Robustification of Multilingual Language Models to Real-world Noise with Robust Contrastive Pretraining

Asa Cooper Stickland⋆¶†, Sailik Sengupta⋆‡, Jason Krone⋆‡, He He‡♦, Saab Mansour‡

†University of Edinburgh, ‡AWS AI Labs, ♦New York University

a.cooper.stickland@ed.ac.uk, {sailiks, saabm, hehea}@amazon.com

Abstract

Advances in neural modeling have achieved state-of-the-art (SOTA) results on public natural language processing (NLP) benchmarks, at times surpassing human performance. However, there is a gap between public benchmarks and real-world applications where ‘noise’ such as typos or grammatical mistakes is abundant, resulting in degraded performance. Unfortunately, works that assess the robustness of neural models on noisy data and suggest improvements are limited to the English language. Upon analyzing noise in different languages, we observe that noise types vary across languages and thus require their own investigation. Thus, to benchmark the performance of pretrained multilingual models, we construct noisy datasets covering five languages and four NLP tasks. We see a gap in performance between clean and noisy data. After investigating ways to boost the zero-shot cross-lingual robustness of multilingual pretrained models, we propose Robust Contrastive Pretraining (RCP). RCP combines data augmentation with a contrastive loss term at the pretraining stage and achieves large improvements on noisy (& original test data) across two sentence-level classification (+3.2%) and two sequence-labeling (+10 F1-score) multilingual tasks.

1 Introduction

Recently, multilingual pre-trained language models like mBERT (Devlin et al., 2019), XLM-R (Conneau et al., 2020) and many others (Chi et al., 2021; Xue et al., 2021; Chi et al., 2022) have improved multilingual language understanding by pretraining large Transformer models on web-scale corpora (such as Wikipedia, Common-Crawl, etc.).

These models achieve state-of-the-art performance on many multilingual NLP tasks and for cross-lingual transfer (Wu and Dredze, 2019; Pires et al., 2019). However, a real-world system will encounter real-world noise (linguistic variations and common errors observed in textual data) that are often absent in benchmark datasets.

While prior works focused on this issue of robustness in monolingual tasks (Peng et al., 2021; Sengupta et al., 2021; Tan et al., 2020), investigation has been scarce for multilingual settings. In this paper, we study the effect of realistic noise in multilingual settings and propose methods to boost the robustness of multilingual language models across four NLP tasks: Intent Classification (IC), Slot Labeling (SL), Named Entity Recognition (NER) and Natural Language Inference (NLI).

Due to the lack of multilingual noisy evaluation data, we synthesize benchmarks by mining noise from public corpora and injecting them into the test sets of the four tasks mentioned above (to be released upon approval). Human validation ensured that this data is indeed realistic (MultiATIS++ examples in Figure 1). The variety of noise-types seen across languages (identified in §3) further highlights the diversity of our test-set and motivates research on the topic of multilingual robustness.

To benchmark performance of multilingual systems, we consider accuracy metrics on two utterance-level tasks (IC% and NLI%) and F1-scores on two token-level classification tasks (SL-F1 and NER-F1). Our goal is to consider model performance on the noised version of the test datasets in a zero-shot cross-lingual setting. In this scenario, we have training data for a task available only in one language (in our case, English) and test-data in various languages (Liu et al., 2019, 2020).

While training data augmentation increases model robustness for monolingual (i.e. English) settings, it is not immediately obvious if robustness gains can transfer across languages, as error types can often be language-specific. For example, typos in Devanagari script can differ from those seen in Latin scripts (e.g. फूल → सफ़ूल in Devanagari showcases how a joined character is separated into
| Language | Noise Injection Ratio | Realistic Utt. % | Realistic Examples (test-set) | Unrealistic Examples (test-set) |
|----------|-----------------------|------------------|-------------------------------|---------------------------------|
| French (fr) | 0.1                   | 95.4%            | Me montré les vols directs de Charlotte à Minneapolis tard le matin. | Me montré des vols entre Détroit et St. Louis sur Delta Northwest US Air est United Airlines. |
| German (de)  | 0.2                   | 94.5%            | Zeige mir der Flüge zwischen Houston und Orlando. | Zeige mir alle Flüge von Charlotte nach Minneapolis zum Samstag morgen. |
| Spanish (es) | 0.1                   | 96.9%            | qué aerolíneas vuelan de baltimore a san francisco muestrame vuelos entre toronto y san diego. | necesito información de un vuelo y la tarifa de oakland a salt lake city para el jueves antes de san 8 am de nuevo york a las vegas el domingo con la tarde. |
| Hindi (hi)   | 0.05                  | 95.4%            | मुझे रिजर्वेशन के संबंध में वायु रेल ट्रेन के क्षेत्रों के बारे में जानना चाहिए। मैं चाहता हूँ कि हम उड़ान देने वाले देशों का पता लगाए। | मुझे रिजर्वेशन के संबंध में वायु रेल ट्रेन के क्षेत्रों के बारे में जानना चाहिए। मैं चाहता हूँ कि हम उड़ान देने वाले देशों का पता लगाए। |
| Japanese (jp) | 0.1                   | 92.3%            | ショックロット空港の土曜日err午后1時に出発するUSエアのフライトをリストアップして。 | ショックロット空港の土曜日err午后1時に出発するUSエアのフライトをリストアップして。 |
| Chinese (zh)  | 0.1                   | 86.2%            | 我需要4点后在达拉斯起飞往旧金山的联程航班。 | 我需要4点后在达拉斯起飞往旧金山的联程航班。 |

Figure 1: MultiATIS++ test set injected with real-world noise mined from Wikipedia edits. The highest error injection ratio found to be realistic by human experts is shown alongside the realistic utterance percentage. We do not include the noisy test sets for Chinese and Japanese in our analysis owing to low (< 95%) realism.

