# 291K
# Deep Learning for Machine Translation
# Multilingual Neural Machine Translation

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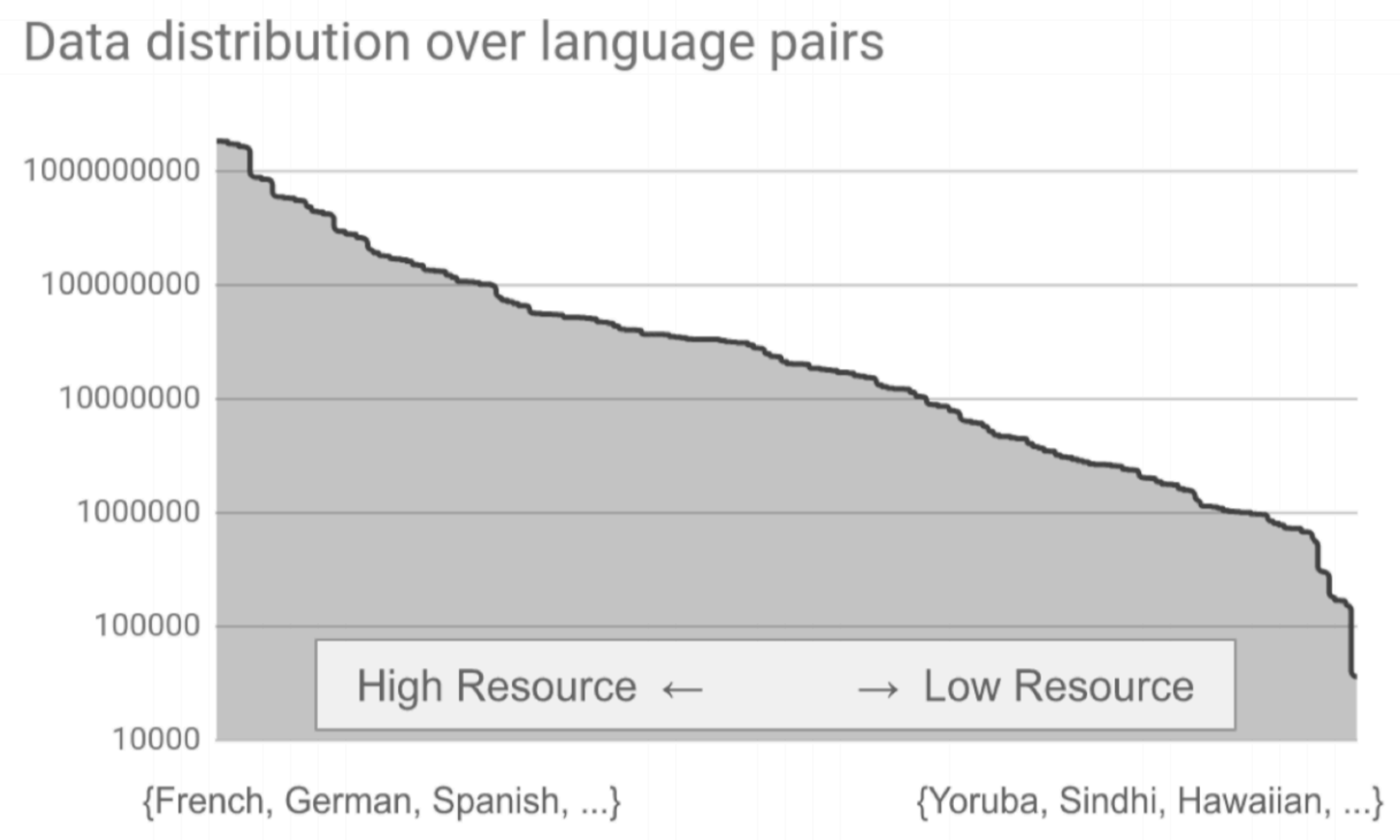
# Outline

- Multilingual NMT
- Architecture for MNMT
  – Multilingual Vocabulary
- Reducing multilingual interference
  – adapters for MNMT

# Corpus Size in Languages

- NMT requires large amount of parallel bilingual data
- Parallel data, However, very expensive/ non-trivial to obtain
  - Low resource language pairs (e.g., English-to-Tamil)
  - Low resource domains (e.g., social network)
  - but additional monolingual data on source side and/or target side. can we do reasonably well?
- Rich resource setting: in addition to parallel data (~10s millions), much larger monolingual data, can we further improve?




[Arivazhagan et al., 2019]

# Multilingual Neural Machine Translation

- Bilingual NMT: one model for each translation direction
- Multilingual NMT: Develop one model to translate between all language pairs.
- Why?
  - Model-side: Languages with rich resource could benefit those with low resource
    - Similar languages share tokens
  - Serving-side: only one model deployment versus of many deployments. Simpler workload and job management and scheduling.
    - Many languages would have much few requests but still need to occupy the servers.

