INDICXNLI: Evaluating Multilingual Inference for Indian Languages

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Abstract

While Indic NLP has made rapid advances recently in terms of the availability of corpora and pre-trained models, benchmark datasets on standard NLU tasks are limited. To this end, we introduce INDICXNLI, an NLI dataset for 11 Indic languages. It has been created by high-quality machine translation of the original English XNLI dataset and our analysis attests to the quality of INDICXNLI. By fine-tuning different pre-trained LMs on this INDICXNLI, we analyze various cross-lingual transfer techniques with respect to the impact of the choice of language models, languages, multi-linguality, mix-language input, etc. These experiments provide us with useful insights into the behaviour of pre-trained models for a diverse set of languages.

1 Introduction

Natural Language Inference (NLI) is a well-studied NLP task (Dagan et al., 2013) that assesses if a premise entails, negates, or is neutral towards the hypothesis statement. The task is well suited for evaluating semantic representations of state-of-the-art transformers (Vaswani et al., 2017) models such as BERT (Devlin et al., 2019; Radford and Narasimhan, 2018). Two large scale datasets, such as SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018), has recently been developed to enhanced the relevance of the NLI task.

With the availability of multi-lingual pre-trained language models such as mBERT (Devlin et al., 2019), and XLM-RoBERTa (Conneau et al., 2020a) promising cross-lingual transfer and universal models, multilingual NLP has recently gained a lot of attention. However, most languages have a scarcity of datasets resources. Some multi-lingual datasets have attempted to fill this gap, including XNLI (Conneau et al., 2018) for NLI, XQUAD (Dumitrescu et al., 2021), MLQA (Lewis et al., 2020) for question answering, and PAWS-X for paraphrase identification (Yang et al., 2019). In many practical circumstances, training sets for non-English languages are unavailable, hence cross-lingual zero-shot evaluation benchmarks such as XTREME (Hu et al., 2020a), XTREME-R (Ruder et al., 2021), and XGLUE (Liang et al., 2020) have been suggested to use these datasets.

However, NLI datasets are not available for major Indic languages. The only exceptions are the test/validation sets in the XNLI (hi and ur), Tax-iXNLI (hi) (K et al., 2021) and MIDAS-NLI (Upal et al., 2020) datasets. Furthermore, because MIDAS-NLI is based on sentiment data recasting, hypotheses are not linguistically diverse and span limited reasoning. In this work, we address this gap by introducing INDICXNLI, an NLI dataset for Indic languages. INDICXNLI consists of English XNLI data translated into eleven Indic languages. We use INDICXNLI to evaluate Indic-specific models (trained only on Indic and English languages) such as IndicBERT (Kakwani et al., 2020) and MuRIL (Khanuja et al., 2021), as well as generic (train on non-Indic languages) such as mBERT and XLM-RoBERTa. Furthermore, we experimented with several training strategies for each multi-lingual model. Our experimental results answers multiple important questions regarding effective training for Indic NLI. Our contributions are as follows:

- We introduce INDICXNLI, an NLI benchmark dataset for eleven prominent Indo-Aryan indi languages from the Indo-European and Dravidian language families.
- We investigate several strategies to train multilingual models for NLI tasks on INDICXNLI. We also explore models cross-lingual NLI transfer ability across Indic languages and Intra-Bilingual NLI ability of pretrained multilingual language models.
2 The INDIC XNLI dataset

We created INDIC XNLI, a NLI dataset for Indic languages. INDIC XNLI is similar to existing XNLI dataset in shape/form, but focusses on Indic language family. INDIC XNLI include NLI data for eleven major Indic languages that includes Assamese (‘as’), Gujarati (‘gu’), Kannada (‘kn’), Malayalam (‘ml’), Marathi (‘mr’), Odia (‘or’), Punjabi (‘pa’), Tamil (‘ta’), Telugu (‘te’), Hindi (‘hi’), and Bengali (‘bn’). Next we describe the INDIC XNLI construction and its validation in details.

INDIC XNLI Construction. To create INDIC XNLI, we follow the approach of the XNLI dataset and translate the English XNLI dataset (premises and hypothesis) to eleven Indic languages. We use the IndicTrans (Ramesh et al., 2022), a state-of-the-art, publicly available translation model for Indic languages, for translating from English to Indic languages. The train (392,702), validation (2,490), and evaluation sets (5,010) of English XNLI were translated from English into each of the eleven Indic languages. IndicTrans is a large Transformer-based sequence to sequence model. It is trained on Samanantar dataset (Ramesh et al., 2022), which is the largest parallel multi-lingual corpus over eleven Indic languages. IndicTrans outperforms other open-source models based on mBART (Liu et al., 2020) and mT5 (Xue et al., 2021) for Indic language translations and is competitive with paid translation models such as Google-Translate or Microsoft-Translate on several benchmarks (Ramesh et al., 2022). Our choice of IndicTrans was motivated by cost, language coverage and speed, refer Appendix §A.

