Evaluating Transferability of BERT Models on Uralic Languages

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Abstract

Transformer-based language models such as BERT have outperformed previous models on a large number of English benchmarks, but their evaluation is often limited to English or a small number of well-resourced languages. In this work, we evaluate monolingual, multilingual, and randomly initialized language models from the BERT family on a variety of Uralic languages including Estonian, Finnish, Hungarian, Erzya, Moksha, Karel, Livvi, Komi Permyak, Komi Zyrian, Northern Sámi, and Skolt Sámi. When monolingual models are available (currently only et, fi, hu), these perform better on their native language, but in general they transfer worse than multilingual models or models of genetically unrelated languages that share the same character set. Remarkably, straightforward transfer of high-resource models, even without special efforts toward hyperparameter optimization, yields what appear to be state of the art POS and NER tools for the minority Uralic languages where there is sufficient data for finetuning.

1 Introduction

Contextualized language models such as BERT (Devlin et al., 2019) drastically improved the state of the art for a multitude of natural language processing applications. Devlin et al. (2019) originally released 4 English and 2 multilingual pretrained versions of BERT (mBERT for short) that support over 100 languages including three Uralic languages: Estonian [et], Finnish [fi], and Hungarian [hu]. BERT was quickly followed by other large pretrained Transformer (Vaswani et al., 2017) based models such as RoBERTa (Liu et al., 2019) and multilingual models such as XLM-RoBERTa (Conneau et al., 2019). Huggingface released the Transformers library (Wolf et al., 2020), a PyTorch implementation of Transformer-based language models along with a repository for pretrained models from community contribution¹. This list now contains over 1000 entries, many of which are domain-specific or monolingual models.

Despite the wealth of multilingual and monolingual models, most evaluation methods are limited to English, especially for the early models. Devlin et al. (2019) showed that the original mBERT outperformed existing models on the XNLI dataset (Conneau et al., 2018), a translation

¹https://huggingface.co/models
of the MultiNLI (Williams et al., 2018) to 15 languages. mBERT was further evaluated by Wu and Dredze (2019) for 5 tasks in 39 languages, which they later expanded to over 50 languages for part-of-speech (POS) tagging, named entity recognition (NER) and dependency parsing (Wu and Dredze, 2020). mBERT has been applied to a variety of multilingual tasks such as dependency (Kondratyuk and Straka, 2019) and constituency parsing (Kitaev et al., 2019). The surprisingly effective multilinguality of mBERT was further explored by Dufter and Schütze (2020).

Uralic languages have received relatively moderate interest from the language modeling community. Aside from the three national languages, no other Uralic language is supported by any of the multilingual models, nor does any have a monolingual model. There are no Uralic languages among the 15 languages of XNLI. Wu and Dredze (2020) do explore all 100 languages that mBERT supports but do not go into monolingual details. Alnajjar (2021) transfer existing BERT models to minority Uralic languages, the only work that focuses solely on Uralic languages.

In this paper we evaluate multilingual and monolingual models on Uralic languages. We consider three evaluation tasks: morphological probing, POS tagging and NER. We also use the models in a crosslingual setting, in other words, we test how monolingual models perform on related languages. We show that

- these language models are very good at all three tasks when finetuned on a small amount of task specific data,
- for morphological tasks, when native BERT models are available (et, fi, hu), these outperform the others on their native language, though the advantage over XLM-RoBERTa is not statistically significant,
- for POS and NER, the use of native models from related, even closely related languages, rarely brings improvement over the multilingual models or even English models,
- as long as the alphabet that the language uses is covered in the vocabulary of the model, we can transfer mBERT (or RuBERT) to the NER and POS tasks with surprisingly little finetuning data.

2 Approach

We evaluate the models through three tasks: morphological probing, POS tagging and NER. Uralic languages have rich inflectional morphology and largely free word order. Morphology plays a key role in parsing sentences. Morphological probing tries to recover morphological tags from the sentence representation from these models.

