Learning Domain-Specialised Representations for Cross-Lingual Biomedical Entity Linking

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Abstract

Injecting external domain-specific knowledge (e.g., UMLS) into pretrained language models (LMs) advances their capability to handle specialised in-domain tasks such as biomedical entity linking (BEL). However, such abundant expert knowledge is available only for a handful of languages (e.g., English). In this work, by proposing a novel cross-lingual biomedical entity linking task (XL-BEL) and establishing a new XL-BEL benchmark spanning 10 typologically diverse languages, we first investigate the ability of standard knowledge-agnostic as well as knowledge-enhanced monolingual and multilingual LMs beyond the standard monolingual English BEL task. The scores indicate large gaps to English performance. We then address the challenge of transferring domain-specific knowledge from resource-rich languages to resource-poor ones. To this end, we propose and evaluate a series of cross-lingual transfer methods for the XL-BEL task, and demonstrate that general-domain bitext helps propagate the available English knowledge to languages with little to no in-domain data. Remarkably, we show that our proposed domain-specific transfer methods yield consistent gains across all target languages, sometimes up to 20 Precision@1 points, without any in-domain knowledge in the target language, and without any in-domain parallel data.

1 Introduction

Recent work has demonstrated that it is possible to combine the strength of 1) Transformer-based encoders such as BERT (Devlin et al., 2019; Liu et al., 2019), pretrained on large general-domain data with 2) external linguistic and world knowledge (Zhang et al., 2019; Levine et al., 2020; Lauscher et al., 2020). Such expert human-curated knowledge is crucial for NLP applications in specialised domains such as biomedicine. There, Liu et al. (2021) recently proposed self-alignment pre-training (SAP), a technique to fine-tune BERT on phrase-level synonyms extracted from the Unified Medical Language System (UMLS; Bodenreider 2004). Their SAPBERT model currently holds state-of-the-art (SotA) across all major English biomedical entity linking (BEL) datasets. However, this approach is not widely applicable to other languages: abundant external resources are available only for a few languages, hindering the development of domain-specific NLP models in all other languages.

Simultaneously, exciting breakthroughs in cross-lingual transfer for language understanding tasks have been achieved (Artetxe and Schwenk, 2019; Hu et al., 2020). However, it remains unclear whether such transfer techniques can be used to improve domain-specific NLP applications and mitigate the gap between knowledge-enhanced models in resource-rich versus resource-poor languages. In this paper, we thus investigate the current performance gaps in the BEL task beyond English, and propose several cross-lingual transfer techniques to improve domain-specialised representations and BEL in resource-lean languages.

In particular, we first present a novel cross-lingual BEL (XL-BEL) task and its corresponding evaluation benchmark in 10 typologically diverse languages, which aims to map biomedical names/mentions in any language to the controlled UMLS vocabulary. After empirically highlighting the deficiencies of multilingual encoders (e.g., mBERT and XLMR; Conneau et al. 2020) on XL-BEL, we propose and evaluate a multilingual extension of the SAP technique. Our main results suggest that expert knowledge can be transferred from English to resource-leaner languages, yielding huge gains over vanilla mBERT and XLMR, UMLS is a large-scale biomedical knowledge graph containing more than 14M biomedical entity names.
and English-only SAPBERT. We also show that leveraging general-domain word and phrase translations offers substantial gains in the XL-BEL task.

**Contributions.** 1) We highlight the challenge of learning (biomedical) domain-specialised cross-lingual representations. 2) We propose a novel multilingual XL-BEL task with a comprehensive evaluation benchmark in 10 languages. 3) We offer systematic evaluations of existing knowledge-agnostic and knowledge-enhanced monolingual and multilingual LMs in the XL-BEL task. 4) We present a new SotA multilingual encoder in the biomedical domain, which yields large gains in XL-BEL especially on resource-poor languages, and provides strong benchmarking results to guide future work. The code, data, and pretrained models are available online at:
https://github.com/cambridgeltl/sapbert.

