Script-Agnostic Language Identification

Anonymous NAACL submission

Abstract

Language identification is used as the first step in many data collection and crawling efforts because it allows us to sort online text into language-specific buckets. However, many modern languages, such as Konkani, Kashmiri, Punjabi etc., are synchronically written in several scripts. Moreover, languages with different writing systems do not share significant lexical, semantic, and syntactic properties in the neural representation spaces, which is a disadvantage for closely related languages and low-resource languages, especially those from the Indian Subcontinent. To counter this, we propose learning *script-agnostic embeddings* using several different experimental strategies (upscaling, flattening, and script mixing) focusing on four major Dravidian languages (Tamil, Telugu, Kannada, and Malayalam). We find that word-level script randomization and exposure to a language written in multiple scripts is extremely valuable for script-agnostic language identification, while also maintaining competitive performance on naturally occurring text.[1]

1 Introduction

In many natural language processing (NLP) tasks or data creation efforts, we often need to first identify the source language of a particular text. For instance, automated translation, part-of-speech (POS) tagging, and web scraping for data collection must typically identify the text's language before performing the given task. The languages involved might occur in non-standard scripts, but as we show in this paper, modern systems are heavily script-dependent in language identification. The result is that most current methods are unable to account for languages written in non-standard scripts. Moreover, script diversity is especially common in low-resource languages. Many bilingual communities choose to write their minority language in the region's dominant system (such as those in Pakistan, Iran, China), instead of their language's traditional writing system (Ahmadi et al., 2023). It is also common for larger standardized languages to be romanized on the internet and in social media. Finally, some languages simply do not possess one standard script, and are written in multiple writing systems. For instance, the Western-Indian Konkani language is actively written in up to 5 scripts: Devanagari, Romi, Kannada, Malayalam, and Perso-Arabic (Lehal and Saini, 2014; Rajan, 2014). However, most Konkani systems only support Devanagari and Romi scripts, and would not recognize the language if written in the other three. This illustrates the need to have script-agnostic or script-diverse language identification systems so we can collect data for low-resource languages more successfully and support their script-diverse nature in NLP applications.

In this paper, we conduct a case study on script-agnosticism for language identification by focusing on the four major Dravidian languages: Tamil, Telugu, Kannada, and Malayalam. We explore three different methods of training script-agnostic embeddings, evaluate across domains, and offer insights for future work. Broadly, we attempt to answer the following research questions:

1. Are embeddings learned from a script-agnostic setup competitive with other modern embeddings?
2. What impact does training on transliterated corpora have on downstream language identification performance?
3. How does projecting all scripts to one script impact performance, vs. projecting each script to a large n scripts.
4. What impact does script mixing have on language identification and on sentence representations?

[1] Anonymized code available here : https://anonymous.4open.science/r/Script-Agnostic-Lang-ID/

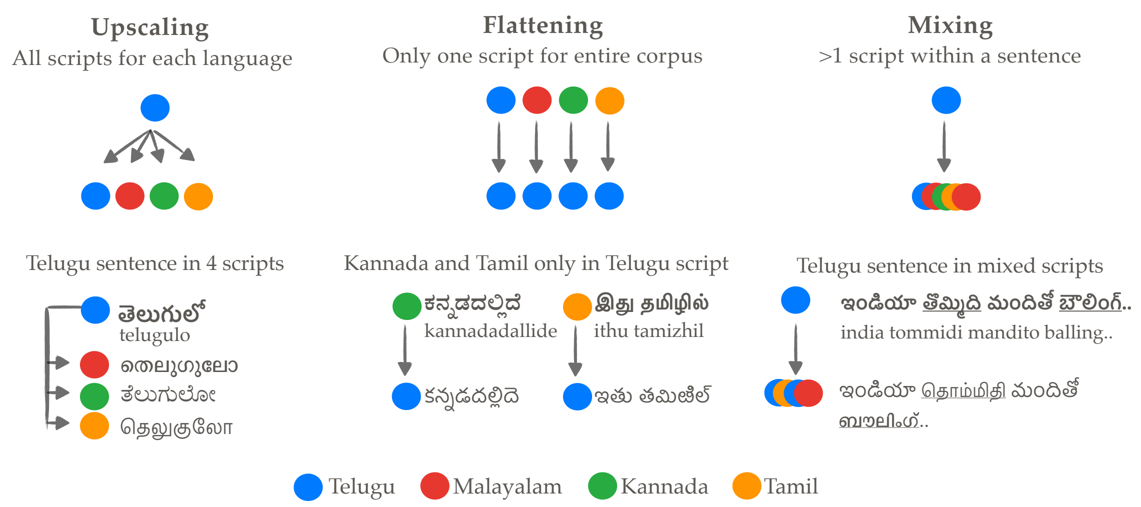


Figure 1: In upscaling, we transliterate each sentence into other scripts to expose the model to data in that language in all 4 writing systems. For flattening, we aim to reduce this potential vocabulary overload and project all scripts into 1 script per experiment. The goal of this experiment is to identify *if* any of the 4 scripts is a suitable target script for transliteration of all languages. As shown in 1, each writing system has a unique number of total letters (even though there is large overlap), and we think that this *may* result in one or the other script to be a suitable script for projection. For the final mixing setup, we transliterate at the word-level instead (at different noise levels) and allow multiple scripts per sentence.

A schematic of our experimental approaches is shown in Figure 1. Overall, our methods are shown to perform well on language identification tasks with both standard and permuted scripts, and appear to improve on current approaches.

2 Methods

Script Flattening Under this setup, we want to explore whether the embedding space will benefit from seeing all the languages in only *one* common script. The idea behind flattening the script space from four to one is that with only one script, the embedding space (and consequently the classification system) can focus on finding discriminative features between the languages. It is worth noting that training word representations in a single script may perform poorly in real-world settings and may not be a practical choice since text will naturally appear in scripts other than the one trained on. However, this experiment is useful to quantify the role that script plays in language identification, compared to the non-visual distinguishing features of the languages.

Script Upscaling This method takes a given training example written in one script and "upscales" it into all 4 scripts. Our intuition is that seeing every example in each script will prevent a model from giving weight to any one writing system in its decision-making, forcing it to rely on inherent features of the language. In other words, we teach the model that a sentence of a given language could be written in any script, so that it learns not to discriminate on the basis of writing system. For our script-upscaled model, we first created four training files for each language, where a file would include all of the language's training examples four times–one for each script. Then we concatenated all of these files into one training set. In essence, we allowed our model to assume that a sentence may appear in any of the four writing systems with the same likelihood.

Noisy Multi-Script Setup Under this setup, we want to explore how well an embedding space can accommodate script changes *within a sentence*. Therefore, we create synthetic sentences following Algorithm 1 (Appendix C) for both FLORES200 data splits. Under this approach, for each noise level n, language *lang*, and sentence *sent*, we choose a base script and then randomly pick $n\%$ words to transform to new non-base scripts. We train separate text classification `fastText` models on each of these noisy datasets and evaluate them on test sets with clean, noisy, and merged datasets. This is to evaluate out-of-distribution generalization and robustness, and the potential usefulness of including noise during the training process. We

Language	693-3	Family	Script	Script Code	Vowels	Consonants
Tamil	`tam`	Southern	தமிழ்	Taml	12	18
Kannada	`kan`	Southern	ಕನ್ನಡ	Knda	16	35
Telugu	`tel`	South-Central	తెలుగు	Telu	16	36
Malayalam	`mal`	Southern	മലയാളം	Mlym	15	42

Table 1: A summary of the characteristics of the four Dravidian languages we study in our experiments. All four languages use abugidas for writing and are written from left to right with diacritics.

perform this experiment with permutations of 25%, 50%, 75%, and 100% script-noise levels in the training data. Finally, we train an "All-Noise" model on merged data from all these script-noise levels.

3 Experiments

We use `fastText` (Bojanowski et al., 2017) to learn word embeddings, because it provides an efficient way to glean subword information. Without this, we would likely end up with completely separate vectors for each word in a language and would need to implement other strategies to handle out-of-vocabulary (OOV) words. Moreoever, `fastText`, like all other language identification systems, does not incorporate transliteration and script-agnosticism into their training. Since our goal is script-agnosticism, we want any given word to be represented with nearly the same vector as its transliterated counterpart. This should allow a model to recognize the language of a given text, even when written in a non-standard script.

Given below are our three primary experimental setups, where we create a training set according to each of these methods, and use it to train word embeddings. We obtain our results based on the original versions and transliterations of the test sets provided by FLORES200, using `fastText` skipgram models on a downstream language identification task (extrinsic evaluation).

