from the MultiSimLex dataset (Vulić et al., 2020a) and use Spearman’s ρ between the cosine similarity of the word-pairs and the corresponding human-assigned similarity scores.

**Task 3: Unsupervised Cross-Lingual Sentence Retrieval.** For cross-lingual sentence retrieval, we use the Tatoe dataset (Artetxe and Schwenk, 2019) which comprises 112 languages, where each language has 1,000 sentences paired with their translations in English. We obtain the sentence embedding by mean-pooling the representations of all of its subword tokens at the output of the last Transformer layer. We straightforwardly compute the similarities between sentences as the cosine of the angles between their embeddings.

**Training Details.** We split the obtained set of multilingual lexical constraints into a training and validation portion, with the purpose of the latter being to inform early stopping and hyperparameter selection. We create the validation split by first creating a set of words $W_{val}$, selecting 20% of the distinct words for each language, and finally move all pairs in the training set made of words in $W_{val}$ to the validation set. After this, we remove all test words from the two BLI datasets and the MultiSimLex dataset from the training set. The resulting training set is made of 1,230,769 constraints while the validation set contains 204,159 constraints. The number of constraints for each language pair (including monolingual constraints) for the training set is shown in Figure 1. We use the MRR@$k$ on the validation set as the (proxy) performance measure with which we track the progress of the specialization training. Precisely, for each distinct word (query) $w$ in the validation set, we rank all the other words from the validation set according to their cosine similarity with the query word: we then identify $r_{w,k}$ as the highest rank at which we find any word that shares any BabelNet synset with $w$. If first such word is not in the first $k$ words in the ranking, we set $r_{w,k} = \infty$ (i.e., $1/r_{w,k} = 0$). The final score is the mean of inverted ranks, averaged across all distinct validation set words. In all our experiments, we set $k = 1000$. We compute MRR@$k$ on the validation set every quarter of epoch and stop training if the score does not improve over 5 consecutive evaluations.

We run two sets of experiments, starting from two different MMTs: multilingual BERT (mBERT) (Devlin et al., 2019) and XLM-R (Conneau et al., 2020a). In all experiments, we set the temperature of the InfoNCE loss to $\tau = 0.5$. To account for the very skewed distribution of constraints across language pairs, following Conneau and Lample (2019), we sample batch constraints from the multinomial distribution $\{q_{i,j}\}$ over language pairs $(L_i, L_j)$, given as follows:

$$q_{i,j} = \frac{p_{i,j}^n}{\sum_{k,l} p_{k,l}^n}, \quad p_{i,j} = \frac{n_{i,j}}{\sum_{k,l} n_{k,l}}$$

where $n_{i,j}$ denotes the number of synonym pairs for a language pair $(L_i, L_j)$ and $\alpha$ is the smoothing factor. We set $\alpha$ to 0.3.

To pick the hyperparameters, we perform one grid-search for the fully fine-tuned models and one for the adapter-based models. For the first category, we search for the learning rate $lr \in \{5e-6, 1e-5, 2e-5, 5e-5\}$ and the batch size $N_B \in \{128, 256\}$. We pick $lr = 1e-5$ and $N_B = 256$ for both XLM-R and mBERT. For adapter-based models, we search for $lr \in \{5e-6, 1e-5, 2e-5, 5e-5\}$, $N_B \in \{128, 256\}$ and adapter reduction factor $H/m \in \{4, 16\}$. We pick $lr = 1e-4$, $N_B = 256$ and $H/m = 4$ for XLM-R and $lr = 2e-5$, $N_B = 128$ and $H/m = 4$ for mBERT. We optimize using AdamW (Loshchilov and Hutter, 2019) and use PytorchLightning (Falcon and The PyTorch Lightning team, 2019) for our implementation, coupled with Huggingface Transformers (Wolf et al., 2020) and Pytorch Metric Learning (Musgrave et al., 2020) for the contrastive objective. For the adapter-based models, we use adapter-transformers (Pfeiffer et al., 2020a). We track our experiments using Weights & Biases (Biewald, 2020).

