Domain Mismatch Doesn’t Always Prevent Cross-Lingual Transfer Learning

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Abstract
Cross-lingual transfer learning without labeled target language data or parallel text has been surprisingly effective in zero-shot cross-lingual classification, question answering, unsupervised machine translation, etc. However, some recent publications have claimed that domain mismatch prevents cross-lingual transfer, and their results show that unsupervised bilingual lexicon induction (UBLI) and unsupervised neural machine translation (UNMT) do not work well when the underlying monolingual corpora come from different domains (e.g., French text from Wikipedia but English text from UN proceedings). In this work, we show that a simple initialization regimen can overcome much of the effect of domain mismatch in cross-lingual transfer. We pre-train word and contextual embeddings on the concatenated domain-mismatched corpora, and use these as initializations for three tasks: MUSE UBLI, UN Parallel UNMT, and the SemEval 2017 cross-lingual word similarity task. In all cases, our results challenge the conclusions of prior work by showing that proper initialization can recover a large portion of the losses incurred by domain mismatch.

Keywords: Domain mismatch, cross-lingual transfer, transfer learning, machine translation

1. Introduction
Zero-shot cross-lingual transfer via representation learning has been studied in many recent works spanning a variety of tasks: cross-lingual text classification and named entity recognition (Devlin et al., 2018), unsupervised neural machine translation (Lample et al., 2018a; Artetxe et al., 2018b) and unsupervised bilingual lexicon induction (Conneau et al., 2018; Zhang et al., 2017), among others. Cross-lingual transfer techniques typically assume that the source and target text come from the same domain (e.g., English and French Wikipedia for UNMT), but many recent papers have reported issues in the domain-mismatched setting (e.g., English Europarl and French Wikipedia).

Particularly, domain mismatch has been shown to have a pernicious effect on UBLI, and has been labeled a “core limitation” (Søgaard et al., 2018), with word embeddings pre-trained on domain-mismatched corpora showing markedly degraded scores. In the case of UNMT, mismatched domains between source and target training data have also been shown to cause large reductions in BLEU scores (Marchisio et al., 2020). The results in Table 1 illustrate the severity of the problem.

In this work, we show that cross-lingual transfer can occur even when there is no overlap between the domains in the same language and no overlap between the languages in the same domain (Figure 1). Earlier work such as mBERT (Devlin et al., 2018) and XLM (Lample and Conneau, 2019) demonstrated that pre-training contextual embeddings on concatenated multilingual Wikipedia text induces cross-lingual transfer effects. We extend these findings to the domain-mismatched case, where we pre-train our embeddings on concatenated multilingual domain-mismatched text. We compare the effect of initializing with and without joint pre-training for three cross-lingual tasks: MUSE BLI (Conneau et al., 2018), UN Parallel MT (Ziemski et al., 2016), and SemEval 17 cross-lingual word similarity (Camacho-Collados et al., 2017). Contrary to the findings on UBLI and UNMT from recent publications, we find that the availability of domain-matched corpora is not a prerequisite for effective cross-lingual transfer, since the domain mismatch issue can be mitigated by using an appropriate initialization.

2. Unsupervised BLI Experiments
2.1. Background
Bilingual lexicon induction refers to a word translation task, with modern methods relying on retrieval in a continuous space shared by both source and target embeddings. BLI has successfully used small seed dictionaries as a form of cross-lingual signal (Mikolov et al., 2013; Duong et al., 2016), but recent unsupervised alternatives have proven competitive with supervised approaches (Artetxe et al., 2018a; Heyman et al., 2019),...
| Language Pair       | Source/Target Domain      | Score | Δ Mismatch vs. Match |
|--------------------|---------------------------|-------|----------------------|
| **UBLI**           |                           |       |                      |
| English-Spanish    | Europarl/Europarl         | 61.0  | –60.9                |
| English-Hungarian  | Wikipedia/Wikipedia        | 6.7   | –6.6                 |
| Søgaard et al. (2018) |                       |       |                      |
| English-Spanish    | Europarl/Wikipedia        | 0.1   |                      |
| English-Hungarian  | Wikipedia/Europarl        | 0.1   |                      |
| **UNMT**           |                           |       |                      |
| French-English     | UN Parallel/UN Parallel   | 27.6  |                      |
| Russian-English    | UN Parallel/UN Parallel   | 23.7  | –24.3                |
| Marchisio et al. (2020) |                  |       |                      |
| French-English     | UN Parallel/UN Parallel   | 3.3   | –24.3                |
| Russian-English    | UN Parallel/UN Parallel   | 0.7   | –23.0                |
|                    | UN Parallel/Common Crawl  |       |                      |

