High-Resource Methodological Bias in Low-Resource Investigations

Maartje ter Hoeve
University of Amsterdam
m.a.terhoeve@uva.nl

David Grangier
Apple MLR
grangier@apple.com

Natalie Schluter
Apple MLR
natschluter@apple.com

Abstract

The central bottleneck for low-resource NLP is typically regarded to be the quantity of accessible data, overlooking the contribution of data quality. This is particularly seen in the development and evaluation of low-resource systems via down sampling of high-resource language data. In this work we investigate the validity of this approach, and we specifically focus on two well-known NLP tasks for our empirical investigations: POS-tagging and machine translation. We show that down sampling from a high-resource language results in datasets with different properties than the low-resource datasets, impacting the model performance for both POS-tagging and machine translation. Based on these results we conclude that naive down sampling of datasets results in a biased view of how well these systems work in a low-resource scenario.

1 Introduction

The field of natural language processing (NLP) has experienced substantial progress over the last few years, with the introduction of neural sequence-to-sequence models (e.g., Kalchbrenner and Blunsom, 2013; Vaswani et al., 2017) and large, pre-trained transformer based language models (e.g., Devlin et al., 2019; Brown et al., 2020). Despite their impressive performance, these models require a lot of training resources, which are not always available. Approaches specifically targeted towards low-resource scenarios try to address this issue (e.g., Agić et al., 2016; Plank and Agić, 2018; Zhu et al., 2019; Bai et al., 2021). Resource scarcity manifests itself in various ways, such as a lack of compute power (e.g., Hedderich et al., 2020) or a lack of (labeled) training data (e.g., Adelani et al., 2021). In this work we focus on the latter.

Whether or when a scenario or language should be considered as “low-resourced” has been topic of debate (e.g., Bird, 2022). In this work, we add to this discussion by highlighting that many low-resource approaches are grounded in high-resource scenarios, as has also been noted previously (e.g., Kann et al., 2020). This is problematic from a cultural or sociolinguistic perspective (e.g., Hämäläinen, 2021; Bird, 2022), as well as from a methodological perspective (e.g., Kann et al., 2020). Although both perspectives are arguably intertwined, we mostly focus on the latter in this work.

For example, a popular approach to develop and evaluate low-resource systems is to down sample uniformly from a high-resource language to simulate a low-resource scenario (e.g., Fadaee et al., 2017; Araabi and Monz, 2020; Chronopoulou et al., 2020; Ding et al., 2020; Kumar et al., 2021). The motivations for this setup are often justifiable, for example if used to investigate the effect of the dataset size, or because low-resource data is hard to obtain. However, we do believe that there are two potential issues with this down sampling approach, that should be carefully considered.

Firstly, a large dataset is potentially much richer in content than a small dataset, for example in terms of the number of domains that are covered, the number of different styles, etc. That is, the vocabulary size of a large dataset is expected to be larger than the vocabulary size of a small dataset. This would affect the vocabulary of the down sample, causing a mismatch between the down sampled dataset and the real low-resource scenario, potentially affecting the scores on the task at hand.

Secondly, we need to consider how datasets are constructed. On the one hand, there are examples of small, low-resource datasets, that are carefully constructed for a specific task (e.g., ter Hoeve et al., 2020; Adelani et al., 2021; ter Hoeve et al., 2022). Obtaining high quality data points is costly, and thus, once the dataset size increases, a different trade-off between quality and cost needs to be made (e.g., Caswell et al., 2020; Luccioni and Vi-
As Kreutzer et al. (2022) point out, this trade-off can also affect the quality of low-resource languages in large multilingual datasets. For these large datasets, the quality and usefulness come from the size of the dataset, but not necessarily from the quality of each individual data point (Kreutzer et al., 2022). When simulating a low-resource language by taking a uniform sample from a high-resource language, this quality-cost trade-off might result in a biased sample, as the sample might actually be of lower quality than can be expected in a truly low-resource scenario. This also links our work to approaches like active learning (Cohn et al., 1996) and curriculum learning (Bengio et al., 2009), that focus on the most helpful data points at any time during training.

More theoretically, we can summarize these points by taking a look at the estimation error that is optimized during training, typically in the form of a cross-entropy loss:

\[
L(\theta; D) = -\frac{1}{|D|} \sum_{y \in D} P_D(y) \log P_M(y|\theta),
\]

in which \(D\) refers to the data, \(M\) to the model, \(y\) to the prediction and \(\theta\) to the model parameters. Uniformly down sampling to the same size as the simulated low-resource dataset deals with the \(1/|D|\) term, but it does not account for the fact that \(D\) itself is different in the low- and high-resource setting. This mismatch is also referred to as the proxy fallacy (Agić and Vulić, 2019).

In this work we investigate the effect of simulating a low-resource scenario by taking a uniform down sample from a high-resource setting in the context of two well-known NLP tasks: part-of-speech (POS)-tagging and machine translation (MT). We empirically find evidence for both issues raised above: (i) down sampling from a high-resource scenario increases the richness of the vocabulary of the sample, and (ii) the quality of the high-resource dataset is sometimes lower than the low-resource variant. As such, our work serves as a reminder to be careful when simulating low-resource scenarios by uniformly down sampling from a high-resource dataset.

2 Related work

In this section we first discuss the definition of ‘low-resource’ (Section 2.1). We then continue with a discussion of low-resource approaches in the NLP literature (Section 2.2). We end with a discussion on different training strategies (Section 2.3).

2.1 On the Definition of ‘Low-Resource’

Despite the amount of work on low-resource languages, or low-resource scenarios, it is hard to find a definition of when a scenario, or even a language, counts as low- or high-resource. It seems questionable to call a language low-resourced if it is spoken by millions of people who communicate in oral and/or written form in that language (e.g., Hämäläinen, 2021; Bird, 2022). In this work we do not explicitly define when a scenario is considered to be low-resource, but instead we use a more relative approach. That is, we will compare languages with different amounts of written data available, which is mainly indicated by the availability of the datasets that we use. In that sense we follow the implicit definition as used in previous work (e.g., Zhu et al., 2019; Hedderich et al., 2021).

2.2 Low-Resource Approaches in NLP

With the recent surge of work on NLP systems that require a lot of resources (e.g., Devlin et al., 2019; Brown et al., 2020; Chowdhery et al., 2022), the question of designing systems that also work in a low-resource scenario has received a lot of attention. We refer to Hedderich et al. (2021) for a recent survey. Although there are many examples of approaches that ground themselves in a ‘truly’ low-resource scenario (e.g., Plank et al., 2016; Kann et al., 2020; Adelani et al., 2021) (but see the discussion in Section 2.1 above), there are also many examples of approaches where assumptions are made that are more plausible in a higher resource scenario (e.g., Li et al., 2012; Gu et al., 2018; Ding et al., 2020; Liu et al., 2021). For example, Kann et al. (2020) investigate the POS-tagging performance when no additional resources, like manually created dictionaries, are available, and they find that performance drops substantially. As mentioned in Section 1, our work focuses on the validity of the common approach to simulate a low-resource scenario by randomly down sampling from a higher resource dataset (e.g., Gu et al., 2018; Chronopoulou et al., 2020; Dehouck and Gómez-Rodríguez, 2020; Kumar et al., 2021; Park et al., 2021; Zhang et al., 2021a).

