Improving Zero-Shot Cross-lingual Transfer Between Closely Related Languages by Injecting Character-Level Noise

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Abstract

Cross-lingual transfer between a high-resource language and its dialects or closely related language varieties should be facilitated by their similarity. However, current approaches that operate in the embedding space do not take surface similarity into account. This work presents a simple yet effective strategy to improve cross-lingual transfer between closely related varieties. We propose to augment the data of the high-resource source language with character-level noise to make the model more robust towards spelling variations. Our strategy shows consistent improvements over several languages and tasks: Zero-shot transfer of POS tagging and topic identification between language varieties from the Finnic, West and North Germanic, and Western Romance language branches. Our work provides evidence for the usefulness of simple surface-level noise in improving transfer between language varieties.

1 Introduction

Recent research has achieved impressive results in zero-shot cross-lingual transfer based on multilingual pre-training (Devlin et al., 2019; Conneau and Lample, 2019) or monolingual transfer of embeddings (Artetxe et al., 2020). However, these methods require large amounts of unlabeled data in the target language (Lauscher et al., 2020) and do not take into account surface similarity between languages except for the sharing of subword units in multilingual models. For the transfer between closely related languages and dialects, we deem it desirable to exploit the similarity of surface representations. Specifically, we target orthographic variations that commonly result from pronunciation differences between closely related languages.

In this paper, we propose to augment the training data of a high-resource language with character-level noise to simulate spelling variations and thus facilitate generalization to closely related low-resource languages.

We test this strategy on two tasks and several language regions. The considered tasks are part-of-speech (POS) tagging on the word level and topic classification on the sentence level; the languages are from the Finnic, West and North Germanic, and Western Romance language branches. We observe that our baseline method for cross-lingual transfer learns undesirable heuristics, e.g., assigning unseen words to open word classes in POS tagging and that injecting noise reduces this bias. Our experiments show absolute accuracy improvements between 1.4 and 22 percentage points over the state of the art, providing evidence that a simple data-augmentation strategy can boost transfer learning for language varieties and dialects with a closely related high-resource language.

2 Related Work

Zero-shot cross-lingual transfer based on multilingual language models (Devlin et al., 2019; Conneau and Lample, 2019) or machine translation models (Siddhant et al., 2020) has turned out to be an effective approach for cross-lingual transfer.

Note that there are also differences on different levels as described in Hollenstein and Aepli (2014) and partly observable in Figure 1 which illustrates a German example sentence with a closely related variant.

Figure 1: Swiss German (GSW) sentence with corresponding standard German (DE) and English (EN) translations. The sentence shows various spelling differences on the word level, and reordering occurs on the sentence level due to different past-tense formation.
to be surprisingly effective. Such representations proved themselves beneficial for a range of diverse tasks (Hu et al., 2020). However, they still require large-scale data sets to train, making them impractical for low-resource languages, to which dialects and language varieties typically belong.

Artetxe et al. (2020) introduce zero-shot cross-lingual transfer by mapping monolingual representations between languages. They also propose adding Gaussian noise to the embeddings during the fine-tuning step. Huang et al. (2021) also operate in the embedding space by constructing robust regions in the embedding space to tolerate noise in the contextual embedding. These are not ideal strategies for closely related languages because words with similar surface forms could still be far from each other in an embedding space.

Surface-level noise such as character substitutions, insertions, and deletions has been proposed as an effective data augmentation strategy for machine translation (Sperber et al., 2017; Heigold et al., 2018; Belinkov and Bisk, 2018; Karpukhin et al., 2019; Vaibhav et al., 2019; Anastasopoulos et al., 2019). Authors report improvements in system accuracy due to more robustness towards speech recognition errors, spelling mistakes, and other naturally occurring noise in text data. Even though cross-lingual transfer between closely related languages has received some attention (Muller et al., 2020; Sakaguchi et al., 2017; Zeman et al., 2017, 2018), it has not been investigated whether this transfer can be improved with character-level noise inserted at training time. We tackle this in our work by adding random character-level noise to the training data of a standard language and applying the model to closely related languages.

Exploiting orthographic similarity to improve cross-lingual transfer between closely related languages is currently an understudied area. Relevant previous work has been done by Sharoff (2018), who used orthographic similarity to refine bilingual dictionary induction.