1. Script Upscaling: Convert a language's sentences into several pre-chosen scripts.
2. Script Flattening: Convert all language's sentences to a single pre-chosen script S. Here, S will by a hyperparameter that can be tuned to find the best script for flattening.
3. Script Mixing: Based on a pre-set noise level N, we convert N% words in the sentence into a randomly sampled script, to simulate script noise.

Dataset and Languages We use the FLORES200 dataset (NLLB Team, 2022; Goyal et al., 2021; Guzmán et al., 2019) for training and in-domain testing in all our experiments. In order to ensure that our models would work well on test data that was not simply from FLORES200, we also tested on three out-of-domain sets: GlotStoryBooks (Kargaran et al., 2023), UDHR (Kargaran et al., 2023), and MCS-350 (Agarwal et al., 2023). We do not transliterate these datasets since the goal is to measure the performance of our script-agnostic models on naturally occurring text (and to identify if this leads to any performance losses over traditional models). We also use a subset of monolingual data from IndicCorp (Kakwani et al., 2020) for an experiment involving non-parallel training in Section 4.2. For this paper, we explore script-agnosticism for 4 major languages (Table 1) that fall within the same language family and use four distinct writing systems. Details about each of the datasets are available in Appendix A and language profiles in Appendix B.

Transliteration We use the Aksharamukha[2] python package to transliterate between our four Dravidian writing systems. Since the library is primarily meant for Indic writing systems, it provides an extremely low-loss transliteration, which is suitable for our purposes. Note that since Tamil has a smaller phonetic inventory than other languages, there may be subscripts introduced during transliteration (see Table 3). We preprocess the Tamil files to remove any such subscripts.

Evaluation We will use top-1 accuracy for our evaluation. While F1 scores are popular in language identification studies, they are hard to interpret and only have significant advantages when there is a class imbalance in the data distribution. We have selected a training and test set that is evenly distributed and is *not* imbalanced. There-

[2] https://pypi.org/project/aksharamukha/

Script:	Tamil		Kannada		Malayalam		Telugu	
	Baseline	Flatten	Baseline	Flatten	Baseline	Flatten	Baseline	Flatten
TAMIL	94.37	80.43	-	80.63	-	80.93	-	80.73
KANNADA	-	91.60	92.59	92.19	-	91.60	-	91.70
MALAYALAM	69.27	99.31	88.93	98.32	100.00	98.42	88.93	98.91
TELUGU	-	93.68	-	93.77	-	93.08	94.07	93.77
AVERAGE	40.91	91.25	45.28	91.23	25.00	91.01	45.75	91.28

Table 2: This table shows the performance of the Baseline model (trained on original script data only on FLORES200) and four Flatten models –one per script (shown in the columns) for each LANGUAGE test set. We find that no particular script is best suited to the flattening task and each script can allow for identification of the four Dravidian languages relatively faithfully. Although marginally, the Telugu script Flatten model performs best and so we include it in cross-domain experiments in 4.4.

IPA	ISO	TEL	KAN	MAL	TAM
/ka/	ka	క	ಕ	ക	க
/k^{h}a/	kha	ఖ	ಖ	ഖ	க$_2$
/ga/	ga	గ	ಗ	ഗ	க$_3$
/g^{h}a/	gha	ఘ	ಘ	ഘ	க$_4$

Table 3: Tamil has only one letter to represent the above-mentioned 4 sounds common in the other 3 Dravidian languages. So, the transliterator introduces subscripts to differentiate the four sounds in the source script. There are 5 such character series but we only show the *velar* phonemes' series.

fore, we opt for reporting top-1 accuracy since it is appropriate and easier to interpret for our data settings.

Baseline Models Our first baseline model (referred to as `FLORES200`) was trained on the raw language .dev files from FLORES200. We chose this as a baseline, given that it represents an easy and intuitive approach to training a language classification model: simply training based on the language data available, without any augmentation or modifications. We also benchmark with a language identification model pre-trained on Wikipedia, SETimes, and Tatoeba, boasting support for 176 languages (Joulin et al., 2016). Since this model is state-of-the-art and trained on a large amount of data outside of FLORES200, we use this as a second baseline and will refer to it as `WIKI`.

4 Results

We present our results for the Baseline, Flattening, Upscaling, and Noisy models here. In general, our script-agnostic models demonstrate good performance above the baselines on the transliterated test sets, and our methods often rival traditional approaches on clean data.

4.1 Script Flattening

Under the Flattening experimental setup, even though certain languages have higher accuracies than others, each language appears to have comparable performance across scripts (Table 2). For instance, Tamil sees 80% accuracy on all flattened tests; in fact, each language's scores vary less than one percent when flattening to any given script. The uniformity suggests that script does not play a major role in the models' decision-making, and that they are classifying with regard to linguistic information rather than writing system. This matches and confirms our initial hypotheses, since there is no alternative script for the model to consider when evaluating language identity.

Upon comparison with the baseline, our flattened models are far superior both in unconventional script scenarios, and when averaged across the four languages. In some cases, the baseline only classifies correctly 25% of the time, while our models consistently perform with over 90% average accuracy on the transliterated FLORES200 test set. With respect to individual language scores, the baseline classifies with slightly more accuracy when language and writing system match, but this is merely due to its heavy reliance on script, and does not speak to its overall performance. When script and language are not the same, the baseline is easily fooled; for example, in many cases it cannot classify even a single example correctly for certain languages.

Interestingly, there is a difference in performance across the individual language scores for

	WIKI		FLORES200		train - 25%		train - 50%		train - 75%		train - 100%	
Size			3,988		3,984		7,968		11,952		15,952	
	ORI	TRA	ORI	TRA	ORI	TRA	ORI	TRA	ORI	TRA	ORI	TRA
TAM	100	25	94.37	23.59	48.02	48.84	77.96	78.04	91.8	92.02	95.26	95.16
KAN	100	25	92.59	23.15	74.41	74.18	89.62	90.02	92.69	92.76	95.06	95.06
MAL	100	25	86.78	95.85	95.41	99.11	97.83	99.7	99.68	99.7	99.65	99.65
TEL	100	25	94.07	23.52	47.23	46.89	92.49	92.86	94.37	94.47	95.36	95.41
AVG	100	25	95.26	39.26	66.38	66.33	89.80	89.69	94.64	94.73	96.35	96.32

Table 4: This table compares the performance of the Baseline models to the Script-Upscaled model, trained on 25%, 50%, 75%, and 100% of the original training examples, transliterated to all scripts. In other words, each % entry represents a Script-Upscaled model, trained on the specified percentage of examples in the original training set, plus the same examples transliterated. The row underneath displays the amount of training data (including transliterations). Each model was tested on the original test set, without any transliterations, and a test set with all examples transliterated to all scripts.

Model	FLORES (transliterated)	FLORES (clean)	GLOT	UDHR	MCS350	average
BASELINE (FLORES200)	39.26	95.26	82.41	79.00	45.34	68.25
4-WAY PARALLEL	**96.32**	96.35	81.67	77.54	44.79	**79.33**
NON-PARALLEL	**94.39**	94.37	84.61	83.86	51.76	**81.80**

Table 5: This table compares two script-upscaled models, each trained on 997 examples per language, which are then transliterated to all scripts. One is trained on 4-way parallel data, and the other on examples that are not parallel. The slight discrepancy of performance is likely a result of different data sources.

both models, where they correctly identify certain languages more often than others. For example, Malayalam receives accuracies near 100%, while Tamil is only correctly classified 80% of the time. This appears to be a result of the `fasttext` model defaulting to a Malayalam prediction, paired with the close similarity between the Tamil and Malayalam languages. For a more thorough interpretability analysis, see Appendix D.

4.2 Upscale

Our upscaled model performs quite well on the test sets, with over 96% accuracy (Table 4). Moreover, while it drastically outperformed the baseline on transliterated data, it scored higher on the noiseless test as well. These results demonstrate that the model was able to correctly disentangle script and language, and was not tricked by noisy data.

Comparison with Flattening When comparing the Flattening results to our Script-Upscaled version, it is important to recognize that the latter model was trained on four times the amount of data, since we transliterated to all four scripts as opposed to flattening to a single script.

In order to analyze the effect of the number of examples on our Script-Upscaled version, we also trained it using three variations of our training data: 25% of the original examples, as well as 50%, and 75%. As expected, the 25% model performed much worse than the 100% model, and we saw improvements as we included more of the data. Interestingly, the results were only comparable to the Flattening model once we trained with at least 75% of the original examples. We suspect this is due to the difference between the number of cross-language examples and the number of cross-script examples. For instance, even though the 25% Upscaled model has nearly the same number of training examples as any of the Flattening models, many of these sentences are merely transliterated versions of each other, rather than full translations or original examples. This distribution appears to allow the model to become script-agnostic, but sacrifices the ability to identify languages in the process. This suggests that although Upscaling may perform better than Flattening overall, Flattening can learn more about both script-agnosticism and language identification from *fewer* examples.

