Evaluating Inclusivity, Equity, and Accessibility of NLP Technology:
A Case Study for Indian Languages

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Abstract

In order for NLP technology to be widely applicable and useful, it needs to be inclusive of users across the world’s languages, equitable, i.e., not unduly biased towards any particular language, and accessible to users, particularly in low-resource settings where compute constraints are common. In this paper, we propose an evaluation paradigm that assesses NLP technologies across all three dimensions, hence quantifying the diversity of users they can serve. While inclusion and accessibility have received attention in recent literature, equity is currently unexplored. We propose to address this gap using the Gini coefficient, a well-established metric used for estimating societal wealth inequality. Using our paradigm, we highlight the distressed state of diversity of current technologies for Indian (IN) languages. Our focus on IN is motivated by their linguistic diversity and their large, varied speaker population. To improve upon these metrics, we demonstrate the importance of region-specific choices in model building and dataset creation and also propose a novel approach to optimal resource allocation during fine-tuning. Finally, we discuss steps that must be taken to mitigate these biases and call upon the community to incorporate our evaluation paradigm when building linguistically diverse technologies.

1 Introduction

NLP has seen large advances in recent years driven by the rapid progress in transfer learning (Ruder et al., 2019; Devlin et al., 2019). The benefits of these advances, however, are not equally distributed across the world’s languages (Joshi et al., 2020) and users. While linguistic diversity and inclusion have evolved to be a pressing concern today, measures to quantify these are still lacking. The progress of any field is tightly coupled with its evaluation paradigm and the community is incentivized to work on highly visible metrics and benchmarks. In order for users around the world to reap the benefits of NLP technology, we must move from an evaluation that focuses on optimizing raw performance on available test data to a more holistic user-centric evaluation (Ethayarajh and Jurafsky, 2020; Ruder et al., 2021). For multilingual systems, such an evaluation should consider three dimensions: inclusivity, equity, and accessibility.1

Inclusivity is important as NLP technology should be available to speakers of any language (European Language Resources Association, 2019). To this end, recent work (Blasi et al., 2021) quantifies inclusivity of NLP technology across the world’s languages by weighing task performance for each language based on its speaker population.

Equity is key as we should aim to develop technology that does not discriminate against speakers of any particular language (Kaneko and Bollegala, 2019). State-of-the-art multilingual models in fact have been shown to perform much better in languages with access to many pre-training resources (Hu et al., 2020). To measure such performance inequity across languages, we propose to use the Gini coefficient (Dorfman, 1979), a measure that has been used to represent the income inequality within social groups.

Finally, accessibility is a concern as the fact that NLP technology is performant in a given task and language does not mean that it is usable. State-of-the-art models have been becoming larger and larger (Fedus et al., 2021) and the low-resource setting of many languages often coincide with constraints on computational resources (Ahia et al., 2021). The value a technology provides to a user thus also needs to consider how easily such technology can be run and deployed in practice, which we quantify based on a model’s efficiency at runtime, specifically its throughput and memory.

Using our paradigm, we highlight the distressing

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1We focus on assessing these dimensions on the language level. Prior work on equity focuses mainly on subpopulations within a language (Katell et al., 2020).
state of diversity in current technologies for Indian (IN) languages. India is a multilingual society with 1369 rationalized languages and dialects being spoken across the country (Chandramouli, 2011). Of these, 22 scheduled languages\(^2\), spoken by almost 97% of the population hold an official recognition and 121 languages have more than 10,000 speakers. Additionally, 21.92% of its population lives below the poverty line (RBI, 2021). Therefore, serving this large varied population justly, requires a multi-faceted effort and basing our case study on IN languages directs the way forward.

We evaluate state-of-the-art models across four standard downstream tasks: Named Entity Recognition (NER), Part-of-Speech Tagging (POS), Natural Language Inference (NLI) and Question Answering (QA). We evaluate a range of state-of-the-art models and transfer settings (Hu et al., 2020). We observe that region-specific choices, i.e. region-specific models (Kakwani et al., 2020; Khanuja et al., 2021) and Hindi as source language generally yield the best results. In terms of efficiency, we find that smaller models are preferable for easier, syntactic tasks while larger models have the edge on more complex, semantic tasks.