2.3 Different Learning Strategies

Different learning strategies have been proposed to optimally make use of available data. Curriculum
learning (CL) (Bengio et al., 2009) is motivated by the idea that humans learn best when following certain curricula. For example, one effective curriculum is to learn new things in increasing order of difficulty. CL aims at finding similar curricula for artificial model training, by finding meaningful orders in which to present data to a model, such that the model learns more effectively. Some studies report improved results when using CL (Xu et al., 2020; Chang et al., 2021; Zhang et al., 2021b), whereas for other studies CL does not seem to help yet (e.g., Liu et al., 2019; Rao Vijjini et al., 2021).

Active learning (AL) (Cohn et al., 1996) is a related learning strategy, in which a model actively selects the data that it can be most effectively trained on at different points during the training process, for example based on its uncertainty for certain data points. Because of this property, AL has often been used as an effective way to decide which data points to label in an unlabeled dataset (e.g., Reichart et al., 2008; Xu et al., 2018; Ein-Dor et al., 2020; Chaudhary et al., 2021).

3 Empirical Investigation

In this section we empirically investigate down sampling from a high- to a low-resource scenario on two well-known NLP tasks: POS-tagging and machine translation. Both tasks are also popular low-resource tasks (e.g., Hedderich et al., 2021; Haddow et al., 2022) for which down sampling strategies have been used (e.g., Irvine and Callison-Burch, 2014; Ding et al., 2020; Kann et al., 2020; Araabi and Monz, 2020), making them suitable for our investigation. Moreover, POS-tagging is especially suitable as the task is relatively quick and straightforward, giving us a good starting point. We found down sampling approaches to be especially prominent in the MT literature (e.g., Irvine and Callison-Burch, 2014; Fadaee et al., 2017; Ma et al., 2019; Araabi and Monz, 2020; Kumar et al., 2021; Xu et al., 2021), making it a natural task for our investigation. Our work serves as a good starting point to investigate other tasks in future work.

3.1 POS-tagging

Briefly, POS-tagging is the task of assigning grammatical parts of speech, such as nouns, verbs, etc., to tokens in the input text. We use the Universal Dependencies (UD) dataset (see de Marneffe et al. (2021) for a recent description) for our experiments (Section 3.1.1). In the first part of our POS-tagging investigation we show that down sampling indeed increases the richness of the sample in terms of vocabulary size (Section 3.1.2). Next, we show that an increased vocabulary size positively affects the performance in POS-tagging tasks (Section 3.1.3).

3.1.1 Data Description

The Universal Dependencies project\footnote{Website: https://universaldependencies.org/. Github: https://github.com/UniversalDependencies.} consists of treebanks for over a hundred languages (de Marneffe et al., 2021), with varying amounts of resources. Languages are labeled with morphosyntactic labels, such as dependency tags and POS-tags. We only make use of the POS-tags.

3.1.2 Effect of Down Sampling on Dataset Statistics

In the first part of our investigation, we down sample datasets from several high-resource languages, until they have the same size as the lower resource language datasets in the UD. We determine size based on the number of tokens or sentences. A natural question to ask at this point is whether tokens in different languages can be equally compared from a typological point of view. Therefore, we start with a typological inspection of different languages in the UD collection.

Typological considerations. Languages differ from each other in their morphological complexity, for example in their morpheme per word ratios (Baker et al., 2012). Although subject to some debate, this can be described as the difference be-
We approach the categorization using two proxies. To do so, it uses the "most synthetic" form of the word ratios for our analysis, we leave these out for simplicity.

Table 1: Average ratio of vocabulary size per total number of tokens for different language types.

| Category       | Count | Avg ratio |
|----------------|-------|-----------|
| **WALS**       |       |           |
| 0 - 1          | 1     | 0.12±0.00 |
| 2 - 3          | 6     | 0.12±0.07 |
| 4 - 5          | 10    | 0.09±0.05 |
| 6 - 7          | 5     | 0.18±0.10 |
| **Wiki**       |       |           |
| Analytic       | 9     | 0.11±0.03 |
| Agglutinative  | 22    | 0.22±0.15 |
| Fusional       | 4     | 0.10±0.05 |

Investigation of data statistics. With these typological considerations in mind, we now proceed to investigating the effect of down sampling on the dataset statistics. The UD provides an excellent test bed for our inspection, as the datasets of the included languages are of different sizes. First, we filter them on a number of criteria:

1. We only include non-extinct languages;
2. We only include languages that have a POS-tagged dataset available on the UD Github page;
3. For some corpora, the tokens are not released but instead marked by an underscore. We filter these out;
4. Some languages have multiple corpora that are very similar, but somewhat differently tagged. Japanese is an example. We filter these corpora to avoid duplication.

Based on these selection criteria, we arrive at a total of 100 languages. A full overview of all languages and corpora that we consider can be found in Appendix C. We select the five highest resource languages in the UD: Czech, French, German, Icelandic, and Russian. We also include English, as it is often used to down sample from and still one of the higher resourced languages in the UD.

Next, we randomly down sample each of these high-resource languages to the size of the remaining lower resource languages. We compute size based on number of tokens and number of sentences. We report the results based on number of tokens in the main body of the paper. We want to know how down sampling affects the vocabulary size. Therefore, we compute the difference in vocabulary size between the down sampled dataset and its respective low-resource dataset. We normalize by the number of tokens in the low-resource dataset, to make a fair comparison. We plot the results of this analysis in Figure 1. In this plot, a positive number indicates that the vocabulary size of the down sample is larger than the original low-resource dataset, whereas a negative number indicates the opposite. We find that down sampling indeed results in a larger vocabulary in the vast majority of cases. This is exactly in line with our intuition from Section 1. We find the same effect for down sampling based on number of sentences (Appendix A, Figure 4). For this setting we also compare how the total number of tokens in the down sampled datasets compare with the original low-resource datasets. We plot the results in Appendix A, Figure 5. We find that the down

---

2 There are also still other categories, like isolating languages. As we simply base ourselves on the morpheme per word ratios for our analysis, we leave these out for simplicity.

3 [https://wals.info/chapter/22](https://wals.info/chapter/22)
sampled corpora mostly contain more tokens than their originals.

3.1.3 Effect of Down Sampling on Model Training
Having shown that down sampling from a higher resource dataset often results in a larger vocabulary than in the original lower resource language, we now investigate the effect of vocabulary size on the modeling performance for POS-tagging. In line with most related work, we now fully focus on English as our high-resource language. We sample a number of smaller datasets from the English UD. Each of these samples has the same number of sentences, but they differ in vocabulary size. To achieve this, we use a greedy approach for the down sampling: we shuffle all sentences and greedily add sentences until we have the desired vocabulary size and the desired number of sentences.\(^4\) Like this, we construct training datasets of 1,000 sentences each, for three vocabulary sizes: 1,000, 2,000 and 3,000 tokens. We limit the validation sets to the same vocabulary as the training set, and use the original test set in order to be able to compare different settings equally. We sample each of these settings five times, for five different random seeds.

Next, we use these sampled datasets to model the POS-tagging task, for which we use the standard POS-tagging setup from the FlairNLP library.\(^5\) We use FlairNLP’s implementation of a sequence-to-sequence tagger, which defaults to a bidirectional RNN-CRF.\(^6\) We compare three different word embedding types: (i) word2vec embeddings (Mikolov et al., 2013) that we train from scratch on our training sets, (ii) pre-trained Glove embeddings, and (iii) pre-trained BERT embeddings. For the latter two we use the implementation from FlairNLP, for the word2vec embeddings we use Gensim.\(^7\) This setting is most realistic, as it is the only embedding type that is trained without access to another dataset or model.

