Robustification of Multilingual Language Models to Real-world Noise in Crosslingual Zero-shot Settings with Robust Contrastive Pretraining

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Text Classification

Sentence-level classification task (eg. Intent Classification, XNLI, etc.)

- Croatia is such a lovely place → +ve

Token-level classification task (eg. NER, Slot-labeling):

- **Croatia** is such a lovely place → {**Croatia**: Country}

Text Classification

Sentence-level classification task (eg. Intent Classification, XNLI, etc.)

- Croatia is such a lovely place → +ve
- Croatia is suhc a lovely place → ?

Token-level classification task (eg. NER, Slot-labeling):

- **Croatia** is such a lovely place → {**Croatia**: Country}
- **Croatia** is suhc a lovely place → ?

🤔 What happens when faced with real-world noise?

In this work, we study this question for languages beyond English.

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   - Creating Evaluation Test-sets
   - Multilingual Noise Characteristics
3. Robust Constrastive Pretraining
4. Experiments
   - Experimental Setup
   - Robustness of Multilingual Models
   - A Study of Errors

Related Work

- *Works have investigated the impact of various noise types, mostly for English* – misspellings [BB17, KLEG19, MKS21], casing [vMvdLCFK20], paraphrases [EGMS19], morphological variance [TJKS20], synonyms [SKM21], dialectical variance [SLS+22]
- *Methods to improve robustness of SOTA models have considered* – Data augmentation during pre-training [TJKS20, SLS+22] or the task-training stage [PLZ+21], token-free models motivate robustness in multilingual settings [CGTW21, XBC+22, TTR+21], Adversarial Logit Pairing [EGMS19]
- *Our works is similar to works in computer vision that have used of Contrastive learning to boost model robustness* [FLC+21, GL21, JCCW20, KTH20]

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Finding Noisy Data

There is a lack of benchmark to investigate the robustness of multilingual models. *Why?* 🤔

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Synthetic noise-generation methods (mostly developed for English) need linguistic expertise to create benchmarks for individual languages.
What to do? 🤔

Finding Noisy Data

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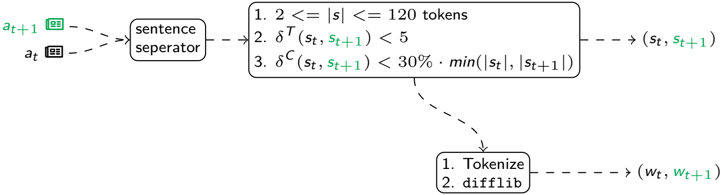
What to do? 🤔

Can we find a data source from where we can obtain such data?

💡 Wikipedia articles are continually updated/edited. Maybe we can mine these edits. (We also leverage other corpora such as Lang8.)

Finding Noisy Data



a_{t+1}

a_t

sentence seperator

1. $2 <= |s| <= 120$ tokens
2. $\delta^T(s_t, s_{t+1}) < 5$
3. $\delta^C(s_t, s_{t+1}) < 30\% \cdot min(|s_t|, |s_{t+1}|)$

(s_t, s_{t+1})

1. Tokenize
2. `difflib`

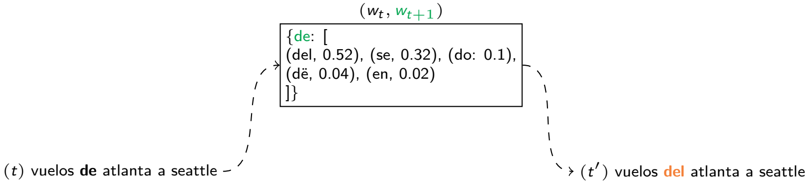
(w_t, w_{t+1})

Similar to [TMKK20], we obtain sentence edit dictionaries and word-edit dictionaries.

Creating Evaluation Test-sets

💡 Use word-edit dictionaries for noisy test-set creation!

We note that this makes our test-data limited to work level edits. But, we can have multiple words manipulated in a single utterance.



(w_t, w_{t+1})

