Lost in Evaluation:
Misleading Benchmarks for Bilingual Dictionary Induction

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Abstract

The task of bilingual dictionary induction (BDI) is commonly used for intrinsic evaluation of cross-lingual word embeddings. The largest dataset for BDI was generated automatically, so its quality is dubious. We study the composition and quality of the test sets for five diverse languages from this dataset, with concerning findings: (1) a quarter of the data consists of proper nouns, which can be hardly indicative of BDI performance, and (2) there are pervasive gaps in the gold-standard targets. These issues appear to affect the ranking between cross-lingual embedding systems on individual languages, and the overall degree to which the systems differ in performance. With proper nouns removed from the data, the margin between the top two systems included in the study grows from 3.4% to 17.2%. Manual verification of the predictions, on the other hand, reveals that gaps in the gold standard targets artificially inflate the margin between the two systems on English to Bulgarian BDI from 0.1% to 6.7%. We thus suggest that future research either avoids drawing conclusions from quantitative results on this BDI dataset, or accompanies such evaluation with rigorous error analysis.

1 Introduction

Bilingual dictionary induction (BDI) refers to retrieving translations of individual words. The task has been widely used for intrinsic evaluation of cross-lingual embedding algorithms, which aim to map two languages into the same embedding space, for transfer learning purposes (Klementiev et al., 2012). Recently, Glavas et al. (2019) reported limited evidence in support of this practice—they found that cross-lingual embeddings optimized for a BDI evaluation metric were not necessarily better on downstream tasks. Here, we study BDI evaluation in itself, as has been done for other evaluation methods in the past (cf. Faruqui et al., 2016's work on word similarity), with concerning findings about its reliability.

A massive dataset of 110 bilingual dictionaries, known as the MUSE dataset, was introduced in early 2018 along with a strong baseline (Conneau et al., 2018). Subsets of the MUSE dictionaries have been used for model comparison in the evaluation of numerous cross-lingual embedding systems developed since (cf. Grave et al., 2018; Jawanpuria et al., 2019; Hoshen and Wolf, 2018a,b; Wada and Iwata, 2018; Joulin et al., 2018). Even though the field has been very active, progress has been incremental for most language pairs. Moreover, there have been very few attempts at a linguistically-informed error analysis of BDI performance as measured on MUSE (cf. Kementchedjhieva et al., 2018). This is problematic for two reasons: on one hand, most systems greatly vary in their approach and architecture, so it is difficult to identify the source of the reported performance gains; on the other hand, the MUSE dataset was compiled automatically, with no manual post-processing to clean up noise, so the real impact of the performance gains is unclear.

In this work, we study the composition and quality of the MUSE data for five diverse languages: German, Danish, Bulgarian, Arabic and Hindi. A manual part-of-speech annotation of the test sets for these languages reveals a strikingly high number of proper nouns. We refer to linguistic literature to argue that proper nouns, having no lexical meaning but rather just a referential function, cannot reliably be used in the evaluation of word-level translation systems. We find that excluding proper noun pairs from the test dictionaries for the aforementioned languages affects the ranking and degree of performance gaps between five of the most influential recent systems for BDI.

With a new, more reliable ranking at hand, we

perform qualitative analysis on the performance gap between the best and second best systems for Bulgarian. This reveals another major issue with the data: limited coverage of morphological variants for the target words. Through manual verification of the models' predictions, we find that the gap in performance between the two systems is far smaller than previously perceived.

The uncovered issues of high noise levels (proper nouns) and limited coverage (missing gold standard targets) clearly have a crucial impact on BDI results obtained on the MUSE dataset, and need to be addressed. Filtering out proper nouns could be achieved automatically, by checking against gazetteers of named entities. We find that an automatic procedure for the filling of missing targets, however, yields only minor improvements. We thus urge researchers to be cautious when reporting quantitative results on MUSE, and to account for the problems presented here through manual verification and analysis of the results. As an alternative, we point them to morphologically complete BDI resources, built bottom-up (Czarnowska et al., 2019). We share our part-of-speech annotations, such that future work can use this resource for analysis purposes. [1]

2 Bilingual Dictionary Induction

Improvements on BDI mostly stem from developments in the space of cross-lingual embeddings, which use BDI for intrinsic evaluation.

