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 in 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) Transformed-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. (2020) recently proposed SAP, a technique to fine-tune BERT on phrase-level synonyms extracted from the Unified Medical Language System (UMLS, Bodenreider 2004).[1] 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 and English-only SAPBERT. We also show that leveraging general-domain word and phrase trans-

[1] UMLS is a large-scale biomedical knowledge graph containing more than 14M biomedical entity names.

lations 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.

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 contextualized representations based on Transformer architectures (Vaswani et al., 2017), biomedical text encoders are pretrained via Masked Language Modeling (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. (2020) proposed SAP (**S**elf-**A**lignment **P**retraning), 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 synonyms 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*[2]*)* pairs, e.g., (*vaccination*, C0042196). While Liu et al. (2020) 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 CUI to obtain similar representations.

Training Examples. Given a mini-batch of N examples $\mathcal{B} = \mathcal{X}_\mathcal{B} \times \mathcal{Y}_\mathcal{B} = \{(x_i, y_i)\}_{i=1}^{N}$, we start from constructing all possible triplets for all names $x_i \in \mathcal{X}_\mathcal{B}$. Each triplet is in the form of (x_a, x_p, x_n) where x_a is the *anchor*, an arbitrary name from $\mathcal{X}_\mathcal{B}$; 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:

$$\|f(x_a) - f(x_p)\|_2 > \|f(x_a) - f(x_n)\|_2 + \lambda,$$

where λ is a predefined margin. 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 $\mathbf{S} \in \mathbb{R}^{|\mathcal{X}_\mathcal{B}| \times |\mathcal{X}_\mathcal{B}|}$ where each entry $\mathbf{S}_{ij}$ 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 triplets:

$$\mathcal{L} = \frac{1}{|\mathcal{X}_\mathcal{B}|} \sum_{i=1}^{|\mathcal{X}_\mathcal{B}|} \left(\frac{1}{\alpha} \log \left(1 + \sum_{n \in \mathcal{N}_i} e^{\alpha(\mathbf{S}_{in} - \epsilon)} \right) + \frac{1}{\beta} \log \left(1 + \sum_{p \in \mathcal{P}_i} e^{-\beta(\mathbf{S}_{ip} - \epsilon)} \right) \right). \quad (1)$$

α, β are temperature scales; ϵ is an offset applied on the similarity matrix; $\mathcal{P}_i, \mathcal{N}_i$ are indices of positive and negative samples of the i-th *anchor*.

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 pseudolabel 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.

[2] In UMLS, "CUI" means **C**oncept **U**nique **I**dentifier.

[3] For instance, *vaccination* (EN), *active immunization* (EN), *vacunación* (ES) and 予防接種 (JA) all share the same CUI (C0042196); thus, they should all have similar representations.

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 representing domain entities and also associates entity names in different languages.

Evaluation Data Creation. For English, we take the available BEL dataset WikiMed (Vashishth et al., 2020), which links Wikipedia mentions to UMLS CUIs. We then follow similar procedures as WikiMed and create a XL-BEL benchmark covering 10 languages (see Tab. 1). For each language, we extract all sentences from their Wikipedia dump, and then find all hyperlinked concepts (i.e., words and phrases), lookup their Wikipedia pages, and retain only concepts that are linked to UMLS.[4] For these UMLS-linked mentions, we add a triplet *(sentence, mention, CUI)* to our dataset.[5] We then filter out examples with mentions that have the same surface form as their Wikipedia article page.[6] Further, only one example per surface form is retrained to ensure diversity. Finally, 1k examples are randomly selected for each language: they serve as the final test sets in our XL-BEL benchmark. The statistics of the benchmark are available in the App. §A.1.

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 ≈15M biomedical entity names associated with ≈4.2M individual 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.2.

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 ("muse+wt").

Training and Evaluation Details. Our SAP fine-tuning largely follows Liu et al. (2020); 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., 2020). 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. Tab. 1 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 XL-BEL across all languages and across all base encoders. Using multilingual UMLS synonyms to SAP-fine-tune the biomedical PUBMEDBERT instead of English-only synonyms 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, which is not represented in UMLS. Fine-tuning multilingual models MBERT and XLMR leads to even larger relative gains.

