Can a Transformer Pass the Wug Test? Tuning Copying Bias in Neural Morphological Inflection Models

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Abstract

Deep learning sequence models have been successfully applied to the task of morphological inflection. The results of the SIGMORPHON shared tasks in the past several years indicate that such models can perform well, but only if the training data cover a good amount of different lemmata, or if the lemmata that are inflected at test time have also been seen in training, as has indeed been largely the case in these tasks. Surprisingly, standard models such as the Transformer almost completely fail at generalizing inflection patterns when asked to inflect previously unseen lemmata—i.e. under “wug test”-like circumstances. While established data augmentation techniques can be employed to alleviate this shortcoming by introducing a copying bias through hallucinating synthetic new word forms using the alphabet in the language at hand, we show that, to be more effective, the hallucination process needs to pay attention to substrings of syllable-like length rather than individual characters or stems. We report a significant performance improvement with our substring-based hallucination model over previous data hallucination methods when training and test data do not overlap in their lemmata.

1 Introduction

The Transformer model has delivered convincing results in many different tasks related to word-formation and analysis (Vylomova et al., 2020). Especially on inflection tasks, where an input lemma such as dog, and input inflectional features such as {N, PL}, are expected to produce an output such as dogs, the model has shown to be particularly adept at generalizing patterns (Wu et al., 2020; Liu and Hulden, 2020). However, we have discovered that this is only true if some variant of the input lemma to be inflected has been witnessed during training. In a “wug test” (Berko, 1958) setting where a previously unseen lemma—like wug—is to be inflected in some way, we find that the Transformer almost completely fails to generalize inflection patterns, despite abundant training data. It has been noted earlier that neural sequence-to-sequence models are apt to perform poorly if they have been exposed to little training data and that autoencoding on hallucinated forms could be useful (Kann and Schütze, 2017). Our starting point is the observation that the poor “wug test” performance is maintained even with abundant training data.

In our study, we show three main results. (1) We demonstrate that, even if trained with relatively large amounts of data, a Transformer model of the kind that has been very successful at recent shared tasks largely fails to generalize inflection patterns if it has not been exposed during training to lemmata in the test set. This is true even for datasets where all words inflect in the same way—i.e. there are no inflectional classes or allomorphs of morphemes, as is found in the low-resource Niger-Congo dataset used in SIGMORPHON 2020 shared task (Vylomova et al., 2020). (2) We also show that simply exposing the model to uninflected lemmata in the
test set—without providing a single inflected form—allows the model to dramatically improve its performance when actually inflecting such lemmata. (3) Further, we investigate several strategies that avoid leveraging test set lemmata. We show that when inducing a copy bias in the model by hallucinating new lemmata, or by hallucinating new inflected forms, the method of hallucination is much more effective if it is sensitive to substrings of syllable-like length rather than individual characters or stems. Our best models significantly improve upon earlier state-of-the-art data hallucination methods such as Silfverberg et al. (2017) and Anastasopoulos and Neubig (2019).

2 Data

2018-languages We use six languages from the CoNLL-SIGMORPHON 2018 shared task 1 medium setting, where each language has 1,000 (LEMMATARGET TAGS, TARGET FORM) triples for training (Cotterell et al., 2018). The six languages, Czech, Finnish, German, Russian, Spanish and Turkish, are selected to provide a diversified representation of language typology and morphological inflection challenges. Although there are only 1,000 triples in the training set, they cover a fair number of lemmata as each lemma appears only once or twice. In the original shared task data split, between 2% and 27% of the lemmata in the dev and test sets are also found in the training set.

To prepare training data for the “wug test”-like circumstance, we select the UniMorph (Kirov et al., 2018) paradigms for the first 100 most frequent lexemes found in Wikipedia text, which are not included in the 2018 shared task 1 dev and test sets. The shared task dev and test sets are used for validation and evaluation without any change. The 100 full inflection tables give us over 1,000 (for Czech, German and Russian) or over 7,000 (for Finnish, Spanish and Turkish) training triples.

Niger-Congo languages In addition, we use six Niger-Congo languages from SIGMORPHON 2020 shared task 0 (Vylomova et al., 2020): Akan, Ga, Lingala, Nyanja, Southern Sotho and Swahili. These languages are low-resource, but the dataset only contains very regular inflections. In the original shared task data split, the overlap between the lemmata in the dev and test sets and those in the training set is 100%. The number of paradigms which we can obtain by combining the training, dev and test sets of this dataset is around 100 for Akan, Ga and Swahili, 227 for Nyanja, 57 for Lingala and only 26 for Southern Sotho.

