

Script Normalization for Unconventional Writing of Under-Resourced Languages in Bilingual Communities

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Abstract

The wide accessibility of social media has provided linguistically under-represented communities with an extraordinary opportunity to create content in their native languages. This, however, comes with certain challenges in script normalization, particularly where the speakers of a language in a bilingual community rely on another script or orthography to write their native language. This paper addresses the problem of script normalization for several such languages that are mainly written in a Perso-Arabic script. Using synthetic data with various levels of noise and a transformer-based model, we demonstrate that the problem can be effectively remediated. We conduct a small-scale evaluation of real data as well. Our experiments indicate that script normalization is also beneficial to improve the performance of downstream tasks such as machine translation and language identification.¹

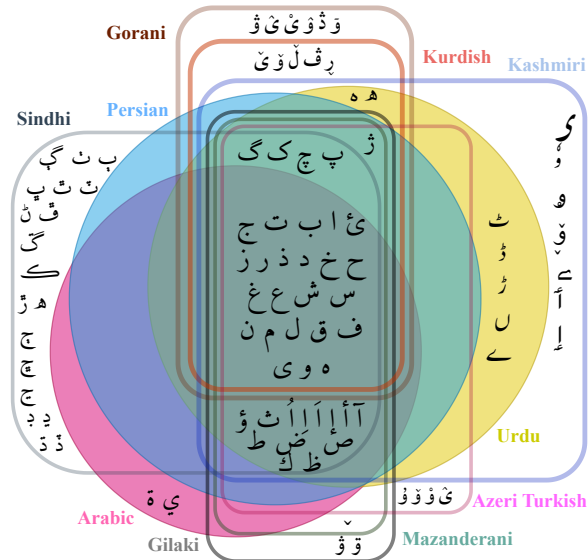


Figure 1: A comparison of the Perso-Arabic scripts used in the selected languages.

1 Introduction

With the increasing accessibility of the internet around the globe, from nomad settlements to megacities, we are living in a critical era that gives voice to different language communities to be represented online. Text as the essential material of many applications in natural language processing (NLP) may not be consistently created by under-represented communities due to the lack of a writing system and/or tradition, a widely-used orthography, and reasons related to regional and geopolitical conditions. Moreover, speakers of a language may opt for another script or prefer to use the script of an administratively dominant language other than the conventional one used in their native language (Gathercole and Thomas, 2009). This can be due to illiteracy in the native or home language, diglossia, or simply, the lack of adequate support for specific languages and scripts re-

¹The data and code are publicly available at <https://github.com/sinaahmadi/ScriptNormalization>.

sulting in remarkable negative effects on writing (Oriyama, 2011; Eisenclas et al., 2013).

Despite the fascinating progress in language technology in recent years, there are many fundamental tasks in NLP that are usually deemed trivial yet are ubiquitous, needed, and *still unsolved* in low-resource settings. One of these tasks is to deal with noisy text which affects the quality and performance of various applications such as text mining (Dey and Haque, 2009) and machine translation (Sperber et al., 2017). In practice, some steps are generally taken to deal with inconsistencies in the text, such as unifying character encoding and rectifying orthographic rules – a task broadly referred to as data cleaning or text preprocessing (Chu et al., 2016). However, unconventional and unsystematic writing such as using the script of a language to write in another language presents challenges beyond traditional data cleaning scenarios.

In this vein, we address the task of script normalization which aims to normalize a text writ-

lies are “normalized”. Therefore, script normalization overlaps considerably with more well-defined tasks such as spelling correction, lexical normalization (van der Goot et al., 2021) where an utterance is transformed into its standard form, pattern recognition (Schenk et al., 2009; Maddouri et al., 2000), language identification and standardization (Partanen et al., 2019; Ahmadi, 2020c).

Script and text normalization have been proven beneficial in various downstream applications such as dependency parsing (Zhang et al., 2013), sentiment analysis (Mandal and Nanmaran, 2018) and named-entity recognition (Baldwin and Li, 2015). Although in some contexts normalization has been used to refer to basic tasks such as stemming and lemmatization, as in (Toman et al., 2006), those are not within the scope of this paper.

Text Normalization One of the most related tasks to script normalization is text normalization which broadly deals with alternative spellings, typos, abbreviations and non-canonical language and is of importance to text-to-speech systems and for handling micro-blogging data such as Tweets (Sproat and Jaitly, 2016). To this end, a wide range of techniques have been proposed using rules based on annotated corpora (Sigurðardóttir et al., 2021) or linguistic information (Xia et al., 2006), edit operations and recurrent neural networks (Chrupała, 2014), machine translation (Graliński et al., 2006), supervised learning (Yang and Eisenstein, 2013), encoder-decoders (Lusetti et al., 2018) and more recently, transformers (Zhang et al., 2019; Tan et al., 2020; Bucur et al., 2021). MoNoise (van der Goot and van Noord, 2017) is a prominent approach to text normalization where the problem is framed as a domain adaptation one and various steps are taken to generate and rank normalized candidates using spell checkers, word embeddings, dictionaries and n -grams features.

Perso-Arabic Script Normalization As one of the important scripts adopted by languages spoken by over 600 million speakers (Doctor et al., 2022), the Perso-Arabic scripts are prevalent on the Web nowadays. Although script normalization in general and addressing ambiguities of writing systems, in particular, have been previously addressed in the related tasks for such languages, such as Arabic (Ayedh et al., 2016; Shaalan et al., 2019), Kashmiri (Lone et al., 2022a), Kurdish (Ahmadi, 2019) and Sindhi (Jamro, 2017), normaliz-

ing Perso-Arabic scripts has not received much attention, let alone for noisy data originated from unconventional writing in bilingual communities. In a recent study, Doctor et al. (2022) address the normalization of Perso-Arabic script for a number of languages, namely Urdu, Punjabi, Sindhi, Kashmiri, Sorani Kurdish, Uyghur and Azeri Turkish. Inspired by Johny et al. (2021)’s approach to using finite-state transducers (FSTs) to normalize Brahmic scripts, Gutkin et al. (2022) implement FSTs for Perso-Arabic scripts for Unicode normalization, visual normalization and reading normalization by focusing on normalization and unification of varieties based on regional orthographies rather than that of specific dominant scripts.

Low-resource Setup Most under-resourced languages that require script normalization face the predicament of data paucity. On the other hand, data annotation is a tedious task that may not be always feasible for all languages. To tackle these, Dekker and van der Goot (2020) create synthetic data in which canonical words are replaced with non-canonical ones. Lusito et al. (2022) use a transformer-based model and employ modern data augmentation techniques for the endangered language of Ligurian; to deal with the scarcity of data, “back-normalization” is proposed where normalized text is transformed to a noisy one, analogous to back-translation (Sennrich et al., 2016). Similarly, many other studies rely on the synthetic generation of noisy data for tasks such as grammatical error correction (Foster and Andersen, 2009), creating noise-resistant word embedding (Doval et al., 2019; Malykh et al., 2018) and machine translation (Bogoychev and Sennrich, 2019).

In comparison to the previous work, our work focuses on text anomalies caused by the usage of a different script in bilingual communities. In addition, we propose modeling the problem as a machine translation and generating synthetic data by script mapping. To the best of our knowledge, our approach to this problem has not been previously explored for the selected languages.

3 Methodology

This section presents our methodology to collect data, create script mapping to generate synthetic data and implement a transformer-based model. Source and dominant in this context respectively refer to the language of the original text and that of the dominant one used unconventionally.

3.1 Data Collection

As the first step, we collect data written in the conventional script of the selected languages. To that end, we create corpora based on Wikipedia dumps.² Since Wikipedia is not available for Gorani, we use Ahmadi (2020b)’s corpus for Gorani. Unlike the Latin script of Kurmanji for which there are corpora and Wikipedia, such as Pewan (Esmaili et al., 2013), there is no corpus for Kurmanji written in its Perso-Arabic script. Instead of relying on unreliable transliteration tools to convert the existing Kurmanji data, we crawl data from mainly news websites in the Iraqi Kurdistan for Kurmanji using the Perso-Arabic script.³ It is worth mentioning that for Sorani Kurdish we use a large existing corpus (Ahmadi and Masoud, 2020) instead of the (smaller) Wikipedia dump.

We clean raw text by removing hyperlinks, email addresses, dates, non-relevant symbols and zero-width non-joiner (ZWNJ), if not systematically used in the script. Different types of numerals, namely Eastern Arabic <٠١٢٣٤٥٦٧٨٩>, Farsi <٠١٢٣٤٥٦٧٨٩> and Hindu-Arabic <0123456789>, are unified with the later ones for consistency. We also deal with script switching in some Wikipedia articles, particularly in Sindhi and Kashmiri, using regular expressions to only keep the Perso-Arabic data.

Following this, we extract vocabularies from the corpora based on a frequency list; depending on the size and quality of the data, we select words appearing with a minimum frequency in the range of 3 to 10. In addition to the vocabulary extracted from corpora, we also collect word lists and bilingual dictionaries in the source and target languages from other sources online. We consulted Wiktionary⁴ for Azeri Turkish, Kashmiri, Mazanderani, Sindhi and Sorani without finding any such resources for the other languages. Additionally, the lexicographical data provided by Ahmadi et al. (2019) were used for Sorani.