Transliteration is another line of related work that focuses on improving the transfer between closely related languages with different alphabets (Durrani et al., 2014; Lin et al., 2016; Murikin nati et al., 2020; Han and Eisenstein, 2019). On the other hand, our work focuses on languages using the same script. The recent report by Muller et al. (2021) investigating transfer between the same and different alphabets involves a zero-shot task transfer which is, however, preceded by a language model training on (unlabeled) target language data. To the best of our knowledge, we are the first to focus on zero-shot transfer learning techniques for closely related languages.

3 Method

Consider a high-resource language $X$ and a closely related low-resource language $Y$. We perform zero-shot cross-lingual transfer by pre-training a model on unlabeled data from $X$ (and optionally $Y$ if available), then fine-tuning on task $T$ in language $X$. The resulting model is applied to task $T$ in language $Y$. This procedure is illustrated in Figure 2. Thus, our question is: How can we best make the model trained on $X$ generalize to $Y$?

Ideally, such a model would take surface similarity of words into account for generalization. We hypothesize that in closely related languages, unknown words in the low-resource language are likely to correspond to similar known words in the high-resource language in function and meaning. However, state-of-the-art language models represent words through subwords (Sennrich et al., 2016). This representation is sensitive to slight surface variations: minor changes to a string will lead to different segmentations and internal representations.

To account for this problem, we apply noise to the surface representation of words in language $X$. We implement this through character-level noise, i.e., we randomly select $10\% – 15\%$ of the tokens.

Figure 2: Methodology for zero-shot cross-lingual transfer: We first continue the pre-training of a language model (LM) on text. Then, we fine-tune the adapted LM to task $T$ in high-resource language $X$. We augment the training data for continued pre-training or fine-tuning with character-level noise and apply the model to task $T$ in a closely related low-resource language $Y$.

Please refer to Table A1 for examples.

We tested more linguistically motivated constraints on the
Table 1: POS tag accuracy for Swiss German (GSW) on different language models fine-tuned on German (DE) training data with and without noise.

| Noise | DE-BERT + GSW | DE-BERT + DE | DE-BERT + DE + Noise |
|-------|---------------|--------------|-----------------------|
| ✗     | 50.66         | 72.1         | 52.08                 | 53.88                 |
| ✓     | 72.77         | 82.11        | 71.13                 | 70.45                 |

Table 1 illustrates that the method works well for closely related language varieties (upper part) but less for other language pairs, which are more distant (lower part). We do see an occasional improvement for more distant language pairs, but they

4 Experiments

We design our experimental procedure to answer the following question: Does character-level noise improve zero-shot transfer to closely related languages? Within three controlled experiments, we

- ablate the importance of the noise-augmentation strategy. We select two cross-lingual tasks: 1) POS tagging (15% noise) and 2) topic classification (10% noise). While the former task illustrates the strategy’s potential on word level, the latter provides insight into how much it helps on text level.

4.1 POS Tagging for Swiss German Dialects

As base models, we use the German “dbmdz” BERT (DE-BERT) and mBERT (Devlin et al., 2019). We continue pre-training on the SwissCrawl corpus (Linder et al., 2020) for the Swiss German (GSW) LM-adaptation and the DE part of The Credit Suisse News Corpus (Volk et al., 2018) for the German LM-adaptation. For task fine-tuning, we use a DE UD treebank and for the evaluation a part of NOAH’s Corpus (Hollenstein and Aepli, 2014).

As shown in Table 1, all settings profit from fine-tuning with noise and bring about improvements of up to 22 percentage points (DE-BERT without pre-training). The best result with an accuracy of 82.11% for zero-shot GSW POS tagging is achieved with a GSW-adapted language model and task fine-tuning on a noised DE corpus. Considering the case where no GSW text data is available for language model adaptation, we still achieve an accuracy of 77.11% for zero-shot GSW POS tagging with mBERT fine-tuned on noised DE data (see Table 2).

4.2 POS Tagging with mBERT

We fine-tune mBERT on a UD corpus of a language already seen during mBERT pre-training: DE, Finnish (FI), Swedish (SV), French (FR), or Icelandic (IS, Arnardóttir et al. (2020)) and test on a closely related language variety absent from mBERT: GSW, Old French (OFR), Livvi (OLO, Pirinen (2019)), Karelian (KRL, Pirinen (2019)), or Faroese (FO, Tyers et al. (2018)). In addition to noise, we added experiments with a BPE-dropout of 0.1 (empirically selected) during the fine-tuning step.

