High-resource Language-specific Training for Multilingual Neural Machine Translation

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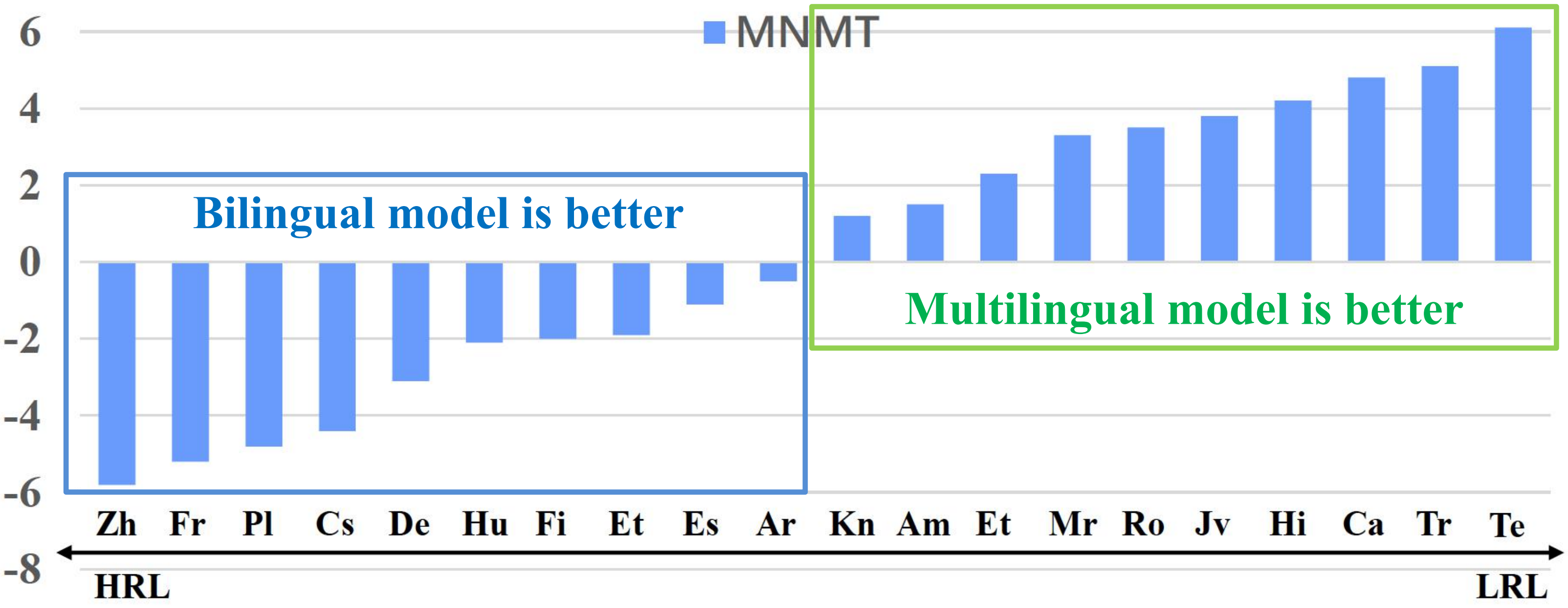
Bilingual vs. Mulilngual