3.2 Script Mapping

To simulate the process that leads to noisy data, we create script mappings that map characters in the conventional script of the source language to that of the dominant language. To do so, we define mapping rules between the scripts based on

the orthographies of the languages, as in the compound characters <ئ> in Kurdish (composed of <ئ> (U+0626) and <ئ> (U+06CE)) that appear so only at the beginning of a word and this can be mapped to either <ئ> (U+0627) or the same character but with the diacritic *Kasrah* as <ئ>. In addition, we take the closest candidates in the other script into account according to Unicode normalization as in <ک> (U+06A9) and <ک> (U+0643), and visual normalization, i.e. resemblance of the graphemes as in <د> (U+068E) and <د> (U+0630). Table 2 shows a few mapping rules.

Language	Unconventional script	Source	Target
Azeri Turkish	Persian	چ	چ
Sorani	Arabic	ز	ذ / ض / ظ / ز
Kashmiri	Urdu	اُ	اُ / ا
Sindhi	Urdu	ي	ي / ي / ے

Table 2: An example of script mapping rules. In unconventional writing, we assume that a character in the source language can be mapped to one or more characters in the target script. ‘/’ specifies different mapping possibilities.

Using the rule-based script mappings, we also determine words in the word lists and bilingual dictionaries that are potential translations and written similarly in the two scripts. We also consider removing diacritics, also known as *Harakat*, as they are not always included in writing. The following words are collected this way: ‘برنج’ (‘rice’) in Kurmanji and Persian, ‘سويدي’ (‘Swedish’) written with <ئ> (U+06CC) in Sorani and ‘سويدي’ written with <ي> (U+064A) in Arabic, ‘آمريکي’ (‘American’) in Kashmiri and ‘آمريکي’ in Urdu and, ‘بُرج’ (‘tower’) in Azeri Turkish and ‘برج’ in Persian by removing <و> (U+06C6). As such, we refer to the set of words collected as spelling pairs.

3.3 Character-alignment Matrix

Although script mapping based on rules and modifications is effective, especially to retrieve common words or words borrowed by the two languages, it may lead to potentially false friends or incorrect spelling pairs as well. Hence, to capture information based on the spelling pairs, we rely on the character alignment of words. To this end, we employ Needleman and Wunsch (1970)’s algorithm for sequence alignment that maximizes the number of matches between sequences, i.e. words,

²Dumps of December 1, 2022.

³This corpus will be released along with the other data.

⁴<https://www.wiktionary.org>

a and b with respect to the length of the two sequences. Therefore, we define the alignment matrix D for each spelling pair by setting elements i in a and j in b according to the following:

$$D_{i,j} = \max \begin{cases} D_{i-1,j-1} + d_{a_i b_j} \\ D_{i-1,j} + w \\ D_{i,j-1} + w \end{cases}$$

where $D_{i,j}$ is the score of character i in the sequence a and character j in the sequence b , $d_{a_i b_j}$ denotes the similarity score of the characters at i and j (1 if similar and -1 otherwise) and, w refers to the gap penalty which is set to -1. A gap penalty is a penalizing score for non-matching characters and is shown by '-' in our implementation. The matrix is initialized with $D_{0,0} = 0$. This algorithm is beneficial for our task as it considers the two sequences globally and allows back-tracing, hence useful to provide sequence matches. The following example shows the alignment of 'فیه تنام' ('Vietnam') in Sorani with the same word 'ویتنام', in Persian using this algorithm:

ف	ی	ه	ت	ن	ا	م		فیه تنام
و	ی	-	ت	ن	ا	م		ویتنام

Finally, we merge all the alignment matrices, i.e. D s, and create a character-alignment matrix for each pair of source and dominant languages. This matrix is normalized to have a unit norm. Furthermore, the mappings based on the rules of script mapping described in the previous subsection are appended to the matrix with a probability of 1. Alignments with a score < 0.1 are removed from the matrix due to the low probability of replacement. Depending on the score, a character can be aligned to more than one character in the dominant script.

3.4 Synthetic Data Generation

Given that there is a limited amount of data available for the selected languages, and that identifying languages in noisy setups is a challenging task, we have to rely on synthetic data generation. To that end, we first extract sentences of minimal and maximal lengths of 5 and 20 tokens (space-delimited) from the corpora described in §3.1. Then, we replace characters in the extracted sentences (clean data) with those in the character-alignment matrix. The replacement is done randomly with uniform sampling from the character alignment matrices to increase diversity. Depend-

ing on the number of replacements, we also consider specific percentages of noise generation at 20%, 40%, 60%, 80% and 100%. We create a last dataset by merging all datasets with all levels of noise; this creates more noisy instances given the randomness of noise generation. The parallel data are then tokenized using regular expressions.

The number of parallel sentences and words per noise scale is provided in Appendix C.

3.5 Implementation and Evaluation

We use JoeyNMT (Kreutzer et al., 2019) to train transformer encoder-decoder models at the character level based on the degree of noise and language pairs. Using this model, our objective is to encode noisy data, i.e. synthetically noisy sentences, and decode normalized ones, i.e. the clean sentences in the collected datasets. We report the performance of the models by BLEU score (Papineni et al., 2002) and character n -gram F-score (chrF Popović, 2015), both calculated based on SacreBLEU (Post, 2018), along with sequence-level accuracy (Seq. Acc.), i.e. number of correct tokens in the hypothesis appearing in the same position as the reference divided by all tokens. Hyperparameter details are outlined in Appendix B.

We evaluate the performance of the trained models based on the noise scale. As a naive baseline system, we calculate the evaluation metrics for the parallel data without applying any normalization technique. Finally, we evaluate the effectiveness of our models in two downstream tasks: language identification and machine translation.

4 Results and Analysis

4.1 Script Normalization

As the first set of experiments, we evaluate the performance of the script normalization models on synthetic noisy data at all levels of noise. In Appendix, Table D.3 provides the results of all the models and compares them with the baseline, and examples of normalization by our models are provided in Table D.1. Furthermore, the performance of a few selected models is presented in Figure 2.

Although our models perform competitively in comparison to the baseline, performance is not identical across the datasets. By increasing the noise level from 20% to 100% making the source data harder to be normalized, a gradual decrease in performance is expected, and we indeed observe this for both the baseline and our model, but for

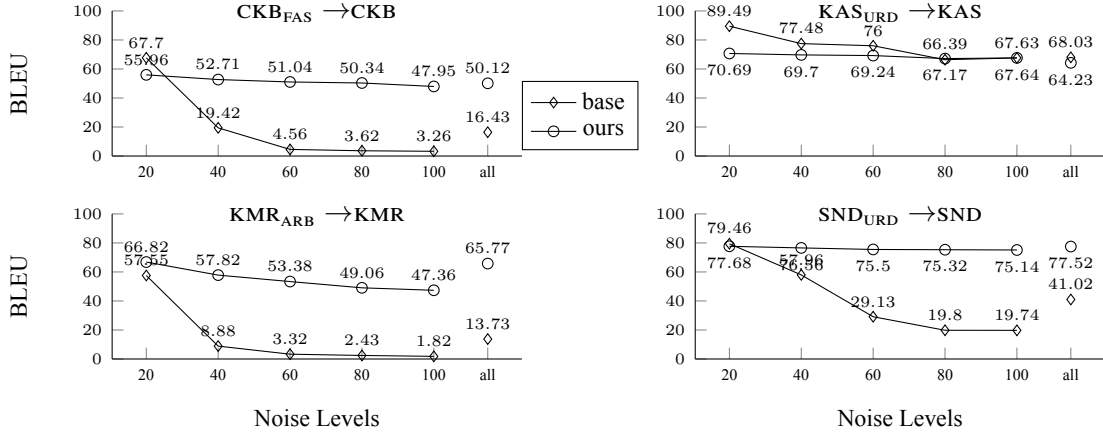


Figure 2: The performance of our models vs. the baseline in script normalization. See Figure D.1 for all languages.

most datasets (7 out of 12) the degradation for the naive baseline is more rapid and pronounced. Our model does seem to handle various levels of noise: in Sindhi, for instance, we get 75.1 BLEU score vs. 19.7 of the baseline (see bottom right $\text{SND}_{\text{URD}}^{100} \rightarrow \text{SND}$ in Figure 2).

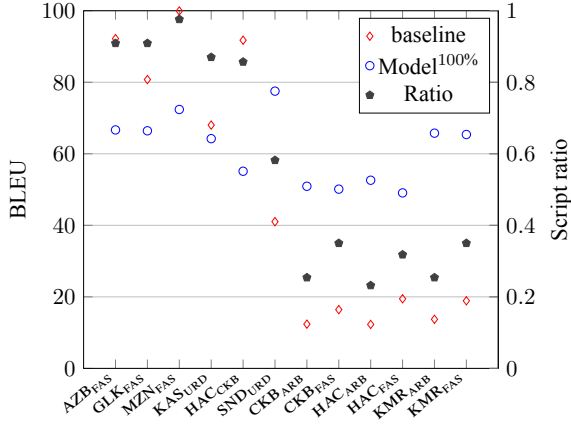


Figure 3: BLEU scores of the baseline and our model evaluated on 100% noisy data. The naive baseline outperforms our model for the settings where the differences between the noisy and “clean” data are minimal, i.e. when the script ratio (right y-axis) is high.

