BanglaBERT: Language Model Pretraining and Benchmarks for Low-Resource Language Understanding Evaluation in Bangla

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Abstract

In this work, we introduce *BanglaBERT*, a BERT-based Natural Language Understanding (NLU) model pretrained in Bangla, a widely spoken yet low-resource language in the NLP literature. To pretrain BanglaBERT, we collect 27.5 GB of Bangla pretraining data (dubbed 'Bangla2B+') by crawling 110 popular Bangla sites. We introduce two downstream task datasets on natural language inference and question answering and benchmark on four diverse NLU tasks covering text classification, sequence labeling, and span prediction. In the process, we bring them under the first-ever Bangla Language Understanding Benchmark (BLUB). BanglaBERT achieves state-of-the-art results outperforming multilingual and monolingual models. We are making the models, datasets, and a leaderboard publicly available at https://github.com/csebuetnlp/banglabert to advance Bangla NLP.

1 Introduction

Despite being the sixth most spoken language in the world with over 300 million native speakers constituting 4% of the world's total population,[1] Bangla is considered a resource-scarce language. Joshi et al. (2020b) categorized Bangla in the language group that lacks efforts in labeled data collection and relies on self-supervised pretraining (Devlin et al., 2019; Radford et al., 2019; Liu et al., 2019) to boost the natural language understanding (NLU) task performances. To date, the Bangla language has been continuing to rely on fine-tuning multilingual pretrained language models (PLMs) (Ashrafi et al., 2020; Das et al., 2021; Islam et al., 2021). However, since multilingual PLMs cover a wide range of languages (Conneau and Lample, 2019; Conneau et al., 2020), they are large (have hundreds of millions of parameters) and require substantial computational resources for fine-tuning. They also tend to show degraded performance for low-resource languages (Wu and Dredze, 2020) on downstream NLU tasks. Motivated by the triumph of language-specific models (Martin et al. (2020); Polignano et al. (2019); Canete et al. (2020); Antoun et al. (2020), *inter alia*) over multilingual models in many other languages, in this work, we present **BanglaBERT** – a BERT-based (Devlin et al., 2019) Bangla NLU model pretrained on 27.5 GB data (which we name '**Bangla2B+**') we meticulously crawled 110 popular Bangla websites to facilitate NLU applications in Bangla. Since most of the downstream task datasets for NLP applications are in the English language, to facilitate zero-shot transfer learning between English and Bangla, we additionally pretrain a model in both languages; we name the model **BanglishBERT**.

We also introduce a Bangla Natural Language Inference (NLI) and a Question Answering (QA) dataset, tasks previously unexplored in Bangla, and evaluate BanglaBERT on four diverse downstream tasks on sentiment classification, NLI, named entity recognition, and QA. We bring these tasks together to establish the first-ever **B**angla **L**anguage **U**nderstanding **B**enchmark (**BLUB**). We compare widely used multilingual models to BanglaBERT using BLUB and find that BanglaBERT excels on all the tasks.

We summarize our contributions as follows:

1. We present two new pretrained models: BanglaBERT and BanglishBERT; and introduce new Bangla NLI and QA datasets.
2. We introduce the Bangla Language Understanding Benchmark (BLUB) and show that, in the supervised setting, BanglaBERT outperforms mBERT and XLM-R (base) by 6.8 and 4.3 BLUB scores, while in zero-shot cross-lingual transfer, BanglishBERT outperforms them by 15.5 and 10.6, respectively.

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[†] Work started while at UCLA.
[1] https://w.wiki/Psq

3. We release the code, models, and also provide a leaderboard to spur future research on Bangla NLU.

2 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 more extensive web-crawled data with heavy filtering and cleaning.

Bangla is a rather resource-constrained language in the web domain; for example, the Bangla Wikipedia dump from July 2021 is only 650 MB, 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 110 Bangla websites by their Amazon Alexa rankings[2] and the volume and quality of extractable texts by inspecting each website. The contents included encyclopedias, news, blogs, e-books, stories, social media/forums, etc. The amount of data totaled around 35 GB.

There are also noisy sources of Bangla data dumps, a couple of prominent ones being OSCAR (Suárez et al., 2019) and CCNet (Wenzek et al., 2020). However, they contained lots of offensive texts; we found them infeasible to clean thoroughly. Fearing their potentially harmful impacts (Luccioni and Viviano, 2021), we opted not to use them. We further discuss ethical considerations at the end of the paper.

