

MuRIL: Multilingual Representations for Indian Languages

Simran Khanuja¹ Diksha Bansal^{* 2} Sarvesh Mehtani^{* 3} Savya Khosla^{* 4} Atreyee Dey¹
 Balaji Gopalan¹ Dilip Kumar Margam¹ Pooja Aggarwal¹ Rajiv Teja Nagipogu¹ Shachi Dave¹
 Shruti Gupta¹ Subhash Chandra Bose Gali¹ Vish Subramanian¹ Partha Talukdar¹

¹Google ²Indian Institute of Technology, Patna

³Indian Institute of Technology, Bombay ⁴Delhi Technological University

1 Why MuRIL?

India is a multilingual society with 1369 rationalized languages and dialects being spoken across the country (INDIA, 2011). Of these, the 22 scheduled languages have a staggering total of 1.17 billion speakers and 121 languages have more than 10,000 speakers (INDIA, 2011). India also has the second largest (and an ever growing) digital footprint (Statista, 2020). Despite this, today’s state-of-the-art multilingual systems perform sub-optimally on Indian (IN) languages (as shown in Figure 1). This can be explained by the fact that multilingual language models (LMs) are often trained on 100+ languages together, leading to a small representation of IN languages in their vocabulary and training data. Multilingual LMs are substantially less effective in resource-lean scenarios (Wu and Dredze, 2020; Lauscher et al., 2020), as limited data doesn’t help capture the various nuances of a language. One also commonly observes IN language text transliterated to Latin or code-mixed with English, especially in informal settings (for example, on social media platforms) (Rijhwani et al., 2017). This phenomenon is not adequately handled by current state-of-the-art multilingual LMs. Few works like Conneau et al. (2020) use transliterated data in training, but limit to including naturally present web crawl data.

To address the aforementioned gaps, we propose MuRIL, a multilingual LM specifically built for IN languages. MuRIL is trained on significantly large amounts of IN text corpora *only*. We explicitly augment monolingual text corpora with *both*

^{*} Work done during a summer internship at Google India. Correspondence to the MuRIL Team (muriil-contact@google.com)

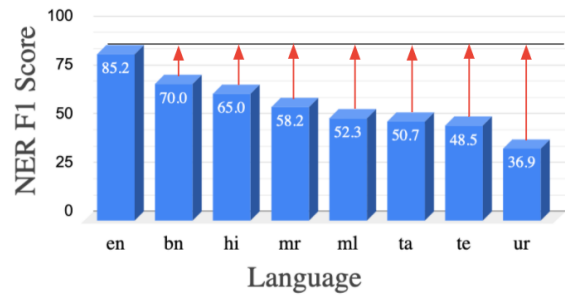


Figure 1: *mBERT*’s (zero-shot) performance on Named Entity Recognition (NER). We observe significant differences between the performance on the English test set and other IN languages. This pattern is representative of current state-of-the-art multilingual models for Indian (IN) languages.

translated and transliterated document pairs, that serve as supervised cross-lingual signals in training. MuRIL significantly outperforms multilingual BERT (mBERT) on all tasks in the challenging cross-lingual XTREME benchmark (Hu et al., 2020). We also present results on transliterated (native → Latin) test sets of the chosen datasets, and demonstrate the efficacy of MuRIL in handling transliterated data.

2 Model and Data

MuRIL currently supports 17 languages for which monolingual data is publicly available. These are further grouped into 16 IN languages and English (*en*). The IN languages include: Assamese (*as*), Bengali (*bn*), Gujarati (*gu*), Hindi (*hi*), Kannada (*kn*), Kashmiri (*ks*), Malayalam (*ml*), Marathi (*mr*), Nepali (*ne*), Oriya (*or*), Punjabi (*pa*), Sanskrit (*sa*), Sindhi (*sd*), Tamil (*ta*), Telugu (*te*) and Urdu (*ur*).

