Generating Derivational Morphology with BERT

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Abstract

Can BERT generate derivationally complex words? We present the first study investigating this question. We find that BERT with a derivational classification layer outperforms an LSTM-based model. Furthermore, our experiments show that the input segmentation crucially impacts BERT’s derivational knowledge, both during training and inference.

1 Introduction

What kind of linguistic knowledge is encoded by the parameters of a pretrained BERT (Devlin et al., 2019) model? This question has attracted a lot of attention in NLP recently, with a focus on syntax (e.g., Goldberg, 2019) and semantics (e.g., Ethayarajh, 2019). It is much less clear what BERT learns about other aspects of language. Here, we present the first study on BERT’s knowledge of derivational morphology. Given a cloze sentence such as this jacket is [MASK]. wear [MASK]. and a base such as wear, we ask: can BERT generate correct derivatives such as unwearable?

The motivation for this study is twofold. On the one hand, we add to the growing body of work investigating BERT’s linguistic capabilities. BERT segments words into subword units using a WordPiece tokenizer (Wu et al., 2016), e.g., unwearable is segmented into un., ##wear., ##able. The fact that many of these subword units are derivational affixes suggests that BERT might acquire knowledge about derivational morphology (Table 1), but this has not been tested. On the other hand, we are interested in derivation generation (DG) per se, a task that has been only addressed using LSTMs ( Cotterell et al., 2017; Vylomova et al., 2017; Deutsch et al., 2018), not models based on Transformers like BERT.

Our contributions are as follows. We show that pretrained BERT overgenerates highly productive affixes and analyze methods to increases its performance. After finetuning, BERT beats an LSTM model. Furthermore, we show that the input segmentation crucially impacts how much derivational knowledge is available to BERT, both during training and inference. We also publish the largest dataset of derivatives in context to date.

2 Dataset of Derivatives

We base our study on a new dataset of derivatives in context similar in form to the one released by Vylomova et al. (2017), i.e., it is based on sentences with a derivative (e.g., this jacket is unwearable.) that are altered by masking the

| Type          | Examples                  |
|---------------|---------------------------|
| Prefixes      | anti, hyper, non, pseudo, un |
| Suffixes      | ##able, ##ful, ##ify, ##ness, ##ster |

Table 1: Examples of derivational affixes in the BERT WordPiece vocabulary.
derivative (this jacket is ______). The sentences are accompanied by the base (wear) and the derivative (unwearable). While Vylomova et al. (2017) use Wikipedia, we extract the dataset from Reddit. Since most productively formed derivatives are not part of the language norm initially (Bauer, 2001), social media is a fertile ground for studies on derivational morphology.

For determining derivatives, we use the algorithm introduced by Hofmann et al. (2020a), which takes as input a set of prefixes, suffixes, and bases and checks for each word in the data whether it can be derived from a base using a combination of prefixes and suffixes. The algorithm is sensitive to morpho-orthographic rules of English (Plag, 2003), e.g., when ity is removed from applicability, the result is applicable, not applicable. Here, we use BERT’s prefixes, suffixes, and bases as input to the algorithm. Drawing upon a representative list of 52 productive prefixes and 49 productive suffixes in English (Crystal, 1997), we find that 48 and 44 of them are contained in BERT’s vocabulary. We assign all fully alphabetic words with more than 3 characters in BERT’s vocabulary except for stopwords and previously identified affixes to the set of bases, yielding a total of 20,259 bases. We then extract every sentence including a word that is derivable from one of the bases using at least one of the prefixes or suffixes from all publicly available Reddit posts. The resulting dataset comprises 413,271 distinct derivatives in 123,809,485 context sentences, making it more than two orders of magnitude larger than the one released by Vylomova et al. (2017).²

3 Experiments

3.1 Setup

To examine whether BERT can generate derivationally complex words, we use a cloze test: given a sentence with a masked word such as this jacket is ______, and a base such as wear, the task is to generate the correct derivative such as unwearable. The cloze setup has been previously used in psycholinguistics to probe derivational morphology (Pierrehumbert, 2006; Apel and Lawrence, 2011) and was introduced to NLP in this context by Vylomova et al. (2017). We frame DG (derivation generation) as an affix classification task, i.e., we predict which affix is most likely to occur in a given context sentence with a given base. A prediction is judged correct if it is the affix in the masked derivative, i.e., we ignore affixes that might generate equally well-formed derivatives. We confine ourselves to three cases: derivatives with one prefix (P), derivatives with one suffix (S), and derivatives with one prefix and one suffix (PS). We use mean reciprocal rank (MRR), macro-averaged over affixes, as the evaluation metric.