Learning without n-way parallel data Based on our primary script-upscaled results, it seems that these models correctly ignore script in their decision-making process. However, it is important to distinguish between models that give correct output versus models that are truly script-agnostic. Thus far, our models have been trained on n-way parallel data; however, this could be a potential confounder in our experiments. Therefore, we compare the performance of two script-upscaled models –one trained on 4-way parallel data, the other on non-parallel data– keeping the number of training examples per language constant for fairness. For non-parallel data, we use subsets of the monolingual corpora from IndicCorp for Telugu, Tamil, and Malayalam. We reuse the FLORES200 examples for Kannada, since these should not be parallel to the data for the other three languages.

Our evaluation on the FLORES transliterated and clean test sets as well as all out-of-domain sets is in Table 5. The two models have largely similar results. The original 4-way parallel model does somewhat better on the FLORES test sets, and the non-parallel model has the better accuracy on average; however, these discrepancies can be expected due to the domain differences in data sources. Overall, it appears that both models can be claimed to be "script-agnostic," and therefore using parallel data likely has a negligible effect in this regard.

4.3 Noisy Multi-Script

In the script-noise setup, performance varies to a large degree between the models, but accuracies per language stay relatively constant across the different test sets (Table 6). Our Script-Upscaled model is the best on average with over 99% accuracy, and the All-Noise model follows closely behind with a 98.82% score. Beyond these two, scores drop significantly to the 50-65% range, which is undesirable for a 4-class classification problem.

This is likely explained by the size of the training sets. The Baseline, as well models with noise settings from 25 to 100, used data from four sets (one for each language) with varying script permutations. However, our All-Noise model was trained on a merged dataset consisting of sentences at *all* noise levels (i.e. four times the data). This is similar to the Script-Upscaled model that had access to each language's sentences transliterated to the four different scripts, and is likely what allowed the two models to perform so well. We believe that the Script-Upscaled model performed the best because it was consistently shown the same sentence in all four scripts, forcing it to become truly script-agnostic. The All-Noise model was able to do this to a large degree, but due to potential randomness and slight inconsistencies in permutations, it likely was not able to completely disregard script in its decision-making process. Therefore, script-mixing *within* sentences seems to be an extremely challenging setup for models and requires explicit data augmentation for reasonable performance.

4.4 Cross-Domain Performance

A comparison of our models on the clean FLORES200 test set, as well as out-of-domain sets is in Table 7. The FLORES200 BASELINE performs well in-distribution and on similar long-length GLOT and UDHR datasets, but poorly on MCS350 (children's stories domain and shorter sentences). The `WIKI` baseline is better than the FLORES200 baseline across all datasets, showing that is has built a better representation space for the languages. The UPSCALE (16K) and NOISE (ALL) models have comparable performance to BASELINE (FLORES200), demonstrating that the multi-script training does not lead to a significant degradation in performance on the languages' conventional/native scripts. The FLATTEN algorithm naturally performs poorly compared to the other models in this setting since it is only exposed to one script. Therefore, it may not be a practical choice for real-world language identification.

5 Discussion

The results demonstrate that all of our script-agnostic language identification models (Flattening, Noise, and Scipt-Upscaled) perform well above the baselines on examples that utilize a non-standard script. In certain cases where data is normal, our baseline models can surpass some script-agnostic ones; this is likely because the baselines use script as a basis for determining language ID.

Our best model overall appears to be the complete Script-Upscaled version. We suspect that seeing each example transliterated to every script allows it to become truly script-agnostic. While the Flattening models also appear to nearly reach this point, they are not trained on the same quantity of data, and so it is understandable that their test

Data	Language	Baseline	N@25	N@50	N@75	N@100	N@all	Upscale
CLEAN	Tamil	23.59	40.19	14.95	42.81	26.75	93.08	95.26
	Kannada	23.15	76.38	58.75	77.32	67.27	93.33	95.16
	Malayalam	86.78	94.54	99.93	95.11	99.51	99.63	99.70
	Telugu	23.52	51.63	40.07	44.64	51.14	94.89	95.45
all	Tamil	40.77	36.86	14.82	39.66	25.55	99.77	100.00
	Kannada	39.72	77.02	56.24	78.59	65.25	99.02	99.14
	Malayalam	86.94	96.34	99.97	96.24	99.57	99.90	99.95
	Telugu	42.40	52.70	38.71	43.32	52.47	99.47	99.77
AVG	*	50.27	65.72	52.60	64.52	60.79	98.82	99.16

Table 6: Even after introducing noise at all levels, the N@all and Upscale models are competitive implying that we can both use the word-level script-mixing without sacrificing performance on clean or noisy data. Table has been abridged due to space constraints, but an extended table with results for 25, 50, 75, and 100% noise-level test sets for all languages in included in Appendix Table 8. N@25,50,75,100 and the baseline models were trained with 3988 sentences per class. The Upscale and N@all models were trained with 15952 sentences per class and are therefore more comparable with each other. The baseline was trained on FLORES200 data.

	FLORES200	GLOT	UDHR	MCS350	AVERAGE
Test Set Size	4048	3934	285	15000	5817
BASELINE (FLORES200)	95.26	82.41	79.00	45.34	**75.50**
FASTTEXT (WIKI)	100.00	99.96	100.00	71.75	**92.93**
UPSCALE (16K)	96.35	81.67	77.54	44.79	**75.09**
FLATTEN (TELU)	91.28	43.18	44.56	33.95	53.24
NOISE (ALL)	95.41	80.19	76.14	43.41	**73.79**

Table 7: We share two baseline models (trained on FLORES200 and Wikipedia) along with the best model from each of our 3 experimental setups (upscale, flatten, noise) and test them on out of domain data to test domain transfer of the learned embeddings. Overall, the UPSCALE (16K) and NOISE (ALL) models have comparable performance to BASELINE (FLORES200) demonstrating that the multi-script training doesn't lead to a significant degradation in performance on the languages' naturally occurring native scripts.

scores would not be as high. Additionally, the All-noise model showed very good performance, and we suspect it remains second to the Upscaled setting primarily due to the variability of the training data. Unlike the Upscaled model, it may not see every example transliterated to all scripts, and thus may not become completely agnostic of script.

In the practical setting, our models –especially Script-Upscaled– appear to be a reasonable alternative to current language identification systems, when noisy script-mixing is a possibility. It seems that when trained on the same set of sentences, a Script-Upscaled model will outperform a standard one. The WIKI baseline performed the best on the non-transliterated test sets, but this is likely due to its huge amount of training data. It is highly possible that had we trained a Script-Upscaled model on Wikipedia, we would have seen results that matched the WIKI baseline on noiseless data. The large amount of storage and computational power for this endeavor, in addition to potential challenges in transliterating to so many scripts, would have been beyond the scope of our current work. However, now that we have established proof-of-concept, future work will attempt to create fully transliterated WIKI language identification models.

Our Upscaling approach is relatively straightforward, and requires no more examples than for a standard language identification system. Since transliteration can be done automatically, we essentially propose a data-augmentation process (for complete sentences and within sentences) that results in an ability to classify languages regardless of script. Future work should explore the impact of these script-agnostic embeddings on other downstream tasks, as well as conducting intrinsic evaluation (word analogy and semantic similarity) experiments.

6 Related Work

Previous work has demonstrated that script barriers discourage transfer learning from high-resource languages into low-resource languages' representation spaces, especially for Neural Machine Translation (Muller et al., 2021; Anastasopoulos and Neubig, 2019). Moreover, script diversity negatively impacts low-resource languages disproportionately because their training data is often of poor quality and small in size (Pfeiffer et al., 2021). Consequently, researchers have focused on transliteration, romanization, phonetic representation etc. to reduce vocabulary sizes and allow lexical sharing between languages with different writing systems (Amrhein and Sennrich, 2020).

Another common approach relies on existing pre-trained models, fine-tuning them with different transliterated versions of the originally supported languages (Muller et al., 2021; Dhamecha et al., 2021). This is an instance of the common hierarchical pipeline (Goutte et al., 2014; Lui et al., 2014; Bestgen, 2017) or fine-tuning-based approach for language identification (Jauhiainen et al., 2018; Agarwal et al., 2023; Ahmadi et al., 2023). Most recently, Moosa et al. (2023) conducted a study on effects of transliteration on multilingual language modeling, which focused on two kinds of models: a multi-script model with native scripts of each language (matching our BASELINE setup) and a uni-script model with only one script for all languages (similar to our FLATTEN setup).