## 2 Methodology

### Background and Related Work.

Learning biomedical entity representations is at the core of BioNLP, benefiting, e.g., relational knowledge discovery (Wang et al., 2018) and literature search (Lee et al., 2016). In the current era of contextualised representations based on Transformer architectures (Vaswani et al., 2017), biomedical text encoders are pretrained via Masked Language Modelling (MLM) on diverse biomedical texts such as PubMed articles (Lee et al., 2020; Gu et al., 2020), clinical notes (Peng et al., 2019; Alsentzer et al., 2019), and even online health forum posts (Basaldella et al., 2020). However, it has been empirically verified that naively applying MLM-pretrained models as entity encoders does not perform well in tasks such as biomedical entity linking (Basaldella et al., 2020; Sung et al., 2020). Recently, Liu et al. (2021) proposed SAP (Self-Alignment Pretraining), a fine-tuning method that leverages synonymy sets extracted from UMLS to improve BERT’s ability to act as a biomedical entity encoder. Their SAPBERT model currently achieves SotA scores on all major English BEL benchmarks.

In what follows, we first outline the SAP procedure, and then discuss the extension of the method to include multilingual UMLS synonyms (§2.1), and then introduce another SAP extension which combines domain-specific synonym lists with general-domain translation data (§2.2).

### 2.1 Language-Agnostic SAP

Let \((x, y) \in \mathcal{X} \times \mathcal{Y}\) denote the tuple of a name and its categorical label. When learning from UMLS synonyms, \(\mathcal{X} \times \mathcal{Y}\) is the set of all \((name, CUI)\) pairs, e.g., \((\text{vaccination}, \text{C0042196})\). While Liu et al. (2021) use only English names, we here consider names in other UMLS languages. During training, the model is steered to create similar representations for synonyms regardless of their language.\(^3\) The learning scheme includes 1) an online sampling procedure to select training examples and 2) a metric learning loss that encourages strings sharing the same CUI to obtain similar representations.

**Training Examples.** Given a mini-batch of \(N\) examples \(\mathcal{B} = \mathcal{X}_B \times \mathcal{Y}_B = \{(x_i, y_i)\}_{i=1}^N\), we start from constructing all possible triplets for all names \(x_i \in \mathcal{X}_B\). Each triplet is in the form of \((x_a, x_p, x_n)\) where \(x_a\) is the anchor, an arbitrary name from \(\mathcal{X}_B\); \(x_p\) is a positive match of \(x_a\) (i.e., \(y_a = y_p\)) and \(x_n\) is a negative match of \(x_a\) (i.e., \(y_a \neq y_n\)). Let \(f(\cdot)\) denote the encoder (i.e., mBERT or XLMR in this paper). Among the constructed triplets, we select all triplets that satisfy the following constraint:

\[
\|f(x_a) - f(x_p)\|_2 + \lambda \geq \|f(x_a) - f(x_n)\|_2,
\]

where \(\lambda\) is a predefined margin. In other words, we only consider triplets with the positive sample further to the negative sample by a margin of \(\lambda\). These ‘hard’ triplets are more informative for representation learning (Liu et al., 2021). Every selected triplet then contributes one positive pair \((x_a, x_p)\) and one negative pair \((x_a, x_n)\). We collect all such positives and negatives, and denote them as \(\mathcal{P}, \mathcal{N}\).

**Multi-Similarity Loss.** We compute the pairwise cosine similarity of all the name representations and obtain a similarity matrix \(S\in \mathbb{R}^{|\mathcal{X}_B| \times |\mathcal{X}_B|}\), where each entry \(S_{ij}\) is the cosine similarity between the \(i\)-th and \(j\)-th names in the mini-batch \(\mathcal{B}\). The Multi-Similarity loss (MS, Wang et al. 2019), is then used for learning from the

\(^3\)In UMLS, “CUI” means Concept Unique Identifier.

\(^4\)For instance, \(\text{vaccination (EN)}, \text{active immunization (EN)}, \text{vacunación (ES)}\) and \(\text{接種 (JA)}\) all share the same Concept Unique Identifier (CUI: C0042196); thus, they should all have similar representations.
### Table 1: Construction of the XL-BEL benchmark; key statistics. See the App. §A.1 for further details.

