BanglaBERT: Combating Embedding Barrier in Multilingual Models for Low-Resource Language Understanding

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Abstract

In this paper, we introduce “Embedding Barrier”, a phenomenon that limits the monolingual performance of multilingual models on low-resource languages having unique typologies. We build ‘BanglaBERT’, a Bangla language model pretrained on 18.6 GB Internet-crawled data and benchmark on five standard NLU tasks. We discover a significant drop in the performance of the state-of-the-art multilingual model (XLM-R) from BanglaBERT and attribute this to the Embedding Barrier through comprehensive experiments. We identify that a multilingual model’s performance on a low-resource language is hurt when its writing script is not similar to any of the high-resource languages. To tackle the barrier, we propose a straightforward solution by transcribing languages to a common script, which can effectively improve the performance of a multilingual model for the Bangla language. As a bi-product of the standard NLU benchmarks, we introduce a new NLI dataset (a task previously unexplored in Bangla), and evaluate BanglaBERT on five downstream tasks. BanglaBERT outperforms multilingual baselines and previous state-of-the-art results on all tasks by up to 3.5%. ¹

1 Introduction

Self-supervised pretraining (Devlin et al., 2019; Radford et al., 2019; Liu et al., 2019) has become a standard practice in natural language processing. This pretraining stage allows language models to learn general linguistic representations (Jawahar et al., 2019) that can later be fine-tuned for different downstream natural language understanding (NLU) tasks (Wang et al., 2018; Rajpurkar et al., 2016; Tjong Kim Sang and De Meulder, 2003). However, the NLU field is yet to be democratized, as most notable works are restricted to only a few high-resource languages. For example, despite being the sixth most spoken language, there has not been any comprehensive study on Bangla NLU. With these shortcomings in mind, we build BanglaBERT – a Transformer-based (Vaswani et al., 2017) NLU model for Bangla, pretrained on 18.6 GB data we crawled from 60 popular Bangla websites, introduce a new downstream dataset on natural language inference (NLI) and show that BanglaBERT outperforms previous state-of-the-art results on all tasks by up to 3.5%. We are making the BanglaBERT language model and the new Bangla NLI dataset publicly available in the hope of advancing the community. The resources can be found at https://github.com/csebuetnlp/banglabert.

Although there have been efforts to pretrain multilingual NLU models (Pires et al., 2019; Conneau and Lample, 2019; Conneau et al., 2020a) that can generalize to hundreds of languages, low-resource languages are not their primary focus, leaving them underrepresented. Moreover, these models often trail in performance compared to language-specific models (Canete et al., 2020; Antoun et al., 2020; Nguyen and Tuan Nguyen, 2020), resulting in a surge of interest in pretraining language-specific models in the NLP community. However, pretrain-

¹We are releasing the BanglaBERT model and the NLI dataset to advance the Bangla NLP community.
ing is highly expensive in terms of data and computational resources, rendering them very difficult for low-resource communities.

To systematically analyze the performance gap in the multilingual models, we use BanglaBERT as a pivot and compare it with the best performing multilingual model, XLM-RoBERTa (XLM-R) (Conneau et al., 2020a) on the Bangla NLU tasks. We identify that even though XLM-R was pretrained with a similar objective, a comparable amount of texts, and had the same architecture as BanglaBERT, the vocabulary dedicated to Bangla scripts in the embedding layer was less than 1% of the total vocabulary (and less than ten folds compared to BanglaBERT), which limited the representation ability of XLM-R for Bangla. Also, since Bangla does not share its vocabulary or writing script with any other high-resource language, the vocabulary is strictly limited within that bound. We name this phenomenon as the ‘Embedding Barrier’. Furthermore, we conduct a series of experiments to establish that Embedding Barrier is indeed a key contributing factor to the performance degradation of XLM-R. Through our experiments, we show that:

1. There is a considerable loss in performance (up to 4% accuracy) because of the Embedding Barrier when vocabularies are limited.
2. Even a distant low-resource language having the same typology as a high-resource one may benefit from borrowing (subword) tokens (albeit having different meanings).
3. On the contrary, linguistically similar languages may be hindered from contributing to each other’s monolingual performance because of being written in different scripts.
4. Sister languages with identical scripts can boost each other’s monolingual performance even when they are low-resource.