As a natural extension of their work, we also consider UPSCALE and NOISE setups for Dravidian languages, as described in Section 3. Unlike their work, we do not fine-tune on downstream tasks, but instead focus on including the transliteration in the original training data to give the model the ability to handle non-native scripts without losing performance on the original script. Moreover, our work is not only motivated from a lexical-sharing and transfer-learning perspective, but is grounded with the aim of supporting synchronic and diachronic digraphia adequately in language models.

7 Conclusion

In conclusion, we introduce and evaluate three new kinds of language identification models that are script-agnostic. All of our systems have been shown to outperform the baseline on examples that are not written in the standard script. Two of our models (Script-Upscaled and All-Noise) perform especially well on both clean and transliterated (noisy) data. Our methods may provide a reasonable alternative to training language identifiers that can correctly classify text based on the language used, rather than the script in which it is written. Future work would expand to include more languages and scripts, as well as performing tests on the learned embeddings to determine if these would be effective on other downstream tasks.

Limitations

Extending to a larger set of languages We note that our models were only trained and evaluated using the four major Dravidian languages - Tamil, Telugu, Malayalam, and Kannada. Extending the successful experiments (upscale and all-noise) to a larger number of writing systems may prove challenging in terms of computational resources and dataset sizes. Data loss associated with script conversion and non-phonetic scripts is a likely challenge (and *potential* limitation) when we scale our approach to more scripts. However, script-agnostic embeddings will be most useful for closely related languages that currently do *not* use the same script - a scenario most commonly occurring in the Indian Subcontinent.

Data loss due to script-conversion Most Indic languages have a one-to-one mapping between sounds and characters in their scripts since they descend from common ancestors, but there may still be letters that are not mapped accurately (unique sounds in certain languages). In our sutdy, three of the four scripts have direct phonetic mappings, while only one (Tamil) includes aspirated sounds that are not translatable to the other writing systems. Tamil also doesn't distinguish between the common /*b*/ and /*p*/, /*g*/ and /*k*/ consonants. This means that two different scripts representing the same word will likely have two different character distributions. When expanding to other languages and scripts, the concern regarding inherent loss from transliteration may become a larger issue, and it is possible that our setup may be limited to phonetic scripts and would exclude non-phonetic scripts such as Mandarin Chinese.

Ethics Statement

Languages may be written in non-native scripts to obfuscate their presence on the internet, and the use script-agnostic embeddings would be able to discover and accurately identify such text during web crawls. This may have some downstream privacy and surveillance related concerns that are out of scope for this work. Currently, our pilot study uses the FLORES200 dataset to train embeddings, but in the future, a larger corpora such as Wikipedia, CommonCrawl, or other publicly crawled data can be used, which may bring with it several concerns around data ownership and copyright.

References

Milind Agarwal, Md Mahfuz Ibn Alam, and Antonios Anastasopoulos. 2023. Limit: Language identification, misidentification, and translation using hierarchical models in 350+ languages.

Sina Ahmadi, Milind Agarwal, and Antonios Anastasopoulos. 2023. PALI: A language identification benchmark for Perso-Arabic scripts. In *Tenth Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial 2023)*, pages 78–90, Dubrovnik, Croatia. Association for Computational Linguistics.

Chantal Amrhein and Rico Sennrich. 2020. On Romanization for model transfer between scripts in neural machine translation. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2461–2469, Online. Association for Computational Linguistics.

Antonios Anastasopoulos and Graham Neubig. 2019. Pushing the limits of low-resource morphological inflection. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 984–996, Hong Kong, China. Association for Computational Linguistics.

Yves Bestgen. 2017. Improving the character ngram model for the DSL task with BM25 weighting and less frequently used feature sets. In *Proceedings of the Fourth Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial)*, pages 115–123, Valencia, Spain. Association for Computational Linguistics.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146.

Tejas Dhamecha, Rudra Murthy, Samarth Bharadwaj, Karthik Sankaranarayanan, and Pushpak Bhattacharyya. 2021. Role of Language Relatedness in Multilingual Fine-tuning of Language Models: A Case Study in Indo-Aryan Languages. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 8584–8595, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Cyril Goutte, Serge Léger, and Marine Carpuat. 2014. The NRC system for discriminating similar languages. In *Proceedings of the First Workshop on Applying NLP Tools to Similar Languages, Varieties and Dialects*, pages 139–145, Dublin, Ireland. Association for Computational Linguistics and Dublin City University.

Naman Goyal, Cynthia Gao, Vishrav Chaudhary, Peng-Jen Chen, Guillaume Wenzek, Da Ju, Sanjana Krishnan, Marc'Aurelio Ranzato, Francisco Guzmán, and Angela Fan. 2021. The flores-101 evaluation benchmark for low-resource and multilingual machine translation.

Francisco Guzmán, Peng-Jen Chen, Myle Ott, Juan Pino, Guillaume Lample, Philipp Koehn, Vishrav Chaudhary, and Marc'Aurelio Ranzato. 2019. Two new evaluation datasets for low-resource machine translation: Nepali-english and sinhala-english.

Tommi Jauhiainen, Marco Lui, Marcos Zampieri, Timothy Baldwin, and Krister Lindén. 2018. Automatic language identification in texts: A survey. *CoRR*, abs/1804.08186.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.

Divyanshu Kakwani, Anoop Kunchukuttan, Satish Golla, NC Gokul, Avik Bhattacharyya, Mitesh M Khapra, and Pratyush Kumar. 2020. Indicnlpsuite: Monolingual corpora, evaluation benchmarks and pre-trained multilingual language models for indian languages. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4948–4961.

Amir Hossein Kargaran, Ayyoob Imani, François Yvon, and Hinrich Schütze. 2023. GlotLID: Language identification for low-resource languages. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.

Gurpreet Singh Lehal and Tejinder Singh Saini. 2014. Sangam: A perso-Arabic to indic script machine transliteration model. In *Proceedings of the 11th International Conference on Natural Language Processing*, pages 232–239, Goa, India. NLP Association of India.

Marco Lui, Ned Letcher, Oliver Adams, Long Duong, Paul Cook, and Timothy Baldwin. 2014. Exploring methods and resources for discriminating similar languages. In *Proceedings of the First Workshop on*

Applying NLP Tools to Similar Languages, Varieties and Dialects, pages 129–138, Dublin, Ireland. Association for Computational Linguistics and Dublin City University.

Scott M Lundberg and Su-In Lee. 2017. A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

Ibraheem Muhammad Moosa, Mahmud Elahi Akhter, and Ashfia Binte Habib. 2023. Does transliteration help multilingual language modeling? In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 670–685, Dubrovnik, Croatia. Association for Computational Linguistics.

Benjamin Muller, Antonios Anastasopoulos, Benoît Sagot, and Djamé Seddah. 2021. When being unseen from mBERT is just the beginning: Handling new languages with multilingual language models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 448–462, Online. Association for Computational Linguistics.

James Cross Onur Çelebi Maha Elbayad Kenneth Heafield Kevin Heffernan Elahe Kalbassi Janice Lam Daniel Licht Jean Maillard Anna Sun Skyler Wang Guillaume Wenzek Al Youngblood Bapi Akula Loic Barrault Gabriel Mejia Gonzalez Prangthip Hansanti John Hoffman Semarley Jarrett Kaushik Ram Sadagopan Dirk Rowe Shannon Spruit Chau Tran Pierre Andrews Necip Fazil Ayan Shruti Bhosale Sergey Edunov Angela Fan Cynthia Gao Vedanuj Goswami Francisco Guzmán Philipp Koehn Alexandre Mourachko Christophe Ropers Safiyyah Saleem Holger Schwenk Jeff Wang NLLB Team, Marta R. Costa-jussà. 2022. No language left behind: Scaling human-centered machine translation.

Odunayo Ogundepo, Tajuddeen R Gwadabe, Clara E Rivera, Jonathan H Clark, Sebastian Ruder, David Ifeoluwa Adelani, Bonaventure FP Dossou, Abdou Aziz DIOP, Claytone Sikasote, Gilles Hacheme, et al. 2023. Afriqa: Cross-lingual open-retrieval question answering for african languages. *arXiv preprint arXiv:2305.06897*.

Jonas Pfeiffer, Ivan Vulić, Iryna Gurevych, and Sebastian Ruder. 2021. UNKs everywhere: Adapting multilingual language models to new scripts. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 10186–10203, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Vinodh Rajan. 2014. Konkanverter - a finite state transducer based statistical machine transliteration engine for Konkani language. In *Proceedings of the Fifth Workshop on South and Southeast Asian Natural Language Processing*, pages 11–19, Dublin, Ireland. Association for Computational Linguistics and Dublin City University.

Lisa Yankovskaya, Maali Tars, Andre Tättar, and Mark Fishel. 2023. Machine translation for low-resource finno-ugric languages. In *The 24rd Nordic Conference on Computational Linguistics*.