2 Related Work

Many prior works demonstrate the brittleness of neural models on different noise phenomena such as misspellings (Belinkov and Bisk, 2017; Karpukhin et al., 2019; Moradi et al., 2021), casing variation (van Miltenburg et al., 2020), paraphrases (Einolghozati et al., 2019), morphological variance (Tan et al., 2020), and synonyms (Sengupta et al., 2021). A popular approach to improve the robustness to noise is fine-tuning models with data augmentation (Feng et al., 2021) at either the pretraining (Tan et al., 2020) or the task-training stage (Peng et al., 2021). These works focus on noise robustness in English, with largely monolingual pre-trained models. Understanding the robustness of multilingual pre-trained models (or improving them) remains largely unexplored. Hence, we investigate—(1) are multilingual models robust to noise seen in different languages (that may be dissimilar to noise types seen in English)? (2) can we obtain and leverage multi-lingual noise data to improve multilingual models? and (3) do automatic data-augmentation methods designed for English improve robustness to multilingual noise?

To boost the robustness of multilingual models...
to multilingual noise, we leverage multilingual data augmentation at the pretraining stage and use contrastive learning. Our effort complements work in computer vision that showcase robustness improvements when contrastive learning with adversarial examples is considered at the task-training (Fan et al., 2021; Ghosh and Lan, 2021) and pretraining stage (Jiang et al., 2020; Kim et al., 2020). Contrastive learning has also been extensively used in NLP (Jaiswal et al., 2020). Specifically, when variants of it are used at task-training time for improving robustness (e.g. adversarial logit pairing) (Einolghozati et al., 2019), they have proven to be less effective than data augmentation approaches (Sengupta et al., 2021). All of these works lack at least one of the two novel aspects of this paper—robustness to real-world (as opposed to adversarial) noise, and/or multilinguality.

Lastly, cross-lingual knowledge transfer has been studied in the context of different NLP tasks; typically, from a high-resource language to a low-resource one, as exemplified by the XTREME benchmark (Hu et al., 2020). In this paper, we investigate the cross-lingual transferability of robustness to real-world noise.

3 Constructing Noisy Test Data

As no existing benchmarks exist to evaluate the robustness of multilingual models, we construct noisy test sets in multiple languages for four tasks. First, we construct a word-level error-and-correction dictionary by leveraging the Wikipedia edit corpora. Then, we sample replacements from this dictionary and inject them into the test data for the various multilingual tasks, focusing on replacements that only affect individual words but do not change word order. Finally, we conduct human evaluation to filter out test sets that are not deemed to be realistic by language experts.

3.1 Wiki-edit Mining

Wikipedia is a public encyclopedia available in multiple languages. Wikipedia editors create and iteratively edit its contents. We leverage these edits to construct error-correction word dictionaries (later used to create noisy test data). Our approach to mining edits is similar to Tanaka et al. (2020), but we consider multiple languages (as opposed to only Japanese), and additionally create dictionaries of word-level edits. Many edits to Wikipedia involve changes to factual information such as dates, rather than incorrect spelling or grammar. To isolate likely useful edits we: consider each revision page of an article and split it into a list of sentences using NLTK (Bird et al., 2009); filter out sentence pairs from two consecutive edit versions ensuring both sentences have (1) 2-120 tokens, (2) a difference if < 5 tokens, and (3) a relative edit-distance within 30% of the shorter sentence, leverage language-specific tokenizers and difflib to extract exact deltas between the pair. Finally, we consider word pairs in these deltas and filter out the ones with a character-level Levenshtein edit-distance of less than < 2. We ensure none of words are only numbers/punctuation.

We can then create a noise dictionary of correct-to-incorrect words with their frequency of occurrence. An element of the dictionary has the following structure (a Spanish e.g.): {de: [(del, 0.52), (se, 0.32), (do, 0.1), (dë, 0.04), (en, 0.02)].

3.2 Injecting Noise into Test sets

We use the noise dictionaries to create a noised version of the original test data for the four tasks—MultiATIS++ (Xu et al., 2020), MultiSNIPS, WikiANN (Pan et al., 2017) and XNLI (Conneau et al., 2018). After tokenization, we randomly sample tokens from a sentence. If the token exists in the noise dictionary, we replace it with a noised version from the dictionary. The noised version is sampled based on its probability in the noise dictionary (that is proportional to its frequency of occurrence). This procedure continues until we hit a number of noised tokens chosen uniformly at random between 1 and the minimum of either \( pL \) or 4 tokens are noised, with \( p \) a controllable fraction (chosen based on human evaluation; see the next section) and \( L \) the number of words in the sentence.

3.3 Human Verification of Noised Test-sets

During human evaluation, we analyse the noisy data created for the MultiATIS++ dataset. We asked the language expert to assume that a user

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2https://meta.wikimedia.org/wiki/List_of_Wikipedias

3https://docs.python.org/3/library/difflib.html

4For Chinese characters, including Kanji, we use a different approach since a two character edit distance covers essentially the whole vocabulary.

5Yet to be released; provided to us privately by the authors.
who may not be a native speaker, or in a hurry, or sloppy, was trying to find out flight information via text chat, and evaluate realism with this in mind. Note that analysis of noise types for MultiATIS++ generalizes well to other datasets as we use the same error-correction dictionaries for injecting noise into all the test-sets.

Our language experts have graduate/doctoral degrees in linguistics, computational linguistics, or natural language processing and are fluent/native speakers of the respective languages. We employed the human experts and compensated them fairly to conduct this study. The experts are given 45 examples without being told that 15 examples have 5%, 15 have 10%, and 15 have 20% noised tokens and asked three questions about each example. Is the noised sentence realistic, moderately realistic, or unrealistic? What type of noise is present in the sentence (we supply an initial list and let them add more)? Are the intent and slot labels unchanged? Based on their initial feedback, we choose the most realistic noise fraction (i.e. 5, 10 or 20%) and provide them with 60 more examples from that set. We considered 15 utterances enough to determine the noise fraction, but used the ratings on 75 utterances for evaluating realism (see realistic utterance % in Figure 1, col. 3).

