Bi-Phone: Modeling Inter Language Phonetic Influences in Text

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Abstract

A large number of people are forced to use the Web in a language they have low literacy in due to technology asymmetries. Written text in the second language (L2) from such users often contains a large number of errors that are influenced by their native language (L1). We propose a method to mine phoneme confusions (sounds in L2 that an L1 speaker is likely to conflate) for pairs of L1 and L2. These confusions are then plugged into a generative model (Bi-Phone) for synthetically producing corrupted L2 text. Through human evaluations, we show that Bi-Phone generates plausible corruptions that differ across L1s and also have widespread coverage on the Web. We also corrupt the popular language understanding benchmark SuperGLUE with our technique (FunGLUE for Phonetically Noised GLUE) and show that SoTA language understating models perform poorly. We also introduce a new phoneme prediction pre-training task which helps byte models to recover performance close to SuperGLUE. Finally, we also release the FunGLUE benchmark to promote further research in phonetically robust language models. To the best of our knowledge, FunGLUE is the first benchmark to introduce L1-L2 interactions in text.

1 Introduction

We live in a multilingual world with over 7,000 languages spoken across the globe (Eberhard and Fennig, 2022). However, technology asymmetrically supports only a few specific languages. For instance, the internet is mostly in English with over 60% of websites using the language despite just around 16% share of its speaking population around the world[1] (Grefenstette and Nioche, 2000). Increasingly, people are forced to navigate and produce content on the web in languages they have not been formally trained on. The English text produced by ESL (English as Second / L2 language) writers is heavily influenced by their native language (L1).

Research in the field of second-language acquisition has found evidence of phoneme-shift based misspellings stemming from L1 influence in L2 text for specific language pairs (Ibrahim, 1978; Cook, 1997; Bestgen and Granger, 2011; Sari, 2014; Ogneva, 2018; Motohashi-Saigo and Ishizawa, 2020). Studies in Natural Language Understanding (NLU) have been limited to spelling correction Nagata et al. (2017); Flor et al. (2019) and native language identification Chen et al. (2017); Nicolai et al. (2013) in English learners. These studies predominantly use the TOEFL11 dataset (Blanchard et al., 2013) which deals with very specific demographics such as test-takers who have formal training in the L2 language.

We make the following four key observations about prior work in the study of L1-L2 influences in text and speech. First, current models for L1-L2 influence on textual spelling are limited to certain language pairs and tasks. We argue that L1-L2 influence phenomenon is much more broad and is language and task agnostic. Second, there is no large scale study to examine the prevalence of this phenomenon on the open web. Third, given that this is an important problem especially for multilingual, new-to-the-internet communities there is no standardized benchmark to study the robustness of natural language understanding(NLU) and Natural Language Generation (NLG) models to inter-language phonetic noise. Finally, there is very sparse literature on architecture / pre-training strategies to introduce phonetic robustness into large language models. In this paper, we present modeling techniques,data analyses and a new benchmark to address the gaps mentioned above. We summarise our contributions as follows:

1. We propose a language-agnostic method to mine phoneme confusions that arise due to interference between a native language (L1)

[1] https://w3techs.com/technologies/overview/content_language

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and second language (L2). Our method exploits the “hidden knowledge" contained in $L1 \rightarrow L2$ and $L2 \rightarrow L1$ transliteration models. We also propose a generative model *Bi-Phone* that is able to synthetically produce spelling corruption in accordance with L1-L2 confusions (Sections 3.1, 3.2).

2. Through human evaluation and coverage analysis we show that *Bi-Phone* produces spelling corruptions that are not only deemed plausible by native L1 speakers but also have substantial coverage in the open web crawl corpus. To the best of our knowledge no prior work has demonstrated the presence of L1-L2 phonetic corruptions in a large scale, common dataset like Common Crawl (Section 4).

3. We release a dataset consisting of sentences with L1-L2 phonetic spelling corruptions found in Common Crawl. We also release a benchmark called FunGLUE, an extension of the SuperGLUE benchmark for L1-L2 spelling corruptions. To the best of our knowledge FunGLUE is the first benchmark to measure the robustness of models to L1-L2 interference in text (Section 5).

4. We show SoTA models do not perform well on FunGLUE. We then introduce a novel pre-training task of phoneme prediction, which together with byte level architectures substantially bridges the gap on the noised benchmark (by up to 11% absolute on certain test sets). This is particularly impressive since this gain is achieved without ever showing the model any noised examples (Section 6).

2 Related Work

We divide the presentation of related work in two sections. (i) First, we discuss prior work spanning multiple research areas regarding phonetic influences in text and how it relates to our work. (ii) Second, we discuss work in the speech domain which studies phonetic variations occurring due to inter-language interference in multi-lingual scenarios.

