Predicting the Performance of Multilingual NLP Models

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Recent advancements in NLP have given us models like mBERT and XLMR that can serve over 100 languages. The languages that these models are evaluated on, however, are very few in number, and it is unlikely that evaluation datasets will cover all the languages that these models support. Potential solutions to the costly problem of dataset creation are to translate datasets to new languages or use template-filling based techniques for creation. This paper proposes an alternate solution for evaluating a model across languages which make use of the existing performance scores of the model on languages that a particular task has test sets for. We train a predictor on these performance scores and use this predictor to predict the model’s performance in different evaluation settings. Our results show that our method is effective in filling the gaps in the evaluation for an existing set of languages, but might require additional improvements if we want it to generalize to unseen languages.

CCS Concepts: • Computing methodologies → Natural language processing; Language resources; Machine learning approaches.

Additional Key Words and Phrases: natural language processing, evaluation, multilingual models, low-resource languages

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1 INTRODUCTION

Multilingual BERT (mBERT) [9] and XLM-Roberta (XLMR) [6] are transformer-based encoders that are pretrained on corpora spanning over 100 languages. The pretraining procedure makes use of only unlabelled data (raw text), which is easy to obtain for a large number of languages from various sources including CommonCrawl1 and Wikipedia dumps2. These models can then be used to solve a variety of downstream tasks by finetuning on a much smaller amount of labelled data for that task.

*Work done while the author was at Microsoft Research
1https://commoncrawl.org/
2https://dumps.wikimedia.org/

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These models have become very popular due to their ability to transfer downstream task performance across languages in a zero-shot manner, i.e., they can be finetuned on labelled data for a task in one language and then be used to solve that task in multiple other languages which do not have any labelled data. This was originally demonstrated on a Natural Language Inference task (XNLI) [7] using mBERT where the model was initially finetuned using only English training data and was then able to solve the task in 14 more languages. Subsequent work [26, 33] have found similar performance on tasks like Parts-of-Speech tagging (POS), Named Entity Recognition (NER) and Dependency Parsing.

When we look at the popular datasets typically used to evaluate these models, we find that none of them support more than a handful of languages: CoNLL NER [29] - 4 languages, MLQA [21] - 7 languages, PAWS-X [37] - 7 languages, TyDiQA-GoldP [5] - 9 languages, XQuAD [2] - 11 languages, XNLI [7] - 15. Datasets like UDPOS and WikiAnn are exceptions, spanning a larger number of languages (57 and 89 respectively for the subsets of the dataset(s) that we used), but the number of such exceptions is too few. This disparity can be attributed to 2 reasons. First is the fact that there is a disparity in the amount of text resources available in different languages. For example, Joshi et al. [15] show that while many Asian and Indian languages have many more speakers than some European languages, they are extremely lacking in the amount of text resources that they have compared to their European counterparts. Many languages spoken in large communities in the world get left behind when it comes to NLP systems built for them. Second is the fact that even for languages that have text resources, there is a disparity in the amount of labelled data present across languages [16]. This is likely due to the high cost of annotating datasets as well as the lack of access to language experts or crowd workers for some languages. This leaves us in a situation where multilingual language models (LMs) can be built for these languages, but the LM cannot be evaluated across different tasks in those languages due to the unavailability of labelled data.

The cross-lingual transfer ability of these models make them very useful in scenarios where a downstream task needs to be supported in multiple languages. A single finetuned model can be deployed to serve many languages at once. We however have the problem that we cannot evaluate these models on all the languages that they support, so what we can do about it? One potential idea is to come up with techniques to automatically or semi-automatically create test sets in new languages. Another way is to use insights from the evaluation on languages and tasks for which labelled data is available and extrapolate these findings to unseen languages.

When it comes to creating test sets in new languages, we could use a couple of techniques to accelerate this process and make it easier. The high quality of current state-of-the-art machine translation (MT) systems [14] makes it viable to use MT for translating test sets from existing languages into newer languages. However, labelled datasets require their annotations to be preserved during translation which is difficult to accomplish, particularly for word-level annotations. Another possible method is to use the technique proposed by Ribeiro et al. [28], in which the creation of datasets can be sped up by using masked language models to fill slots in user generated templates. This can also be potentially used along with translation to scale up testing to multiple languages. However, often the creation of initial templates for slot filling is time consuming and requires linguistic expertise.

