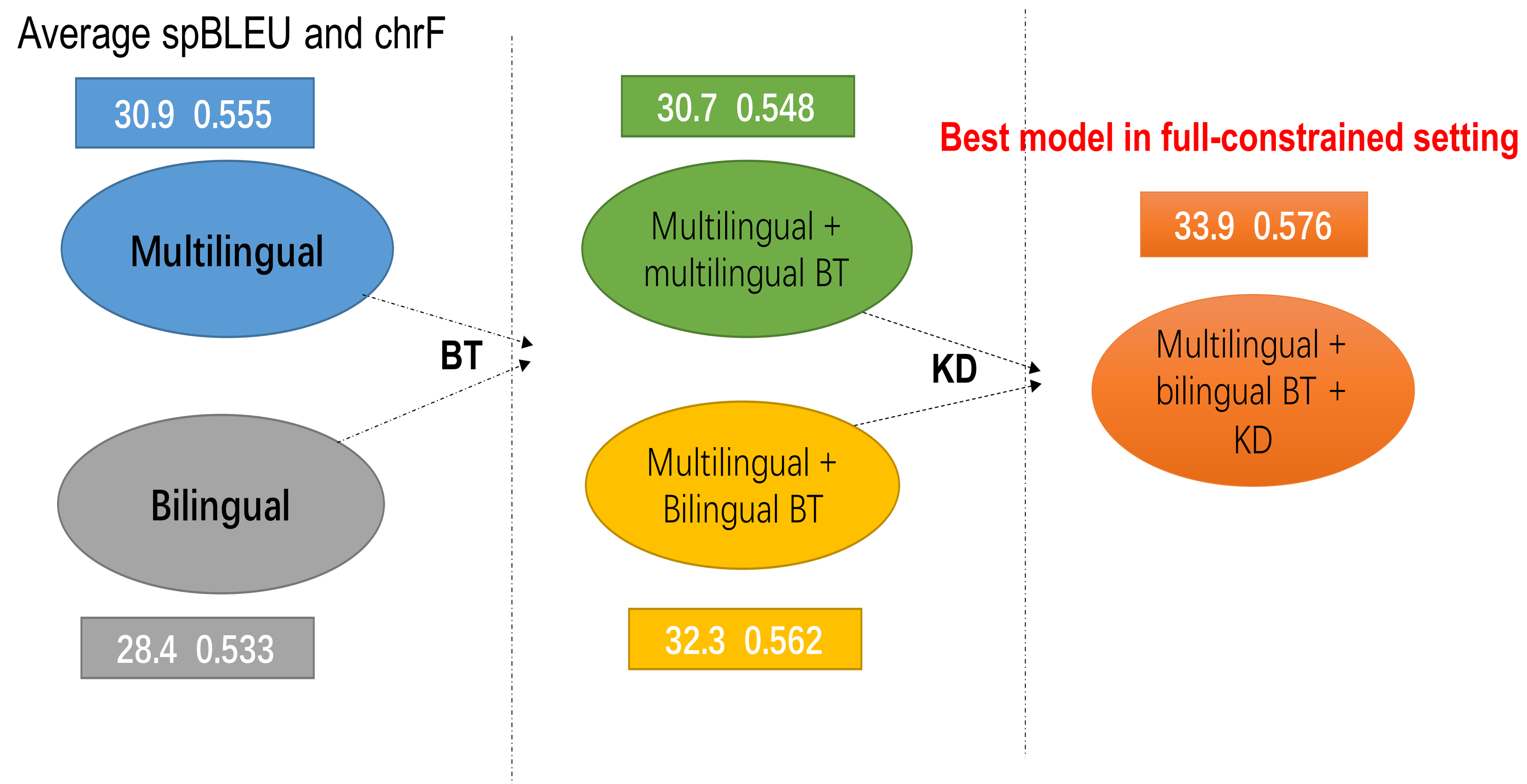
The LMU Munich System for the WMT 2021 Large-Scale Multilingual Machine Translation Shared Task