For assessing the sentence level behavior of the models we chose two token-level sentence tagging tasks, POS and NER. Part of speech tagging is a common subtask of downstream NLP applications such as dependency parsing. Named entity recognition is indispensable for various high level semantic applications such as building knowledge graphs. Our model architecture is identical for POS and NER.

2.1 Morphological probing

Probing is a popular evaluation method for black box models. Our approach is illustrated in Figure 1. The input of a probing classifier is a sentence and a target position (a token in the sentence). We feed the sentence to the contextualized model and extract the representation corresponding to the target token. Early experiments showed that lower layers retain more morphological information than higher layers so instead of using the top layer, we take the weighted average of all Transformer layers and the embedding layer. The layer weights are learned along with the other parameters of the neural network. We train a small classifier on top of this representation that predicts a morphological tag. We expose the classifier to a limited amount of training data (2000 training and 200 validation instances). If the classifier performs well on unseen data, we conclude that the representation includes the relevant morphological information.

We generate the probing data for Estonian and Finnish from the Universal Dependencies (UD) Treebanks (Nivre et al., 2020; Haverinen et al., 2014; Pyysalo et al., 2015; Vincze et al., 2010) and from the automatically tagged Webcorpus 2.0 for Hungarian since the Hungarian UD is very small. Unfortunately we could not extend the list of languages to other Uralic languages because their treebanks are too small to sample enough data.

The sampling method is constrained so that the target words have no overlap between train, validation and test, and we limit class imbalance to 3-to-1 which resulted in filtering some rare values. We
were able to generate enough probing data for 11 Estonian, 16 Finnish and 11 Hungarian tasks, see Table 4 for the full list of these.

2.2 Sequence tagging tasks

Our setup for the two sequence tagging tasks is similar to that of the morphological probes except we train a shared classifier on top of all token representations. We use the vector corresponding to the first subword in both tasks. Although this may be suboptimal in morphology, Ács et al. (2021) showed that the difference is smaller for POS and NER. We also finetune the models which seems to close the gap between first and last subword pooling for morphology, see 4.1. For sequence tagging tasks, unlike for morphology, we found that the weighted average of all layers is suboptimal compared to simply using the top layer, so the experiments presented here all use the top layer.

We sample 2000 train, 200 validation and 200 test sentences when available, see Table 1 for actual training set sizes.

2.3 Training details

We train all classifiers with identical hyperparameters. The classifiers have one hidden layer with 50 neurons and ReLU activation. The input and the output dimensions are determined by the choice of language model and the number of target labels. The classifiers have 40 to 60k trainable parameters which are randomly initialized and updated using the backpropagation algorithm. We run experiments both with and without finetuning the language models. Finetuning involves updating both the language model (all 110M parameters) and the classification layer (end-to-end training).

All models are trained using the AdamW optimizer (Loshchilov and Hutter, 2019) with $lr = 0.0001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$. We use 0.2 dropout for regularization and early stopping based on the development set. We set the batch size to 128 when not finetuning the models, and we use batch size 8, 12 or 20 when we finetune them.

The evaluated models, all from

| Language       | Code | Morph | POS | NER |
|----------------|------|-------|-----|-----|
| Hungarian      | [hu] | 26k   | 2000| 2000|
| Finnish        | [fi] | 38k   | 2000| 2000|
| Estonian       | [et] | 26k   | 2000| 2000|
| Erzya          | [myv]| 0     | 1680| 1800|
| Moksha         | [mdf]| 0     | 164 | 400 |
| Karelian       | [krl]| 0     | 224 | 0   |
| Livvi          | [olo]| 0     | 122 | 0   |
| Komi Permyak   | [koi]| 0     | 78  | 2000|
| Komi Zyrian    | [kpv]| 0     | 562 | 1700|
| Northern Sámi  | [sme]| 0     | 2000| 1200|
| Skolt Sámi     | [sms]| 0     | 101 | 0   |

Table 1: Size of training data for each language. Although none of these languages are officially supported by any of the language models we evaluate, we train crosslingual models and find that the models have remarkable crosslingual capabilities.