5 Results and Discussion

We present the main results on the three tasks (BLI, XLSIM, cross-lingual sentence retrieval) (§5.1) and then provide further analysis with respect to different language samples for multilingual lexical specialization (§5.2).
Table 1: Results of multilingual lexical specialization for two MMTs — mBERT and XLM-R on three tasks (four datasets): BLI – on G-BLI and PanLex-BLI (PL-BLI), XLSIM, and cross-lingual sentence retrieval on the Tatoeba dataset (Ttb). Performance reported in terms of MRR ($\times 100$) for BLI, Spearman’s $\rho$ for XLSIM and accuracy ($\times 100$) for Ttb. For each dataset, we reporting averages across all language pairs (28 for G-BLI, 210 for PL-BLI, 66 for XLSIM, and 112 for Ttb). The highest scores per column and MMT in bold.

| MMT     | Model    | BLI   | XLSIM | Ttb   |
|---------|----------|-------|-------|-------|
|         |          | G-BLI | PL-BLI|
| vanilla | vanilla  | 23.9  | 16.8  | 11.6  | 32.3  |
| mBERT   | Babel-Ad | 29.6  | 22.3  | 17.5  | 32.4  |
|         | Babel-F | **40.1** | **28.1** | **25.8** | **39.6** |
| vanilla | vanilla  | 14.4  | 11.9  | 5.9   | 37.6  |
| XLM-R   | Babel-Ad | 42.9  | 31.9  | 32.3  | 53.9  |
|         | Babel-F | **47.2** | **34.4** | **35.7** | **56.5** |

5.1 Main Results

We present our main results in Table 1: for the vanilla MMTs (i.e., mBERT and XLM-R without any lexical specialization), we report the results for the word representations that come from the layer for which the best performance is obtained on the given dataset: for mBERT the “best layers” are layer 5 for both BLI datasets and XLSIM and layer 7 for cross-lingual sentence retrieval on Tatoeba; for XLM-R, layer 1 provides the best representations for the G-BLI dataset and XLSIM, layer 4 for the PanLex-BLI dataset and layer 7 for Tatoeba. For the lexical specialized model, Babel-F (full fine-tuning of the respective MMT) and Babel-Adapt (adapter-based fine-tuning of the MMT), we, expectedly, always obtain the best word representations from the last Transformer layer (layer 12).

Multilingual lexical fine-tuning substantially improves the performance of both MMTs (mBERT and XLM-R) on all tasks, with full fine-tuning (Babel-F) consistently bringing much larger gains than adapter-based fine-tuning (Babel-Ad). Interestingly, despite the fact that vanilla mBERT produces substantially higher quality word representations than vanilla XLM-R (e.g., 23.9 vs. 14.4 on G-BLI or 11.6 vs. 5.9 on XLSIM), the same multilingual lexical specialization procedure (Babel-F or Babel-Ad) results with a much better lexical encoder when applied on XLM-R than on mBERT (e.g., 47.2 vs. 40.1 on G-BLI or 35.7 vs. 25.8 on XLSIM in favor of XLM-R, with full lexical fine-tuning – Babel-F). This suggests that XLM-R actually contains richer multilingual lexical knowledge than mBERT, which is, however, hidden deeper in the model (this is corroborated by the fact that for XLM-R we generally get better lexical representations from lower Transformer layers): once triggered with our multilingual lexical specialization, this richer lexical information of XLM-R comes to the surface. This would also suggest that XLM-R has more of its capacity dedicated to semantic compositionality than mBERT: this is corroborated by the fact that vanilla XLM-R outperforms mBERT on Tatoeba, the only sentence-level task in our evaluation.