Our findings, however, also highlight that we are still a long way from building perfectly inclusive and equitable NLP technology. Towards bridging this gap, we explore how we can most effectively fine-tune pre-trained models. Specifically, we propose a fully computational approach to model the space of source and target languages, and derive the optimal allocation of a fixed annotation budget to maximize performance on our proposed metrics.

Our contributions are the following: 1) We propose a holistic evaluation paradigm that assesses NLP technology based on their inclusivity, equity and accessibility. 2) Using this paradigm, we evaluate model capabilities for IN languages and quantify their shortcomings. 3) We propose a novel approach to fine-tune these models with the objective of maximizing performance for the proposed metrics. 4) We discuss steps that must be taken to mitigate these biases and call upon the community to incorporate our evaluation paradigm when building models to track progress towards building linguistically inclusive and diverse technologies.

\(^2\)Assamese, Bengali, Bodo, Dogri, Gujarati, Hindi, Kashmiri, Kannada, Konkani, Maithili, Malayalam, Manipuri, Marathi, Nepali, Oriya, Punjabi, Tamil, Telugu, Sanskrit, Santali, Sindhi, Urdu

2 Background and Related Work

Multilingual Models Transformer-based language models (LMs) (Vaswani et al., 2017) trained on massive amounts of text from multiple languages have enabled the inclusion of an unprecedented number of languages in NLP technologies (Conneau et al., 2019; Devlin et al., 2018). However, previous research has shown that these models do not serve all languages equally, with resource-poor languages in the long tail suffering the most (Hu et al., 2020; Lauscher et al., 2020). These models go through a critical step of fine-tuning for the downstream task before being deployed. Several recent works focus on optimal fine-tuning strategies that mitigate transfer gaps and improve overall performance across target languages. Lin et al. (2019) propose a tool that chooses optimal transfer languages based on linguistic features. Lauscher et al. (2020) demonstrate the effectiveness of investing in few-shot in-language training examples. Most recently, Debnath et al. (2021) show that investing in an equal number of fine-tuning instances across target languages performs best. These past approaches however, have all been heuristically designed based on the knowledge and intuition of the experimenter, unlike our proposed method that is purely empirical.

User-centric Evaluation At its core, the need for language diversity in technologies is tied to the people it serves. Previous work (Ethayarajh and Jurafsky, 2020; Ma et al., 2021) has highlighted the need for more transparent and user-centric leaderboard evaluation, reporting practically relevant statistics such as model size, energy efficiency, and inference latency. It is common for speaker populations of under-represented languages to operate in resource-constrained settings. Therefore, in addition to evaluating linguistic diversity, we employ efficiency metrics to assess accessibility of these technologies. With regards to linguistic diversity, Ruder et al. (2021) highlight the need for more fine-grained evaluation across languages and introduce language-specific leaderboards. Blasi et al. (2021) quantify the value of NLP technology weighed by speaker population and determine utilities of several technologies across the world’s languages.

Indian Languages The research community has actively been contributing to the advancement of IN NLP by collecting and open-sourcing data (Kak-
wani et al., 2020; Ramesh et al., 2021; Abraham et al., 2020; Roark et al., 2020; Kunchukuttan et al., 2017; Khanuja et al., 2020a), building region-specific multilingual models (Khanuja et al., 2021; Kakwani et al., 2020; Ramesh et al., 2021) and creating evaluation benchmarks (Kakwani et al., 2020; Khanuja et al., 2020b). Several of these efforts have been undertaken by AI4Bharat, a non-profit open-source community that has additionally been working on developing resources for IN signed languages (Sridhar et al., 2020) and creating input tools to type in IN scripts. Recently, Google Research India launched a question answering (QA) challenge named ChAII. Microsoft Research India has also made significant contributions to IN NLP with several efforts directed towards code-mixed language processing and building tools and datasets for under-represented languages in India.

3 Inclusion, Equity and Accessibility

3.1 Inclusion: Utility, Demand and the Global Metric

The global metric introduced by Blasi et al. (2021) helps quantify linguistic inclusion. Formally, this metric is composed of the utility of a technology weighed by its demand. The utility $u_l$ of a system for a task and language is its performance normalized by the best possible performance afforded by such a task, i.e.,

$$u_l = \frac{\text{performance}_l}{\text{theoretical max performance}}$$

The best possible performance is dictated by human-level performance achieved for the corresponding task.