Our NER data is sampled from WikiAnn (Pan et al., 2017). WikiAnn has data in Erzya, Estonian, Finnish, Hungarian, Komi Permyak, Komi Zyrian, Moksha, and Northern Sámi.² Similarly to the POS training data, we sample 2000 training, 200 validation and 200 test sentences when available, see Table 1 for actual training set sizes.

²WikiAnn also has Udmurt data, but the transcription is problematic: Latin and Cyrillic are used inconsistently, Wikipedia Markup is parsed incorrectly etc.
BERT/RoBERTa family, differ only in the choice of training data and the training objective. They all have 12 Transformer layers, with 12 heads, and 768 hidden dimensions, for a total of 110M parameters.

3 The models evaluated

Our goal is twofold: we want to assess monolingual models against multilingual models, and we want to evaluate the models on ‘unsupported’ languages, both typologically related and unrelated.

We pick two multilingual models, mBERT and XLM-RoBERTa. Our choices for monolingual models are EstBERT for Estonian, FinBERT for Finnish and HuBERT for Hungarian (See Table 2). As a control, we also test the English BERT as a general test for cross-language transfer. Since many Uralic speaking communities are in Russia and the languages are heavily influenced by Russian, we test RuBERT on these languages. Finally, we also test a randomly initialized mBERT. We do this because the capacity of the BERT-base models is so large that they may memorize the probing data alone. Many models have cased and uncased version, the latter often removing diacritics along with lowercasing. Since diacritics play an important role in many Uralic languages, we only use the cased models. We return to this issue in 3.1.

The models along with their string identifier are summarized in Table 2.

3.1 Subword tokenization

Subword tokenization is a key component in achieving good performance on morphologically rich languages. There are two different tokenization methods used in the models we compare: XLM-RoBERTa uses the SentencePiece algorithm (Kudo and Richardson, 2018), the other models use the WordPiece algorithm (Schuster and Nakajima, 2012). The two types of tokenizers are algorithmically very similar, the differences between them are mainly dependent on the vocabulary size per language. The multilingual models consist of about 100 languages, and the vocabularies per language upper sublinearly proportional to the amount of training data available per language: in case of mBERT, 77% of the word pieces are pure ascii (Ács, 2019).

The native models, trained on monolingual data, have longer and more meaningful subwords (see the bolded entries in Table 3). This greatly facilitates the sharing of train data, a matter of great importance for Uralic languages where there is little text available to begin with.

Both BERT- and RoBERTa-based models first tokenize along whitespaces, but the handling of missing characters differs significantly. In BERT-based models, if there is a character missing from the tokenizer’s vocabulary, the model discards the whole segment between whitespaces, labeling it [UNK]. In cross-lingual cases many words are lost since monolingual models tend to lack the extra characters of a different language. In contrast, XLM-RoBERTa deletes the unknown characters, but the string that remains between whitespaces is segmented, so the loss of information is not as severe.

Table 3 summarizes different measures in language-model pairs. As a general observation, Latin script models (FinBERT, HuBERT, EstBERT) are unusable on Cyrillic text, as seen e.g. on Erzya, where Latin script models produce [UNK] token for 97.5% of the word types. This is also seen for Northern Sámi and Hungarian, which have many non-ascii characters (á, é, í, ö, ü, ű for Hungarian, č, đ, ň, š, ť, ž for Northern Sámi) see the Hungarian-EstBert/FinBERT pairs and the Northern Sámi-FinBERT/HuBERT pairs.