Figure 2 shows the subset of language pairs for which the multilingual lexical specialization brings the largest gains, on PanLex-BLI and XLSIM, respectively. Interestingly, all 10 language pairs for which we obtain the largest PanLex-BLI gains involve Bulgarian (bg) as one of the languages. We believe that this is because Bulgarian is the PanLex-BLI language with the largest presence in XLM-R pretraining (we investigate the effects of the languages’ pretraining participation in more detail in §5.2). Language pairs for which we observe the largest gains on XLSIM predominantly include Mandarin Chinese (cmn) and Yue Chinese (Cantonese, yue). Mandarin is the language that is (i) well-represented in XLM-R’s pretraining and (ii) has among the largest number of constraints (including the most monolingual constraints) in our massively multilingual specialization dataset. Cantonese, on the other hand, is not among the 50 languages for which we obtain the constraints from BabelNet: we believe it benefits transitively through its close proximity to Mandarin.

In Table 2, we compare the performance of our BabelNet-specialized MMTs against the bilingual word embedding spaces induced by Vulić et al. (2021a) using the state-of-the-art VecMap approach (Artetxe et al., 2018) for aligning monolingual static word embedding spaces. Besides aligning (a) monolingual FastText embeddings (Bojanowski et al., 2017) as a competitive baseline, Vulić et al. (2021a) align with VecMap monolingual type-level word embeddings produced by monolingual BERT models, each first lexically specialized with monolingual lexical constraints of the respective language.

Full massively multilingual lexical fine-tuning
Figure 2: Language pairs for which our massively multilingual lexical specialization with BabelNet constraints brings the largest gains (for XLM-R as the initial MMT): (a) for PanLex-BLI (10 out of 210 language pairs) (Vulić et al., 2021a) and (b) for XLSIM (10 out of 66 language pairs).

Table 2: BLI results on a subset of 10 language pairs from G-BLI (Glavaš et al., 2019): comparison against the bilingual word embedding spaces induced by Vulić et al. (2021b) using VecMap (with 1000 and 5000 word translation pairs, i.e., cross-lingual synonymy constraints, used to induce the bilingual projection matrix, respectively) from (i) monolingual FastText embeddings (Bojanowski et al., 2017) and (ii) monolingual embeddings obtained with contrastively fine-tuned monolingual BERT models, i.e., the LexFit approach of (Vulić et al., 2021a). For Babel-FT, we report in the last row for each language pair the number of constraints for that pair in our multilingual lexical specialization dataset. The highest scores per column in bold.

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5.2 Further Analysis

To further investigate the robustness of our specialization approach, we perform language ablation studies to see what happens when we train only on constraints from a subset of 50 languages of our original multilingual specialization dataset. We perform these experiments using our best-performing model across all tasks, i.e. XLM-R Babel-FT, adopting the same hyperparameter values as in in the main experiments.

Linguistic Diversity. We investigate how changing typological or language family diversity of the sample of languages from which we draw the special alignment with VecMap between word representations spaces of two languages obtained with the Babel-FT-ed mBERT/XLM-R, which is all but guaranteed to lead to further BLI improvements.

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Note that there is nothing preventing the additional bilin-
Table 3: Selection of 10 subsets of 10 languages each in increasing $d_{typ}$ order, together with PTQI and PL-BLI average performance.