# MNMT Categorization

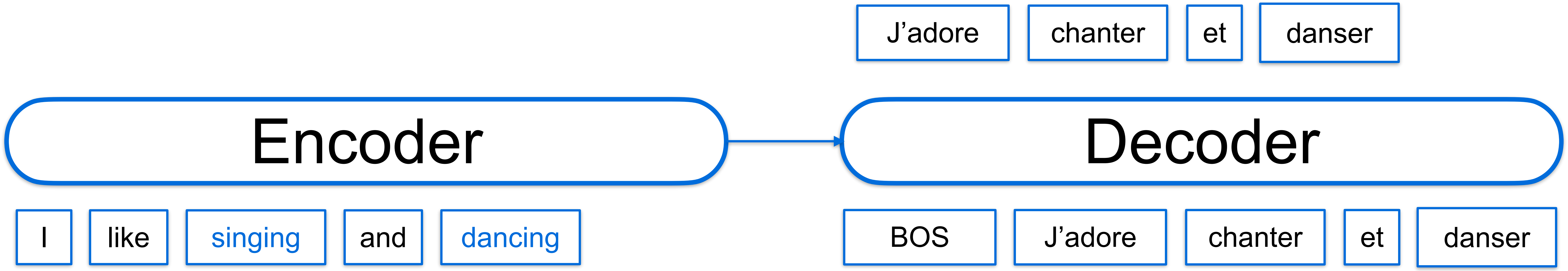
- Many-to-one:
  - Many source language to a target language
  - Usually the target is English
- One-to-Many:
  - One source language to many target languages
  - Usually the source is English
- Many-to-many:
  - Many source language to many target languages
  - Should include non-English pairs (often low-resource or zero-resource setting), very challenging!
- Which is simpler?

# MNMT at Testing Time

- Regular:
  - Testing language appeared during training (but not the sentence)
- Exotic (Unseen) pair
  - Both the testing source language and target language appeared in the training, but the source-target pair never appeared in the training
  - Also known as zero-shot MNMT
- Exotic (Unseen) source
  - Testing source language never occur in the training
- Exotic (Unseen) target
  - Testing target language never occur in the training
- Exotic (Unseen) full
  - Neither the source language nor the target language for testing occur in the training
  - Is it even possible? Yes, for the pre-train fine-tuning paradigm.

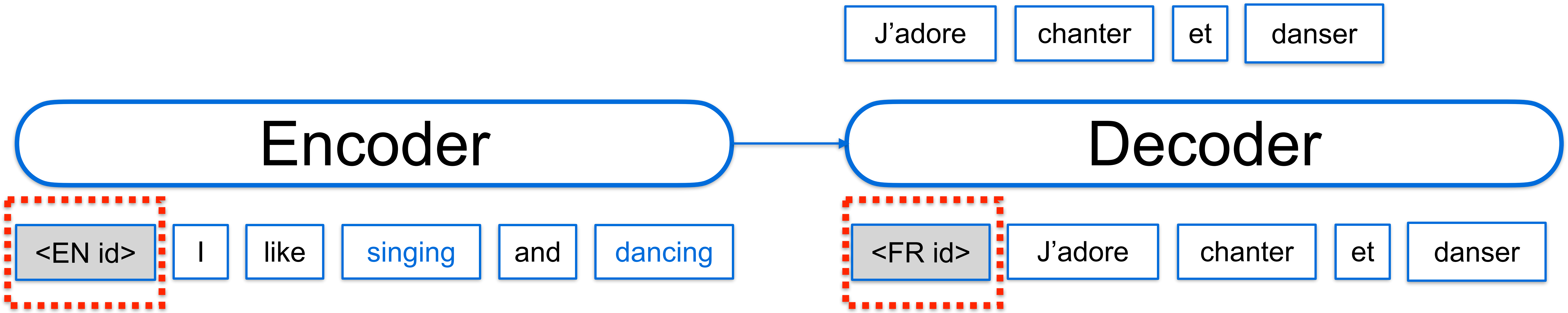
# A single model for Multilingual NMT

- Language-specific encoding (@en@car, @de@automobile)
- But hard to learn a joint embedding.
- Challenge:
  - large vocabulary (twice many)
  - how does the model know it is to translate into German or French?