In Figure 1, we summarize the results of the human evaluation. Column two shows the error injection ratio that was deemed to have more than 95% realistic utterances. We set a high cut-off of 95% to ensure we can make confident statements about the robustness of multilingual models to realistic alterations exhibited in our benchmarks. Hence, Chinese and Japanese (with a realism of 86.2% and 92.3% resp.) are omitted in our benchmarks. The last two columns highlight examples deemed as realistic and unrealistic by human experts with the noised tokens highlighted in orange.

Given the sentence length and similarity in task types, we use the error injection percentage determined to be the most realistic for MultiATIS++ as the error injection percentage for MultiSNIPS and Wiki-ann. For XNLI, experts deemed higher noise injection ratios (of > 0.05) to be unrealistic (15% for 0.1, 27% for 0.2) because (1) the premise, usually much longer than sentences in MultiATIS++, had (impractically high) number of noise tokens, and (2) the classification label (implies/neutral/contradicts) sometimes flipped. Thus, for XNLI, we choose 0.05 to be the default noise injection ratio. Finally, one expert noted the Turkish data in MultiATIS++ lacked many diacritic characters, muddling the distinction between noise injected by our procedure and existing misspellings; hence, it was ignored.

In Figure 2, we list the noise-types identified by our experts in different languages. While certain noise-types, such as typographical errors, misspellings are common across multiple languages, there are various language-specific noise-types, such as homophonic errors (for zh), Kanji conversion errors (for ja), anglicization (for tr) (examples in Appendix A). Given disjoint noise types across languages, we expect that augmentation with errors seen in English (using approaches proposed by prior works) will generalize better to languages that share error types (e.g. Fr, De).

4 Robust Contrastive Pre-training (RCP)

Motivation and Approach While task-time data augmentation (aka adversarial training) has been effective to boost the robustness of pre-trained models for English, we face two major challenges—(1) lack of supervised multilingual training data in our zero-shot setting, and (2) approaches to gen-
We additionally use the standard MLM loss at pre-training time which uses the multilingual Wikipedia edit corpus to expose our models to human errors during pre-training. Here, the need of ex-situ injection of noise (for test-data creation §3) is unnecessary. Further, our edit corpus contains pairs of sentences— a version of the sentence before and after revision by a Wikipedia contributor (§3.1). To encourage the model to align the representations of these two versions in the encoder’s output space, we use a contrastive loss function.

### Table 1: Data-set characteristics and hyper-parameters for our experiments (chosen based on dev set performance).

| Dataset            | Task       | Size (training) | Languages | Epochs | Learning Rate | Seeds |
|--------------------|------------|-----------------|-----------|--------|---------------|-------|
| MultiATIS++ (Xu et al., 2020) | IC/SL      | 5k              | de,en,es,fr,hi | 80     | 1E-04         | 5     |
| + training data aug. |            | 18k             | de,en,es,fr,hi | 20     | 1E-04         | 5     |
| MultiSNIPS         | IC/SL      | 13k             | en,es,fr,hi  | 40     | 1E-04         | 5     |
| + training data aug. |            | 72k             | en,es,fr,hi  | 10     | 1E-04         | 5     |
| WikiANN (Pan et al., 2017) | NER        | 20k             | de,en,es,fr,hi, tr | 3      | 2E-05         | 5     |
| WNLI (Conneau et al., 2018) | NLI        | 392k            | de,es,fr,hi, tr | 5      | 2E-05         | 5     |

$\ell(i, j) = -\log \frac{\exp(\text{sim}(e_i, e_j))}{\sum_{i \neq k} \exp(\text{sim}(e_i, e_k) / \tau)}$  \hspace{1cm} (1)

where $\text{sim}(u, v) = \frac{u^T v}{||u||_2 ||v||_2}$ denotes the cosine similarity of two vectors $u$ and $v$ and $\tau > 0$ denotes the temperature hyper-parameter. Our final contrastive loss function is

$\mathcal{L}_{\text{contrastive}} = \sum_{i=1}^{N} \ell(i, i^n) + \ell(i^n, i)$

We additionally use the standard MLM loss at pre-training time, masking 15% of the input tokens of every sentence (i.e. both noisy and clean) independently. Therefore, our final loss function is

$\mathcal{L} = \mathcal{L}_{\text{contrastive}} + \mathcal{L}_{\text{MLM-noisy}} + \mathcal{L}_{\text{MLM-original}}$

$\mathcal{L}_{\text{MLM-original}}$ is the MLM loss on original sentences, and ensures the model does not ‘forget’ its original pre-training task. $\mathcal{L}_{\text{MLM-noisy}}$ is the MLM loss on noisy sentences, and can be thought of as data-augmentation at pre-training time.

### Pre-training Details

Following the Domain Adaptive Pre-Training (DAPT) approach (Gururangan et al., 2020), we start with an existing multilingual pre-trained model and fine tune it with our RCP objective. Unlike DAPT, we are not interested in specializing in a particular domain, but in increasing robustness to errors. As mentioned before, we use (unfiltered) pairs of correct/incorrect sentences from the multilingual Wikipedia archive.\(^7\) Note that this is not the same set of sentences used to construct our noise dictionaries (section 3.1). In this case, the only criteria for inclusion is a length difference of < 5 tokens, and a relative edit-distance within 30% of the shorter sentence (see appendix C for more details). Thus, changes beyond simple typos (e.g. sentence structure) are incorporated too.