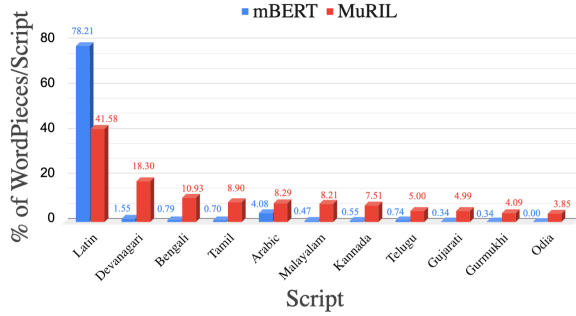


Figure 4: *Percentage of WordPieces/Script* in mBERT and MuRIL vocabularies. A WordPiece belongs to the category if all of its characters fall into the category or are digits.

library from Tensorflow Text³. Since our data is upsampled, we set the language smoothing exponent from the vocabulary generation tool to 1, and the rest of the parameters are set to their default value. The final vocabulary size is **197,285**. Figure 3 shows a few common IN language words tokenized using mBERT and MuRIL vocabularies. We also plot the *fertility ratio* (average number of sub-words/word) of mBERT and MuRIL tokenizers on a random sample of text from our training data in Figure 5. Here, a higher fertility ratio equates to a larger number of sub-words per word, eventually leading to a loss in preservation of semantic meaning. We observe a higher fertility ratio for mBERT as compared to MuRIL because of two reasons. First, there is very little representation of IN languages in the mBERT vocabulary⁴ (refer to Figure 4 for a comparison) and second, the vocabulary does not take transliterated words into account. Since vocabulary plays a key role in the performance of transformer based LMs (Chung et al., 2020; Artetxe et al., 2020), MuRIL’s vocabulary (specifically focused on IN languages) is a significant contributor to the model’s improved performance over mBERT.

Pre-training Details: We pre-train a BERT base encoder model making use of the MLM and TLM objectives. We keep a maximum sequence length of 512, a global batch size of 4096, and train for 1M steps (with 50k warm-up steps and a linear decay

³https://github.com/tensorflow/text/blob/master/tensorflow_text/tools/wordpiece_vocab/generate_vocab.py

⁴<http://juditacs.github.io/2019/02/19/bert-tokenization-stats.html>

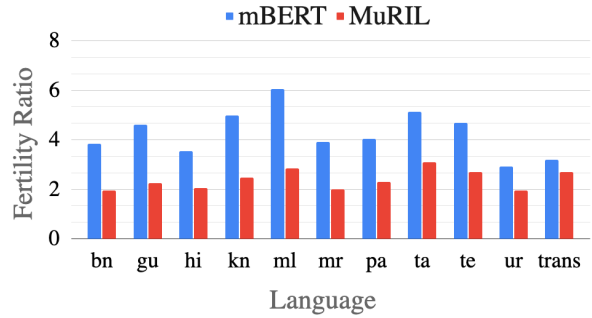


Figure 5: *Fertility Ratio for IN languages* using mBERT and MuRIL tokenizers. Here, *trans* subsumes all IN languages transliterated from their native script to Latin.

after). We make use of the AdamW optimizer with a learning rate of $5e-4$. Our final model has 236M parameters, is trained on $\sim 16B$ unique tokens, and has a vocabulary of 197,285. Please note that we preserve the case to prevent stripping off accents, often present in IN languages.

3 Evaluation

In all our experiments, the goal has been to improve the model’s performance for cross-lingual understanding. For this reason, the results are computed in a zero-shot setting, i.e., by fine-tuning models on the labeled training set of one language and evaluating on test sets for all languages. Here, our labeled training sets are in English for all tasks. We choose the XTREME benchmark (Hu et al., 2020) as a test-bed. XTREME covers 40 typologically diverse languages spanning 12 language families and includes 9 tasks that require reasoning about different levels of syntax or semantics (Hu et al., 2020).

We present our results in Table 1. Since MuRIL currently supports IN languages only, we compute average performances across IN language test sets for all tasks. We also transliterate IN language test sets (native \rightarrow Latin) using the *indic-trans* library (Bhat et al., 2015), and report results on the same in Table 2. Detailed results for each language and task can be found in Appendix B. On average, MuRIL significantly beats mBERT across *all* tasks. This difference is more so for the transliterated test sets, which is expected because mBERT does not include transliterated data in training. We analyse predictions of mBERT and MuRIL on a random sample of test examples in Appendix C.

Fine-tuning Details: For each task, we report re-

Model	PANX F1	UDPOS F1	XNLI Acc.	Tatoeba Acc.	XQuAD F1/EM	MLQA F1/EM	TyDiQA-GoldP F1/EM	Avg.
mBERT	58.0	71.2	66.8	18.4	71.2/58.2	65.3/51.2	63.1/51.7	59.1
MuRIL	77.6	75.0	74.1	25.2	79.1/65.6	73.8/58.8	75.4/59.3	68.6

Table 1: *Results for MuRIL and mBERT on XTREME (IN).* We observe that MuRIL significantly outperforms mBERT on all the datasets in XTREME. Note that here we present the average performance on test sets for IN languages only that MuRIL currently supports. Please refer to Section 3 for more details.