Systems Five influential recent systems for cross-lingual embeddings are MUSE (Conneau et al., 2018), which can be supervised (**MUSE-S**) or unsupervised (**MUSE-U**); VecMap, which also can be supervised (**VM-S**) (Artetxe et al., 2018a) or unsupervised (**VM-U**) (Artetxe et al., 2018b); and RCSLS (Joulin et al., 2018), a supervised system (**RCSLS**), which scores best on BDI out of the five. We refer the reader to the respective publications for a general description of the systems.

Metrics Performance on BDI in these works is evaluated by verifying the system-retrieved translations for a source word against a set of gold-standard targets. The metric used is Precision at k (P@k), which measures how often the set of k top predictions contains one of the gold-standard targets, i.e. what is the ratio of True Positives to the sum of True Positives and False Positives.

Data All systems listed above report results on one or both of two test sets: the MUSE test sets Conneau et al. (2018) and/or the Dinu test sets (Dinu et al., 2015; Artetxe et al., 2017). Similarly to MUSE, the Dinu dataset was compiled automatically (from Europarl word-alignments), but it only covers four languages. Due to the bigger size of MUSE (110 language pairs), we deem its impact larger and focus our study entirely on it.

3 Annotation-based observations

In order to gain insights into the linguistic composition of the MUSE dictionaries, we employ annotators fluent in German, Danish, Bulgarian, Arabic and Hindi (hereafter, DE, DA, BG, AR, HI) to annotate the entire dictionaries from English to one of these languages (hereafter, from-EN) and the entire dictionaries from these languages to English (hereafter, to-EN) with part-of-speech (POS) tags. Details on the annotation procedure can be found in Appendix A. Below, we discuss our findings on the POS composition of the data, and we evaluate the performance of RCSLS per POS tag.[2]

3.1 Analysis of POS composition

The average percentage of common nouns, proper nouns, verbs, and adjectives/adverbs in the dictionaries to-EN was respectively 49.6, 24.9, 12.5, and 12.9.[3] Nouns constitute half of the dictionaries' volume, while verbs and adjectives/adverbs collectively make up only about a fourth of the average dictionary. A skewed ratio between these three categories is not surprising: in the EWT dependency treebank, for example, which contain gold-standard POS tags, the proportion of noun, verb and adjective/adverb types is 34, 17 and 14 percent, respectively. Notice, however, that in the case of the MUSE data, the ratio is even more skewed in favour of nouns over the other two categories.

The large number of proper nouns in the dictionaries seems even more problematic. Proper nouns are considered to have no lexical meaning, but rather just a referential function (Pierini, 2008). Personal names usually refer to a specific referent in a given context, but they can, in general, be attributed to different referents across different contexts, and they are almost univer-

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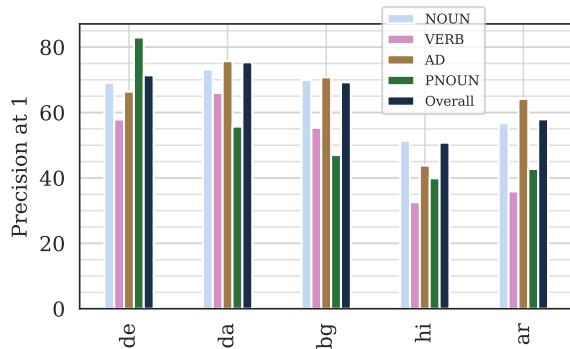
Figure 1: Precision of RCSLS by POS tag on to-EN data.

Corpora	NOUN	VERB	AD	PNOUN
Wikipedia	69.0	57.9	66.4	83.0
Mixed*	64.0	55.5	59.4	37.6

Table 1: Comparison in performance by POS category with two different embedding sets. * The out-of-vocabulary rate for items in the dictionaries is negligible: 2, 0, and 1 for NOUN, VERB , and AD , respectively.

sally interchangeable in any given context. Some personal names and most place and organization names may have a unique referent, e.g. *Barack Obama, Wisconsin, Skype*, but these names still do not carry a *sense*, their referent is resolved through access to encyclopedic knowledge (Pierini, 2008). Considering that the pretrained embeddings which we use were trained on Wikipedia, we can expect that such encyclopedic information would indeed appear in the context of certain unique names, but importantly, the alignability of the embeddings for such entities would depend on the level of parallelism between the contents of Wikipedia articles in the different languages.