Similar to Gururangan et al. (2020), we fine tune for 25k steps with a batch size of 2048 sentences to create two pretrained models— one with $\mathcal{L}_{\text{contrastive}} + \mathcal{L}_{\text{MLM-noisy}} + \mathcal{L}_{\text{MLM-clean}}$ (referred to as Robust Contrastive Pre-training or RCP) and an ablation without the contrastive term, i.e. $\mathcal{L}_{\text{MLM-noisy}} + \mathcal{L}_{\text{MLM-clean}}$. The latter setting represents a pure (pre-training time) data augmentation approach such as Tan et al. (2020) (termed $p(aug)$ in Table 3). See Appendix D for more hyperparameters and settings.

\(^6\)One obvious choice would be for clean sentence with index 2$i$, the noisy sentence has index 2$i – 1$
### 5 Experiments and Results

We divide this section into three parts. In §5.1, we analyze the robustness of popular multilingual language models in the zero-shot cross-lingual setting. In §5.2, we show that Robust Contrastive Pre-training (RCP) improves the robustness of existing baselines on noisy test-data for all tasks—joint intent classification and slot labeling (IC-SL), Slot-Labeling (SL) Named Entity Recognition (NER) and Natural Language Inference (NLI)—and not only maintains but improves performance on clean data. Finally, in §5.3, we conduct failure mode analysis for MultiATIS++ and discover that the model trained with RCP makes sequence-labeling errors (for slot-value prediction) more explicable in comparison to existing baselines.

### Setup

We consider four datasets (shown in Table 1) and four metrics for evaluation. Two of these metrics consider sentence classification accuracy—Intent classification Accuracy (IC%) for the goal-oriented dialog text datasets MultiATIS++ and MultiSNIPS, and classification accuracy (NLI%) for XNLI. We also consider F-score for sequence-labeling tasks—Slot Labelling (SL-F1) for MultiATIS++ and Multi-SNIPS++ and Named Entity Recognition (NER-F1) for Wiki-ann. Table 1 shows the languages present in the noisy test data and the size of the English training data used in our zero-shot cross-lingual setting. Note that for task-time data augmentation, we follow the strategy of aggregate noise augmentation proposed in (Sengupta et al., 2021) for English, which involves augmenting training data with a variety of synthetic noise types such as typos, making words ALL-CAPS, abbreviations etc. As this augmentation procedure increases the size of the training data-set ≈ 3.5 times for MultiATIS++ and ≈ 5.5 times for MultiSNIPS, we find that training for fewer epochs yields the best results.

### 5.1 Robustness of Multilingual Models

We compare the robustness of two popular pre-trained language models—XLM-R$_{\text{base}}$ and multilingual BERT in the zero-shot cross-lingual setting. In this setup, we finetune the pre-trained models on the task-training data in English and test on multilingual test sets. The results reported in Table 2 are averaged across multiple languages for brevity (a breakdown by language is included in the Appendix). A secondary goal of this experiment is to decide which pre-trained model to use for further experiments. We base our judgements on twelve metrics across four datasets.

Noise always leads to a decrease in performance. On average, the accuracy of both models decreases by ≈ 2% for sentence-level tasks (IC%, NLI%), and by ≈ 6.6 F1-points on sequence-labeling tasks (SL, NER), on noisy data compared to clean data. This can perhaps be explained by the ability to ignore a particular token for sentence-level tasks, whereas every token, including ‘noisy’, ones need to be assigned a label for sequence-labeling tasks.

We observe that XLM-R$_{\text{base}}$ outperforms mBERT on all the twelve metrics. For sentence-level tasks (i.e. IC%, NLI%), XLM-R$_{\text{base}}$ outperforms mBERT by 8.43% on average on the noisy test-sets and for sequence-tagging tasks (i.e. SL, NER), XLM-R$_{\text{base}}$ outperforms mBERT by 5.1 F1-points. In general, XLM-R$_{\text{base}}$ also seems to be a model better suited for these tasks in zero-shot cross-lingual setting as we also see similar gains when using XLM-R$_{\text{base}}$ on the clean data.

Breaking the results down by language (see Appendix for detailed results), XLM-R$_{\text{base}}$ outperforms mBERT on all languages. Specifically XLM-R$_{\text{base}}$ outperforms mBERT on German in 6/8 metrics, on Spanish (10/10), on French (8/12), on Hindi (12/12), and on Turkish (4/4). As German is missing in MultiATIS++ and Turkish is only present in WikiANN and XNLI among the four datasets, the overall number of metrics is less than
Table 3: Average performance across languages and five seeds. We abbreviate the baselines, multi-lingual pre-training time augmentation as p(aug), and English task-time (aggregate) data augmentation as t(En-aug). ‘RCP’ stands for ‘Robust Contrastive Pre-training’, and ‘RCP + t’ means combining RCP with task-time data augmentation. ‘Gain’ refers to the increase in performance of the best method vs. XLM-R<sub>base</sub>.

| Task       | Metric      | XLM-R <sup>p(aug)</sup> | XLM-R <sup>t(En-aug)</sup> | XLM-R <sup>RCP</sup> (Ours) | XLM-R <sup>RCP+t</sup> (Ours) | Gain    |
|------------|-------------|--------------------------|----------------------------|-----------------------------|-------------------------------|---------|
| MultiATIS++| IC%         | 89.65                    | 91.26                      | 93.80                       | 94.57                         | +4.92   |
|            | SL-F1       | 62.30                    | 74.62                      | 67.45                       | 80.68                         | +18.38  |
| MultiSNIPS | IC%         | 90.46                    | 91.60                      | 93.79                       | 94.53                         | +4.07   |
|            | SL-F1       | 61.63                    | 66.44                      | 67.69                       | 70.20                         | +8.57   |
| Wiki-ann   | NER-F1      | 69.48                    | -                          | 72.37                       | -                             | +2.89   |
| XNLI       | NER-F1      | 74.38                    | 74.83                      | -                           | -                             | +0.68   |