For five datasets, namely, $\text{AZB}_{\text{FAS}} \rightarrow \text{AZB}$, $\text{GLK}_{\text{FAS}} \rightarrow \text{GLK}$, $\text{MZN}_{\text{FAS}} \rightarrow \text{MZN}$, $\text{KAS}_{\text{URD}} \rightarrow \text{KAS}$ and $\text{HAC}_{\text{CKB}} \rightarrow \text{HAC}$, the naive baseline outperforms our models. We believe that this is explained by the level of similarity of the source and dominant scripts, which in turn determines the difficulty of script normalization. To quantify our assumption, we define $R_{A:B}$ as the script ratio of scripts A and B, both as two sets of characters, as follows:

$$R_{A:B} = \frac{A \cap B}{A \cup B} \times \frac{A \cap B}{A \cap B}$$

where $A \cap B$ refers to the intersection of characters in scripts A and B which are mapped in the rule-based script mapping (see §3.2) without any other alternative in the other script while $A \cap B$ is the intersection of A and B regardless of the mapping. Intuitively speaking, the script ratio of two identical scripts should be closer to 1 while more different scripts with various mappings between characters should get a lower value. Table A.1 provides the script ratios.

Figure 3 shows the BLEU score (left y-axis) of the baseline and our model to normalize the datasets containing 100% noise, e.g. $\text{GLK}_{\text{FAS}}^{100} \rightarrow \text{GLK}$ along with the script ratio for each language (right y-axis). This indicates that the normalization model (model₁₀₀) performs better where the script ratio is relatively low (< 0.6 , i.e. the two scripts are not that similar). On the other hand, the baseline performs better for higher script ratios, because in general the two scripts are very similar and hence there is less “noise”. We leave for future work an exploration as to why our transformer models fail to even simply learn to copy their input to perform at least on par with the baseline.

Real Data Evaluation Given the scarcity of real data, we resorted to generating synthetic data for training models and consequently evaluating them. However, working with real data is also crucial to evaluate the effectiveness of our approach. As such, we collected 100 sentences from social media in Sorani Kurdish written in unconventional scripts of Persian and Arabic. These sentences are then manually normalized by native and expert speakers based on the standard orthography of Kurdish.

Sorani Eval Set	Original (Unconventional)		Normalized	
	BLEU	chrF	BLEU	chrF
$\text{CKB}_{\text{FAS}} \rightarrow \text{CKB}$	1.2	38.4	20.1	69.6
$\text{CKB}_{\text{ARB}} \rightarrow \text{CKB}$	0.4	19.4	12.7	65.2

Table 3: Experiments on normalization of real-world data. The source sentences in Sorani Kurdish are written in the unconventional scripts of Persian (CKB_{FAS}) and Arabic (CKB_{ARB}). Even in this challenging setting (note how different the unconventional sentences are, as evidenced by low scores in the left column), model₁₀₀ manages to decently normalize them.

The results of the small-scale evaluation on the real data are provided in Table 3. In these datasets, calculating BLEU scores of the source sentences (noisy) with respect to the reference ones (clean) for $\text{CKB}_{\text{FAS}} \rightarrow \text{CKB}$ and $\text{CKB}_{\text{ARB}} \rightarrow \text{CKB}$ gets to 1.2 and 0.4 points, respectively. Once the source sentences are normalized using model₁₀₀, the corresponding BLEU scores increase to 20.1 for $\text{CKB}_{\text{FAS}} \rightarrow \text{CKB}$ and 12.7 for $\text{CKB}_{\text{ARB}} \rightarrow \text{CKB}$. We selected this model as it has been trained on the most diverse training set. We believe that such a boost in BLEU scores indicates the robustness of our models to effectively normalize unconventional writing.

4.2 Language Identification

Language identification is the task of detecting the language of a text, usually a sentence. It is modeled as a probabilistic classification problem. As the first downstream task, we carry out a few experiments on language identification in three setups:

1. **CLEAN**: identifying languages without injecting any noise in the datasets, i.e. the target sentences in the parallel data. This is equivalent to 0% of noise in the data.
2. **NOISY**: identifying languages with noisy data at various levels, starting from 20% of noise and gradually increasing 20% up to 100%. We combine all data with all levels of noise in a separate dataset referred to as **ALL**.
3. **MERGED**: merging **CLEAN** with **ALL** dataset, i.e. with all noisy data.

We use the Tatoeba sentence dataset⁵ for data in Persian, Urdu and Arabic, with additional data for Urdu from the TED corpus on Opus (Tiedemann,

⁵<https://tatoeba.org>

Noise %	Model	P@1	R@1	F@1	P@2	R@2	F@2
0	ours	0.52	0.54	0.51	0.32	0.64	0.32
	fastText	0.69	0.69	0.69	0.39	0.78	0.39
20	ours	0.93	0.93	0.93	0.48	0.97	0.48
	fastText	0.71	0.71	0.71	0.44	0.89	0.44
40	ours	0.91	0.9	0.91	0.48	0.96	0.48
	fastText	0.56	0.56	0.56	0.38	0.76	0.38
60	ours	0.9	0.9	0.9	0.48	0.96	0.48
	fastText	0.41	0.41	0.41	0.31	0.63	0.31
80	ours	0.9	0.9	0.9	0.48	0.96	0.48
	fastText	0.37	0.37	0.37	0.28	0.57	0.28
100	ours	0.89	0.89	0.89	0.48	0.96	0.48
	fastText	0.37	0.37	0.37	0.28	0.57	0.28
All	ours	0.91	0.91	0.91	0.48	0.96	0.48
	fastText	0.48	0.48	0.48	0.34	0.68	0.34
Merged	ours	0.72	0.72	0.72	0.4	0.8	0.4
	fastText	0.69	0.69	0.69	0.4	0.79	0.4

Table 4: The performance of language identification using the pretrained fastText model as the baseline in comparison to our model trained on our datasets with various noise levels. Our model handles different levels of noise (rows 20 to All) and outperforms the baseline that is only trained on “clean” data. Models with the highest F₁ measure in first suggestions (F@1) are **bold**.

2012). To tackle data imbalance, we downsampled all the datasets to only include 6000 sentences for each language⁶. In the **MERGED** setup where there are 12,000 sentences per language (half noisy, half clean), additional sentences (clean) in Persian, Urdu and Arabic are added to avoid data imbalance. Finally, we then split datasets into train and test sets with an 80-20% split. To train supervised language identification models, we use fastText (Bojanowski et al., 2017) with subword features with minimum and maximum character n -gram sizes of 2 and 4, word vectors of size 16 and hierarchical softmax as the loss function.

Table 4 presents the results of the performance of our models in comparison to fastText’s language identification model trained on data from Wikipedia, Tatoeba and SETimes on 176 languages,⁷ including, Persian, Arabic, Urdu, Sindhi, Sorani and Mazanderani. Although Azeri Turkish is supported, it is not clear which script it is trained on in fastText. The results are reported based on precision, recall and F₁ score of the first and second detection of the models, respectively denoted by ‘@1’ and ‘@2’. Since Gorani and Gilaki are not among the Fairseq-supported languages, we focus our analysis on the top-two predictions (@2) to en-

⁶Kashmiri had only 4700 instances.

⁷As of January 2023.

sure fairness against the baseline.

Our models outperform fastText in noisy conditions, regardless of the level of noise. The baseline performance degrades faster as the level of noise increases. Our models perform less effectively on clean data but recall that they are trained on a substantially smaller amount of data.⁸

Gold Labels	Azeri	1383	312	301	0	0	98	114	112	6	2	0
	Gilaki	98	1116	107	1	1	75	98	83	6	26	0
	Mazanderani	126	149	1199	1	19	85	89	70	18	11	0
	Arabic	1	2	1	2368	10	3	0	0	0	4	5
	Persian	0	5	13	10	2366	0	0	0	2	0	3
	Gorani	215	222	199	9	4	1327	330	321	0	12	0
	Sorani	320	327	325	3	0	483	1336	477	0	8	0
	Kurmanji	170	170	156	0	0	239	301	1223	2	10	2
	Kashmiri	4	4	5	2	0	2	5	5	2086	46	1
	Sindhi	83	93	94	5	0	87	125	108	18	2271	5
	Urdu	0	0	0	1	0	0	2	1	2	10	2383
Model Predictions		Azeri	Gilaki	Mazanderani	Arabic	Persian	Gorani	Sorani	Kurmanji	Kashmiri	Sindhi	Urdu

Figure 4: Language identification using the MERGED model. The number of classifications is annotated.

Figure 4 illustrates the results of classification in our MERGED model where the detected languages (x-axis) are compared with the references (y-axis). Although the model performs well in detecting Arabic, Persian, Sindhi, Urdu and Kashmiri, the other languages are often confused. The misclassified languages can be categorized into two groups of [Azeri, Gilaki, Mazanderani] and [Sorani, Kurmanji, Gorani]. This can be explained by the similarity of scripts. Surprisingly, Sindhi and Kashmiri represent a less salient overlap in classification.

4.3 Neural Machine Translation

Furthermore, we evaluate the performance of the script normalization models in neural machine translation (NMT). To do so, we use the devtest data of the FLORES 200 dataset (Costa-jussà et al., 2022) that contains 1012 parallel sentences for 204 languages including Kashmiri, Sorani and Sindhi in their Perso-Arabic scripts along with English. With English as the target language and the other available languages as sources, we carry out the evaluation in the following three setups:

1. **CLEAN**: translating the devtest of the source languages as it is in the FLORES dataset (with no noise), e.g. $CKB \rightarrow ENG$ for translating Sorani (CKB) to English (ENG). This is a skyline setting (best possible).
2. **NOISY**: translating the devtest by synthetically applying a certain amount of noise. For this setting, we specify the maximum amount of “interference” with the dominant language’s script (100% following the previous notation). The noise generation is random similar to language identification (§3.4). This is the baseline setting (worst possible, no normalization).
3. **NORMALIZED**: we normalize the data from the NOISY setting with our text normalization models (§4.1), and then translate the normalized text to English.

