EstBERT: A Pretrained Language-Specific BERT for Estonian

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Abstract

This paper presents EstBERT, a large pre-trained transformer-based language-specific BERT model for Estonian. Recent work has evaluated multilingual BERT models on Estonian tasks and found them to outperform the baselines. Still, based on existing studies on other languages, a language-specific BERT model is expected to improve over the multilingual ones. We first describe the EstBERT pretraining process and then present the results of the models based on finetuned EstBERT for multiple NLP tasks, including POS and morphological tagging, named entity recognition, and text classification. The evaluation results show that the models based on EstBERT outperform multilingual BERT models on five tasks out of six, providing further evidence towards a view that training language-specific BERT models are still useful, even when multilingual models are available.1

1 Introduction

Pretrained language models, such as BERT (Devlin et al., 2019) or ELMo (Peters et al., 2018), have become the essential building block for many NLP systems. These models are trained on large amounts of unannotated textual data which enables them to capture the general regularities in the language and thus can be used as a basis for training the subsequent models for more specific NLP tasks. Bootstrapping NLP systems with pretraining is particularly relevant and holds the greatest promise for improvements in the setting of limited resources, either when working with tasks of limited annotated training data, or less resourced languages like Estonian.

Since the first publication and release of the large pretrained language models on English, considerable effort has been made to develop support for other languages. In this regard, multilingual BERT models, simultaneously trained on text of many different languages, have been published, several of which also include Estonian language (Devlin et al., 2019; Sanh et al., 2019; Conneau and Lample, 2019). The performance of these multilingual models was recently evaluated on several Estonian NLP tasks, including POS and morphological tagging, named entity recognition, and text classification (Kittask et al., 2020). The overall conclusions drawn from these experiments are in line with previously reported results on other languages, i.e. for many or even most tasks, multilingual BERT models help to improve the performance over baselines that do not use language model pretraining.

Besides multilingual models, language-specific BERT models have been trained for an increasing number of languages, including for instance CamembERT (Martin et al., 2020) and FlaubERT (Le et al., 2020) for French, FinBERT for Finnish (Virtanen et al., 2019), RobBERT (Delobelle et al., 2020) and BERTJe (de Vries et al., 2019) for Dutch, Chinese BERT (Cai et al., 2019), BETO for Spanish (Cañete et al., 2020), RuBERT for Russian (Kuratov and Arkhipov, 2019) and others. For a recent overview about these efforts refer to Nozza et al. (2020). Aggregating the results over different language-specific models and comparing them to those obtained with multilingual models shows that depending on the task, the average improvement of the language-specific BERT over the multilingual BERT varies from 0.70 accuracy points in paraphrase identification up to 6.37 in sentiment classification (Nozza et al., 2020). The overall conclusion one can draw from these results is that while existing multilingual BERT models can bring along improvements over language-specific baselines, using language-specific BERT models can further considerably improve the performance of various NLP tasks.

Following the line of reasoning presented above, we set forth to train EstBERT, a language-specific BERT model for Estonian. In the following sections, we first give details about the data used for BERT pretraining and then describe the pretraining process. Finally, we will provide evaluation results on the same tasks as presented by Kittask et al. (2020) on multilingual BERT models, which include POS and morphological tagging, named entity recognition and text classification. The EstBERT model achieves the best results on five tasks out of six, providing further evidence for the usefulness of pretraining language-specific BERT models.

1The model is available via HuggingFace Transformers library: https://huggingface.co/tartuNLP/EstBERT
2 Data Preparation

The first step for training the EstBERT model involves preparing a suitable unlabeled text corpus. This section describes both the steps we took to clean and filter the data, as well as the process of generating the vocabulary and the pretraining examples.

2.1 Data Preprocessing

For training the EstBERT model, we used the Estonian National Corpus 2017 (Kallas and Koppel, 2018), which was the largest Estonian language corpus available at the time. It consists of four sub-corpora: Estonian Reference Corpus 1990-2008, Estonian Web Corpus 2013, Estonian Web Corpus 2017 and Estonian Wikipedia Corpus 2017. The top row of the Table 1 shows the initial statistics of the corpus.