Table 4: Comparison of our RCP method with the baseline XLM-R<sub>base</sub> model on the original (clean) test data.

| Task       | Metric      | XLM-R <sub>base</sub> | Ours | Gain    |
|------------|-------------|------------------------|------|---------|
| MultiATIS++| IC%         | 90.68                  | 95.32| +4.64   |
|            | SL-F1       | 71.45                  | 84.07| +12.62  |
| MultiSNIPS | IC%         | 92.93                  | 96.66| +3.73   |
|            | SL-F1       | 68.01                  | 74.39| +6.38   |
| Wiki-ann   | NER-F1      | 74.14                  | 76.34| +2.2    |
| XNLI       | NER-F1      | 76.69                  | 76.75| +0.06   |

Given these results, we consider XLM-R<sub>base</sub> as the baseline multilingual language model in the rest of our experiments.

### 5.2 Robust Contrastive Pre-training Results

We find our contrastive pre-training approach improves robustness. We compare our approach to a popular multilingual model, XLM-R<sub>base</sub> which performed best in the previous section, and two augmentation ideas that have been proposed to improve robustness to real-world noise for English language models. 1) We consider a pre-training time data augmentation approach, similar to Tan et al. (2020), by continuing to pre-train XLM-R<sub>base</sub> on noisy multilingual data; see section 4. 2) We consider augmenting task-time data with a combination of various noise types, following Sengupta et al. (2021), who show using this aggregate data augmentation during task-time finetuning improved performance on both noisy and clean data for IC-SL tasks like ATIS and SNIPS. We treat it as a baseline for zero-shot cross-lingual transfer for the dialog-datasets–MultiATIS++ and MultiSNIPS– and it can also be combined with our pre-training time approaches.

As shown in Table 3, our approach can improve the performance of current multilingual models across all 4 tasks and datasets. For the multilingual goal-oriented dialog datasets, our approach coupled with task-time augmentation outperforms all the other methods. We observe that the gain for SL tasks is higher than that obtained for IC tasks. Although we analyze the SL results further in §5.3, we highlight that IC accuracy is less affected by noise than SL F1, providing more headroom for improvement. The highest gains are observed for Hindi where the XLM-R<sub>base</sub> model has the worst SL performance on noisy data (42.86 for Multi-ATIS++, 36.93 for MultiSNIPS). Likewise, we also observe improvement on XNLI% and NER-F1; the largest improvement is on the noisy data for Hindi. The increase on sequence-labelling tasks (SL, NER) is larger than the increase on sentence-level classification tasks (IC, NLI).

Does this improvement of robustness on noisy data comes at the cost of worse performance on clean data? In Table 4, we show that the best performing models shown in Table 3 (XLM-R+RCP+t for MultiATIS++ and MultiSNIPS, and XLM-R+RCT for WikiANN and XNLI) also improve the performance on clean test data. Further, the magnitude of gains seen on clean data are similar to the ones seen on the noisy test data. For slot-labeling errors, we observe a particular kind of error which occurs on both clean and noisy data that our model mitigates; we provide more details on this in the next section. For IC and XNLI, we found no specific error pattern that distinguishes between XLM-R<sub>base</sub> and our model. Thus, we believe that our approach mostly improves the pre-trained model’s overall quality rather than robustness. We leave it to future work to determine if there is an upper bound on model quality above which the tension between accuracy on clean data and robustness to real-world noise shows up (Tsipras et al., 2018).

Nonetheless, beyond improving performance on clean and noisy data, our approach reduces the...
disparity in performance between the clean and noisy test sets. For MultiATIS++, the disparity reduces by 0.3% for IC% and 5.76 for SL-F1; for MultiSNIPS, it reduces by 1.34% for IC% and 2.19 for SL-F1; for WikiANN, it reduces by 0.68 for NER-F1; and for XNLI, it reduces by 0.9% for NLI%.

5.3 Result Analysis

Given the large improvement seen on sequence labeling tasks, we zoom in on the SL metrics for MultiATIS++. In Figure 3, we show the number of slot labels on which our method outperforms the baseline, vice versa, and where they perform equally. Our method clearly outperforms the baseline on at least twice the number of slot-labels—2× better on German, ≈2-3× on Hindi and Spanish, and ≈4× on French. Further, our model always outperforms XLM-Rbase on 8 slot-labels across languages. These slots correspond to relative times (leaves in the evening), relative dates (traveling the day after tomorrow), relative costs (cheap flights), meal names (that offer breakfast), and carrier tokens/non-slot values (that offer breakfast). We postulate these slot values are more common in the pre-training data (in contrast with proper nouns such as airline, airport or city names) and thus, seen (1) in noisy variations and (2) in noisy contexts. Variations of these words could be mapped closer in embedding space and the classifier could be more robust to similar errors.

Table 5: Examples of slot labeling errors in German—errors are in italics; misclassified tokens are bold.

| Error Type | Utterance | Slot-labels |
|------------|-----------|-------------|
| Hallucination | Ich brauche einen Flug von Memphis nach Tacoma, der über Los Angeles fliegt | airline code |
| Contextual | Zeige mit der Erste-Klasse und Coach-Flüge von JFK nach Miami | fromloc.airport_code, toloc.airport_code |

Table 6: Reduction in hallucination error (i.e. model identifies irrelevant tokens as a slot value) counts.

| N/O | Model | de | es | fr | hi |
|-----|-------|----|----|----|----|
| Noisy | XLMR   | 315| 358| 413| 671|
|       | XLMR+RCP+t | 21 | 123| 33 | 204|
| Original | XLMR | 208| 262| 334| 460|
|       | XLMR+RCP+t | 19 | 106| 22 | 180|

Table 7: Number of slot-labels that our model misclassified to (r1) a no-slot or (r2) a more explicable slot-label.

| Languages | de | es | fr | hi |
|-----------|----|----|----|----|
| (r1) Top-confusion changes to no-label (w/ RCP) | 7 | 8 | 6 | 17 |
| (r2) Confusions becomes more explicable (w/ RCP) | 8 | 3 | 3 | 4 |

Upon further analysis, we observe two distinct patterns—(1) reduction in hallucination errors, i.e. errors where an irrelevant carrier phrase token is labeled to be a slot value, and (2) errors become more contextual—misclassification is to related classes (see examples in Table 5).