| # sentences | EN | ES | DE | BI | RU | TR | KO | ZH | JA | TH |
|-------------|----|----|----|----|----|----|----|----|----|----|
| sentences   | 223,506 | 350,193 | 77,736 | 206,060 | 29,473 | 47,702 | 136,054 | 157,670 | 19,066 |
|unique titles (Wiki page) | 60,598 | 37,935 | 24,059 | 15,182 | 21,044 | 5,251 | 10,618 | 17,972 | 11,002 | 4,541 |
|mentions     | 1,067,083 | 204,253 | 431,781 | 105,182 | 221,383 | 29,958 | 60,979 | 197,317 | 220,452 | 31,177 |
|unique mentions | 121,669 | 25,169 | 44,390 | 26,184 | 28,302 | 11,002 | 4,541 |
|unique mentions mention\(≠\)title | 69,199 | 22,162 | 43,753 | 19,409 | 23,935 | 2,833 | 3,740 | 12,046 | 12,571 | 2,480 |

### 3 The XL-BEL Task and Evaluation Data

A general cross-lingual entity linking (EL) task (McNamee et al., 2011; Tsai and Roth, 2016) aims to map a mention of an entity in free text of _any language_ to a controlled English vocabulary, typically obtained from a knowledge graph (KG). In this work, we propose XL-BEL, a cross-lingual _biomedical_ EL task. Instead of grounding entity mentions to English-specific ontologies, we use UMLS as a language-agnostic KG: the XL-BEL task requires a model to associate a mention in any language to a _language-agnostic_ CUI in UMLS. XL-BEL thus serves as an ideal evaluation benchmark for biomedical entity representations: it challenges the capability of both 1) representing domain entities and also 2) associating entity names in different languages.

### 4 Experiments and Results

#### UMLS Data.

We rely on the UMLS (2020AA) as our SAP fine-tuning data, leveraging synonyms in _all_ available languages. The full multilingual fine-tuning data comprises \(\approx\)15M biomedical entity names associated with \(\approx\)4.2M individual

#### 2.2 SAP with General-Domain Bitext

We also convert word and phrase translations into the same format (§2.1), where each ‘class’ now contains only two examples. For a translation pair \((x_p, x_q)\), we create a unique pseudo-label \(y_{x_p, x_q}\) and produce two new name-label instances \((x_p, y_{x_p, x_q})\) and \((x_q, y_{x_p, x_q})\), and proceed as in §2.1. This allows us to easily combine domain-specific knowledge with general translation knowledge within the same SAP framework.

\[\mathcal{L} = \frac{1}{|X_B|} \sum_{i=1}^{|X_B|} \left( \frac{1}{\alpha} \log \left( 1 + \sum_{n \in N_i} e^{\alpha \langle \mathbf{s}_{i,n} \rangle} \right) + \frac{1}{\beta} \log \left( 1 + \sum_{p \in P_i} e^{-\beta \langle \mathbf{p}_{i,p} \rangle} \right) \right).\]
Table 2: Various base models combined with SAP, using either all synonyms (all_syn) or only English synonyms (en_syn) in UMLS. $\{\text{LANG}\}$ denotes the language of the corresponding column (also in Table 4). See Table 6 (App. §A.3) for the language codes. avg refers to the average performance across all target languages. Grey and light blue rows are off-the-shelf base models and models fine-tuned with the UMLS knowledge, respectively.

Table 3: Results when applying SAP with 1) UMLS knowledge + 2) word and/or phrase translations.

CUIs. As expected, English is dominant (69.6% of all 15M names), followed by Spanish (10.7%) and French (2.2%). The full stats are in App. §A.3.

Translation Data. We use (a) “muse” word translations (Lample et al., 2018), and (b) the parallel Wikipedia article titles (phrase-level translations; referred to as “wt”). We also list results when using “muse” and “wt” combined (“wt+muse”).

Training and Evaluation Details. Our SAP fine-tuning largely follows Liu et al. (2021); we refer to the original work and the Appendix for further technical details. The evaluation measure is standard Precision@1 and Precision@5. In all experiments, SAP always denotes fine-tuning of a base LM with UMLS data. [CLS] of the last layer’s output is used as the final representation (Liu et al., 2021). Without explicit mentioning, we use the BASE variants of all monolingual and multilingual LMs. At inference, given a query representation, a nearest neighbour search is used to rank all candidates’ representations. We restrict the target ontology to only include CUIs that appear in WikiMed (62,531 CUIs, 399,931 entity names).