The other way of solving this does not involve creating test sets, and we look into this in this paper. If we consider the task of XNLI from before, English, the language that mBERT is finetuned on, is considered to be the pivot language, and the 15 languages that the finetuned model is evaluated on are considered as the target languages. More generally, if the task in concern has training data in \( p \) pivot languages and test data in \( t \) target languages, the model can be finetuned on any mix of data from these \( p \) languages and the finetuned model can be evaluated on \( t \) languages. If the model is finetuned on just one language, we refer to it just as the pivot language, but if the language is
finetuned on a mix of data from multiple pivots, we refer to the mix as a *training configuration*. We should however remember that the model supports many more than the p or t languages that we have data for.

In this paper looks into the task of predicting the performance of multilingual models on training configurations and languages that we can not easily test for. We define a set of features that characterize the model’s performance on a particular language. These features are used to train a predictor on the known (for some configurations) performance scores of the multilingual model to predict performance for the unknown configurations for a given task. The predictor is evaluated via different error metrics simulating different use cases scenarios of the predictor.

## 2 RELATED WORK

mBERT [9] and XLMR [6] are multilingual transformer models that have been pretrained on text from around 100 languages. These models have been evaluated on tasks like natural language inference, document classification, parts of speech tagging, named entity recognition, dependency parsing [7, 26, 33, 34] and have shown excellent cross-lingual transfer of performance. These models were found to perform well on tasks involving code-mixed text too [1, 18]. Given that these models have to support over 100 languages with the limited model capacity they have, some works have found that they are outperformed by monolingual versions, even on some low-resourced languages [8, 25, 27, 31].

Some of the aforementioned works [26, 33, 34] have theorized about the reasons why cross-lingual transfer works and have stated that factors like pretraining data size and vocabulary overlap between languages could affect the transfer performance of a language in these models. Lauscher et al. [20] study the correlation between transfer performance and factors like syntax, phonology, data size when English is used as the finetuning language. Turc et al. [30] study the performance of mBERT and mT5 [36] on a wider variety of tasks and look at the impact of using different languages as the finetuning/pivot language.

The task of predicting an NLP model’s performance is something that has been looked into in the traditional train-transfer scenario that was popular before pretrained NLP models, with the goal of determining which high-resourced transfer language to use to maximize the performance in a lower-resourced target language. Lin et al. [22] develop a set of features based on the overlap between the 2 languages and use that to predict which transfer language would be the best. Xia et al. [35], Ye et al. [38] evaluate similar techniques on a wider range of tasks and look into better reliability estimates for prediction. Vu et al. [32] meanwhile look at intermediate task finetuning in English, i.e finetuning on a high resourced intermediate task before finetuning on the target task that might have lesser data. They build a set of task embeddings from the transformer model’s representations that can be used to predict which intermediate task to finetune on to maximize the performance on the final task. In contrast to these existing works, our work looks specifically into pretrained multilingual transformer models, where a single model can be trained and tested on multiple languages.

## 3 METHODOLOGY

In this section, we describe a set of factors that could influence the zero/few-shot performance of a multilingual model. These factors are represented by a set of features for each language. We then briefly describe the regression model used to build the predictor. Furthermore, we go on to describe the evaluation setup where a predictive model is trained to predict the performance of a language given a set of features about the language. We also describe the 2 methods by which the performance of the predictor is evaluated.
3.1 Choice of Features

Most multilingual models are pre-trained on monolingual corpora spanning a large number of languages. For example, mBERT is pre-trained on a Wikipedia corpus spanning 104 languages, while XLMR is pre-trained on a CommonCrawl corpus spanning 100 languages. Some models, such as Huang et al. [13], Lample and Conneau [19], have parallel data added in during pre-training as well. A single shared sub-word vocabulary spanning all the languages is used by these models, leading to overlap between the tokens spanning languages, which could serve as a potential cross-lingual signal [3]. Based on these properties of the models, we propose a set of features. The features fall in 2 categories: ones that are dependent only on the target language (Target dependent) and ones that are a function of both the pivot and target language (Pivot-Target dependent). The number of Pivot-Target dependent features that we will have eventually will depend on the number of pivot languages during finetuning.

3.1.1 Size of pre-training data. For each language, we take the $\log_{10}$ of the size of the corpus used in pre-training. Figure 1 shows that languages like English have exponentially more data than the next lowest language German, so a logarithm was taken to reduce these values to a more linear scale. This metric is independent of the pivot language used for fine-tuning. The metric is denoted in the results as Data Size.