We applied different cleaning and filtering techniques to preprocess the data. First, we used corpus processing methods from EstNLTK (Laur et al., 2020), which is an open source tool for Estonian natural language processing. Using the EstNLTK, we removed all XML/HTML tags from the text and also removed all documents that had a language tag other than Estonian. Additionally, we further filtered out non-Estonian documents using the language-detection library.

Next, we removed all duplicate documents. For that, we used hashing—all documents were lowercased and then the hashed value of each document was subsequently stored into a set. Only those documents whose hash value did not yet exist in the set (i.e. the first document with each hash value) were retained.

We also used hand-written heuristics developed for preprocessing data for training the FinBert model (Virтанен et al., 2019) to filter out documents with too few words, too many stopwords or punctuation marks, etc. We applied the same thresholds as were used for Finnish BERT. Finally, we truecased the corpus by lemmatizing the corpus with EstNLTK tools and using the casing information of the lemma to decide whether the word should be upper- or lowercased. The statistics of the corpus after all the preprocessing and cleaning steps are given in the bottom row of the Table 1.

2.2 Vocabulary and Pretraining Example Generation

Originally, BERT uses WordPiece tokenizer which is not available open source. Instead, we used the BPE tokenizier available in the open source sentencepiece library, which is the closest to the WordPiece algorithm, to construct a vocabulary of 50K subword tokens.

Then, we used BERT tools to create the pretraining examples for the BERT model in the TFRecord format. In order to enable parallel training on four GPUs, the data was split into four shards.

We also created separate pretraining examples with sequences of length 128 and 512, masking 15% of the words in the input in both cases. This means that the maximum of 20 and 77 words were masked in sequences of both lengths respectively.

3 Evaluation Tasks

Before proceeding to describe the EstBERT model pretraining process itself, we will describe the tasks used to both validate and evaluate our model. These tasks include POS and morphological tagging, named entity recognition and text classification. In the following subsection, we describe the available Estonian datasets for these tasks.

3.1 Part of Speech and Morphological Tagging

For part of speech (POS) and morphological tagging, we use the Estonian treebank from the Universal Dependencies (UD) v2.5 collection that contains annotations of lemmas, parts of speech, universal morphological features, dependency heads and universal dependency labels. We train models to predict both universal POS (UPOS) and language-specific POS (XPOS) tags as well as morphological features. We use the predefined train/dev/test splits for training and evaluation. Table 2 shows the statistics of the treebank splits. The accuracy of the POS and morphological tagging tasks are evaluated with the conll18_ud_eval script from the CoNLL 2018 Shared Task.

3.2 Named Entity Recognition

Estonian named entity recognition (NER) corpus (Tkachenko et al., 2013) annotations cover three types of named entities: locations, organizations and persons. It contains 572 news stories published in local online newspapers Postimees and Delfi covering local and international news on a range of different topics. We utilize the same training, development and testing splits used in previous work (Kittask et al., 2020). Table 3 displays statistics of the splits.

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| Documents | Sentences | Words |
|-----------|-----------|-------|
| Initial   | 3.9M      | 87.6M | 1340M |
| After cleanup | 3.3M | 75.7M | 1154M |

Table 1: Statistics of the corpus before and after the cleanup.

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2 https://github.com/shuyo/language-detection
3 https://github.com/TurkuNLP/deepfin-tools
4 https://github.com/google/sentencepiece
5 https://github.com/google-research/bert
Table 3: Statistics of the Estonian NER corpus.

|        | Tokens  | PER | LOC | ORG | Total |
|--------|---------|-----|-----|-----|-------|
| Train  | 155981  | 6174| 4749| 4784| 15707 |
| Dev    | 32890   | 1115| 918 | 742 | 2775  |
| Test   | 28370   | 1201| 644 | 619 | 2464  |

Table 4: Statistics about the sentiment labels of the Estonian Valence corpus.

|        | Train  | Dev | Test | Total |
|--------|--------|-----|------|-------|
| Positive| 612    | 87  | 175  | 874   |
| Negative| 1347   | 191 | 385  | 1923  |
| Neutral | 505    | 74  | 142  | 721   |
| Ambiguous| 385   | 55  | 110  | 550   |
| Total   | 2849   | 407 | 812  | 4068  |

The performance of the NER models is evaluated with the conlleval script from the CoNLL 2000 shared task.