A Out-of-Domain Datasets

1. **FLORES200**: n-way parallel dataset consisting of sentences from 842 web articles, translated into a large number of languages (NLLB Team, 2022; Goyal et al., 2021; Guzmán et al., 2019). Each language's example are in the same order, and are separated into `.dev` and `.devtest` files, containing 997 and 1012 sentences, respectively.

2. **GlotStoryBooks**[3]: Open-licensed curated library of books (Kargaran et al., 2023) from a variety of sources in 176 languages (Yankovskaya et al., 2023; Ogundepo et al., 2023). Each sample contains a sentence along with its language identifier and script.

3. **UDHR (Universal Declaration of Human Rights)**: We use Kargaran et al. (2023)'s public domain preprocessed version of the UDHR dataset, where each sample is a paragraph along with a language identifier. The authors removed errors and formatting issues in the original UDHR data and made this clean version available[4].

4. **MCS-350**: Multilingual Children's Stories dataset, released by Agarwal et al. (2023), contains over 50K children's stories curated primarily from two sources - African Storybooks Initiative and Pratham Storyweaver, both open-source story repositories for African and Indian languages respectively. For our experiments, we use the monolingual data files available on the authors' GitHub repository[5] for Tamil, Malayalam, Kannada, and Telugu. Compared to UDHR, the sentences are relatively smaller in length since they are not from the legal domain, and unlike GlotStoryBooks, the authors don't apply any length-based filtering to the curated stories.

5. **IndicCorp**[6]: Monolingual, sentence-level corpora for English and 11 Indian languages from the Dravidian and Indo-Aryan families (Kakwani et al., 2020). It consists of 8.8 billion tokens and is sourced mostly from Indian news crawls (articles, blog posts, magazines), though it also takes data from the OSCAR corpus.

[3]https://huggingface.co/datasets/cis-lmu/GlotStoryBook

[4]https://huggingface.co/datasets/cis-lmu/udhr-lid

[5]https://github.com/magarw/limit

[6]https://paperswithcode.com/dataset/indiccorp

B Brief Language Profiles

1. Tamil (`tam`), a Southern-Dravidian language, is spoken by over 80 million people and is an official language in Sri Lanka, the Indian states of Tamil Nadu and Puducherry, and of the Indian Constitution's Eighth Schedule. It is curently most widely written in the Tamil abugida - தமிழ் எழுத்து (*tamizh ezhuttu*).

2. Telugu (`tel`), a South-Central Dravidian language, is spoken by about 100 million people and is the most spoken Dravidian language. It is also an Eighth Schedule language of the Indian Constitution and is official in the Indian states of Andhra Pradesh, Telangana, and Puducherry (Yanam). It is written in Telugu abugida - తెలుగు లిపి (*telugu lipi*)

3. Malayalam, (`mal`), another Southern-Dravidan language is the smallest language from our selection, spoken by about 40 million people in Southern India. It is an Eighth Schedule language and is official in the southernmost Indian state of Kerala. It is written in the Malayalam abugida - മലയാളം അക്ഷരങ്ങൾ (*malayalam aksharangal*).

4. Kannada (`kan`), also a member of the Southern-Dravidian language subfamily, is spoken by about 60 million people, mostly within India. It is an official language of the Indian Constitution's eighth schedule and is the sole official language of Karnataka state. It is widely written in Kannada script, which is closely related to the Telugu script and is also an abugida, but diverged around 1300 CE - ಕನ್ನಡ ಅಕ್ಷರಮಾಲೆ (*kannada aksharamale*).

C Noise-Experiments Extended Results

D Interpreting Flattening Results

The default baseline (in-distribution) is a `fastText` model trained on FLORES200 data, keeping the languages in their original scripts without any transliterations. For the *flattening* experiments, we project all data to one script at a time. Since the test data is flattened to a single

Data	Language	Baseline	N@25	N@50	N@75	N@100	N@all	Upscale
CLEAN	Tamil	23.59	40.19	14.95	42.81	26.75	93.08	95.26
	Kannada	23.15	76.38	58.75	77.32	67.27	93.33	95.16
	Malayalam	86.78	94.54	99.93	95.11	99.51	99.63	99.70
	Telugu	23.52	51.63	40.07	44.64	51.14	94.89	95.45
25	Tamil	35.05	36.25	14.20	39.98	25.08	99.90	100.00
	Kannada	31.38	77.21	56.93	78.82	64.76	99.40	99.60
	Malayalam	85.74	95.58	99.90	96.18	99.80	99.90	100.00
	Telugu	36.18	52.66	38.29	43.82	51.96	99.10	99.90
50	Tamil	38.87	36.86	14.30	39.68	26.38	99.70	100.00
	Kannada	41.84	77.30	55.83	79.23	66.67	99.29	99.59
	Malayalam	86.00	96.48	100.00	96.17	96.17	99.90	99.90
	Telugu	43.50	52.47	38.67	42.50	52.77	99.40	99.70
75	Tamil	45.01	37.34	14.83	39.35	25.93	99.80	100.00
	Kannada	44.08	76.34	56.22	78.77	64.91	98.79	98.89
	Malayalam	88.56	96.86	100.00	95.85	99.39	100.00	100.00
	Telugu	47.61	52.59	39.19	43.65	52.79	99.59	99.70
100	Tamil	44.21	36.99	15.96	39.63	24.80	99.70	100.00
	Kannada	41.19	77.23	55.97	77.53	64.68	98.58	98.48
	Malayalam	87.46	96.43	100.00	96.74	99.39	99.80	99.90
	Telugu	42.35	53.09	38.70	42.96	52.38	99.80	99.80
all	Tamil	40.77	36.86	14.82	39.66	25.55	99.77	100.00
	Kannada	39.72	77.02	56.24	78.59	65.25	99.02	99.14
	Malayalam	86.94	96.34	99.97	96.24	99.57	99.90	99.95
	Telugu	42.40	52.70	38.71	43.32	52.47	99.47	99.77
AVG	*	50.27	65.72	52.60	64.52	60.79	98.82	99.16

Table 8: Even after introducing noise at all levels, the N@all and Upscale models are competitive implying that we can both use the word-level script-mixing without sacrificing performance on clean or noisy data. Among the noise@25,50,75 settings, we observe that 50% and 100% noise have drastic impact on classification accuracy for ≥ 2 languages. N@25,50,75,100 and the baseline models were trained with 3988 sentences per class. The Upscale and N@all models were trained with 15952 sentences per class and are therefore more comparable with each other. The baselinen was trained on FLORES200 data.

Algorithm 1 Synthetic Noise Within Sentences

for $noise = 25, 50, 75, 100$ **do**
  for $lang = tam, kan, mal, tel$ **do**
    for $sent = 0, 1, \ldots..N$ **do**
      Choose 1 base script
      Choose noise% words to transform
      for *index in chosen indices* **do**
        nonbase = Chose new script
        Transform word into *nonbase*
  Save transformed data at *noise*-level
Merge-save sentences at all *noise* levels into a new file for the *all*-noise setting

script, we would expect the model to only predict the language that is representative of the writing system. For instance, the baseline model would predict Tamil when it's shown data from any language in the Tamil script. But, we find that the models (trained on data in 4 different scripts and languages) tend to default to a Malayalam prediction for sentences that it knows are not Tamil (Table 2). This can be seen by the presence of a Malayalam signal across experiments for all 4 projection scripts. It also seems that several Malayalam sentences are being misclassified as Tamil (as evident by the less-than-100% accuracy for the Malayalam row for non-Malayalam

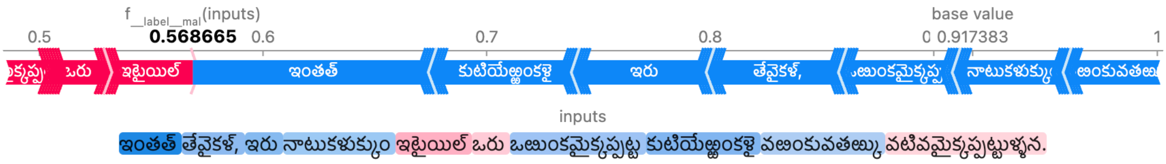


Figure 2: Example: Sentence 0's SHAP visualization for gold TAM sentence and weights when predicted class is MAL. Red indicates positive signal for MAL (unwanted) and blue indicates negative signal for MAL (wanted).

scripts).

For the Upscale experiments (Table 4), we find that the Wikipedia pre-trained model does not have the same bias towards Malayalam as our model, and instead is perfectly fit to each language's writing system (100% and 25% accuracy on Original and Transliterated data). The custom-trained FLORES200 baseline, on the other hand, has similar performance (between 86-94% for Original and 23% for Transliterated). We observe the Malayalam-defaulting phenomenon here as well, and it is likely that the model is over-predicting Malayalam, treating it as an "other" prediction bucket.