4.1 Main Results and Discussion

Multilingual UMLS Knowledge Always Helps (Table 2). Table 2 summarises the results of applying multilingual SAP fine-tuning based on UMLS knowledge on a wide variety of monolingual, multilingual, and in-domain pretrained encoders. Injecting UMLS knowledge is consistently beneficial to the models’ performance on XLM-BERT across all languages and across all base encoders. Using multilingual UMLS synonyms to SAP-fine-tune the biomedical PUBMED-BERT (SAPBERT_all_syn) instead of English-only synonyms (SAPBERT) improves its performance across the board. SAP-ing monolingual BERTs for each language also yields substantial gains across all languages; the only exception is Thai (TH), which is not represented in UMLS. Fine-tuning
multilingual models MBERT and XLMR leads to even larger relative gains.

Performance across Languages (Table 2). UMLS data is heavily biased towards Romance and Germanic languages. As a result, for languages more similar to these families, monolingual LMs (upper half, Table 2) are on par or outperform multilingual LMs (lower half, Table 2). However, for other (distant) languages (e.g., KO, ZH, JA, TH), the opposite holds. For instance, on TH, XLMR+SAP_all_syn outperforms THBERT+SAP_all_syn by 20% Precision@1.

General Translation Knowledge is Useful (Table 3). Table 3 summarises the results where we continue training on general translation data (§2.2) after the previous UMLS-based SAP. With this variant, base multilingual LMs become powerful multilingual biomedical experts. We observe additional strong gains (cf., Table 2) with out-of-domain translation data: e.g., for MBERT the gains range from 2.4% to 12.7% on all languages except ES. For XLMR, we report Precision@1 boosts of >10% on RU, TR, KO, TH with XLMR+SAP_all_syn, and similar but smaller gains also with XLMR+SAP_all_syn.

We stress the case of TH, not covered in UMLS. Precision@1 rises from 11.5% (XLMR+SAP_all_syn) to 30.9%↑19.4% (XLMR+SAP_all_syn+[en-th wt+ muse]), achieved through the synergistic effect of both knowledge types: 1) UMLS synonyms in other languages push the scores to 20.6%↑79.1%, 2) translation knowledge increases it further to 30.9%↑10.3%. In general, these results suggest that both external in-domain knowledge and general-domain translations boost the performance in resource-poor languages.

The More the Better (Table 4)? According to Table 4 (lower half), it holds almost universally that all_syn > en+{$LANG$}_syn > en_syn/{$LANG$}_syn on XLMR, that is, it seems that more in-domain knowledge (even in non-related languages) benefit cross-lingual transfer. However, for MBERT (Table 4, upper half), the trend is less clear, with en+{$LANG$}_syn sometimes outperforming the all_syn variant. Despite modest performance differences, this suggests that the choice of source languages for knowledge transfer also plays a role; this warrants further investigations in future work.

Are Large Models (Cross-Lingual) Domain Experts (Table 5)? We also investigate the LARGE variant of XLMR, and compare it to its BASE variant. On English, XLMRLARGE gets 73.0% Precision@1, being in the same range as SAPBERT (78.7%), without SAP-tuning (Table 5). The scores without SAP fine-tuning on XLMRLARGE, although much higher than of its BASE variant, decrease on other (‘non-English’) languages. At the same time, note that XLMR BASE achieves random-level performance without SAP-tuning. After SAP fine-tuning, on average, XLMRLARGE+SAP still outperforms BASE models, but the gap is much smaller: e.g., we note that the performance of the two SAP-ed models is on par in English. This suggests that with sufficient knowledge injection, the underlying base model is less important (English); however, when the external data are scarce (other languages beyond English), a heavily parameterised large pretrained encoder can boost knowledge transfer to resource-poor languages.

Table 5: Comparing BASE and LARGE models on XLM-BEL. Both EN results and avg across all languages are reported. Full table available in Appendix Table 9.

5 Conclusion

We have introduced a novel cross-lingual biomedical entity task (XLM-BEL), establishing a wide-coverage and reliable evaluation benchmark for cross-lingual entity representations in the biomedical domain in 10 languages, and have evaluated
current SotA biomedical entity representations on XL-BEL. We have also presented an effective transfer learning scheme that leverages general-domain translations to improve the cross-lingual ability of domain-specialised representation models. We hope that our work will inspire more research on multilingual and domain-specialised representation learning in the future.

Acknowledgements

We thank the three reviewers and the AC for their insightful comments and suggestions. FL is supported by Grace & Thomas C.H. Chan Cambridge Scholarship. IV and AK are supported by the ERC Consolidator Grant LEXICAL (no. 648909) awarded to AK. NC kindly acknowledges grant-in-aid support from the UK ESRC for project EPI-AI (ES/T012277/1).

