

Making Sentence Embeddings Robust to User-Generated Content

Lydia Nishimwe

Inria, France

lydia.nishimwe@inria.fr

Benoît Sagot

Inria, France

benoit.sagot@inria.fr

Rachel Bawden

Inria, France

rachel.bawden@inria.fr

User-Generated Content (UGC)

Ergographic phenomena
(encoding simplification)

i don wanna fyt witchu

al b an our l8

c u 2moro

Neologisms

The math is not **mathing**.

burkini

Transverse phenomena

i aint playin

idk

afaik

N. E. V. E. R

Foreign language influence

Cette fête a l'air **fun, let's go !**

likez et commentez

Marks of expressiveness

superrrr !!!!

<3

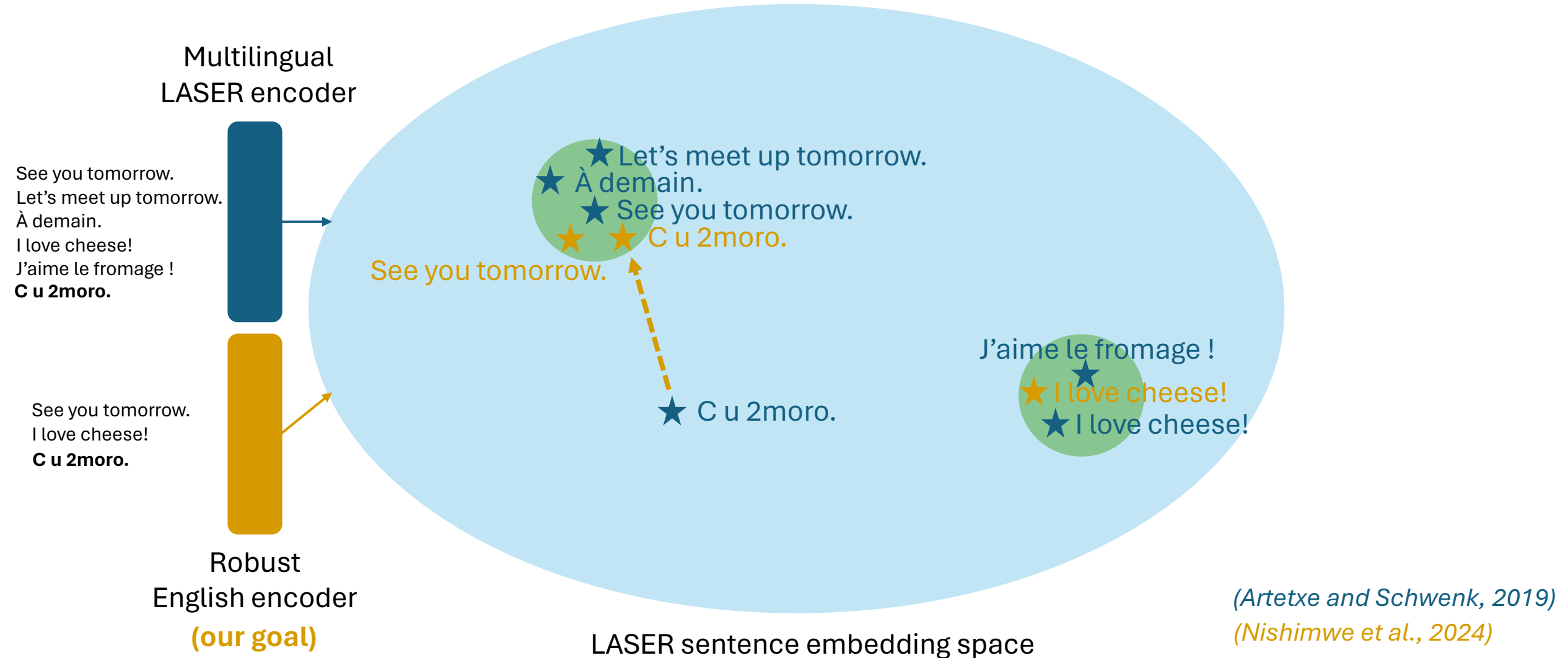


!d10t

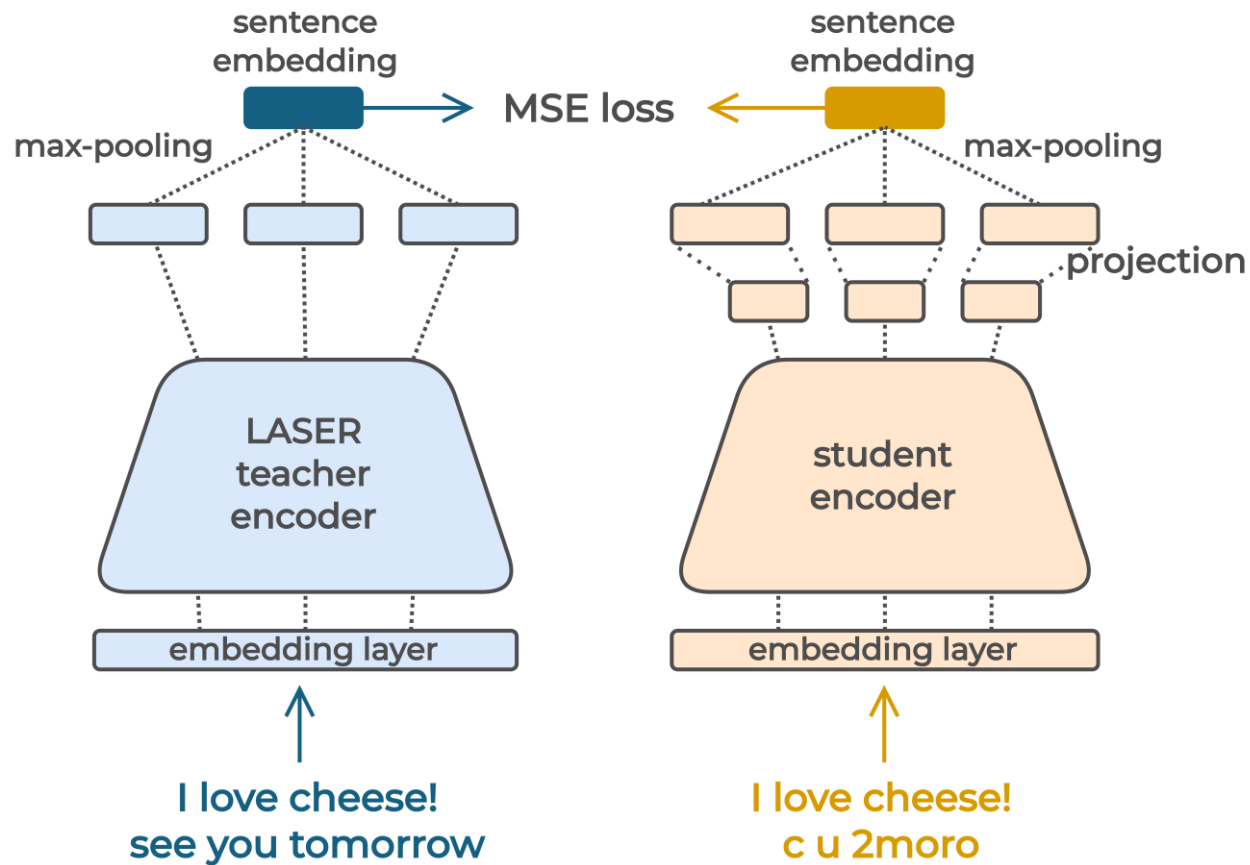
sh*t

(Seddah et al., 2012)
(Zalmout et al., 2019)
(Sanguinetti et al., 2020)

Multilingual sentence embeddings



Proposed approach: Teacher-Student training



- **LASER (teacher):**
 - 45M parameters
 - 5-layer bi-LSTM
 - 1024 output dimension
 - **fixed during training**
- **RoLASER [Robust LASER] (student):**
 - 108M parameters
 - 12-layer Transformer
 - 768 output dimension
 - **projection layer -> 1024**
- **c-RoLASER (student):**
 - 104M parameters
 - same as RoLASER, except for
 - **Character-CNN input embedding layer**