In Table 6, we highlight the distribution of hallucination errors and observe that the number of carrier phrase tokens that the baseline XLM-Rbase misclassifies as a slot-value reduces (by >10× for German and French, and ≈2-3× for Hindi and Spanish) with our approach for both the original and the noisy test data. This observation aligns with our initial reasoning—the contrastive loss term at pre-training time helps the model develop a better understanding of non-slot words as the model learns to identify this word and its noisy forms in the context of both correct and noisy words that may surround them. The latter signal is missing for the XLM-Rbase baseline.

For a subset of the slot labels, the class to which it was misclassified (with the highest frequency) differed between the XLM-Rbase baseline and our model. In Table 7, we highlight two scenarios where the most-confused label changed from (r1) an incorrect slot label (e.g. meal_code → airline_code) to no-label (i.e. meal_code → O), and (r2) from an inexplicable slot label (state_code → transport_type) to a more explicable one (state_code → state_name) when the RCP method is used (we use the explicable/inexplicable terminology of Olmo et al. (2020)). Thus, our approach inadvertently improves the explicability of the failures made during slot-labeling.
6 Conclusion

In this paper, we investigate the robustness of pre-trained multilingual models in the zero-shot cross-lingual setting on four tasks—intent classification, slot labeling, named entity recognition, and natural language inference. Given the dearth of existing datasets to benchmark the robustness of existing multilingual models, we develop noisy test data by injecting errors mined from an edit corpus (and conduct expert evaluation for quality assurance). Our identification of noise types across various languages motivates the necessity of language specific investigation in the future. Finally, we show existing baselines perform poorly in the presence of noise in the test data and propose Robust Contrastive Pretraining to boost the robustness of these multilingual models.

7 Limitations

7.1 The Umbrella of Realistic Noise

‘Realistic noise’ is too abstract a category. We mostly concern ourselves with real-world errors and their corrections appearing in existing corpora (with criteria like a small character-level edit distance). But this could include things like better paraphrasing, use of more appropriate synonyms or morphology that can be viewed as language variation rather than noise; this could be one reason we notice improvements on the original (i.e. unnoised) test data. Yet, to distinguish ourselves from the terminology of synthetic or adversarial noise, we choose this (imperfect) terminology of real-world/realistic noise as in Sengupta et al. (2021) to bracket all our noise types under a single class.

7.2 Language Choice and Diversity

This work considers (relatively) high-resource languages. This makes it easier for us to find publicly available corpora from where we can mine error/correction data and use it to improve the model’s understanding of errors and, in turn, boost their robustness to real-world noise. But this is only the first step towards developing an understanding of noise phenomena in languages beyond English, benchmarking multi-lingual model performance in such settings, and improving their robustness. Further, we do notice that Hindi (and, to some extent, Turkish) are relatively low resource languages when it comes to pre-training data (see Table 8 in Appendix). We hope future work builds on this and explores a greater variety of languages.

7.3 Zooming-in on Individual Tasks

Many of our human studies are based on a subset of datasets (eg. MultiATIS, XNLI). It is possible individual tasks and further, individual datasets need more fine-grained human attention. Given language expertise for several datasets and several languages is difficult/costly, we made the choice to concentrate on a smaller number of datasets in order to provide a more rigorous analysis. We hope future work can expand the number of tasks and datasets covered so we have a more comprehensive analysis of how multilingual noise affects pre-trained models.

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A Examples of Noise/Errors in the test set

In this section, we highlight an example of some of the unique noise types observed for certain languages shown in Figure 4.

![Figure 4: Noise types seen across various languages.](image)

A.1 Typographic Errors (Typos)

Two examples follow for Hindi and Chinese, where experts evaluated based on the Indic Script and the Pinyin keyboards (which is what they use regularly) respectively.

| Language | Examples |
|----------|----------|
| Hindi (hi) | सोमवार को बरबैंक [से | के] िमल्‍वौकी तक उड़ानें |
| Chinese (zh) | 列出美国航空周三从密尔沃基飞往圣何塞的航班 [列出 | 例出] 美国航空周三从密尔沃基飞往圣何塞的航班 |

A.2 Preposition Errors

We noticed language experts tagged preposition errors for French and German. Examples follow:

| Language | Examples |
|----------|----------|
| French (fr) | Je veux un vol aller-retour [de | à] Memphis à Seattle |
| German (de) | Wie sieht es [am | im] Mittwoch morgen mit Flügen von DC nach Oakland aus |
A.3 Diacritic Errors

Some languages use diacritic characters; although even these diacritics may greatly differ depending on script. Examples from Hindi and Spanish follow.

| Language  | Examples                                      |
|-----------|-----------------------------------------------|
| Spanish (es) | ¿puedo tomar el vuelo [más | mas] corto de milwaukee a orlando ? |
| Hindi (hi) | दोहे किस [तरह | तरह्] का विमान हैं |

A.4 Conversion Errors

Kanji conversion error. This error was unique to the Japanese language. Examples follow.

| Language | Examples                                      |
|----------|-----------------------------------------------|
| Japanese (ja) | アトランタからセントルイスまでの火曜日午後 2 時 30 分 [以前 | 依然] のフライト |