3.1.2 Typological features. Typological features capture the structural properties exhibited by languages, and there is evidence that shows that similarity in linguistic typology has an impact on multilingual language modeling [11]. One such feature is word order, and K et al. [17] show that it has an impact on cross-lingual performance. Xia et al. [35] also find correlations between typology and cross-lingual transfer. Hence, we decide to use typological features as a factor in our predictive model.

We consult the WALS database [10] to obtain information about these features. This database comprises of over 2000 languages and 150 typological features, with each language’s entry specifying which form (if present) the typological feature takes for the language. The typological feature entries in WALS are sparse, i.e many languages have entries for only a subset of the typological features. If these entries weren’t sparse, we could use them as is without any modification or processing. Since this is not the case, we develop a score for each language based on how well represented it’s typological features are in the data used for pre-training the model.

The intuition behind such a score is as follows: suppose, during pre-training, a multilingual model was not exposed to enough text exhibiting a particular feature, it could possibly struggle when it is run on languages having that feature. We quote an example of this from the WALS
database. Yoruba uses a pure vigesimal\(^3\) number system and is one of the few languages among the ones mBERT is pre-trained on that has this number system. Whereas, there are 25+ languages that use the decimal number system\(^4\). Due to this, it is possible that the model is much better at recognizing and handling text with the decimal number system, impacting its performance on a language like Yoruba.

A language having a large number of such features that the model has not seen during pre-training may not perform as well as other languages. Thus, for each language, we define a metric that determines how well represented its typological features are. We use the WALS database to obtain typological features for each language and exclude the features based on phonology, taking the features starting from “20A” onward. Since each feature is multi-valued, we binarize the database and derive 541 binary features.

Using the training data sizes for each language, we determine the total amount of training data present for each feature (as the sum of the training data of the languages that exhibit that feature) and rank the features in descending order of data present. Based on these ranked features, we obtain the final metric to estimate how well they are represented:

\[
\text{Well Rep Feat}(L_i) = \mathbb{E}_{k \in \text{feat}[i]} \frac{1}{\text{rank}(k)}
\]

where feat\([i]\) are the features that language \(L_i\) exhibits and rank\((k)\) is the rank of feature \(k\) as per the ordering defined. In essence, this metric is the mean reciprocal rank of all the features that language \(L_i\) exhibits. A language with a large number of underrepresented features would have a lower value for this metric as its features would be ranked low, whereas a language with well represented features would have a higher value for this metric. This metric is independent of the pivot language used and is denoted in the results as \textbf{Well Rep Feat}.

3.1.3 Type overlap with pivot language. Subword overlap has been used to study the performance of languages in different transfer learning settings and in machine translation [22, 24, 35]. More recently, the vocabulary overlap between languages has been reported as one of the reasons for mBERT’s powerful cross-lingual abilities [26, 33]. Hence, we wish to incorporate the vocabulary overlap between the target and pivot language into our model. We consider the set of possible

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\(^3\)A Vigesimal number system is a base 20 number system, unlike the more commonly known Decimal number system that is base 10

\(^4\)Many of mBERT’s languages do not have an entry for their number system in WALS
subwords (types) that cover a language. For each language \( L_i \), we obtain a metric that signifies the overlap between its vocabulary and the vocabulary of the pivot language \( L_p \).

\[
\text{Type Overlap}(L_i, L_p) = \frac{|T_i \cap T_p|}{|T_i| + |T_p|}
\]

where \( T_i \) is the set of types that cover language \( L_i \). \( T_i \) is obtained by using the model’s tokenizer. Multilingual Wikipedia dumps were used for this purpose. We discard from \( T_i \) types that occur \( \leq 5 \) times. Figure 2 shows that the number of types occurring \( \leq 5 \) times contribute to as much as 50\% of \(|T_i|\) for some languages [39]. These are unlikely to contribute to the language’s performance and hence we discard them before calculating Type Overlap to prevent the metric from being skewed. This metric is dependent on the pivot language used and is denoted in the results as **Pivot Overlap**.

### 3.1.4 Distance from Pivot Language

For each language \( L_i \), we obtain a metric signifying the distance between it and the pivot language \( L_p \). For this, we use lang2vec [23], which contains vectors for each language spanning different categories like syntax, phonology etc. The syntax vectors are based on the entries from WALS, SSWL and Ethnologue. The distance between these vectors is used as the distance between the languages. Like the previous metric, this one is dependent on the pivot language used. The metric is denoted in the results as **Pivot Distance**.