We use Facebook’s No Language Left Behind (NLLB) model on HuggingFace⁹ which is trained on parallel multilingual data from a variety of sources to translate into English and evaluate using SacreBLEU (Post, 2018). Table D.2 presents results of the translation quality of the NLLB model in our intended setups, with a sample in Table 5. Except for $KAS_{URD} \rightarrow ENG$, the translation quality of unnormalized data (S) deteriorates as noise levels increase while it remains steady when using normalization models as a preprocessing step (H). In Sorani, for example, even with a 100% of noise (CKB_{ARB}^{100}), our normalization approach (H) recovers almost 20 BLEU points out of the 26 points that were lost due to the non-conventional setting. The importance of a trustworthy text normalization system is clear in the case of Kashmiri, where our normalization model fails to reduce noise, resulting in subpar performance.

From a qualitative point of view, the noisy input affects the quality of translations depending on the type of noise. Although the NLLB model shows resilience to certain types of errors, particularly where a character is substituted by an incorrect one without an impact on word boundaries, i.e. no spaces being added or removed, noisy characters that can possibly affect tokenization lead to incorrect translations. For instance in Table D.4, the translation of noisy sentences in Sindhi is less different from that of the reference, while the Sorani noisy sentence is translated terribly differently and

⁸We conduct a similar study on a wider range of languages in (Ahmadi et al., 2023).

⁹The nllb-200-distilled-600M variant.

Language	Noise %	Test set	BLEU	chrF
$\text{SND}_{\text{URD}}^{100} \rightarrow \text{ENG}$	0	R	30.81	55.96
	100	S	7.09	27.59
		H	23.97	49.47
$\text{CKB}_{\text{ARB}}^{100} \rightarrow \text{ENG}$	0	R	30.81	55.96
	100	S	4.72	24.33
		H	24.53	50.55
$\text{CKB}_{\text{FAS}}^{100} \rightarrow \text{ENG}$	0	R	29.69	45.79
	100	S	17.29	25.39
		H	26.27	46.7
$\text{KAS}_{\text{URD}}^{100} \rightarrow \text{ENG}$	0	R	28.40	55.71
	100	S	27.93	55.13
		H	11.39	35.97

Table 5: Our normalization model –results with (H) data– largely (except for Kashmiri) mitigates the quality issues suffered from unconventional noisy inputs (S), almost to the levels of clean reference data (R).

incorrectly. Needless to say, the meaning of some words varies with incorrect characters.

5 Conclusion and Discussion

This paper discusses the challenge of script normalization of unconventional writing of languages that are spoken in bilingual communities. Under the influence of the dominant language of such communities, speakers tend to use scripts or orthographies of the dominant language rather than the one that is conventionally used in their native language. This leads to noisy data that hinder NLP applications and reduce data availability.

Framing the problem as a machine translation one where noisy data is ‘translated’ into clean one, we address the task of script normalization for the Perso-Arabic scripts of several languages, namely Azeri Turkish, Mazanderani, Gilaki, Sorani and Kurmanji Kurdish, Gorani, Kashmiri and Sindhi, with dominant languages being Arabic, Persian and Urdu. Given that these languages are less-resourced, we rely on synthetic data to create parallel datasets by injecting noise based on script mapping. We then train transformer-based encoder-decoders and show that the models can tackle the problem effectively, even for real data, but differently based on the level of noise.

We demonstrate that script normalization can be effectively addressed, particularly where there are many dissimilarities between the source and dominant languages. It can also alleviate the impact of noisy data on downstream tasks, namely language identification and machine translation. In

addition to script normalization that can help retrieve texts for the selected under-resourced languages, the trained models along with the collected data, with or without noise, can pave the way for further developments for those languages.

Limitations One of the limitations of the current study is the lack of annotated data for all languages. This is also the case of machine translation for which data could only be found for Kashmiri, Sorani and Sindhi, while other languages do not have much parallel data yet. On the other hand, the notion of noisy data is limited to the replacement of the missing characters in a script when compared to another one, i.e. that of the dominant language. As an ablation study, injecting other types of noise, beyond those discussed in this paper, may improve the performance of the models to tackle not only script normalization but several related tasks such as spelling error correction and may also increase the robustness of the models for morphologically rich languages or languages with versatile word boundaries using ZWNJ. Although we did our best to filter out code-switched data in the corpora, our datasets may contain data in other languages (in Perso-Arabic scripts).

In future work, we would like to apply our approach to other scripts and languages in bilingual communities. We also suggest evaluating the impact of script normalization on more downstream tasks, especially transliteration and tokenization.

Ethics Statement

All corpora and datasets used in this study are publicly available, ensuring compliance with data privacy regulations. Although we did our best to remove any personally identifiable information and preserve the privacy and anonymity of individuals, it is possible that some of the selected corpora contain sensible or offensive information. Filtering such content is challenging given that all the targeted languages are low-resourced and lack proper NLP tools for this purpose. We believe that it is unlikely that the normalization models cause benefits or harm to individuals. Regarding the annotation of the data (§4.1), annotators were fairly compensated for their time and effort. By upholding these ethical principles, we aimed to conduct the study in a responsible and conscientious manner.

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References

- Sina Ahmadi. 2019. A rule-based Kurdish text transliteration system. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, 18(2):1–8.
- Sina Ahmadi. 2020a. A Tokenization System for the Kurdish Language. In *Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects*, pages 114–127.
- Sina Ahmadi. 2020b. [Building a corpus for the Zaza-gorani language family](#). In *Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects*, pages 70–78, Barcelona, Spain (Online). International Committee on Computational Linguistics (ICCL).
- Sina Ahmadi. 2020c. KLPT–Kurdish Language Processing Toolkit. In *Proceedings of Second Workshop for NLP Open Source Software (NLP-OSS)*, pages 72–84.
- 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.
- Sina Ahmadi, Hossein Hassani, and John P McCrae. 2019. Towards electronic lexicography for the Kurdish language. In *Proceedings of the sixth biennial conference on electronic lexicography (eLex)*. eLex 2019.
- Sina Ahmadi and Maraim Masoud. 2020. Towards Machine Translation for the Kurdish Language. In *Proceedings of the 3rd Workshop on Technologies for MT of Low Resource Languages*, pages 87–98.
- Mohamed Al-Badrashiny, Ramy Eskander, Nizar Habash, and Owen Rambow. 2014. Automatic transliteration of Romanized dialectal Arabic. In *Proceedings of the eighteenth conference on computational natural language learning*, pages 30–38.
- Abdullah Ayedh, Guanzheng Tan, Khaled Alwesabi, and Hamdi Rajeh. 2016. The effect of preprocessing on arabic document categorization. *Algorithms*, 9(2):27.
- Tyler Baldwin and Yunyao Li. 2015. [An in-depth analysis of the effect of text normalization in social media](#). In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 420–429, Denver, Colorado. Association for Computational Linguistics.
- Steven Bird. 2020. Decolonising speech and language technology. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 3504–3519.
- Nikolay Bogoychev and Rico Sennrich. 2019. [Domain, translationese and noise in synthetic data for neural machine translation](#). *CoRR*, abs/1911.03362.
- 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.
- Habib Borjian. 2008. Two Mazandarani texts from the nineteenth century. *Studia Iranica*, 37:7–49.
- Maryam Borjian and Habib Borjian. 2023. At the Crossroads: Caspian Languages through a Sociolinguistic Lens. *Iranian and Minority Languages at Home and in Diaspora*, page 9.
- Ana-Maria Bucur, Adrian Cosma, and Liviu P Dinu. 2021. Sequence-to-sequence lexical normalization with multilingual transformers. *arXiv preprint arXiv:2110.02869*.
- Grzegorz Chrupała. 2014. [Normalizing tweets with edit scripts and recurrent neural embeddings](#). In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 680–686, Baltimore, Maryland. Association for Computational Linguistics.
- Xu Chu, Ihab F. Ilyas, Sanjay Krishnan, and Jiannan Wang. 2016. [Data cleaning: Overview and emerging challenges](#). In *Proceedings of the 2016 International Conference on Management of Data, SIGMOD Conference 2016, San Francisco, CA, USA, June 26 - July 01, 2016*, pages 2201–2206. ACM.
- Marta R Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, et al. 2022. No language left behind: Scaling human-centered machine translation. *arXiv preprint arXiv:2207.04672*.
- Maya Khemlani David, Mumtaz Ali, and Gul Muhammad Baloch. 2017. Language shift or maintenance: The case of the Sindhi language in Pakistan. *Language Problems and Language Planning*, 41(1):26–45.
- Kelly Dekker and Rob van der Goot. 2020. [Synthetic data for English lexical normalization: How close](#)