We extract all derivatives with a frequency \( f \in [1, 128) \) from the dataset. We divide the derivatives into 7 frequency bins with \( f = 1 \) (B1), \( f \in [2, 4) \) (B2), \( f \in [4, 8) \) (B3), \( f \in [8, 16) \) (B4), \( f \in [16, 32) \) (B5), \( f \in [32, 64) \) (B6), and \( f \in [64, 128) \) (B7). For each bin, we randomly split the data into 60% training, 20% development, and 20% test. Following Vylomova et al. (2017), we distinguish two lexicon settings as to whether bases seen during training reappear during test (SHARED) or not (SPLIT). Notice we focus on low-frequency derivatives since BERT is likely to have seen high-frequency derivatives multiple times during pretraining and might be able to predict the affix because it has memorized the connection between the base and the affix, not because it has knowledge of derivational morphology.

Since BERT distinguishes word-initial (wear) from word-internal (##wear) tokens, predicting prefixes requires the word-internal form of the base. However, only 795 bases have a word-internal form. We test four strategies for remedy: adding a hyphen between prefix and base in its word-initial form (HYP); simply using the word-initial instead of the word-internal form (INIT); tokenizing the base into word-internal subword units (TOK); and a projection matrix on the bases with both forms to map word-initial to word-internal tokens (PROJ). Despite its simplicity, the first option clearly performs best with pretrained BERT and is adopted for BERT models on P and PS (Table 2). See Appendix A.1 for details on this preliminary experiment.

| Strategy | B1 | B2 | B3 | B4 | B5 | B6 | B7 |
|----------|----|----|----|----|----|----|----|
| HYP      | 159| 166| 159| 175| 175| 184| 179|
| INIT     | 164| 201| 211| 227| 241| 253| 264|
| TOK      | 141| 157| 170| 189| 214| 248| 270|
| PROJ     | 150| 166| 159| 175| 175| 184| 179|

²We draw upon the entire Baumgartner Reddit Corpus, a collection of all public Reddit posts available at https://files.pushshift.io/reddit/comments/.

³Due to the large number of prefixes, suffixes, and bases, the dataset can be valuable for any study on derivational morphology, irrespective of whether or not it focuses on DG.
Vylomova et al. (2017), which combines the left and right contexts of the masked derivative with a character-level representation of the base form. To allow for a direct comparison with BERT, we do not use the character-based decoder proposed by Vylomova et al. (2017) but instead add a dense layer to perform the prediction. However, for comparability, we evaluate the LSTM and the best BERT-based model on the suffix dataset released by Vylomova et al. (2017) against the reported performance of the encoder-decoder model.}

**Random Baseline (RB):** The prediction is a random ranking of all affixes.

### 3.3 Results

Results are shown in Tables 3 and 4. For P and S, BERT-DCL+ clearly performs best. BERT-DCL- is better than LSTM on SPLIT but worse on SHARED. BERT-DCL+ performs better than BERT-DCL-, even on SPLIT (except for S on B7). S has higher scores than P for all models and frequency bins, which might be due to the fact that suffixes carry information about the part of speech and hence are easier to predict given the syntactic context. Regarding frequency effects, the models benefit from higher frequencies on SHARED since they can connect bases with certain groups of affixes. The results on the dataset released by Vylomova et al. (2017) confirm the superior performance of BERT+DCL+ (Table 5), beating even the LSTM with additional POS information on SHARED (but not on SPLIT).

For PS, BERT+DCL+ also performs best in general but is beaten by LSTM on one bin and BEAM on two bins. The smaller performance gap as compared to P and S can be explained by the fact that BERT does not learn statistical dependencies between two masked tokens (Yang et al., 2019).