Generating artificial UGC (NL-Augmenter)

abbreviations, acronyms, slang

abr1 because → cuz

abr2 easy → ez

abr3 ASAP ↔ as soon as possible

slng jewellery → bling bling

contractions and expansions

cont I am ↔ I'm

week Monday ↔ Mon.

visual and segmentation

leet love → l0V3

spac hello there → h elloth ere

misspellings

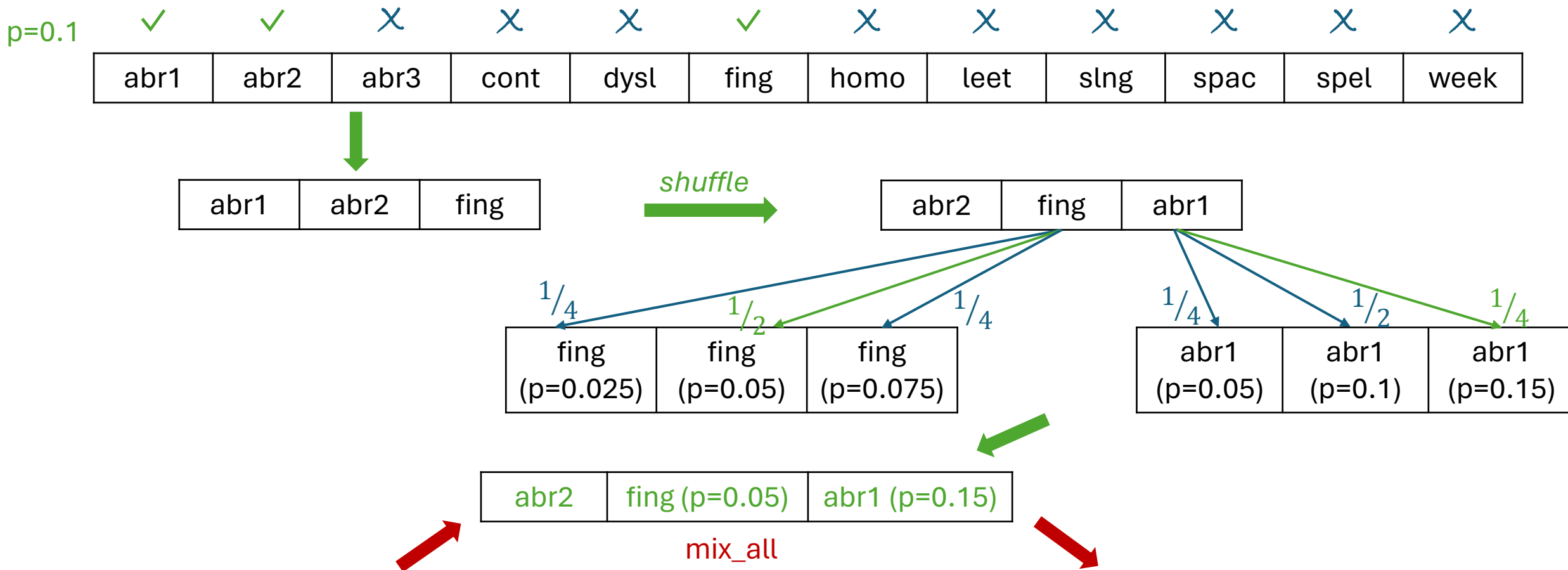
fing tried → triwd

homo there ↔ their

dysl lose ↔ loose

spel absent → apsent

Generating artificial UGC training data



"Luckily **nothing** happened **to** me, but I saw a macabre scene, as **people tried to** break windows in order **to get** out."

"Luckily **nthing** happened **2** me, but I saw a macabre scene, as **ppl triwd 2** break windows in order **2 gt** out."