Model	PANX F1	UDPOS F1	XNLI Acc.	Tatoeba Acc.	Avg.
mBERT	14.2	28.2	39.2	2.7	21.1
MuRIL	57.7	62.1	64.7	11.0	48.9

Table 2: *Results for MuRIL and mBERT on XTREME (IN-tr).* We transliterate IN language test sets (native → Latin) and present the average performance across all transliterated test sets. Please refer to Section 3 for more details.

Task	Dataset	Batch Size	Learning Rate	No. of Epochs	Warmup Ratio	Maximum Sequence Length
Structured Prediction	PANX	32	2e-5	10	0.1	128
	UDPOS	32	2e-5	10	0.1	128
Classification	XNLI	32	2e-5	5	0.1	128
Question Answering	XQuAD	32	3e-5	2	0.1	384
	MLQA	32	3e-5	2	0.1	384
	TyDiQA-GoldP	32	3e-5	2	0.1	384

Table 3: *Fine-tuning hyperparameter details for each dataset in XTREME.* We use the same hyperparameters for fine-tuning both mBERT and MuRIL. Please refer to Section 3 for more details.

sults of the best performing checkpoint on the evaluation set. We present the hyperparameter details for each task in Table 3. Note that we use the same hyperparameters for evaluating both mBERT and MuRIL. We fine-tune the model on the English training set for each task, and evaluate on the test sets of all IN languages. For TyDiQA-GoldP, we augment the training set with SQuAD English training set, similar to Fang et al. (2020), and then fine-tune the model. For Tatoeba, we do not fine-tune the model, and use the *pooled_output* of the last layer as the sentence embedding.

4 How to use MuRIL?

We have released the MuRIL encoder on TFHub⁵ with detailed usage instructions. We have also released a pre-processor module with the same, that processes raw text into the expected input format for the encoder. Additionally, we have released the MuRIL pre-trained model, i.e., with the MLM layer intact (to enable masked word predictions) on HuggingFace⁶. We sincerely hope MuRIL aids

⁵<https://tfhub.dev/google/MuRIL/1>

⁶<https://huggingface.co/google/muril-base-cased>

in building better technologies and applications for Indian languages.

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Example	Translation	mBERT	MuRIL	Label
अटलांटा फाल्कन्स	Atlanta Falcons	B-LOC I-LOC	B-ORG I-ORG	B-ORG I-ORG
शिरडी के साई बाबा	Shirdi's Sai Baba	B-LOC I-LOC I-LOC I-LOC	B-PER I-PER I-PER I-PER	B-PER I-PER I-PER I-PER
बाजीराव मस्तानी (फिल्म)	Bajirao Mastani (Film)	B-PER I-PER	B-ORG I-ORG	B-ORG I-ORG
1988 wimbledon tennis pratyogita	1988 wimbledon tennis championship	B-LOC I-LOC I-LOC I-LOC	B-ORG I-ORG I-ORG I-ORG	B-ORG I-ORG I-ORG I-ORG

Figure 6: NER Predictions

A Pre-training Data Statistics

The upsampled token counts for each language and corpus are reported in Table 4.

B Detailed Results

We report per language results for each *XTREME* (IN) dataset in Tables 5 (PANX), 6 (UDPOS), 7 (XNLI), 8 (Tatoeba), 9 (XQuAD, MLQA) and 10 (TyDiQA-GoldP). The detailed results for transliterated test sets are shown in Tables 11 (PANX), 12 (UDPOS), 13 (XNLI), 14 (Tatoeba).

C Analysis

In this section, we analyse the predictions of mBERT and MuRIL on a random sample of test examples.

Named Entity Recognition (NER): NER is the task of locating and classifying entities in unstructured text into pre-defined categories such as person, location, organization etc. In Figure 6, we present entity predictions of mBERT and MuRIL on a random sample of test examples.

In the first example, we observe that *Atlanta Falcons*, a football team, is predicted as *ORG* (Organisation) by MuRIL but *LOC* (Location) by mBERT, probably looking at the word *Atlanta* without context.

In the second example, MuRIL correctly takes the context into account and predicts *Shirdi's Sai Baba* as *PER* (Person), whereas mBERT resorts to predicting *LOC* taking a cue from the word *Shirdi*. A similar pattern is observed in other examples like *Nepal's Prime Minister*, *the President of America* etc.