HRL: High-Resource Language; **LRL**: Low-Resource Language

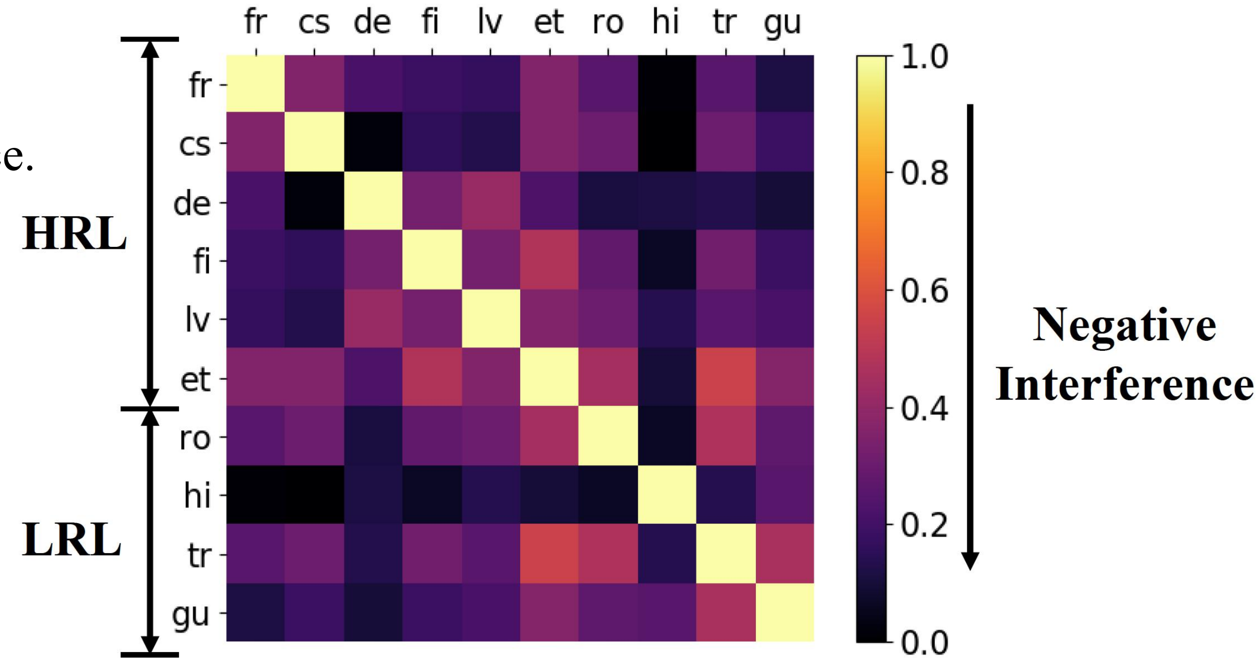


ΔBLEU socre between MNMT and BiNMT on En→X and X→En (averaged)

Negative Language Interference

Different directions conflict with each other to various extents.

The less gradient similarity,
the darker the color,
the more negative interference.



cosine similarities between
gradients of two translation directions

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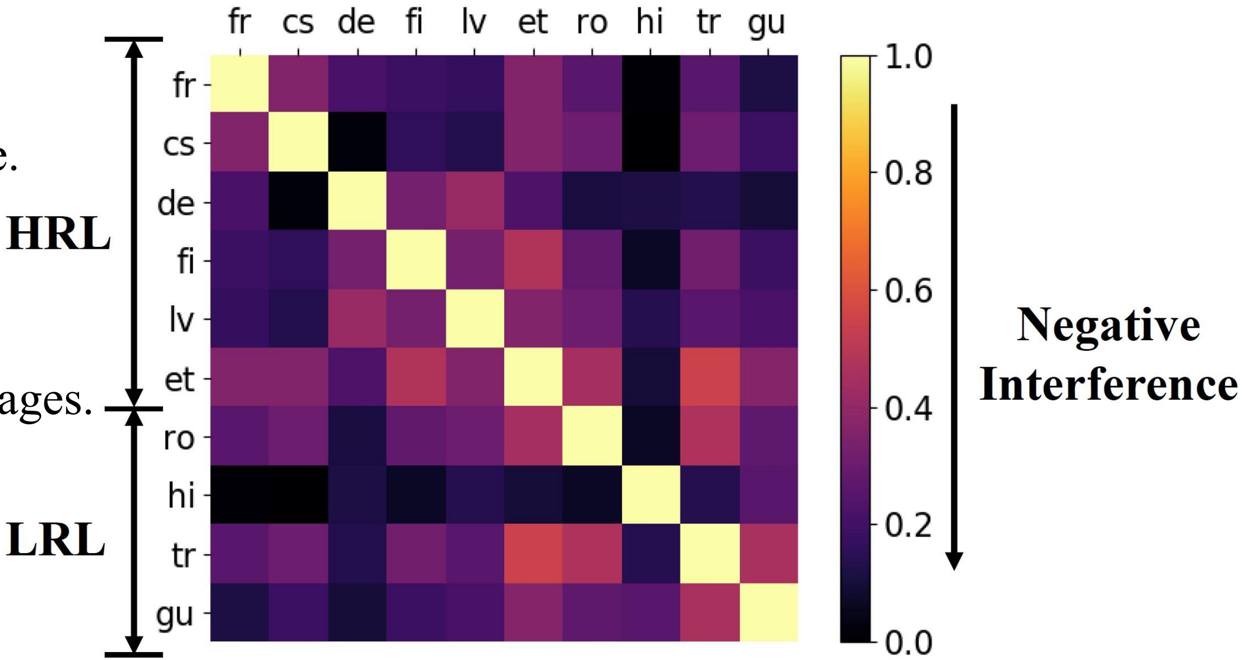
Our Goals