Experimental setup

- **Training data:**

- 2M “bilingual” standard-UGC sentences
- 2M standard English sentences from the OSCAR dataset
(Ortiz Suárez et al., 2019)
- augmented with the *mix_all* transformation

- **RoLASER training:**

- initialised with RoBERTa
(Liu et al., 2019)
- 98 epochs

- **c-RoLASER training:**

- initialised with CharacterBERT
(El Boukkouri et al., 2020)
- 32 epochs

Evaluation data and metrics

Data

- MultiLexNorm (*van der Goot et al., 2021*)
 - **Twitter**
 - 1967 standard ↔ UGC sentences in English
- RoCS-MT (*Bawden and Sagot, 2023*)
 - **Reddit**
 - 1922 standard ↔ UGC sentences in English
 - translations into other 5 languages
- FLORES-200 (*NLLB Team et al., 2022*)
 - **WikiNews, WikiBooks, WikiVoyage**
 - parallel texts in 200 languages
 - 997 dev and 1012 test sentences
 - **artificially augmented**

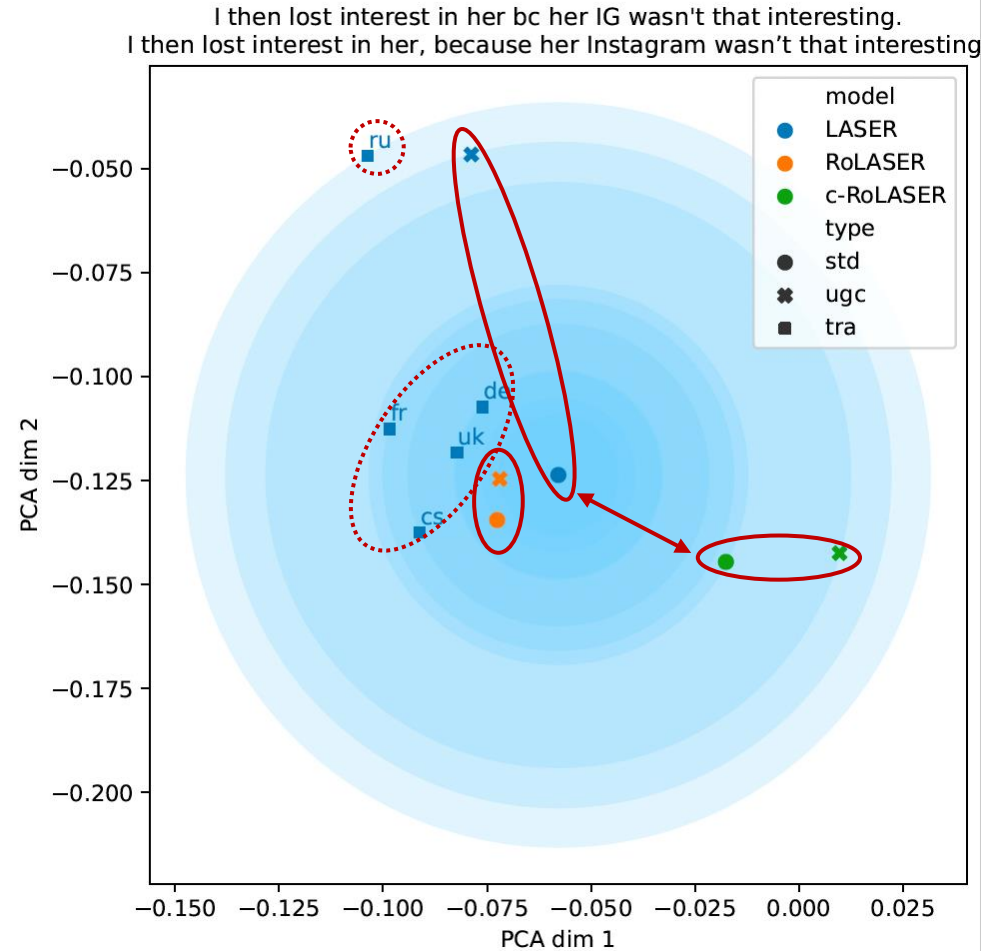
Metrics

- Average pairwise cosine distance
- xSIM (*Artetxe and Schwenk, 2019*)
 - cross-lingual similarity search
 - proxy metric for bitext mining
 - **error rate of aligning translation pairs**
- xSIM++ (*Chen et al., 2023*)
 - **augmenting the English set of FLORES-200**
 - altering the meaning
 - minimal surface changes
 - **more challenging than xSIM**