With these considerations in mind, one should wonder how stable the representation of names can be in an embedding space. This question has previously been raised by Artetxe et al. (2017). We address it empirically below.

3.2 Evaluation by POS

Figure 1 shows the precision of the RCSLS embedding alignment method on different POS segments of the test data in mapping to-EN (results from-EN were similar and are shown in Appendix B). Verbs pose a greater challenge to BDI systems than nouns and adjectives do. Generally, we can attribute this observation to the higher abstraction of concepts described by verbs. This is a known problem for word embedding methods in general (Gerz et al., 2016), which BDI systems naturally inherit.

With respect to proper nouns, we observe that they indeed introduce a level of instability in the evaluation of BDI systems. Notice that while the other parts of speech follow a similar pattern across languages, with higher precision obtained for nouns and adjectives/adverbs than for verbs,

relative precision on proper nouns is highly variable. For DE, proper nouns are easier to translate than other parts of speech by a margin of 15%, for HI and AR they are easier than nouns and adjectives/adverbs, but harder than verbs, and for DA and BG they are hardest out of all four categories. We looked into the individual word pairs marked as proper nouns in the DE and DA data, as these languages are related and RCSLS performs comparably on them otherwise, and did not find any patterns that could explain the large differences. In fact, between the 384 proper noun pairs in the EN-DE dictionary and the 330 proper noun pairs in the EN-DA dictionary, there was an overlap of 279 pairs, retrieved with precision of 89.21% in the EN-DE setting and 51.30% in the EN-DA setting. We conjecture that this result relates to the level of parallel content between the Wikipedia dumps for the different language pairs, which is likely higher for EN-DE , since the dumps for these languages are also closer in size: 5.8M articles in EN, 2.3M in DE (and only 0.2M in DA).[4]

We evaluate this hypothesis through an experiment where we train an RCSLS alignment for DE-EN using the DE embeddings of Artetxe et al. (2017), trained on SdeWaC (Baroni et al., 2009) and the EN embeddings of Dinu et al. (2015), trained on ukWaC (Baroni et al., 2009), Wikipedia and the BNC [5] corpora. The level of parallel content between the data used to train the two sets of embeddings is thus far more limited in this case, and the DE embeddings are not explicitly trained on Wikipedia data. Table 1 summarizes the results: while with the new embeddings performance is somewhat reduced for nouns, verbs and adjectives/adverbs, precision at 1 for proper nouns, in particular, drops by over 50%, indicating that this category of test word pairs is indeed highly sensitive to the nature of the training data.

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[4]https://meta.wikimedia.org/wiki/List_of_Wikipedias
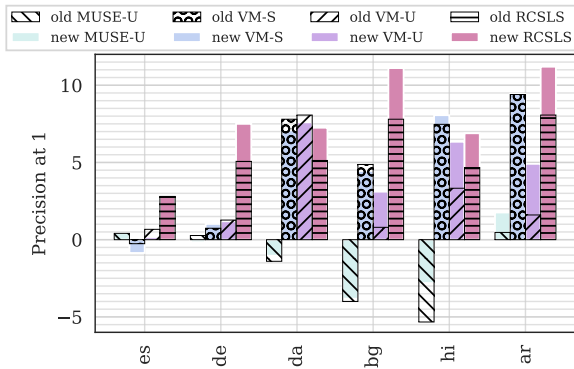[5]Available at http://www.natcorp.ox.ac.uk

Figure 2: Absolute difference in performance on from-EN BDI, relative to MUSE-S. Pattern-filled bars show results as estimated on the original data (*old*), while colored bars show results as estimated on the cleaned data (*new*).