### 3.2 Predictive Model

The aforementioned features are used as inputs for a regression model. Each regression model is trained on performance scores over multiple target languages on a particular task. This is detailed more in the subsequent sections. We use XGBoost [4] as the regressor. XGBoost has been used in other work that does prediction of the performance of NLP models [22, 35]. We also found that it outperformed a dense natural network when we evaluated on a few datasets. Each regressor is trained with squared error as the loss function, a learning rate of 0.1, max depth of 10 and num estimators of 100. All the input features are converted to a \([0, 1]\) range via min-max normalization. The performance scores used are also converted to a \([0, 1]\) range. The predictor’s error is measured using Mean Absolute Error (MAE). This error is also in a \([0, 1]\) range, so an error of 0.04 will correspond to 4\%.

### 3.3 Evaluating the Predictive Model

We evaluate the predictor via two different methods. The difference between these methods is in whether there is any overlap between languages in the data used for training and testing the predictor.

- **E1** - In this method, we allow for an overlap between the languages in the train and test set. This represents the scenario where we have a predictor trained on a set of languages and want to use it to predict on these languages but on different training configuration.
- **E2** - This method is referred to as Leave One Language Out (LOLO). We create a test set containing scores only from a particular language \( l \), with the train set not containing any examples (neither as pivot or target) from language \( l \). We measure the error of the predictor in this setup and average it over all the target languages we have. This represents a scenario where a predictor trained on a set of languages and we want to use it on a new language that it has not seen during training.

In addition to this, we report a baseline error value for E2. The **baseline** is a simple mean of the scores using training the XGBoost model in each case.
Table 1. Number of Pivot and Target languages in the datasets used for training the predictive model for Section 3. For UDPOS and WikiANN, we restrict the datasets to the languages used by the XTREME benchmark [12]

| Dataset | Pivot Langs | Target Langs | Num Training Examples |
|---------|-------------|--------------|-----------------------|
| XNLI    | 15          | 15           | 225                   |
| UDPOS   | 29          | 33           | 957                   |
| WikiANN | 40          | 40           | 1600                  |

4 EXPERIMENTS: SINGLE PIVOT

4.1 Experimental Setup

We first evaluate our technique in a setup where the multilingual model is finetuned on data from a single pivot language (no mixing of training data from multiple pivot languages). We collect performance scores of mBERT and XLMR Large on existing datasets that are available in multiple pivot and target languages. The details of the datasets used are in Table 1. The model is finetuned on each of the \( p \) pivot languages separately, and each of these \( p \) finetuned models is evaluated on the \( t \) target languages. Thus, if a dataset has \( p \) pivot languages and \( t \) target languages, we obtain \( p \ast t \) performance scores and these are used as the data points for training the predictive model. Since each model is finetuned on a single pivot, we do not need to worry about adding the Pivot-Target dependent features multiple times. We have 4 features (2 Target dependent + 2 Pivot-Target dependent) in total as input for the predictor.

4.2 Error Computation

We compute the error in the E1 setup as follows. For each \((\text{pivot}, \text{target})\) combination, we take all the \( p \ast t \) data points, leave that particular point out, train a predictor on the remaining \((p \ast t) - 1\) points and use this predictor to predict the score for the left out point. This gives the estimate for the error for the case when we have some data points for a target language and want to estimate the scores for the missing ones.

The E2 error is computed in the following manner. For each \((\text{pivot}, \text{target})\) combination, we take all the \( p \ast t \) data points, leave out the \( p \) points corresponding to the target language \text{target}, train a predictor on the remaining \( p \ast (t - 1) \) points and use this predictor to predict the score for the left out point. This gives the estimate for the error for the case when we have no data points for a target language, which is a realistic scenario for most untested languages. The mean baseline for the E2 scenario is computed by taking the mean of the \( p \ast (t - 1) \) data points used for training the predictor.

4.3 Results

Table 3 contains the errors for the predictor and the baseline methods. We observe that the E2 error of our predictor is around 2% on XNLI and 10-15% on UDPOS and WikiAnn. The errors of both the mean baseline and predictor are very low for XNLI because the range of scores (highest - lowest value observed in training data) is much lower than the other tasks.

