MuRIL: Multilingual Representations for Indian Languages

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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 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 2: Upsampled Token Distribution. We upsample monolingual Wikipedia corpora as described in Section 2, to enhance low resource language representation in the pre-training data.

We train our model with two language modeling objectives. The first is the conventional Masked Language Modeling (MLM) objective (Taylor, 1953) that leverages monolingual text data only (unsupervised). The second is the Translation Language Modeling (TLM) objective (Lample and Conneau, 2019) that leverages parallel data (supervised). We use monolingual documents to train the model with MLM, and both translated and transliterated document pairs to train the model with TLM.

Monolingual Data: We collect monolingual data for the 17 languages mentioned above from the Common Crawl OSCAR corpus\(^1\) and Wikipedia\(^2\).

Translated Data: We have two sources of translated data. First, we use the PMINDIA (Haddow and Kirefu, 2020) parallel corpus containing sentence pairs for 8 IN languages (bn, gu, hi, kn, ml, mr, pa, ta, te, ur). Each pair comprises of a sentence in a native language and its English translation. Second, we translate the aforementioned monolingual corpora (both Common Crawl and Wikipedia) to English, using an in-house translation system. The source and translated documents are used as parallel instances to train the model. Note that we translate corpora of all IN languages except as, ks and sa, for which the current translation system lacks support.

Transliterated Data: We have two sources of transliterated data as well. First, we use the Dakshina Dataset (Roark et al., 2020) that contains 10,000 sentence pairs for 12 IN languages (bn, gu, hi, kn, ml, mr, pa, ta, te, ur). Each pair is a native script sentence and its manually romanized transliteration. Second, we use the indic-trans library (Bhat et al., 2015) to transliterate Wikipedia corpora of all IN languages to Latin (except ks, sa and sd, for which the library doesn’t have support). The source document and its Latin transliteration are used as parallel instances to train the model.

Upsampling: In the corpora collected above, the percentage of tokens per language is highly uneven in its distribution. Hence, data smoothing is essential so that all languages have their representation reflect their usage in the real world. To achieve this, we upsample monolingual Wikipedia corpora of each language according to its multiplier value given by:

\[
m_i = \left( \frac{\max_{j \in L} n_j}{n_i} \right)^{(1-\alpha)}
\]

In the above equation, \(m_i\) represents the multiplier value for language \(i\), \(n_i\) is its original token count, \(L\) represents the set of all 17 languages and \(\alpha\) is a hyperparameter whose value is set to 0.3, following Conneau et al. (2020). Hence, the upsampled token count for language \(i\) is \(m_i \times n_i\). The final data distribution after upsampling is shown in Figure 2. The upsampled token counts for each language and corpus are reported in Appendix A.

Vocabulary: We learn a cased WordPiece (Schuster and Nakajima, 2012; Wu et al., 2016) vocabulary from the upsamped pre-training data using the wordpiece vocabulary generation

\(^1\)https://oscar-corpus.com
\(^2\)https://www.tensorflow.org/datasets/catalog/wikipedia
library from Tensorflow Text\textsuperscript{3}. 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 vocabulary\textsuperscript{4} (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 after). We make use of the AdamW optimizer with a learning rate of 5e-4. Our final model has 236M parameters, is trained on ~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.

**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-
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 | UDPOS | XNLI | Tatoeba | Avg. |
|----------|------|-------|------|---------|------|
| mBERT    | 58.0 | 71.2  | 66.8 | 18.4    | 59.1 |
| MuRIL    | 77.6 | 75.0  | 74.1 | 25.2    | 68.6 |

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          | 384                     |
| 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.

4 How to use MuRIL?

We have released the MuRIL encoder on TFHub\(^5\) 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 HuggingFace\(^6\). We sincerely hope MuRIL aids in building better technologies and applications for Indian languages.

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References

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4623–4637, Online. Association for Computational Linguistics.

Irshad Ahmad Bhat, Vandana Mujadia, Aniruddha Tamnawar, Riyaz Ahmad Bhat, and Manish Shrivastava. 2015. Iiit-h system submission for fire2014 shared task on transliterated search. In Proceedings of the Forum for Information Retrieval Evaluation, FIRE ’14, pages 48–53, New York, NY, USA. ACM.