In addition to addressing the embedding barrier, we propose a simple solution to overcome it – transcribing texts into a common script. Our proposed method alleviates this embedding barrier by increasing the effective vocabulary size beyond the native scripts. Although not being a perfect solution, it establishes that having an uncommon typology indeed limits the performance of multilingual models. We call for new ways to represent vocabularies of low-resource languages in multilingual models that can better lift this barrier.

2 BanglaBERT

In this section, we describe the pretraining data, preprocessing steps, model architecture, objectives, and downstream task benchmarks of BanglaBERT.

2.1 Pretraining Data

A high volume of good quality text data is a prerequisite for pretraining large language models. For instance, BERT (Devlin et al., 2019) is pretrained on the English Wikipedia and the Books corpus (Zhu et al., 2015) containing 3.3 billion tokens. Subsequent works like RoBERTa (Liu et al., 2019) and XLNet (Yang et al., 2019) used an order of magnitude larger web-crawled data that have passed through heavy automatic filtering and cleaning.

Bangla is a rather resource-constrained language in the web domain; for example, the Bangla Wikipedia dump from June 2020 is only 350 megabytes in size, two orders of magnitudes smaller than the English Wikipedia. As a result, we had to crawl the web extensively to collect our pretraining data. We selected 60 Bangla websites by their Amazon Alexa website rankings and volume of extractable texts. The contents included encyclopedias, news, blogs, e-books, and story sites. The amount of collected data totaled around 30 GB.

There are other noisy sources of data dumps publicly available, a prominent one being OSCAR (Suárez et al., 2019). However, the OSCAR dataset contained a lot of offensive texts and repetitive contents, which we found too difficult to clean thoroughly, and hence opted not to use it.

2.2 Pre-processing

We performed thorough deduplication on the pretraining data, removed non-textual contents (e.g., HTML/JavaScript tags), and filtered out non-Bangla pages using a language classifier (Joulin et al., 2017). After the processing, the dataset was reduced to 18.6 GB in size. A detailed description of the corpus can be found in the Appendix.

We trained a Wordpiece (Wu et al., 2016) vocabulary of 32k tokens on the resulting corpus with a 400 character alphabet, kept larger than the native Bangla alphabet to capture code-switching (Poplack, 1980) and allow romanized Bangla contents for better generalization. While creating a training sample, we limited the sequence length to 512 tokens and did not cross document boundaries (Liu et al., 2019) while creating a sample.

www.alexa.com/topsites/countries/BD
| Model/Baseline                  | SC (Acc.) | EC (Weighted F-1) | DC (Acc.) | NER (Macro F-1) | NLI (Acc.) |
|--------------------------------|-----------|-------------------|-----------|----------------|-----------|
| Previous SoTA                  | 85.67     | 69.73             | 72.50     | 57.44          | N/A       |
| mBERT                          | 83.39     | 56.02             | 98.64     | 67.40          | 71.41     |
| XLM-R                          | 89.49     | 66.70             | 98.71     | 70.63          | 76.76     |
| monsoon-nlp/bangla-electra    | 73.54     | 34.55             | 97.64     | 52.57          | 64.43     |
| sagorsarker/bangla-bert-base   | 87.30     | 61.51             | 98.79     | 70.97          | 69.18     |
| BanglaBERT (ours)              | **92.18** | **72.75**         | **99.07** | **71.54**      | **80.15** |

Table 1: Performance comparison on different downstream tasks

2.3 Pretraining Objective and Model

Language models are pretrained with self-supervised objectives that can take advantage of unannotated text data. BERT (Devlin et al., 2019) was pretrained with masked language modeling (MLM) and next sentence prediction (NSP). Several works built on top of this, e.g., RoBERTa (Liu et al., 2019) removed NSP and pretrained with longer sequences, SpanBERT (Joshi et al., 2020) masked contiguous spans of tokens, while works like XLNet (Yang et al., 2019) introduced novel objectives like factorized language modeling.