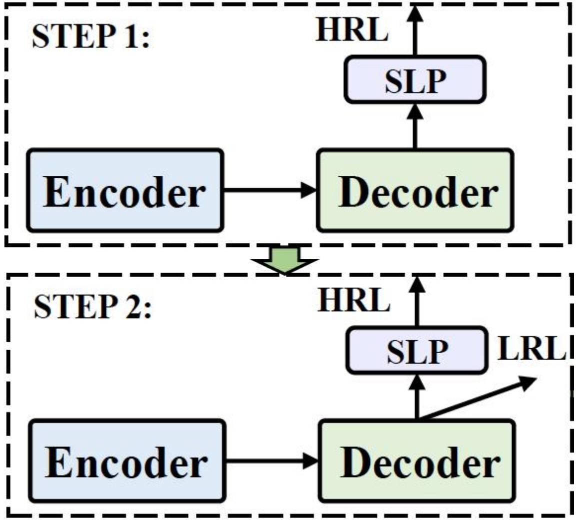
I. Mitigate the negative interference among languages.
II. Prevent the HRL from negative interference introduced by LRL.
III. Retain high translation quality of all directions.



cosine similarities between
gradients of two translation directions

Method Overview

Two-Stage Traning



(a) Two-Stage Training

Step 1: train a MNMT model on HRLs

Step 2: continue training the model on all pairs

Method Overview

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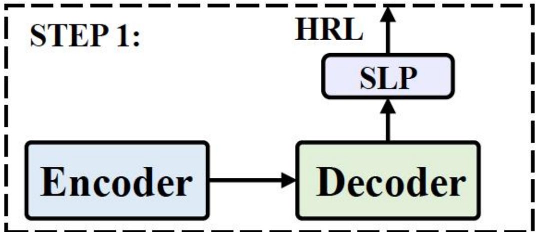
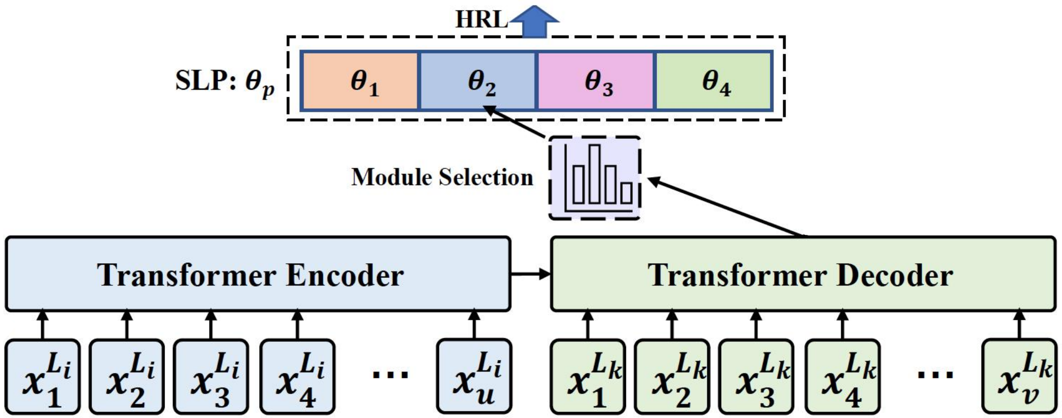