Evaluation on natural UGC



(lower is better)



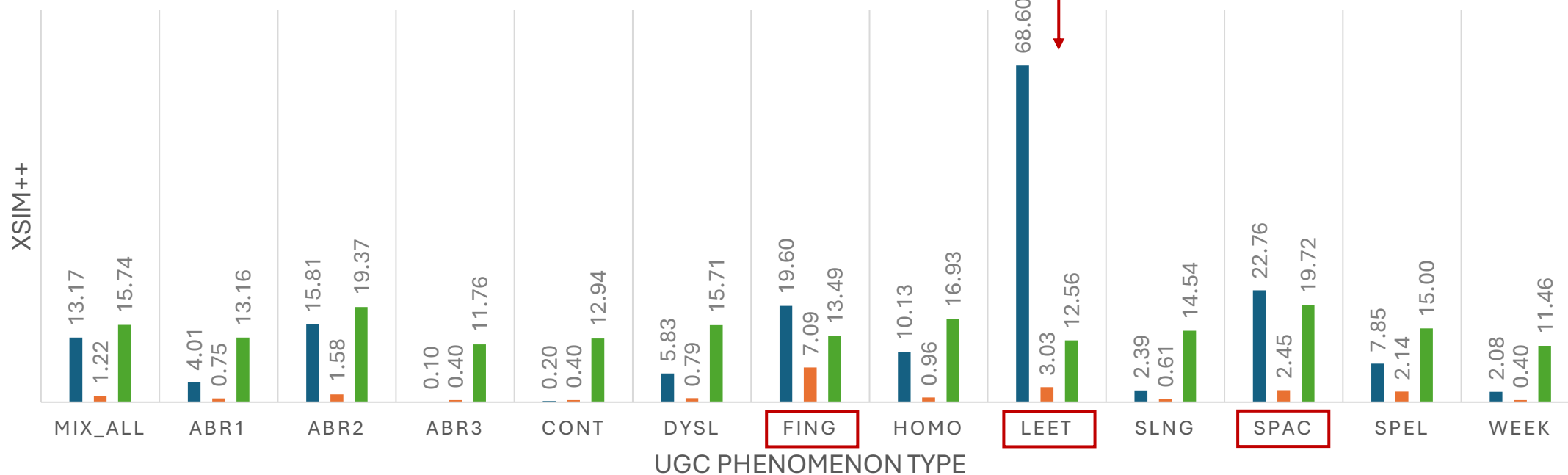
Evaluation on artificial UGC

Hello world → _Hel lo _world

H3ll0 w0rld → _H 3 ll 0 _w 0 r ld

FLORES-200

■ LASER ■ RoLASER ■ c-RoLASER