A.5 Homophonic Errors

This error was unique to Chinese. Words with the same pronunciation (potentially with different tones), but different spelling. Examples follow.

| Language | Examples                                      |
|----------|-----------------------------------------------|
| Chinese (zh) | 请列出从 [洛杉矶 | 洛杉机] 飞往夏洛特的航班 |

A.6 Synonym

Experts marked these as use of a different synonym in Spanish and Chinese only. Note that such variations may not be erroneous but is still considered a noise given they are not used in the original training/testing data in the given context as much. Examples follow.

| Language | Examples                                      |
|----------|-----------------------------------------------|
| Spanish (es) | el próximo miércoles , me gustaría salir de kansas city en [un | el] viaje a chicago que llegue a chicago alrededor de las 7 p m. |
| Chinese (zh) | 请列出从 ewr [到 | 直到] 纽约市的地面交通 |

A.7 Anglicized

We observed this errors only for Turkish and noticed that experts marked scenarios where an alphabet in the native script was replaced with a particular one in the latin script. Examples follow (note that Turkish examples are drawn from the XNLI dataset, while the others were drawn from MultiATIS++).

| Language | Examples                                      |
|----------|-----------------------------------------------|
| Turkish (tr) | Sonrasında, ilk ziyareti yapmış olan aynı temsilci, soruları cevaplamak ve şikayet örneğinde not edilen sorunları tartışmak [için | için] yeni sağlayıcıyı yeniden ziyaret eder. |
|          | Konfederasyonun hukuk felsefesi, hem maddi hem de üslupla [karşı | karsı] karşıya geldi. |
B  Chinese and Japanese Edit Mining

Our two character edit distance criteria for obtaining word-level correct-noisy pairs of words does not work well for Chinese characters, including Kanji for Japanese. This is because words are made up of only a small number of characters (relative to e.g. latin scripts). So we can completely change the semantics with only a small character-level edit distance. We therefore used different noise types: Homophonic and Synonym errors for Chinese and Kanji Conversion errors for Japanese, with brief descriptions and examples in Appendix A. In order to collect homophonic errors we converted words to pinyin\(^8\) (without tone markers) and checked if they were the same in pinyin but different in Chinese characters. To collect synonym noise we labelled words with part-of-speech (POS) tags\(^9\), and kept words that weren’t labeled as nouns, verbs, adverbs, keeping e.g. prepositions and conjunctions, with the hope that these would be less likely to involve the kind of big semantic changes you might get with changes to e.g. proper nouns like place names.

However this process was largely driven by trial and error and more work is needed to create a principled pipeline that creates a realistic noise dictionary for these languages.

Finally for Kanji we re-use the criteria of Tanaka et al. (2020) as we re-use their dataset of sentence pairs: checking if the two sentences (containing Kanji) have the same reading.

C  Data Details

Table 8 shows the number of Wikipedia and Lang8 sentences (in Millions) we used for fine-tuning the multilingual models in the pre-training stage (§4). As stated earlier, the proportion of data obtained from the Lang8 corpus is less than Wikipedia for most languages except English (where it is comparable) and Japanese (where Lang8 has \(\approx 4\times\) the data compared to the Wikipedia corpus). In general, Hindi (and Turkish) stand out as a relatively low-resource language in our investigation with less than 0.5 Million sentences.

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Table 8: Number of sentences (in millions) used for pre-training.

| Language | Lang8 | Wikipedia | Total |
|----------|-------|-----------|-------|
| en       | 2.5   | 3.8       | 6.3   |
| de       | 0.2   | 13        | 13.2  |
| es       | 0.2   | 7.6       | 7.8   |
| fr       | 0.2   | 10.7      | 10.9  |
| hi       | 0.001 | 0.1       | 0.101 |
| ja       | 4.2   | 1         | 5.2   |
| tr       | 0.02  | 0.4       | 0.42  |
| zh       | 0.6   | 1.9       | 2.5   |

Table 9: Number of Error pairs by language.

| Language | # Pairs (in Millions) |
|----------|-----------------------|
| en       | 0.13                  |
| de       | 0.33                  |
| es       | 0.21                  |
| fr       | 0.27                  |
| hi       | 0.04                  |
| ja       | 0.05                  |
| tr       | 0.25                  |
| zh       | 0.01                  |

Table 9 lists the number of correct/incorrect pairs (in Millions) used for noise dictionaries to create the test-sets for the various languages (§3). Here too, we can observe that the number of corrections are relatively less for Hindi. Interestingly, the number of errors for Chinese are the least although it representation is significantly more compared to Hindi. This low number of errors is inline with our human studies where even the 5% error injection was deemed to be unrealistic; further, such low pairs of errors also reduced the diversity of our test set, which would eventually results in a lower-quality test-set. Hence, we drop it from our evaluation benchmarks.

D  Pre-training Settings

For our experiments with Robust Contrasting Pretraining (§4) and variants we use the following hyperparameters and setup. We train on 4 Nvidia V100 GPUs, with a per-gpu batch size of 8 sentences with a maximum sequence length of 128 tokens, and 64 gradient accumulation steps, for an overall batch size of \(64 \times 8 \times 4 = 2048\) sentences. We use a masked language modeling mask probability of 15% and a