Demand $d_l$ is characterized by taking into consideration demographic and linguistic perspectives. Under the demographic perspective, the demand for a given technology in a language is estimated to be proportional to the number of speakers of the language itself $n_l$ $(d_l \propto n_l)$. Under the linguistic perspective, the demand across languages is identical $(d_l \propto 1)$. These two alternatives, as well as any intermediate combination of them, is parametrized through a single exponent $\tau$:

$$d_l^{(\tau)} = \frac{n_l^\tau}{\sum_{l' \in L} n_{l'}^\tau}$$

where $\tau = 1$ correspond to a demographic notion of demand and $\tau = 0$ to a linguistic one. The global metric can now be defined as:

$$M_\tau = \sum_{l \in L} d_l^{(\tau)} \cdot u_l$$

In essence, $M_\tau = 0$ means that no user benefits from language technology and $M_\tau = 1$ corresponds to each language user enjoying perfect technology. Importantly, the higher the difference in $M$ under the linguistic and demographic notions of utility, the greater is the bias towards languages with large speaker populations.

3.2 Equity: Gini Coefficient

While linguistic utility assigns equal weight across languages, it does not take into account inequalities in the performance across languages. A model that achieves a performance of 0.9 in Hindi and 0.1 in Tamil is assigned the same linguistic utility as a model that obtains 0.5 in both languages, despite the first one being much less equitable. We propose to use the Gini coefficient to measure such inequality in language performance. The Gini coefficient (Dorfman, 1979) is a measure of statistical dispersion popularly used to quantify income inequality within a social group.

While several past works have highlighted transfer gaps in performance across languages (Hu et al., 2021; Khanuja et al., 2020a), building region-specific multilingual models (Khanuja et al., 2021; Sridhar et al., 2020) and creating input tools to type in IN scripts. Recently, Google Research India launched a question answering (QA) challenge named ChAII. Microsoft Research India has also made significant contributions to IN NLP with several efforts directed towards code-mixed language processing and building tools and datasets for under-represented languages in India.
none have quantified this dispersion.\textsuperscript{8} The Gini coefficient has several useful properties compared to alternative metrics to compute performance inequity such as the standard deviation, the difference between minimum and maximum, etc: it is a) scale-independent; b) bounded; and c) less influenced by outliers (De Maio, 2007).

The Gini coefficient is mathematically computed based on the Lorenz curve, which plots the relation between population size and the cumulative income earned by that population as shown in Figure 1. To plot the Lorenz curve, individuals are sorted in increasing order of income ($x$-axis) and their cumulative wealth is plotted on the $y$-axis. In essence, a point ($x, y$) indicates that the bottom $x\%$ of the population holds $y$ amount of wealth. The line at 45 degrees represents perfect equality of incomes. The Gini coefficient $G$ is then calculated as the ratio of the area that lies between the line of equality and the Lorenz curve (A in Figure 1), over the total area under the line of equality ($A + B$ in Figure 1). If $G = 0$, every person in the population receives an equal percentage of income and if $G = 1$, a single person receives 100% of the income. Since the axes scale from 0 to 1, $A + B = 0.5$. In essence, if the Lorenz curve is represented by the function $Y = L(X)$ then $G$ can be given as:

$$G = \frac{A}{A + B} = 2A = 1 - 2 \int_0^1 L(X) dX$$

For a population with values $y_i$, $i = 1 \ldots n$, that are indexed in non-decreasing order ($y_i \leq y_{i+1}$):

$$G = \frac{1}{n} \left( n + 1 - 2 \sum_{i=1}^n (n + 1 - i) y_i \right)$$

### Memory Saved:

We additionally consider the size of the model as a measure of how expensive a model is to use in practice. Since we wish to minimize this metric, we transform memory used into memory saved by subtracting it from a maximum available memory of 16 GB (Ma et al., 2021). We show the memory and throughput values for our models in Appendix A.1.