However, sometimes low-resource work still makes use of these large pre-trained models, which is why we include them. Moreover, a model like English BERT has been shown to be surprisingly multilingual (Pires et al., 2019). The results are given in Table 4.\(^8\) We also give additional micro F1-scores in Appendix A.1, Table 2. We find that the model scores increase when the vocabulary size increases.\(^9\) In line with our down sampling analysis in the previous section, we find that the total number of tokens also increases. Unsurprisingly, we find that pre-trained word embeddings substantially outperform our own word2vec model.

Summarizing, in our POS-tagging investigation we found that down sampling from high-resource languages often results in a richer vocabulary size. We also found that a larger vocabulary size positively affects the scores on the POS-tagging task, in our settings for English. This is in line with the first issue that we raised in Section 1. Of course, our experiments did not cover all possible settings that one can encounter in a low-resource scenario, and there are many follow up questions in the space of POS-tagging alone. For this work, we decide to take our results on the POS-tagging experiments as a first strong indication that one needs to be careful with naive down sampling, as we already find differences in the current, still limited, scenario. Encouraged by these findings, we now shift our focus to one more task that is often the focus of low-resource investigations: machine translation.

3.2 Machine Translation
Machine translation aims at translating text from a source to a target language. Machine learning systems address this task primarily by learning from bilingual documents with corresponding human translations (Koehn, 2020). These systems have shown substantial progress in recent years (e.g., Barrault et al., 2019, 2020a; Akhbardeh et al., 2021) and have been applied to a growing number of language pairs (e.g., Platanios et al., 2018; Costa-jussà et al., 2022). We make use of the WMT datasets (see Akhbardeh et al. (2021) for a recent overview

---

\(^{4}\)We also experimented with implementing token based down sampling, instead of sentence based. However, we did not find a good trade-off where the vocabulary size increased, whereas the number of tokens stayed the same. We also experimented with different methods than greedy sampling, but this did not change our findings.

\(^{5}\)https://github.com/flairNLP/flair/blob/master/resources/docs/TUTORIAL_7_TRAINING_A_MODEL.md

\(^{6}\)https://github.com/flairNLP/flair/blob/master/seq/seq_tagger_model.py

\(^{7}\)https://github.com/RaRe-Technologies/gensim

\(^{8}\)For the setting with a vocabulary size of 1,000 we had to remove the results of one of the seeds, as it did not find enough sentences.

\(^{9}\)We also find that the scores for a vocabulary size of 2,000 and 3,000 tokens are similar, although the average for 3,000 is higher.
The normalized difference in vocabulary size between the down sample and the original low-resource reference language is shown on the y-axis. A positive number indicates that the vocabulary size of the down sample is larger than the original low-resource dataset, whereas a negative number indicates the opposite. We find that down sampling indeed results in a larger vocabulary in the vast majority of cases.
Table 2: POS-tagging scores for different vocabulary sizes, while keeping the number of sentences equal. We report macro F1-scores for different word embeddings.

| Vocab size | Nr Sents | Nr Toks               | Word2Vec     | Glove       | BERT        |
|------------|----------|-----------------------|--------------|-------------|-------------|
| 1,000      | 1,000    | 7,235.75 ± 174.485    | 0.328 ± 0.021| 0.743 ± 0.005| 0.921 ± 0.003|
| 2,000      | 1,000    | 11,252.0 ± 227.885    | 0.350 ± 0.024| 0.773 ± 0.005| 0.937 ± 0.003|
| 3,000      | 1,000    | 14,867.2 ± 292.534    | **0.360 ± 0.006** | **0.778 ± 0.010** | **0.940 ± 0.005** |

as well as Section 3.2.1) for our experiments. We again divide our investigation into two parts. In the first part we show that down sampling again increases the richness of the sample in terms of vocabulary size (Section 3.2.2). Next, we show that low-resource and down sampled high-resource training datasets on the same task yield models with different accuracy: the down sampled dataset leads to a less accurate translation system than the original low-resource dataset (Section 3.2.3).

3.2.1 Data Description

The WMT is a collection of datasets for machine translation belonging to the WMT shared tasks, which were first organized in 2006 (Koehn and Monz, 2006). The first WMT collection consisted of three European language pairs: English-German, English-French and English-Spanish. Since then, the WMT has been expanded each year, with additional translation pairs for the original language pairs, and with additional data for new language pairs and new tasks (Callison-Burch et al., 2007, 2008, 2009, 2010, 2011, 2012; Bojar et al., 2013, 2014, 2015, 2016, 2017, 2018; Barrault et al., 2019, 2020a; Akhbardeh et al., 2021). An especially large jump in resources was made in 2017. This expansion gives us a unique opportunity to test the effect of down sampling. In our investigation we treat the early versions of the WMT as low-resource setting, and later versions of the WMT as high-resource setting. We focus on the English-German translation pairs.

3.2.2 Effect of Down Sampling on Dataset Statistics

To explore the effect of down sampling on the dataset statistics, we use the WMT 2014 German-English dataset as our low-resource dataset (WMT14), and the 2018 version as our high-resource dataset (WMT18). We focus on the English-German translation task. We again apply two types of down sampling: sentence based and token based. For the sentence based down sampling we shuffle the WMT18 dataset, and sample the same number of sentences as in the WMT14 dataset. For the token based down sampling, we also shuffle the WMT18 dataset, but now we greedily add sentences until we reach the same number of tokens as in the WMT14 dataset.

We plot the down sampling effect in Figure 2. These plots reflect the WMT train sets over different years. Even though we focus our investigations on WMT14 and WMT18, we plot all years from 2013 till 2019 for reference. The last two light green bars show our two down sampled datasets. If we down sample based on sentences (first light green bar right to the dotted line), we find that the number of tokens decreases, whereas the vocabulary size increases. If we down sample based on tokens, both the number of sentences and the vocabulary size increase.

We also qualitatively inspect the vocabulary distributions. In Appendix A, Figure 6 we plot the 100 most frequent words in each data set that we compare. We find that there are quite a few differences, especially in the second half of the plot.

3.2.3 Effect of Down Sampling on Model Training

In this section we investigate the effect of down sampling on model training. To this end, we train and evaluate transformer sequence-to-sequence models (Vaswani et al., 2017) in different data settings. We use the Flax transformer code\(^\text{10}\) for our implementation, and only adapt the data pipeline to be able to work with our down sampled datasets. We train these models on the standard WMT14 and WMT18 training sets, and on our two down sampled datasets (token and sentence based). We test on the WMT14 and WMT18 test sets (i.e., newstest data (Barrault et al., 2020b)). This leaves us

\(^{10}\)https://github.com/google/flax/tree/main/examples/wmt
Figure 2: Statistics of different WMT datasets (ds = down sampled, sent = sentence based, tok = token based).

Figure 3: How many words occur $N$ times in the different WMT datasets, normalized.

Datasets perform worse on the WMT14 test set than the models trained on the WMT14 dataset itself. This is the opposite finding from the POS-tagging experiments. For the MT experiments, having a richer vocabulary does not seem to help performance. We hypothesize that this can be explained by the quality of the WMT18 datasets, i.e., the second issue that we raised in Section 1. As shown in Figure 2, the amount of data increased heavily in 2017, mostly driven by the inclusion of the Paracrawl data source (Bañón et al., 2020). This data source is known to be noisy, and hence people have worked on filtering it (e.g., Junczys-Dowmunt, 2018; Aulamo et al., 2020; Zhang et al., 2020).