INDIC XNLI Validation. While translation may lose the semantic link between the sentences, recent study by K et al. (2021) disproved this. K et al. (2021) qualitative analysis illustrate that when a high-quality machine translation system is utilized, classification labels and reasoning categories are only minimally altered for translated NLI datasets. We also demonstrate the high quality of IndicTrans translation for INDIC XNLI in two ways (a.) manual human validation and, (b.) automatic metric BERTScore (Zhang* et al., 2020). Our validation approach guarantee correctness for the INDIC XNLI labels. Next, we’ll discuss on how to evaluate IndicTrans translations.

| Score | hi  | te  | pa  | bn  | as  | gu  | ta  | ml  | kn  | mr  | or  |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| HSI   | 88  | 89  | 91  | 87  | 87  | 89  | 89  | 87  | 89  | 86  | 88  |
| HS2   | 81  | 84  | 93  | 84  | 89  | 87  | 87  | 87  | 90  |     |     |
| PC    | 73  | 75  | 89  | 79  | 78  | 78  | 76  | 85  | 83  | 83  | 75  |
| SC    | 82  | 87  | 94  | 90  | 88  | 85  | 88  | 93  | 86  | 89  | 85  |

Table 1: Human Validation Score (×10^-2): HSI, HS2 represents human1, human2 annotation score respectively. PC and SC represents Pearson and Spearman correlation respectively.

HUMAN VALIDATION: We followed SemEval-2016 Task-1 (Agirre et al., 2016) guidelines. We hired 2 annotators per languages and calculated the Pearson (Kirch, 2008) and spearman (Spe, 2008) correlation over annotations scores of sentences.

DIVERSE SAMPLING: Since human validation is time-consuming and expensive. We sampled 100 diverse sentences of the test set for validation. We apply the Determinantal Point Process (Kulesza, 2012) (DPP) over sentence representations for diverse sampling. DPP maximizes coverage volume using a minimal sampled set, thus guaranteeing diversity during sampling. We first used sentence transformers to convert data to BERT embeddings, and then use k-DPP (Kulesza and Taskar, 2011) with k = 100 to sample 100 examples. Using DPP for diverse sampling is a cost-effective method of evaluating translation quality. For scoring guidelines refer to Appendix §B.

HIRING EXPERTS: We recruited, 2 speakers for each of the 11 indic languages as annotators. These professional annotators are multilingual (English, Indic) and fluent in both mother-tongue indic and English language. The remuneration paid was 6.6 cents per sentence ¹ for each indic language.

EVALUATION: Table 1 shows the final human evaluation scores. In general, we see that average human scores is more than 0.85 for all languages. The Pearson and Spearman Correlation values are more than 0.7 and 0.8 for all languages respectively. High human ratings and high correlation between the annotations support high quality IndicTrans translation, hence validating INDIC XNLI quality.

AUTOMATIC VALIDATION: Given the absence of Indic language XNLI reference data, we use BERTScore similarity between the original English and English translated INDIC XNLI for automatic evaluation. Here too, we use the IndicTrans model for translating INDIC XNLI into English. This approach estimates the upper bound on error for the

¹ above minimum wage in India.
English to Indic translation (i.e. INDICXNLI quality), as it approximates the combined error of both English to Indic translation (INDICXNLI creation), and Indic to English translation (evaluation) (Rapp, 2009; Miyabe and Yoshino, 2015; Edunov et al., 2020; Behr, 2017). We utilize BERTScore for assessment since it correlates better with human judgment at the sentence level than BLEU (Zhang et al., 2020; Papineni et al., 2002).

We evaluate two translation models, Google Translate and IndicTrans on the testsets of INDICXNLI dataset. We incorporate Google Translate to demonstrate IndicTrans’s competitiveness in comparison to commercial translation approaches. In Table 2, we used two evaluation strategies for our evaluation (a.) EngTrans: which take the INDICXNLI sentence and translated it back to English using BERT model. (b.) Multilingual: directly compare the English sentences with multilingual INDICXNLI sentences using mBERT model.