In the efficiency score, we wish to capture the benefit associated with per unit increase in cost, where cost is given by the decrease in throughput or memory saved. The model performance is taken as a proxy for its benefit. Let $x$ denote our set of pre-trained models and $M(x)$ denote metric values. Following Ma et al. (2021), we make two key assumptions: i) All models lie on the same indifference curve; ii) if $M(x_i) > M(x_{i+1})$ and $\text{perf}(x_i) > \text{perf}(x_{i+1})$, then there exists a model $(\text{perf}(x_{i+1}), M(x_i) + (M(x_i) - M(x_{i+1})))$ on the same indifference curve as $x_i$. Under these assumptions, we can calculate the average benefit-cost ratio (ABCR) for each metric and define Efficiency($x_i$) as:

$$\text{Efficiency}(x_i) = \sum_{M} w_M * \frac{M(x_i)}{\text{ABCR}(M, \text{perf})}$$

$$\text{ABCR}(M, \text{perf}) = \frac{M(x_\ast)}{\text{BCR}}$$

$$\text{BCR} = \left\{ \frac{\text{perf}(x_i) - \text{perf}(x_{i+1})}{M(x_i) - M(x_{i+1})} \left| 1 \leq i < n \right. \right\}$$

where we choose $w_{\text{perf}} = 0.5$, $w_{\text{throughput}} = 0.25$ and $w_{\text{memory}} = 0.25$ as default weights. In practice, these weights can be adjusted as per user requirements based on their constraints to calculate the final efficiency score.

Note that we compute the ABCR value for each language per task as opposed to prior work focusing on the task alone. Intuitively, we want to calibrate the efficiency of a technology for each language. For high-resource languages and relatively-simpler tasks, smaller models achieve good performances and scaling up merely leads to a 1–2% performance increase. Here, the ABCR will be low, hence increasing the relative importance of metric $M$ in the efficiency calculation. If we only measure raw performance, larger models are ranked higher, but with efficiency considerations, smaller models

\textsuperscript{8}Hu et al. (2020) only considered the difference between English and other languages as cross-lingual transfer gap.
As fine-tuning on a few labeled examples in the target language (Lin et al., 2019) or labels examples across all source languages equally (Debnath et al., 2021). We propose a fully computational approach for modeling the space of source and target languages. This is done by empirically estimating performance of language \( t \in T \) on a held-out set, when fine-tuned on \( x \) labeled instances of language \( s \in S \), \( \forall (s, t) \) pairs, which follows a power-law distribution (Rosenfeld et al., 2019). We now seek to find the optimal allocation \( \{ x_s : s \in S \} \) subject to \( \sum_{s \in S} x_s \leq \chi \) (details in Appendix A.5).

We follow a simple greedy approach to solve this constrained optimization problem as shown in Table 10. Specifically, at each step we allocate our sample to the source language conferring the highest marginal gain to all target languages, which is quantified by the summation of the increase in the global metric and the reduction in Gini.\(^{11} \) At present, we assign equal weight to each metric but this can be changed according to user preferences.

### 4 Experiments

#### 4.1 Experimental setup

**Languages** We base our case-study on the 22 scheduled languages of India spoken by 97% of its population. We also include English, since a sizeable population of 128.5M speakers report English to be their first, second or third language. We show the number of speakers per language in Table 1.

**Tasks** We select tasks from the XTREME (Hu et al., 2020) benchmark. Dataset details and the human performance (HP) for each task can be found in Table 2. For each task, we only evaluate on IN language test sets.

**Models** Model selection is motivated by two key factors that we wish to explore in our study: i) general v/s region-specific choices; ii) model efficiency. We choose IndicBERT, MuRIL and XLM-R, the first two being region-specific models and the third one being general.

| Language | as | bn | brx | doi | en | gu | hi | kn | kok | ks | mai | ml |
|----------|----|----|-----|-----|----|----|----|----|-----|----|-----|----|
| Speakers (in M) | 23.6 | 107.4 | 1.6 | 2.8 | 128.5 | 60.3 | 691.6 | 58.8 | 2.6 | 7 | 14.3 | 35.6 |

Table 1: The number of speakers (in millions) for each of the 22 scheduled languages and English. We take the sum total of first, second and third language speakers for each language.

\(^{10}\) An alternative approach is to rely on feature-based performance prediction (Xia et al., 2020; Ye et al., 2021), which we leave for future work.