To add to the investigation of the data quality, we count how many words occur $N$ times in the datasets, normalized by the total number of words in the datasets. The rationale behind this is that if a dataset contains many words that only occur once, this indicates that this dataset contains more noise (such as links) than datasets with fewer words that only occur once. We plot the results in Figure 3. We find that WMT18 contains more words that only occur once than WMT14, an indicator that the average quality of the WMT18 dataset is indeed lower, negatively impacting our down sampled experiments.

Summarizing, for our MT experiments we find that down sampling also increases the vocabulary size, in line with our hypothesis and with our findings for the POS-tagging experiments. We also found that the down sampled datasets did not increase the translation performance, which can be explained by the lower quality of the high resource data.

4 Discussion

In our experiments we found evidence for both issues that we raised regarding simulating a low-resource scenario by taking a uniform down sample from a high-resource language. In this section with eight different settings in total. We report the scores in Table 3.

A few observations stand out. First, the models trained on down sampled versions of the WMT18 score lower on the WMT18 test set than the model trained on the original WMT18 dataset. This is as expected, if we assume that the additional WMT18 data would lead to better results. We also find that training on WMT14 and testing on WMT18 leads to higher scores than testing on the WMT14 test set. This is remarkable, but in line with earlier findings (Edunov et al., 2018). Finally, we observe that the models trained on the down sampled WMT18 datasets perform worse on the WMT14 test set than the models trained on the WMT14 dataset itself. This is the opposite finding from the POS-tagging experiments. For the MT experiments, having a richer vocabulary does not seem to help performance. We hypothesize that this can be explained by the quality of the WMT18 datasets, i.e., the second issue that we raised in Section 1. As shown in Figure 2, the amount of data increased heavily in 2017, mostly driven by the inclusion of the Paracrawl data source (Bañón et al., 2020). This data source is known to be noisy, and hence people have worked on filtering it (e.g., Junczys-Dowmunt, 2018; Aulamo et al., 2020; Zhang et al., 2020).

To add to the investigation of the data quality, we count how many words occur $N$ times in the datasets, normalized by the total number of words in the datasets. The rationale behind this is that if a dataset contains many words that only occur once, this indicates that this dataset contains more noise (such as links) than datasets with fewer words that only occur once. We plot the results in Figure 3. We find that WMT18 contains more words that only occur once than WMT14, an indicator that the average quality of the WMT18 dataset is indeed lower, negatively impacting our down sampled experiments.

Summarizing, for our MT experiments we find that down sampling also increases the vocabulary size, in line with our hypothesis and with our findings for the POS-tagging experiments. We also found that the down sampled datasets did not increase the translation performance, which can be explained by the lower quality of the high resource data.

4 Discussion

In our experiments we found evidence for both issues that we raised regarding simulating a low-resource scenario by taking a uniform down sample from a high-resource language. In this section
Table 3: BLEU scores MT experiments. Models are trained and tested on different (down sampled) train and test sets.

```markdown
|     | WMT 14 | 18   | ds-sent-18 | ds-tok-18 |
|-----|--------|------|------------|-----------|
| Test| 32.62  | 32.12| 29.37      | 30.23     |
| 18  | 41.49  | 39.70| 37.66      | 38.20     |
```

we reflect on these findings. We hope that our work serves as additional evidence for the proxy fallacy of using high-resource methodologies for low-resource investigations. Being aware of this fallacy puts individual researchers and the field as a whole in a better position. Clearly, the best strategy is to use truly low-resource data whenever possible when conducting low-resource experiments. Fortunately, there are many examples of works that do this, or that only perform low-resource experiments on high-resource data for additional data points (e.g., Kann et al., 2020; Kumar et al., 2021; Adelani et al., 2021). There can still be good reasons why using truly low-resource data is not an option, for example because the type of data that is needed is just not available. In this case, we first want to echo Hedderich et al. (2020), who show that by only labeling very few data points large improvements can already be made. We believe that we can also use recommendations from active learning and curriculum learning to choose which data points are best to label. We hope to experiment with this question in future work. If one is truly bound to simulating a low-resource scenario by using a high-resource language, one needs to be aware of the fallacies that we found in this work. The down sampled dataset is likely not a good reflection of the low-resource setting, which can result in scores that are either too high (because of the richness of the data) or rather too low (because the high-resource data may be of insufficient quality).

5 Conclusion

In this work we investigated the validity of simulating a low-resource scenario by down sampling from a high-resource dataset. We argued that this process might be a poor proxy for a truly low-resource setting, for two reasons: (i) a high-resource dataset might be much richer in content than a low-resource dataset, and (ii) the high-resource dataset might be of lower quality than a low-resource dataset that was carefully crafted. We empirically studied this on two well-known NLP tasks: POS-tagging and machine translation. Our investigation showed that uniform down sampling is indeed a poor proxy in these two scenarios, and we found evidence for both hypothesized reasons. As such, our work serves as a warning for work in low-resource domains. This work also serves as a starting point to formalize best practices to grow datasets, and to more reliable simulations of low- to high-resource settings. In future work, we plan to expand our analysis to more tasks and more languages.

6 Limitations

Throughout this work we flagged some of the limitations of our approach. In this section we summarize these in more detail, to help future investigations.

The datasets. In this work we concentrated on corpora from two data sources: the UD and the WMT. Although this is a good start and these datasets are a good fit for our investigation, we hope that future work investigates different corpora, to get an even better understanding of the effect of uniform down sampling.

The tasks. The same holds for the types of tasks that we chose. Although we believe POS-tagging and MT to be a good start, future work should investigate different tasks to be able to form a more general understanding.

7 Ethical Statement

In this work we developed an understanding for the effect of simulating a low-resource language by down sampling uniformly from a high-resource language. By pointing out biases that occur, we hope to have raised awareness for this issue, making follow-up work on low-resource languages more inclusive. However, there are around 7,000 languages world-wide, of which we have only been able to cover a few.

References

David Ifeoluwa Adelani, Jade Abbott, Graham Neubig, Daniel D’souza, Julia Kreutzer, Constantine Lignos, Chester Palen-Michel, Happy Buzaabah, Shruti Rijhwani, Sebastian Ruder, Stephen Mayhew, Israel Abebe Azime, Shamsudeen H. Muhammad, Chris Chinenyeb Emezue, Joyce Nakatumba-
 filtering toolbox. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 150–156, Online. Association for Computational Linguistics.

Yu Bai, Yang Gao, and Heyan Huang. 2021. Cross-lingual abstractive summarization with limited parallel resources. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6910–6924, Online. Association for Computational Linguistics.

Anne E Baker, Jan Don, and Kees Hengeveld. 2012. Taal en taalwetenschap. John Wiley & Sons.

Marta Bañón, Pinzhen Chen, Barry Haddow, Kenneth Heafield, Hieu Hoang, Miquel Esplà-Gomis, Mikel L. Forcada, Amir Kamran, Faheem Kirefu, Philipp Koehn, Sergio Ortiz Rojas, Leopoldo Pla Sempere, Gema Ramírez-Sánchez, Elsa Sarrías, Marek Strelce, Brian Thompson, William Waites, Dion Wiggins, and Jaume Zaragoza. 2020. ParaCrawl: Web-scale acquisition of parallel corpora. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4555–4567, Online. Association for Computational Linguistics.