On Indic languages, we notice that IndicTrans is comparable to, and sometimes outperforms, Google Translate. Additionally, when results are compared in a Multilingual setting, we observe a marginal decrement in scores. This can be because mBERT does not produce as precise multilingual embedding as BERT does for English. Additionally, we see a similar pattern in the distribution of scores across languages for both assessment strategies on both models. We also computed the BERTScore (using mBERT) between the Hindi test set of XNLI and INDICXNLI was found to be 0.87, supporting the high quality of INDICXNLI.

### 3 Experiments

**Experiment Setup:** Our experiments compare the performance of several multi-lingual models, including one particularly developed for Indic languages. We consider 2 broad categories, (a) Indic Specific which includes IndicBERT and MuRIL due to their indic specific pretraining, and (b) Generic which includes mBERT and XLM-Roberta due to their pretraining in more than 100 languages. We fine-tuned pre-trained multi-lingual models to develop NLI classifiers. The classifiers take two sentence as input, i.e. the premise and the hypothesis and predicts the inference label. See Appendix §C and §D for models and hyper-parameters details respectively.

**Training-Evaluation Strategies.** To train the NLI classifier, we investigate several strategies. While the pre-trained multi-lingual models remain constant, the training and evaluation datasets vary.

1. **Indic Train:** The models are trained and evaluated on INDICXNLI. The training set is translated from the XNLI English, thus a translate-train scenario.
2. **English Train:** The models are trained on original English XNLI data and evaluated on INDICXNLI data. This is a zero-shot evaluation training scenario.
3. **English Eval:** The model is trained on original English XNLI data, but evaluated on English translation of INDICXNLI data. This is the translate-test scenario.
4. **English + Indic Train:** This approach combines approaches (1) and (2). The model is first pre-finetuned (Lee et al., 2021; Aghajanyan et al., 2021) on English XNLI data and then finetuned on Indic language of INDICXNLI data.
5. **Train All:** This approach begins by fine-tuning the pre-trained model on English XNLI data, followed by training on all eleven Indic languages of INDICXNLI sequentially.
6. **Cross Lingual Transfer:** Additionally, we assess the models’ capacity to transfer between languages. Where the model is trained on a single Indian language and then assessed on all other Indian languages as well as the training language.

7. **Intra-Bilingual Inference:** Lastly, we also assess the model’s capability to perform natural language inference with premise in English and hypothesis in Indic language.

### Results and Analysis

We summarize our findings from Table §3 results across 4 categories:

**Across Models:** In all experiments, MuRIL performs the best across all indic languages except in English Eval setup. This can be attributed to (a.) The large model size (b.) indic-specific pre-training data, (c.) A Mixture of Masked Language Modeling (MLM), Translation Language Modeling (TLM), and (d.) use of transliterated data in pre-training. XLM-RoBERTa beats MuRIL in rare scenarios, notably in which the model solely deals with English data (e.g. English Eval). XLM-RoBERTa outperforms MuRIL in such cases because it is better at assessing English than MuRIL.
which is designed mostly for indic language. Additionally, we discover that, compared to XLM-RoBERTa, MuRIL indic-specific training further enhances the model’s performance. Despite indic-specific pretraining, IndicBERT performs worse than mBERT. This can be attributed to the smaller size of the IndicBERT model, i.e. only 33M compared to 167M mBERT (c.f. Table §5 in appendix).

**ACROSS LANGUAGE:** We see a strong positive correlation between language performance with their resource availability. Hindi and Bengali outperform, whereas Odia mostly underperform on majority of benchmarks. Low-resource languages such as Marathi, Assamese, and Kannada surprising also perform well. This can be attributed to the similarity of Marathi with Hindi script, Assamese with Bengali script, and Kannada with Tamil and Telugu scripts. This is discussed in detail in appendix 4. Odia, a low resource language, lacks script sharing language partners and hence performs poorly. Overall, English + Indic Train method outperforms, with MuRIL performing best.

**ACROSS STRATEGIES:** Our experiments show that models benefit from language-specific fine tuning. English + Indic train and Train All have the best results with minimal deviation across languages for XLM-R and MuRIL. Additionally, Train All follows a high-to-low resource hierarchy to mitigate the impact of catastrophic forgetting (Goodfellow et al., 2015). Due to the followed language order English + Indic train outperform Train All setting marginally for high resource languages. Overall, English + Indic Train strategy performs the best and MuRIL performs the best in that strategy. This can be attributed to the indic specific pre-training process of MuRIL which include both translation and transliteration. Furthermore, MuRIL has the second largest size after XLM-R.