3.3 Re-ranking on clean data

Based on the analysis presented above, we removed all pairs that were annotated as proper nouns and all pairs that were marked as invalid during the annotation process.[6] This clean-up resulted in a drop in the size of the test dictionaries of about 25% on average. A detailed size comparison between the old test dictionaries and their new cleaned versions is presented in the top rows of Table 4 in Appendix B. Figure 2 visualizes a re-evaluation of the five systems for BDI listed in Section 2, on the original test data and on the new clean versions of the test dictionaries from-EN.[7] The results are reported in terms of change in performance relative to MUSE-S (chosen as a baseline) as estimated on the original MUSE data (pattern-filled bars) and on the cleaned version of the data (colored bars). The absolute system performances before and after the clean-up can be found in Table 4 in Appendix B.

We see that the ranking between the models changes most notably for AR, where RCSLS appears inferior to VM-S on the original test data, but on the clean data it emerges as best. For BG, the evaluation on the clean test data reveals that RCSLS outperforms the next best system, VM-S, by a larger factor than it appeared on the original test data. Lastly, for DA, evaluation on the original test data makes RCSLS seem far inferior to VM-S and VM-U, but on the clean test data we see that it outperforms VM-S and matches the performance of VM-U. These observations show that the noise coming from proper nouns has a large

impact on the perceived ranking and difference in performance between systems.

4 *False* False Positives

With a more reliable estimate of the models' performance at hand, we next manually study the remaining performance gap between RCSLS, the best-performing model overall, and VM-S, the second best model overall, for EN–BG.[8] We present some examples in Table 2 and more can be found in Table 5, Appendix C.

We find that there are 125 source words that RCSLS translated correctly and VM-S did not. Upon closer inspection, we find that for 54% of these words, both RCSLS and VM-S predicted a valid translation, but RCSLS predicted a more *canonical* translation, which was listed among the gold-standard targets, while VM-S predicted another word form that was missing from the list of gold-standard targets. By more canonical we mean, for example, indefinite instead of definite forms of nouns and adjectives (see Ex. A, Table 2, masculine instead of feminine or neuter forms of adjectives (see Ex. B), singular instead of plural forms. To the extent that a more canonical translation should be considered better, RCSLS is definitely showing superiority over VM-S. It is not clear, however, if that should be the case, since for some words, the test dictionary exhibits higher coverage than for others, i.e. the less canonical translations are not omitted by design, but appear to be accidental gaps.

Another 19% of the instances where RCSLS outperformed VM-S, we find to be clear cases of a missing translation in the test dictionary, i.e. not a missing form of a listed target, but a missing synonym or a missing sense altogether (see Ex. C and D).

The two types of errors in precision at 1 discussed above can be considered cases of *false* False Positives, because they really should have been True Positives. The remaining 27% of the gap between the two models' performance indeed illustrate that RCSLS provides better translations in some cases (see Ex. E).

Notice, however, that it is not the case that RCSLS outperformed VM-S in all cases–for 50 test words, VM-S predicted a correct translation and RCSLS did not. Among these, there are cases of missing translations from the dictionary as well

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[6]The latter constitute less than 1% of the removed data.

[7]The to-EN results were similar, see Appendix B.

[8]We also analyzed EN–DE, with very similar results.

Ex.	SRC	TGT	RCSLS	VM-S	Description
A	joke	шега лаф виц	<u>шега</u> [INDEF]	шегата [DEF]	definite form missing from targets
B	remembered	запомнен	<u>запомнен</u>[MASC]	запомнена[FEM]	feminine form missing from targets
C	hide	скриване	скриване [NOUN]	скриват[VERB]	*hide* as a verb vs. *hide* as a noun
D	bench	пейка пейката	пейка	скамейка	synonym missing from targets
E	depot	депо	депо	гара	VM-S predicted 'train station'
F	crowned	коронован	коронована[FEM]	<u>коронован</u>[MASC]	feminine form missing from targets
G	pond	езерце	къщичка	езерце	RCSLS predicted 'cottage'
H	grants	субсидии	стипендии	стипендии	synonym missing from targets
I	armies	армии	армиите	армиите	definite form missing from targets

Table 2: Example translations from EN to BG. Underlined forms are more canonical. Grey forms are incorrect.

(see Ex. F), but they can explain less of the lack in performance of RCSLS, i.e. 50% of the translations of RCSLS are indeed erroneous (see Ex. G).