For our “wug test”, we divide the inflection tables reconstructed from this dataset into a 7:1:2 train-dev-test split, i.e. we use the same ratio as the shared task, but the division is by inflection tables rather than lemma-tag-form triples, to ensure that the lemmata used for validation and test are disjoint from those for training. We provide details on the data statistics in Appendix A for reference.

3 Experiments

Inflection model The Transformer (Vaswani et al., 2017) is the seq2seq architecture which produces the current state-of-the-art result on the morphological inflection task (Wu et al., 2020; Vylomova et al., 2020; Liu and Hulden, 2020). It takes the lemma and target tag(s) as input and predicts the target form character by character. Our experiments use the Transformer model implemented in Fairseq (Ott et al., 2019) and adopt the same hyperparameter settings as Liu and Hulden (2020).

Evaluation metric The evaluation metric is accuracy. For the original shared task data and experiments on 2018-languages, we train five inflection models each with different random initialization and report the average accuracy with standard deviation. Due to data scarcity, for Niger-Congo languages at the “wug test”-like setting, we perform a 5-fold cross-validation and report the average accuracy and the standard deviation.

Common-practice test and “wug test” We first compare the performance of the Transformer in the common-practice setting and the “wug test”-like setting. The “common practice” is represented by previous years’ shared tasks and related work (Cotterell et al., 2016, 2017, 2018; McCarthy et al., 2019; Vylomova et al., 2020); here the training data usually covers a fair number of lemmata and there is overlap between lemmata in the training and test sets. We use the shared task data to represent the common-practice setting. In the “wug test” setting, the lemmata to be inflected are always previously unseen. To our surprise, the performance of the Transformer at the “wug test”-like setting is very poor despite the large amount of training triples for 2018-languages or the very regular and straightforward inflection for Niger-Congo languages. The performance is dramatically inferior to the common-practice setting, even when the
In order to test the first hypothesis that the model does not learn to copy parts of a stem it has not seen at the training stage, we augment the training data for each language by adding the lemmata in its development and test parts of a stem it has not seen at the training stage, hypothesis that the model does not learn to copy letter subsequences of letters, i.e. the model can’t copy sequence ab if the sequence is underrepresented in training. (4) some combination of all factors. To test these hypotheses, we conduct five experiments designed to help the model learn to copy with different biases by adding to the training set for each language 2,000\footnote{The choice of 2,000 is in order to match the augmentation size of +copy-dev-test-lemmas method for 2018-languages.}

dummy datapoints generated in different ways, explained below.

+copy-dev-test-lemmas  In order to test the first hypothesis that the model does not learn to copy parts of a stem it has not seen at the training stage, we augment the training data for each language by adding the lemmata in its development and test sets with a special tag COPY. In other words, 2000 (LEMMATA, COPY, LEMMA) triples are added to the initial “wug test” training set for each language.

+copy-2k-char and +copy-2k-substr  Previous work found that adding random strings can help seq2seq models learn a copy bias and thus improve the performance when the training data is limited (Kann and Schütze, 2017). We adopt a similar method to augment the training data with dummy lemmata generated by the process shown in Figure 2 (a). The +copy-2k-char method takes as input the alphabet created by collecting characters in the language’s training set. Considering that a natural linguistic sub-unit of a word is a syllable, we propose to use substrings of syllable-like length for the +copy-2k-substr method. The input of this method is the set of bigrams, trigrams and four-grams from the language’s training data. For both methods, we generate the dummy lemma by uniformly sampling from the input and concatenating the sampled items to a random length between the minimum and maximum word length we see in the training data. The output of the dummy lemma generation process is a triple of a dummy lemma, a special symbol COPY and the dummy lemma, which is added to the initial “wug test” training set for data augmentation.

+hall-2k-char and +hall-2k-substr  The dummy lemma generation methods do not leverage knowledge about word structure which can be inferred from the training data. Silfverberg et al. (2017) found that augmenting training data in low-resource situations with data hallucination by replacing a hypothesized stem of the training triples with a random string is very effective. Anastasopoulos and Neubig (2019) improves this data hallucination method by taking into consideration of discontinuous stems as well, which is the best data hallucination method so far. We conduct the +hall-2k-char experiment by augmenting the initial “wug test” training set with dummy data generated with Anastasopoulos and Neubig (2019)’s method. The implementation from SIGMORPHON 2020 shared task 0 baseline is used. In addition, we propose to generate the dummy stem by uniformly sampling from substrings of syllable-like length, i.e. the bigram, trigram and four-gram set. This experiment is referred to as +hall-2k-substr. Specifically, both data hallucination methods (illustrated in Figure 2 (b)) take as input a triple from the training set, align the lemma and the target form with the alignment method from SIGMORPHON 2016 shared task baseline (Cotterell et al., 2016), find the common substrings between the lemma and the target form as the stem, replace the stem with a dummy stem, and output a dummy triple which is adopted for data augmentation. Our proposed method is different from Anastasopoulos and Neubig (2019)’s method at the dummy stem generation step in two ways, explained below.