\(^{11}\) Future work may consider more complex approaches that consider language relatedness based on work on transfer relationship learning (Zamir et al., 2018; Song et al., 2019).
Table 2: Finetuning Tasks and Datasets. HP denotes the human performance for each task. For QA, HP is 91.2 F1 for XQuAD and 90.1 F1 for TyDiQA.

| Language | NER | POS | NLI | QA |
|----------|-----|-----|-----|-----|
| English  | 20,000 | 21,261 | 392,702 | 88,602 |
| Hindi    | 5,000  | 13,305 | 392,702 (-train) | 88,602 (-train) |

Table 3: Number of training instances for English and Hindi. (-train) denotes that the English fine-tuning set has been translated to Hindi.

Fine-tuning Following convention, we initially fine-tune the selected models using training data in English (EN) given the availability of labeled data across tasks. However, several past works have highlighted that this choice is sub-optimal and one can obtain much better performance by transferring from closely related languages (Lauscher et al., 2020; Cotterell and Heigold, 2017; Dong et al., 2015; Turc et al., 2021). To examine its effect in our case-study, we additionally fine-tune models on Hindi (HI) because: i) 15 out of 22 languages belong to the same language family as HI (Indo-Aryan); ii) we have training data available for all tasks in HI; iii) HI has the highest speaker population, which may lead to higher demographic utility and is also a future-safe choice to obtain annotations for any task. Table 3 summarizes training data statistics for EN and HI.

12Training sets for NLI and QA have been machine-translated from English, which has been shown to perform similar to human-generated train sets (Turc et al., 2021).

4.2 Zero-shot transfer results

Where are we today? We report results of fine-tuning models on EN and HI in Table 4. Overall, the linguistic and demographic global utility metric is highest for MuRIL_large, when fine-tuned on HI. Generally, the linguistic metric is much worse than the demographic one, indicating that past efforts have been skewed towards popular languages, leaving under-represented languages behind. We also observe that utility increases with region-specific choices, both in pre-training and fine-tuning. The Gini coefficient remains relatively high at around 0.76 even for the best models, which highlights the disparity in performance even among languages within a single region. For comparison, for OECD countries from 2008–2009, the Gini coefficient on income for the entire population ranged between 0.34 and 0.45.
Overall, the absolute performance for all languages supported by the model. Refer to Section 4.2 for more details.

0.53 while the Gini coefficient for the entire world has been estimated to be between 0.61 and 0.68 (Hillebrand et al., 2009; Klugman and Nations, 2010).

How to handle the lack of evaluation data? In large part, this can be attributed to the absence of evaluation sets across tasks, with as few as 3 (out of 23) languages having test sets for XNLI. As detailed in Section 3.4, languages with no test data are assigned a score of zero, even if models would obtain non-zero performance. Hence, we calculate projected estimates using our best-performing model MuRIL\textsubscript{large} in Table 5. While there is a significant increase across all metrics, the absolute values are still low with the linguistic utility being below 50%.

How accessible are these models? With regards to the efficiency metric, averaging across languages and tasks, MuRIL\textsubscript{large} and MuRIL\textsubscript{base} perform equally. MuRIL\textsubscript{base} has a higher efficiency score (1-3 points) for simpler token-level tasks like NER and POS, while MuRIL\textsubscript{base} has higher scores on complex, semantic tasks like NLI (<1 point) and QA (2-5 points). Larger, more expressive models may thus be preferable in the latter cases despite being costlier on the accessibility front, since smaller models cannot obtain good performance. We illustrate per language efficiency scores in Appendix A.1 and discuss fine-grained observations.

What is the way forward? Overall, the absolute values of the global metric and the Gini coefficient indicate that there lies great potential in both increasing the utility of our models and making them more equitable. Since model performances largely reflect the amount of raw data used in pre-training (Lauscher et al., 2020), creating equitable unlabeled data resources would alleviate these issues. However, this is an ambitious undertaking that is extremely resource intensive and can certainly not be achieved for 6500 languages in the near future. We thus investigate how limited amounts of data can be used to maximally improve utility and equity during fine-tuning.