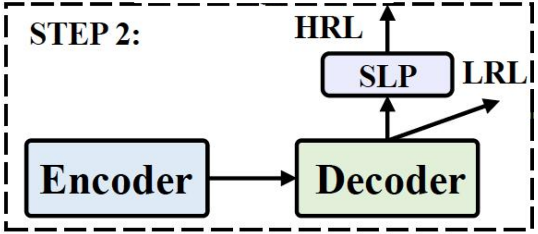


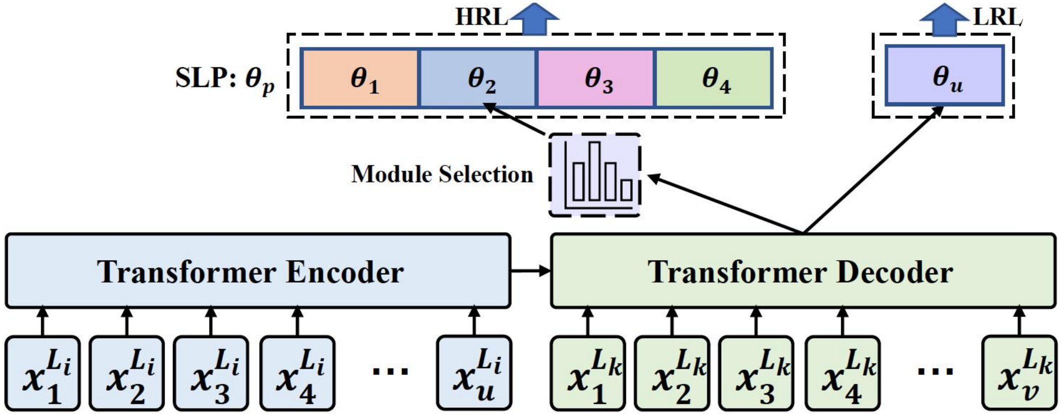
(b) Model Architecture

- no negative interference from LRLs
- mitigate negative interference among HRLs
  - **SLP**: Selective Language-specific Pool

Method Overview

Step 2: continue training on all pairs (HRLs & LRLs)





(b) Model Architecture

- ➢ HRLs still use SLP selection mechanism
- ➢ LRLs utilize the trained MNMT model
  - ✓ share the same MNMT → Knowledge Transfer
  - ✓ less training batches on LRLs → avoid overfitting

Dataset

WMT-10: En-X (X in {Fr, Cs, De, Fi, Lv, Et, Ro, Hi, Tr, Gu})

HRLs: Fr, Cs, De, Fi, Lv, and Et;   LRLs: Ro, Hi, Tr, and Gu

Code	Language	#Bitext	Training	Valid	Test
Fr	French	10M	WMT15	Newstest13	Newstest15
Cs	Czech	10M	WMT19	Newstest16	Newstest18
De	German	4.6M	WMT19	Newstest16	Newstest18
Fi	Finnish	4.8M	WMT19	Newstest16	Newstest18
Lv	Latvian	1.4M	WMT17	Newsdev17	Newstest17
Et	Estonian	0.7M	WMT18	Newsdev18	Newstest18
Ro	Romanian	0.5M	WMT16	Newsdev16	Newstest16
Hi	Hindi	0.26M	WMT14	Newsdev14	Newstest14
Tr	Turkish	0.18M	WMT18	Newstest16	Newstest18
Gu	Gujarati	0.08M	WMT19	Newsdev19	Newstest19

OPUS-100: 94 En-X pairs: 95 langs including En, except 5 langs w/o valid/test sets

High-resource: 45 pairs;   Medium-resource: 21 pairs;   Low-resource: 28 pairs.