- can we get to manually annotated data? In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 6300–6309, Marseille, France. European Language Resources Association.
- Lipika Dey and S. K. Mirajul Haque. 2009. [Studying the effects of noisy text on text mining applications](#). In *Proceedings of the Third Workshop on Analytics for Noisy Unstructured Text Data, AND 2009, Barcelona, Spain, July 23-24, 2009 (in conjunction with ICDAR 2009)*, pages 107–114. ACM.
- Raiomond Doctor, Alexander Gutkin, Cibu Johny, Brian Roark, and Richard Sproat. 2022. [Graphemic Normalization of the Perso-Arabic Script](#). *CoRR*, abs/2210.12273.
- Ehsan Doostmohammadi, Minoo Nassajian, and Adel Rahimi. 2020. [Joint persian word segmentation correction and zero-width non-joiner recognition using BERT](#). In *Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020*, pages 4612–4618. International Committee on Computational Linguistics.
- Yerai Doval, Jesús Vilares, and Carlos Gómez-Rodríguez. 2019. [Towards robust word embeddings for noisy texts](#). *CoRR*, abs/1911.10876.
- Susana A Eisenchlas, Andrea C Schalley, and Diana Guillemin. 2013. The importance of literacy in the home language: The view from australia. *Sage Open*, 3(4):2158244013507270.
- Kyumars Sheykh Esmaili, Donya Eliassi, Shahin Salavati, Purya Aliabadi, Asrin Mohammadi, Somayeh Yosefi, and Shownem Hakimi. 2013. Building a test collection for Sorani Kurdish. In *2013 ACS International Conference on Computer Systems and Applications (AICCSA)*, pages 1–7. IEEE.
- Jennifer Foster and Øistein E. Andersen. 2009. Generate: Generating errors for use in grammatical error detection. In *Proceedings of the Fourth Workshop on Innovative Use of NLP for Building Educational Applications, EdAppsNLP '09*, page 82–90, USA. Association for Computational Linguistics.
- Virginia C Mueller Gathercole and Enlli Môn Thomas. 2009. Bilingual first-language development: Dominant language takeover, threatened minority language take-up. *Bilingualism: language and cognition*, 12(2):213–237.
- Masood Ghayoomi and Saeedeh Momtazi. 2009. Challenges in developing Persian corpora from online resources. In *2009 International Conference on Asian Language Processing*, pages 108–113. IEEE.
- Filip Graliński, Krzysztof Jassem, Agnieszka Wagner, and Mikołaj Wypych. 2006. Text normalization as a special case of machine translation. In *Proceedings of the International Multiconference on Computer Science and Information Technology, Wisła, Poland*, pages 51–56.
- Alexander Gutkin, Cibu Johny, Raiomond Doctor, Brian Roark, and Richard Sproat. 2022. Beyond Arabic: Software for Perso-Arabic Script Manipulation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 381–389.
- Daniel Hládek, Ján Staš, and Matúš Pleva. 2020. [Survey of automatic spelling correction](#). *Electronics*, 9(10).
- Wazir Ali Jamro. 2017. Sindhi language processing: A survey. In *2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT)*, pages 1–8. IEEE.
- Cibu Johny, Lawrence Wolf-Sonkin, Alexander Gutkin, and Brian Roark. 2021. [Finite-state script normalization and processing utilities: The Nisaba Brahmic library](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations, EACL 2021, Online, April 19-23, 2021*, pages 14–23. Association for Computational Linguistics.
- Siavash Khoshrouz. 2021. Acquisition of the English vowel system by Farsi and Gilaki speakers. Master’s thesis, UiT Norges arktiske universitet.
- Julia Kreutzer, Jasmijn Bastings, and Stefan Riezler. 2019. Joey NMT: A Minimalist NMT Toolkit for Novices. 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): System Demonstrations*, pages 109–114.
- Ron Lockwood. 2011. Machine Parsing of Gilaki Verbs with Fieldworks Language Explorer. *SIL International*.
- Nawaz Ali Lone, Kaiser J Giri, and Rumaan Bashir. 2022a. Issues in Machine Translation—A Case Study of the Kashmiri Language. In *Machine Intelligence and Data Science Applications*, pages 117–123. Springer.
- Nawaz Ali Lone, Kaiser J Giri, and Rumaan Bashir. 2022b. Natural Language Processing Resources for the Kashmiri Language. *Indian Journal of Science and Technology*, 15(43):2275–2281.
- Massimo Luseti, Tatyana Ruzsics, Anne Göhring, Tanja Samardžić, and Elisabeth Stark. 2018. [Encoder-decoder methods for text normalization](#). In *Proceedings of the Fifth Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial 2018)*, pages 18–28, Santa Fe, New Mexico, USA. Association for Computational Linguistics.
- Stefano Lusito, Edoardo Ferrante, and Jean Maillard. 2022. [Text normalization for endangered languages: the case of Ligurian](#). *CoRR*, abs/2206.07861.

- Samia Maddouri, Hamid Amiri, and Abdel Belaïd. 2000. [Local Normalization Towards Global Recognition of Arabic Handwritten Script](#). In *4th International Workshop on Document Analysis Systems - DAS'2000*, page 13 p, Rio de Janeiro, Brésil. Colloque avec actes et comité de lecture. internationale.
- Valentin Malykh, Varvara Logacheva, and Taras Khakhulin. 2018. [Robust word vectors: Context-informed embeddings for noisy texts](#). In *Proceedings of the 2018 EMNLP Workshop W-NUT: The 4th Workshop on Noisy User-generated Text*, pages 54–63, Brussels, Belgium. Association for Computational Linguistics.
- Soumil Mandal and Karthick Nanmaran. 2018. Normalization of transliterated words in code-mixed data using Seq2Seq model & Levenshtein distance. *arXiv preprint arXiv:1805.08701*.
- Seyyed-Abdolhamid Mirhosseini. 2015. Loving but not living the vernacular: A glimpse of Mazandarani-Farsi linguistic culture in northern Iran. *Language Problems and Language Planning*, 39(2):154–170.
- Rakesh Mohan. 1989. *Language planning and language conflict: the case of Kashmiri*. Walter de Gruyter, Berlin/New York Berlin, New York.
- Saul B Needleman and Christian D Wunsch. 1970. A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of molecular biology*, 48(3):443–453.
- Kaya Oriyama. 2011. The effects of the sociocultural context on heritage language literacy: Japanese–English bilingual children in Sydney. *International Journal of Bilingual Education and Bilingualism*, 14(6):653–681.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318.
- Niko Partanen, Mika Härmäläinen, and Khalid Alnajjar. 2019. [Dialect text normalization to normative standard Finnish](#). In *Proceedings of the 5th Workshop on Noisy User-generated Text (W-NUT 2019)*, pages 141–146, Hong Kong, China. Association for Computational Linguistics.
- Maja Popović. 2015. [chrF: character n-gram F-score for automatic MT evaluation](#). In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.
- Matt Post. 2018. [A call for clarity in reporting BLEU scores](#). In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Belgium, Brussels. Association for Computational Linguistics.
- Vera Sergeevna Rastorgueva, Aza Alimovna Kerimova, Akhmed Kerimovich Mamedzade, LA Pireiko, Džoy I Edel'man, and Ronald M Lockwood. 2012. *The Gilaki Language*. Acta Universitatis Upsalien-sis.
- Zobia Rehman, Waqas Anwar, and Usama Ijaz Bajwa. 2011. Challenges in Urdu text tokenization and sentence boundary disambiguation. In *Proceedings of the 2nd workshop on south southeast asian natural language processing (WSSANLP)*, pages 40–45.
- Saeed Rezaei, Ashkan Latifi, and Arash Nematzadeh. 2017. Attitude towards Azeri language in Iran: a large-scale survey research. *Journal of Multilingual and Multicultural Development*, 38(10):931–941.
- Joachim Schenk, Johannes Lenz, and Gerhard Rigoll. 2009. [Novel script line identification method for script normalization and feature extraction in on-line handwritten whiteboard note recognition](#). *Pattern Recognition*, 42(12):3383–3393. New Frontiers in Handwriting Recognition.
- A. Sedighi. 2023. [Iranian and Minority Languages at Home and in Diaspora](#). The Companions of Iranian Languages and Linguistics [CILL]. De Gruyter.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. [Improving neural machine translation models with monolingual data](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 86–96, Berlin, Germany. Association for Computational Linguistics.
- Khaled Shaalan, Sanjeera Siddiqui, Manar Alkhatib, and Azza Abdel Monem. 2019. Challenges in Arabic natural language processing. In *Computational linguistics, speech and image processing for arabic language*, pages 59–83. World Scientific.
- Sayed Mehtab Ali Shah. 1997. Ethnic tensions in Sindh and their possible solution. *Contemporary South Asia*, 6(3):259–272.
- Jaffer Sheyholislami. 2022. Linguistic Human Rights in Kurdistan. *The Handbook of Linguistic Human Rights*, pages 357–371.
- Helga Svala Sigurðardóttir, Anna Björk Nikulásdóttir, and Jón Guðnason. 2021. [Creating data in icelandic for text normalization](#). In *Proceedings of the 23rd Nordic Conference on Computational Linguistics, NoDaLiDa 2021, Reykjavik, Iceland (Online), May 31 - June 2, 2021*, pages 404–412. Linköping University Electronic Press, Sweden.
- Matthias Sperber, Jan Niehues, and Alex Waibel. 2017. [Toward robust neural machine translation for noisy input sequences](#). In *Proceedings of the 14th International Conference on Spoken Language Translation, IWSLT 2017, Tokyo, Japan, December 14-15, 2017*, pages 90–96. International Workshop on Spoken Language Translation.