Loïc Barrault, Magdalena Biesialska, Onêde Bojar, Marta R. Costa-jussà, Christian Federmann, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Matthias Huck, Eric Joanis, Tom Kocmi, Philipp Koehn, Chi-kiu Lo, Nikola Ljubesić, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Santanu Pal, Matt Post, and Marcos Zampieri. 2020a. Findings of the 2020 conference on machine translation (WMT20). In Proceedings of the Fifth Conference on Machine Translation, pages 1–55, Online. Association for Computational Linguistics.

Loïc Barrault, Magdalena Biesialska, Marta R. Costa-jussà, Fethi Bougares, and Olivier Galibert. 2020b. Findings of the first shared task on lifelong learning machine translation. In Proceedings of the Fifth Conference on Machine Translation, pages 56–64, Online. Association for Computational Linguistics.

Loïc Barrault, Onêde Bojar, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. 2019. Findings of the 2019 conference on machine translation (WMT19). In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 1–61, Florence, Italy. Association for Computational Linguistics.

Joshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In Proceedings of the 26th annual international conference on machine learning, pages 41–48.
Baltsasar Bickel and Johanna Nichols. 2013. *Inflectional synthesis of the verb*. In Matthew S. Dryer and Martin Haspelmath, editors, *The World Atlas of Language Structures Online*. Max Planck Institute for Evolutionary Anthropology, Leipzig.

Steven Bird. 2022. *Local languages, third spaces, and other high-resource scenarios*. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7817–7829, Dublin, Ireland. Association for Computational Linguistics.

Ondřej Bojar, Christian Buck, Chris Callison-Burch, Christian Federmann, Barry Haddow, Philipp Koehn, Christof Monz, Matt Post, Radu Soricut, and Lucia Specia. 2013. *Findings of the 2013 Workshop on Statistical Machine Translation*. In *Proceedings of the Eighth Workshop on Statistical Machine Translation*, pages 1–44, Sofia, Bulgaria. Association for Computational Linguistics.

Ondřej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Aleš Tamchyňa. 2014. *Findings of the 2014 workshop on statistical machine translation*. In *Proceedings of the Ninth Workshop on Statistical Machine Translation*, pages 12–58, Baltimore, Maryland, USA. Association for Computational Linguistics.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Shujian Huang, Matthias Huck, Philipp Koehn, Qun Liu, Varvara Logacheva, Christof Monz, Matteo Negri, Matt Post, Raphael Rubino, Lucia Specia, and Marco Turchi. 2017. *Findings of the 2017 conference on machine translation (WMT17)*. In *Proceedings of the Second Conference on Machine Translation*, pages 169–214, Copenhagen, Denmark. Association for Computational Linguistics.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonino Jimeno Yepes, Philipp Koehn, Varvara Logacheva, Christof Monz, Matteo Negri, Aurélie Névèol, Mariana Neves, Martin Popel, Matt Post, Raphael Rubino, Carolina Scarton, Lucia Specia, Marco Turchi, Karin Verspoor, and Marcos Zampieri. 2016. *Findings of the 2016 conference on machine translation*. In *Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers*, pages 131–198, Berlin, Germany. Association for Computational Linguistics.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Barry Haddow, Matthias Huck, Chris Hokamp, Philipp Koehn, Varvara Logacheva, Christof Monz, Matteo Negri, Matt Post, Carolina Scarton, Lucia Specia, and Marco Turchi. 2015. *Findings of the 2015 workshop on statistical machine translation*. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 1–46, Lisbon, Portugal. Association for Computational Linguistics.

Ondřej Bojar, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, and Christof Monz. 2018. *Findings of the 2018 conference on machine translation (WMT18)*. In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*, pages 272–303, Belgium, Brussels. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. *Language models are few-shot learners*. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Chris Callison-Burch, Cameron Fordyce, Philipp Koehn, Christof Monz, and Josh Schroeder. 2007. *(meta-) evaluation of machine translation*. In *Proceedings of the Second Workshop on Statistical Machine Translation*, pages 136–158, Prague, Czech Republic. Association for Computational Linguistics.

Chris Callison-Burch, Cameron Fordyce, Philipp Koehn, Christof Monz, and Josh Schroeder. 2008. *Further meta-evaluation of machine translation*. In *Proceedings of the Third Workshop on Statistical Machine Translation*, pages 70–106, Columbus, Ohio. Association for Computational Linguistics.

Chris Callison-Burch, Philipp Koehn, Christof Monz, Kay Peterson, Mark Przybocki, and Omar Zaidan. 2010. *Findings of the 2010 joint workshop on statistical machine translation and metrics for machine translation*. In *Proceedings of the Joint Fifth Workshop on Statistical Machine Translation and MetricsMATR*, pages 17–53, Uppsala, Sweden. Association for Computational Linguistics.

Chris Callison-Burch, Philipp Koehn, Christof Monz, Matt Post, Radu Soricut, and Lucia Specia. 2012. *Findings of the 2012 workshop on statistical machine translation*. In *Proceedings of the Seventh Workshop on Statistical Machine Translation*, pages 10–51, Montréal, Canada. Association for Computational Linguistics.

Chris Callison-Burch, Philipp Koehn, Christof Monz, and Josh Schroeder. 2009. *Findings of the 2009 Workshop on Statistical Machine Translation*. In *Proceedings of the Fourth Workshop on Statistical Machine Translation*, pages 1–28, Athens, Greece. Association for Computational Linguistics.
Aakanksha Chowdhery, Philo Koehn, Christof Monz, and Omar Zaidan. 2011. Findings of the 2011 workshop on statistical machine translation. In Proceedings of the Sixth Workshop on Statistical Machine Translation, pages 22–64, Edinburgh, Scotland. Association for Computational Linguistics.

Isaac Caswell, Theresa Breiner, Daan van Esch, and Ankur Bapna. 2020. Language ID in the wild: Unexpected challenges on the path to a thousand-language web text corpus. In Proceedings of the 28th International Conference on Computational Linguistics, pages 6588–6608, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Ernie Chang, Hui-Syuan Yeh, and Vera Demberg. 2021. Does the order of training samples matter? improving neural data-to-text generation with curriculum learning. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 727–733, Online. Association for Computational Linguistics.

Aditi Chaudhary, Antonios Anastasopoulos, Zaid Sheikh, and Graham Neubig. 2021. Reducing confusion in active learning for part-of-speech tagging. Transactions of the Association for Computational Linguistics, 9:1–16.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chang, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kenshi Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tai, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Gheewat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassgi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennna Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. Palm: Scaling language modeling with pathways. CoRR, abs/2204.02311.

Alexandra Chronopoulou, Dario Stojanovski, and Alexander Fraser. 2020. Reusing a pretrained language model on languages with limited corpora for unsupervised NMT. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2703–2711, Online. Association for Computational Linguistics.

David A Cohn, Zoubin Ghahramani, and Michael I Jordan. 1996. Active learning with statistical models.
Marzieh Fadaee, Arianna Bisazza, and Christof Monz. 2017. Data augmentation for low-resource neural machine translation. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 567–573, Vancouver, Canada. Association for Computational Linguistics.

Jiatao Gu, Yong Wang, Yun Chen, Victor O. K. Li, and Kyunghyun Cho. 2018. Meta-learning for low-resource neural machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3622–3631, Brussels, Belgium. Association for Computational Linguistics.

Barry Haddow, Rachel Bawden, Antonio Valerio Miceli Barone, Jindrich Helcl, and Alexandra Birch. 2022. Survey of low-resource machine translation. Computational Linguistics, 48(3):673–732.

Mika Hämmäinen. 2021. Endangered languages are not low-resourced! CoRR, abs/2103.09567.