Wen Lai, Jindřich Libovický and Alexander Fraser

Center for Information and Language Processing, LMU Munich, Germany

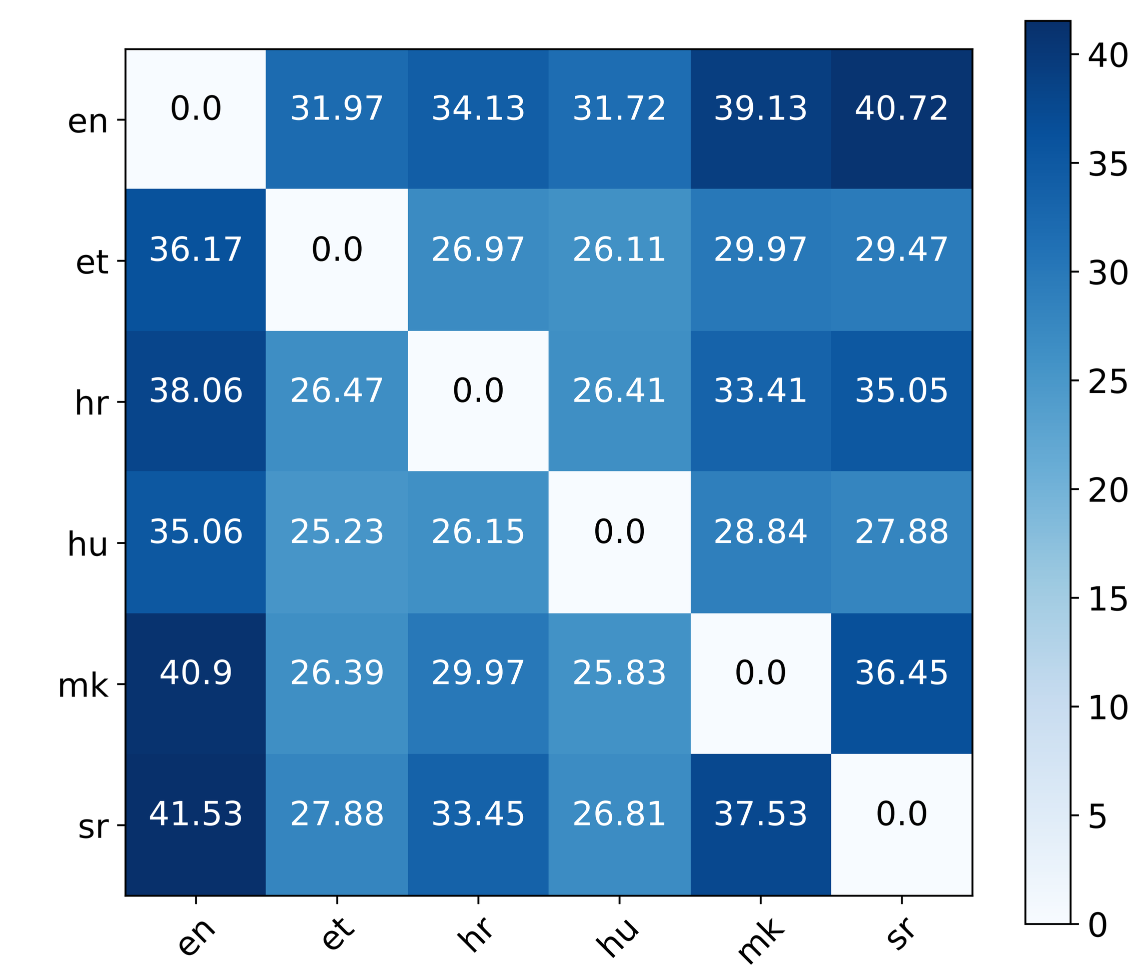
Introduction

- **MNMT** aims to handle the translation from multiple source languages into multiple target languages with singled unfied model (Johnson et al., 2017; Fan et al., 2021).
- **Back Translation (BT)** (Sennrich et al., 2016; Caswell et al., 2019) is a simple and effective data augmentation technique, which makes use of monolingual corpora and has proven to be effective for MNMT(Zhang et al., 2020).
- **Knowledge Distillation (KD)** (Kim and Rush, 2016) is a commonly used technique to improve model performance. We follow a recent approach to KD (Wang et al., 2021), which uses selection at the batch level and global level to choose suitable samples for distillation.



Overview of the best-performing system of our proposed approach. we report spBLEU scores and chrF on the provided devtest set.