- Richard Sproat and Navdeep Jaitly. 2016. [RNN approaches to text normalization: A challenge](#). *CoRR*, abs/1611.00068.
- Fei Tan, Yifan Hu, Changwei Hu, Keqian Li, and Kevin Yen. 2020. [TNT: Text normalization based pre-training of transformers for content moderation](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4735–4741, Online. Association for Computational Linguistics.
- Jörg Tiedemann. 2012. [Parallel data, tools and interfaces in OPUS](#). In *Proceedings of the Eighth International Conference on Language Resources and Evaluation, LREC 2012, Istanbul, Turkey, May 23-25, 2012*, pages 2214–2218. European Language Resources Association (ELRA).
- Michal Toman, Roman Tesar, and Karel Jezek. 2006. Influence of word normalization on text classification. *Proceedings of InSciT*, 4:354–358.
- Rob van der Goot, Alan Ramponi, Arkaitz Zubiaga, Barbara Plank, Benjamin Muller, Iñaki San Vicente Roncal, Nikola Ljubešić, Özlem Çetinoğlu, Rahmad Mahendra, Talha Çolakoglu, et al. 2021. Multi-LexNorm: A shared task on multilingual lexical normalization. In *Seventh Workshop on Noisy User-generated Text (W-NUT 2021)*, pages 493–509. Association for Computational Linguistics.
- Rob van der Goot and Gertjan van Noord. 2017. MoNoise: Modeling noise using a modular normalization system. *arXiv preprint arXiv:1710.03476*.
- Yunqing Xia, Kam-Fai Wong, and Wenjie Li. 2006. A phonetic-based approach to Chinese chat text normalization. In *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 993–1000.
- Yi Yang and Jacob Eisenstein. 2013. [A log-linear model for unsupervised text normalization](#). In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 61–72, Seattle, Washington, USA. Association for Computational Linguistics.
- Congle Zhang, Tyler Baldwin, Howard Ho, Benny Kimelfeld, and Yunyao Li. 2013. Adaptive parser-centric text normalization. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1159–1168.
- Hao Zhang, Richard Sproat, Axel H Ng, Felix Stahlberg, Xiaochang Peng, Kyle Gorman, and Brian Roark. 2019. Neural models of text normalization for speech applications. *Computational Linguistics*, 45(2):293–337.

A Selected Languages

In this work, we focus on script normalization for a few languages that are spoken in bilingual communities and use a Perso-Arabic script.

Even though the Perso-Arabic script is not limited to our selected languages, we did not include languages that are spoken in countries where the administratively dominant language uses another script, such as Uyghur and Malay, or those that have historically used a Perso-Arabic script that is now obsolete, like Dogri, Turkish and Tajik Persian. This said, there are other languages that would fit into our study but due to lack of data could not be included, such as Luri (LDD), Balochi, Shina, or Burushaski.

Azeri Turkish also known as Azerbaijani or Azari, is a Turkic language mainly spoken in Azerbaijan, Iranian Azerbaijan and broadly the Caucasus by 20 million speakers (Rezaei et al., 2017). The two varieties of Azeri Turkish, Northern Azeri Turkish and Southern Azeri Turkish respectively use the Latin and the Perso-Arabic scripts. In this study, we focus on the latter variety. The Perso-Arabic script of Azeri Turkish is similar to that of Persian, with additional graphemes such as <ئ> (U+063D) and <ژ> (U+06C7).

Mazanderani also known as Mazandarani or Tabari (Borjian and Borjian, 2023), is an Indo-Aryan language spoken in regions adjoining the Caspian Sea in Iran, chiefly in Mazandaran Province, by 2.5-3 million speakers (Mirhosseini, 2015, p. 157). The Perso-Arabic script adopted for Mazandarani is almost identical to the one used for Persian, with the additional diacritic <^> (U+02C7).

Gilaki is an Indo-Aryan language, similar to Mazanderani spoken in regions adjoining the Caspian Sea in Iran by over 2 million speakers (Rastorgueva et al., 2012; Khoshrouz, 2021). Although Mazanderani and Gilaki have been historically written using the Persian script (Borjian, 2008) without a recognized orthography, there have been recently many efforts, particularly on Wikipedia¹⁰, to adopt a Latin-based script. This said, the Latin script did not survive and the Perso-Arabic scripts are used for both Gilaki and Mazanderani (Sedighi, 2023, p. 20). The Perso-Arabic script adopted for Gilaki has graphemes in addition

to those in Persian, such as <ژ> (U+06CB) and <ز> (U+06CA).

Kurdish is an Indo-Aryan language spoken by over 25 million speakers in Iraq, Iran, Turkey and Syria, in varieties classified as Northern Kurdish or Kurmanji, Central Kurdish or Sorani, and Southern Kurdish (Ahmadi and Masoud, 2020). Kurdish has historically employed various scripts for writing, such as Cyrillic, Armenian, Latin and Perso-Arabic. Among these, the two latter scripts are still widely used. While the Latin script is more popular for writing Kurmanji spoken in Turkey, speakers of other varieties prefer the Perso-Arabic script of Kurdish, mainly due to the widespread usage of those scripts by the regional administrations. This is particularly the case of Sorani and Kurmanji spoken in Iraq and to some extent, in Syria. The Kurmanji variant spoken in Kurdistan of Iraq is called Behdini (also spelled Badini). Kurdish is a phonemic alphabet which is known by its distinct characters such as <ژ> (U+06C6) and <ئ> (U+06CE), and absence of varying phonetically-related graphemes of Arabic such as <ض> (U+0636) and <ظ> (U+0638) even for loanwords (Ahmadi, 2020a).

It is worth noting that the Perso-Arabic script that is used for both Sorani and Kurmanji follow the same orthographies. However, this is less established for Kurmanji given the popularity of the Latin script for that dialect. Throughout the paper, we consider Kurmanji and Sorani differently due to the considerable lexical and morpho-syntactic differences. It is worth noting that Gorani speakers oftentimes use Sorani script without the additional characters of Gorani making Sorani a dominant language.

Gorani also known as Hawrami, is an Indo-Aryan language spoken by 300,000 speakers in the parts of the Iranian of Iraqi Kurdistan (Ahmadi, 2020b). Due to the mutual linguistic and cultural influences of Sorani and Gorani, Gorani speakers rely on the Perso-Arabic script and the orthography used for Kurdish. However, there are a few additional graphemes that are unique to Gorani and cannot be found in Kurdish, such as <ژ> (U+068E) and <ژ> (U+06CB).

Kashmiri also known as Koshur, is an Indo-Aryan language spoken by over 7 million speakers in the disputed territories administered by three countries: India, Pakistan, and China (Lone et al.,

¹⁰<https://www.wikipedia.org>

2022b). Although Kashmiri’s Perso-Arabic script relies much on that of Urdu, the extensive use of diacritics and distinct characters such as <و> (U+06C4) and <ي> (U+0620) make the adopted script discernible. Moreover, Kashmiri extensively uses diacritics to specify vowels, while diacritization is less frequent in everyday writing of the other languages, except for disambiguation.

Sindhi is an Indo-Aryan language primarily spoken in Pakistan and parts of India by over 20 million speakers (David et al., 2017). Although influenced by Urdu, Sindhi uses a more diverse set of letters (62 vs. 40 in Urdu) (Doctor et al., 2022). It can be distinguished by unique letters such as <ڙ> (U+068F) and <ڻ> (U+06BB).

Language	Script ratio
MZN _{FAS}	0.976
AZB _{FAS}	0.909
GLK _{FAS}	0.909
KAS _{URD}	0.87
HAC _{CKB}	0.857
SND _{URD}	0.582
CKB _{FAS}	0.35
KMR _{FAS}	0.35
HAC _{FAS}	0.318
CKB _{ARB}	0.254
KMR _{ARB}	0.254
HAC _{ARB}	0.232

Table A.1: Script ratios as defined in §4.1

Similar to Persian and Urdu, Azeri Turkish, Mazanderani and Gilaki use the zero-width non-joiner (ZWNJ, U+200C) character (Lockwood, 2011) which creates lexical variations and adds to the complexity of downstream tasks like tokenization (Ghayoomi and Momtazi, 2009; Rehman et al., 2011; Doostmohammadi et al., 2020). Furthermore, the usage of some graphemes such as <ض> (U+0636) and <ظ> (U+0638) in the adopted scripts is mainly limited to loanwords from Arabic and Persian, unless conventionally used to represent a specific phoneme in the language. Moreover, the final glyph <ه> (U+06BE) is used in all languages except Persian, Mazanderani, Azeri Turkish and Gilaki. While the Perso-Arabic script of Kurdish, Gorani and Kashmiri are alphabets, the other selected languages are impure Abjads. Similarly, all the selected languages use Naskh style for writing, unlike Urdu that uses Nastaliq.

A summary of various aspects of the selected languages is provided in Table B.1. We also provide the script ratio (as defined in §4.1) of the script of the selected languages and that of the dominant one in Table A.1.

B Models Details

We train the normalization models in different configuration of hyper-parameters as follows:

- Training:
 - level: character
 - maximum number of characters: 100
 - character minimal frequency: 5
 - optimizer: adam
 - learning rate: 0.001
 - learning rate min: 0.0002
 - patience: 5
 - number of layers: 6
 - number of heads: 8
 - embedding dimension: 128
 - hidden size: 128
 - position-wise feed-forward layer size: 512
- Testing:
 - number of best prediction: 1
 - beam size: 4
 - beam alpha: 1.0
 - max output length: 100
 - batch size: 10

In addition to these common hyper-parameters, we set different hyper-parameters depending on the size of the datasets. The approximate overall number of pairs in all noisy datasets are provided in parentheses.

- (<10k pairs) KAS_{URD}, HAC_{CKB}
epochs: 100 / dropout: 0.2 / batch size: 64
- (<50k pairs) KMR_{ARB}, HAC_{ARB}, KMR_{FAS}, HAC_{FAS}, GLK_{FAS}, MZN_{FAS}
epochs: 80 / dropout: 0.2 / batch size: 64
- (<600k pairs) SND_{URD}, AZB_{FAS}
epochs: 40 / dropout: 0.1 / batch size: 64
- (<6.6M pairs) CKB_{ARB}, CKB_{FAS}
epochs: 6 / dropout: 0.1 / batch size: 10

For each configuration (72 in total), the training was carried out on a cluster using one GPU per configuration with 32GB memory.