Experimental Results: WMT-10

En→X on WMT-10: 1→1 (bilingual), 1→N (one-to-many), N→N (many-to-many) models

En→X test sets		#Params	Fr	Cs	De	Fi	Lv	Et	Ro	Hi	Tr	Gu	Avg_{all}
			HRLs						LRLs				
1→1	BiNMT [Vaswani *et al.*, 2017]	242M/10M	36.3	22.3	40.2	15.2	16.5	15.0	23.0	12.2	13.3	7.9	20.2
1→N	MNMT [Johnson *et al.*, 2017]	242M	34.2	20.9	40.0	15.0	18.1	20.9	26.0	14.5	17.3	13.2	22.0
	mBART [Liu *et al.*, 2020]	611M	33.7	20.8	38.9	14.5	18.2	20.5	26.0	15.3	16.8	12.9	21.8
	XLM-R [Conneau *et al.*, 2020]	362M	34.7	21.5	40.1	15.2	18.6	20.8	26.4	15.6	**17.4**	**14.9**	22.5
	LS-MNMT [Fan *et al.*, 2020]	409M	35.0	21.7	40.6	15.5	18.9	21.0	26.2	14.8	16.5	12.8	22.3
	HLT-MT (Our method)	381M	**36.2**	**22.2**	**41.8**	**16.6**	**19.5**	**21.1**	**26.6**	**15.8**	17.1	14.6	**23.2**
N→N	MNMT [Johnson *et al.*, 2017]	242M	34.2	21.0	39.4	15.2	18.6	20.4	26.1	15.1	17.2	13.1	22.0
	mBART [Liu *et al.*, 2020]	611M	32.4	19.0	37.0	13.2	17.0	19.5	25.1	**15.7**	16.7	14.2	21.0
	XLM-R [Conneau *et al.*, 2020]	362M	34.2	21.4	39.7	15.3	18.9	20.6	26.5	15.6	17.5	14.5	22.4
	LS-MNMT [Fan *et al.*, 2020]	409M	34.8	21.1	39.3	15.2	18.7	20.5	26.3	14.9	17.3	12.3	22.0
	HLT-MT (Our method)	381M	**35.8**	**22.4**	**41.5**	**16.3**	**19.6**	**21.0**	**26.6**	**15.7**	**17.6**	**14.7**	**23.1**

- ➢ significantly outperform BiNMT on LRLs, yet retain high perfomance on HRLs
- ➢ clear improvement over previous multilingual baselines on HRLs and LRLs
- ➢ the extra model parameters for our SLP pool and Universal layer are modest

Experimental Results: OPUS-100

X→En and En→X on OPUS-100: N→N (many-to-many) models

Models (N→N)	#Params	X→En					En→X				
		High$_{45}$	Med$_{21}$	Low$_{28}$	Avg$_{94}$	WR	High$_{45}$	Med$_{21}$	Low$_{28}$	Avg$_{94}$	WR
Previous Best System [Zhang *et al.*, 2020]	254M	30.3	32.6	31.9	31.4	-	23.7	25.6	22.2	24.0	-
MNMT [Johnson *et al.*, 2017]	242M	32.3	35.1	35.8	33.9	*ref*	26.3	31.4	31.2	28.9	*ref*
XLM-R [Conneau *et al.*, 2020]	362M	33.1	35.7	36.1	34.6	-	26.9	31.9	31.7	29.4	-
LS-MNMT [Fan *et al.*, 2020]	456M	33.4	35.8	35.9	34.7	-	27.5	31.6	31.5	29.6	-
HLT-MT (Our method)	381M	**34.2**	**36.7**	**36.1**	**35.3**	75.5	**27.6**	**33.3**	**31.8**	**30.1**	78.7

➢ consistently outperform previous multilingual baselines on high/medium/low resource language pairs (both X→En and En→X directions)

Conclusion

- ✓ In this work, we propose **a novel multilingual translation model** with the high-resource language-specific training called **HLT-MT**.
- ✓ The proposed **two-stage training strategy** and **selective language-specific pool (SLP)** mitigate the **negative inference** among different directions.
- ✓ Experimental results evaluated on **WMT-10** and **OPUS-100** benchmarks demonstrate that HLT-MT **significantly outperforms all previous baselines**.

- ✓ Our **code** has been released
  - ➢ https://github.com/YuweiYin/HLT-MT

Thanks!