We pretrained BanglaBERT using ELECTRA (Clark et al., 2020), pretrained with the Replaced Token Detection (RTD) objective. In this setup, a generator model and a discriminator model are trained jointly. The generator is fed as input a sequence with a portion of the tokens masked (15% in our case) and is asked to predict the masked tokens using the rest of the input (i.e., standard MLM). For the discriminator input, the masked tokens are replaced by tokens sampled from the generator’s output distribution for the corresponding masks. The discriminator then has to predict whether each token is from the original sequence or not. After pretraining, the discriminator is used for fine-tuning. Clark et al. (2020) argued that RTD back-propagates loss from all tokens of a sequence, in contrast to 15% tokens of the MLM objective, giving the model more signals to learn from. Evidently, ELECTRA achieves comparable downstream task performance to RoBERTa or XLNet with only a quarter of their training time. This computational efficiency motivated us to use this model for our implementation of BanglaBERT.

We pretrained the base model (a 12-layer Transformer encoder with 768 hidden size, 12 attention heads, 3072 feed-forward size, 110M parameters; generator-to-discriminator ratio $\frac{1}{3}$) with 256 batch size for about 534k steps (28 epochs) on an 8-GPU p3.16xlarge instance on AWS. We used the Adam (Kingma and Ba, 2015) optimizer with a 2e-4 learning rate and linear warmup of 10,000 steps.

2.4 Downstream Tasks and Results

We fine-tuned BanglaBERT on the five downstream tasks and compared with two multilingual models, mBERT (110M parameters) (Devlin et al., 2019) and XLM-RoBERTa (270M parameters) (Conneau et al., 2020a), two pretrained Bangla models\(^3\) available on the web, as well as previous state-of-the-art results mentioned below:

1. Sentiment Classification (SC), (Sharfuddin et al., 2018)
2. Emotion Classification (EC), (Das et al., 2021)
3. Document Classification (DC), (Kunchukuttan et al., 2020)
4. Named Entity Recognition (NER), (Ashrafi et al., 2020)
5. Natural Language Inference (NLI), introduced by us in this work

We refer our readers to the Appendix for full details of each dataset, evaluation, and previous works. All pretrained models were fine-tuned for three epochs on each task with batch size 32 and the learning rate was tuned from the set: \{2e-5, 3e-5, 4e-5, 5e-5\}. The results on different downstream tasks are detailed in Table 1. In all the downstream tasks, BanglaBERT outperformed previous state-of-the-art works, multilingual baselines, and monolingual models by a considerable margin ranging from 1%-3.5%.

\(^3\)https://huggingface.co/sagorsarker/bangla-bert-base, https://huggingface.co/monsoon-nlp/bangla-electra
Performance Analysis: Addressing the Embedding Barrier

From the results in Table 1, we see that XLM-R came head-to-head with BanglaBERT on many tasks, even coming within a 1% range on the DC and NER. Although the original purpose of XLM-R was not to perform monolingual NLU (rather cross-lingual NLU Conneau et al., 2018), due to its surprising multilingual effectiveness, XLM-R has become the de-facto choice as the baseline for comparing language-specific models (Antoun et al., 2020; Martin et al., 2020) on monolingual tasks, and also for benchmarking when language-specific models aren’t available for any language (Kakwani et al., 2020). It is also worth mentioning that similar high scores for XLM-R are also reported for other languages, and there have been cases where XLM-R even outperformed the language-specific models on some tasks (Koutsikakis et al., 2020), as has happened with the two additional Bangla models we have experimented with. This prompted us to further investigate the reason behind the underperformance of XLM-R on Bangla NLU tasks.

3.1 BanglaBERT vs. XLM-R

By careful examination of the models and the training pipeline, we identified four key differences between XLM-R and BanglaBERT:

Pretraining Objective: XLM-R was pretrained with the RoBERTa objective (Liu et al., 2019), whilst BanglaBERT was pretrained using ELECTRA (Clark et al., 2020). Though ELECTRA is computationally more efficient than RoBERTa, both are shown to have comparable performance when trained for a high number of steps. XLM-R being heavily pretrained, the objective cannot certainly affect performance by a high margin.