| Language subsets | $d_{typ}$ | PTQI   | PL-BLI Avg |
|------------------|-----------|--------|------------|
| {ar, en, it, ja, pl, pt, ro, es, uk} | 0.320     | 0.7352 | 0.293      |
| {ar, en, fr, kk, pt, ro, ru, es, tl, uk} | 0.332     | 0.7194 | 0.287      |
| {ar, de, el, en, fa, it, pt, ru, uk, zh} | 0.345     | 0.7339 | 0.301      |
| {ar, de, el, it, kk, nl, es, tl, uk, ur} | 0.354     | 0.7022 | 0.290      |
| {ar, el, en, fr, ms, pl, ro, tl, ur, zh} | 0.373     | 0.7056 | 0.278      |
| {ar, az, fa, ms, nl, pl, qu, ro, uk, zh} | 0.376     | 0.6847 | 0.288      |
| {ar, de, fa, ja, nl, pl, pt, qu, ur, zh} | 0.389     | 0.6724 | 0.276      |
| {az, el, fa, it, ja, kk, ms, ro, es, ur} | 0.408     | 0.6584 | 0.282      |
| {az, de, it, ja, kk, pl, ru, es, ur, zh} | 0.421     | 0.6768 | 0.279      |
| {az, el, en, fa, it, ja, kk, pl, qu, uk} | 0.424     | 0.6664 | 0.283      |

Table 4: Selection of 7 subsets of 10 languages each in increasing $d_{fam}$ order, together with PTQI and PL-BLI average performance.

| Language subsets | $d_{fam}$ | PTQI   | PL-BLI Avg |
|------------------|-----------|--------|------------|
| {el, en, fr, it, pl, pt, ro, ru, uk, ur} | 0.1       | 0.758  | 0.297      |
| {de, el, en, fa, fr, kk, nl, pt, ro, es} | 0.2       | 0.720  | 0.287      |
| {en, fr, it, kk, nl, pl, ro, es, tl, uk} | 0.3       | 0.726  | 0.291      |
| {ar, az, el, kk, ms, pl, pt, ru, tl, uk} | 0.4       | 0.695  | 0.289      |
| {ar, az, el, en, fr, ms, pl, pt, tl, zh} | 0.5       | 0.702  | 0.286      |
| {ar, en, ja, kk, ms, nl, pl, qu, ru, uk} | 0.6       | 0.685  | 0.285      |
| {ar, it, ja, kk, ms, nl, qu, ru, uk, zh} | 0.7       | 0.673  | 0.280      |

Specialization constraints affect the generalization to unseen languages. We follow the definitions introduced in Ponti et al. (2020) to define the typological diversity index $d_{typ}$ and the language family diversity index $d_{fam}$. To compute $d_{typ}$ for a sample of languages $s$, we take the lang2vec vectors (Littell et al., 2017) for each of the languages in $s$ and compute an entropy value for each of the features (such value is 0 if all the languages have identical values for that feature): we then simply take the average across all features. The language family index $d_{fam}$ is the number of language families in $s$ divided by the size of $s$.

To study the interaction between typological diversity and degree of alignment, we first create 10 subsets, each containing 10 languages as follows: we first sample 1,000,000 language subsets of 10 languages and filter only those in which we have at least $min_p = 250$ synonym pairs for each of its 45 language pairs as well as monolingual language pairs (total training size 13,750). We then divide the filtered subsets in 10 equally spaced bins according to their $d_{typ}$ and pick one subset from each bin at random. We evaluate the performance of the XLM-R specialized with each of the 10 constraints sets obtained this way on PanLex-BLI because it is the BLI dataset with the most typologically diverse languages. When sampling from $d_{typ}$ buckets, we additionally select samples that do not contain any of the languages from PanLex-BLI. We then compute the correlation between $d_{typ}$ scores of language samples $s$ and the corresponding PanLex-BLI performance of XLM-R when specialized only with constraints from the respective languages included in samples $s$. Following the same procedure, we also create 7 subsets of 10 languages, each having a different $d_{fam}$ with the same number of constraints and no overlap with the PanLex-BLI languages. We show these language subsets along with their diversity (typological or language family) index and PanLex-BLI performance in Tables 3 and 4. We observe the following Spearman’s $\rho$ correlation coefficient between the sample diversity index and Panlex-BLI performance: $\rho_{d_{typ}}$ of -0.624 for typological diversity scores while for language diversity scores we have $\rho_{d_{fam}}$ of -0.667. Counterintu-

\footnote{We use the syntax_knn vectors which contain 103 syntactic features.}
itively, increasing either the language family or typological diversity of the training languages seems to have a negative impact on downstream BLI performance (on unseen languages). We note that the sizes of language-specific portions of MMT’s pretraining corpora also generally exhibit a negative correlation with linguistic diversity: languages most represented in MMT pretraining tend to come from few language families (predominantly from the Indo-European family).