The errors in the E1 case are much lower, about half of the E2 error in many cases. The difference between the E1 and E2 methods is that in the E1 method, the model has been exposed to data points with the same language as the one on which error has been calculated. This suggests that the predictor’s ability to generalize to unseen languages isn’t the best across tasks. However, we have
Table 2. Feature Importance values from XGBoost for different input features used

| Model  | Task       | Data Size | Well Rep Feat | Pivot Overlap | Pivot Distance |
|--------|------------|-----------|---------------|---------------|---------------|
| mBERT  | XNLI       | 0.8317    | 0.0851        | 0.0310        | 0.0521        |
|        | UDPOS      | 0.1749    | 0.3765        | 0.0987        | 0.3499        |
| WikiAnn|            | 0.2662    | 0.3390        | 0.2236        | 0.1712        |
| XLMR   | XNLI       | 0.9218    | 0.0459        | 0.0202        | 0.0121        |
|        | UDPOS      | 0.2687    | 0.2073        | 0.1328        | 0.3912        |
|        | WikiAnn    | 0.4542    | 0.2344        | 0.2344        | 0.1524        |

Table 3. Two types of predictor error (E1 and E2) and the mean baseline for E2 on different datasets. Lower is better. Predictions/Task Scores are in the range [0,1], so the same range applies for the error

| Model  | Dataset       | Predictor Error | Baseline   |
|--------|---------------|-----------------|------------|
|        | XNLI          | 0.0082          | 0.0279     | 0.0325     |
| mBERT  | UDPOS         | 0.0636          | 0.1015     | 0.1004     |
|        | WikiAnn       | 0.0940          | 0.1554     | 0.1369     |
| XLMR   | XNLI          | 0.0052          | 0.0259     | 0.0298     |
|        | UDPOS         | 0.0825          | 0.1149     | 0.1160     |
|        | WikiAnn       | 0.0856          | 0.1285     | 0.1253     |

Fig. 3. XLMR XNLI performance scores for 15 target languages (columns) with 15 pivot languages (rows)

to keep in mind that the E1 and E2 settings are 2 extreme ends of a spectrum (w.r.t the number of examples used from a particular target language). The predictor’s performance on a new language could potentially be improved by adding just a few examples from that language.

4.4 Observations
4.4.1 Trends in Feature Importance Values. Table 2 contains the feature importance values returned by the XGBoost predictor used for the different tasks. We observe a clear difference in which features are important between XNLI, a semantic task, and UDPOS/WikiAnn, which are more syntactic tasks. For syntactic tasks, the predictor relies more on the features that are based on typology and the relation/overlap between languages. For the semantic task, the predictor is relying mainly on the pretraining data size. This could be a more general indication of the performance of multilingual models on different tasks, possibly suggesting that using more pretraining data is likely to a help a language more in semantic tasks, while syntactic tasks are likely to benefit not by this, but rather by finetuning on related languages.

4.4.2 Performance of Target Languages on Different Pivots. In the process of collecting data points to train the predictor, we end up with the performance scores of $p$ finetuned models on $t$ target languages for each task. These performance scores, on XLMR, are visualized in the form of heatmaps
Predicting the Performance of Multilingual NLP Models

Fig. 4. XLMR UDPOS performance scores for 33 target languages (columns) with 29 pivot languages (rows) (Figures 3, 4, 5) and these heatmaps give us some insights into the performance of the multilingual models themselves.

Figure 3 shows the distribution of scores on XNLI. The languages along the X-axis and Y-axis here are sorted by the amount of resources available in them. The scores on a particular target do not vary significantly depending on the pivot. English does well irrespective of which pivot language is used, and the performance gradually decreases as we move towards targets on the right.

Figures 4 and 5 show similar heatmaps for UDPOS and WikiAnn. In these plots, the languages along the X-axis and Y-axis are grouped based on language family and arranged as per this grouping. With this kind of an ordering, we are able to see many cases of transfer happening within language families. This is present in the form of green boxes around the diagonal in many instances. We can see this clearly for the languages from the Indo-European family (from Afrikaans(af) to Bulgarian(bg)), and to a lesser extent among the Indo-Aryan/Dravidian languages (from Urdu(ur) to Malayalam(ml)).