**CROSS-LINGUAL TRANSFER:** Models favour high resource languages such as Hindi and Bengali training for cross-lingual transfer. These language are pre-trained on large mono-lingual corpora which enhanced performance (Conneau et al., 2020a). This setting can be thought equivalent of Hindi and Bengali substitution for English training. Additionally, when evaluated for all indic languages, model trains on non-Hindi and non-Bengali perform substantially better for Hindi and Bengali. Table 3 present results summary as average evaluation score across all indic language(rows) when train on the several indic languages(columns).

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Table 3: Here, LangAvg represents the language wise average score across models, while ModAvg average score represents the model average score across languages. Values in Blue, Red and Green represents the model average best score, language-wise average best score, and values where both model-wise and language-wise best score coincide. For Indic Cross Lingual Transfer, each row represent the average evaluation score of all Indic language when trained on the column language. For more detailed cross-lingual transfer results refer to Appendix §E. *iBERT stand for Indic-iBERT and XLM-R stand for XLM-RoBERTa.*

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2 For model-wise cross-lingual results c.f. Appendix §E.
train model on mixed input using English + Indic Train and Train All strategies. Table 4 shows performance of English + Indic Train and Train All models on EN-INDICXNLI. Compared to unilingual inference task, mixed-language input task perform poorly. Furthermore, contrary to earlier observations, general model such as XLM-R outperforms the Indic specific models. However, IndicBERT and MuRIL both perform substantially better than mBERT. Furthermore, English data augmentation enhance the English + Indic Train setting performance. This can be because, the model "meta-learns" the task successfully with English data training (premise language), and further prioritises the model's language-specific abilities with the follow-up indic data training.  

4 Error Analysis

In this section, we investigate the correlation between the language similarity and the model performance. We see that the model performs similarly on similar languages. We evaluate our results on MuRIL on the English+Indic finetuning Strategy.

In Figure 1 (Appendix), we observe that the overall Correct and Incorrect predictions, Bengali vs Assamese pair has the total of 81% overlap, Tamil vs Kannada has 83% overlap, Hindi vs Marathi has 82% overlap. All the language pairs have the largest overlap for entailment label for correct labels and largest overlap in contradiction label for incorrect overlaps. In Figure 2 (Appendix), interestingly Bengali vs Assamese pair and Hindi vs Marathi has the highest percentage of overlap in predictions where the most overlap is in entailment and minimum overlap is in contradiction. While for Tamil vs Kannada pair has the highest overlap for neutral and minimum for contradiction.

We have also done error analysis of model performance on original Hindi test data already present in XNLI and data obtained through translations from IndicTrans in Figure 3 (Appendix). We observe a total of 82% overlap in error consistency, and we observe that the greatest number of correct overlaps is for the entailment label, whereas the greatest number of incorrect predictions is for the contradiction label. We see the maximum overlap in neutral prediction and the least overlap in contradiction prediction in terms of consistency. This demonstrates that the model performs identically on both the original Hindi data and the machine-translated Hindi data, bolstering the legitimacy of our dataset.

5 Related Work

Recently many Indic-specific resources are developed such as IndicNLPSuite (Kakwani et al., 2020), which include (a.) word embeddings: IndicFT, (b.) transformer models: IndicBERT, (c.) monolingual corpora: IndicCorp, (d.) and, evaluation benchmark: IndicGLUE. Furthermore, Indic-specific pre-processing libraries such as iNLTK (Arora, 2020) and Indic-nlp-library (Kunchukuttan, 2020), multilingual parallel corpora: PMIndia (Haddow and Kirefu, 2020) and Samantar (Ramesh et al., 2022), transformer model MuRIL (Khanuja et al., 2021) and language specific IndicTransformers (Jain et al., 2020) exists.

6 Conclusion

With INDICXNLI we extend the XNLI dataset for Indic languages family. We benchmark INDICXNLI with several multi-lingual models using various train-test strategies. We also study the use of English XNLI as pre-finetuning dataset. Furthermore, we also evaluate models on mixed-language inference input and cross-lingual transfer ability. We aim to integrate INDICXNLI and benchmark models in IndicGLUE (Kakwani et al., 2020). We also intend to enhance INDICXNLI with advanced translation techniques. Another direction is accessing model performance on INDIC-INDICXNLI task, where both premises and hypothesis are in two distinct Indic languages.