2.1 Phonetic Influences in Text

Phonetic influence on spelling errors has been studied in the past (Kukich, 1992; Toutanova and Moore, 2002; Hládek et al., 2020). The source of such errors is that both native and non-native speakers resort to phonetic spellings for unfamiliar words or names. This direction of work does not address the effect of native language (L1) based phoneme shifts on second-language (L2) spellings.

There has also been work that focuses on learner English [2] for different applications. Nagata et al. (2017); Flor et al. (2019) study automatic spell correction with distributional methods that require a larger learner corpus. Chen et al. (2017); Nicolai et al. (2013) explore Native Language Identification (NLI) on such text. A widely used dataset for these learner English tasks is the TOEFL11 corpus (Blanchard et al., 2013) which contains English essays written by non-native test-takers. It is important to note that these analysis are limited to misspellings made by authors with sufficient L2 knowledge/ training that qualifies them to take the test. They also do not explicitly study the causes of the misspellings or the inter-language interference.

There has also been a fair amount of interest in the second-language acquisition field on the influence of L1 on L2 spelling. Ibrahim (1978); Cook (1997); Bestgen and Granger (2011); Sari (2014); Ogneva (2018); Motohashi-Saigo and Ishizawa (2020) all find evidence of such influence in specific language pairs. These often stem from the lack of certain sounds in L1 leading to difficulty in distinguishing similar sounds in L2. They also find more interesting phenomenon like L1 constraints on consonant clusters are reflected in L2 spellings by learners. While this direction of research is highly pertinent to our work, our goal is to generate plausible L1-L2 phonetic shift based misspellings more generally instead of studying the phenomenon in particular language pairs.

2.2 Inter-language Influence for Phonetic Deviations in Speech

Phonetic variations of words have been well-studied in the context of speech applications. Several studies (Radzikowski et al., 2019; Shah et al., 2020; Radzikowski et al., 2021; Bird et al., 2019) discuss the drop in performance of speech applications such as ASR, spoken-term detection, etc., when presented with non-native speech data. They attribute this drop mainly to the nuances in pronunciation that are often not present in the training data, due to the lack of sufficient non-native speech data. To address and close this gap, several strategies

[2] learner English refers to English as a foreign language

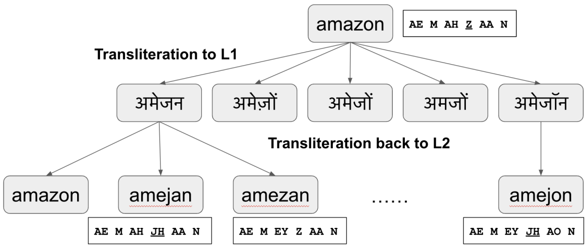
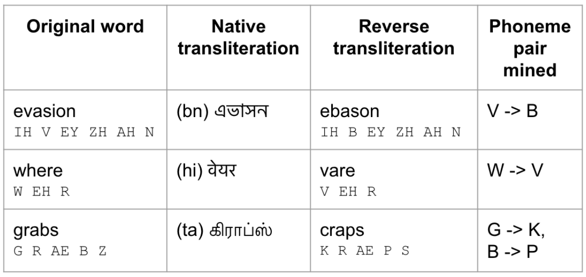


Figure 1: Overview of the Round Trip Transliteration method for creating word pairs from which phoneme confusions are mined. In this example, we create pairs for the dictionary word “amazon" with round-trip transliteration through Hindi as the pivot language. Phoneme sequences for the original and round-trip transliterated words are also shown. Multiple words with *JH* in the round-trip transliterations enables us to map the *Z* sound to the *JH* sound for Hindi speakers.



Original word	Native transliteration	Reverse transliteration	Phoneme pair mined
evasion IH V EY ZH AH N	(bn) এভাসন	ebason IH B EY ZH AH N	V -> B
where W EH R	(hi) वेयर	vare V EH R	W -> V
grabs G R AE B Z	(ta) கிராப்ஸ்	craps K R AE P S	G -> K, B -> P

Figure 2: Examples of round trip transliterations of dictionary words with different pivot languages, the corresponding phoneme sequences, and the phoneme confusion mined. While the third example also has a Z -> S shift, it is not mined because we only consider the top-10 most frequent confusions per (L1, L2) pair.

ranging from the use of cross-lingual/multi-lingual phonological inventories to end-to-end training have been applied. However, these studies do not focus on how the same phonetic influences manifest in written text.

3 Method

In this section we introduce our method for creating inter-language influenced phonetic misspellings (or corruptions). We present the technique in two parts. Section 3.1 presents a method for mining native-language influenced phonetic confusions. Section 3.2 contains details of Bi-Phone, our model that uses mined phonetic confusions to create misspellings.