We also see instances of rows or columns that are completely red. These are cases where transfer across languages does not happen at all. The red rows are what we refer to as Bad Pivots. This is the case for Japanese(ja), Chinese(zh), Korean(ko) for UDPOS and Thai(th), Yoruba(yo), Burmese(my), Japanese(ja) on WikiAnn. Finetuning with data on these languages does not seem to help any language other than itself. The red columns are what we refer to as Bad Targets. This is the case for Yoruba(yo), Japanese(ja) for UDPOS and Thai(th), Yoruba(yo), Chinese(zh), Japanese(ja) for WikiAnn. Finetuning on languages other than themselves do not help these languages. There is also the case of German(de) in UDPOS, where finetuning on it produces very bad performance on en alone, a language very similar to it.
Fig. 5. XLMR WikiAnn performance scores for 40 target languages (columns) with 40 pivot languages (rows)

| Dataset  | Training Data Combinations | Target Langs | Num Training Examples |
|----------|----------------------------|--------------|-----------------------|
| XNLI     | 256                        | 15           | 3840                  |
| UDPOS    | 1664                       | 57           | 94848                 |
| WikiANN  | 1592                       | 89           | 141688                |

Table 4. Number of Input Data combinations (training runs) and Target languages in the datasets used for training the predictive model for Section 4. For UDPOS and WikiANN, we used versions of these datasets with more languages than the previous section (which was limited to the XTREME benchmark’s languages)

We see that there is a good overlap between the languages in Bad Pivots and Bad Targets. This could suggest that the reason for these phenomenon could be that the multilingual model isn’t able to support these languages well. The bad performance of the (de, en) pair is a strange one as en is the only language on which the de model does not do well. This could possibly due to some difference in the annotation done for both datasets.
5 EXPERIMENTS: MULTI PIVOT

5.1 Experimental Setup

We now evaluate our technique in a setup where the multilingual model can be finetuned on a mix of data from $p$ different pivot languages. We finetune XLMR Large on existing datasets in this manner, finetuning on $m$ different combinations of training data across the $p$ languages. Each of these $m$ models are then evaluated on $t$ target languages and we end up with $m \times t$ examples in total for the predictor. The details about the datasets are in Table 4.

Since we have multiple pivot languages, we need to change the set of input features to the model. Each training configuration has a mix of data from the $p$ pivot languages. We represent this via a $p$ dimensional vector (referred to as the input data vector or finetuning data size), with element $i$ of the vector representing the amount of data used from pivot language $i$ during finetuning. Also, since we have not 1 but $p$ pivot languages, we will need to increase the number of Pivot-Target dependent features from 1 to $p$ to capture the overlap between each pivot and the target. We summarize the set of input features in Table 5.

Given that we have more than 50 pivot languages in some datasets, we experiment with different methods of adding in the Pivot-Target dependent features, so as to prevent the model from having a very large input space

1. None - None of these features are added
2. All - $2p$ features are added like described above
3. Data-Only - $2p$ features are added like above, but we then 0 out the values for languages that have a 0 in their training configuration

The total number of input features is either $2 + p$ or $2 + 3p$ depending on the method used

5.2 Error Computation

The E1 error (cf. Section 3.3) is computed as follows. We divide the data into 5 folds and compute the error in a 5-fold cross-validation manner (train on 4 folds, test on the 5th fold). The E1 error in the previous section was computed in a similar manner, the only difference being that it used a $n$ fold cross-validation instead of the 5-fold we are using here ($n$ is the total number of training examples). We reduce $n$ to 5 here as $n$ is large and the error computation will be very computationally expensive.

The E2 error is computed for each target language in the following manner and is then averaged over all the languages. We sample 1000 train and 100 test points from the data. The test data points are all from the target language and the train data points do not contain any data points from the target language. In addition to this, we ensure that the train data points have the input data vector’s value for the target language to be 0, i.e no data from that language was in the mix of data used to finetune the model. This models the scenario where we have training (pivot) or test (target) data.
for the language. The mean baseline for the E2 scenario is similarly computed by taking the mean of the 1000 data points used for training the predictor.

5.3 Results

Table 6 contains the errors for the predictor in the new evaluation setup. We can see that the E1 errors are extremely low, while the E2 errors are reasonably high, particularly for UDPOS and WikiAnn. The E2 error is still lower than the mean baseline in most cases, so using the predictor brings in an improvement. The E1 errors being low imply that the predictor is able to predict well on different combinations of finetuning data for languages that it has seen during training. The higher E2 errors indicate that the ability of the predictor to generalize to unseen languages relatively harder.