C Datasets

The number of words and sentence pairs in the synthetic datasets generated for the selected languages is provided in Table C.1.

Language	639-3	WP	script type	diacritics	ZWNJ	Dominant
Azeri	azb	azb	Abjad	✓	✓	Persian
Turkish						
Kashmiri	kas	ks	Alphabet	✓	✗	Urdu
Gilaki	glk	glk	Abjad	✓	✓	Persian
Gorani	hac	-	Alphabet	✗	✗	Persian, Arabic, Sorani
Kurmanji	kmr	-	Alphabet	✗	✗	Persian, Arabic
Sorani	ckb	ckb	Alphabet	✗	✗	Persian, Arabic
Mazanderani	mzn	mzn	Abjad	✓	✓	Persian
Sindhi	snd	sd	Abjad	✓	✗	Urdu
Persian	fas	fa	Abjad	✓	✓	-
Arabic	arb	ar	Abjad	✓	✗	-
Urdu	urd	ur	Abjad	✓	✓	-

Table B.1: Selected languages studied in this paper. Columns 2 and 3 show the codes of the languages in ISO 639-3 and on their specific Wikipedia (WP). Diacritics refers to the usage of diacritics (Harakat) as individual characters, dominant is the administratively dominant language in the bilingual community where the language is spoken.

SRC-TRG		Noise %					
		20	40	60	80	100	All
AZB _{FAS}	Pairs	517860	517860	517860	517860	517860	584229
	Words	4266950	4266950	4266950	4266950	4266950	4987065
CKB _{ARB}	Pairs	1220386	1326715	1411998	1441641	1451201	6663362
	Words	13522986	14554313	15183038	15381207	15457911	72697912
CKB _{FAS}	Pairs	1186567	1325960	1408885	1435023	1442000	6491240
	Words	12838133	14381425	15125839	15305707	15363441	70402972
GLK _{FAS}	Pairs	16779	16779	16779	16779	16779	22215
	Words	176602	176602	176602	176602	176602	240833
HAC _{ARB}	Pairs	4718	4767	4802	4805	4802	23398
	Words	49804	50244	50457	50476	50464	248025
HAC _{CKB}	Pairs	4668	4669	4672	4686	4687	6474
	Words	49191	49195	49218	49417	49424	71246
HAC _{FAS}	Pairs	4712	4773	4798	4803	4802	23104
	Words	49646	50232	50429	50469	50464	244911
KAS _{URD}	Pairs	4729	4729	4734	4761	4759	9463
	Words	43907	43907	43925	44060	44064	96159
KMR _{ARB}	Pairs	10659	10963	11334	11417	11412	54430
	Words	96441	98403	100463	100877	100874	490034
KMR _{FAS}	Pairs	10631	10997	11336	11420	11417	53272
	Words	95971	98474	100454	100906	100884	482298
MZN _{FAS}	Pairs	36663	36663	36663	36663	36663	36665
	Words	365428	365428	365428	365428	365428	365446
SND _{URD}	Pairs	122446	122537	122865	122908	122946	496239
	Words	1328696	1329684	1333815	1334417	1334770	5581407

Table C.1: Number of words and aligned sentences (pairs) in the synthetic datasets

D Experiments Results and Examples

This section presents examples of script normalization and machine translation. Given the source sentence, the model trained on all noisy datasets, i.e. All, generates a hypothesis which is then translated. The selected sentences are taken from the 100% noisy dataset. The source, hypothesis and reference sentences are specified as S, H and R, respectively.

Language	S/H/R	Sentence
CKB _{ARB} →CKB	S	دزی حذیة دۆسه لاطدار و براوه کانی کوردستان کار دهکهن
	H	دۆی حزیه دهمسه لاتدار و براوه کانی کوردستان کار دهکهن
	R	دۆی حزیه دهمسه لاتدار و براوه کانی کوردستان کار دهکهن
GLK _{FAS} →GLK	S	کلا احمد شنه عزیز خونه و نگاره خوش همرا بئنه
	H	کلا احمد شنه عزیز خونه و نگاره خوش همرا بئنه
	R	کلا احمد شنه عزیز خونه و نگاره خوش همرا بئنه
HAC _{FAS} →HAC	S	یاگی ویشن ای زوانانی ب نیم مرد نامیشان بنییمی
	H	یاگی ویشمنه ئی زوانانی به نیم مهرده نامیشان بنییمی
	R	یاگی ویشمنه ئی زوانانی به نیمه مهرده نامیشان بنیهیمی
KAS _{URD} →KAS	S	رامه بۆنه سبز ماد چههه رامه بۆنه
	H	رامه بۆن ی سببز ماد چههه رامه بۆن ی
	R	رامه بۆن ی سبز ماد چههه رامه بۆن ی
KMR _{FAS} →KMR	S	دلن والا ژ کهرب و کینه نه دهرد و کول نه ژێ کههسر
	H	دلین فاللا ژ کهرب و کینه نه دهرد و کول نه ژێ کههسر
	R	دلین فاللا ژ کهرب و کینه نه دهرد و کول نه ژێ کههسر
SND _{URD} →SND	S	کالانڈ علم کیمیا یا کیمستری م هک مرکب جو نالو آبی
	H	کالانڈ علم کیمیا یا کیمستری م هک مرکب جو نالو آبی
	R	کالانڈ علم کیمیا یا کیمستری م هک مرکب جو نالو آبی

(a) Script normalization of sentences containing 100% noise

Source	شارى اھ ھىطرە كان، ب باشتىرىن گرانى رە ھە ن پالوران
Reference	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رەسەن پالئوران
	City of Stars, received nominations for best original song
20	شارى اھ ھىطرە كان، ب باشتىرىن گرانى رە ھە ن پالوران
40	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رەسەن پالئوران
60	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رەسەن پالئورانشا
80	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رەسەن پالئوران
100	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رە ھە ن پالئور
All	شارى ئەستىزەكان، بۇ باشتىرىن گۇرانى رەسەن پالئوران

(b) Script normalization of a Sorani sentence with varying noise

Language	Noise %	Test set	BLEU	chrF
$\text{KAS}_{\text{URD}}^{100} \rightarrow \text{ENG}$	0	R	28.40	55.71
	20	S	28.42	55.70
		H	11.60	36.15
	40	S	27.86	55.22
		H	11.38	36.03
	60	S	27.88	55.14
		H	11.38	36.05
	80	S	27.94	55.23
		H	11.31	35.96
	100	S	27.93	55.13
		H	11.39	35.97
$\text{CKB}_{\text{ARB}}^{100} \rightarrow \text{ENG}$	0	R	30.81	55.96
	20	S	21.54	46.63
		H	24.52	50.43
	40	S	15.16	39.49
		H	21.76	47.49
	60	S	8.88	31.05
		H	19.87	45.73
	80	S	4.75	24.59
		H	24.11	50.06
	100	S	4.72	24.33
		H	24.53	50.55
$\text{CKB}_{\text{FAS}}^{100} \rightarrow \text{ENG}$	0	R	29.69	45.79
	20	S	21.04	39.95
		H	23.27	38.07
	40	S	17.61	29.14
		H	17.29	30.41
	60	S	21.04	38.56
		H	26.31	44.04
	80	S	9.98	25.43
		H	19.45	35.45
	100	S	17.29	25.39
		H	26.27	46.7
$\text{SND}_{\text{URD}}^{100} \rightarrow \text{ENG}$	0	R	30.81	55.96
	20	S	23.15	48.29
		H	23.57	49.32
	40	S	18.03	42.60
		H	21.84	47.57
	60	S	12.42	35.53
		H	19.43	45.23
	80	S	6.95	27.45
		H	23.39	49.51
	100	S	7.09	27.59
		H	23.97	49.47

Table D.2: Evaluation of NLLB model for translation of reference data (R), noisy data (S) and normalized data (H) using normalization models trained on all levels of noise (All)

Table D.1: Examples of script normalization of sentences in different languages containing 100% noise (a) and in Sorani Kurdish with various levels of noise (b) using a model trained on all noisy datasets