\(^5\)https://tfhub.dev/google/MuRIL/1
\(^6\)https://huggingface.co/google/muril-base-cased
Hyung Won Chung, Dan Garrette, Kiat Chuan Tan, and Jason Riesa. 2020. *Improving multilingual models with language-clustered vocabularies*. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4536–4546, Online. Association for Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. *Unsupervised cross-lingual representation learning at scale*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, Online. Association for Computational Linguistics.

Yuwei Fang, Shuohang Wang, Zhe Gan, Siqi Sun, and Jingjing Liu. 2020. *Filter: An enhanced fusion method for cross-lingual language understanding*. arXiv preprint arXiv:2009.05166.

Barry Haddow and Faheem Kirefu. 2020. *Pmindia–a collection of parallel corpora of languages of India*. arXiv preprint arXiv:2001.09907.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. *Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization*. arXiv preprint arXiv:2003.11080.

INDIA. 2011. *Census of India, 2011*. https://www.censusindia.gov.in/2011Census/C-16_25062018_NEW.pdf.

Guillaume Lample and Alexis Conneau. 2019. *Cross-lingual language model pretraining*. arXiv preprint arXiv:1901.07291.

Anne Lauscher, Vinit Ravishankar, Ivan Vulić, and Goran Glavaš. 2020. *From zero to hero: On the limitations of zero-shot language transfer with multilingual Transformers*. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4483–4499, Online. Association for Computational Linguistics.

Shruti Rijhwani, Royal Sequiera, Monojit Choudhury, Kalika Bali, and Chandra Shekhar Maddila. 2017. *Estimating code-switching on twitter with a novel generalized word-level language detection technique*. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1971–1982, Vancouver, Canada. Association for Computational Linguistics.

Brian Roark, Lawrence Wolf-Sonkin, Christo Kirov, Sabrina J. Mielke, Cibu Johny, Isin Demirsahin, and Keith Hall. 2020. *Processing South Asian languages written in the Latin script: the dakshina dataset*. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 2413–2423, Marseille, France. European Language Resources Association.

Mike Schuster and Kaisuke Nakajima. 2012. *Japanese and korean voice search*. In *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5149–5152. IEEE.

Statista. 2020. *Statista, 2020*. https://www.statista.com/statistics/255146/number-of-internet-users-in-india/.

Wilson L Taylor. 1953. “cloze procedure”: A new tool for measuring readability. *Journalism quarterly*, 30(4):415–433.

Shije Wu and Mark Dredze. 2020. *Are all languages created equal in multilingual BERT?* In *Proceedings of the 5th Workshop on Representation Learning for NLP*, pages 120–130, Online. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. *Google’s neural machine translation system: Bridging the gap between human and machine translation*.
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 (vimbledon) 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.
Table 4: Number of tokens/corpus for each language. Note, X-tr stands for the transliterated counterpart of language X.

| 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  | 2.7e+6  | 1.5e+5  |
| en-tr    | -           | -          | -        | -           | -       | 2.7e+6  | 1.5e+5  |
| 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  | -       | 3.4e+6  | -        |
| 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 5: PANX (F1) Results for each language.

| 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 6: UDPOS (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 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 en | XQuAD hi | XQuAD avg | MLQA en | MLQA hi | MLQA 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  | TyDiQA bn | TyDiQA en | TyDiQA te | TyDiQA 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  | PANX bn-tr | PANX hi-tr | PANX ml-tr | PANX mr-tr | PANX ta-tr | PANX te-tr | PANX ur-tr | PANX 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  | UDPOS hi-tr | UDPOS mr-tr | UDPOS ta-tr | UDPOS te-tr | UDPOS ur-tr | UDPOS 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  | XNLI hi-tr | XNLI ur-tr | XNLI avg |
|--------|------------|------------|---------|
| mBERT  | 39.6       | 38.9       | 39.2    |
| MuRIL  | 68.2       | 61.2       | 64.7    |

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

| Model  | Tatoeba bn-tr | Tatoeba hi-tr | Tatoeba ml-tr | Tatoeba mr-tr | Tatoeba ta-tr | Tatoeba te-tr | Tatoeba ur-tr | Tatoeba 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.