Performance across Languages. UMLS data is heavily biased towards Romance and Germanic languages. As a result, for languages more similar to these families, monolingual LMs (upper half, Tab. 1) are on par or outperform multilingual LMs (lower half, Tab. 1). However, for other (distant) languages (e.g., KO, ZH, JA, TH), the opposite holds. For instance, on TH, XLMR+$\text{SAP}_{\text{all\_syn}}$ outper-

[4] For instance, given a sentence from German Wikipedia *Die [Inkubationszeit] von COVID-19 beträgt durchschnittlich fünf bis sechs Tage.*, we extract the hyperlinked word *Inkubationszeit* as an UMLS-linked entity mention. Since Wikipedia is inherently multilingual, if *Inkubationszeit* is linked to UMLS, its cross-lingual counterparts, e.g., *Incubation period* (EN), are all transitively linked to UMLS.

[5] Note that though each mention is accompanied with its context, we regard it as out-of-context mention following the tradition in prior work (Sung et al., 2020; Liu et al., 2020; Tutubalina et al., 2020). According to Basaldella et al. (2020), biomedical entity representations can be easily polluted by its context. We leave contextual modeling for future work.

[6] Otherwise, the problem is easily solved by comparing surface forms of the mention and the article title.

language→	EN		ES		DE		FI		RU		TR		KO		ZH		JA		TH		**avg**	
model↓	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5
SAPBERT (Liu et al., 2020)	**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
SAPBERT$_{\text{all_syn}}$	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
{$LANG}BERT	-	-	41.3	42.5	16.8	18.4	4.9	5.2	1.1	1.6	19.5	21.8	1.1	1.6	2.1	3.2	2.7	2.8	0.4	0.4	10.0	10.8
{$LANG}BERT+SAP$_{\text{all_syn}}$	-	-	60.9	66.8	**35.5**	**40.0**	**18.8**	**23.9**	**36.4**	**42.4**	**44.9**	**49.7**	13.5	16.0	18.5	**23.8**	21.2	25.9	0.6	0.6	27.8	32.1
MBERT	0.8	1.7	0.5	0.7	0.3	0.4	0.4	0.8	0.0	0.0	0.7	1.2	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.3	0.5
MBERT+SAP$_{\text{en_syn}}$	75.5	79.9	50.6	55.8	26.0	29.6	8.7	10.7	10.1	12.6	31.0	34.4	2.7	3.2	4.1	5.7	4.7	5.9	3.1	3.5	21.7	24.1
MBERT+SAP$_{\text{all_syn}}$	75.0	79.7	**61.4**	**67.0**	33.4	37.8	18.4	21.9	35.1	40.3	44.5	47.7	15.1	17.6	**19.5**	22.7	19.9	25.0	2.8	3.4	32.5	36.3
XLMR	1.0	2.0	0.3	0.7	0.0	0.1	0.1	0.2	0.1	0.2	0.4	0.5	0.0	0.3	0.1	0.2	0.2	0.4	0.0	0.1	0.2	0.5
XLMR+SAP$_{\text{en_syn}}$	78.1	80.9	47.9	53.5	27.6	32.0	12.2	14.7	21.8	25.9	29.3	35.9	4.5	6.7	7.9	11.3	8.3	11.3	11.5	16.2	24.9	28.8
XLMR+SAP$_{\text{all_syn}}$	78.2	81.0	56.4	62.7	31.8	37.3	18.6	22.2	35.4	41.2	42.8	48.9	**16.7**	**21.4**	18.8	23.0	**24.0**	**28.1**	**20.6**	**27.5**	**34.3**	**39.3**

Table 1: Various base models applied with SAP using either all synonyms (*all_syn*) or only English synonyms (*en_syn*) in UMLS. {$LANG} denotes the language of the corresponding column (also in Tab. 3). See Tab. 5 (App. §A.2) for the language codes. **avg** refers to the average performance across all target languages.