### Table 4: EN-INDICXNLI model performance (refer §3) with English + Indic train and Train All setting. Here, ModAvg, LangAvg, and Color Code mean same as in table 3.

| Model   | English+Indic Train | Train All |
|---------|---------------------|-----------|
|         | as gu kn ml mr or pa ta te bn hi | as gu kn ml mr or pa ta te bn hi |
| XLM-R   | 74 72 75 74 77 72 70 72 72 79 76 | 74 57 59 58 62 61 53 57 59 61 63 63 59 |
| iBERT   | 70 68 63 65 69 68 71 64 64 69 69 | 67 49 53 46 37 52 51 59 39 51 57 50 50 |
| mBERT   | 51 56 59 50 62 31 63 57 60 61 63 | 56 39 39 43 38 43 33 40 42 41 40 42 40 |
| MuRIL   | 71 70 73 69 71 39 71 71 69 72 69 | 67 51 52 58 56 53 55 58 65 55 62 54 56 |

LangAvg: 65 65 66 64 68 65 65 67 71 70 65 47 49 51 48 41 45 52 50 51 54 51 30 30

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3 Further Analysis in appendix §F
7 Limitations

One of our work’s key limitations is that the dataset IndicXNLI was created by machine translation of the original English XNLI dataset. Although IndicXNLI is not human translated, it has been carefully evaluated for translation accuracy by a number of natural bilingual Indic speakers (2 for each language). Furthermore, as shown in our research (Table 2), employing automatic assessment measures such as round trip English-English evaluation via back translation and direct Indic-English sentence comparison is effective. In the past, such a metric has been shown to be highly beneficial for comparing without-reference machine translation (Bapna et al., 2022; Huang, 1990; Moon et al., 2020a,b). Furthermore, as did with the Hindi dataset in Appendix E, we might use correlation in the prediction score between human and machine translated sets for evaluating translation quality.

Second, adapting an existing dataset risks transferring biases and shortcomings from the original XNLI dataset into ours. However, it has been established that XNLI is a typical benchmark for evaluating multilingual and cross-lingual sentence representation, and it has been used to evaluate several multilingual models (Conneau et al., 2020b; Hu et al., 2020b). Morphological analysis of related languages, as well as insights into their performance behavior, may be useful. The authors, however, are not experts in that area, and such an assessment would have been outside the scope of the current work. This study might be expanded to include language groups other than Indian languages such as Indo-European. Third, because of limited resources, the current study did not include large versions of well-known models such as XLM-RoBERTa-Large and MuRIL-Large. However, for IndicBert, mBERT, XLM-RoBERTa, and MuRIL, we assessed model performance in relation to model size (#parameters) in Table 5.

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A Further Discussions

Why Indic languages? Indic languages are spoken by more than a billion people in the Indian sub-continent. With the introduction of IndicNLP suite (Kakwani et al., 2020) by AI4Bharat, there has been has an increased interest and effort towards the research for Indic languages model. Recently, IndicBERT, MuRIL (Khanuja et al., 2021) based on BERT (Devlin et al., 2019) were introduced for the Indic languages. Furthermore, generation model IndicTrans (Ramesh et al., 2022) and IndicBART (Dabre et al., 2022) based on seq2seq architecture was also published recently. These model use the Indic enrich monolingual corpora: Common Crawl, Oscar and IndicCorp and parallel corpora: Samantar and PMIndia (Haddow and Kirefu, 2020) on Indic languages for training. Despite significant progress through large transformer-based Indic language models in addition to existing multilingual models e.g. mBERT (Devlin et al., 2019), XLM-RoBERTa (Conneau et al., 2020a), and mBART (seq2seq) (Liu et al., 2020) there is currently a paucity of benchmark data-sets for evaluating these huge language models in the Indic language research field. Such benchmark dataset is necessary for studying the linguistic features of Indic languages and how well they are perceived by different multilingual models. Recently, IndicGLUE (Kakwani et al., 2020) was introduced to handle this scarcity. However, the scope of this benchmark, is confined to only few tasks and datasets.