3.3 Sentiment and Rubric Classification

Estonian Valence corpus (Pajupuu et al., 2016) consists of 4085 news extracts from Postimees Daily. All documents in the corpus are labeled with both sentiment and rubric classes. There are nine rubrics: Opinion, Estonia, Life, Comments-Life, Comments-Estonia, Crime, Culture, Sports and Abroad. The four sentiment labels include Positive, Negative, Neutral, and Ambiguous. We again utilize the same 70/10/20 training, development and test splits used in previous work (Kittask et al., 2020). These splits are stratified over both rubric and sentiment analysis. Table 4 and Table 5 show the statistics about sentiment and rubric view of the classification dataset respectively.

Table 5: Statistics about the rubric labels of the Estonian Valence corpus.

|        | Opinion | Estonia | Life | Comments-Life | Comments-Estonia | Crime | Culture | Sports | Abroad | Total |
|--------|---------|---------|------|---------------|------------------|-------|---------|--------|--------|-------|
| Train  | 676     | 289     | 364  | 354           | 351              | 146   | 182     | 269    | 218    | 964   |
| Dev    | 96      | 41      | 52   | 50            | 50               | 21    | 27      | 39     | 31     | 192   |
| Test   | 192     | 43      | 101  | 102           | 100              | 42    | 51      | 77     | 64     | 413   |

Table 6: Hyperparameters used in the first two pretraining phases with the sequence length 128.

| Hyperparameter       | Value |
|----------------------|-------|
| train_batch_size     | 32    |
| max_seq_length       | 128   |
| max_predictions_per_seq | 20  |
| num_train_steps      | 900000|
| num_warmup_steps     | 9000  |
| learning_rate        | 1e-4  |
| save_checkpoints_step | 50000 |
4.2 Pretraining Validation

During pretraining, a checkpoint was saved after every 50K steps for later evaluation. In order to monitor the pretraining process, we evaluated the performance of both MLM, NSP and the evaluation tasks described in section 3 on all these checkpoints.

For POS and morphological tagging, and named entity recognition we fine-tuned EstBERT using scripts from HuggingFace transformers\(^6\) library. All hyperparameters were kept at their default values, which involves training for three epochs, using the learning rate of 5e-5 and batch size of 8.

Both the task-specific classification layer as well as the EstBERT parameters were finetuned.

For rubric and sentiment classification tasks, we used the classifier training scripts available in google’s BERT repository.\(^7\)

Here again, the default values for hyperparameters were used: training for three epochs with the learning rate 5e-5 and batch size 32.

The validation results of the masked language model, next sentence prediction accuracy and all the evaluation tasks for all the eighteen checkpoints from stage one and other eighteen models from stage two were compared to pick the best model. The examples of validation curves for the UPOS tagging and the rubric classification tasks are shown in Figure 1.

Although the checkpoint validation results from both phases showed more or less steady improvement with the increase of the number of steps trained, we observed that the checkpoint at 750K steps from phase two performs slightly better on all tasks compared to the rest of the checkpoints. Thus, this checkpoint was chosen as a final model with sequence length 128.

4.3 Pretraining with Sequence Length 512

The starting point for training the model with sequence length of 512 was the final model with sequence length 128.

The longer model was trained further up to 600K steps. The batch size was reduced to 16 as the size of the tensors would be larger for the sequence length 512 compared to 128. The hyperparameters used to train the longer model are shown in Table 7.

During training, again checkpoints were saved to the disk after every 50K steps and these were evaluated on all evaluation tasks as previously explained in Section 4.2. Based on these evaluations, the last checkpoint obtained after the 600K steps was chosen as the final model with 512 sequence length.

| train batch size | 16 |
|------------------|----|
| max seq length   | 512|
| max predictions per seq | 77 |
| num train steps  | 600000 |
| num warmup steps | 6000 |
| learning rate    | 1e-4 |
| save checkpoints step | 50000 |

Table 7: Hyperparameters used to pretrain the EstBERT model with the sequence length 512.