language→	ES		DE		FI		RU		TR		KO		ZH		JA		TH		**avg**	
model↓	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5
XLMR+SAP$_{\text{en_syn}}$	47.9	53.5	27.6	32.0	12.2	14.7	21.8	25.9	29.3	35.9	4.5	6.7	7.9	11.3	8.3	11.3	11.5	16.2	19.0	23.1
XLMR+SAP$_{\text{en_syn}}$(+en-{$LANG} wt)	55.0	62.2	34.6	41.4	18.6	24.4	35.0	41.5	43.3	50.6	15.9	22.3	15.9	23.0	18.7	24.4	25.1	32.4	29.1	35.8
XLMR+SAP$_{\text{en_syn}}$(+en-{$LANG} muse)	54.4	61.0	28.7	34.4	16.7	20.6	33.6	39.0	41.9	48.8	11.9	16.3	12.3	16.7	15.7	19.9	18.6	25.1	26.0	31.3
XLMR+SAP$_{\text{en_syn}}$(+en-{$LANG} wt+muse)	49.4	59.6	30.3	36.9	20.4	28.9	33.2	41.9	42.7	51.7	16.1	22.3	16.0	22.9	17.8	24.3	26.2	34.0	28.0	35.8
XLMR+SAP$_{\text{all_syn}}$	56.4	62.7	31.8	37.3	18.6	22.2	35.4	41.2	42.8	48.9	16.7	21.4	18.8	23.0	24.0	28.1	20.6	27.5	29.5	34.7
XLMR+SAP$_{\text{all_syn}}$(+en-{$LANG} wt)	57.2	63.7	35.1	42.3	20.3	27.6	35.8	43.8	48.8	55.0	22.1	27.9	20.6	27.3	24.8	**31.3**	30.0	37.6	32.7	**39.6**
XLMR+SAP$_{\text{all_syn}}$(+en-{$LANG} muse)	57.9	63.9	33.0	38.4	23.0	27.3	39.8	45.9	47.2	54.5	22.1	25.7	19.2	25.6	**25.2**	30.2	25.9	32.8	32.6	38.3
XLMR+SAP$_{\text{all_syn}}$(+en-{$LANG} muse+wt)	51.4	61.2	31.3	38.9	22.8	28.4	36.4	45.2	42.2	51.6	**24.4**	**29.2**	21.1	28.2	23.2	30.4	**30.9**	**37.9**	31.5	39.0
MBERT+SAP$_{\text{all_syn}}$	**61.4**	67.0	33.4	37.8	18.4	21.9	35.1	40.3	44.5	47.7	15.1	17.6	19.5	22.7	19.9	25.0	2.8	3.4	27.8	31.5
MBERT+SAP$_{\text{all_syn}}$(+en-{$LANG} wt)	59.2	66.9	**37.5**	**43.9**	25.6	33.0	39.6	47.2	52.7	59.7	19.8	24.3	24.1	31.9	23.5	28.7	4.8	5.9	31.9	37.9
MBERT+SAP$_{\text{all_syn}}$(+en-{$LANG} muse)	59.9	66.2	34.3	38.8	21.6	27.5	36.5	41.7	51.0	56.7	18.1	21.2	22.2	26.4	22.0	25.5	3.4	3.8	29.2	34.2
MBERT+SAP$_{\text{all_syn}}$(+en-{$LANG} muse+wt)	59.2	**67.5**	35.3	42.4	**30.5**	**37.3**	**41.6**	**49.2**	**57.2**	**64.7**	19.8	25.0	**24.6**	**32.1**	24.3	28.0	5.2	6.3	**33.1**	39.2

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

forms THBERT+SAP$_{\text{all_syn}}$ by 20% Precision@1.

General Translation Knowledge is Useful. Tab. 2 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., Tab. 1) 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$_{\text{en_syn}}$, and similar but smaller gains also with XLMR+SAP$_{\text{all_syn}}$.