To summarize, originally the performance gap between the two models appeared to be $(125 - 50)/1125 * 100 = 6.67\%$, while after the manual verification, it is $(27\% * 125 - 50\% * 50)/1125 * 100 = 0.1\%$.[9] Such a substantial narrowing in the gap between the two models clearly indicates that conclusions drawn on the original result, i.e. that RCSLS is far superior that VM-S for this language pair, is hardly supported by the updated result.

A surface analysis of the subset of words for which neither RCSLS nor VM-S retrieved correct translations revealed similar patterns of extensive false False Positives, due to gaps in the coverage of the dictionary (see Ex. H and I). Our takeaway from these observations is two-fold. Firstly, when RCSLS retrieves a correct target form, it also usually retrieves its most *canonical* form. More importantly, the evaluation of BDI systems on even the cleaned test dictionaries still does not represent accurately the differences in quality between them, due to major gaps in the coverage of the test dictionaries.

5 Concluding remarks

Our study of the MUSE dataset revealed two striking problems: a high level of noise coming from proper nouns, and an issue of *false* False Positives, due to gaps in the gold-standard targets. The former problem, we conjecture, can be solved by filtering names out with gazetteers. The quality of this solution would depend on the coverage of the gazetteers. The more challenging problem, how-

ever, is filling in the gaps, especially in terms of inflectional forms. We carried out preliminary experiments aiming to enrich the EN−BG and EN-DE dictionaries. We extracted additional word forms of verbal and nominal targets from the Uni-Morph inflectional tables (Kirov et al., 2018), according to a manually designed morphosyntactic correspondence map.[10] Unfortunately, due to limited coverage of the UniMorph data, and, in the case of BG, limited vocabulary of the pretrained embeddings, the impact of this procedure was almost negligible. Alternative approaches for enrichment exists, of course, but we wonder how worthwhile further efforts would be. That is, especially in light of Glavas et al. 2019's findings that BDI performance is not necessarily indicative of cross-lingual embedding quality. We therefore hope that our work adds weight to the call of Glavas et al. (2019) for more reliable evaluation methods in cross-lingual embedding research. When BDI performance is used for evaluation purposes, it should be accompanied by manual verification, of the type presented here.

6 Acknowledgements

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[9]1125 is the total dictionary size.

[10]Details can be found in Appendix D.

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A Appendix

In order to obtain a reliable part-of-speech (POS) tagging of the `MUSE` test dictionaries efficiently, we used a two-step procedure. First, we ran the Stanford POS tagger (Toutanova et al., 2003) on the English side of each dictionary. We reduced the annotation schema to five categories: nouns (NOUN), proper nouns (PNOUN), verbs (VERB), adjectives and adverbs combined (AD), and others. Next, we asked NLP researchers with the appropriate language background to verify and correct the generated tags, based on both words in a pair. Where one word in the pair is ambiguous with respect to POS, but the other is not, they were told them to use the tag of the latter. If both words were ambiguous, we told them to use the tag they considered more frequent for these words.

We instructed annotators that if a word can be both a proper noun and a common noun, it should be marked as the latter. We told them to mark pairs of identical words as proper nouns, under the assumption that they can be part of a company name or a brand, for example. That is, unless the words in the pair are actual cognates between the source and target language, or they are loanwords. See Table 3 for some examples. Lastly, we asked the annotators to mark pairs as invalid, if the source word is not a valid word in either the source or the target language, or the target word is not a valid translation of the source word. We note that this was a considerable annotation effort if over 40 hours in total. Each annotator had to process over 2000 word pairs: the dictionaries each consist of 1,500 source words, many of which have multiple translations, each processed separately. Annotation was performed in Microsoft Excel.

SRC	TGT	POS	valid	explanation
tea	té	NOUN	✓	actual translation
tea	tea	PNOUN	✓	part of a name, e.g. "Lipton Iced Tea"
rugby	rugby	NOUN	✓	loanword
ugby	ugby	–	✗	not a word in either language

Table 3: Example of annotated gold-standard word pairs from English to Spanish.