Figure 2: (a) Dummy lemma generation with a German example. +copy-2k-char generates random strings by uniformly sampling from the alphabet, while +copy-2k-substr samples from the set of 2-, 3- and 4-grams; (b) Data hallucination with a German example. +hall-2k-substr is different from +hall-2k-char in how the dummy stem is generated.
main aspects: (1) Instead of sampling from the alphabet, we sample from the set of bigrams, trigrams and four-grams. (2) Instead of forcing the dummy stem to be of the same length as the stem to be replaced, we only constrain the minimum and maximum length of the stem based on the training data. In addition, for discontinuous stems, we only replace the first part of the stem.

4 Results and discussion

“Wug test” with data augmentation Figure 3 shows results for the “wug test”-like setting and results after augmenting the initial training set with different methods. Every language gets significant improvement with data augmentation, indicating that the Transformer model at the vanilla “wug test” circumstance will not learn a copy bias well.

The substring-based data hallucination we propose, +hall-2k-substr, achieves accuracies which are significantly higher than other methods for most languages. For Turkish and Nyanja, +hall-2k-substr is lower than the best performance, but the difference is not significant. For Lingala, +hall-2k-substr has the same best performance as +hall-2k-char. The outstanding advantage of +hall-2k-substr indicates that substrings of syllable-like length is more helpful than individual characters for data hallucination. It also provides support to the fourth hypothesis we made in section 3 that the poor performance of the Transformer in the vanilla “wug test”-like setting is due to a combination of factors including missing copying bias for letters, subsequences of letters and even entire stems.

Common practice vs “wug test” Figure 1 plots the Transformer accuracies with standard deviations in the common-practice setting, vanilla “wug test”-like setting, and “wug test”-like setting with data augmentation by the substring-based data hallucination methods (+hall-2k-substr). Though data augmentation can improve the model’s performance for “wug test”, results are still inferior to the common practice setting without any data augmentation for most languages, especially the morphologically challenging 2018-languages.

5 Conclusion

In this work, we examine keeping training lemmata disjoint from the evaluation sets in morphological inflection. By comparing the performance of the Transformer under the “wug test”-like circumstances with the common practice, we find that the common-practice setting where there is overlap of lemmata has obscured the difficulty of the inflection task. We propose to augment the training data with substring-based data hallucination, and achieve significant improvement over previous data hallucination methods.
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A Data information

| Language  | triple-counts (train) | lemma-counts (train) | lemma-overlap (%) (dev-train) |
|-----------|-----------------------|----------------------|-------------------------------|
| czech     | 1000                  | 848                  | 24.53                         |
| finnish   | 1000                  | 985                  | 2.34                          |
| german    | 1000                  | 961                  | 9.42                          |
| russian   | 1000                  | 973                  | 3.65                          |
| spanish   | 1000                  | 906                  | 15.74                         |
| turkish   | 906                   | 764                  | 26.06                         |

Table 1: CoNLL-SIGMORPHON 2018 shared task 1 medium-size data information.

| Language  | triple-counts (train) | lemma-counts (train) | lemma-overlap (%) (dev-train) |
|-----------|-----------------------|----------------------|-------------------------------|
| czech     | 1582                  | 100                  | 100.0                         |
| finnish   | 7136                  | 100                  | 100.0                         |
| german    | 1290                  | 100                  | 100.0                         |
| russian   | 7132                  | 100                  | 100.0                         |
| spanish   | 7632                  | 100                  | 100.0                         |

Table 2: Data information of the training set we create for 2018-languages. We use the same dev and test sets as CoNLL-SIGMORPHON 2018 shared task 1.

| Language  | triple-counts (train) | lemma-counts (train) | lemma-overlap (%) (dev-train) |
|-----------|-----------------------|----------------------|-------------------------------|
| akan      | 2793                  | 96                   | 100.0                         |
| ga        | 607                   | 95                   | 100.0                         |
| lingala   | 159                   | 57                   | 100.0                         |
| nyanja    | 3031                  | 227                  | 100.0                         |
| southern sothe | 345       | 26                   | 100.0                         |
| swahili   | 3374                  | 97                   | 100.0                         |

Table 3: Data information of Niger-Congo languages from SIGMORPHON 2020 shared task 0.

B Data augmentation size comparison

Figure 4: Performance on the dev set in “wug test” after adding different amounts of dummy data generated with our substring-based hallucination method.