Why INDICXNLI task? This research provides an excellent chance to investigate the efficacy of various Multilingual models on Indic languages that are rarely evaluated or explored before. Some of these Indic languages such as ‘Assamese’ and ‘Odia’ serve as unseen (zero-shot) evaluation for models such as mBERT (Pires et al., 2019), i.e. not pre-trained on ‘Assamese’. While other models, such as XLM-RoBERTa, IndicBERT and MuRIL covers all our languages but in widely varying proportions in their training data. Our work investigate the correlation effect of cross-lingual training...
for English on these rare Indic languages, which are not explore by prior studies. Furthermore, we also investigate the cross-lingual transfer effect across Indic languages, also not explored before. We explore the impact of Multilingual training, English-data augmentation, unified Indic model performance, cross-lingual transfer of closely related Indic family and English-Indic NLI through our work. All the above mention topics are not explore for Indic language before. We aim to integrate IndicXNLI and benchmark models in IndicGLUE (Kakwani et al., 2020). Such a benchmark dataset is required for investigating the linguistic properties of Indian languages and how accurately they are interpreted by various multilingual models. Another direction is accessing model performance on INDIC-INDICXNLI task, where both premises and hypothesis are in two distinct Indic languages.

**Why IndicTrans for Translation?** We use the IndicTrans as a translation model for converting English XNLI to INDICXNLI because of the following reasons: (a.) **Open-Source:** IndicTrans is open-source to public for non-commercial usage without additional fees, while Google-Translate and Microsoft-Translate require a paid subscription. (b.) **Light Weight:** IndicTrans is the fastest and the lightest amongst mBART and mT5 on single GPU machines. Google-Translate and Microsoft-Translate are also relatively slower due to repeated network-intensive API calls. (c.) **Indic Coverage:** Seq2Seq models like mBART and mT5 are not designed for all languages in the Indic family. mBART supports seven (excludes kn,or,pa,as) while mT5 supports nine languages (excludes or,as) out of eleven indic languages. Google-Translate supports ten out of eleven indic languages (excludes Assamese). Microsoft Translate supports all the eleven indic languages. In future, we plan to enhance INDICXNLI with better translation.

**B Human Validation Scoring**

We provide English and indic language INDICXNLI (IndicTrans translated) sentence to the recruited native speaker of that indic language for validation. Before the annotation work, each expert was given a full explanation of the guidelines that needed to be followed. The validation instructions (mturk template and detailed examples) are taken from the Semeval-2016 Task-I. The native speaker access the sentence pairs assign an integer score between 0 and 5, as follows: **0:** The two sentences are completely dissimilar. **1:** The two sentences are not equivalent, but are on the same topic. **2:** The two sentences are not equivalent, but share some details. **3:** The two sentences are roughly equivalent, but some important information differs/missing. **4:** The two sentences are mostly equivalent, but some unimportant details differ. **5:** The two sentences are exactly equivalent, as they mean the same. The score depicts the goodness of translated sentence in terms of semantics, i.e. same meaning as original English sentence. Scores are then normalized to a probability range (between 0 and 1). The final validation score for each language is determined as the average of all 100 instances’ scores.

Additionally, we also computed the BERTScore between the English and the Hindi test split of the XNLi, using multi-lingual strategy which came out to be 70 ($\times 10^{-2}$). We presume that the lower score is attributable to the fact that human-translated dataset encapsulates a large number of linguistic nuances, resulting in a change in the structure and tonality of the sentences, which is frequently overlooked by machine translation systems, as highlighted by Bianchi et al. (2022).

**C Details: Multi-lingual Models**

**Indic Specific:** These models are specially pre-trained using Mask Language Modeling (MLM) or Translation Language Model (TLM) (CONNEAU and Lample, 2019) on monolingual / bilingual Indic language corpora. These include models such as MuRIL and IndicBERT trained on 17 and 11 Indic languages (+English) respectively. MuRIL is pre-trained using Common-Crawl Oscar Corpus (Ortiz Su’arez et al., 2019), PMIndia (Haddow and Kirefu, 2020) on the following languages: en, hi, bn, gu, te, ta, or, ml, pa, kn, mni, as, ur. IndicBERT is pre-trained using Indic-Corp(Kakwani et al., 2020) on the following languages: en, hi, bn, ta, ml, te, Mr, kn, gu, pa, or, as. Moreover, MuRIL is also pre-trained with TLM objective (with MLM objective) on machine translated data and machine transliterated data.

**Generic:** These are massive multi-lingual models pre-trained on large number of languages with MLM. These include multi-lingual BERT i.e. mBERT (cased/uncased) and multi-lingual RoBERTa i.e. XLm-RoBERTa which are trained on more than 100 languages. XLm-RoBERTa also

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5 For NLI task, same syntax, i.e. grammar (e.g. Tense) lesser important than same Semantic, i.e. meaning preservation.
6 XNLi hindi test splits was human translated.
includes pre-training on all eleven Indic languages. XLM-RoBERTa is pre-trained using the common crawl monolingual data. mBERT (cased/uncased) includes pre-training on nine of eleven Indic languages (Assamese and Odia excluded) and uses multi-lingual Wikipedia data for pre-training.