### 4.3 Few-shot results

Problem Formulation For few-shot fine-tuning, we focus on NER where sufficient labeled training data for seven IN languages is available. We employ the source languages $S = \{bn, en, hi, ml, mr, ta, ur\}$ and seek to optimize metrics on the target languages $T = \{bn, en, gu, hi, ml, mr, pa, ta, te, ur\}$. In each setting, we have a limited annotation budget, which we can divide among the source languages. We compare against several competitive baselines: i) using only examples from EN or HI respectively; ii) distributing the annotation budget in an egalitarian (uniform) way across all source languages (Debnath et al., 2021); iii) the greedy approach proposed in Section 3.5. For the greedy approach, we illustrate the best-fit curves for each $(s, t)$ pair in Appendix A.5 (Table 11). As the original calculation of the Gini coefficient takes into account all 23 IN languages, we also calculate the metric over our 10 target languages only, to observe how it differs across baselines.\textsuperscript{14}

\textsuperscript{14}In the original calculation, languages with no test sets have zero performance. Therefore, dispersion in the performances of our target language set is not as effectively captured and differences across alternative approaches are not observable.
Results  We show the results under various annotation budgets in Table 6. Overall, we find that our method yields a higher global metric under most budgets (5 of 6 cases) and also yields a lower Gini coefficient under all budget schemes. The optimal allocations for each budget are shown in Table 12. As we can see, the greedy algorithm converges to a solution that is close to uniform. This provides further evidence for the benefits of an egalitarian distribution of annotation budget in order to maximize performance across all languages as the expected marginal gain for languages that have been under-represented during training will be highest. Both the egalitarian and greedy approaches significantly outperform fine-tuning on EN or HI only, where the former approaches outperform fine-tuning on 10,000 examples of EN with a limited budget of 1,000 examples by 1–3%.

5 Discussion

Building evaluation datasets  Having uncovered the linguistic inequity and exclusivity of current NLP technologies, we seek to identify practical measures we can take in order to mitigate these biases. As a first step, it is paramount to build representative evaluation sets for all languages as they are required to accurately measure utility and equity. Out of the 23 languages in our case study, most do not have evaluation data across tasks despite holding official recognition and being spoken by 97% of the population. In light of the benefits of an egalitarian data distribution during few-shot learning, we also recommend the collection of small amounts of data across many languages for training, in order to maximize marginal gain. These datasets should be collected at the grass-roots level, involving the community they need to serve to capture culturally relevant phenomenon. A prime example of this is the Masakhane organisation\(^{15}\) steering efforts towards data collection in African languages, involving the local community. Incentivizing rural, low-income workers to provide for such data also serves as a viable source of supplementary income, and does not degrade dataset quality (Abraham et al., 2020).

Trading off multilinguality and regionality  From a modeling perspective, multilingual pre-trained models have been instrumental to NLP systems supporting an unprecedented number of languages, because of their zero-shot transfer capabilities. However, while these are a big step towards linguistic inclusion, they are subject to limitations such as highly skewed pre-training distributions and limited transfer to under-represented languages (Hu et al., 2020; Lauscher et al., 2020), a bias towards the source language, and sub-optimal tokenization (Wang et al., 2021). A way to combat these issues is to make region-specific choices, both in pre-training and fine-tuning, as observed in Section 4.2. Localizing the problem also enables one to incorporate linguistic expertise and provide support for culturally relevant phenomena like transliteration or code-mixing. Despite this, we must be wary of excessive fragmentation in pre-training as it leads to higher maintenance costs and there is a possibility that these benefits will be overcome with advances in compute and model capacity in the near-future. Optimal fine-tuning however, is promising, as evidenced in Section 4.3 where we observe significant gains in moving away from the zero-shot paradigm. There is still a lot of room for improvement, however, as the best linguistic utility is still less than 40%.

6 Conclusion

We have proposed a framework for the evaluation of NLP technology based on inclusivity, equity, and accessibility. To quantify equity, we have proposed to use the Gini coefficient, a standard metric to measure income inequality within social groups. Focusing on Indian languages, we have assessed to what extent several modeling and data choices affect the value NLP technology confers to users, highlighting the importance of region-specific choices and efficient models. We have also proposed an algorithmic method for resource allocation for task-specific fine-tuning, which outperforms a purely egalitarian distribution of data labeling. Finally, we highlight the importance of building representative evaluation sets from the grass-roots level to enable tracking progress, and discuss how even with the best modeling strategies, we have a long road ahead in building inclusive, equitable systems. While region-specific choices help to a certain extent, building a single global multilingual model without compromising on the three metrics is something we should move towards in the future. We sincerely hope our evaluation paradigm aids in tracking the community’s progress in building linguistically diverse technologies.