For Noise experiments (Table 6), we observe similar performance by the FLORES200 baseline as on the Upscaling experiments. However, the accuracy for non-Malayalam languages seems to increase as we increase the amount of noise.

To interpret differences in accuracy scores across languages, we utilize a game-theoretic metric, Shapley Additive Explanations, or SHAP (Lundberg and Lee, 2017), to compute global-level explanations across the training dataset for all 4 languages. As discovered in 4.1, we find that Tamil receives a significantly lower accuracy (around 80%) compared to the other 3 languages, especially compared to Malayalam (95%+). Therefore, we focus on finding explanations for false positive features in Tamil sentences that have been predicted as Malayalam. Readers should note that Tamil and Malayalam are closely related since they were the most recent to diverge from each other among the four major Dravidian languages (around the 9th century CE). Therefore, there are substantial vocabulary and grammatical similarities between them.

Table 9 displays all the relevant words and characters in mispredicted Tamil sentences. We obtained translations for TAM using Agarathi[7] and Google Translate, and for MAL using Google Translate and Olam[8]. While not all positively weighted words may have exact parallels in Malayalam, we think the score may come from positively correlated morphological features within the word itself, since Tamil and Malayalam share many word suffixes, prefixes, pluralization rules, prepositions etc. It is worth noting that our interpretability study revealed that for the flattened script condition, the `fastText` trained models always predict MAL as default. This is not inherently bad because we still receive over 90% accuracy for MAL, KAN and TEL, indicating that the models find sufficient non-MAL signal in the sentence when it's present. However, for TAM, we saw that there was a 10% gap in performance (i.e TAM prediction accuracy stayed around 80%). Our interpretability investigation revealed that this is due to presence of some positive MAL signal in TAM sentences, due to the lexical, semantic, and phylogenetic similarity of the two languages. This overlap causes a small number of sentences to be assigned a high probability of both TAM and MAL, with MAL having the maximum since it is the default prediction being downscored.

Results and all graphs from the Interpretability Jupyter notebook have been attached below. It shows the sentence-level explanations for each of the Tamil sentences that were misclassified in the training set with a small margin.

[7] `https://agarathi.com`. அகராதி/*agarathi* means dictionary in Tamil

[8] Malayalam Dictionary - `https://olam.in/`

Sent	TAM in TELU script	Weight	Transliteration	MAL	TAM
WORDS					
0	**ఇటైయిల్**	0.039	*itaiyil*	during	in between
0	**ఒరు**	0.025	*oru*	a, an	a, an
0	వటివమైక్కప్పట్టుళ్ళన	0.021	*vativamaikkuppattullana*	shaped	are designed
1	వఴంకప్పట్టతు	0.041	*vazhaankappattathu*	indulgence	provided
2	**ఇల్లై**	0.021	*illai*	no, not	no, not, ain't
3	**చిఴియవై!**	0.031	*chizhiyavai*	small ones	small ones
4	నిఴువప్పట్టతు	0.039	*nizhuuvappattathu*		established
5	వరుక్కైక్కు	0.059	*varukkaikku*		to visit
5	**ఒరు**	0.058	*oru*	a, an	a, an
5	**వఴంకాతు.**	0.029	*vazhankaathu*	don't give in	doesn't provide
6	పతివాకిన.	0.033	*pativaakina*	regularly	were recorded.
7	**ఒరు**	0.035	*oru*	a, an	a, an
7	చమైక్కప్పటుకిఴతు.	0.024	*chamaikkappatukizhathu*		is being cooked
8	ఆతరవళిక్కవిల్లై.	0.043	*aatharavalikkavillai*		not supported
CHARACTERS					
0	వటివమైక్కప్పట్టు**ళ్ళన**	0.052	*vativamaikkappattu**llana***		
0	**ఒరు_**	0.037	***oru_***	a, an	one
0	కు**టి**యేఴ్ఴంకళై	0.037	*ku**ti**yezzhankalai*	above	
0	ఇ**టైయిల్**	0.035	*it**aiyil***	in	
1	వఴంకప్ప**ట్టత**	0.102	*vazhankappa**ttatha***	suffix	suffix
1	కు**టి**నీర్	0.033	*ku**ti**niir*	above	
1	అవర్క**ళు**క్కు	0.024	*avarku**lu**kku*	to them	they
2	కు**టి**యిరుప్పినుళ్	0.152	*ku**ti**yiruppinul*	above	
3	చి**ఴియవ**	0.125	*chiz**hiyava***	small ones	small ones
4	ఉరు**వా**క్కుం	0.033	*uru**vaa**kkum*	emerge	create
5	ని**ఴు**వప్పట్ట**త**	0.112	*niz**hu**vappatta**tha***		
6	**క్కు_**	0.079	***kku_***		
6	వఴంకా**త**	0.045	*vazhanka**atha***		
6	**_ఒరు**	0.037	***_oru***	a, an	one
7	పతి**వాకిన**	0.119	*pati**vaakina***		
7	మలై**యిన్**	0.022	*malai**yin***		
8	చమైక్కప్పటుకి**ఴత**	0.048	*chamaikkappatuki**zhatha***		
8	**కుఴి**	0.035	***kuzhi***	pit	pit
9	చే**ర్ప్ప**త్తై (ర్)	0.035	*chee**rppa**thai (r)*		

Table 9: Words and characters that have a positive Malayalam explanation weight of > 0.02 for ground-truth Tamil sentences. All sentences under consideration had a difference of > 0.15 between the Tamil and Malayalam classes. We pick this threshold since it gives us Tamil sentences that have a high-enough Malayalam signal (or low Tamil signal) causing the classifier to mispredict.

Character Level Explanations > 0.15

In [ ]:

```
ix_array
```

Out[ ]:

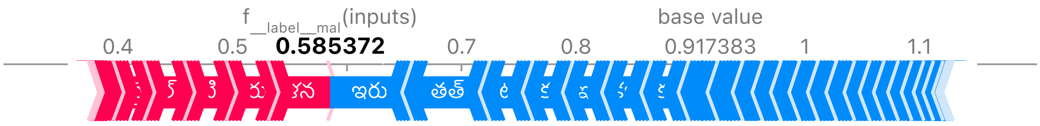
```
array([ 906, 1113, 1395, 1687, 2080, 2108, 2224, 2270, 2801])
```

In [ ]:

```
for i in ix_array:
    shap.plots.text(shap_values[i])
```

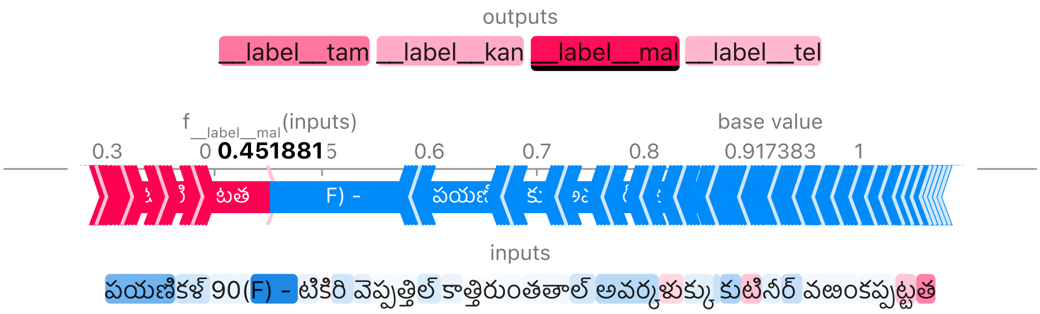
outputs

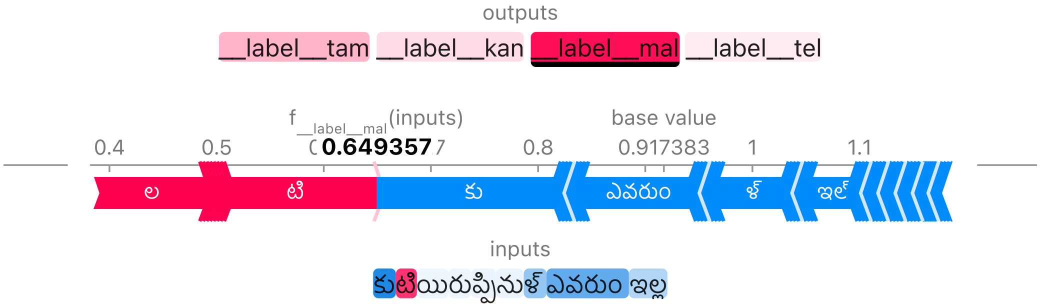
__label__tam __label__kan __label__mal __label__tel