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 27.5 GB in size containing 5.25M documents having 306.66 words on average.[3]

We trained a Wordpiece (Wu et al., 2016) vocabulary of 32k subword 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. We limited the length of a training sample to 512 tokens and did not cross document boundaries (Liu et al., 2019) while creating a data point. After tokenization, we had 7.18M samples with an average length of 304.14 tokens and containing 2.18B tokens in total; hence we named the dataset '*Bangla2B+*'.

2.3 Pretraining Objective

Self-supervised pretraining objectives leverage unlabeled data. For example, 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., 2020a) masked contiguous spans of tokens, while works like XLNet (Yang et al., 2019) introduced objectives like factorized language modeling.

We pretrained BanglaBERT using ELECTRA (Clark et al., 2020b), pretrained with the Replaced Token Detection (RTD) objective, where a generator 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 them using the rest of the input (i.e., standard MLM). The masked tokens are then replaced by tokens sampled from the generator's output distribution for the corresponding masks, and 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. (2020b) 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 performance to RoBERTa or XLNet with only a quarter of their training time. This computational efficiency motivated us to use ELECTRA for our implementation of BanglaBERT.

2.4 Model Architecture & Hyperparameters

We pretrained the base ELECTRA model (a 12-layer Transformer encoder with 768 embedding size, 768 hidden size, 12 attention heads, 3072 feed-forward size, generator-to-discriminator ratio $\frac{1}{3}$, 110M parameters) with 256 batch size for 2.5M steps on a v3-8 TPU instance on GCP. We used

[2] www.alexa.com/topsites/countries/BD

[3] The complete list and statistics can be found in the Appendix.

Task	Corpus	|Train|	|Dev|	|Test|	Metric	Domain
Sentiment Classification	SentNoB	12,575	1,567	1,567	Macro-F1	Social Media
Natural Language Inference	BNLI	381,449	2,419	4,895	Accuracy	Miscellaneous
Named Entity Recognition	MultiCoNER	14,500	800	800	Micro-F1	Miscellaneous
Question Answering	BQA, TyDiQA	127,771	2,502	2,504	EM/F1	Wikipedia

Table 1: Statistics of the Bangla Language Understanding Evaluation (BLUB) benchmark.

the Adam (Kingma and Ba, 2015) optimizer with a 2e-4 learning rate and linear warmup of 10k steps.

2.5 BanglishBERT

Often labeled data in a low-resource language for a task may not be available but be abundant in high-resource languages like English. In these scenarios, zero-shot cross-lingual transfer (Artetxe and Schwenk, 2019) provides an effective way to be still able to train a multilingual model on that task using the high-resource languages and be able to transfer to low-resource ones. To this end, we pre-trained a bilingual model, named **BanglishBERT**, on Bangla and English together using the same set of hyperparameters mentioned earlier. We used the BERT pretraining corpus as the English data and trained a joint bilingual vocabulary (each language having $\sim$16k tokens). We upsampled the Bangla data during training to equal the participation of both languages.

3 The Bangla Language Understanding Benchmark (BLUB)

Many works have studied different Bangla NLU tasks in isolation, e.g., sentiment classification (Das and Bandyopadhyay, 2010; Sharfuddin et al., 2018; Tripto and Ali, 2018), semantic textual similarity (Shajalal and Aono, 2018), parts-of-speech (PoS) tagging (Alam et al., 2016), named entity recognition (NER) (Ashrafi et al., 2020). However, Bangla NLU has not yet had a comprehensive, unified study. Motivated by the surge of NLU research brought about by benchmarks in other languages, e.g., English (Wang et al., 2018), French (Le et al., 2020), Korean (Park et al., 2021), we establish the first-ever Bangla Language Understanding Benchmark (BLUB). NLU generally comprises three types of tasks: text classification, sequence labeling, and text span prediction. Text classification tasks can further be sub-divided into single-sequence and sequence-pair classification. Therefore, we consider a total of four tasks for BLUB. For each task type, we carefully select one downstream task dataset. We emphasize the quality and open availability of the datasets while making the selection. We briefly mention them below:

1. **Single-Sequence Classification**: Sentiment classification is perhaps the most-studied Bangla NLU task, with some of the earlier works dating back over a decade (Das and Bandyopadhyay, 2010). Hence, we chose this as the single-sequence classification task. However, most Bangla sentiment classification datasets are not publicly available. We could only find two public datasets: *BYSA* (Tripto and Ali, 2018) and *SentNoB* (Islam et al., 2021). We found BYSA to have many duplications. Even worse, many duplicates had different labels. SentNoB had better quality and covered a broader set of domains, making the classification task more challenging. Hence, we opted to use the latter.