Michael A. Hedderich, David Adelani, Dawei Zhu, Jesujoba Alabi, Udia Markus, and Dietrich Klakow. 2020. Transfer learning and distant supervision for multilingual transformer models: A study on African languages. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2580–2591, Online. Association for Computational Linguistics.

Michael A. Hedderich, Lukas Lange, Heike Adel, Janik Strötgen, and Dietrich Klakow. 2021. A survey on recent approaches for natural language processing in low-resource scenarios. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2545–2568, Online. Association for Computational Linguistics.

Ann Irvine and Chris Callison-Burch. 2014. Hallucinating phrase translations for low resource MT. In Proceedings of the Eighteenth Conference on Computational Natural Language Learning, pages 160–170, Ann Arbor, Michigan. Association for Computational Linguistics.

Marcin Junczys-Dowmunt. 2018. Dual conditional cross-entropy filtering of noisy parallel corpora. In Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pages 888–895, Belgium, Brussels. Association for Computational Linguistics.

Naïl Kalchbrenner and Phil Blunsom. 2013. Recurrent continuous translation models. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1700–1709, Seattle, Washington, USA. Association for Computational Linguistics.

Katharina Kann, Ophélie Lacroix, and Anders Søgaard. 2020. Weakly supervised POS taggers perform poorly on Truly low-resource languages. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 8066–8073. AAAI Press.

Philipp Koehn. 2020. Neural machine translation. Cambridge University Press.

Philipp Koehn and Christof Monz. 2006. Manual and automatic evaluation of machine translation between European languages. In Proceedings on the Workshop on Statistical Machine Translation, pages 102–121, New York City. Association for Computational Linguistics.

Julia Kreutzer, Isaac Caswell, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Alahsera Tapo, Nishant Subramani, Artem Sokolov, Claytone Sikasote, Monang Setyawan, Supheakmungkol Sarin, Sokhtar Samb, Benoît Sagot, Clara Rivera, Annette Rios, Isabel Papadimitriou, Salomey Osei, Pedro Ortiz Suarez, Iroko Orife, Kelechi Ogueji, Andre Niyongabo Rubungo, Toan Q. Nguyen, Mathias Müller, André Müller, Sham-suddeen Hassan Muhammad, Nanda Muhammad, Ayanda Mnyakeni, Jamshidbek Mirzakhahlov, Tapawanashe Matangira, Colin Leong, Nze Lawson, Sneha Kudugunta, Yacine Jermite, Mathias Jenny, Orhan Firat, Bonaventure F. P. Dossou, Sakhiile Dlamini, Nisansa de Silva, Sakine Çabuk Balli, Stella Biderman, Alessia Battisti, Ahmed Baruwa, Ankur Bapna, Pallavi Baljekar, Israel Abebe Azime, Ayodele Awokoya, Duygu Ataman, Oreaoghene Ahia, Oghenefego Ahia, Sweta Agrawal, and Mofetolula Adeyemi. 2022. Quality at a glance: An audit of web-crawled multilingual datasets. Transac-
tions of the Association for Computational Linguistics, 10:50–72.

Sachin Kumar, Antonios Anastasopoulos, Shuly Wintner, and Yulia Tsvetkov. 2021. Machine translation into low-resource language varieties. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th Interna-
tional Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 110–121, Online. Association for Computational Linguistics.

Shen Li, João Graça, and Ben Taskar. 2012. Wiki-ly supervised part-of-speech tagging. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 1389–1398, Jeju Island, Korea. Association for Computational Linguistics.

Linlin Liu, Bosheng Ding, Lidong Bing, Shaﬁq Joty, Luo Si, and Chunyan Miao. 2021. MulDA: A
multilingual data augmentation framework for low-resource cross-lingual NER. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 5834–5846, Online. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Alexandra Luccioni and Joseph Viviano. 2021. What’s in the box? an analysis of undesirable content in the Common Crawl corpus. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 182–189, Online. Association for Computational Linguistics.

Shuming Ma, Pengcheng Yang, Tianyu Liu, Peng Li, Jie Zhou, and Xu Sun. 2019. Key fact as pivot: A two-stage model for low resource table-to-text generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2047–2057, Florence, Italy. Association for Computational Linguistics.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositional properties. Advances in neural information processing systems, 26.

Cheonbok Park, Yunwon Tae, TaeHee Kim, Soyoung Yang, Mohammad Azam Khan, Lucy Park, and Jaegul Choo. 2021. Unsupervised neural machine translation for low-resource domains via meta-learning. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2888–2901, Online. Association for Computational Linguistics.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.

Barbara Plank and Željko Agić. 2018. Distant supervision from disparate sources for low-resource part-of-speech tagging. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 614–620, Brussels, Belgium. Association for Computational Linguistics.

Barbara Plank, Anders Søgaard, and Yoav Goldberg. 2016. Multilingual part-of-speech tagging with bidirectional long short-term memory models and auxiliary loss. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 412–418, Berlin, Germany. Association for Computational Linguistics.

Emmanouil Antonios Platanios, Mrinmaya Sachan, Graham Neubig, and Tom Mitchell. 2018. Contextual parameter generation for universal neural machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 425–435, Brussels, Belgium. Association for Computational Linguistics.

Anvesh Rao Vijjini, Kaveri Anuranjana, and Radhika Mamidi. 2021. Analyzing curriculum learning for sentiment analysis along task difficulty, pacing and visualization axes. In Proceedings of the Eleventh Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 117–128, Online. Association for Computational Linguistics.

Roi Reichart, Katrin Tomanek, Udo Hahn, and Ari Rappoport. 2008. Multi-task active learning for linguistic annotations. In Proceedings of ACL-08: HLT, pages 861–869, Columbus, Ohio. Association for Computational Linguistics.

Maartje ter Hoeve, Julia Kiseleva, and Maarten de Rijke. 2022. Summarization with graphical elements. arXiv preprint arXiv:2204.07551.

Maartje ter Hoeve, Robert Sim, Elnaz Nouri, Adam Fourney, Maarten de Rijke, and Ryen W White. 2020. Conversations with documents: An exploration of document-centered assistance. In Proceedings of the 2020 Conference on Human Information Interaction and Retrieval, pages 43–52.

Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 5998–6008.

Benfeng Xu, Licheng Zhang, Zhendong Mao, Quan Wang, Hongtao Xie, and Yongdong Zhang. 2020. Curriculum learning for natural language understanding. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6095–6104.

Weijia Xu, Yuwei Yin, Shuming Ma, Dongdong Zhang, and Haoyang Huang. 2021. Improving multilingual neural machine translation with auxiliary source languages. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 3029–3041, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Yang Xu, Yu Hong, Huibin Ruan, Jianmin Yao, Min Zhang, and Guodong Zhou. 2018. Using active
learning to expand training data for implicit discourse relation recognition. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 725–731, Brussels, Belgium. Association for Computational Linguistics.

Boliang Zhang, Ajay Nagesh, and Kevin Knight. 2020. Parallel corpus filtering via pre-trained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8545–8554, Online. Association for Computational Linguistics.

Meng Zhang, Liangyou Li, and Qun Liu. 2021a. Two parents, one child: Dual transfer for low-resource neural machine translation. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2726–2738, Online. Association for Computational Linguistics.

Wei Zhang, Wei Wei, Wen Wang, Lingling Jin, and Zheng Cao. 2021b. Reducing bert computation by padding removal and curriculum learning. In 2021 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS), pages 90–92. IEEE.