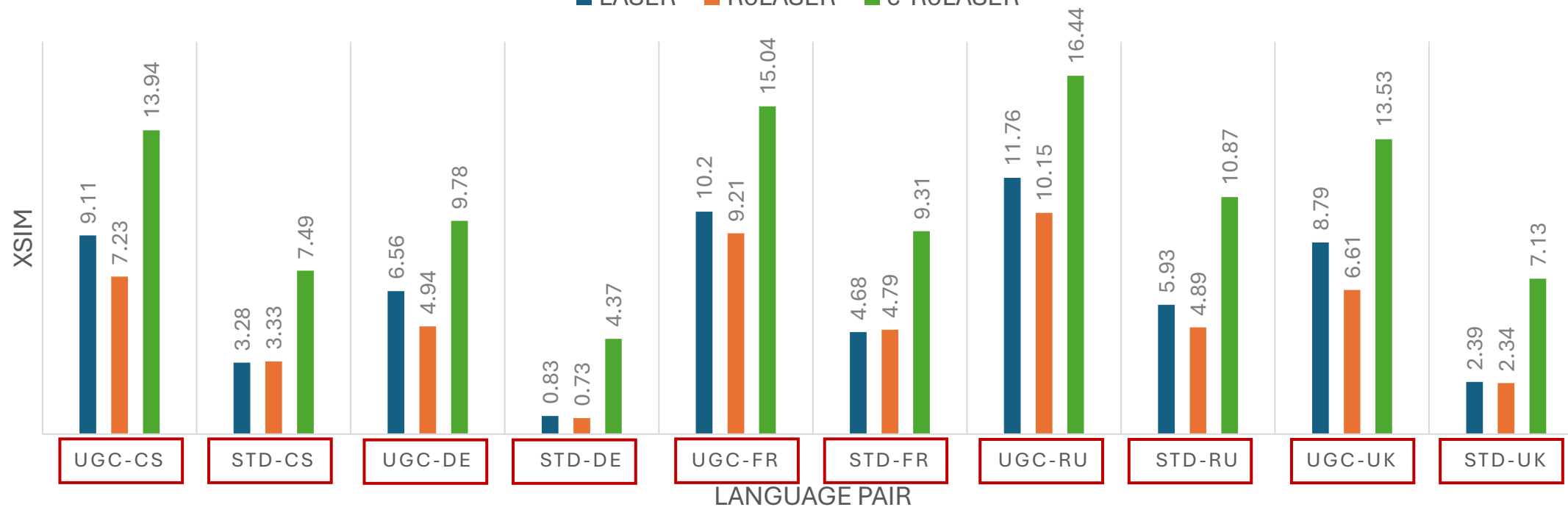


(lower is better)

Evaluation on UGC and standard data in a multilingual setting (1)

ROCS-MT ENGLISH→XX

■ LASER ■ RoLASER ■ c-RoLASER

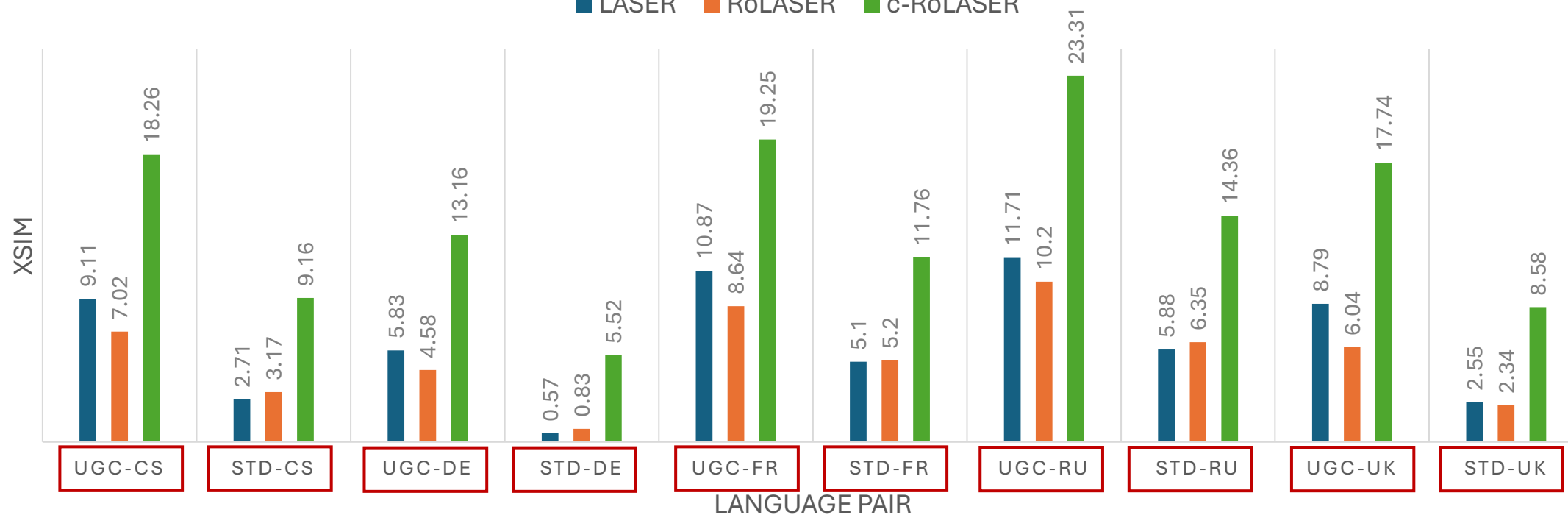


(lower is better)