{de: [
(del, 0.52), (se, 0.32), (do: 0.1),
(dë, 0.04), (en, 0.02)
]}

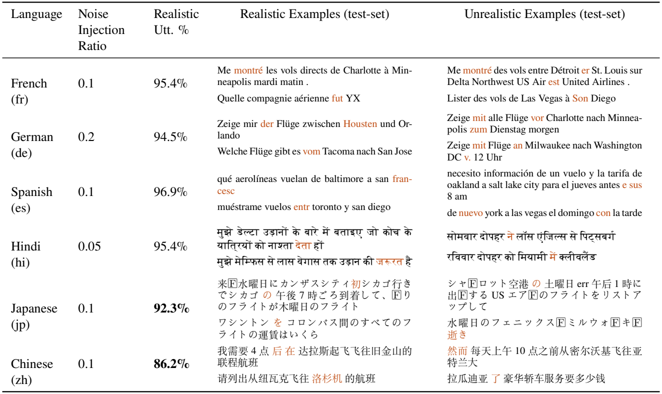
(t) vuelos **de** atlanta a seattle

(t') vuelos **del** atlanta a seattle

Creating Evaluation Test-sets – QA

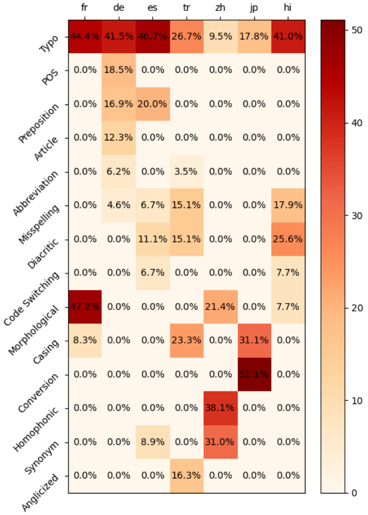
We inject various degrees of noise and conduct evaluation to decide which test sets are more realistic.

We keep test-data on if they have $< 5\%$ unrealistic errors.



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 mardi matin . Quelle compagnie aérienne fut YX	Me montré des vols entre Détroit er St. Louis sur Delta Northwest US Air est United Airlines . Lister des vols de Las Vegas à Son Diego
German (de)	0.2	94.5%	Zeige mir der Flüge zwischen Housten und Orlando Welche Flüge gibt es vom Tacoma nach San Jose	Zeige mit alle Flüge vor Charlotte nach Minneapolis zum Dienstag morgen Zeige mit Flüge an Milwaukee nach Washington DC v. 12 Uhr
Spanish (es)	0.1	96.9%	qué aerolíneas vuelan de baltimore a san francesc muéstrame vuelos entr toronto y san diego	necesito información de un vuelo y la tarifa de oakland a salt lake city para el jueves antes e sus 8 am de nuevo york a las vegas el domingo con la tarde
Hindi (hi)	0.05	95.4%	मुझे डेल्टा उड़ानों के बारे में बताइए जो कोच के यात्रियों को नाश्ता देता हों मुझे मेम्फिस से लास वेगास तक उड़ान की जरूरत है	सोमवार दोपहर ने लॉस एंजिल्स से पिट्सबर्ग रविवार दोपहर को मियामी में क्लीवलैंड
Japanese (jp)	0.1	**92.3%**	来🄵水曜日にカンザスシティ初シカゴ行きでシカゴ の 午後 7 時ごろ到着して、🄵りのフライトが木曜日のフライト ワシントン を コロンバス間のすべてのフライトの運賃はいくら	シャ🄵ロット空港 の 土曜日 err 午后 1 時に出🄵する US エア🄵のフライトをリストアップして 水曜日のフェニックス🄵ミルウォ🄵キ🄵逝き
Chinese (zh)	0.1	**86.2%**	我需要 4 点 后 在 达拉斯起飞飞往旧金山的联程航班 请列出从纽瓦克飞往 洛杉机 的航班	然而 每天上午 10 点之前从密尔沃基飞往亚特兰大 拉瓜迪亚 了 豪华轿车服务要多少钱

Multilingual Noise Characteristics



	fr	de	es	tr	zh	jp	hi
Typo	44.4%	41.5%	46.7%	26.7%	9.5%	17.8%	41.0%
POS	0.0%	18.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Preposition	0.0%	16.9%	20.0%	0.0%	0.0%	0.0%	0.0%
Article	0.0%	12.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Abbreviation	0.0%	6.2%	0.0%	3.5%	0.0%	0.0%	0.0%
Misspelling	0.0%	4.6%	6.7%	15.1%	0.0%	0.0%	17.9%
Diacritic	0.0%	0.0%	11.1%	15.1%	0.0%	0.0%	25.6%
Code Switching	0.0%	0.0%	6.7%	0.0%	0.0%	0.0%	7.7%
Morphological	47.2%	0.0%	0.0%	0.0%	21.4%	0.0%	7.7%
Casing	8.3%	0.0%	0.0%	23.3%	0.0%	31.1%	0.0%
Conversion	0.0%	0.0%	0.0%	0.0%	0.0%	51.1%	0.0%
Homophonic	0.0%	0.0%	0.0%	0.0%	38.1%	0.0%	0.0%
Synonym	0.0%	0.0%	8.9%	0.0%	31.0%	0.0%	0.0%
Anglicized	0.0%	0.0%	0.0%	16.3%	0.0%	0.0%	0.0%

Human evaluation of injected noise surfaces many interesting insights.

- Certain noise types are language specific (eg. `jp` has conversion, `tr` has anglicization errors).
- Certain noise types are common across languages (although `zh` has less typos due to `pinyin` style keyboards).

See our paper for more [Sec 3.3].

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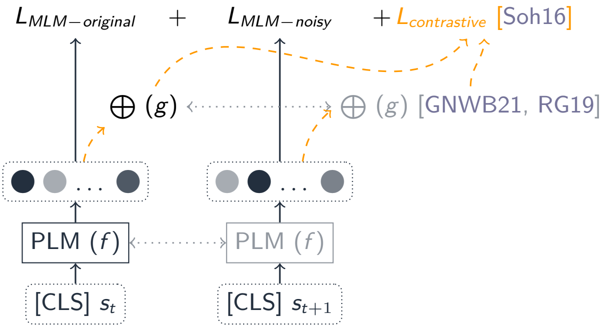
Robust Constrastive Pretraining

💡 Use sentence-edit dictionaries to pre-train multilingual models!