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A Appendix A

A.1 XL-BEL: Full Statistics

Table 1 in the main paper summarises the key statistics of the XL-BEL benchmark. It was extracted from the 20200601 version of Wikipedia dump. “sentences” refers to the number of sentences that contain biomedical mentions in the Wiki dump. “unique titles (Wiki page)” denotes the number of unique Wikipedia articles the biomedical mentions link to. “mentions” denotes the number of all biomedical mentions in the Wikipedia dump. “unique mentions” refers to the number of unique mentions after filtering out examples containing duplicated mention surface forms. “unique mentions\_mention!=title” denotes the number of unique mentions that have surface forms different from the Wikipedia articles they link to. The 1k test sets for each language are then randomly selected from the examples in “unique mentions\_mention!=title”.

A.2 XL-BEL: Selection of Languages

Our goal is to select a diverse and representative sample of languages for the resource and evaluation from the full set of possibly supported languages. For this reason, we exclude some Romance and Germanic languages which were too similar to some languages already included in the resource (e.g., since we include Spanish as a representative of the Romance language, evaluating on related languages such as Portuguese or Italian would not yield additional and new insights, while it would just imply running additional experiments). The language list covers languages that are close to English (Spanish, German); languages that are very distant from English (Thai, Chinese, etc.); and also languages that are in the middle (e.g., Turkish, which is typologically different, but shares a similar writing script with English).

The availability of biomedical texts in Wikipedia also slightly impacted our choice of languages. The overlapping entities of Wikipedia and UMLS are not evenly distributed in the biomedical domain. For example, since animal species are comprehensively encoded in UMLS, they become rather dominant for certain low-resource languages. We manually inspected the distribution of the covered entities in each language to ensure that they are indeed representative biomedical concepts. Languages with heavily skewed entity distributions are filtered out. E.g., biomedical concepts in Basque Wikipedia are heavily skewed towards plant and animal species (which are valid UMLS concepts but not representative enough). As a result, we dropped Basque as our evaluation language. The current 10 languages all have a reasonably fair distribution over biomedical concepts categories.

A.3 UMLS Data Preparation

All our UMLS fine-tuning data for SAP is extracted from the MRCONSO.RRF file downloaded at https://www.nlm.nih.gov/research/umls/licensedcontent/umlarchives04.html#2020AA. The extracted data includes 147,706,62 synonyms distributed in more than 20 languages.

The detailed statistics are available in Table 6.

| code | language | # synonyms | percentage |
|------|----------|------------|------------|
| EN   | English  | 10,277,246 | 69.6%      |
| ES   | Spanish  | 1,575,109  | 10.7%      |
| JA   | Japanese | 329,333    | 2.2%       |
| RU   | Russian  | 291,554    | 2.0%       |
| DE   | German   | 231,098    | 1.6%       |
| KO   | Korean   | 145,865    | 1.0%       |
| ZH   | Chinese  | 80,602     | 0.5%       |
| TR   | Turkish  | 51,328     | 0.3%       |
| FR   | French   | 428,406    | 2.9%       |
| NL   | Dutch    | 290,415    | 2.0%       |
| IT   | Italian  | 242,133    | 1.3%       |
| CS   | Czech    | 196,760    | 0.7%       |
| NO   | Norwegian| 63,075     | 0.4%       |
| PL   | Polish   | 51,778     | 0.4%       |
| ET   | Estonian | 31,107     | 0.2%       |
| SV   | Swedish  | 29,716     | 0.2%       |
| HR   | Croatian | 10,035     | 0.1%       |
| EL   | Greek    | 2,281      | <0.1%      |
| LV   | Latvian  | 1,405      | <0.1%      |

Total 147,706,62 100%

Table 6: The amount of UMLS synonyms per language. The first 10 languages are included in our XL-BEL test languages. However, note that Thai has no UMLS data.

A.4 Translation Data

The full statistics of the used word and phrase translation data are listed in Table 7. The “muse” word translations are downloaded from https://github.com/facebookresearch/MUSE while the Wikititle pairs (“wt”) are extracted by us, and are made publicly available.