3.1 Mining Phoneme-Phoneme Confusions

The first problem is to identify possible phoneme confusions that a speaker of a given native language (L1) is likely to encounter when speaking a second language (L2). These confusions can be imagined as a matrix $C(L1, L2)$, which contains likelihood of the i_{th} L2 phoneme (ph_i) being confused as the j_{th} L2 phoneme (ph_j) by a native speaker of L1 as the value in the cell $C(L1, L2)[i][j]$.

$$C(L1, L2)[i][j] = P(ph_j|ph_i) \tag{1}$$

Building this matrix across all pairs of languages is an expensive task. It is also challenging to accurately determine the likelihood of such confusions without large datasets of parallel words.

Transliteration models are trained on large parallel datasets with the objective of transcribing sounds representing words in one language with in the script of a different language. They imbibe important information about sounds in one language that are indistinguishable in another (and therefore lexicalized identically). We propose a round-trip transliteration based method which aims to mine these phoneme confusions and their likelihoods from this knowledge hidden in transliteration models. We collect a large dictionary of English words (our chosen L2) and apply two steps of transliteration [3] (Bhat et al., 2015) to convert them back to English via a pivot language (L1), as shown in Figure 1. We then align the phoneme sequence of the original word with that of its round-trip transliterated version using the Needleman-Wunsch algorithm (Needleman and Wunsch, 1970). We count the frequency of each of the possible sound-shifts in the whole corpus to estimate likelihood. Figure 2 shows examples of word pairs created through different pivot languages and the phoneme confusion mined from these. We consider only the top-10 most frequent phoneme confusions per (L1, L2) for the next step.

3.2 BiPhone: A Generative Model for L1-L2 Phonetic Misspellings

The second problem we focus on is to create a model for sampling phonetic misspellings ($\tilde{\boldsymbol{w}}$) for a given word ($\boldsymbol{w}$) in L2 that a native speaker of L1 is likely to make. We can represent the probability distribution learnt by this model as $P(\tilde{\boldsymbol{w}}|\boldsymbol{w})$. Assuming a deterministic mapping from the word $\boldsymbol{w}$ to its phoneme sequence $\boldsymbol{ph_w}$, and introducing the corrupted phoneme sequence ($\boldsymbol{ph_{\tilde{w}}}$) that finally

[3] https://github.com/libindic/indic-trans

generates $\tilde{\boldsymbol{w}}$, we can rewrite it as -

$$\begin{aligned} P(\tilde{\boldsymbol{w}}|\boldsymbol{w}) &= P(\tilde{\boldsymbol{w}}|\boldsymbol{ph_w}) \\ &= \sum_{\boldsymbol{ph_{\tilde{w}}}} P(\boldsymbol{ph_{\tilde{w}}}|\boldsymbol{ph_w}) * P(\tilde{\boldsymbol{w}}|\boldsymbol{ph_{\tilde{w}}}) \end{aligned} \tag{2}$$

Here a word $\boldsymbol{w}$ is comprised of graphemes $\{w^1, w^2, ..\}$ where $w^i \in Graphemes(L2)$ and a phoneme sequence $\boldsymbol{ph_w}$ is comprised of phonemes $\{ph^1, ph^2, ..\}$ where each individual phoneme ph^i is from the set of available phonemes for $L2$. In our experiments, we use the ARPAbet phoneme set for English [4].

Phoneme-Phoneme Error Model: The first term under the summation in Equation 2 models the likelihood of generating a corrupted phoneme sequence $\boldsymbol{ph_{\tilde{w}}}$ given that a native speaker of L1 is attempting to speak a phoneme sequence $\boldsymbol{ph_w}$ in L2. With simplifying independence assumptions that each phoneme is corrupted individually, independent of phonemes around it, we can factorize this term to utilize the phoneme confusion matrix we have mined.

$$\begin{aligned} P(\boldsymbol{ph_{\tilde{w}}}|\boldsymbol{ph_w}) &= \prod_i P(ph^i_{\tilde{w}}|ph^i_w) \\ &= \prod_i C(L1, L2)[ph^i_w][ph^i_{\tilde{w}}] \end{aligned} \tag{3}$$

Phoneme-Grapheme Density Model: The second term in Equation 2 expresses the probability of generating the grapheme sequence to represent $\tilde{\boldsymbol{w}}$ given the phoneme sequence $\boldsymbol{ph_{\tilde{w}}}$. We can assume equal lengths for the two sequences, by allowing some phonemes to not generate any graphemes, when necessary. Again, we make independence assumptions where the grapheme used to represent a given phoneme does not depend on neighbouring phonemes or graphemes.

$$P(\tilde{\boldsymbol{w}}|\boldsymbol{ph_{\tilde{w}}}) = \prod_i P(\tilde{w}^i|ph^i_{\tilde{w}}) \tag{4}$$

To compute $P(\tilde{w}^i|ph^i_{\tilde{w}})$, we use a pronunciation dictionary in L2 (CMUDict[5] for English). First, phoneme-character probabilities are generated through alignment. Next, for each word, character sequences are converted to graphemes by maximizing the alignment score. Finally, the various phoneme-grapheme alignments along with their frequencies are converted to probabilities by dividing it by the frequency of the phoneme.