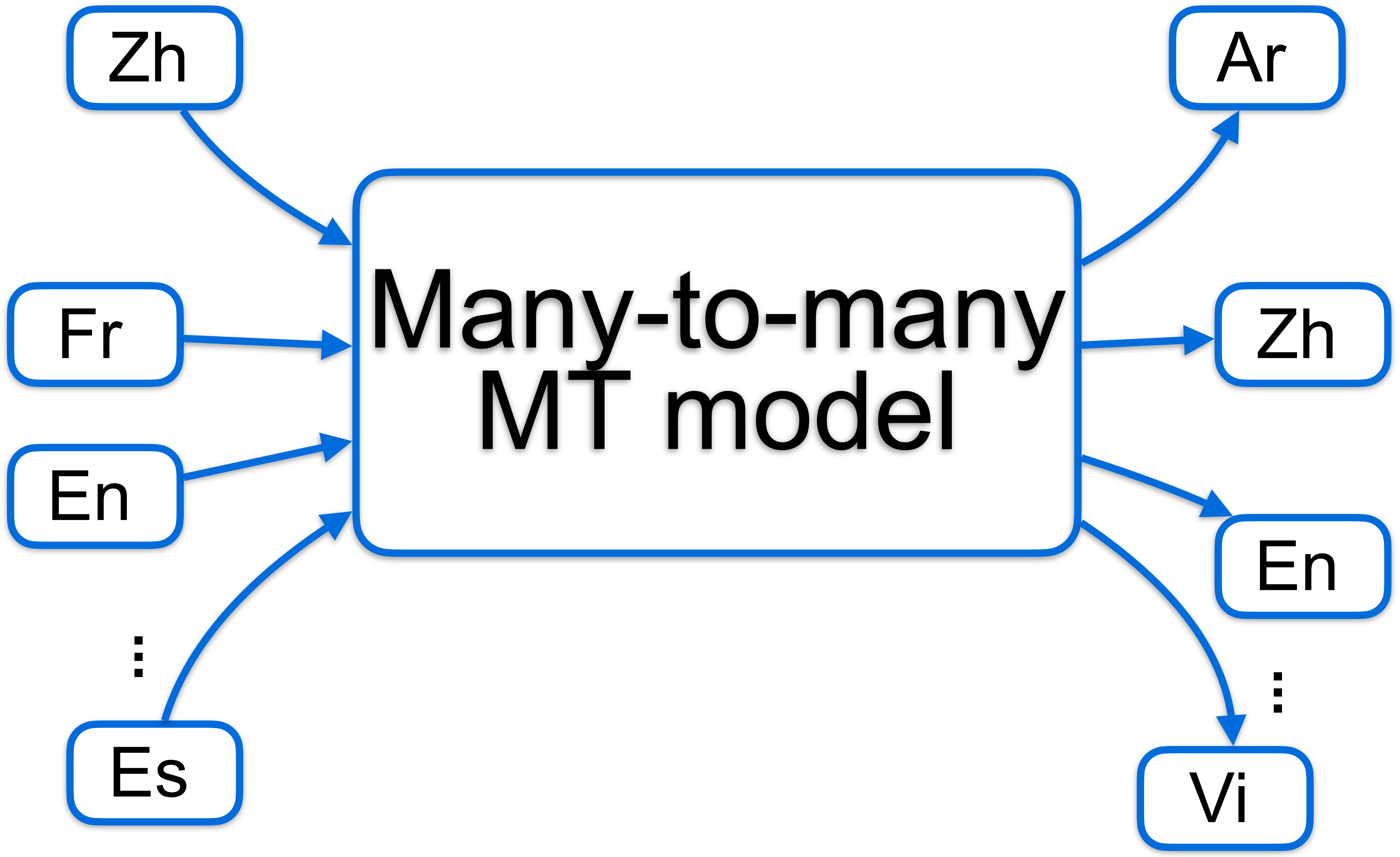



Ha et al. Toward Multilingual Neural Machine Translation with Universal Encoder and Decoder. 2016

# Multilingual Machine Translation - Language Tag



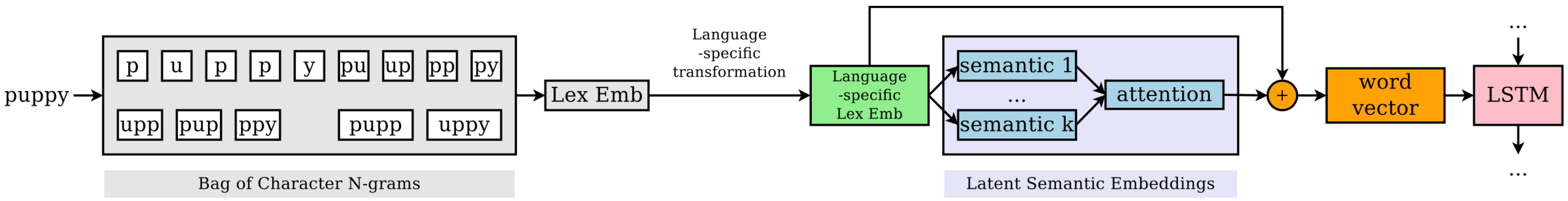

- One model can translate between many languages.
- Language Tag is used to indicate the source and target language.
- Vocabulary is built jointly