D Details: Hyper Parameters Settings

All the models were trained on google collaboratory on TPU-v2 with 8 cores. The code was built in the PyTorch-lightning framework. We used accuracy as mentioned in the original XNLI paper (Conneau et al., 2018) as our metric of choice. The training was run with an early stopping callback with the patience of 3, validation interval of 0.5 epochs and AdamW as optimizer (Loshchilov and Hutter, 2019). In Table 5 the hyperparameters are abbreviated as mentioned below: (a.) PO: Pre-training Objective. Where MLM stands for masked Language Modelling, TLM stands for Translation Language Modelling and TrLM stands for Translation Language Modelling, (b.) CU: Corpus Used, (c.) LR: Learning Rate, (d.) BS: Batch Size, (e.) WD: Weight Decay, (f.) MSL: Maximum Sequence Length, (g.) MS: Model Size described as number of parameters in millions, (h.) WS: Warm-up Step.

E Indic Cross-lingual Transfer

Table 6 (extension §3) are the cross-lingual transfer results of XLM-R, IndicBERT, mBERT and MuRIL respectively. The rows of the table consist of the languages on which the model is trained, while the columns represent the evaluation languages. E.g., in table 6 the first row represents that the model is trained on “as” and then tested on all the languages in the column. The values in the row are the accuracy scores of the model when trained on the language in its leftmost column and tested on the language in its top-most row column.

XLM-R. the model perform best for the “bn” language. The model gives the best performance average across all other languages if trained on “bn”. A model trained in other languages, on average, also performs best for “bn” language. XLM-R also struggles to correlate with “kn”, “or”, and “ml”, thus performs poorly on average if trained for them. At the same time, all models have poor cross-lingual ability transferability for the “as” language.

IndicBERT. the overall score is comparable to XLM-R despite it’s smaller size. On average, across languages, the cross-lingual transfer ability for models trained on varying indic languages were consistently similar (b/w 0.5-0.6). However, the evaluation performance for cross-lingual models evaluated on “ml” were poor for all indic trained models. For model trained on some languages, “kn”, “ml” and “pa”, the best performance was across diagonal, i.e. indicating the model performs best on the trained language. This trend was, however, was not shown in other indic languages, indicating remarkable cross-lingual transfer ability of the IndicBERT model.

mBERT. the model performs worse for “or” on average for both when evaluated and train on. However, all models performs very consistently for other indic languages. Model trained on kn, pa, ta, hi, and bn perform best on average across languages. Here too, the best cross-lingual transfer ability was shown for bn language. mBERT also have best performance across diagonal for some languages e.g. “as”, “gu”, “ml”, “pa” and “te”.

MuRIL. shows the best overall cross-lingual transfer ability amongst all the models. MuRIL only fails to generalize well when trained for “or” language. However, model train on other indic language when evaluated on “or” performs well. Model trained on “ta” and “ml” performs best across all languages. The best cross-lingual transfer ability was shown for “bn” and “hi”. Overall, MuRIL has better cross-lingual transfer ability across all languages compared to other models. It also shows less performance bias for languages such as “bn” and “hi”, as compared to XLM-R.

F Intra-Bilingual Inference

We observed a performance loss except for XLM-RoBERTa when the model is evaluated on EN-INDICXNLI inference task. The inference models struggle to correlate and reason together on two different languages (English, Indic) sentences. Contrary to earlier observation, a generic model such as XLM-RoBERTa outperforms the Indic specific models. However, IndicBERT and MuRIL perform better than mBERT. Bengali perform best for both the training strategies. We also observe the benefit of English data augmentation English + Indic Train model, rather than all language augmentation Train All model.