Language	Noise %	Baseline			Our models		
		BLEU	chrF	seq. acc.	BLEU	chrF	seq. acc.
AZB _{FAS} → AZB	20	95.99	98.98	87.47	67.37	0.77	54.15
	40	92.37	98.05	79.51	67	0.77	54.01
	60	91.73	97.86	77.51	66.94	0.77	53.87
	80	91.53	97.8	76.68	66.89	0.76	53.67
	100	91.52	97.79	76.61	66.86	0.76	53.62
	All	92.2	97.95	77.41	66.67	0.76	51.75
GLK _{FAS} → GLK	20	90.36	96.59	77.77	67.33	0.77	45.17
	40	82.93	93.16	65.91	67.4	0.77	44.87
	60	81.38	92.37	63.29	66.94	0.77	43.92
	80	80.99	92.11	61.92	66.47	0.77	42.61
	100	80.95	92.11	61.8	66.76	0.77	42.55
	All	80.75	92.22	58.51	66.43	0.77	38.16
HAC _{ARB} → HAC	20	55.47	83.92	13.35	47.1	0.65	28.39
	40	10.44	46.13	1.05	38.95	0.63	17.4
	60	1.35	28.31	0	31.23	0.59	8.52
	80	1.53	18.88	0	25.16	0.56	7.28
	100	0.81	17.27	0	26	0.56	9.36
	All	12.29	38.79	2.39	52.61	0.68	27.69
HAC _{FAS} → HAC	20	68.74	88.98	35.17	54.88	0.69	31.14
	40	17.75	53.16	7.32	33.65	0.6	14.02
	60	3.32	35.12	0.42	26.43	0.57	8.96
	80	2.71	28.12	0.42	23.05	0.54	6.86
	100	2.24	26.41	0.42	21.52	0.53	5.82
	All	19.46	46.84	8.09	49.07	0.66	25.14
HAC _{CKB} → HAC	20	99.97	99.98	99.79	62.65	0.72	41.54
	40	99.44	99.75	97	62.24	0.72	40.26
	60	98.81	99.51	95.51	60.67	0.71	37.18
	80	93.04	97.83	78.46	60.04	0.71	38.38
	100	92.55	97.66	75.48	59.14	0.71	37.53
	All	91.75	97.33	71.91	55.12	0.68	30.56
KAS _{URD} → KAS	20	89.49	96.91	71.25	70.69	0.81	49.89
	40	77.48	93.28	53.07	69.7	0.81	49.05
	60	76	92.65	48.1	69.24	0.81	46.41
	80	66.39	88.28	40.04	67.17	0.8	44.23
	100	67.63	88.77	41.18	67.64	0.8	46.22
	All	68.03	89.28	33.05	64.23	0.77	35.16
MZN _{FAS} → MZN	20	99.93	99.98	99.86	72.38	0.8	50.97
	40	99.93	99.98	99.86	72.38	0.8	50.97
	60	99.93	99.98	99.86	72.38	0.8	50.97
	80	99.93	99.98	99.86	72.39	0.8	50.97
	100	99.93	99.98	99.86	72.39	0.8	50.97
	All	99.93	99.98	99.86	72.39	0.8	51
KMR _{ARB} → KMR	20	57.55	82.52	12.1	66.82	0.78	43.43
	40	8.88	45.55	0.46	57.82	0.75	34.18
	60	3.32	31.48	0	53.38	0.73	27.78
	80	2.43	21.68	0	49.06	0.71	24.69
	100	1.82	19.81	0	47.36	0.7	24.61
	All	13.73	39.91	2.35	65.77	0.77	43.28
KMR _{FAS} → KMR	20	69.98	88.35	27.26	68.92	0.79	45.39
	40	16.02	51.11	6	54.81	0.73	34.73
	60	5.5	36.06	0.18	50.11	0.72	26.1
	80	3.95	30.62	0.09	49.19	0.72	23.82
	100	3.52	28.72	0.18	45.11	0.7	23.73
	All	18.9	46.12	5.48	65.39	0.77	42.7
CKB _{ARB} → CKB	20	55.89	84.47	9.15	54.54	0.66	30.93
	40	12.92	51.51	0.35	53.85	0.66	29.44
	60	3.27	31.48	0.04	53.38	0.66	28.33
	80	2.17	19.3	0.04	51.92	0.66	26.46
	100	2.14	17.36	0.04	50.11	0.65	26.16
	All	12.37	39.31	1.72	50.92	0.65	25.17
CKB _{FAS} → CKB	20	67.7	89.45	26.9	55.96	0.67	33.49
	40	19.42	55.9	6.3	52.71	0.66	28.97
	60	4.56	35.67	0.2	51.04	0.65	26.89
	80	3.62	29.04	0.12	50.34	0.65	25.14
	100	3.26	26.43	0.14	47.95	0.64	24.44
	All	16.43	44.73	5.34	50.12	0.65	25.34
SND _{URD} → SND	20	79.46	89.83	41.54	77.68	0.84	51.4
	40	57.96	78.51	14.91	76.56	0.83	48.57
	60	29.13	57.93	4.72	75.5	0.83	46.37
	80	19.8	49.49	3.52	75.32	0.83	46.24
	100	19.74	49.38	3.22	75.14	0.82	46.06
	All	41.02	64.43	11.15	77.52	0.83	48.79

Table D.3: Comparison of the results of our script normalization models vs. the baseline. ‘All’ refers to a model trained and tested on the merged datasets (20% to 100%) as a separate case.

Language	Test _{Noise%}	Sentence
SND _{FAS} →ENG	R _{SND}	ساڳئي هائڪنگ روٽ وانگر اسڪائينگ روٽ ڪي سمجهو.
	R _{ENG}	Think of the skiing route as of a similar hiking route.
	S _{100%}	ساڳئي هائڪنگ روٽ وانگر اسڪائينگ روٽ ڪي سمجهو.
	T _{100%}	Think of a skiing route as the same as a hiking route.
	$\hat{S}_{100\%}$	ساڳئي هائڪنگ روٽ وانگر اسڪائينگ روٽ ڪي سمجهو.
CKB _{ARB} →ENG	$\hat{T}_{100\%}$	Think of a skiing route as the same as a hiking route.
	R _{CKB}	بيير له ريڙهي خليسڪينه سهر بهر بڪهوه پڙهه ويڪي هاوشيوه سهر شاخ كهوتن.
	R _{ENG}	Think of the skiing route as of a similar hiking route.
	S _{100%}	بيير له ريڙهي خليسڪينه سهر بهر بڪهوه پڙهه ويڪي هاوشيوه سهر شاخ كهوتن.
	T _{100%}	The church is divided into two parts, each of which is a mountain.
	$\hat{S}_{100\%}$	بيير له ريڙهي خوليسڪونه سهر بهر پيڪهوه پڙهه ويڪي هاوشيوه سهر شاخ كهوتن.
	$\hat{T}_{100\%}$	They thought of the snow-capped roller coaster route together to a similar route on the mountain.

Table D.4: Examples of translating sentences into English using the NLLB model given a reference (R), a noisy sentence (S) and a normalized sentence ($\hat{S}$). Translations are shown with T.

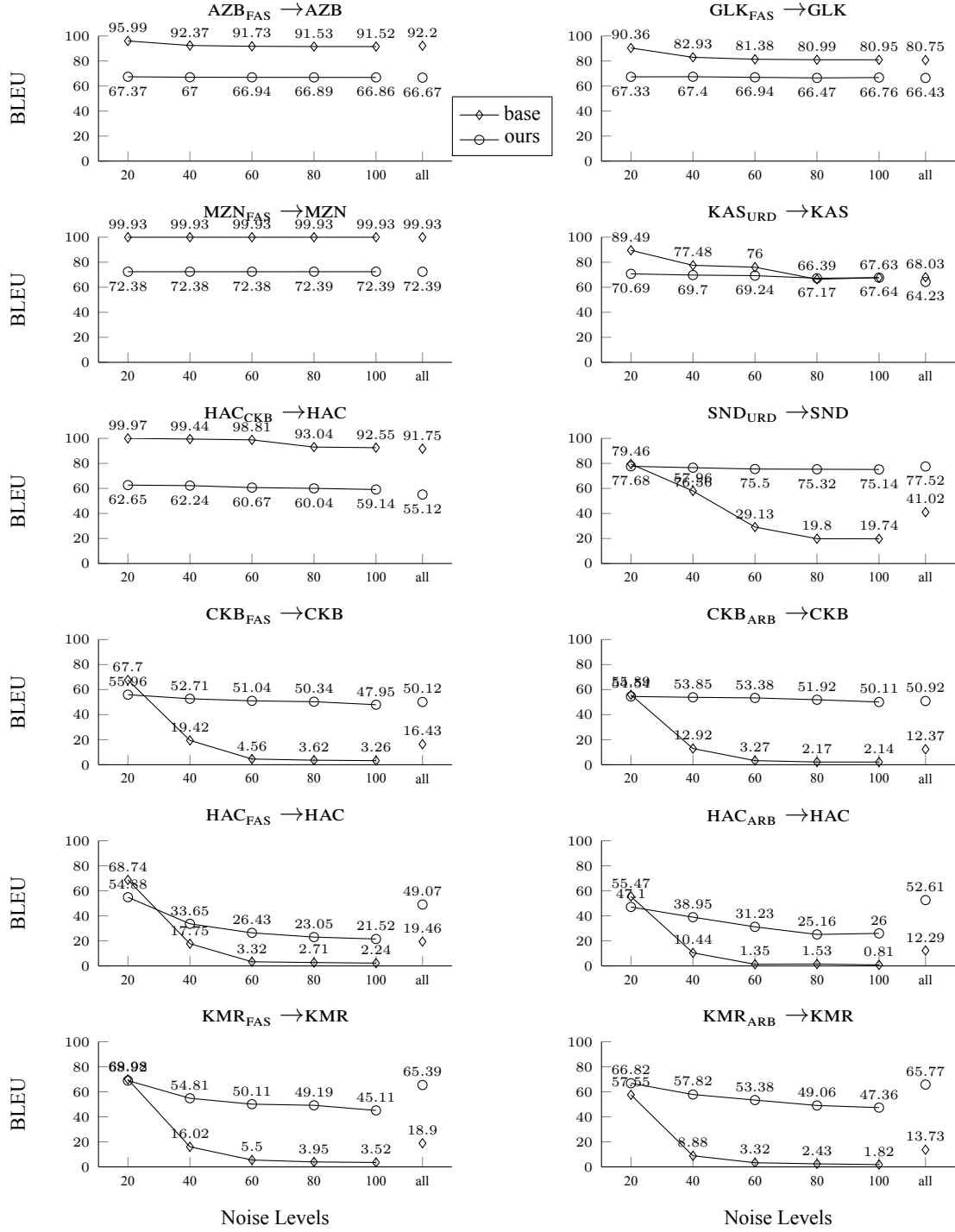


Figure D.1: Comparison of our normalization models to the naive “copy” baseline. In most languages, our normalization models dramatically improve over the baseline.