Yi Zhu, Benjamin Heinzerling, Ivan Vulić, Michael Strube, Roi Reichart, and Anna Korhonen. 2019. On the importance of subword information for morphological tasks in truly low-resource languages. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 216–226, Hong Kong, China. Association for Computational Linguistics.

A Additional Plots POS-tagging Experiments

A.1 Additional micro F1-Scores for POS-tagging Experiments

B Additional Plots MT Experiments
Figure 4: Effect of down sampling on vocabulary size. Down sampling based on number of sentences. Each plot describes a different language that we are down sampling. The x-axis describes the language that we use as reference.
Figure 5: Effect of down sampling on number of tokens. Down sampling based on number of sentences. Each plot describes a different language that we are down sampling. The x-axis describes the language that we use as reference.
Table 4: POS-tagging scores for different vocabulary sizes, and different word embeddings. Micro F1-scores.

| Vocab size | Nr Sents | Nr Toks     | Word2Vec | Glove | BERT  |
|------------|----------|-------------|----------|-------|-------|
| 1,000      | 1,000    | 7,235.75 ± 174.485 | 0.189 ± 0.013 | 0.581 ± 0.021 | 0.801 ± 0.007 |
| 2,000      | 1,000    | 11,252.0 ± 227.885  | 0.208 ± 0.015 | 0.624 ± 0.017 | 0.853 ± 0.008 |
| 3,000      | 1,000    | 14,867.2 ± 292.534  | **0.215 ± 0.005** | 0.622 ± 0.030 | **0.880 ± 0.015** |

Figure 6: Top 100 words in the train sets of WMT14, WMT18 and down sampled WMT18.
## UD Languages