Phoneme Shift	Hi	Ta	Bn
AH2 -> AH0	100%	-	100%
IH2 -> IH0	100%	-	100%
ER2 -> ER0	100%	-	-
DH -> TH	54%	-	62%
ER2 -> ER0	95%	-	-
D -> T	-	30%	-
B -> P	-	39%	-
DH -> D	-	0%	-
G -> K	-	47%	-
V -> B	-	-	58%
Z -> S	-	-	50%

Table 1: Plausibility scores for different phoneme shifts across Hindi, Tamil, and Bengali.

L1	Correct Word	Misspelt Word	Phoneme Variation
Hindi	they	thay	DH -> TH
Tamil	exam bacterial	eksam pactirial	G -> K B -> P
Bengali	very equation	bery ikvasan	V -> B ZH -> S

Table 2: Examples of highly plausible misspellings as rated by native speakers for various L1 languages with L2 language as English

Inference: Given an original phoneme sequence for a word to be corrupted, we begin sampling with a fixed width (K) beam from left to right. At each position, we pick the top-K candidates comprising both phoneme-phoneme shifts and phoneme-grapheme alternatives greedily. Since both Phoneme-Phoneme Error Model and Phoneme-Grapheme Density Model are context independent, the greedy strategy gives us the global top-K misspellings. Identity corruptions are removed as a final step.

4 Evaluations

We evaluate the misspellings generated by our model along two distinct dimensions.

4.1 Plausibility

For evaluating plausibility of generated misspellings from Bi-Phone, we focus on three native languages (L1) : Hindi, Tamil and Bengali with English as the non-native language (L2). Hindi and Bengali are the two most widely spoken languages in India and among the top few in the world. Tamil is also a widely spoken language in India and intro-

[4] https://en.wikipedia.org/wiki/ARPABET

[5] http://www.speech.cs.cmu.edu/cgi-bin/cmudict

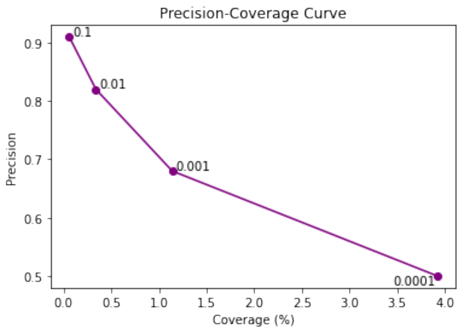


Figure 3: Precision and coverage plotted at different misspelling confidence scores (labels on points). Coverage is represented as a fraction of 31,755,066 sentences that have atleast one non-English dictionary word.

duces typological diversity in our analysis. Finally, our choice of L1 is also based on availability of native speakers for the annotation task.

For each language, we present 150 randomly selected word, misspelling pairs generated from Bi-Phone to native speakers (5 for Hindi, 3 for Tamil and Bengali each). Rater instructions are as follows: Given a list of pairs in English (correct word, misspelling), the task is to evaluate if the misspelling is plausible for pronunciation shifts often made by speakers of the given first language. For example - Bengali speakers often shift the “v” sound to “b” so, “evicted” could be plausibly misspelt as “ebicted” or “abicted”. Each rater provides a 1 or 0 to indicate whether the variant looks plausible or not, respectively. We use a simple majority to assign an overall label to each pair. The raters for this task are our colleagues who are native speakers of the language they are annotating for.

Table 1 reports the percentage of misspellings rated as plausible for each phoneme shift. We observe that misspellings for Tamil are rated as less plausible than for other languages. The reason for this is the more drastic phoneme shifts uncovered in Tamil (B -> P and G -> K). However, misspellings stemming from these shifts are still not rated as completely implausible, which emphasizes that these shifts are indeed common. We also measure inter-annotator agreement through kappa scores which are 0.40 for Hindi, 0.37 for Tamil, and 0.34 for Bengali.

4.2 Prevalence: Coverage Analysis

In the previous section we investigate the plausibility of phoneme-shifts mined by Bi-Phone and the misspellings created as a result. However, this investigation does not throw light on the pervasiveness of such misspellings in real world content.

In this section, we aim to evaluate the severity of the phonetic misspelling issue by uncovering such misspellings in web data. For our analysis, we use the Common Crawl[6] corpus, which is a publicly available scrape of real web data. While most existing language work deals with a highly cleaned version of this corpus (Raffel et al., 2020b), we skip such filtering and cleaning steps to retain noisy, user-generated text. We only use Hindi as the native language (L1) in this analysis. Our analysis has three distinct steps - (1) Candidate Sentence Retrieval, (2) Misspelling Confidence Scoring, and (3) Human Evaluation.