2. **Sequence-Pair Classification**: In contrast to single-sequence classification, there has been a dearth of sequence-pair classification works in Bangla. We found work on semantic textual similarity (Shajalal and Aono, 2018), but the dataset is not publicly available. As such, we curated a new Bangla Natural Language Inference (*BNLI*) dataset for sequence-pair classification. We chose NLI as the representative task due to its fundamental importance in NLU. Given two sentences, a premise and a hypothesis as input, a 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.[4] Due to the possibility of the incursion of errors 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 and discarded all sentences below a simi-

[4]More details are presented in the ethical considerations section.

Models	|Params.|	SC	NLI	NER	QA	BLUB Score
Zero-shot cross-lingual transfer learning						
mBERT	180M	27.05	62.22	39.27	59.01/64.18	50.35
XLM-R (base)	270M	42.03	72.18	45.37	55.03/61.83	55.29
XLM-R (large)	550M	49.49	78.13	56.48	71.13/77.70	66.59
BanglishBERT	110M	48.39	75.26	55.56	**72.23**/77.94	65.88
Supervised fine-tuning						
mBERT	180M	67.59	75.13	68.97	67.12/72.64	70.29
XLM-R (base)	270M	69.54	78.46	73.32	68.09/74.27	72.82
XLM-R (large)	550M	70.97	**82.40**	**78.39**	**73.15/79.06**	76.79
IndicBERT	18M	68.41	77.11	54.13	50.84/57.47	61.59
sahajBERT	18M	71.12	76.92	70.94	65.48/70.69	71.03
BanglaBERT	110M	**72.89**	**82.80**	**77.78**	**72.63/79.34**	**77.09**

Table 2: Performance comparison of pretrained models on different downstream tasks. Scores in bold texts have statistically significant ($p < 0.05$) difference from others with bootstrap sampling (Koehn, 2004).

larity threshold of 0.70. Moreover, to ensure good-quality human translation, we used similar quality assurance strategies as Guzmán et al. (2019).

3. **Sequence Labeling**: In this task, all words of a text sequence have to be classified. Named Entity Recognition (NER) and Parts-of-Speech (PoS) tagging are two of the most prominent sequence labeling tasks. We chose the Bangla portion of SemEval 2022 *MultiCoNER* (Malmasi et al., 2022) dataset for BLUB.

4. **Span Prediction**: Extractive question answering is a standard choice for text span prediction. Similar to BNLI, we machine-translated the *SQuAD 2.0* (Rajpurkar et al., 2018) dataset and used it as the training set (BQA). For validation and test, We used the Bangla portion of the *TyDiQA*[5] (Clark et al., 2020a) dataset. We posed the task analogous to SQuAD 2.0: presented with a text passage and a question, a model has to predict whether or not it is answerable. If answerable, the model has to find the minimal text span that answers the question.

We present detailed statistics of the BLUB benchmark in Table 1.

4 Experiments & Results

Setup We fine-tuned BanglaBERT and BanglishBERT on the four downstream tasks and compared them with several multilingual models: mBERT (Devlin et al., 2019), XLM-R base and large (Conneau et al., 2020), and IndicBERT (Kakwani et al., 2020), a multilingual model for Indian languages; and sahajBERT (Diskin et al., 2021), an ALBERT-based (Lan et al., 2020) pretrained Bangla model. All pretrained models were fine-tuned for 3-20 epochs with batch size 32, and the learning rate was tuned from {2e-5, 3e-5, 4e-5, 5e-5}. The final models were selected based on the validation performances after each epoch. We performed fine-tuning with three random seeds and reported their average scores in Table 2. We reported the average performance of all tasks as the BLUB score.

Zero-Shot Transfer We show the zero-shot cross-lingual transfer results of the multilingual models fine-tuned on the English counterpart of each dataset (SentNob had no English equivalent; hence we used the Stanford Sentiment Treebank (Socher et al., 2013) for the zero-shot sentiment classification task). Here BanglishBERT achieves strong cross-lingual performance over similar-sized models but falls short of XLM-R (large) by about 1 BLUB score. This is an expected outcome since cross-lingual effectiveness depends explicitly on model size (K et al., 2020).

Supervised Fine-tuning In the supervised fine-tuning setup, BanglaBERT outperformed multilingual models and monolingual sahajBERT on all the tasks, achieving a BLUB score of 77.09, even coming head-to-head with XLM-R (large). BanglaBERT is not only superior in performance but also substantially compute- and memory-efficient. For instance, it may seem that sahajBERT is more efficient than BanglaBERT due to its smaller size, but it takes 2-3.5x time and 2.4-

[5] We removed the Yes/No questions from TyDiQA and subsampled the unanswerable questions to have equal proportion.