| UD Language | UD Corpus | Train | Dev | Test | WALS | Wiki |
|-------------|-----------|-------|-----|------|------|------|
| Afrikaans   | UD AFRIKAANS | x     | x   | x    |      |      |
| Akuntsu     | UD AKUNTSU |       |     | x    |      |      |
| Albanian    | UD ALBANIAN |       |     | x    |      |      |
| Amharic     | UD AMHARIC |       |     | x    |      |      |
| Apurina     | UD APURINA | x     |     |      | 6    |      |
| Arabic      | UD ARABIC-PADT | x | x | x | 6 |      |
| Arabic      | UD ARABIC-PUD |       |     | x |      |      |
| Armenian    | UD ARMENIAN-ArmTDP | x | x | x | 2 |      |
| Armenian    | UD ARMENIAN-BSUT | x | x | x |      |      |
| Assyrian    | UD ASSYRIAN |       |     | x    |      |      |
| Bambara     | UD BAMBARA | x |     |      | agglutinative |      |
| Basque      | UD BASQUE | x     | x   | x    | 4    | agglutinative |
| Belarusian  | UD BELARUSIAN | x | x | x |      |      |
| Bengali     | UD BENGALI |       |     | x    |      |      |
| Bhojpuri    | UD BHOJPURI |       |     | x    |      |      |
| Breton      | UD BRETON |       |     | x    |      |      |
| Bulgarian   | UD BULGARIAN | x | x | x | analytic |      |
| Buryat      | UD BURYAT | x |     | x    |      |      |
| Catalan     | UD CATALAN | x     | x   | x    | agglutinative |      |
| Cebuano     | UD CEBUANO |       |     | x    |      |      |
| Chinese     | UD CHINESE-GSD | x | x | x | analytic |      |
| Chinese     | UD CHINESE-GSDSimp | x | x | x |      |      |
|             | UD CLASSICAL CHINESE-Kyoto | x | x | x |      |      |
| Croatian    | UD CROATIAN | x     | x   | x    |      |      |
| Czech       | UD CZECH-CAC | x | x | x | fusional |      |
|             | UD CZECH-CLTT | x | x | x |      |      |
|             | UD CZECH-FicTree | x | x | x |      |      |
|             | UD CZECH-PDT-I | x | x | x |      |      |
|             | UD CZECH-PDT-c | x |     |      |      |      |
|             | UD CZECH-PDT-m | x |     |      |      |      |
|             | UD CZECH-PDT-v | x |     |      |      |      |
|             | UD CZECH-PUD | x |     |      |      |      |
| Danish      | UD DANISH | x     | x   | x    | analytic |      |
| Dutch       | UD DUTCH-Alpino | x | x | x |      |      |
|             | UD DUTCH-LassySmall | x | x | x |      |      |
| English     | UD ENGLISH-Atis | x | x | x | 2 | analytic |      |
|             | UD ENGLISH-EWT | x | x | x |      |      |
|             | UD ENGLISH-GUM | x | x | x |      |      |
| Language       | UD ENGLISH-LinES | UD ENGLISH-ParTUT | UD ENGLISH-Pronouns | UD ENGLISH-PUD |
|----------------|------------------|-------------------|---------------------|----------------|
| Erzya          | x                | x                 | x                   | x              |
| Estonian       | UD ESTONIAN-EDT  | x                 | x                   | x              |
|                | UD ESTONIAN-EWT  | x                 | x                   |                |
| Faroese        | UD FAROEOSE-FarPaHC | x              | x                   |                |
|                | UD FAROEOSE-OFT  |                   | x                   |                |
| Finnish        | UD FINNISH-FTB   | x                 | x                   |               |
|                | UD FINNISH-OOD   |                   | x                   |                |
|                | UD FINNISH-PUD   |                   | x                   |                |
|                | UD FINNISH-TDT   | x                 | x                   |                |
| French         | UD FRENCH-FQB    |                   | x                   | 4             |
|                | UD FRENCH-FTB    | x                 | x                   |                |
|                | UD FRENCH-GSD    | x                 | x                   |                |
|                | UD FRENCH-ParisStories | x      | x                   |                |
|                | UD FRENCH-ParTUT |                   | x                   |                |
|                | UD FRENCH-PUD    | x                 | x                   |                |
|                | UD FRENCH-Rhapsodie | x            | x                   |                |
|                | UD FRENCH-Sequoia | x                 | x                   |                |
| Galician       | UD GALICIAN-CTG  | x                 | x                   |                |
|                | UD GALICIAN-TreeGal | x            | x                   |                |
| German         | UD GERMAN-GSD    | x                 | x                   | 2             |
|                | UD GERMAN-HDT-a1 |                   | x                   |                |
|                | UD GERMAN-HDT-a2 | x                 | x                   |                |
|                | UD GERMAN-HDT-b1 | x                 | x                   |                |
|                | UD GERMAN-HDT-b2 | x                 | x                   |                |
|                | UD GERMAN-LIT    |                   | x                   |                |
|                | UD GERMAN-PUD    | x                 | x                   |                |
| Greek          | UD GREEK         | x                 | x                   | 4             |
| Guajarara      | UD GUAJAJARA     | x                 | agglutinative       |
| Hebrew         | UD HEBREW-IAHLTwiki | x            | x                   | 4             |
|                | UD HEBREW-HTB    | x                 | x                   |                |
| Hindi          | UD HINDI-HDTB    | x                 | x                   | 2             |
| Hungarian      | UD HUNGARIAN     | x                 | x                   | 4             |
|                |                   |                   | agglutinative       |
| Icelandic      | UD ICELANDIC-IcePaHC | x          | x                   |                |
|                | UD ICELANDIC-Modern | x           | x                   |                |
|                | UD ICELANDIC-PUD | x                 | x                   |                |
| Indonesian     | UD INDONESIAN-CSUI | x           | x                   | 4             |
|                | UD INDONESIAN-PUD |                   | x                   |                |
|                | UD INDONESIAN-GSD | x                 | x                   |                |
| Irish          | UD IRISH-IDT     | x                 | x                   |                |
|                | UD IRISH-TwittIrish |               | x                   |                |
| Italian        | UD ITALIAN-ISDT  | x                 | x                   |                |
| Language         | UD Name                  | x  | x  | x  | x  | x  | 4  | agglutinative |
|------------------|--------------------------|----|----|----|----|----|----|---------------|
| Japanese         | UD JAPANESE-GSD          | x  | x  | x  | x  |    |    | agglutinative |
|                  | UD JAPANESE-Modern       |    |    |    |    |    |    |               |
|                  | UD JAPANESE-PUD          |    |    |    |    |    |    |               |
| Javanese         | UD JAVANESE              | x  |    |    |    |    |    |               |
| Kaapor           | UD KAAPOR               | x  |    |    |    |    |    |               |
| Karelian         | UD KAREELIAN             | x  |    |    |    |    |    |               |
| Karo             | UD KARO                 | x  |    |    |    |    |    |               |
| Kazakh           | UD KAZAKH               | x  | x  |    |    |    |    | agglutinative |
| Khunsari         | UD KHUNSARI             | x  |    |    |    |    |    |               |
| Kiche            | UD KICHE               | x  |    |    |    |    |    |               |
| Komi permyak     | UD KOMI PERMYAK         | x  |    |    |    |    |    | agglutinative |
| Komi zyrian      | UD KOMI ZYRIAN-IKDP     | x  |    |    |    |    |    |               |
|                  | UD KOMI ZYRIAN-Lattice | x  |    |    |    |    |    |               |
| Korean           | UD KOREAN-GSD           | x  | x  | x  |    |    |    | agglutinative |
|                  | UD KOREAN-Kaist         | x  | x  | x  |    |    |    |               |
|                  | UD KOREAN-PUD           | x  |    |    |    |    |    |               |
| Kurmanji         | UD KURMANJ              | x  | x  |    |    |    |    |               |
| Ligurian         | UD LIGURIAN             | x  | x  |    |    |    |    |               |
| Lithuanian       | UD LITHUANIAN-ALKSNIS   | x  | x  | x  |    |    |    |               |
|                  | UD LITHUANIAN-HSE       | x  | x  | x  |    |    |    |               |
| Livvi            | UD LIVVI                | x  | x  |    |    |    |    |               |
| Low saxon        | UD LOW SAXON            | x  |    |    |    |    |    |               |
| Madi jarawara    | UD MADI JARAWARA        | x  |    |    |    |    |    | agglutinative |
| Makurap          | UD MAKURAP              | x  |    |    |    |    |    |               |
| Manx             | UD MANX                 | x  |    |    |    |    |    |               |
| Marathi          | UD MARATHI              | x  | x  | x  |    |    |    |               |
| Mbya             | UD MBYA GUARANI-Thomas  | x  |    |    |    |    |    |               |
| Moksha           | UD MOKSHA               | x  |    |    |    |    |    | agglutinative |
| Munduruku        | UD MUNDURUKU            | x  |    |    |    |    |    |               |
| Naija            | UD NAIJA                | x  | x  | x  |    |    |    |               |
| Nayini           | UD NAYINI               | x  |    |    |    |    |    |               |
| North sami       | UD NORTH SAMI           | x  | x  | x  |    |    |    | agglutinative |
| Norwegian        | UD NORWEGIAN Bokmaal    | x  | x  | x  |    |    |    | analytic      |
| Language               | UD Name | Description          | Details |
|-----------------------|---------|----------------------|---------|
| Norwegian             | NORWEGIAN Nynorsk | x x x |
| Norwegian LNynorsk    | x x x |
| Persian               | UD PERSIAN-PerDT | x x x | 4 |
| Persian LIA           | x x x |
| Polish                | UD POLISH-LFG | x x x | fusional |
| Polish PDB            | x x x |
| Polish PUD            | x x x |
| Pomak                 | UD POMAK | x x x |
| Portuguese            | UD PORTUGUESE-BOSQUE | x x x |
| Portuguese GSD        | x x x |
| Romanian              | UD Romanian-ArT | x x x |
| Romanian Nonstudy      | x x x |
| Romanian RRT          | x x x |
| Romanian SiMoNERo     | x x x |
| Russian               | UD RUSSIAN-GSD | x x x | 4 |
| Russian PUD           | x x x |
| Russian SynTagRus-a   | x x x |
| Russian SynTagRus-b   | x x x |
| Russian SynTagRus-c   | x x x |
| Russian Taiga         | x x x |
| Scottish Gaelic       | UD SCOTTISH GAELIC | x x x |
| Serbian               | UD SERBIAN | x x x |
| Skolt Sami            | UD SKOLT SAMI | x x x |
| Slovak                | UD SLOVAK | x x x |
| Slovenian             | UD SLOVENIAN-SSJ | x x x |
| Slovenian SST          | x x x |
| Soi                   | UD SOI | x |
| South Levantine Arabic| UD SOUTH LEVANTINE ARABIC | x |
| Spanish               | UD SPANISH-AnCora | x x x | 4 |
| Spanish GSD           | x x x |
| Spanish PUD           | x x x |
| Swedish               | UD SWEDISH LinES | x x x | analytic |
| Tagalog               | UD TAGALOG-TRG | x x x |
| Tagalog Ugnayan       | x x x |
| Tamil                 | UD Tamil-MWTT | x x x | agglutinative |
| Tamil TTB             | x x x |
| Tatar                 | UD TATAR | x | agglutinative |
| Teko                  | UD TEKO | x |
| Turkish               | UD TURKISH-Atis | x x x | 6 |
| Turkish BOUN           | x x x |
| Turkish FrameNet      | x x x |
| Turkish GB            | x x x |
| Language                  | UD Name            | POS-tagg | Parse  | Morph  |
|---------------------------|--------------------|---------|--------|--------|
| Turkish-IMST              | UD TURKISH-IMST    | x       | x      | x      |
| Turkish-Kenet             | UD TURKISH-Kenet   | x       | x      | x      |
| Turkish-Penn              | UD TURKISH-Penn    | x       | x      | x      |
| Turkish-PUD               | UD TURKISH-PUD     | x       |        |        |
| Turkish-Tourism           | UD TURKISH-Tourism | x       | x      | x      |
| Ukrainian                 | UD UKRAINIAN       | x       | x      | x      |
| Upper sorbian             | UD UPPER SORBIAN   | x       |        |        |
| Urdu                      | UD URDU            | x       | x      | x      |
| Uyghur                    | UD UYGHUR          | x       | x      | x      | agglutinative |
| Vietnamese                | UD VIETNAMESE      | x       | x      | x      | 0 analytic |
| Warlpiri                  | UD WARLPIRI        | x       |        |        |
| Welsh                     | UD WELSH           | x       | x      | x      |
| Western armenian          | UD WESTERN ARMENIAN| x       | x      | x      |
| Wolof                     | UD WOLOF           | x       | x      |        |
| Xibe                      | UD XIBE            | x       |        |        |
| Yakut                     | UD YAKUT           | x       |        |        | agglutinative |
| Yoruba                    | UD YORUBA          | x       | 6      |        | analytic |
| Yupik                     | UD YUPIK           | x       |        |        | agglutinative |

Table 5: Languages and corpora from the UD included in the POS-tagging experiments.