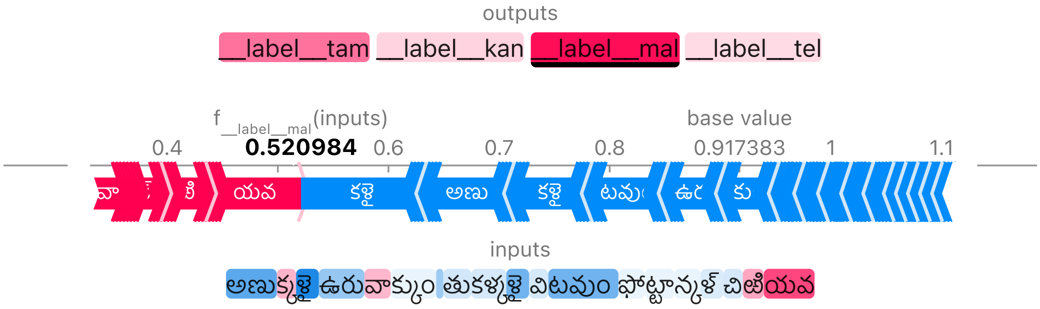


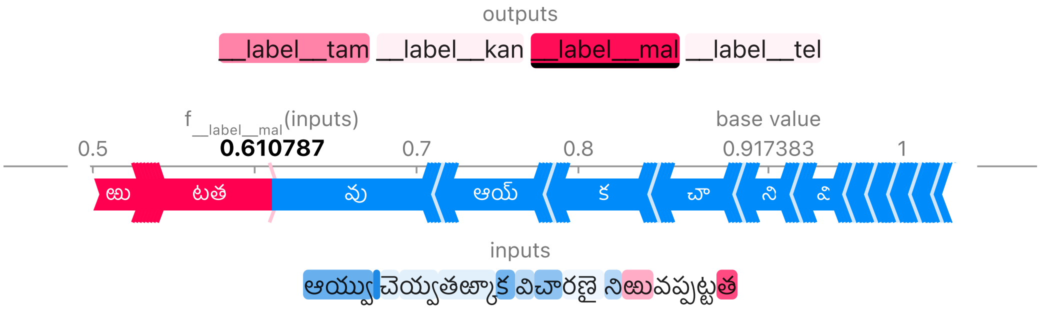
inputs

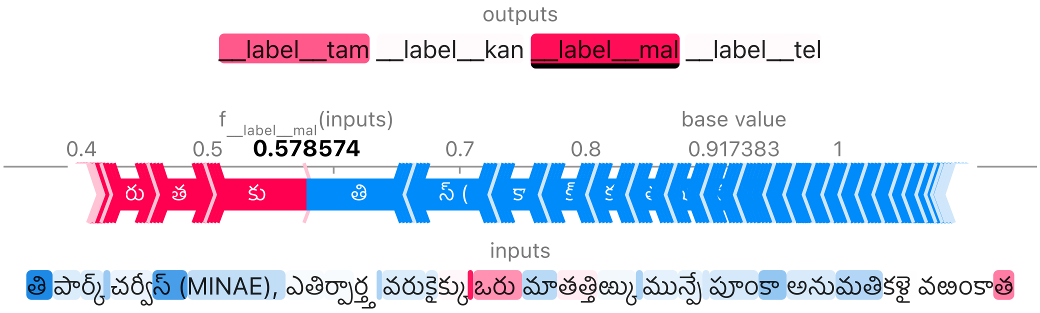
ఇంతత్ తేవైకళ్, ఇరు నాటుకళుక్కుం ఇట్టైయిల్ ఒరు ఒటుంకమైక్కప్పట్ట కుటియేట్టంకళై వటంకువతఱ్కు
వటివమైక్కప్పట్టుళ్ళన

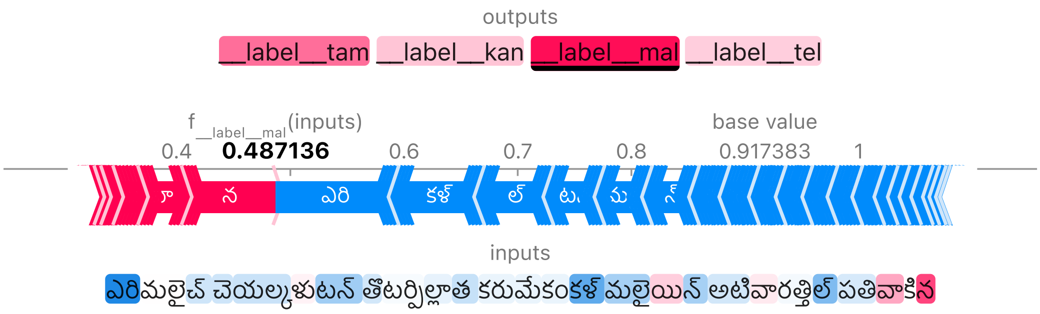

outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.451881
base value
0.917383
0.3 0.6 0.7 0.8 1
inputs
పయణికళ్ 90(F) - టికిరి వెప్పత్తిల్ కాత్తిరుంతతాల్ అవర్కళుక్కు కుటినీర్ వఅంకప్పట్టత

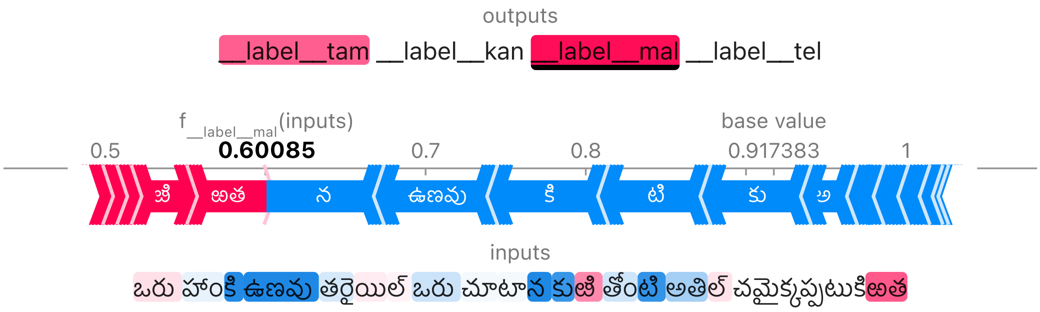

outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.649357
base value
0.917383
0.4 0.5 0.8 1 1.1
inputs
కుటియురుప్పినుళ్ ఎవరుం ఇల్ల

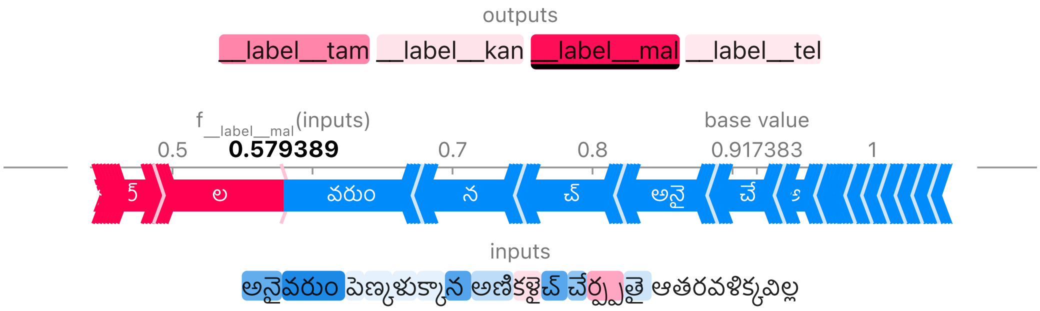

outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.520984
base value
0.917383
0.4 0.6 0.7 0.8 1 1.1
inputs
అణుక్కళై ఉరువాక్కుం తుకళ్కళై విటవుం ఫోట్టాన్కళ్ విటియవ


outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.610787
base value
0.917383
0.5 0.7 0.8 1
inputs
ఆయ్వు చెయ్యతఱ్కాక విచారణై నిఋవప్పట్టత


outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.578574
base value
0.917383
0.4 0.5 0.7 0.8 1
inputs
తిపార్క్ చర్వీస్ (MINAE), ఎతిర్వార్త వరుక్కైక్కు ఒరు మాతత్తిఱ్కు మున్పే పూంకా అనుమతికళై వఴంకాత