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Table 7: Statistics of muse word translations (“muse”) and Wikipedia title pairs (“wt”).

| #\text{}_{i}. language\rightarrow | EN-ES | EN-DE | EN-FI | EN-RU | EN-TR | EN-KO | EN-ZH | EN-JA | EN-TH |
|---------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| muse                            | 112,583 | 101,931 | 43,102 | 48,714 | 68,611 | 20,549 | 39,334 | 25,969 | 25,332 |
| wt                              | 1,079,547 | 1,241,104 | 338,284 | 886,760 | 260,392 | 319,492 | 638,900 | 547,923 | 107,398 |

A.5 Pretrained Encoders
A complete listing of URLs for all used pretrained encoders hosted on huggingface.co is provided in Table 8. For monolingual models of each language, we made the best effort to select the most popular one (based on download counts).

A.6 Full Table for Comparing with LARGE Models
Table 9 list results across all languages for comparing BASE and LARGE models.

A.7 Future Work
Investigating Other Cross-Lingual Transfer Learning Schemes. We also explored adapting multilingual sentence representation transfer techniques like Reimers and Gurevych (2020) that leverage parallel data. However, we observed no improvement comparing to the main transfer scheme reported in the paper. We plan to investigate existing techniques more comprehensively, and benchmark more results on XL-BEL in the future.

Comparison with in-Domain Parallel Data. While we used general-domain bitexts to cover more resource-poor languages, we are aware that in-domain bitexts exist among several “mainstream” languages (EN, ZH, ES, PT, FR, DE, Bawden et al. 2019). In the future, we plan to also compare with biomedical term/sentence translations on these languages to gain more insights on the impact of domain-shift.

A.8 Number of Model Parameters
All BASE models have \approx 110M parameters while LARGE models have \approx 340M parameters.

A.9 Hyperparameter Optimisation
Table 10 lists the hyperparameter search space. Note that the chosen hyperparameters yield the overall best performance, but might be suboptimal in any single setting. We used the same random seed across all experiments.

A.10 Software and Hardware Dependencies
All our experiments are implemented using PyTorch 1.7.0 with Automatic Mixed Precision (AMP)\footnote{https://pytorch.org/docs/stable/amp.html} turned on. The hardware we use is listed in Table 11. On this machine, the SAP fine-tuning procedure generally takes 5-10 hours with UMLS data. SAP fine-tuning with translation data takes 10 minutes to 5 hours, depending on the amount of the data. Inference generally takes <10 minutes.
Table 8: A listing of HuggingFace URLs of all pretrained models used in this work.

| language | model               | URL                                               |
|----------|---------------------|--------------------------------------------------|
| EN       | SAPBERT             | https://huggingface.co/cambridgeltl/SapBERT-from-PubMedBERT-fulltext |
| ES       | ES-BERT             | https://huggingface.co/dccuchile/bert-base-spanish-wwm-uncased |
| DE       | DE-BERT             | https://huggingface.co/dbmdz/bert-base-german-uncased |
| FI       | FI-BERT             | https://huggingface.co/TurkuNLP/bert-base-finnish-uncased-v1 |
| RU       | RUBERT              | https://huggingface.co/DeepPavlov/rubert-base-cased |
| TR       | TR-BERT             | https://huggingface.co/loodos/bert-base-turkish-uncased |
| KR       | KRBERT              | https://huggingface.co/snnlp/KR-BERT-char16424 |
| ZH       | ZHBERT              | https://huggingface.co/cl-tohoku/bert-base-japanese |
| TH       | TH-BERT             | https://huggingface.co/monsoon-nlp/bert-base-thai |
| JA       | JABERT              | https://huggingface.co/monsoon-nlp/bert-base-thai |

Table 9: A comparison of BASE (upper half) and LARGE (lower half) multilingual encoders on XL-BEL.