How does the performance of BERT vary across affixes? Firstly, pretrained BERT (BERT-DCL-) overgenerates several affixes, in particular non, re, er, ly, and y, which are among the most productive affixes in English (Plag, 1999) (see Appendix A.3 for details). To probe this effect more...
quantitatively, we measure the number of hapaxes formed by means of all affixes in the entire Reddit data, a common measure of morphological productivity (Pierrehumbert and Granell, 2018). This analysis shows a positive correlation: the more productive an affix, the higher its MRR value (Figure 2). Secondly, several affixes seem to be particularly prone to confusion. Examples include semantically very similar affixes (e.g., *ify* and *ize*) and affixes denoting points on the same scale, often antonyms (e.g., *anti* and *pro*). This can be related to work showing that BERT has difficulties with negated expressions (Kassner and Schütze, 2019).

3.4 Impact of Input Segmentation

We have shown that BERT can generate derivatives if it is provided with the morphologically correct segmentation. At the same time, we observed that BERT’s WordPiece tokenizations are often morphologically incorrect, an observation that led us to impose the correct segmentation using hyphenation (HYP). We now examine more directly how BERT’s derivational knowledge is affected by using the original WordPiece segmentations versus the HYP segmentations.

We train binary classifiers using BERT$_{BASE}$ and one of two input segmentations, the morphologically correct segmentation (MP) or BERT’s WordPiece tokenization (WP). The BERT output embeddings for all subword units belonging to the derivative in question are max-pooled and fed into a dense layer with a sigmoid activation. We examine two settings: training only the dense layer while keeping BERT’s model weights frozen (FR), or finetuning the entire model (FT). See Appendix A.4 for details about hyperparameters.

Morphologically correct segmentation (MP) consistently outperforms WordPiece tokenization (WP), both on FR and FT (Table 6). We interpret this in two ways. Firstly, the type of input segmentation used by BERT crucially impacts how much derivational knowledge can be learned, with positive effects of morphologically valid segmentations. Secondly, the fact that there is a performance gap even for models with frozen weights indicates that a morphologically invalid input segmentation can blur the derivational knowledge that is in principle available to BERT. Taken together, this provides further evidence for the importance of morphologically valid segmentation strategies in language model pretraining (Bostrom and Durrett, 2020).

4 Related Work

BERT (Devlin et al., 2019) has been the focus of much recent work in NLP. Several studies have been devoted to the linguistic knowledge encoded by BERT’s model weights, particularly syntax (Goldberg, 2019; Hewitt and Manning, 2019; Lin et al., 2019) and semantics (Ethayarajh, 2019; Wiedemann et al., 2019; Ettinger, 2020). There is also a recent study examining morphosyntactic information in BERT (Edmiston, 2020).

There has been relatively little recent work on derivational morphology in NLP. Both Cotterell et al. (2017) and Deutsch et al. (2018) propose neural architectures that represent derivational meanings as tags. More closely related to our study, Vylomova et al. (2017) develop an encoder-decoder
model that uses the context sentence for predicting deverbal nouns. Hofmann et al. (2020b) propose a graph auto-encoder that models the morphological well-formedness of derivatives.

5 Conclusion

We show that BERT can generate derivationally complex words and even beats LSTM-based models when finetuned on this task. Furthermore, we demonstrate that the input segmentation crucially impacts how much derivational knowledge is available to BERT. This is of relevance for the subject of language model pretraining in general.

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We provide details about the four segmentation tricks, using as a running example the word unallowed. Both un and allowed are in the BERT vocabulary, but BERT tokenizes the word into una, ##llo. Since our goal is to predict the prefix, we only examine segmentations containing the prefix as individual element.

**HYP**: We insert a hyphen between the prefix and the base, yielding the three tokens un, –, allowed in our example. Since both prefix and base are guaranteed to be in the BERT vocabulary, and since there are no multicharacter tokens starting with a hyphen in the BERT vocabulary, BERT always tokenizes words of the form prefix-hyphen-base into prefix, hyphen, and base, making this a natural segmentation for BERT.