1. Candidate Sentence Retrieval: We begin our analysis by creating 10 misspellings of the top 10,000 most common English words from the Google ngram corpus (Michel et al., 2011) and words that make up 90%-ile of the English words in the Common Crawl corpus. Our hypothesis is that the most common words in English are also the most likely to be misspelt with native language influences. Our pool of sentences is the set of all sentences with at least one non-English dictionary word. The size of this pool is 31,755,066 sentences. From this pool, we create our candidate set by retrieving all sentences that contain one of our generated misspellings.

2. Misspelling Confidence Scoring: The next step is to ascertain that the misspellings retrieved are indeed a noisy form of the intended original word and not a completely different word. For example, “vare" could be a corruption of the English word “where" with the W -> V sound shift, or it could be the less used English word meaning a weasel [7]. We use a simple 1-word left and right context for this disambiguation. For every occurrence of a potentially misspelt word $\hat{W}$ in context $(L_{\hat{W}}, \hat{W}, R_{\hat{W}})$, we evaluate the probability of seeing the corresponding clean word (W) in the same context. This likelihood, $P(L_{\hat{W}}, W, R_{\hat{W}})$ computed as follows can be used as a score to represent our confidence in the retrieved misspelling.

[6] https://commoncrawl.org/

[7] https://www.merriam-webster.com/dictionary/vare

$$
\begin{aligned}
&P(L_{\hat{W}}, W, R_{\hat{W}}) \\
&= \frac{F(L_{\hat{W}}, W, R_{\hat{W}})}{\sum_w F(L_{\hat{W}}, w, R_{\hat{W}})}, \quad \text{if} \sum_w F(L_{\hat{W}}, w, R_{\hat{W}}) > 0 \\
&= 0.4 * \left[\frac{F(L_{\hat{W}}, W)}{\sum_w F(L_{\hat{W}}, w)} + \frac{F(W, R_{\hat{W}})}{\sum_w F(w, R_{\hat{W}})} \right], \text{otherwise}
\end{aligned}
$$

Here 0.4 is the backoff-weight following the *Stupid Backoff* technique from Brants et al. (2007).

We can compute the coverage of Bi-Phone in web data by considering the fraction of sentences where the misspelling confidence score is greater than a certain threshold over the total number of sentences in our original pool.

3. Human Evaluation: Finally, we also sample a subset of the sentences to have human raters verify that our retrieved misspellings indeed correspond to the original word. We show raters the original retrieved sentence which contains the generated misspelling and a parallel sentence where the misspelling has been replaced with the original word and ask raters if this correction is valid in the given context. We can compute a reliable metric for precision with this human evaluation. Ratings for this task are fetched from a cloud rating service where raters are bilingual Hindi-English speakers with a graduate degree.

Figure 3 presents the precision and coverage at different thresholds of misspelling confidence score. At threshold 0.001, we have roughly 70% precision while still having a coverage of 1.14% (362,472 sentences*). The size of the initial pool (30 million candidate sentences) and the simple method used for our analysis underline how prevalent such misspellings are. Also it is important note that such misspellings will be even more prevalent in a purely UGC (user generated content) corpus. C4 contains a significant fraction of clean English web pages.

5 The FunGLUE Benchmark

Significant progress has been made in recent research to substantially improve performance of language understanding tasks. SuperGLUE (Wang et al., 2019) is a very popular benchmark with ten diverse and hard language understanding tasks. These tasks are BoolQ, CommitmentBank (CB), Multi-Sentence Reading Comprehension (MultiRC), Choice of Plausible Alternatives (COPA), Reading Comprehension with Commonsense Reasoning (ReCoRD), Recognizing Textual Entailment (RTE), Words in Context (WiC), Broadcoverage Diagnostics (AX-b), The Winograd Schema Challenge (WSC), and Winogender Schema Diagnostics (AX-g). We argue that for language understanding models to be effective for bi-lingual users, they must be robust to inter-language phonetic spelling variations. Towards this end, we introduce FunGLUE which stands for Ph(F)onetically noised GLUE where randomly selected words from tasks in the SuperGLUE benchmark are corrupted with Bi-Phone based misspellings. It is extremely important to note that we only create a hold-out evaluation set created by introducing misspellings to the SuperGLUE development set. The training set is left clean to mimic real world scenarios where noised training data is difficult to obtain. Additionally, it would be unfair to train and evaluate models on synthetic misspellings from the same source. Table 3 summarizes the training, validation, and test sets in FunGLUE.

Split	**Description**	**Contains Phonetic Noise**
train	Train split from SuperGLUE as is	No
dev	Dev split from SuperGLUE as is	No
test	Dev split from SuperGLUE noised with BiPhone	Yes

Table 3: Description of splits in FunGLUE. Checkpoint selection is done on the dev set which does not contain phonetic misspellings. The test set is used only for reporting results.