Table 1: Unsupervised bilingual lexicon induction (UBLI) and neural machine translation (UNMT) results from some previous papers. When the domains of the monolingual text are mismatched, UBLI and UNMT yield retrieval accuracy and BLEU scores very close to 0.

with methods based on adversarial learning (Zhang et al., 2017; Conneau et al., 2018) and point-cloud matching (Hoshen and Wolf, 2018).

We use the MUSE model of Conneau et al. (2018) for all UBLI experiments, with all experiments conducted on AWS p3.16xlarge hosts. MUSE uses an adversarial objective (Goodfellow et al., 2014) to learn a transformation from the word embedding space of the source language to that of the target language, along with a discriminator to distinguish transformed source embeddings from target embeddings. Word translation is achieved using margin-based nearest-neighbors to retrieve target embeddings from transformed source embeddings, and evaluated using the test sets provided with MUSE.

In UBLI with MUSE, word embeddings for the source and target languages are pre-trained independently (e.g., French and English word embeddings are trained separately on Wikipedia text). When the domains are mismatched (e.g., Wikipedia and UN), UBLI retrieval accuracy has been shown to suffer greatly (Søgaard et al., 2018), as mentioned above.

We compare the standard way of pre-training for MUSE UBLI—pre-training word embeddings separately for each language—with joint pre-training, where we train multilingual word embeddings on concatenated domain-mismatched corpora (Lample et al., 2018a). Note that this is a simple form of multilingual joint pre-training, and does not include any post-hoc processing steps (cf. Wang et al. (2020), who perform a vocabulary reallocation step to eliminate spurious anchors in the shared embedding space).

We study the following language pairs in both directions: English-French, English-Spanish, and English-Russian. For each experiment, we initialize embeddings via fastText (Bojanowski et al., 2016) using Wiki and UN corpora and perform grid search over MUSE hyperparameters, reporting scores for the configuration with the highest CSLS (cross-domain similarity local scaling) score, which is an unsupervised metric discussed in Conneau et al. (2018). We optimize CSLS score for four random seeds (123, 456, 789, and 321), three choices of iterations for Procrustes refinement (1, 3, and 5), and three choices of epochs (1, 3, and 5).

2.2. Results

We present our retrieval accuracies at 1 for UBLI experiments in Table 2. As expected, MUSE works well with domain-matched corpora, while our domain-mismatched experiments show large degradations relative to matched domain baselines in all cases. In particular, scores for Es-En, En-Es, and En-Ru all fall to near 0.0, showing that cross-lingual transfer has failed in these cases. However, in all cases, joint pre-training recovers a large portion of the losses incurred by mismatched corpora, showing cross-lingual transfer is still possible, contrary to the conclusions drawn in Søgaard et al. (2018) and Vulić et al. (2019).

2.3. The Role of Identical Words in UBLI Performance

It is important to note that a large proportion of word pairs in the MUSE test dictionaries are identical (e.g., Paris-Paris in Fr-En), and joint-training is able to take advantage of identical spellings, since words with the same spelling map to the same embedding vector.

We lemmatize all Russian data for the UBLI experiments with the pymorphy2 (Korobov, 2015) morphological analyzer, abstracting out challenges posed by morphologically rich languages like Russian.

We used Wiki dumps from June 2020 and UN corpus v1.0 (Ziemski et al., 2016). To address the disparity in corpus sizes, we sampled 5M lines from each for training. Tokenization was done with Moses (Koehn et al., 2007).

The unsupervised CSLS scores are computed using only the training corpora.
same spelling will always have the same word embedding (Lample et al., 2018a). In Table 3, we show the performance of the ‘copying baseline’, which simply treats each word as its own translation. This baseline is surprisingly strong; its accuracy at 1 exceeds 40% for English-French in both directions.

Søgaard et al. (2018) explicitly use identical words to create a seed dictionary to improve performance in the cross-domain scenario. While Søgaard et al. (2018)’s best reported score for En-Es with the seed dictionary approach actually falls below the simple copying baseline at 25.5%, we show that the joint pre-training approach yielded 56.9%. A comparison between results from the two approaches and the copying baseline are shown in Table 3.