Table 2 illustrates that the method works well for closely related language varieties (upper part) but less for other language pairs, which are more distant (lower part). We do see an occasional improvement for more distant language pairs, but they
Table 2: Zero-shot POS tagging accuracy of different strategies for several languages (TRAIN→TEST). The training and test languages are closely related in the upper but not in the lower part of the table as indicated by the colors (Finnic, West Germanic, North Germanic, and Western Romance language branches.) Noise consistently adds additional accuracy points beyond BPE-dropout performance increase.

| Languages | Baseline | BPE-Dropout | Noise | BPE-Drop-out+Noise |
|-----------|----------|-------------|-------|-------------------|
| DE→GSW   | 73.14    | 76.48       | 77.11 | **78.13**          |
| FI→OLO   | 69.32    | 69.66       | 73.03 | 71.76             |
| FI→KRL   | 72.44    | 76.35       | **79.18** | 78.57         |
| SV→FO    | 84.76    | 86.20       | **87.63** | 87.31         |
| IS→FO    | 85.94    | 86.80       | 87.43 | **87.46**         |
| FR→OFR   | 63.42    | 66.65       | 67.63 | **67.27**         |
| DE→FO    | 81.74    | 81.34       | 81.38 | **82.27**         |
| DE→OLO   | 52.63    | 52.09       | 51.10 | 49.26             |
| DE→KRL   | 57.51    | 57.47       | 55.71 | 53.37             |
| DE→OFR   | 44.08    | 39.17       | 38.32 | 40.03             |
| FR→OLO   | 56.49    | 56.72       | **58.59** | 56.64         |
| FR→KRL   | 59.46    | 62.27       | **64.52** | 64.15         |
| FR→FO    | 81.13    | 82.09       | 81.81 | **82.62**         |

Table 3: Results for Moldavian (MD) vs. Romanian (RO) cross-dialect topic identification. Training with noise improves the transfer by 5.1 (MD→RO) respectively 1.3 (RO→MD) percentage points.

| Languages | Noise | Test | Accuracy  |
|-----------|-------|------|-----------|
| MD        | x     | RO   | 63.34     |
| RO        |       | MD   | 81.65     |
|           |       |      | **83.01** |

5 Analysis

Figure 3 illustrates the prediction differences of a model trained with and without noise. We observe that the models trained without noise have learned a tendency towards labeling unknown words as open-class words such as names (NE) or adjectives (ADJD), with the label for foreign words (FM) being massively overpredicted, while it tends to under-generate closed-class tags such as articles (ART) or adverbs (ADV). In contrast, the model trained with noise comes much closer to the gold standard tag distribution. It has learned to rely more on probable POS tag sequences than on the surface form of a token. Figure 4 depicts the per-type F1 change for the most frequent STTS (Schiller et al., 1999) tags. The past participles of the auxiliary verbs (VAPP) form another closed class which profits substantially from a model focusing on tag sequences given the compound structure of the perfect tense. As Swiss German does not have a simple past, the.
Figure 3: Number of tokens per POS tag in the gold standard vs. predictions of two models, fine-tuned with and without noise. Only the most frequent STTS tags are displayed.

Figure 4: Per-type F1 change of the most frequent STTS tags illustrating which tags profit the most when the model is fine-tuned with noise.

The perfect tense is much more frequent than it is in German.

5.1 Conditional Random Field

Given that one potential consequence of adding noise is that the model relies more on surrounding context and probable POS tag sequences (rather than strict word-level mappings), we compare our results to a method that explicitly models tag sequences, Bi-LSTMs+CRF (bidirectional long-short-term memory + conditional random field). This method was used to achieve state-of-the-art performance for POS tagging (Huang et al., 2015). For the implementation, we added a CRF layer on top of BERT.\footnote{Making use of the TorchCRF library: \url{https://github.com/s14t284/TorchCRF}.}

The added CRF layer did not improve the performance of the fine-tuned mBERT model for zero-shot POS tagging for Swiss German trained on German, as presented in Table 4. In contrast, noise injection has proven effective in both configurations.

| Noise          | mBERT  | mBERT+CRF |
|----------------|--------|-----------|
|                | 70.24  | 69.26     |
| ✓              | 78.57  | 76.90     |

Table 4: Zero-shot POS tag accuracy for Swiss German on mBERT & mBERT+CRF models trained on German with and without noise.

6 Discussion

Our investigation into cross-lingual zero-shot transfer between closely related languages demonstrates that simple data augmentation with character-level noise can successfully improve transfer, with absolute improvements ranging from 1.4 (RO→MO transfer of topic identification) to 22 (DE→GSW transfer of POS tagging in the case of DE-BERT without pre-training) percentage points.