Pretraining Data: XLM-R was pretrained with CCNet (Wenzek et al., 2020). We found the Bangla portion of CCNet to be comparable in size (9 GB) to our BanglaBERT pretraining data, and also found significant overlap (~6 GB) between their contents. Liu et al. (2019) showed that downstream performance does improve by scaling up pretraining data (from 16 GB to 160 GB), but the gain was marginal (0.3-0.4%). Moreover, Martin et al. (2020) showed that a model pretrained on 4 GB data achieved identical performance as one trained on 138 GB data. This provides ample evidence that the scale of data does not have a significant impact beyond the 4 GB volume.

Pretraining Setup: XLM-R is pretrained on a multilingual setup with 100 languages, while BanglaBERT is pretrained with Bangla only. Conneau et al. (2020a) showed that multilingual training hinders the performance for high-resource languages (dubbed as the ‘Curse of Multilinguality’), it is however beneficial for low and mid-resource languages since it allows positive transfer among similar languages. Since Bangla is definitely not a high-resource language in XLM-R, it is unlikely that Bangla is affected by multilingual training.

Model Architecture: Both BanglaBERT and XLM-R have the Transformer encoder architecture, with the same number of layers and dimensions. However, there is one difference: ‘the embedding layer’. Input texts are tokenized using a pre-determined vocabulary and ID-mapped to learnable parameters in the embedding layer before being passed on to the deeper layers. The size of the embedding layer depends on the vocabulary. We used a vocabulary of 32k tokens for BanglaBERT, while XLM-R used a combined vocabulary of 250k tokens for all languages.

3.2 Multilingual Vocabulary: Effect of Writing Script

Interestingly, we found that despite XLM-R having a large embedding layer containing 250k vocabulary tokens, less than 2.5k tokens were allocated to Bangla vocabulary. A small native subword vocabulary over-segments the input sequence (Ács, 2019), making the learning task more challenging (Wang et al., 2021). We conjecture 2.5k native tokens is too low to convey the morphological richness of Bangla. Moreover, Bangla does not share its writing script with any high-resource language, thereby eliminating the possibility of finding better tokenizations (Figure 1) from other languages. This limits the vocabulary usage within this bound only, despite the seemingly large combined vocabulary.

Low-resource languages having a common script as a high-resource language may not necessarily suffer from the same effect. For instance, a 36 MB Swahili Wikipedia dump tokenized on the XLM-R vocabulary had more than 6.5k tokens with 100+ frequencies. The same size dump for Bangla has only about 2.1k tokens with the same threshold. Although the pretraining corpus for Bangla used in XLM-R is an order of magnitude larger than Swahili, the latter managed to make use of more tokens. Since Swahili uses Latin scripts, it can bor-
row tokens by finding better subword segmentation from other high and mid-resource languages that use Latin (57 out of 100 languages supported in XLM-R use Latin scripts and almost half of the total vocabularies are from the Latin unicode block⁴). Although the borrowed tokens may not necessarily convey the same meaning across different languages, contextualization of their representations (Peters et al., 2018) overcomes this problem. Unfortunately, this opportunity is inapplicable to low-resource languages that don’t share their scripts with any high or mid-resource language.

We further explored the vocabulary of XLM-R and found about 193k tokens out of 250k belonging to the top five scripts (i.e., Latin, Cyrillic, Arabic, CJK, and Devanagari). Twenty-one languages did not share their scripts with any of these, and consequently, their vocabularies were limited to 2.5k tokens on average. We introduce the term ‘Embedding Barrier’ to refer to this issue and hypothesize it as a key reason behind the underperformance of XLM-R on such languages (Bangla in our case).

4 Simulating the Embedding Barrier

Although the discussions in Section 3 ruled out the possibility of the pretraining objective, data, and setup having a considerable impact on the performance loss of XLM-R, it is still too early to conclude that the Embedding Barrier is a contributing factor behind it. As such, in this section, we simulated the barrier in a controlled environment.