### 2.4. The Source-Target Domain Mismatch (STDM) Score

The considerable improvement of joint-training over the unsupervised seed dictionary method as detailed in Table 3 could be the result of the relative distances between source and target domains rather than of the differing techniques. For instance, if the Wikipedia and UN corpora were more similar than the Wikipedia and Europarl corpora, domain mismatch would be more pronounced in the Wikipedia-Europarl case and lower scores would be expected. The recently proposed Source-Target Domain Mismatch (STDM) score of Shen et al. (2021) provides a means of measuring domain similarity between corpora, and we show that the Europarl and UN corpora are not dramatically different from the Wikipedia corpora in all cases. This suggests that the disparity between the results is attributable to the different methods rather than the relative similarity between domains.

The STDM score is computed in the following way. Let \( A = \text{concat}(A_1, A_2) \), or the concatenation of two corpora \( A_1 \) and \( A_2 \), where \( A_1 \) and \( A_2 \) are the corpora we wish to compare and which consist of \( n \) and \( m \) documents respectively. Then let \( A_{\text{stdm}} \in \mathbb{R}^{(n+m) \times |V|} \) be the result of applying TF-IDF (Jones, 1972) to the concatenated corpora, thus giving a matrix whose top \( n \) rows are representations of the documents from \( A_1 \) and the bottom \( m \) rows are representations of the documents from \( A_2 \). Then the (truncated) SVD decomposition of \( A_{\text{stdm}} \) is \( A_{\text{stdm}} = USV = (U\sqrt{S})(\sqrt{S}V) = \hat{U}\hat{V} \), where \( \hat{U} \) contains topic representations of the corpora’s documents, again with the first \( n \) rows (\( \hat{U}_1 \)) being the representations of corpus \( A_1 \) and the bottom \( m \) rows (\( \hat{U}_2 \)) the representations of corpus \( A_2 \). Then define \( s_{A,B} \) as in Equation 1:

\[
s_{A,B} = \frac{1}{n \cdot m} \sum_{i=1}^{n} \sum_{j=1}^{m} (\hat{U}_A U_B^T)_{i,j}
\]  

\( s_{A,B} \) then measures the average similarity of documents between corpus \( A \) and corpus \( B \). Given \( s_{A,B} \) for each combination of corpora, then the STDM score is defined as in Equation 2.

\[
STDM = \frac{s_{1,2} + s_{2,1}}{s_{1,1} + s_{2,2}}
\]

The STDM score, which in practice ranges from 0 (completely dissimilar) to 1 (identical), thus uses latent semantic analysis (LSA) (Dumais et al., 1988) on a combined corpus to derive topic representations of the individual corpora, using the intuition that similar corpora will have similar documents. We use this score to quantify the similarity between mismatched corpora and rule out relative domain divergence as a causal factor in the disparity between our scores and those of Søgaard et al. (2018).^5^ The STDM scores for the mismatched corpora for each experiment are found in the STDM column of Table 3. The STDM comparisons between corpora show that, while on average the Wikipedia and UN corpora are more similar than the Wikipedia and Europarl corpora, this difference is small and unlikely to account for the

| Source Domain-Target Domain | Es-En | En-Es | Fr-En | En-Fr | Ru*-En | En-Ru* |
|-----------------------------|-------|-------|-------|-------|--------|--------|
| **Matched Domain**          |       |       |       |       |        |        |
| Wiki - Wiki                 | 81.8  | 82.5  | 81.3  | 82.2  | 59.5   | 64.0   |
| UN - UN                     | 68.7  | 70.8  | 74.2  | 75.2  | 55.2   | 56.7   |
| **Mismatched Domain**       |       |       |       |       |        |        |
| Wiki - UN                   | 0.1   | 0.2   | 35.2  | 33.8  | 16.6   | 0.1    |
| Wiki - UN w/ Joint Pre-training | 65.2  | 56.9  | 68.3  | 54.4  | 28.0   | 20.1   |

\( \Delta \) +65.1 +56.7 +33.1 +20.6 +11.4 +20.0

Table 2: Retrieval accuracy@1 for UBLI across language pairs on MUSE test dictionaries. \( \Delta \) pre-training uses word embeddings that are jointly pre-trained on concatenated source Wiki and target UN corpora. Ru* denotes lemmatized Russian.