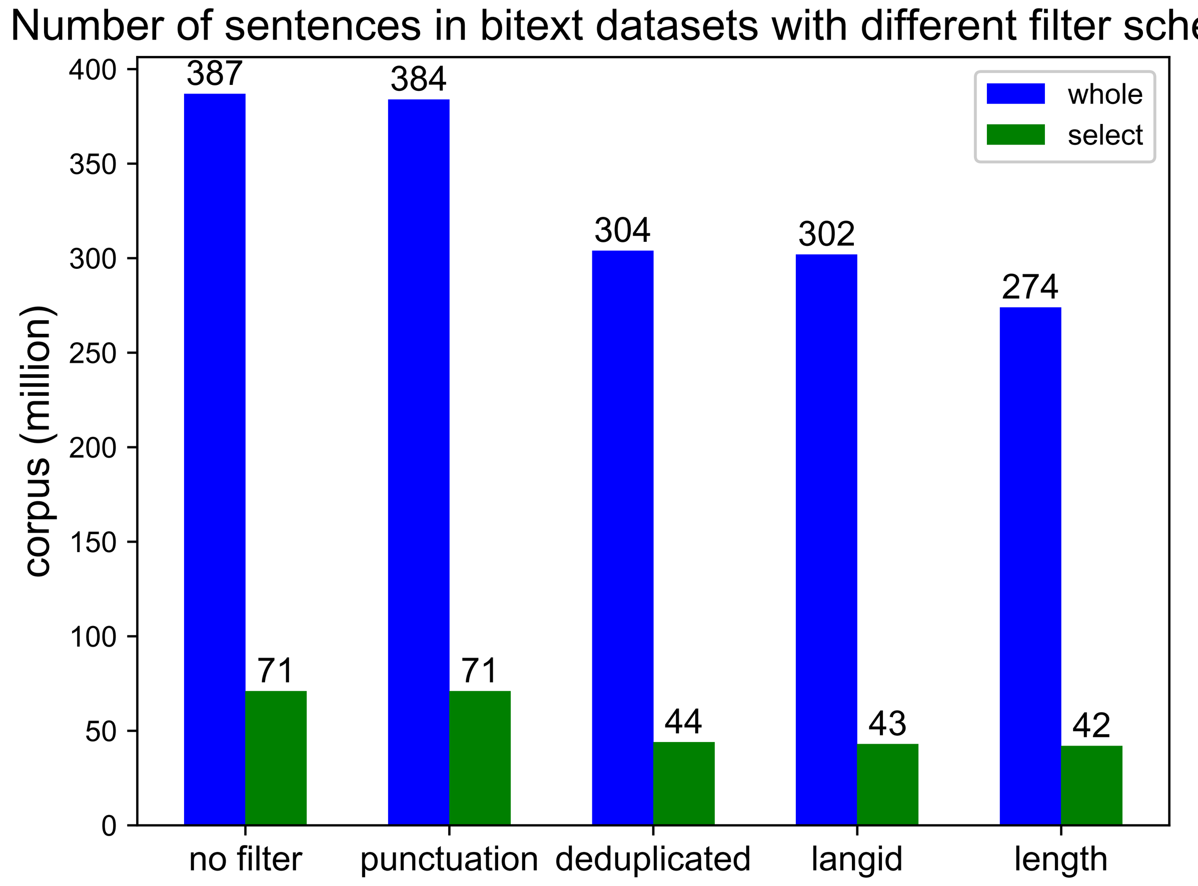
flores small1 devtest Performance Grid (BLEU score)



Data

- Moses truecased and punctuation normalized.
- Sentences containing 50% punctuation are removed.
- Duplicate sentences are removed.
- Using `langid` filter out sentences with mixed language.
- SentencePiece was used to produce subword units.
- Remove sentences with more than 250 subwords.

Number of sentences in bitext datasets with different filter schemes



Contact Information

Wen Lai

Ph.D. Candidate at LMU Munich
lavine@cis.lmu.de

Results

#	Systems	spBLEU	chrF	BERTScore	BEST BLEU
0	Flores	28.0	0.528	0.867	sr-mk (36.0)
1	Bilingual$_{whole}$	21.1	0.477	0.831	en-mk (31.3)
2	Bilingual$_{select}$	28.4	0.533	0.863	sr-en (40.6)
3	Multilingual$_{whole}$	16.7	0.431	0.827	sr-en (26.1)
4	Multilingual$_{select}$	30.9	0.555	0.874	sr-en (40.0)
5	Multilingual$_{select}$ + TaggedBT(Multilingual$_{select}$)	30.7	0.548	0.873	sr-en (40.5)
6	Multilingual$_{select}$ + TaggedBT(Bilingual$_{select}$)	**32.3**	**0.562**	**0.879**	sr-en (41.5)
7*	Multilingual$_{select}$ + TaggedBT(Bilingual$_{select}$) + KD$_{batch}$	33.2	0.572	0.883	sr-en (42.0)
8*	Multilingual$_{select}$ + TaggedBT(Bilingual$_{select}$) + KD$_{global}$	**33.9**	**0.576**	**0.887**	sr-en (42.4)

Analysis

- Our multilingual model (#4) performs competitively with the Flores strong baseline (Model #0).
- Although the overall performance of the Multilingual model (#4) is better than the Bilingual model (#2), back-translation using the Bilingual model (model #6) is better than back-translation using the Multilingual model (model #5).
- Knowledge Distillation further improves performance slightly (Model # 7* and Model # 8*).

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Conclusion

- Our goal is to investigate the impact of bilingual systems on multilingual systems.
- Our best translation system scores 5 to 6 BLEU higher than a strong baseline system provided by the organizers (Goyal et al., 2021).
- Our model only has 313M parameters, which is smaller than the other submissions.
- Our submission is the only fully constrained submission that uses only the corpus provided by the organizers and does not use any pre-trained models.

References

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