\(^8\)Using the pinyin Python package https://pypi.org/project/pinyin/

\(^9\)With the jieba Python package https://pypi.org/project/jieba/.
learning rate of 1e-4 with the Adam optimizer (Kingma and Ba, 2015), and used 16-bit floating point 
operations. See below for the arguments of the Huggingface transformers (Wolf et al., 2020) masked 
language modelling script which we modified\textsuperscript{10}

\begin{verbatim}
python -m torch.distributed.launch --nproc_per_node 4 run_mlm.py \
  --model_name_or_path xlm-roberta-base \
  --gradient_accumulation_steps 64 \
  --validation_split_percentage 1 \
  --per_gpu_train_batch_size 8 \
  --dataloader_num_workers 32 \
  --model_type xlm-roberta \
  --mlm-probability 0.15 \
  --learning_rate 1e-4 \
  --num_train_epochs 5 \
  --max_seq_length 128 \
  --line_by_line \
  --do_train \
  --do_eval \
  --seed 42 \
  --fp16
\end{verbatim}

E  Per-language Results

Table \textsuperscript{10} shows the performance of multilingual models like m-BERT and XLM-R\textsubscript{base} on individual 
languages. We note that the reduction in performance for high-resource language (e.g. German, French, 
English) is higher than low-resource languages for several settings. To explain this seemingly surprising 
result, first notice that the metrics on low-resource languages are already bad, even on clean data. Second, 
the variety of noise seen for low resource languages is less (see Table \textsuperscript{9}) compared to high-resource 
settings. Hence, the effect of less diverse noise in low-resource languages doesn’t have as large an adverse 
effect on already poorly performing models.\textsuperscript{11}

Another hypothesis, pending future investigation, is that multi-lingual models trained on more high-
resource language data overfit to clean test-sets for these languages and fail to generalize better when 
faced with noise. For low resource languages, the performance on clean data is already poor because of a 
lack of sufficient language understanding that prevents over-fitting.

\textsuperscript{10}\url{https://github.com/huggingface/transformers/blob/main/examples/pytorch/language-modeling/run_mlm.py}
\textsuperscript{11}We are told a saying goes (coincidentally) in Hindi, \textit{mare hue ko kya maroge, saheb?}. It implies you cannot do much (by 
adding noise) to kill the (model that is already) dead.
| Dataset   | Model | Metric | C/N | de | en | es | fr | hi | tr | Avg. |
|-----------|-------|--------|-----|----|----|----|----|----|----|------|
| **MultiATIS++** | XLMR  | IC%    | C   | 92.4 | 98.7 | 92.0 | 90.6 | 79.6 | -   | 90.7 |
|           |       | N      |     | 90.9 | 97.6 | 91.8 | 89.5 | 78.4 | -   | 89.6 |
|           | SL-F1 | C      | 74.4 | 96.0 | 73.6 | 70.4 | 42.9 | -   | 71.5 |
|           |       | N      | 67.3 | 82.2 | 68.2 | 65.6 | 38.2 | -   | 62.3 |
| mBERT     |       | IC%    | C   | 83.3 | 98.3 | 84.7 | 88.8 | 76.3 | -   | 86.3 |
|           |       | N      | 81.2 | 97.6 | 84.3 | 87.9 | 76.1 | -   | 85.4 |
|           | SL-F1 | C      | 59.9 | 96.0 | 65.1 | 69.8 | 33.9 | -   | 65.0 |
|           |       | N      | 51.6 | 78.5 | 60.2 | 64.3 | 31.3 | -   | 55.2 |
| (XLMR vs mBERT) |       |        | 4.0 | 1.3 | 4.0 | 4.0 | 4.0 |   |      |
| **MultiSNIPS++** | XLMR  | IC%    | C   | -   | 98.8 | 94.0 | 91.3 | 87.6 | -   | 92.9 |
|           |       | N      | -   | 98.4 | 92.4 | 87.0 | 84.1 | -   | 90.5 |
|           | SL-F1 | C      | -   | 96.9 | 72.0 | 66.2 | 36.9 | -   | 68.0 |
|           |       | N      | -   | 92.7 | 63.3 | 57.7 | 32.8 | -   | 61.6 |
| mBERT     |       | IC%    | C   | -   | 98.9 | 88.0 | 88.5 | 39.3 | -   | 78.6 |
|           |       | N      | -   | 98.2 | 84.1 | 82.9 | 36.2 | -   | 75.4 |
|           | SL-F1 | C      | -   | 96.5 | 65.4 | 59.9 | 14.5 | -   | 59.1 |
|           |       | N      | -   | 91.3 | 58.1 | 52.4 | 13.0 | -   | 53.7 |
| (XLMR vs mBERT) |       |        | 3.1 | 4.0 | 2.2 | 4.0 |      |   |      |
| **WikiANN** | XLMR  | NER-F1 | C   | 74.9 | -   | 75.2 | 77.2 | 67.5 | 75.9 | 74.1 |
|           |       | N      | 71.6 | -   | 70.0 | 71.1 | 65.1 | 69.5 | 69.1 |      |
| mBERT     |       | NER-F1 | C   | 78.6 | -   | 72.1 | 79.5 | 66.2 | 73.1 | 73.9 |
|           |       | N      | 75.4 | -   | 67.1 | 74.2 | 63.0 | 67.3 | 69.4 |      |
| (XLMR vs mBERT) |       |        | 0.2 | 2.0 | 0.2 | 2.0 | 2.0 |   |      |
| **XNLI**  | XLMR  | NLI%   | C   | 76.4 | 84.6 | 78.8 | 77.9 | 69.7 | 72.9 | 76.7 |
|           |       | N      | 72.6 | 80.7 | 76.4 | 75.7 | 70.3 | 70.6 | 74.4 |      |
| mBERT     |       | NLI%   | C   | 71.1 | 82.0 | 74.9 | 74.2 | 60.5 | 62.2 | 70.8 |
|           |       | N      | 67.5 | 77.9 | 73.1 | 71.8 | 61.5 | 59.1 | 68.4 |      |
| (XLMR vs mBERT) |       |        | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |   |      |

Table 10: Per-language results of cross-lingual transfer from English data (average of 5 random seeds) across 4 datasets analyzed in §5.1 to compare between existing pre-trained multilingual models.