We varied the set of Type 2 features (Pivot Feats in Table 6), to see if adding them brought any improvement to the predictor. The performance of each method varies and there does not seem to be a single best option. For both the All and Data-Only option, we end up adding a large number of input features to the model (30 for XNLI, 50+ for UDPOS and WikiAnn). Adding these in does not seem to affect the predictor’s performance, so we conduct the rest of the experiments using None option.

Distribution of Errors Across Languages: Since the E2 errors were higher overall, we take the E2 errors for each language (without averaging over all languages) and plot the distribution of this across different languages in Figure 6. This figure is for the predictor trained on the UDPOS dataset. The error of the baseline error (mean baseline for E2) is depicted by the black line. The languages are coloured and ordered by language family. We can see that the E2 errors vary significantly across languages. For many languages, the errors are under 0.05 (5%), but for others, the distribution is very wide. The rightmost 3 languages, zh, ja and ko show some of the widest ranges in error.

6 RELATIVE EVALUATION OF PREDICTOR

We have observed so far that the predictor’s E1 performance is very good, but the errors in the E2 scenario are not as low as the E1 scenario. To get a better insight into the functioning of the predictor, we propose a new method of evaluation that does not look at the magnitude of the predictor’s errors, but rather at whether the relative trends in the predictions match the test data. We construct 2 scenarios for testing the predictor. The test set for each scenario contains a set of

| Model/Dataset | Pivot Feats | E1  | E2  | Baseline |
|---------------|-------------|-----|-----|----------|
|               | None        | 0.0040 | 0.0783 |
| UDPOS         | All         | 0.0039 | 0.0686 | 0.0786 |
|               | Data-Only   | 0.0067 | 0.0736 |
| WikiAnn       | None        | 0.0061 | 0.0993 |
|               | All         | 0.0063 | 0.0915 | 0.0953 |
|               | Data-Only   | 0.0085 | 0.0743 |
| XNLI          | None        | 0.0129 | 0.0286 |
|               | All         | 0.0105 | 0.0244 | 0.0541 |
|               | Data-Only   | 0.0149 | 0.0307 |

Table 6. 2 types of predictor error and one baseline error for different datasets on XLMR in the mixed language finetuning setup. Lower is better. E1 - Similar to Leave One Out, E2 - Similar to Leave One Target Out. Predictions/Task Scores are in the range [0, 1], so the same range applies for the error.
Fig. 6. Distribution of E2 Errors across different languages along with the error of the mean baseline method.

pairs of data points. Predictions are computed for each pair in the test set and the relation between them is obtained (either >, < or =). This is then compared to the relation between the gold scores. We compute and report the accuracy of the relation matching over pairs of data points sampled from the test set.

6.1 Evaluation Setup
We use the same data collected for evaluation in Section 5. This data contains \( m \) training configs and the performance score for \( t \) different languages for each config. This is split into a train and test set, and a predictor is trained on the train set. Suppose \( L \) is a target language and \( a \) is training configuration. For the data points in the test set, \( \text{score}(L, a) \) represents the actual score for this combination in the data and \( \text{prediction}(L, a) \) represents the models prediction for this data point. Given these definitions, the 2 evaluation scenarios are described below:

Case 1 (Keep target language same, vary training config): For a target language \( T \) and 2 training configs \( a \) and \( b \) we check if the relation between \( \text{score}(T, a) \) and \( \text{score}(T, b) \) is the same as the relation between \( \text{prediction}(T, a) \) and \( \text{prediction}(T, b) \)

Case 2 (Keep training config same, vary target language): For a target languages \( T_1 \) and \( T_2 \) and a training config \( a \), we check if the relation between \( \text{score}(T_1, a) \) and \( \text{score}(T_2, a) \) is the same as the relation between \( \text{prediction}(T_1, a) \) and \( \text{prediction}(T_2, a) \)

We report the accuracy for both the Case 1 and Case 2 evaluation methods. In addition to this, we implement a naive baseline for each method and report its accuracy. The baseline methods learn an ordering of the data points based on the target language or the training config and make a prediction based on the ordering. These baselines should give an estimate of how difficult each task is.

Case 1 Baseline: Since we vary the training config while making the comparison, the baseline is an ordering of scores is based on the sum of data across pivot languages in the training config.