Task	Field Name
BoolQ	question
CB	premise
COPA	premise
MultiRC	question
ReCoRD	query
RTE	hypothesis
WiC	sentence1

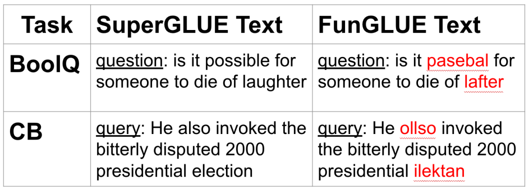
Table 4: Fields we noise for different task when creating FunGLUE.

Misspellings for words in the original task are created from Bi-Phone with the following design choices:

(i) What to noise: Since we want to keep the task realistic, we only introduce misspellings in certain pre-selected fields and not all text fields. This reflects real world situations where content is often available in well spelt English but user queries have phonetic errors. Table 4 presents the fields we actually noise.

Task	Tokens misspelt	Examples w/ noise
boolq	30.6%	96.2%
cb	29.5%	96.4%
multirc	33.8%	96.4%
copa	25.2%	78.0%
record	29.5%	99.4%
rte	35.9%	97.1%
wic	28.9%	84.0%

Table 5: Stats on amount of noise added in FunGLUE.



Task	SuperGLUE Text	FunGLUE Text
BoolQ	question: is it possible for someone to die of laughter	question: is it pasebal for someone to die of lafter
CB	query: He also invoked the bitterly disputed 2000 presidential election	query: He ollso invoked the bitterly disputed 2000 presidential ilektan

Figure 4: Examples from validation set of two tasks in FunGLUE against SuperGLUE. Words which are replaced with their noised versions are in red.

(ii) Which misspellings to use: Since we expect benchmarks to have a high quality, we put in a number of guardrails to ensure poor quality misspellings do not make it through to the benchmark. First, we only use Bi-Phone misspellings with Hindi and Bengali as native language since Tamil misspellings were rated as less plausible by native speakers. Next, we noticed that plausibility scores drop for words smaller than 4 characters, so we only noise longer words. We also filter out misspellings that contain certain patterns of implausible noise generated by our Grapheme2Phoneme model with rules. Finally, all (word, misspelling) pairs used in FunGLUE are manually verified by members of the team as plausible.

(iii) How much noise to add: Since we do not want to artificially introduce too much noise, we only replace 30% of words from the original benchmark across tasks. Table 5 contains stats on the amount of noise added to each task. We were currently unable to include the noised version of the WSC, AX-b and AX-g tasks due to some difficulties in accessing the eval sets. We plan to include this with the final data release.

5.1 Models

In this section we investigate if state-of-the-art models are robust to the phonetic noise introduced by FunGLUE by comparing their performance on SuperGLUE. For this purpose, we consider mT5 (Xue et al., 2021b) and ByT5 (Xue et al., 2021a) models. These are both transformer based sequence-to-sequence models that frame all language understanding tasks as sequence generation. mT5 uses sub-word tokenization built on a multilingual corpus, to represent text. It should therefore be more robust to input variations than comparable models with tokenization on monolingual corpora with lower diversity. ByT5 avoids the tokenization step by building input representations from individual bytes, and is designed to perform more gracefully on noisy text across a range of tasks.

For all models, we use the base architecture. Since training these models is expensive, we do not perform any hyper-parameter search. Instead, we use fine-tuning parameter values from the original papers. Crucially, fine-tuning for all models is performed identically on clean data from SuperGLUE. We use the same mixture of tasks as in Raffel et al. (2020a). Fine-tuning is done for up to 200,000 steps and the best checkpoint is picked based on performance on the clean dev set from SuperGLUE. We use 16 TPUv3s for fine-tuning all models.

5.2 Spell Correction Baselines

Spell correction methods provide obvious baselines when dealing with incorrectly spelt data. Spell corrected data can then be use to run inference with existing models. To evaluate the merit of this technique, we measure performance after correction from two state of the art approaches: (1) NeuSpell BERT (Jayanthi et al., 2020) - spell corrector built on top of BERT. (2) BERT-Large mask prediction - using a BERT Large model for predicting the correct word in positions where we have misspellings. In both of these approaches, we provide the positions of incorrectly spelt words. This is an advantage since this information is not available in real world noisy text. We compare the performance of both mT5 and ByT5 on FunGLUE eval sets corrected by these approaches.

5.3 Results

Rows 1-4 in Table 6 show the performance of mT5 and ByT5 on SuperGLUE and FunGLUE. There is a clear drop in performance for both models on FunGLUE, with both mT5 and ByT5 dropping upto 16 F1 points on the CB dataset. The mT5 model also drops by roughly 9 points in accuracy on the BoolQ dataset, and similarly 9 F1 points on the ReCoRD dataset. While the ByT5 model is in general more robust than the mT5 model, its performance also drops by 10 points in accuracy on RTE.