Effect of Pretraining Quality. To shed further light on this, we analyze how the pretraining presence of the languages involved in the specialization can affect the BLI performance. To this end, we make use of the reported metadata for CC-100 (pretraining corpus for XLM-R) and for every language \( L_i \) we compute the pretraining corpus ratio \( PT_{\text{ratio}}(L_i) \) as the size in GiB of the pretraining data in language \( L_i \) divided by the total corpus size. For the subsets chosen according to typological diversity and language family diversity, we compute \( PT_{\text{ratio}} \) of each subset as the average over languages in that subset. We then compute the correlations of these ratios with the PanLex-BLI average performance, observing: \( \rho_{PT_{\text{ratio}}} = 0.333 \) for 10 samples in Table 3 and \( \rho_{PT_{\text{ratio}}-\text{PL-BLI}} = 0.321 \) for 7 samples in Table 4. Although there is positive correlation, the relative pretraining corpus size of languages does not entirely explain the effectiveness of the multilingual lexical specialization w.r.t. to the languages from which the constraints originate.

Acknowledging that MMT’s quality of representations for a language is also affected by the MMT’s “knowledge” of closely related languages, we propose a modified measure of pretraining presence of a language, which we dub \textit{pretraining quality index} (PTQI). We compute PTQI of a language \( l \) as a weighted average of pretraining ratios \( PT_{\text{ratio}} \) of all languages on which the MMT was pretrained, with language similarities as weights. Let \( L \) be the set of pretraining languages of an MMT. The PQTI of a single language is then computed as:

\[
PTQI(l) = \sum_{l' \in L} PT_{\text{ratio}}(l') \cdot s(l, l')
\]

where \( s(l, l') \) is the cosine similarity of typological lang2vec vectors of languages \( l \) and \( l' \). We compute the correlation between PTQI and the average performance on PanLex-BLI for the language subsets from Tables 3 and 4: we find \( \rho_{PTQI} \) of 0.624 \((p\text{-value } 0.05)\) and \( \rho_{PTQI} \) of 0.893 \((p\text{-value } 0.007)\) respectively. In both cases we observe a very strong (and statistically significant) correlation between the PTQI and BLI performance.

This points to the usefulness of picking high-resource languages, i.e. those having higher PTQI, when creating training sets for multilingual lexical specialization as they have a greater impact on making the model generalize to \textit{unseen} languages: this is encouraging, as the languages rich with unlabeled corpora generally also tend to be the languages between which word translations and synonymy constraints are more abundant and easier to obtain.

6 Conclusion

In this work, we present BabelBERT, a multilingual lexical specialization approach that leverages the massively multilingual lexical knowledge available in BabelNet. Differently from prior approaches, which perform monolingual or bilingual specialization procedures, we subject MMTs to a single training regime with lexical constraints from 50 languages and report massive gains over unspecialized baseline (i.e., MMT not subject to lexical specialization) and competitive performance with prior work on two word-level tasks and on cross-lingual sentence retrieval. Furthermore, we prove that our method improves the performance the lexico-semantic performance for languages for which no lexical constraints were seen in specialization. We perform a series of experiments to study the role of language diversity (either typological or based on language families) in the alignment of cross-lingual lexical representations: we prove that type-level knowledge gained during pretraining, as measured by the newly introduced PTQI index, much better predicts the successfulness of multilingual lexical specialization than the linguistic diversity of the set of constraints. This encourages the injection of lexical knowledge from high-resource languages (languages with largest pretraining corpora), for which lexical data for specialization is much easier to obtain.

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