7 https://colab.research.google.com/
Table 5: Model Hyper-Parameters

| Model        | PO | CU | LR | BS | WD | MSL | MS | WS |
|--------------|----|----|----|----|----|-----|----|----|
| XLM-R        |    |    |    |    |    |     |    |    |
| MLM (Dynamic) | Wikipedia Corpus | 2e-5 | 64 | 0.01 | 128 | 278M | 1500 |
| iBERT        |    |    |    |    |    |     |    |    |
| MLM IndicCorp |        |    |    |    |    |     |    |    |
| MuRIL        |    |    |    |    |    |     |    |    |
| MLM, TLM and TrLM OSCAR and PM India | 2e-5 | 64 | 0.01 | 128 | 237M | 1500 |
| mBERT        |    |    |    |    |    |     |    |    |
| MLM Wikipedia Corpus |        |    |    |    |    |     |    |    |

Table 6: Indic Cross-lingual Transfer

| TrLang | XLM-RoBERTa | TrAvg | IndicBERT | TrAvg |
|--------|-------------|-------|-----------|-------|
|        | as | gu | kn | ml | or | te | pa | ta | te | bn | hi | TrAvg |
| as    | 64 | 69 | 63 | 68 | 68 | 64 | 66 | 65 | 66 | 65 | 66 | 58 |
| gu    | 65 | 72 | 70 | 64 | 67 | 67 | 66 | 65 | 74 | 74 | 66 | 60 |
| kn    | 33 | 35 | 31 | 33 | 33 | 33 | 33 | 33 | 34 | 34 | 34 | 59 |
| ml    | 35 | 32 | 31 | 32 | 32 | 31 | 31 | 31 | 34 | 34 | 34 | 60 |
| mr    | 66 | 70 | 68 | 69 | 65 | 75 | 73 | 71 | 62 | 65 | 59 | 63 |
| or    | 65 | 69 | 67 | 67 | 67 | 67 | 66 | 73 | 63 | 68 | 60 | 64 |
| pa    | 64 | 67 | 69 | 72 | 71 | 68 | 70 | 70 | 70 | 70 | 70 | 70 |
| ta    | 61 | 70 | 71 | 70 | 71 | 68 | 67 | 65 | 75 | 75 | 72 | 71 |
| te    | 61 | 70 | 71 | 70 | 71 | 68 | 67 | 65 | 75 | 75 | 72 | 71 |
| bn    | 67 | 72 | 73 | 73 | 72 | 74 | 74 | 70 | 70 | 70 | 71 | 70 |
| hi    | 65 | 70 | 70 | 70 | 69 | 71 | 71 | 71 | 76 | 73 | 71 | 70 |

| TrLang | mBERT | TrAvg | MuRIL | TrAvg |
|--------|-------|-------|-------|-------|
|        | as | gu | kn | ml | or | pa | ta | te | bn | hi | TrAvg |
| as    | 69 | 69 | 63 | 68 | 68 | 64 | 66 | 65 | 66 | 66 | 66 | 60 |
| gu    | 48 | 70 | 64 | 55 | 60 | 62 | 64 | 60 | 67 | 65 | 60 | 60 |
| kn    | 49 | 62 | 68 | 60 | 60 | 65 | 65 | 64 | 59 | 62 | 61 | 59 |
| ml    | 51 | 60 | 71 | 60 | 60 | 61 | 61 | 61 | 61 | 60 | 60 | 60 |
| mr    | 45 | 63 | 56 | 69 | 35 | 64 | 56 | 57 | 69 | 66 | 60 | 64 |
| or    | 34 | 29 | 32 | 36 | 34 | 35 | 34 | 34 | 35 | 35 | 35 | 35 |
| pa    | 47 | 65 | 59 | 59 | 62 | 35 | 70 | 63 | 61 | 68 | 64 | 60 |
| ta    | 48 | 64 | 67 | 63 | 60 | 62 | 65 | 66 | 63 | 69 | 62 | 60 |
| te    | 51 | 59 | 63 | 63 | 60 | 62 | 61 | 64 | 67 | 66 | 62 | 60 |
| bn    | 51 | 64 | 65 | 62 | 62 | 60 | 62 | 66 | 67 | 66 | 67 | 60 |
| hi    | 50 | 66 | 65 | 61 | 62 | 30 | 65 | 63 | 61 | 71 | 63 | 60 |

Figure 1: Consistency Matrix: Predictions of MuRIL for (a) Tamil vs Kannada (b) Bengali vs Assamese, (c) Hindi vs Marathi. The percentage on top in each block represents the average across all three labels with each label percentage given below it in the order of Entailment, Neutral and Contradiction. (cf. Appendix § 4)
Figure 2: Confusion Matrix: for MuRIL (a) Tamil vs Kannada, (b) Bengali vs Assamese, (c) Hindi vs Marathi.

Figure 3: Consistency Matrix and Confusion Matrix for Predictions of MuRIL on Original Hindi data in XNLI and Machine Translated Data generated from IndicTrans.