The examination of prediction errors shows that a baseline BERT model has learned heuristics for unseen words that are undesirable for transfer between closely related languages. In contrast, a model trained with noise can combat this bias without substantial performance losses in the source languages.

We expect that the final effectiveness of using character-level noise for zero-shot cross-lingual transfer depends on the task and language characteristics. We plan to evaluate the effect of character-level noise in a broader range of settings in future work. More broadly, we encourage further research that exploits surface-level word similarity for cross-lingual transfer between related languages and dialects, rather than focusing purely on vector space representations.

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Ethical Considerations

Our work did not involve any new data collection or annotation and did not require in-house workers or introduce any new models and related risks. Instead, we examine how character-level noise can help the transfer between closely related languages, especially in low-resource zero-shot settings.
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A Appendix

A.1 Analysis

Table A1 shows Swiss German (GSW) words (and their corresponding standard German (DE) form and English (EN) translation) that had the highest accuracy increase when using a part-of-speech (POS) tagging model trained with character-level noise compared to the model trained without noise. These words were wrongly tagged with open-class tags by the baseline model. However, the model trained with noise was able to reduce this bias and thus correctly tag them with their closed-class tag.

Furthermore, in most cases, one substitution/insertion/deletion-operation on the DE word would not suffice to get an exact match with the GSW word. This indicates that it is unnecessary to design a noise function that closely mirrors the linguistic differences between variants.

A.2 Data Sets

A.2.1 Universal Dependencies

Table A2 contains the Universal Dependencies treebanks (UD, Nivre et al. (2016)) we used in this work. The treebanks can be downloaded via https://universaldependencies.org/#download.

A.2.2 Other Data Sets

Table A3 shows data sets apart from UD that we used in this work.
Most frequent Error reduction with GSW

| GSW | DE | EN | Most frequent POS without noise | Correct POS | Error reduction with noise (relative/absolute) |
|-----|----|----|---------------------------------|-------------|-----------------------------------------------|
| ond | und | and | FM | KON | 99.00% (-104) |
| worde | geworden | become | VVPP, ADJJ | VAPP | 98.73% (-156) |
| dr | der | the | FM, NE, NN | ART | 98.46% (-128) |
| häd | hat | had | VVFIN, FM | VAFIN | 98.21% (-55) |
| gsi | gewesen | been | VVPP, FM | VAPP | 98.19% (-434) |
| vu | von | from | FM, NE | APRR | 98.18% (-108) |
| eme | einem | a | ADJA, FM | ART | 97.96% (-48) |
| grad | gerade | just | ADJD | ADV | 97.59% (-81) |
| vum | vom | from the | FM, APPR | APPRART | 96.49% (-55) |
| de | der | the | FM, NE, ADJA | ART | 95.76% (-1558) |

Table A1: Swiss German (GSW) words (and their corresponding standard German (DE) form and English (EN) translation) with the highest error reduction using a part-of-speech (POS) tagging model trained with character-level noise compared to the model trained without noise.

| Usage | Language (ISO) | Language Branch | Treebank | # Sentences |
|-------|----------------|-----------------|----------|-------------|
| Training | Finnish (FI) | Finnic | TDT | 15K |
| | French (FR) | Western Romance | GSD | 16K |
| | German (DE) | West Germanic | HDT | 190K |
| | Icelandic (IS) | North Germanic | IcePaHC | 39K |
| | Swedish (SV) | North Germanic | Talbanken | 5K |
| Test | Faroese (FAO) | North Germanic | OFT | 1208 |
| | Karelian (KRL) | Finnic | KKPP | 228 |
| | Livvi (OLO) | Finnic | KKPP | 125 |
| | Old French (OFR) | Western Romance | SRCMF | 1927 |

Table A2: Universal Dependency treebanks we used for our experiments with the number of sentences ("# Sentences") we used for training or testing (specified in "usage").

| Corpus name (Language) | Size | Link |
|------------------------|------|------|
| Morocco (MD & RO) | 33.5K text samples | https://github.com/butnaruandrei/MOROCO |
| NOAH's Corpus (GSW) | 7.3K sentences | https://noe-eva.github.io/NOAH-Corpus/ |
| SwissCrawl (GSW) | 500K sentences | https://icosys.ch/swisscrawl |
| The Credit Suisse News Corpus (DE) | 105K sentences | https://pub.cl.uzh.ch/projects/b4c/en/corpora.php |

Table A3: Data sets we used for our experiments in addition to the UD treebanks in Table A2.