**INIT**: We segment the derivative into the prefix followed by the base, i.e., un, allowed in our example. Notice that this looks like two words to BERT since allowed is a word-initial unit.

**TOK**: To overcome the problem of INIT, we use the word-internal counterpart of the base. If this token does not exist, we segment the base into word-internal tokens. The token ##allowed in our example does not exist, so the segmentation is un, ##all, ##owed.

**PROJ**: Using bases that have both word-initial and word-internal forms, we fit a matrix $T \in \mathbb{R}^{d \times d}$ ($d$ being the embedding size) via least squares,

$$T = \arg \min_{W} \|E - EW\|_2^2,$$  

where $E, EW \in \mathbb{R}^{n \times d}$ are the word-initial and word-internal token input embeddings of bases with both forms. We then map bases with no word-internal form and a word-initial input token embedding $e$ such as allow onto the projected word-internal embedding $e^\top T$.

We use the HYP segmentation trick for the main experiments on DG.

### A.2 Hyperparameters

We tune hyperparameters on the development data separately for each frequency bin and report results on the test data. All models are trained using categorical cross-entropy as the loss function and Adam (Kingma and Ba, 2015) as the optimizer.

**BERT+DCL+**: We use a batch size of 16 and perform grid search for the learning rate $l \in \{1 \times 10^{-6}, 3 \times 10^{-6}, 1 \times 10^{-5}, 3 \times 10^{-5}\}$ and the number of epochs $n \in \{1, \ldots, 8\}$. All other hyperparameters as for BERTBASE. For BEAM on PS, we start one search on the prefix and one on the suffix, using a beam size of 10. We add the prefix and suffix log probabilities and predict the prefix-suffix combination with the highest score from both searches.

**BERT-DCL+**: We use a batch size of 16 and perform grid search for the learning rate $l \in \{1 \times 10^{-4}, 3 \times 10^{-4}, 1 \times 10^{-3}, 3 \times 10^{-3}\}$ and the number of epochs $n \in \{1, \ldots, 8\}$. All other hyperparameters as for BERTBASE.

**LSTM**: For PS, we treat prefix-suffix bundles as individual affixes (e.g., un##able). We initialize word embeddings with 300-dimensional GloVe (Pennington et al., 2014) vectors and character embeddings with 100-dimensional random vectors. The BiLSTMs consist of three layers and have a hidden size of 100. We use a batch size of 64 and perform grid search for the learning rate $l \in \{1 \times 10^{-4}, 3 \times 10^{-4}, 1 \times 10^{-3}, 3 \times 10^{-3}\}$ and the number of epochs $n \in \{1, \ldots, 40\}$. 

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A.3 Suffix Confusion Matrix
Confusion matrices of predicted prefixes and suffixes on B1 for BERT-DCL- and BERT+DCL+ are given in Figure 3 and 4, respectively.

A.4 Hyperparameters
For the morphologically correct segmentation, we use the HYP segmentation trick. All models are trained using binary cross-entropy as the loss function and Adam (Kingma and Ba, 2015) as the optimizer. For FR, we use a batch size of 16 and perform grid search for the learning rate $l \in \{1 \times 10^{-4}, 3 \times 10^{-4}, 1 \times 10^{-3}, 3 \times 10^{-3}\}$ and the number of epochs $n \in \{1, \ldots, 8\}$. For FT, we use a batch size of 16 and perform grid search for the learning rate $l \in \{1 \times 10^{-6}, 3 \times 10^{-6}, 1 \times 10^{-5}, 3 \times 10^{-5}\}$ and the number of epochs $n \in \{1, \ldots, 8\}$. All other hyperparameters as for BERT$_{\text{BASE}}$. 
Figure 3: Prefixes predicted by BERT-DCL- (left) and BERT+DCL+ (right). Vertical lines indicate that a prefix has been overgenerated (particularly non and re on the left side).

Figure 4: Suffixes predicted by BERT-DCL- (left) and BERT+DCL+ (right). Vertical lines indicate that a suffix has been overgenerated (particularly er, ly, and y on the left side).