Case 2 Baseline: Since we vary the target language while making the comparison, we learn a single score for each target language (as a mean of all its examples) and do the ordering based on...
Table 7. Accuracy of the Predictor and Baseline methods on the relative evaluation method. Higher is better.

| Dataset | Accuracy | Case 1 | Case 2 |
|---------|----------|--------|--------|
|         |          | E1     | E2     | E1     | E2     |
| UDPOS   | Predictor| 92.60  | 92.56  | 98.28  | 96.48  |
|         | Baseline | 49.22  | 48.89  | 82.73  | 46.91  |
| WikiAnn | Predictor| 90.10  | 90.08  | 98.05  | 95.52  |
|         | Baseline | 52.83  | 52.93  | 89.25  | 47.97  |
| XNLI    | Predictor| 95.71  | 95.78  | 99.02  | 98.26  |
|         | Baseline | 63.48  | 64.06  | 71.04  | 40.10  |

this. In the case where a target language was not seen during training, we output the mean of all the learnt language scores as the prediction.

We simulate both the E1 and E2 evaluation scenarios just like before, by computing the train/test sets in appropriate ways.

**E1**: For the E1 scenario, we create a 80/20 train/test split of the data. On the test split, we sample data points appropriately for Case 1 and Case 2 by taking points that have a common target language/training config (for Case 1/Case 2, respectively).

**E2**: For the E2 scenario, we sample 1000 train and 100 test points from the data just like before, ensuring that the test language overlap between train and test is not present. For Case 1, since the target language $T$ is kept constant and only the training configs $a$ and $b$ are varied, all the test points can be from one language. For Case 2, since the target language is varied (as $T_1$ or $T_2$), the test split is created such that all the data points for $T_1$ are from the test language and all the data points for $T_2$ are from all other possible languages.

### 6.2 Results

#### 6.2.1 Case 1

We observe that the predictor’s accuracies are extremely high in both the E1 and E2 cases, and that the baseline accuracies are low. The baseline here is just based on the sum of the training data sizes in the pivots, and the low performance numbers indicate that an ordering just based on this is not enough to predict the relative trends in the data. Since we vary the training configuration for Case 1, while keeping the target language same, the high predictor accuracies indicate that the predictor has modelled which pivot languages are important in affecting the performance score.

#### 6.2.2 Case 2

The predictor’s accuracies are high again, both in the E1 and E2 cases, but we can see that the baseline accuracy is high in the E1 case. The baseline method learns a single value for each target language. It’s accuracy being high indicates that this task is a much simpler task and that the model doing well here could just mean that it’s learning a similar mapping. The baseline accuracy in the E2 case however is extremely low. Since the target language being tested here is something that was not present during training, the baseline cannot learn a single value for it and it struggles. The predictor however does well here, and this gives us the indication that it’s able to generalize to a new language, at least in terms of the relative values that it predicts.

### 6.3 Predictor’s Absolute vs Relative Performance

Although the absolute errors in the E2 case are high, the predictor does well when we just look at the relative trends in the predictions. It is able to generalize to a new language in this manner.
as well. For an input example in a new language, the predictor has learnt which direction to push the prediction towards based on the features, but is unable to predict the absolute value. There are potential uses for such a predictor where we do not want it to predict the absolute performance value, but just want it to compare 2 training configs or 2 target languages. One such potential use could be to look at which pivot languages to add training data in, to maximize performance. By iterating through the space of training data configs, we only need to make comparison based operations to pick which language to add data in. Based on these results, the predictor would be expected to do well in such a scenario.

7 CONCLUSION
Evaluating large multilingual models on all possible tasks and languages is challenging due to the unavailability of labelled data in most languages. However, it is crucial to be able to evaluate LMs across all languages they serve. In this work, we propose using a model to predict the performance of a multilingual model on different (pivot, target) combinations to serve as a proxy for creating test sets for individual languages and tasks. The model uses a set of features about the pivot and target languages, including typological features and ones that capture language similarity. These are fed to a regression model to predict scores for unseen languages.

We observe that the feature importances returned by our predictor give insights into what factors are more important in predicting for different tasks, with semantic tasks relying more on pretraining and semantic tasks relying more on the typology and subword vocabulary. We compare the predictive model with baselines that take into account the average performance on a pivot language and find that the predictive model only performs well when predicting on a language for which some (pivot, target) data points are available. We also proposed an evaluation method that only looks at the relative values between the predictions. Although we find that the predictor does much better in this form of evaluation, the results indicate that the ability of the predictive model to generalize to unseen languages is still limited, suggesting that improvements are needed to be able to replace the creation of test datasets for new languages.

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