In the third example, the *Bajirao Mastani* movie is being spoken about, specified with the word (film) in parentheses, which MuRIL correctly captures.

In the last example, we observe that MuRIL can correctly classify misspelled words (*wimbledon*)

Example	Translation	mBERT	MuRIL	Label
अच्छा हुआ अकाउंट बंद नहीं हुआ	It's good that the account hasn't closed	negative	positive	positive
raamu ne kahani kii raftaar kahin thamane nahin di.	Ramu didn't let the film's pace slow down	negative	positive	positive

Figure 7: Sentiment Predictions

ID	Context	Question	Answer	mBERT	MuRIL
1)	रिया को अंग्रेजी में "Rhea" लिखा जाता है। प्राचीन यूनानी धर्म में रिया देवताओं की माता थीं।	Titan Rhea का ग्रीक भाषा में क्या मतलब है?	देवताओं की माता	रिया को अंग्रेजी में "Rhea"	देवताओं की माता
2)	बैंक की परिभाषा हर देश के अनुसार अलग-अलग है।	प्रत्येक देश में क्या अलग है?	बैंक की परिभाषा	बैंक	बैंक की परिभाषा
TRANSLATION					
1)	RHEIA is spelled "Rhea" in English. RHEIA was the mother of gods in ancient Greek religion.	What does Titan Rhea mean in Greek?	Mother of gods	RHEIA in English "Rhea"	Mother of gods
2)	The definition of a bank varies from country to country.	What is different in each country?	Definition of a bank	Bank	Definition of a bank

Figure 8: Question Answering

utilising the context.

Sentiment Analysis: Sentiment analysis is a sentence classification task wherein each sentence is labeled to be expressing a positive, negative or neutral sentiment. We present the sentiment predictions on a sample set of sentences in Figure 7.

In the first example, "*It's good that the account hasn't closed*", we observe that the original Hindi sentence borrows an English word (*account*) and also contains a negation (*not*) word, but MuRIL correctly predicts it as expressing a positive statement. A similar observation can be made in the second example where MuRIL correctly predicts the sentiment of the transliterated sentence, "*Ramu didn't let the film's pace slow down*".

Question Answering (QA): QA is the task of answering a question based on the given context or world knowledge. We show two context-question pairs, with their answers and predicted answers in Figure 8.

In the first example, despite the fact that the word *Greek* is referred to by its Hindi translation in the context and its transliteration in the question (as highlighted), MuRIL correctly infers the answer from the context.

In the second example, MuRIL understands that "*bank ki paribhasha*" (the definition of a bank), as a whole entity, is what differs across countries and not banks.

Language	Monolingual		Translated			Transliterated	
	Wikipedia	Common Crawl	Wikipedia	Common Crawl	PMINDIA	Wikipedia	Dakshina
as	2.5e+6	4.4e+6	-	-	-	2.5e+6	-
as-tr	-	-	-	-	-	2.5e+6	-
bn	2.7e+7	3.7e+8	2.7e+7	3.7e+8	4.4e+5	2.7e+7	1.2e+5
bn-tr	-	-	-	-	-	2.7e+7	1.2e+5
en	2.8e+9	1.7e+9	2.3e+8	2.3e+9	5.8e+6	-	-
gu	6.7e+6	5.1e+7	6.7e+6	5.1e+7	8.5e+5	6.7e+6	1.5e+5
gu-tr	-	-	-	-	-	6.7e+6	1.5e+5
hi	3.8e+7	7.5e+8	3.8e+7	7.5e+8	1.2e+6	3.8e+7	1.8e+5
hi-tr	-	-	-	-	-	3.8e+7	1.8e+5
kn	1.5e+7	5.0e+7	1.5e+7	5.0e+7	4.7e+5	1.5e+7	1.1e+5
kn-tr	-	-	-	-	-	1.5e+7	1.1e+5
ks	1.1e+4	-	-	-	-	-	-
ml	1.4e+7	9.8e+7	1.4e+7	9.8e+7	3.6e+5	1.4e+7	8.6e+4
ml-tr	-	-	-	-	-	1.4e+7	8.6e+4
mr	8.3e+6	8.3e+7	8.3e+6	8.3e+7	5.2e+5	8.3e+6	9.8e+4
mr-tr	-	-	-	-	-	8.3e+6	9.8e+4
ne	5.0e+6	7.2e+7	5.0e+6	7.2e+7	-	5.0e+6	-
ne-tr	-	-	-	-	-	5.0e+6	-
or	3.4e+6	1.1e+7	3.4e+6	1.1e+7	-	3.4e+6	-
or-tr	-	-	-	-	-	3.4e+6	-
pa	9.1e+6	3.8e+7	9.1e+6	3.8e+7	-	9.1e+6	1.8e+5
pa-tr	-	-	-	-	-	9.1e+6	1.8e+5
sa	2.6e+6	1.7e+6	-	-	-	-	-
sd	3.4e+6	3.3e+7	3.4e+6	3.3e+7	-	-	-
ta	2.6e+7	2.3e+8	2.6e+7	2.3e+8	5.2e+5	2.6e+7	9.5e+4
ta-tr	-	-	-	-	-	2.6e+7	9.5e+4
te	3.0e+7	8.0e+7	3.0e+7	8.0e+7	5.7e+5	3.0e+7	9.4e+4
te-tr	-	-	-	-	-	3.0e+7	9.4e+4
ur	2.3e+7	2.2e+8	2.1e+7	2.2e+8	-	2.3e+7	1.7e+5
ur-tr	-	-	-	-	-	2.3e+7	1.7e+5