The mean subword length generally lies between 3.0 and 3.5 for most pairs - naturally, the corresponding language-model pairs have much higher mean subword length, 5.0 to even 5.9. This range is true not only for Latin script languages, but for Cyrillic script languages as well, as indicated by Erzya, which has a mean subword length of 3.1 to 3.4 on the multilingual models and on RuBERT.

Fertility (Ács, 2019) is defined as the average number of BERT word pieces found in a single real word type. EstBERT on Estonian and FinBERT on Finnish have very similar fertility values (2.1 and 1.9), but HuBERT on Hungarian has much higher fertility. This is mainly caused by the different vocabulary sizes - the Finnic models have 50000 subwords in their vocabulary, HuBERT only contains 32000 subwords. The rest of the fertility values are mostly over 3. In extreme cases, a word is segmented into letters, which is the case for EngBERT on Erzya, but the non-Hungarian models on Hungarian also produce very high fertility values.
| Model       | Identifier                        | Language(s) | Reference           |
|-------------|-----------------------------------|-------------|---------------------|
| mBERT       | bert-base-multilingual-cased     | 100+ inc. et, fi, hu | Devlin et al. (2019) |
| XLM-RoBERTa | xlm-roberta-base                  | 100 inc. et, fi, hu  | Liu et al. (2019)   |
| EstBERT     | turtuNLP/EstBERT                  | Estonian    | Tanvir et al. (2021) |
| FinBERT     | TurkuNLP/bert-base-finns-cased-v1 | Finnish    | Virtanen et al. (2019) |
| HuBERT      | SZTAKI-HLT/hubert-base-cc         | Hungarian   | Nemeskey (2020)     |
| EngBERT     | bert-base-cased                   | English     | Devlin et al. (2019) |
| RuBERT      | DeepPavlov/rubert-base-cased      | Russian     | Kuratov and Arkhipov (2019) |
| rand-mBERT  | mBERT with random weights         | any         | described in Section 3 |

Table 2: List of models we evaluate.

|                      | mBERT | RoBERTa | EstBERT | FinBERT | HuBERT | RuBERT | EngBERT |
|----------------------|-------|---------|---------|---------|--------|--------|---------|
| Vocab. size          | 120k  | 250k    | 50k     | 50k     | 32k    | 120k   | 29k     |
| Missing [et] (%)     | .0    | .0      | .2      | .0      | .5     | .1     | .2      |
| Missing [fi] (%)     | .0    | .0      | .0      | .0      | .4     | .0     | .0      |
| Missing [hu] (%)     | .1    | .0      | 21.5    | 48.3    | .1     | 2.7    | .2      |
| Missing [sme] (%)    | .2    | .0      | 15.0    | 47.4    | 5.1    | 4.8    | .2      |
| Missing [myv] (%)    | .0    | .0      | 97.5    | 97.5    | 97.5   | .0     | .0      |
| Subword length [et]  | 3.7±1.4 | 4.2±1.7 | 5.8±2.6 | 3.7±1.4 | 3.1±1.2 | 3.1±1.2 | 3.5±1.4 |
| Subword length [fi]  | 3.8±1.4 | 4.5±1.9 | 3.8±1.4 | 5.9±2.5 | 3.1±1.1 | 3.1±1.1 | 3.4±1.4 |
| Subword length [hu]  | 3.5±1.5 | 4.2±2.0 | 3.3±1.2 | 3.1±1.1 | 5.0±2.4 | 3.0±1.1 | 3.3±1.4 |
| Subword length [sme] | 3.2±1.0 | 3.4±1.1 | 3.2±1.1 | 3.2±1.1 | 3.1±1.2 | 2.9±1.0 | 3.0±1.0 |
| Subword length [myv] | 3.1±1.2 | 3.2±1.0 | 1.0±0.0 | 1.0±0.0 | 1.0±0.0 | 3.4±1.2 | 1.1±0.4 |
| Character length [et]| 9.2   | 9.2     | 9.2     | 9.2     | 9.2    | 9.2    | 9.2     |
| Character length [fi]| 9.3   | 9.3     | 9.3     | 9.3     | 9.3    | 9.3    | 9.3     |
| Character length [hu]| 9.8   | 9.8     | 9.6     | 8.8     | 9.8    | 9.8    | 9.9     |
| Character length [sme]| 8.5   | 8.5     | 8.3     | 7.6     | 8.5    | 8.4    | 8.5     |
| Character length [myv]| 7.3   | 7.3     | 1.8     | 1.8     | 1.7    | 7.3    | 7.3     |
| Fertility [et]       | 3.4   | 2.8     | 2.1     | 3.6     | 4.4    | 4.3    | 4.3     |
| Fertility [fi]       | 3.3   | 2.7     | 3.5     | 1.9     | 4.6    | 4.4    | 4.5     |
| Fertility [hu]       | 4.0   | 3.2     | 5.2     | 4.5     | 2.8    | 5.4    | 5.6     |
| Fertility [sme]      | 3.7   | 3.6     | 4.1     | 3.3     | 4.5    | 4.6    | 4.7     |
| Fertility [myv]      | 3.6   | 3.3     | 1.1     | 1.1     | 1.1    | 3.0    | 7.2     |