3.33x memory as BanglaBERT to fine-tune.[6]

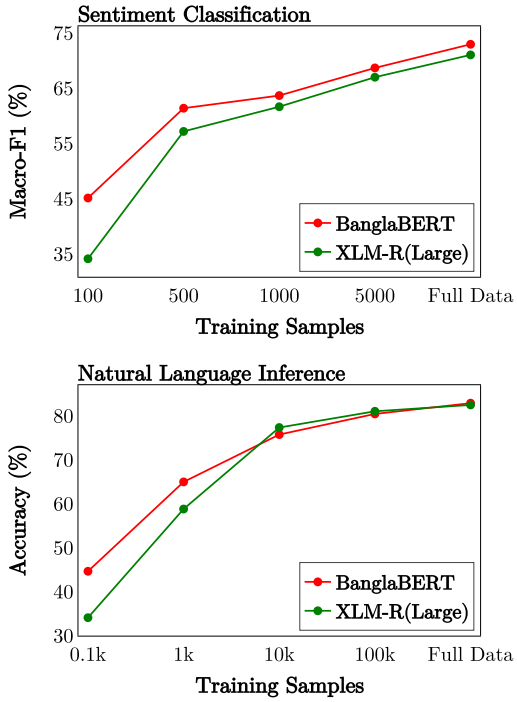

Figure 1: Sample-efficiency tests with SC and NLI.

Sample efficiency It is often challenging to annotate training samples in real-world scenarios, especially for low-resource languages like Bangla. So, in addition to compute- and memory-efficiency, sample-efficiency (Howard and Ruder, 2018) is another necessity of PLMs. To assess the sample efficiency of BanglaBERT, we limit the number of training samples and see how it fares against other models. We compare it with XLM-R (large) and plot their performances on the SC and NLI tasks[7] for different sample size in Figure 1.

Results show that when we have fewer number of samples ($\leq 1k$), BanglaBERT has substantially better performance (2-9% on SC and 6-10% on NLI with $p < 0.05$) over XLM-R (large), making it more practically applicable for resource-scarce downstream tasks.

5 Conclusion & Future Works

Creating language-specific models is often infeasible for low-resource languages lacking ample data. Hence, researchers are compelled to use multilingual models for languages that do not have strong pretrained models. To this end, we introduced BanglaBERT and BanglishBERT, two NLU models in Bangla, a widely spoken yet low-resource language. We presented new downstream datasets on NLI and QA, and established the BLUB benchmark, setting new state-of-the-art results with BanglaBERT. In future, we will include other Bangla NLU benchmarks (e.g., dependency parsing (de Marneffe et al., 2021)) in BLUB and investigate the benefits of initializing Bangla NLG models from BanglaBERT.

[6]We present a detailed comparison in the Appendix.

[7]Results for the other tasks can be found in the Appendix.

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Ethical Considerations

Dataset and Model Release The **Copy Right Act, 2000**[8] of Bangladesh allows reproduction and public release of copy-right materials for non-commercial research purposes. As a transformative research work, we will release BanglaBERT under a non-commercial license. Furthermore, we will release only the pretraining data for which we know the distribution will not cause any copyright infringement. The downstream task datasets can all be made publicly available under a similar non-commercial license.

Quality Control in Human Translation Translations were done by expert translators who provide translation services for renowned Bangla newspapers. Each translated sentence was further assessed for quality by another expert. If found to be of low quality, it was again translated by the original translator. The sample was then discarded altogether if found to be of low quality again. Fewer than 100 samples were discarded in this process. Translators were paid as per standard rates in local currencies.

Text Content We tried to minimize offensive texts by explicitly crawling the sites where such contents would be nominal. However, we cannot guarantee that there is absolutely no objectionable content present and therefore recommend using the model carefully, especially for text generation purposes. Furthermore, we removed the personal information of the content writers by discarding the author fields while collecting the data.

[8]http://bdlaws.minlaw.gov.bd/act-details-846.html

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Appendix

Pretraining Data Sources

We used the following sites for data collection. We categorize the sites into six types:

Encyclopedia:

- bn.banglapedia.org
- bn.wikipedia.org
- songramernotebook.com

News:

- anandabazar.com
- arthoniteerkagoj.com
- bangla.24livenewspaper.com
- bangla.bdnews24.com
- bangla.dhakatribune.com
- bangla.hindustantimes.com
- bangladesherkhela.com
- banglanews24.com
- banglatribune.com
- bbc.com
- bd-journal.com
- bd-pratidin.com
- bd24live.com
- bengali.indianexpress.com
- bigganprojukti.com
- bonikbarta.net
- chakarianews.com
- channelionline.com
- ctgtimes.com
- ctn24.com
- daily-bangladesh.com
- dailyagnishikha.com
- dainikazadi.net
- dainikdinkal.net
- dailyfulki.com
- dailyinqilab.com
- dailynayadiganta.com
- dailysangram.com
- dailysylhet.com
- dainikamadershomoy.com
- dainikshiksha.com
- dhakardak-bd.com
- dmpnews.org
- dw.com
- eisamay.indiatimes.com
- ittefaq.com.bd
- jagonews24.com
- jugantor.com
- kalerkantho.com
- manobkantha.com.bd
- mzamin.com
- ntvbd.com
- onnodristy.com
- pavilion.com.bd
- prothomalo.com
- protidinersangbad.com
- risingbd.com
- rtvonline.com
- samakal.com
- sangbadpratidin.in
- somoyerkonthosor.com
- somoynews.tv
- tbsnews.net
- teknafnews.com
- thedailystar.net
- voabangla.com
- zeenews.india.com
- zoombangla.com

Blogs:

- amrabondhu.com
- banglablog.in
- bigganblog.org
- biggani.org
- bigyan.org.in
- bishorgo.com
- cadetcollegeblog.com
- choturmatrik.com
- horoppa.wordpress.com
- muktangon.blog
- roar.media/bangla
- sachalayatan.com
- shodalap.org
- shopnobaz.net
- somewhereinblog.net
- subeen.com
- tunerpage.com
- tutobd.com

E-books/Stories:

- banglaepub.github.io
- bengali.pratilipi.com
- bn.wikisource.org
- ebanglalibrary.com
- eboipotro.github.io
- golpokobita.com
- kaliokalam.com
- shirisherdalpala.net
- tagoreweb.in

Social Media/Forums:

- banglacricket.com
- bn.globalvoices.org
- helpfulhub.com
- nirbik.com
- pchelplinebd.com
- techtunes.io

Miscellaneous:

- banglasonglyric.com
- bdlaws.minlaw.gov.bd
- bdup24.com
- bengalisongslyrics.com
- dakghar.org
- gdn8.com
- gunijan.org.bd
- hrw.org
- jakir.me
- jhankarmahbub.com
- jw.org
- lyricsbangla.com
- neonaloy.com
- porjotonlipi.com
- sasthabangla.com
- tanzil.net

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

Additional Sample Efficiency Tests

We plot the the sample efficiency results of the NER and QA tasks in Figure 2.

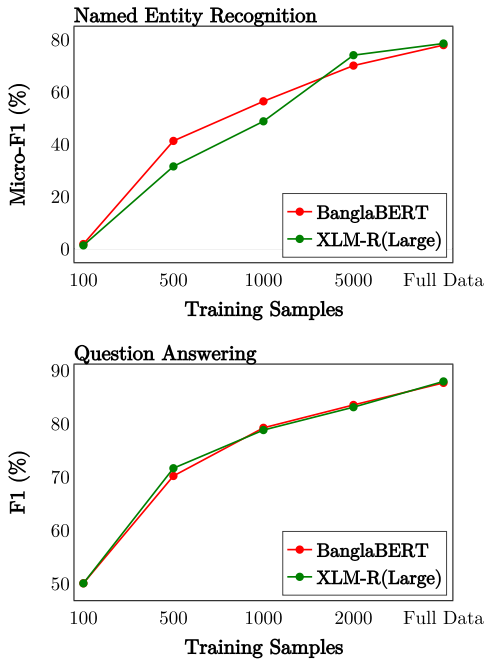

Figure 2: Sample-efficiency tests with NER and QA.

Similar results are also observed here for the NER task, where BanglaBERT is more sample-efficient when we have $\leq 1k$ training samples. In the QA task however, both models have identical performance for all sample counts.

Compute and Memory Efficiency Tests

To validate that BanglaBERT is more efficient in terms of memory and compute, we measured each model's training time and memory usage during the fine-tuning of each task. All tests were done on a desktop machine with an 8-core Intel Core-i7 11700k CPU and NVIDIA RTX 3090 GPU. We used the same batch size, gradient accumulation steps, and sequence length for all models and tasks for a fair comparison. We use relative time and memory (GPU VRAM) usage considering those of BanglaBERT as units. The results are shown in Table 3. (We mention the upper and lower values of the different tasks for each model)

Model	Time	Memory Usage
mBERT	1.14x-1.92x	1.12x-2.04x
XLM-R (base)	1.29-1.81x	1.04-1.63x
XLM-R (large)	3.81-4.49x	4.44-5.55x
SahajBERT	2.40-3.33x	2.07-3.54x
BanglaBERT	**1.00x**	**1.00x**

Table 3: Compute and memory efficiency tests