\(^{15}\)https://www.masakhane.io/
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Iulia Turc, Kenton Lee, Jacob Eisenstein, Ming-Wei Chang, and Kristina Toutanova. 2021. Revisiting the primacy of english in zero-shot cross-lingual transfer. *arXiv preprint arXiv:2106.16171*.
A.1 Efficiency

As detailed in Section 3.3, we report the throughput and memory for each model and task in Table 7. For NLI, POS and NER, the maximum sequence length is 128 and for QA it’s 384.

We plot per-language efficiency scores for two tasks namely POS and QA in Figure 2 for all models when fine-tuned on English. For most languages, efficiency scores drop when we move from the base to large versions in POS, and for EN even the smallest model, IndicBERT, has an efficiency score similar to large models. However for QA, we observe a uniform gain in efficiency across languages as we move to larger models.

A.2 Pre-training Languages

In Section 4.1, we choose IndicBERT, MuRIL and XLM-R as pre-trained multilingual models to base our analysis upon. IndicBERT is trained on 11 IN languages that include Assamese (as), Bengali (bn), Gujarati (gu), Hindi (hi), Kannada (kn), Malayalam (ml), Marathi (mr), Oriya (or), Punjabi (pa), Tamil (ta), Telugu (te). XLM-R includes 15 IN languages in training with the addition of Nepali (ne), Sanskrit (sa), Sindhi (sd) and Urdu (ur) over IndicBERT and MuRIL is trained on 16 IN languages, with the addition of Kashmiri (ks) over XLM-R.

A.3 Gini Coefficient

As mentioned in Section 4.2, calculating the gini coefficient across all 23 languages doesn’t reflect the dispersion in performances across languages for which we have test sets. To compare between baselines, we additionally report the Gini coefficient evaluated only across those languages for which we have test sets as shown in Table 8. We observe that region-specific choices (MuRIL_base fine-tuned on HI) lead to the lowest value, similar to what we observe with the global metric.

A.4 Fine-tuning Details

We fine-tune all models using the hyperparameters mentioned in Table 9 for each task and model consistently throughout the paper. We make an exception for IndicBERT when fine-tuning on NER, where we fine-tune for 15 epochs instead of 10, to reach convergence.
In Section 3.5, we describe an empirical budget allocation scheme for fine-tuning of pre-trained models that can jointly optimize on our proposed metrics. We follow a greedy approach to solve this problem, as shown in Table 10. In this paper, we solve this for one task, namely NER, but the methodology proposed is generally extensible to any task and combination of languages since it is purely empirical. We select seven source languages for which we have enough training data and fine-tune MuRILlarge and XLM-Rlarge for each of these source languages independently, for two epochs. During fine-tuning, we evaluate on each of our target languages after every 10 steps of training. Given our batch-size is 32, we gather data-points at a step size of 320 training instances. Consequently, say we have 5000 training instances for a source language, we gather approximately 30 sample points for that source language and any target language. Using these, we plot best-fit curves for \( \forall (s, t) \) pairs using the `scipy.optimize.curve_fit` package. Given a function, \( f(x) \), `curve_fit` uses non-linear least squares to fit \( f(x) \) to the observed data-points. We define \( f(x)_{s,t} = a_{s,t} + b_{s,t} \times x^{-c_{s,t}} \), because the relation between model performance and training data follows a power-law distribution (Rosenfeld et al., 2019). The best-fit curves for each source and target pair are shown in Table 11. The visualizations of the best-fit curves for a sample training language (Tamil) are shown in Figures 3, 4.
Greedy Algorithm