Table 3: Major characteristics of cross-language tokenization. Boldface font marks the corresponding language-model pairs.
Figure 2: Mean accuracy of morphological tasks by language. The bars are grouped in two, the left one is the result of probing the first subword, the right one is the result of probing the last subword. Blue bars are without finetuning, green bars are with finetuning. Monolingual models are highlighted.

4 Results

4.1 Morphology

Morphological tasks are generally easy for most models and we see reasonable accuracy from crosslingual models as illustrated by Figure 2. Mean accuracies, especially after finetuning, are generally above 90%, except, unsurprisingly, for the randomly initialized models.

Subword choice We first start by examining the choice of subword on morphological tasks. We try probing the first and the last subword and we find that there is a substantial gap in favor of the last subword. This is unsurprising considering that Uralic languages are mainly suffixing. This gap on average shrinks from 0.21 to 0.032 when we finetune the models on the probing data (Figure 2 shows this gap in green). Without finetuning there is only one task, (Hungarian, Degree, ADJ), where probing the first subword is better than probing the last one for some models. This is explained by the fact that the superlative in Hungarian is formed from the comparative by a prefix.

Monolingual models are only slightly better than the two multilingual models, XLM-RoBERTa in particular. We run paired t-tests on the accuracy of each model pair over the 11 (et, hu) or 16 (fi) morphological tasks in a particular language and find that the difference between the monolingual model and XLM-RoBERTa is never significant, and for Estonian, neither is the difference between EstBERT and mBERT.

Cross-lingual transfer works only if we finetune the models. Interestingly, language relatedness does not seem to play a role here. FinBERT transfers
worse to Estonian than HuBERT, and EstBERT transfers worse to Finnish than HuBERT. Interestingly, EngBERT transfers better to all three models than the other native BERTs, and for Finnish and Hungarian it is actually on par with mBERT.

**Diacritics** As seen from the first panel of Table 3, EstBERT and FinBERT replace words with unknown characters with [UNK] to such an extent that a large proportion of types end up being filtered. We try to mitigate this issue by preemptively removing all diacritics from the input. It appears that this has little effect on the original language, but cross-lingual transfer is improved for Finnish. In the sequence tagging tasks that we now turn to, we remove the diacritics when we evaluate EstBERT or FinBERT in a cross-lingual setting.

### 4.2 POS and NER

![Figure 3: POS and NER results on languages that use the Latin alphabet.](image)

Figure 3: POS and NER results on languages that use the Latin alphabet.

We extend our studies to all Uralic languages with any training data (see Table 1) and we limit the discussion to finetuned models since cross-lingual transfer does not work without finetuning. We split the languages into two groups, Latin and Cyrillic, and we only test models with explicit support for the script that the language uses. Multilingual models support both scripts. Figures 3 and 4 show the results by language.