To see how the size of the native vocabulary affects downstream performance, we pretrained multiple multilingual models on three languages: Bangla, Swahili, and English, with different vocabulary size combinations. We chose Swahili as it is also a low-resource language, shares its writing script with English (contrary to Bangla), and is linguistically distant from Bangla and English. Moreover, the XNLI dataset (Conneau et al., 2018) has support for Swahili, so we would have a common NLI task to evaluate the languages on. We collected about 280 MB of Swahili data from the Swahili Wikipedia and by crawling 7 Swahili news and blog sites. We downsampled our Bangla corpus to have about the same size as its Swahili counterpart and used similar domains in equal proportion to ensure as much uniformity as possible. We used the Books corpus (Zhu et al., 2015) and English Wikipedia dump as the English pretraining corpus.

4.1 Experimental Setup

We trained Wordpiece vocabularies of size 2k, 3k, 4k, 5k, and 8k on the Bangla and Swahili data separately. We trained the English vocabularies such that each combined vocabulary for all combinations would total to 32k. For instance, a combined vocabulary containing 2k Bangla tokens and 2k Swahili tokens would have ~28k tokens from English (28611 in reality, because of common tokens between Swahili and English). We tokenized all corpora on the combined vocabularies so that each language could borrow tokens from others.

We pretrained five small ELECTRA (12 layers, 256 hidden size, 4 attention heads, 1024 feed-forward size, 14M parameters) models on the five vocabulary combinations for 250k steps. We ensured all samples of a batch to be from one language and used a smoothing factor of 0.3 (Conneau and Lample, 2019) to upsample Bangla and Swahili batches during pretraining. We referred to these models as ‘TriBERT-X’ where X represents the vocabulary size of Bangla and Swahili (e.g., TriBERT-2k has 2k Bangla and 2k Swahili tokens). Note that, other than the vocabularies, pretraining data and training setups are identical across all models. We also pretrained two models solely on the Swahili and downsampled Bangla data (which we name MonoBERT-sw and MonoBERT-bn) to see how a monolingual model would compare with the trilingual models (the monolingual models would have the full 32k vocabulary trained on the native corpus). We plotted the performances of each model on the Swahili NLI (NLI-sw) and our Bangla NLI (NLI-bn) datasets in Figure 2a, 2b. The horizontal lines indicate performances of the MonoBERTs.

From the figures, it becomes apparent that Bangla is affected more than Swahili due to the limited native vocabulary size: the respective TriBERT-2k model exhibits more than 4% (2%) lower accuracy than the Bangla (Swahili) MonoBERT. As the vocabulary grows, accuracy improves for both languages, but the curve is steeper for Bangla suggesting higher improvement with the increase of vocabulary size. This substantiates that embedding barrier limits performance of Bangla significantly.⁵

⁴https://jrgraphix.net/r/Unicode/

⁵We also trained a model replacing Bangla with Hindi (which too uses a non-Latin script) with identical setups, and observed similar underperformance as Bangla. We understand that training with more such languages would provide a more general argument, but due to the computational costs of training these models, we had to limit our experiments to Bangla and Swahili only.
A closer inspection into the vocabulary usage of the fine-tuning datasets would provide us a better understanding of the number of tokens effectively used by the TriBERT models. In Figure 2c, we plot the number of tokens with 100+ frequencies in the NLI-bn and NLI-sw datasets for the different models. These counts can be roughly interpreted as the effective vocabulary size on the NLI datasets for these models. For contrast, we also show the frequencies tokenized only on the Swahili portion of the vocabularies (marked blue) for NLI-sw.

We can see that Swahili went beyond its native tokens: borrowing 3-4k tokens from the English side as seen from the green and blue curves. Even the model with 2k native Swahili tokens was able to make use of thrice as many tokens by borrowing from the English vocabulary and performed better than the model with 5k Bangla tokens (and only slightly worse than the 8k one) in the sense of performance degradation with respect to the respective monolingual model (Figure 2a, 2b). Not surprisingly, the tendency of borrowing tokens subsides as the native vocabulary size grows. The slow increase in effective vocabulary in contrast to Bangla also explains the low increase of performance for Swahili as the native vocabulary grows. We further computed Pearson coefficient between the effective vocabularies and accuracies and found strong correlation: 0.993 for Bangla and 0.994 for Swahili.