5 Results

The next subsections present the results obtained with the final EstBERT models with both sequence lengths on the tasks described in section 3.

We follow the same setup of Kittask et al. (2020) to enable direct comparison with the multilingual models. Some additional steps were taken to prepare the Estonian Valence corpus. First, all duplicate items, 17 in total, were removed. Also all items with the Ambiguous label were removed as retaining them has been shown to lower the accuracy of the classification (Pajuupuu et al., 2016). The same preprocessing was applied also in the evaluation of the multilingual BERT models for Estonian (Kittask et al., 2020).

For fine-tuning, we use the same scripts from the HuggingFace transformers repository that were also used for the pretraining validation in section 4.2 and for the multilingual models evaluation by Kittask et al. (2020). For each task, the learning rate of the AdamW optimizer was searched from the grid of (5e-5, 3e-5, 1e-5, 5e-6, 3e-6) and the batch size from (8, 16) on the
Table 8: POS and morphological tagging accuracy on the Estonian UD test set. The highest scores in each column are in bold. The highest overall score of each task is underlined.

| Model       | UPOS | XPOS | Morph | UPOS | XPOS | Morph |
|-------------|------|------|-------|------|------|-------|
|             | Seq = 128 | Seq = 512 |       | Seq = 128 | Seq = 512 |       |
| EstBERT     | 97.89 | 98.40 | 96.93 | 97.84 | 98.43 | 96.80 |
| mBERT       | 97.42 | 98.06 | 96.24 | 97.43 | 98.13 | 96.13 |
| XLM-RoBERTa | 97.78 | 98.36 | 96.53 | 97.80 | 98.40 | 96.69 |

Table 9: Rubric (Rubr.) and sentiment (Sent.) classification accuracy. The highest scores in each column are in bold. The highest overall score of each task is underlined.

| Model       | Rubr. | Sent. | Rubr. | Sent. |
|-------------|-------|-------|-------|-------|
|             | Seq = 128 | Seq = 512 | Seq = 128 | Seq = 512 |
| EstBERT     | 81.70 | 74.36 | 80.96 | 74.50 |
| mBERT       | 75.67 | 70.23 | 74.94 | 69.52 |
| XLM-RoBERTa | 80.34 | 74.50 | 78.62 | 76.07 |

5.1 POS and Morphological Tagging

POS and morphological tagging results are summarized in Table 8, which show the accuracy for universal POS tags (UPOS), language-specific POS tags (XPOS) and morphological features. Language-specific EstBERT outperforms both multilingual models although the difference with the XLM-RoBERTa—the best-performing multilingual model—is quite small.

Similarly to multilingual results, using longer sequence length on this task with EstBERT model does not seem to be beneficial as the accuracy slightly increases only for XPOS tags but not for others. Overall, as the performance on these tasks is already very high, the absolute performance gains obtained cannot be large. EstBERT obtains consistent improvements over mBERT, with the relative error reduction with both models on all tasks falling between 16-18%. The relative error reduction of the EstBERT compared to XLM-RoBERTa is smaller, in the range of 2-5%. The highest reduction of error of EstBERT compared to XLM-RoBERTa can be observed on the morphological tagging task with the shorter model where the relative error reduction is 12%.

5.2 Rubric and Sentiment Classification

Rubric and sentiment classification results are shown in Table 9. EstBERT outperforms mBERT on both tasks by a large margin but XLM-RoBERTa exceeds EstBERT on sentiment classification. The difference between the two accuracy scores is quite small when the model with sequence length 128 is used but it increases when the longer sequence length is used.

Similar to XLM-RoBERTa, the EstBERT model with shorter sequence length is somewhat better on rubric classification and the opposite is true for sentiment classification. Overall, the differences between the performances of the EstBERT models with both sequence lengths are again quite small.

5.3 Named Entity Recognition

Table 10 shows the entity-based precision, recall and F-score of the named entity recognition task. Although XLM-RoBERTa achieves the highest recall in the short model category and both highest recall and F-score in the long model category, the EstBERT model achieves the overall highest F1-score on this task with the shorter model.