^5^Note that a corpus similarity score based on TF-IDF cannot compare corpora from different languages directly. Shen et al. (2021) work around this issue by comparing the corpora in the target language. For example, to quantify the domain mismatch in an English-Wikipedia to Spanish-Europarl experiment, the corpora of comparison would be the Spanish Wikipedia and the Spanish Europarl, since Spanish and English Wikipedia would cover similar topics.
large disparity in results. On the one point of direct comparison, namely UBLI from English into Spanish, the Wikipedia and Europarl corpora are shown to be more similar (STDM=0.27) than the Wikipedia and UN corpora (STDM=0.25), yet joint-training on the more dissimilar corpora still produces better results (56.9% vs. 25.5%).

2.5. On Domain Mismatch in UBLI
We emphasize three points from the results of these experiments. Firstly, in many cases, initialization by a simple joint-training regimen can largely overcome the deleterious effects of domain mismatch for the UBLI task, challenging the conclusions of Søgaard et al. (2018) and Vulić et al. (2019). This is seen primarily in experiments involving closely related languages (English-Spanish, English-French), where mismatched domain experiments run with joint-training initialization approach the scores of the matched domain experiments.

Secondly, while still beneficial, joint-training initialization is less effective on distantly related languages, such as English-Russian. Improvements from joint-training are considerable, but scores still fall below the matched domain experiments, suggesting that this method does not fully solve domain mismatch in all cases.

Lastly, task-agnostic joint-training initialization performs favorably when compared against the identical-word seed dictionary method of Søgaard et al. (2018) in terms of ameliorating the effects of domain mismatch, as shown by comparison of each method against a copying baseline.

3. Unsupervised NMT Experiments
3.1. Task Description
Unsupervised NMT systems address the paucity of available parallel data for most language pairs, relying only on monolingual data from the source and target languages. The models of Lample et al. (2018a) and Artetxe et al. (2018b) are representative, each employing encoder-decoder architectures with weight-sharing between languages. Models are trained via the dual tasks of sentence reconstruction and back-translation (Sennrich et al., 2016). Follow-up work has incorporated statistical machine translation (SMT) systems (Koehn et al., 2003; Artetxe et al. (2019) and Marie and Fujita (2018) use unsupervised SMT systems to initialize UNMT systems, while Ren et al. (2019) incorporate SMT as a form of posterior regularization. For all UNMT experiments, we adopt the encoder-decoder model of Lample et al. (2018b), a sequence-to-sequence model with 6 transformer layers for both the encoder and decoder, and use the implementation provided by the authors. We study the English-French and English-Russian language pairs in both directions, training all models for ten epochs. We used 5 million sentences per language in the monolingual data used for UNMT training. We trained two English-French and two English-Russian UNMT models on the following sets of 10 million sentences: (En Wiki, Fr UN), (En UN, Fr Wiki), (En Wiki, Ru UN), and (En UN, Ru Wiki).

In a manner similar to our UBLI experiments, we compare UNMT performance with and without jointly pre-trained contextual embeddings. In the baseline system, we follow the UNMT approach outlined in Lample and Conneau (2019), where the encoder and decoder are initialized with a contextual embedding pre-trained on Wikipedia text only. In the jointly pre-trained case, the encoder and decoder are initialized with a contextual embedding that was pre-trained on a mix of Wikipedia and UN text.

3.2. Results
In Tables 4 and 5, we show the difference in the UN development BLEU scores between a UNMT system with and without joint pre-training. Table 4 shows results for experiments in which the monolingual data contains UN text in the target language, while Table 5 shows results for experiments in which it does not. We
4. Cross-lingual Semantic Word Similarity Experiments

4.1. Task Description

In addition to investigating the UBLI and UNMT tasks, we also examine cross-lingual transfer via word similarity tasks, and in doing so show that joint-training via concatenation is useful generally, even for non-translation related tasks. The semantic word similarity task consists of evaluating pairs of words via cosine similarity (Finkelstein et al., 2001) via a similarity metric (e.g., cosine similarity) on their embeddings, and comparing these scores with human judgments. The SemEval 17 cross-lingual semantic word similarity task (Camacho-Collados et al., 2017) evaluates pairs of words from different languages for similarities in their underlying meaning on a scale from 0–4, with a step size of 0.5. Given semantic similarity predictions for a list of word pairs constructed per Camacho-Collados et al. (2015), performance is measured as the harmonic mean of Pearson and Spearman correlations with human judgments. Datasets were constructed from English, Farsi, German, Italian, and Spanish. As in the UBLI experiments, we train fastText embeddings for each language pair using domain-matched (Wiki-Wiki) and domain-mismatched (UN-Wiki) corpora, and compare separate and joint pre-training. Finally, semantic similarity is computed by cosine similarity.