In addition to the raw counts of tokens in the subword vocabulary, it is crucial to know their granularity. A small subword vocabulary will split a given text into more tokens than a larger one. This influences the length of input sequences and the representation capability of the over-segmented tokens. Heavy segmentation results in frequent observations of tokens, but is not necessarily ideal for task performance (Wang et al., 2021; Rust et al., 2021). Therefore, raw frequency counts may not be sufficiently expressive. Hence, we calculate the ‘subword fertility’ (Ács, 2019) for the TriBERTs on NLI-bn and NLI-sw and plot them in Figure 2d.

We can see from the figure that Bangla has a higher fertility than Swahili. In the TriBERT-2k model, each word is segmented almost twice on average. The curve is also steeper for Bangla with the growth of native vocabulary. This may also explain why the increase in native vocabulary helps Bangla more than Swahili. The addition of the English vocabulary helped Swahili decrease fertility by 0.2-0.4, reaching almost the same as the monolingual vocabulary with the TriBERT-8k vocabulary. These observations suggest that Swahili gains advantage with the incorporation of the English vocabulary.

5 Borrowed Tokens or Positive Transfer?

It might be argued that the superior performance of Swahili in comparison with Bangla in the TriBERT models was not because of borrowed tokens, but due to positive transfer from English to Swahili (e.g., both languages have the same SVO typography). In order to validate that this is not the case, we eliminate positive transfer altogether by pretraining two models with the Swahili corpus only: one with the TriBERT-2k vocabulary of 32k tokens and another with a native 2k vocabulary. We show the accuracy of all models in Table 2.

The MonoBERT-sw model with 32k combined vocabulary triumphed over the TriBERT-2k model, suggesting the English data in TriBERT was not a strong contributing factor to the performance of

4.2 Vocabulary Probing

The purpose of the illustration is to show how the performance drops as the native vocabulary size is restricted. Here, Bangla is observed to suffer more in than Swahili. Figures 2c, 2d try to explain this phenomenon by drawing a correlation of the performances with the models’ effective vocabularies and subword fertilities respectively.
Table 2: Borrowing of tokens improves performance

Table 3: Difference in writing scripts hinders positive transfer even among similar languages

Table 4: Even low-resource languages having identical typologies can contribute to others’ performance.

7 Lifting the Embedding Barrier

From the experiments in the previous three sections, we can conclude that Bangla can neither borrow tokens nor enjoy a strong positive transfer from other languages because of the embedding barrier. In this section, we propose a simple solution to lift the barrier. A straightforward way of allowing the languages to borrow tokens from one another would be to convert them into a common script. Script conversion has been applied in multilingual neural machine translation (Chakravarthi et al., 2019; Amrhein and Sennrich, 2020) for similar languages with different scripts and for adapting new languages to already pretrained multilingual models (Muller et al., 2021). We hypothesized that it might also prove helpful in pretraining language models.
models from scratch and used the Aksharamukha library\(^6\) to convert the pretraining corpora into ISO phonetic transcription alphabet. We show the results on the Bangla NLI dataset in Table 5.

| Model Name               | Accuracy |
|--------------------------|----------|
| TriBERT-2k (bn-sw-en)    | 69.74    |
| TriBERT-3k (bn-sw-en)    | 70.21    |
| Tribert-2k ISO (bn-sw-en)| 70.29    |

Table 5: Phonetic transcription allows performance improvement by increasing the effective vocabulary

The TriBERT-2k ISO model improved by 0.5% when compared to TriBERT-2k. In hindsight, it might seem that the improvement is insignificant. We argue otherwise: the accuracy is comparable to a TriBERT-3k model. We further looked into the transcribed NLI-bn dataset and found \(~3.1k\) tokens having 100+ frequencies. The transcription indeed increased effective vocabulary size and thus the performance improved. We would further emphasize that the increase is not because of any phonetic relation, since Bangla and English are distant languages with little to no phonetic similarity.\(^7\)

Note that the scheme used is completely rule-based on a character level and fails to capture the real transcriptions of words in many cases, explaining why the effective vocabulary is smaller compared to Swahili in TriBERT-2k. If some advanced scheme (e.g., Dakshina Roark et al., 2020) were used and the model were pretrained with a language similar to Bangla, the effective vocabulary would perhaps have been larger, and the barrier would have probably been better combated. Moreover, the scheme hurts performance for Swahili (by 3%). We leave further investigations as future works and call for better ways to lift the barrier.