| language | model                | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | @1 | @5 | avg |
|----------|----------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| EN       | SAPBERT              | 78.7 | 81.6 | 47.3 | 51.4 | 22.7 | 24.7 | 8.2 | 10.2 | 5.8 | 6.0 | 26.4 | 29.7 | 2.0 | 2.4 | 1.9 | 2.2 | 3.0 | 3.2 | 3.1 | 3.4 | 19.9 | 21.6 |
| EN       | SAPBERT + syn        | 78.3 | 80.7 | 55.6 | 61.3 | 30.0 | 34.2 | 11.8 | 14.8 | 9.3 | 11.3 | 35.5 | 39.5 | 2.0 | 2.4 | 6.4 | 8.2 | 6.9 | 8.3 | 3.0 | 3.3 | 23.9 | 26.4 |
| ES       | XLMR                 | 78.2 | 81.0 | 56.4 | 62.7 | 31.8 | 37.3 | 18.6 | 22.2 | 35.4 | 41.2 | 24.8 | 28.9 | 16.7 | 21.4 | 18.8 | 23.0 | 24.0 | 28.1 | 20.6 | 27.5 | 34.3 | 39.3 |
| ES       | XLMR + syn           | 73.0 | 75.0 | 20.7 | 24.6 | 7.8 | 9.1 | 1.9 | 2.7 | 3.0 | 3.3 | 11.8 | 13.5 | 1.2 | 1.2 | 0.7 | 0.9 | 1.6 | 1.8 | 0.9 | 1.2 | 12.3 | 13.3 |
| DE       | XLMR                 | 72.6 | 75.1 | 30.1 | 33.5 | 10.7 | 12.2 | 3.4 | 4.6 | 5.9 | 7.4 | 16.4 | 18.4 | 1.9 | 2.6 | 1.3 | 2.0 | 2.0 | 2.5 | 1.3 | 2.0 | 14.6 | 16.0 |
| DE       | XLMR + syn           | 74.6 | 76.2 | 31.4 | 35.3 | 11.9 | 13.2 | 3.5 | 4.4 | 5.2 | 6.5 | 16.9 | 19.2 | 1.4 | 1.5 | 0.6 | 0.9 | 1.8 | 2.1 | 2.0 | 2.3 | 14.9 | 16.2 |
| FI       | XLMR                 | 78.3 | 81.3 | 61.0 | 66.8 | 35.0 | 40.0 | 25.2 | 29.2 | 41.9 | 47.3 | 46.1 | 52.4 | 22.2 | 26.7 | 23.5 | 29.0 | 28.5 | 33.6 | 28.7 | 35.5 | 39.0 | 44.2 |
| RU       | XLMR                 | 73.0 | 75.0 | 20.7 | 24.6 | 7.8 | 9.1 | 1.9 | 2.7 | 3.0 | 3.3 | 11.8 | 13.5 | 1.2 | 1.2 | 0.7 | 0.9 | 1.6 | 1.8 | 0.9 | 1.2 | 12.3 | 13.3 |
| RU       | XLMR + syn           | 72.6 | 75.1 | 30.1 | 33.5 | 10.7 | 12.2 | 3.4 | 4.6 | 5.9 | 7.4 | 16.4 | 18.4 | 1.9 | 2.6 | 1.3 | 2.0 | 2.0 | 2.5 | 1.3 | 2.0 | 14.6 | 16.0 |
| JA       | XLMR                 | 74.6 | 76.2 | 31.4 | 35.3 | 11.9 | 13.2 | 3.5 | 4.4 | 5.2 | 6.5 | 16.9 | 19.2 | 1.4 | 1.5 | 0.6 | 0.9 | 1.8 | 2.1 | 2.0 | 2.3 | 14.9 | 16.2 |
| TH       | XLMR                 | 78.3 | 81.3 | 61.0 | 66.8 | 35.0 | 40.0 | 25.2 | 29.2 | 41.9 | 47.3 | 46.1 | 52.4 | 22.2 | 26.7 | 23.5 | 29.0 | 28.5 | 33.6 | 28.7 | 35.5 | 39.0 | 44.2 |

Table 10: Hyperparameters along with their search grid. * marks the values used to obtain the reported results. The hparams without any defied search grid are adopted directly from Liu et al. (2021).

| hyperparameters       | search space |
|-----------------------|--------------|
| pretraining learning rate | 2e-5         |
| pretraining batch size  | 512          |
| pretraining training epochs | 1            |
| bitext fine-tuning learning rate | 2e-5         |
| bitext fine-tuning batch size | {64, 128, 256*} |
| bitext fine-tuning epochs | {1, 2, 3, 4, 5, 10} |
| max_seq_length of tokeniser | 25           |
| λ in Online Mining     | 0.2          |
| α in MS loss (Eq. (1)) | 2            |
| β in MS loss (Eq. (1)) | 50           |
| ε in MS loss (Eq. (1)) | 1            |

Table 11: Hardware specifications of the used machine. For LARGE model training, we use another server with two NVIDIA GeForce RTX 3090 (24 GB).