B Appendix

The pattern of performance per POS tag is similar for to-EN mappings (see Figure 3), as we saw it for from-EN mapping—proper nouns yield highly variable performance.

Similarly to mappings from-EN, in mappings to-EN (see Figure 4) we see RCSLS outperforming other systems on the clean data for all languages (and by a large margin for most of them), whereas on the original data it appeared inferior to VM-S for DA and HI. Another interesting observation here is that MUSE-U and VM-U occasionally appear inferior to the MUSE-S baseline (for DA and HI, respectively) on the original test data, but on the clean test data all models yield an improvement over the baseline.[11]

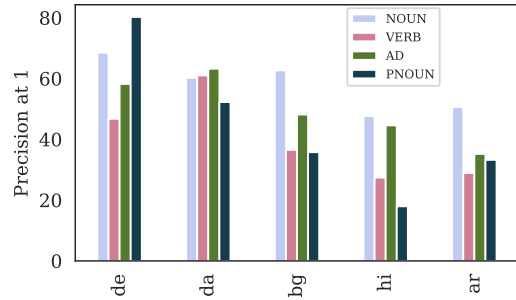Figure 3: Precision of the RCSLS system, measured per POS tag, on to-EN data.
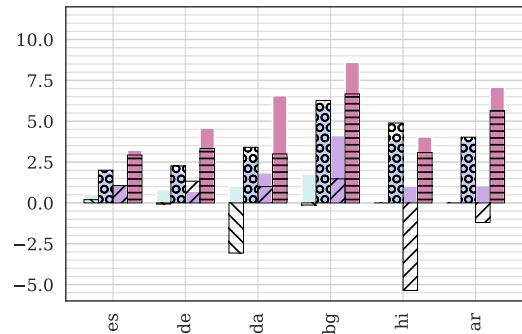

Figure 4: Change in performance on to-EN BDI relative to MUSE-S. Pattern-filled bars show results as estimated on the original data, while colored bars show results as estimated on the cleaned data.

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[11]That is, excluding MUSE-U evaluated on HI and AR, where all solutions found were degenerate, so they have been excluded.

	es		de		da		bg		hi		ar	
	→en	en→	→en	en→	→en	en→	→en	en→	→en	en→	→en	en→
Source words	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500
	1145	1171	1111	1188	974	1158	1124	1125	963	1104	1212	1080
MUSE-S	83.47	81.66	72.67	73.93	67.07	56.80	56.93	43.93	44.07	33.60	49.93	34.13
	79.56	73.36	66.79	64.47	68.79	55.44	60.63	45.33	46.73	37.68	50.83	34.63
MUSE-U	83.67	82.07	72.60	74.20	64.00	55.40	56.80	39.93	0.00	28.27	0.00	34.60
	80.09	73.78	67.60	64.31	69.82	54.40	62.39	41.51	0.00	34.87	0.00	36.39
VM-S	85.47	81.40	74.93	74.67	70.47	64.60	63.20	48.80	48.96	41.07	53.95	43.53
	81.48	72.50	68.68	65.49	71.46	62.52	66.61	49.78	50.57	45.74	54.62	44.07
VM-U	84.53	82.33	74.00	75.20	68.07	64.87	58.40	44.73	38.71	36.93	48.73	35.73
	80.70	73.53	67.51	65.66	70.64	63.04	64.76	48.44	47.77	44.02	51.90	39.54
RCSLS	86.40	84.46	76.00	79.00	70.07	61.93	63.60	51.73	47.15	38.27	55.56	42.20
	82.79	76.17	71.38	71.97	75.36	62.69	69.24	56.44	50.78	44.57	57.92	45.83

Table 4: Cyan rows correspond to the original test data and white rows to the clean test data. The top rows report the sizes of the dictionaries, measured in terms of source words. For unstable models, e.g. MUSE-U, we train ten models and report results from one random successful model. For a fair comparison of MUSE-U and MUSE-S, we run Procrustes for 5 iterations in both cases, and use the same model selection criterion, mean cosine similarity, in both cases. All systems are evaluated using CSLS for retrieval. * Instead of full annotation for Spanish, we only mark proper nouns and remove them from the test dictionaries to and from English.