8 Related Works

Natural language processing has witnessed a sea change with the advent of pretrained language models like ULMFit (Howard and Ruder, 2018), ELMo (Peters et al., 2018), GPT (Radford et al., 2019), and most notably BERT (Devlin et al., 2019). CamemBERT (Martin et al., 2020), trained in French, was one of the first non-English language-specific models. Subsequently, many works (Polig-

\(^6\)github.com/virtuallvinodh/aksharamukha
\(^7\)An inspection into the vocabulary revealed that the overlapping tokens had completely different meanings across the two languages (e.g., the Bangla word having the same transcription as the English word ‘book’ means ‘chest’ in Bangla)

nano et al., 2019; de Vries et al., 2019; Canete et al., 2020; Antoun et al., 2020) did pretraining for other languages. mBERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019), XLM-R (Conneau et al., 2020a) explored multilingual pretraining on hundreds of languages and showed cross-lingual effectiveness of multilingual models.

Wu and Dredze (2020) showed that despite the excellent cross-lingual transfer ability of mBERT on high-resource languages, it does much worse for many low-resource languages. Muller et al. (2021) attributed the failure to transfer on unseen languages largely to the impact of their typologies. Rust et al. (2021) showed that languages that are adequately represented in multilingual models’ vocabulary exhibit negligible performance loss over their monolingual counterparts. Chung et al. (2020) proposed language clustering to train multilingual vocabularies to mitigate low native tokens, while Clark et al. (2021) introduced a vocabulary-free pretraining strategy.

Pretraining in Bangla: Although many Bangla pretrained models are publicly available through the Hugging Face library (Wolf et al., 2020), none have pretrained on a high volume of good-quality data (resulting in a sub-par performance, as shown in Table 1) nor did fine-tune on a variety of tasks.

9 Discussion and Concluding Remarks

A detailed review of recent literature reveals that creating language-specific models is often infeasible for low-resource languages lacking ample data. Moreover, compute resources for pretraining these models are beyond the grasp of most researchers. As such, they are compelled to use multilingual models for languages that do not have strong pretrained models. Unfortunately, due to the embedding barrier, low-resource languages with unique scripts often fail to reap the full benefit of these multilingual models. Thus it is in the best interest of the community to rather focus on making the multilingual models stronger through carefully designed decision choices, like ensuring the allocation of sufficient vocabulary to low-resource languages, especially those with unique and uncommon scripts, or via using a common typology; than to pretrain language-specific models. Until then, it is hoped that BanglaBERT will remain as the state-of-the-art language-specific model for Bangla NLU and the methodologies applied in this paper would help other low-resource languages advance further.
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Appendix

Pretraining Data Sources

We used the following sites for data collection:

**Bangla:**
- amrabondhu.com
- anandabazar.com
- bangla.24livenews.com
- banglablog.com.bd
- bangladeshpratidin.com
- banglaepub.github.io
- banglanews24.com
- banglamedia.org
- banglatribune.com
- bd24live.com
- bdlaws.minlaw.gov.bd
- bdnews24.com
- biganblog.org
- biggan.org
- bigganprojukti.com
- bigyan.org.in
- bn.wikipedia.org
- bn.wikisource.org
- channelionline.com
- thedailystar.net
- dinikamadershomoy.com
- dainikshiksha.com
- dakghar.org
- dhakatribune.com
- dpnews.org
- ebanglalibrary.com
- eboipotro.github.io
- eisamay.indiatimes.com
- globalvoices.org
- hindustantimes.com
- hrw.org
- indianexpress.com
- iquilib.com
- ittfaq.com
- jagones24.com
- jugantor.com
- jw.org
- kalerkrantho.com
- kolkatanews.com
- nirbik.com
- ntvbd.com
- onnordistry.com
- pcheiplinebd.com
- prothomalo.com
- risingbd.com
- roar.media/bangla
- rtnonline.com
- sachalayatan.com
- samakal.com
- sangbadpratidin.com
- saasthabangla.com
- shopnobaz.net
- somewhereinblog.net
- somoynews.tv
- subeen.com
- tanzil.org
- techtunes.com
- tunerpage.com
- tutorialbd.com
- zoombangla.com

**Hindi:**
- dw.com/hi
- gyanipandit.com
- hi.wikipedia.org
- hindime.net
- jagrah.com

**Nepali:**
- aakarpost.com
- ekantipur.com
- mysansar.com
- ne.wikipedia.org

We wrote custom crawlers for each site above (except the Wikipedia dumps).