Table 4: Number of tokens/corpus for each language. Note, X-tr stands for the transliterated counterpart of language X.

Model	bn	en	hi	ml	mr	ta	te	ur	avg.
mBERT	68.6	84.4	65.1	54.8	58.4	51.2	50.2	31.4	58.0
MuRIL	86.0	84.4	78.1	75.8	74.6	71.9	65.0	85.1	77.6

Table 5: PANX (F1) Results for each language.

Model	en	hi	mr	ta	te	ur	avg.
mBERT	95.4	66.1	71.3	59.6	77.0	57.9	71.2
MuRIL	95.6	64.5	83.0	62.6	85.6	58.9	75.0

Table 6: UDPOS (F1) Results for each language.

Model	en	hi	ur	avg.
mBERT	81.7	60.5	58.2	66.8
MuRIL	83.9	70.7	67.7	74.1

Table 7: XNLI (Accuracy) Results for each language.

Model	bn	hi	ml	mr	ta	te	ur	avg.
mBERT	12.8	27.8	20.2	18.0	12.4	15.0	22.7	18.4
MuRIL	20.2	31.5	26.4	26.6	36.8	17.5	17.1	25.2

Table 8: Tatoeba (Accuracy) Results for each language.

Model	XQuAD			MLQA		
	en	hi	avg	en	hi	avg.
mBERT	83.9/72.9	58.5/43.5	71.2/58.2	80.4/67.3	50.3/35.2	65.3/51.2
MuRIL	84.3/72.9	73.9/58.3	79.1/65.6	80.3/67.4	67.3/50.2	73.8/58.8

Table 9: XQuAD and MLQA (F1/EM) Results for each language.

Model	bn	en	te	avg.
mBERT	60.6/45.1	75.2/65.0	53.6/44.5	63.1/51.7
MuRIL	78.0/66.4	74.1/64.6	74.0/46.9	75.4/59.3

Table 10: TyDiQA (F1/EM) Results for each language.

Model	bn-tr	hi-tr	ml-tr	mr-tr	ta-tr	te-tr	ur-tr	avg.
mBERT	41.8	25.5	7.5	8.3	1.0	8.2	7.3	14.2
MuRIL	72.9	69.8	63.4	68.8	7.0	53.6	68.4	57.7

Table 11: PANX (F1) Results for each language.

Model	hi-tr	mr-tr	ta-tr	te-tr	ur-tr	avg.
mBERT	25.0	33.7	24.0	36.2	22.1	28.2
MuRIL	63.1	67.2	58.4	65.3	56.5	62.1

Table 12: UDPOS (F1) Results for each language.

Model	hi-tr	ur-tr	avg.
mBERT	39.6	38.9	39.2
MuRIL	68.2	61.2	64.7

Table 13: XNLI (Accuracy) Results for each language.

Model	bn-tr	hi-tr	ml-tr	mr-tr	ta-tr	te-tr	ur-tr	avg.
mBERT	1.8	3.0	2.2	2.4	2.0	5.1	2.3	2.7
MuRIL	8.1	14.9	10.3	7.2	11.1	11.5	13.7	11.0

Table 14: Tatoeba (Accuracy) Results for each language.