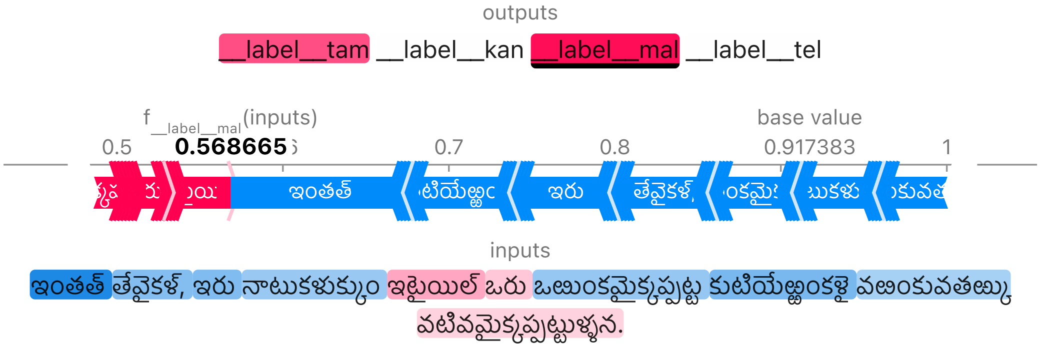


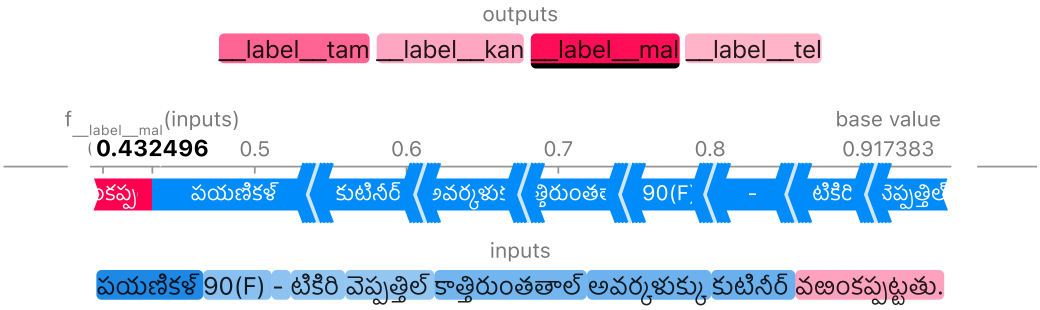


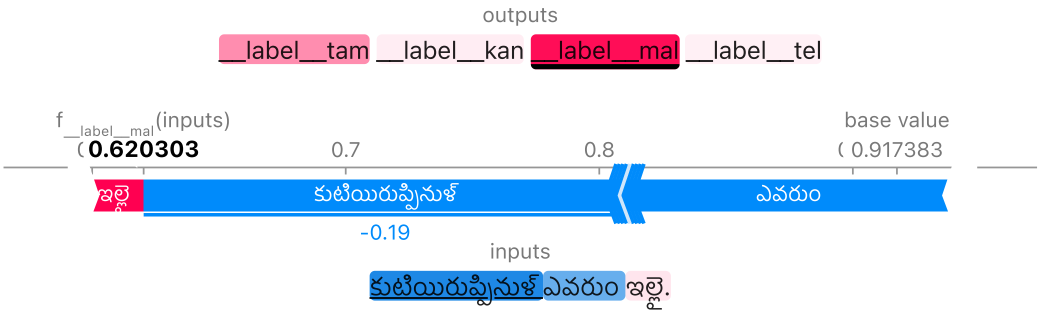
In [ ]:
```
for i in ix_array:
    shap.plots.bar(shap_values[i][:,2], max_display=20)
```

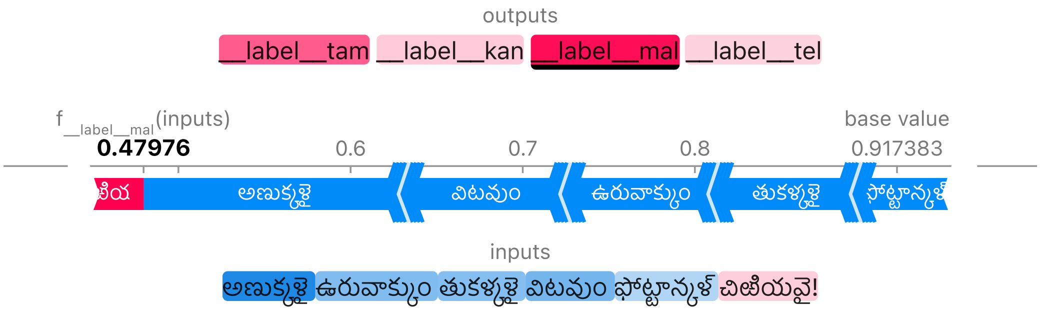
Explanations > 0.15

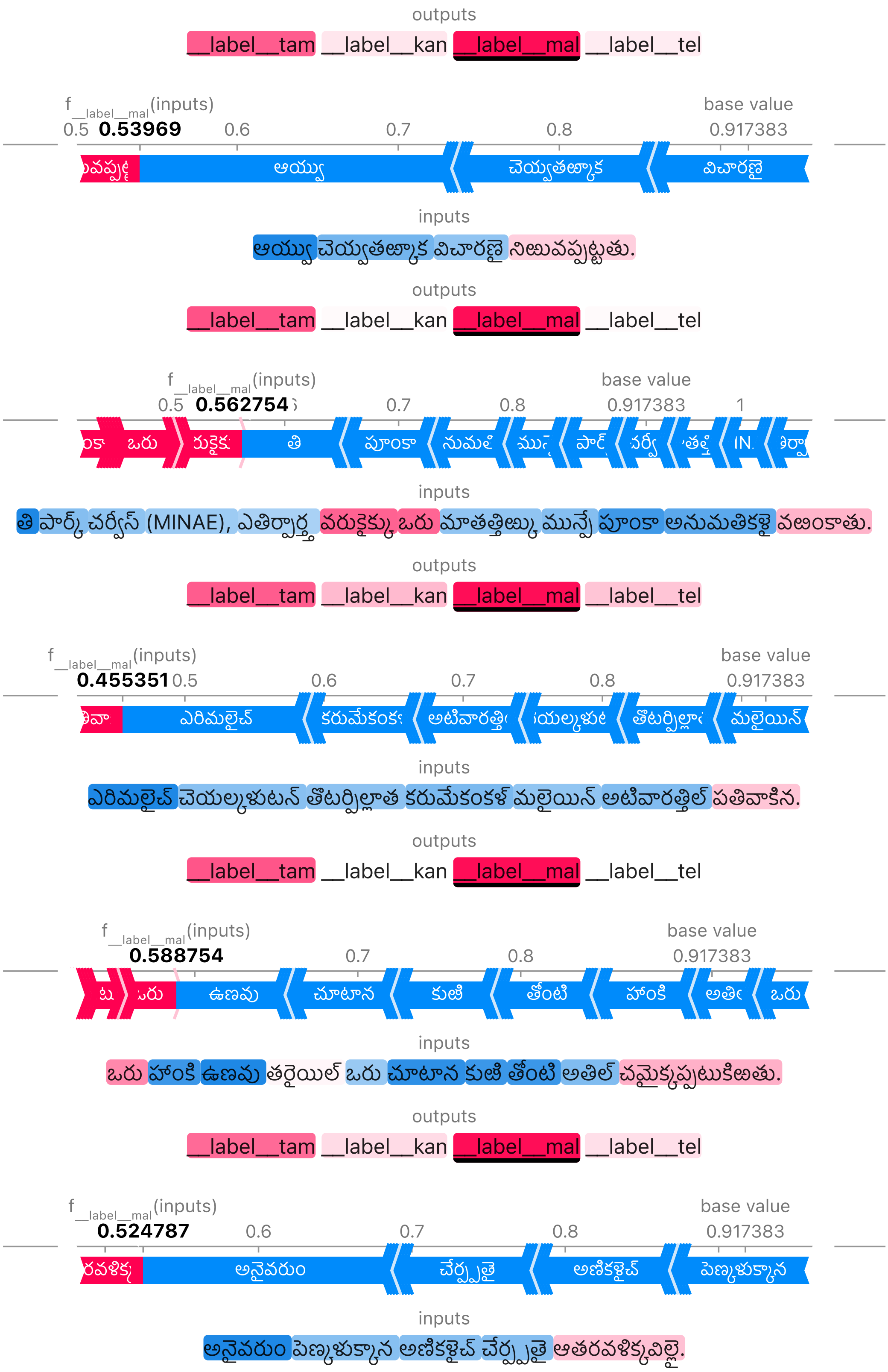
In [ ]:
```
for i in ix_array:
    shap.plots.text(shap_values[i])
```










outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.53969
base value
0.917383
0.5 0.6 0.7 0.8
inputs
outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.562754
base value
0.917383
0.5 0.7 0.8 1
inputs
outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.455351
base value
0.917383
0.5 0.6 0.7 0.8
inputs
outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.588754
base value
0.917383
0.7 0.8
inputs
outputs
__label__tam __label__kan __label__mal __label__tel
f__label__mal(inputs)
0.524787
base value
0.917383
0.6 0.7 0.8
inputs