No.	Model	BoolQ	CB		COPA	MultiRC		ReCoRD		RTE	WiC
		Acc	Acc	F1	Acc	EM	F1	EM	F1	Acc	Acc
SuperGLUE											
1	mT5	78.10	92.86	90.53	61.00	33.68	73.03	67.22	68.26	74.37	68.03
2	ByT5	79.20	91.07	90.37	58.00	32.00	70.14	72.10	72.79	81.23	70.85
FunGLUE											
3	mT5	68.81	80.36	74.21	55.00	28.23	70.37	58.46	59.46	67.87	63.64
3a	mT5 - NeuSpell	67.92	76.79	74.99	64.00	30.43	70.85	60.36	61.33	65.34	65.83
3b	mT5 - Bert-L mask pred	66.42	71.43	79.6	57.00	27.70	67.91	55.6	56.63	58.84	62.54
4	ByT5	74.04	80.36	73.67	58.00	32.42	72.73	67.54	68.19	70.40	66.46
4a	ByT5 - NeuSpell	72.84	76.79	67.86	54.00	32.53	72.47	63.64	64.25	69.68	66.46
4b	ByT5 - Bert-L mask pred	70.52	75.00	70.7	55.00	26.76	68.60	59.75	60.35	64.62	64.26
5	Phonetic mT5	71.80	80.36	73.66	53.00	25.81	72.2	55.85	56.86	61.37	63.17
6	Phonetic ByT5	74.37	87.50	85.46	66.00	33.26	75.15	70.21	70.88	76.17	66.77

Table 6: **First 4 rows**: Performance of SoTA models on tasks in the SuperGLUE and FunGLUE (noised) benchmarks. Performance of both mT5 and ByT5 (rows 3 and 4 compared to 1 and 2) drops on the noised benchmark, although ByT5 (row 4) is slightly more robust. **Rows 3a, 3b, 4a, and 4b** show the performance of mT5 and ByT5 after misspelt words in the eval set are replaced with corrections from SoTA techniques. While mT5 benefits slightly from such corrections, ByT5 performance is worse across all tasks after spell correction is applied. This demonstrates the inability of current spell correction models to handle such misspellings. Rows 3a and 4a correspond to corrections from the NeuSpell (Jayanthi et al., 2020) model. Rows 3b and 4b correspond to corrections using mask prediction from a Bert-Large model. **Last 2 rows**: Performance of the same models when trained on a few additional steps with the phoneme prediction task on clean data (Phonetic mT5 and ByT5). The ByT5 (row 6 compared to row 4) model gains substantially with such pre-training.

The spell correction baselines (Rows 3a, 3b, 4a, 4b) also fail to recover performance. With NeuSpell, mT5 sees a drop in BoolQ and RTE, slight improvement on CB, MultiRC, Record, WIC (<2 points Acc/F1). On COPA, we observe a substantial recovery (55 -> 64). For ByT5 however, there is a drop in performance across the board. NeuSpell is not well equipped to handle phonetic misspellings. Therefore the spell corrected word is often farther from the original word than the misspelling. These bad corrections hurt ByT5, which is slightly more robust to misspellings than mT5. With Bert-Large mask prediction, for mT5 there is a slight improvement on COPA and improvement on CB(74.21 ->79.6), but worse performance on all other tasks. Again for ByT5, we see degradation in performance across the board. Since 30% of the tokens are phonetically misspelt, the contextual mask prediction task is also not accurate. Another failure mode we observed was that the prediction is often the correct type (adjective for adjective) but not the original token.

This clearly demonstrates the challenge posed by phoneme-shift based noisy misspellings introduced in FunGLUE . Current models and training schemes are ill-equipped to function on such data.

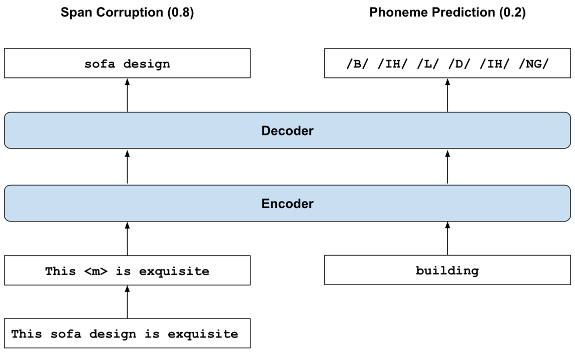


Figure 5: Demonstration of our mixture pre-training task that combines standard span-corruption with the novel phoneme prediction task in an 80:20 ratio. All weights and embeddings in the model are shared.

6 Phoneme Prediction as a Pre-training Task

Given the inadequacy of existing State-of-the-Art models in handling phonetic noise in inputs, we propose a novel pre-training task of phoneme prediction. We posit that the task of predicting phoneme sequences will have the effect of teaching the model “phonetic information". Since different lexicalizations of the same sound will have the same phoneme sequence, the model will learn to embed these close. Additionally since close sounds often appear in similar intra-word contexts, their graphemic representations will also be pushed closed together.