We stress the case of TH, not covered in UMLS. Precision@1 rises from 11.5% (XLMR+SAP$_{\text{en_syn}}$) to 30.9%$^{\uparrow 19.4\%}$ (XLMR+SAP$_{\text{all_syn}}$(+en-th muse+wt)), achieved through the synergistic effect of both knowledge types: **1) UMLS synonyms in other languages** push the scores to 20.6%$^{\uparrow 9.1\%}$; **2) translation knowledge** increases it further to 30.9%$^{\uparrow 10.3\%}$. 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? According to Tab. 3 (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 (Tab. 3, 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.

language→	ES		DE		RU		KO		**avg**	
model↓	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5
MBERT+SAP$_{\text{en_syn}}$	50.6	55.8	26.0	29.6	10.1	12.6	2.7	3.2	22.4	25.3
MBERT+SAP$_{\{\text{\$LANG}\}\text{_syn}}$	57.1	62.8	28.9	33.6	25.8	31.7	2.1	2.6	28.5	32.7
MBERT+SAP$_{\text{en+}\{\text{\$LANG}\}\text{_syn}}$	61.1	**68.5**	**35.2**	**39.8**	**35.6**	**40.9**	14.4	16.3	**36.6**	**41.4**
MBERT+SAP$_{\text{all_syn}}$	**61.4**	67.0	33.4	37.8	35.1	40.3	**15.1**	**17.6**	36.6	40.7
XLMR+SAP$_{\text{en_syn}}$	47.9	53.5	27.6	32.0	21.8	25.9	4.5	6.7	25.5	29.5
XLMR+SAP$_{\{\text{\$LANG}\}\text{_syn}}$	52.9	55.8	25.9	30.4	28.7	34.2	2.4	2.9	24.5	30.8
XLMR+SAP$_{\text{en+}\{\text{\$LANG}\}\text{_syn}}$	55.8	62.5	27.7	32.3	**36.4**	**42.2**	15.8	19.8	33.9	39.2
XLMR+SAP$_{\text{all_syn}}$	**56.4**	**62.7**	**31.8**	**37.3**	35.4	41.2	**16.7**	**21.4**	**35.1**	**40.7**

Table 3: Varying UMLS synonymy sets.

5 Conclusion

We have introduced a novel cross-lingual biomedical entity task (XL-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.

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A Appendix A

A.1 XL-BEL: Full Statistics

Tab. 4 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 mentions after filtering out examples containing duplicated mention surface forms. "unique $\text{mentions}_{\text{mention!=title}}$" 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 $\text{mentions}_{\text{mention!=title}}$". The test sets are uploaded as a separate file. We will release the full dataset upon acceptance.

A.2 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/umlsarchives04.html#2020AA. The extracted data includes 147,706,62 synonyms distributed in more than 20 languages. The detailed statistics are available in Tab. 5.

A.3 Translation Data

The full statistics of the used word and phrase translation data are listed in Tab. 6. The "muse" word translations are downloaded from https://github.com/facebookresearch/MUSE while the Wikititle pairs ("wt") are extracted by us own (we will release the resource upon acceptance).

A.4 Pretrained Encoders

A complete listing of URLs for all used pretrained encoders hosted on huggingface.co is provided in Tab. 7. For monolingual models of each language, we made the best effort to select the most popular one (based on download counts).

A.5 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.

Are Large Models (Cross-Lingual) Domain Experts? We also investigated the LARGE variants of XLMR, finding their performances to be much better than BASE models. On English, all XLMR-LARGE variants can get >70% Precision@1 (Tab. 8), being close to SAPBERT (78.7%). However, their performance is still below XLMR+SAP on other languages (still significantly better than BASE models without SAP). In the future, we plan to investigate rewiring the English domain knowledge contained in such LARGE models to resource-poor languages.

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).[7] 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.6 Number of Model Parameters

All BASE models have ≈110M parameters while LARGE models have ≈340M parameters.