4.2. Results

Results on the cross-lingual semantic word similarity task consist of evaluating pairs of words (e.g., WS353) via a similarity metric (e.g., cosine similarity) on their embeddings, and comparing these scores with human judgments. The SemEval 17 cross-lingual semantic word similarity task (Camacho-Collados et al., 2017) evaluates pairs of words from different languages for similarities in their underlying meaning on a scale from 0–4, with a step size of 0.5. Given semantic similarity predictions for a list of word pairs constructed per Camacho-Collados et al. (2015), performance is measured as the harmonic mean of Pearson and Spearman correlations with human judgments. Datasets were constructed from English, Farsi, German, Italian, and Spanish. As in the UBLI experiments, we train fastText embeddings for each language pair using domain-matched (Wiki-Wiki) and domain-mismatched (UN-Wiki) corpora, and compare separate and joint pre-training. Finally, semantic similarity is computed by cosine similarity.
Table 4.

tersity (SemEval 2017 Task 2, Subtask 2).

| Monolingual Data | Task | Epoch | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|------------------|------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| En UN, Fr Wiki   | En UN → Fr UN | UNMT Baseline | +0.41 | +0.48 | +0.22 | +0.50 |
|                  |      | w/ Joint Pre-train. | +0.47 | +0.47 | +0.26 | +0.49 |
| Fr UN, En Wiki   | Fr UN → En UN | UNMT Baseline | +0.43 | +0.47 | +0.23 | +0.45 |
|                  |      | w/ Joint Pre-train. | +0.49 | +0.49 | +0.28 | +0.50 |
| Ru UN, En Wiki   | Ru UN → En UN | UNMT Baseline | +0.45 | +0.48 | +0.25 | +0.47 |
|                  |      | w/ Joint Pre-train. | +0.51 | +0.51 | +0.30 | +0.53 |

Table 6: Correlation scores for cross-lingual word similarity (SemEval 2017 Task 2, Subtask 2). ∆ refers to the difference between the domain-mismatched scores with and without joint pre-training.

| Monolingual Data | Task | Epoch | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|------------------|------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| En UN, Fr Wiki   | En UN → Fr UN | UNMT Baseline | +6.39 | +6.60 | +5.94 | +6.89 |
|                  |      | w/ Joint Pre-train. | +6.65 | +6.65 | +6.00 | +6.95 |
| Fr UN, En Wiki   | Fr UN → En UN | UNMT Baseline | +3.44 | +3.51 | +3.73 | +4.10 |
|                  |      | w/ Joint Pre-train. | +3.68 | +3.68 | +3.11 | +3.53 |
| Ru UN, En Wiki   | Ru UN → En UN | UNMT Baseline | +1.24 | +1.09 | +1.19 | +0.89 |
|                  |      | w/ Joint Pre-train. | +1.48 | +1.48 | +1.00 | +1.00 |

Table 5: UNMT BLEU scores when the monolingual data doesn’t contain target language UN text, in contrast to Table 4.

5. Conclusion

Recent publications on UBLI and UNMT have noted that domain mismatch hinders zero-shot cross-lingual transfer, which we expect will be useful guidance for NLP practitioners.

While the results reported here are encouraging, future work should include experimentation with a wider assortment of language pairs and corpus domains, as well as an investigation of how the distance between languages can affect joint-training’s ability to mitigate domain mismatch for different tasks. While in all three tasks it proved very effective for closely related language pairs, the UBLI and UNMT improvements for the more distant language pair of English-Russian were less pronounced. Conversely, on the cross-lingual semantic word similarity experiment, language distance seemed less relevant as joint-training on English-Farsi resulted in scores comparable to the domain matched scenario.

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