C   Appendix

	SRC	TGT	RCSLS	VM-S	Description
VM-S ✗, RCSLS ✓	joke	шега лаф виц	<u>шега</u>	шегата	definite form missing from targets
	arbitrators	арбитри	<u>арбитри</u>	арбитрите	definite form missing from targets
	revolt	бунт въстание	<u>бунт</u>	бунта	definite form missing from targets
	remembered	запомнен	<u>запомнен</u>	запомнена	feminine form missing from targets
	hide	скриване	скриване	скриват	*hide* as a verb vs. *hide* as a noun
	bench	пейката пейка	пейка	скамейка	synonym missing from targets
	depot	депо	депо	гара	VM-S predicted 'station'
	gaelic	келтски	келтски	ирландският	VM-S predicted 'the irish'
	footage	кадри	кадри	заснети	VM-S predicted 'shot'
VM-S ✓, RCSLS ✗	egg	яйцето яйца яйце	яйчен	яйце	translation for attributive use of noun missing from targets
	crowned	коронован	коронована	<u>коронован</u>	feminine form missing from targets
	volcanic	вулканична	<u>вулканичен</u>	вулканична	masculine form missing from targets
	penny	пени	паричка	пени	synonym missing from targets
	pound	паунд кг	кило	паунд	RCSLS predicted a non-word
	thursday	четвъртък	петък	четвъртък	RCSLS predicted 'friday'
	striker	нападател страйкър	защитник	нападател	RCSLS predicted 'defender'
	pond	езерце	къщичка	езерце	RCSLS predicted 'cottage'
	flute	флейтата флейта	тромпет	флейта	RCSLS predicted 'trumpet'
VM-S ✗, RCSLS ✗	circular	кръгло	кръгла	кръгла	feminine form missing from targets
	sailed	отплава	отплавал	отплавал	participle form missing from targets
	grants	субсидии	стипендии	стипендии	synonym missing from targets
	spots	петна	петната	петната	definite form missing from targets
	armies	армии	армиите	армиите	definite form missing from targets
	nose	нос носа носът	врат	задницата	RCSLS predicted 'neck', VM-S predicted 'bottom'
	foods	храни	сладкиши	напитки	RCSLS predicted 'sweets', VM-S predicted 'drinks'
	cliff	скала клиф	терас	скалата	RCSLS predicted non-word, definite form missing from targets
	elevated	повишени повишена повишен	понижен	понижен	models predicted 'reduced'

Table 5: Example translations from EN to BG. In cases where both models predicted forms of the same word, one being more canonical than the other, we underline the canonical form. Truly incorrect translations are marked in grey. Notice the high number of correct translations that are not listed as gold-standard targets.

D Appendix

Table 6 shows an example of an inflectional correspondence map. It signifies that whenever an English word is encountered which is a verb in the infinitive, seven Bulgarian forms would be added to the list of targets, if not in it already. Addition of targets is also conditioned on their presence in the pretrained embeddings vocabulary.

The modifications performed in this manner narrowed the gap in performance between RCSLS and VM-S by only 0.1 percentage points for EN–BG (from 6.7% to 6.4%) and by 1.6 percentage points for EN–DE (from 6.5% to 4.9%). Detailed results can be found in Table 7. Recall that for Bulgarian, we estimated 54% of the gap in performance to stem from false False Positives. If the enrichment procedure was perfect, it should have reduced the gap from 6.6% to less than 3.3%. Unfortunately, due to limited coverage of the inflectional tables and of the pretrained embeddings, only 240 additional word forms were added to the EN–BG dictionary, making for a an almost negligible effect on precision.

SRC	TGT
V;NINF	V;IMP;2;SG
	V;IMP;2;PL
	V;IND;PRS;1;SG
	V;IND;PRS;1;PL
	V;IND;PRS;2;SG
	V;IND;PRS;2;PL
	V;IND;PRS;3;PL

Table 6: Example of an inflectional correspondence map.

	DE	BG
VM-S	65.5	49.8
	67.6	50.3
RCSLS	72.0	56.4
	72.5	56.8
Δ	6.5	6.7
	4.9	6.5

Table 7: Results before (cyan rows) and after (white rows) coverage enrichment for DE and BG