**National languages** We generally find the best performance in the three languages with native support: Estonian, Finnish and Hungarian. Monolingual models perform the best in their respective language but the two multilingual models are also very capable.

**Cross-lingual transfer** does not seem to benefit from language relatedness, EngBERT transfers just as well as other monolingual models. Even extremely close relatives such as Livvi and Finnish do not transfer better than XLM-RoBERTa to Livvi. On the other hand, FinBERT is the best for Karelian POS, another close relative of Finnish. The writing system and shared vocabulary also seem to play an important role, as seen from RuBERT’s usefulness on unrelated but Cyrillic-using Uralic languages, see Figure 4.

**XLM-RoBERTa** is generally a strong model for cross-lingual transfer for all Uralic languages. We suspect that this is due to its large subword vocabulary, which may provide a better generalization basis for capturing the orthographic cues that are often highly indicative in agglutinative languages.

**North Sámi** Both POS and NER in North Sámi are relatively easy as long as the orthographic cues can be captured (i.e. the Latin script is supported). rand-mBERT is surprisingly successful at NER in North Sámi, suggesting that orthographic cues (rand-mBERT uses mBERT’s tokenizer) are highly predictive of named entities in North Sámi.

### 5 Conclusion

Altogether we find that it is possible, and relatively easy, to transfer models to new languages with fine-tuning on very limited training data, though extremely limited data still hinders progress: compare Erzya (1680 train sentences) to Moksha (164 train sentences) on Fig. 4.
| Morph tag | POS | Estonian | Finnish | Hungarian |
|-----------|-----|----------|---------|-----------|
| Case      | adj | 8 classes| 11 classes| 18 classes|
| Case      | noun| 15 classes| 12 classes|            |
| Case      | proprn| 8 classes|         | 12 classes|
| Case      | verb|          |         |            |
| Degree    | adj |          | Cmp, Pos, Sup| Cmp, Pos, Sup|
| Derivation| adj |          | Inen, Lainen, Llinen, Ton|            |
| Derivation| noun|          | Ja, Lainen, Minen, U, Vs|            |
| InfForm   | verb|          | 1, 2, 3|            |
| Mood      | verb|          | Cnd, Imp, Ind| Cnd, Imp, Ind, Pot|
| Number    | noun| Sing, Plur| Sing, Plur| Sing, Plur|
| Number    | a/n/v| Sing, Plur| Sing, Plur|            |
| PartForm  | verb|          | Pres, Past, Agt|            |
| Person    | noun| 1, 2, 3| 1, 2, 3|            |
| Person    | verb| 1, 2, 3|            |            |
| Tense     | adj | Pres, Past| Pres, Past| Pres, Past|
| Tense     | verb| Pres, Past| Pres, Past| Pres, Past|
| VerbForm  | verb| Conv, Fin, Inf, Part, Sup| Inf, Fin, Part| Inf, Fin|
| Voice     | adj | Act, Pass|            |            |
| Voice     | verb| Act, Pass|            |            |

Table 4: List of morphological probing tasks.

EngBERT and RuBERT, which we introduced as a control for language transfer among genetically unrelated languages, transfer quite well: in particular the Latin-script EngBERT transfers better to Hungarian than FinBERT or EstBERT.

We note that we did not perform monolingual hyperparameter search or any preprocessing, and there is probably room for improvement for each of these languages. The biggest immediate gains are expected from extending the UD and WikiAnn datasets, and from careful handling of low-level character set and subword tokenization issues. There are many Uralic languages that still lack basic resources, in particular the entire Samoyedic branch, Mari, and Ob-Ugric languages, are currently out of scope. Another avenue of research could be to work towards a stronger mBERT interlingua, or perhaps one for each script family, as the charset issues are clearly relevant.

Our data, code and the full result tables will be available along with the final submission.

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