Evaluation on UGC and standard data in a multilingual setting (2)

ROCS-MT XX→ENGLISH

■ LASER ■ RoLASER ■ c-RoLASER

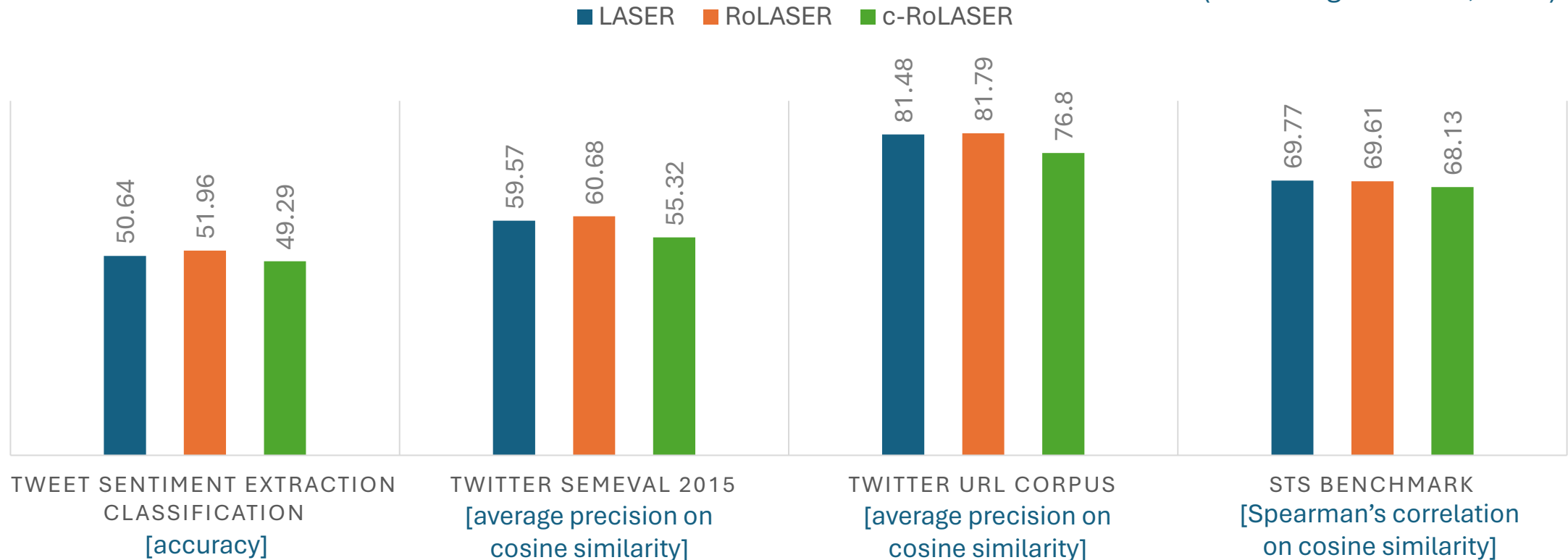


(lower is better)

Evaluation on downstream tasks

MTEB: MASSIVE TEXT EMBEDDING BENCHMARK

(Muenninghoff et al., 2023)



(higher is better)

Takeaways

Approach:

Making LASER more robust to UGC English

1. Teacher-Student training
2. Minimising the standard-UGC distance in the embedding space
3. Generating and training on synthetic UGC-like data

Extending RoLASER to **more languages** and their corresponding UGC phenomena...

Future work

Results:

RoLASER is significantly more robust than LASER

- on natural and artificial UGC
- on standard data and downstream tasks (improves/matches LASER's performance)

Findings:

1. c-RoLASER struggles to map its standard embeddings to LASER's
2. Most challenging UGC phenomena: character-level perturbations that shatter subword tokenisation

Read our paper for more details and references!