Corpus Description

Our BanglaBERT pretraining corpus has a total of 18.6 GB of data containing 3,807,462 documents/pages in total. The average length of each document was 303.58 words. After tokenization, we had 4,873,472 data points with an average sequence length of 414.02 tokens.

Downstream Tasks and Evaluation

1. **Sentiment Classification (SC):** We used the sentiment analysis dataset from Sharfuddin et al. (2018). The dataset had two labels: positive and negative, both classes being balanced. There were 8181 samples in total. Sharfuddin et al. (2018) did not provide any train-dev-test split for their dataset. Hence, we made an 80%-10%-10% split randomly. Positive and negative classes were split separately and then merged into respective sets to ensure that all three sets remained balanced. As the dataset was collected from YouTube comments, a lot of emojis were present therein. We converted the emojis into texts using the bnemo package.\(^8\) We used accuracy as the performance metric as the dataset is binary-class and fully balanced. (As the test set is different from Sharfuddin et al. (2018), the comparison is not perfectly apples-to-apples.)

2. **Emotion Classification (EC):** We used the BEmoC dataset from Das et al. (2021). The dataset has six emotion classes: Anger, Disgust, Fear, Joy, Sadness, Surprise. The dataset was provided with a 4994-624-625 split. Due to class imbalance, we used Weighted-F1 as the performance metric.

\(^8\)https://pypi.org/project/bnemo/
3. **Document Classification (DC)**: For document classification, we used the ai4bharat Bangla news article classification dataset (Kunchukuttan et al., 2020). There were two classes: sports and entertainment, both balanced. A 11284-1411-1411 split and a baseline were provided. Notably, while fine-tuning, we had to limit the maximum sequence length to 512.

4. **Named Entity Recognition (NER)**: For this task, we used the NER dataset from Karim et al. (2019). The dataset had some annotation errors that did not conform to the IOB2 sequence labeling scheme. We fixed the annotations before fine-tuning. To be more precise, the dataset uses an amalgam of IOB and IOB2 tagging schemes. We converted all examples to IOB2 for uniformity. In IOB2, every chunk must start with the “B-” tag. For example, tokens with I-LOC tags can’t be preceded by tokens with I-PER tags (which is allowed in IOB however). We fixed this by considering all such “I-” tags as “B-” tags where the preceding tag is not of the same type. A 64155-3565-3564 split was provided. We compared used the results from BANNER (Ashrafi et al., 2020) as a baseline. As we had to correct some labels in the NER dataset, we reproduced the experiments of BANNER to ensure a fair comparison. We followed a fine-tuning-based (as opposed to a feature-based) approach for NER and used Macro-F1 for evaluation.

5. **Natural Language Inference (NLI)**: Due to the unavailability of any double sentence classification dataset in Bangla, we curated an NLI dataset. For this task, two sentences are given as input: a premise and a hypothesis. The model is tasked to predict whether or not the hypothesis is entailment, contradiction, or neutral to the premise. We used the same curation procedure as the XNLI (Conneau et al., 2018) dataset: we translated the MultiNLI (Williams et al., 2018) training data using the English to Bangla translation model by Hasan et al. (2020) and had the evaluation sets translated by expert human translators. Due to the possibility of incursions of error during automatic translation, we used the Language-Agnostic BERT Sentence Embeddings (LaBSE) (Feng et al., 2020) of the translations and original sentences to compute their similarity. All sentences below a similarity threshold of 0.70 were discarded. Moreover, to ensure good-quality human translation, we used similar quality assurance strategies as Guzmán et al. (2019).