The intuition is that this will teach these multilingual models to represent incorrect and edited sentence closer to one another.


$L_{MLM-original}$ + $L_{MLM-noisy}$ + $L_{contrastive}$ [Soh16]
$\oplus$ (g)
$\oplus$ (g) [GNWB21, RG19]
...
...
PLM (f)
PLM (f)
[CLS] s_t
[CLS] s_{t+1}

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Setup – Tasks, 0-shot Cross-lingual Transfer, Base models

The training data is the original english training set of each task.

Test data had two-splits for each lanaguage– the original test-set (Original) and the noise-added test-set (Noisy).

Dataset	Task	Training size (only en)	Languages (test)
MultiATIS++ [XHM20]	IC/SL	5k	de,en,es,fr,hi
+ training data aug. (en)		18k	de,en,es,fr,hi
MultiSNIPS	IC/SL	13k	en,es,fr,hi
+ training data aug. (en)		72k	en,es,fr,hi
WikiANN [PZM+17]	NER	20k	de,en,es,fr,hi,tr
XNLI [CRL+18]	NLI	392k	de,es,fr,hi,tr

Multilingual Model Robustness (as-is)

XLM-R$_{\textbf{base}}$ [CKG+20] > m-BERT [DCLT19] > Canine-c [CGTW21]

Robustness of Multilingual Models

Task	Metric	XLMR	XLMR	XLMR	XLMR	XLMR	Gain
			+p(aug)	+t(En-aug)	+RCP	+RCP+t	
					(Ours)	(Ours)	
MultiATIS++	IC%	89.65	93.10	91.26	93.80	**94.57**	+4.92
	SL-F1	62.30	67.47	74.62	67.45	**80.68**	+18.38
MultiSNIPS	IC%	90.46	93.98	91.60	93.79	**94.53**	+4.07
	SL-F1	61.63	66.67	66.44	67.69	**70.20**	+8.57
Wiki-ann	NER-F1	69.48	72.32	-	**72.37**	-	+2.89
XNLI	NLI%	74.38	74.83	-	**75.06**	-	+0.68

RCP ↑ model robustness across all tasks metrics – Accuracy of IC & XNLI, F1-score for SL & NER (avg across languages).

Gains ↑↑ when agg. English noise data [SKM21] is used during task-time augmentation.

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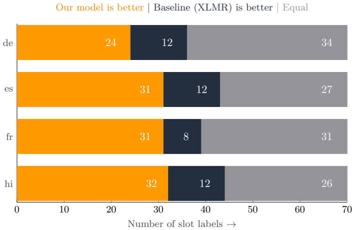
Gains ↑↑ when agg. English noise data [SKM21] is used during task-time augmentation.

RCP ↑ model performance on clean data too!

Task	Metric	XLMR	Ours	Gain
MultiATIS++	IC%	90.68	95.32	+4.64
	SL-F1	71.45	84.07	+12.62
MultiSNIPS	IC%	92.93	95.66	+2.73
	SL-F1	68.01	74.39	+6.38
Wiki-ann	NER-F1	74.14	76.34	+2.2
XNLI	NLI%	76.69	76.75	+0.06

A Study of Errors (on MultiATIS++)

Improvement in slot-label classification ($2\times$ `de`, $2.6\times$ `es`, `hi`, $4\times$ `fr`)



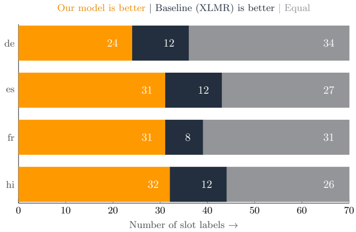
↑ Explicability of errors [OSK20]

👎 fromloc.airport_code → date

👍 fromloc.airport_code → toloc.airport_code

A Study of Errors (on MultiATIS++)

Improvement in slot-label classification (2× `de`, 2.6× `es`, `hi`, 4× `fr`)



↑ Explicability of errors [OSK20]

👎 fromloc.airport_code → date
👍 fromloc.airport_code → toloc.airport_code

We see a sharp drop in *hallucination* errors across all languages.

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

↓ Hallucination errors

Model identifies irrelevant tokens as slot values. Eg.

"Ichs brauche einen Flug von Memphis nach Tacoma, der uber Los Angeles fliegt."

👍 O (über) ⟶ 👎 airline_code (uber)

Conclusion

- Multilingual test data to evaluate the robustness of multilingual models to noise.
- Performance of existing multilingual language models deteriorates on four tasks when tested on the noisy test data.
- Robust Contrastive Pretraining (RCP) can boost the robustness of existing multilingual language models.

Data & Code

https://github.com/amazon-science/multilingual-robust-contrastive-pretraining

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✋ Questions? ✋

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