EstBERT and XLM-RoBERTa both benefit from using the smaller sequence length rather than longer, while mBERT shows the opposite behaviour.

6 Discussion

The objective of this paper was to describe the process of pretraining the language-specific BERT model for Estonian and compare its performance with multilingual BERT models on several NLP tasks. Overall, the pretrained EstBERT was better than the best multilingual XLM-RoBERTa model on five tasks out of six: UPOS, XPOS and morphological tagging, rubric classification and NER, only in the sentiment classification task the XLM-RoBERTa was better. We did not observe any consistent difference between the models of different sequence lengths, although the model 512 sequence length was trained longer. It is possible that the shorter model was already trained long enough and the subsequent training of the longer model did not add any effect in that respect, aside from the fact that it can accept longer input sequences.

When preprocessing the data and pretraining the model, we largely followed the process of training the FinBERT model for Finnish (Virtanen et al., 2019). One of the important aspects of this work was obtaining a large-enough corpus in order to pretrain the model. We used the Estonian National Corpus 2017, which was the largest corpus available at the time. A newer and larger version of this corpus—the Estonian National Corpus 2019 (Kallas and Koppel, 2019)—has
| Model      | Precision Seq = 128 | Recall Seq = 128 | F1-Score | Precision Seq = 512 | Recall Seq = 512 | F1-Score |
|------------|---------------------|------------------|----------|---------------------|------------------|----------|
| EstBERT    | 88.42               | 90.38            | 89.39    | 88.35               | 89.74            | 89.04    |
| mBERT      | 85.88               | 87.09            | 86.51    | 88.47               | 88.28            | 88.37    |
| XLM-RoBERTa| 87.55               | **91.19**        | 89.34    | 87.50               | **90.76**        | **89.10** |

Table 10: NER tagging results. The highest scores in each column are in **bold**. The highest overall score of each measure is underlined.

become available meanwhile. There are also few other resources, such as the Estonian parts of the CoNLL 2017 raw data (Ginter et al., 2017) and the Oscar Crawl, which probably at least partially overlap with each other and with the Estonian National Corpus. Still, these corpora would potentially provide additional data that was currently not used.

Another challenge was related to finding annotated datasets for downstream tasks. While there exists the Estonian UD dataset that provides annotations to the common dependency parsing pipeline tasks, datasets for other, especially semantic NLP tasks are scarce. We adopted the Estonian Valence corpus for two-way text classification. However, the labels in this corpus are semi-automatically derived from user ratings and thus the quality of these annotations cannot be guaranteed.

Although for the NER task, we did see some improvements with EstBERT compared to XLM-RoBERTa on the smaller model, the differences in scores were generally quite small. We have observed, however, that the annotations of this NER dataset are occasionally erroneous, containing for instance label sequences (I-PER, I-PER) instead of (B-PER, I-PER). We have also observed unlabelled entities in the text. Thus, the small variations in the systems’ results might not be informative about the systems themselves but can rather stem from the noise in the data. Although these annotation errors have been noticeable enough, the magnitude of these errors has not been quantified.

The differences between the EstBERT and the XLM-RoBERTa model were in most cases very small. In previous experiments with several multilingual BERT models on the same Estonian tasks (Kittask et al., 2020), the XLM-RoBERTa proved to be the best multilingual model. This suggests that training a RoBERTa model for Estonian, initialized with the parameters of the multilingual model, might be beneficial.

7 Conclusion

We presented EstBERT, the first BERT model pre-trained specifically on Estonian language. While several existing multilingual BERT models include Estonian, no language-specific Estonian BERT model has been available until now. In order to pretrain the model, we used the largest Estonian text corpus available at the time. The EstBERT model was put to test by fine-tuning it for several tasks, including POS and morphological annotation, named entity recognition and text classification. On five tasks out of six, the classifiers based on EstBERT achieved better performance than the models based on multilingual BERT models, although in several cases the gap with the best-performing multilingual XLM-RoBERTa was quite small. This suggests that training a RoBERTa model for Estonian, initialized with the parameters of the multilingual model, might be beneficial.

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