However, to perform NLP tasks, semantic similarity is still crucial. In current models this is often achieved through some variation of the span corruption task (corrupting a span in the input and predicting it on the output). We propose a mixture of these two tasks where a small amount of the phoneme prediction task (20%) is mixed into the standard span corruption task. Figure 5 demonstrates our proposal through two example instances. In the first instance the span “sofa design" is masked in the input (replaced with a sentinel) and is expected to be produced on the output. This teaches the model that adjectives like “exquisite" are semantically close. The second instance has the word “building" in the input and the phoneme sequence corresponding to this word (B, IH, L, D, IH, NG) on the output. This task teaches the model that all tokens that produce the same sound (like “ui" or “e" for IH) should be embedded close.

We train both mT5 and ByT5 checkpoints for an additional 100,000 steps (10% additional steps) on this mixture task. We call this step of additional pre-training, “Phonetic pre-training". Finally, we fine-tune these models on the standard clean SuperGLUE training set. The phoneme prediction data is created by taking roughly 2,000,000 highest frequency words from the Common Crawl English data and getting their pronunciations from an off-the-shelf Grapheme to Phoneme model. As we will see later, this kind of noisy supervision (not human labelled) is still useful in making models phonetically robust.

The last two rows in Table 6 show the performance of these models on FunGLUE. We find that the simple additional pre-training step of phoneme-prediction substantially improves performance of the ByT5 model on the noised benchmark (row 6 against row 4). Performance on CB increases by 11 F1 points, on COPA there is a 8 point accuracy gain, and a 5 point accuracy gain on RTE. While performance still lags compared to the clean benchmark SuperGLUE (row 6 against row 2) on most tasks, for MultiRC and COPA, we find that the phonetically pre-trained ByT5 model even outperforms the vanilla pre-trained model (row 2) numbers on the clean task. This is particularly impressive because the Phonetic ByT5 model (row 6) has never seen any noisy data during its training. The mT5 model does not however see the same impressive gains through this pre-training task. We hypothesize this is because of the harder sub-word tokenization in mT5. Many tokens that this model needs on the noised task are never seen when it’s trained on clean data and therefore have poor representations.

The ByT5 model does however have certain drawbacks. Since input sequences are much longer with byte level representations, both training and inference times are much slower than a sub-word tokenized alternative (like mT5). Additionally, the byte-level representation also restricts input sequence lengths. Using these phonetically robust byte-level models as teachers for sub-word tokenized student models remains an interesting direction for future work.

7 Conclusion

Language is a significant barrier to technology especially for new internet users. For such users, English often is not their first language. The speech community has made significant progress in making technology (ASR for instance) accessible for such users by making models robust to account for inter-language interactions. We argue that a similar line of effort is needed in the Natural Language Understanding for Text community as well. To this end, we first propose a generative model *Bi-Phone* that can account for L1-L2 interactions in text. Next we show the inter-language perturbations generated by Bi-Phone are indeed present in non-trival amount in the common crawl corpus. We also release a new benchmark FunGLUE to help further research in this area. We also present our early yet very promising explorations on making natural language understanding models robust to L1-L2 phonetic shifts through a novel phoneme prediction based pre-training.

8 Limitations

Algorithmic Limitations: The current approach assumes each phoneme / grapheme corruption is independent of the surrounding phonemes / graphemes, which can be relaxed to get further insights and model any contextual phonetic shifts. The relative importance between grapheme and phoneme corruptions could also be explored as a hyperparameter to personalize more to the type of errors of a community.

Other Limitations (with respect to available data and existing resources): Our coverage analysis is conservative since it does not cover the user generated data from various social media where such

L1-L2 phonetic misspellings are bound to be more common. The coverage analysis also relies on the context not being corrupted. However, this might not necessarily hold and the analysis could benefit from a careful formulation of a relaxed matching criteria that also considers cases with corrupted contexts. With transliteration playing a major role in our solution, it is difficult to immediately extend the work to low-resource languages that do not have models or appropriate datasets to build transliteration modules.

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ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
8

☒ A2. Did you discuss any potential risks of your work?
Our paper focuses on building inclusive technology and we don't see any potential risks.

☑ A3. Do the abstract and introduction summarize the paper's main claims?
1

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☑ Did you use or create scientific artifacts?

3,4,5,6,

☑ B1. Did you cite the creators of artifacts you used?
3,4,5,6,

☑ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
3,4,5 (provided links in footnotes to the artifacts from which the license or terms are available)

☑ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
5

☒ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
We only create binary annotations on datasets from an existing benchmark (SuperGLUE).

☑ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
3,4,5

☑ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
4,5

C ☑ Did you run computational experiments?

4,5,6

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
5,6

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☑ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
5,6 Since we are training large models (Byt5 and mT5 base arch) we could not do hyperparameter search. We used values from original papers.

☑ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
4,5,6

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
3,5

D ☑ Did you use human annotators (e.g., crowdworkers) or research with human participants?
4

☑ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
4

☑ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
4

□ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
Not applicable. We are not using any personal data.

□ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
Not applicable. Left blank.

☑ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
4