A.7 Hyperparameter Optimisation

Tab. 9 lists the hyperparameter search space. Note that the chosen hyperparameters yield the overall best performance, but might be suboptimal on any single setting. We used the same random seed across all experiments.

A.8 Software and Hardware Dependencies

All our experiments are implemented using PyTorch 1.7.0 with Automatic Mixed Precision (AMP)[8] turned on. We will open-source the code on GitHub upon acceptance. The hardware we use is listed in Tab. 10. 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

[7] http://www.statmt.org/wmt19/biomedical-translation-task.html

[8] https://pytorch.org/docs/stable/amp.html

#↓, language→	EN	ES	DE	FI	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	4,110	9,032	24,825	21,949	5,064
unique $\text{mentions}_{\text{mention!=title}}$	237,851	22,162	43,753	19,409	23,935	2,833	3,740	12,046	12,571	2,480

Table 4: Construction of the XL-BEL benchmark; key statistics.

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%
FI	Finnish	24,767	0.2%
TH	Thai	0	0.0%
FR	French	428,406	2.9%
PT	Portuguese	309,448	2.1%
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 5: 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.

amount of the data. Inference generally takes <10 minutes.

#↓, language→	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

Table 6: Statistics of muse word translations ("muse") and Wikipedia title pairs ("wt").

model	URL
MBERT	https://huggingface.co/bert-base-multilingual-uncased
XLMR	https://huggingface.co/xlm-roberta-base
XLMR-LARGE	https://huggingface.co/xlm-roberta-large
XLMR-LARGE-XNLI	https://huggingface.co/joeddav/xlm-roberta-large-xnli
XLMR-LARGE-SQUAD2	https://huggingface.co/deepset/xlm-roberta-large-squad2
SAPBERT	https://huggingface.co/cambridgeltl/SapBERT-from-PubMedBERT-fulltext
ESBERT	https://huggingface.co/dccuchile/bert-base-spanish-wwm-uncased
DEBERT	https://huggingface.co/dbmdz/bert-base-german-uncased
FIBERT	https://huggingface.co/TurkuNLP/bert-base-finnish-uncased-v1
RUBERT	https://huggingface.co/DeepPavlov/rubert-base-cased
TRBERT	https://huggingface.co/loodos/bert-base-turkish-uncased
KRBERT	https://huggingface.co/snunlp/KR-BERT-char16424
ZHBERT	https://huggingface.co/bert-base-chinese
JABERT	https://huggingface.co/cl-tohoku/bert-base-japanese
THBERT	https://huggingface.co/monsoon-nlp/bert-base-thai

Table 7: A listing of HuggingFace URLs of all pretrained models used in this work.

language→	EN		ES		DE		FI		RU		TR		KO		ZH		JA		TH		**avg**	
model↓	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5	@1	@5
SAPBERT (Liu et al., 2020)	**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
$\text{SAPBERT}_{\text{all\_syn}}$	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
XLMR	1.0	2.0	0.3	0.7	0.0	0.1	0.1	0.2	0.1	0.2	0.4	0.5	0.0	0.3	0.1	0.2	0.2	0.4	0.0	0.1	0.2	0.5
$\text{XLMR+SAP}_{\text{all\_syn}}$	78.2	81.0	**56.4**	**62.7**	**31.8**	**37.3**	**18.6**	**22.2**	**35.4**	**41.2**	**42.8**	**48.9**	**16.7**	**21.4**	**18.8**	**23.0**	**24.0**	**28.1**	**20.6**	**27.5**	**34.3**	**39.3**
XLMR-LARGE	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
XLMR-LARGE-XNLI	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
XLMR-LARGE-SQUAD2	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

Table 8: A comparison of BASE (upper half) and LARGE (lower half) multilingual encoders on XL-BEL.

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 BERT 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 9: 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. (2020).

hardware	specification
RAM	192 GB
CPU	Intel Xeon W-2255 @3.70GHz, 10-core 20-threads
GPU	NVIDIA GeForce RTX 2080 Ti (11 GB) $\times$ 4

Table 10: Hardware specifications of the used machine.