1: **Input**: Fine-tuning labeled data $\forall s \in S$. A fixed budget of labeled data instances $X$.
2: **Initialize**: Set the total number of allocated instances to zero, i.e., allocated = 0, the number of allocated samples for each source language to zero, i.e. samples$[s] = 0 \forall s \in S$, the current global metric for each source language to -inf, i.e. current$._{gm}[s] = -\infty \forall s \in S$ and the current gini coefficient for each source language to 1, i.e. current$._{gini}[s] = 1 \forall s \in S$.
3: **while** allocated $< X$ **do**
4: \hspace{1em} highest$._{marginal\_gain} = 0$
5: \hspace{1em} **for** $s \in S$ **do**
6: \hspace{2em} gm$[s] = \sum_{t \in T} d(\tau_t \ast (a_s + b_s \ast (samples[s] + 1)^{-\alpha_s}))$
7: \hspace{2em} gini$[s] = F(abs(performance_s(t \in T)) \forall t \in T)$
8: \hspace{2em} $\Delta_{gm}[s] = gm - current._{gm}[s]$
9: \hspace{2em} $\Delta_{gini}[s] = current._{gini}[s] - gini$[s]
10: \hspace{2em} marginal$._{gain} = \alpha \ast \Delta_{gm}[s] + \beta \ast \Delta_{gini}[s]$
11: \hspace{2em} **if** marginal$._{gain} > highest\_marginal\_gain$ **do**
12: \hspace{3em} highest\_marginal\_gain = marginal\_gain
13: \hspace{3em} best\_language = $s$
14: \hspace{3em} best\_gm = gm$[s]$
15: \hspace{3em} best\_gini = gini$[s]$
16: \hspace{2em} **end if**
17: \hspace{1em} **end for**
18: \hspace{1em} samples$[s] = samples[s] + 1$
19: \hspace{1em} allocated = allocated + 1
20: **end while**

Table 10: A greedy approach to solve constrained optimization for the budget allocation problem as described in Appendix A.5.

Figure 3: Best-fit curves for XLM-R when fine-tuned on Tamil for each of the target languages.

Figure 4: Best-fit curves for MuRIL when fine-tuned on Tamil for each of the target languages.
| Test | Train | MaRIL | XLM-R |
|------|-------|-------|-------|
| Edge Weight | R-squared | Edge Weight | R-squared |
| bu | 1.2 - 20.0 x⁻⁰⁵ | 0.88 | 1.3 - 11.5 x⁻⁰³ | 0.93 |
| en | 1.2 - 11.4 x⁻⁰⁴ | 0.78 | 1.1 - 8.1 x⁻⁰³ | 0.89 |
| hi | 1.4 - 9.4 x⁻⁰³ | 0.85 | 1.1 - 8.1 x⁻⁰³ | 0.92 |
| ml | 1.2 - 10.7 x⁻⁰³ | 0.86 | 2.3 - 4.9 x⁻⁰¹ | 0.92 |
| mr | 1.9 - 6.5 x⁻⁰³ | 0.88 | 1.9 - 4.6 x⁻⁰¹ | 0.93 |
| ta | 1.2 - 10.5 x⁻⁰³ | 0.85 | 1.3 - 6.1 x⁻⁰² | 0.90 |
| ur | 1.0 - 13.5 x⁻⁰⁴ | 0.88 | 1.0 - 6.5 x⁻⁰³ | 0.91 |
| bu | 0.9 x⁺⁰⁴ | 0.86 | 0.9 x⁻⁰³ | 0.80 |
| en | 1.1 - 16.4 x⁻⁰⁴ | 0.82 | 1.1 - 14.6 x⁻⁰³ | 0.85 |
| hi | 1.0 - 5.6 x⁻⁰³ | 0.88 | 1.0 - 7.6 x⁻⁰³ | 0.90 |
| ml | 1.9 - 3.5 x⁻⁰³ | 0.88 | 1.0 - 6.1 x⁻⁰² | 0.86 |
| mr | 1.2 - 3.2 x⁻⁰³ | 0.84 | 1.2 - 4.8 x⁻⁰³ | 0.91 |
| ta | 0.8 - 4.2 x⁻⁰³ | 0.76 | 0.7 - 6.9 x⁻⁰³ | 0.76 |
| ur | 0.9 x⁻⁰³ | 0.88 | 1.0 - 3.9 x⁻⁰² | 0.90 |

Table 11: Power-law equations empirically determined for each source and target pair. Please refer to Section A.5 for more details.

Table 12: Optimal allocations under different budgets. Please refer to Section A.5 for more details.