Johnson et al. Google’s Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

# Vocabulary

- Single joint vocabulary [Johnson 2017]
  - combine all corpus together, and apply BPE
- Soft-decoupled encoding [Wang et al 2019]
- Even better: learned vocabulary [Xu 2021], (later in class)



# Google's MNMT System

- LSTM-s2s:
  - 8 layer LSTM encoder, 1st layer bidirectional
  - 8 layer LSTM decoder with attention
- Combine De-En and Fr-En to train a joint NMT
- One model to translate two directions

Table 1: Many to One: BLEU scores on for single language pair and multilingual models. $\star$: no oversampling

| Model | Single | Multi | Diff |
|---|---|---|---|
| WMT De→En | 30.43 | 30.59 | +0.16 |
| WMT Fr→En | 35.50 | 35.73 | +0.23 |
| WMT De→En$^\star$ | 30.43 | 30.54 | +0.11 |
| WMT Fr→En$^\star$ | 35.50 | 36.77 | +1.27 |
| Prod Ja→En | 23.41 | 23.87 | +0.46 |
| Prod Ko→En | 25.42 | 25.47 | +0.05 |
| Prod Es→En | 38.00 | 38.73 | +0.73 |
| Prod Pt→En | 44.40 | 45.19 | +0.79 |

Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

# Google's MNMT System

- One-to-many is more difficult than many-to-one MNMT
-

Table 2: One to Many: BLEU scores for single language pair and multilingual models. *: no oversampling

| Model | Single | Multi | Diff |
|---|---|---|---|
| WMT En→De | 24.67 | 24.97 | +0.30 |
| WMT En→Fr | 38.95 | 36.84 | -2.11 |
| WMT En→De* | 24.67 | 22.61 | -2.06 |
| WMT En→Fr* | 38.95 | 38.16 | -0.79 |
| Prod En→Ja | 23.66 | 23.73 | +0.07 |
| Prod En→Ko | 19.75 | 19.58 | -0.17 |
| Prod En→Es | 34.50 | 35.40 | +0.90 |
| Prod En→Pt | 38.40 | 38.63 | +0.23 |

Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

# Google's MNMT

- Combining multiple source languages and multiple target languages together will degrade the performance a bit, but still surprising to see one model work as well for many-to-many English-centric pairs. ß

English-centric Many-to-Many

| Model | Single | Multi | Diff |
|---|---|---|---|
| WMT En→De | 24.67 | 24.49 | -0.18 |
| WMT En→Fr | 38.95 | 36.23 | -2.72 |
| WMT De→En | 30.43 | 29.84 | -0.59 |
| WMT Fr→En | 35.50 | 34.89 | -0.61 |
| WMT En→De⋆ | 24.67 | 21.92 | -2.75 |
| WMT En→Fr⋆ | 38.95 | 37.45 | -1.50 |
| WMT De→En⋆ | 30.43 | 29.22 | -1.21 |
| WMT Fr→En⋆ | 35.50 | 35.93 | +0.43 |
| Prod En→Ja | 23.66 | 23.12 | -0.54 |
| Prod En→Ko | 19.75 | 19.73 | -0.02 |
| Prod Ja→En | 23.41 | 22.86 | -0.55 |
| Prod Ko→En | 25.42 | 24.76 | -0.66 |
| Prod En→Es | 34.50 | 34.69 | +0.19 |
| Prod En→Pt | 38.40 | 37.25 | -1.15 |
| Prod Es→En | 38.00 | 37.65 | -0.35 |
| Prod Pt→En | 44.40 | 44.02 | -0.38 |

Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

# Google's MNMT

- Training 12 language pairs together

Table 4: Large-scale experiments: BLEU scores for single language pair and multilingual models.

| Model | Single | Multi | Multi | Multi | Multi |
|---|---|---|---|---|---|
| #nodes | 1024 | 1024 | 1280 | 1536 | 1792 |
| #params | 3B | 255M | 367M | 499M | 650M |
| En→Ja | 23.66 | 21.10 | 21.17 | 21.72 | 21.70 |
| En→Ko | 19.75 | 18.41 | 18.36 | 18.30 | 18.28 |
| Ja→En | 23.41 | 21.62 | 22.03 | 22.51 | 23.18 |
| Ko→En | 25.42 | 22.87 | 23.46 | 24.00 | 24.67 |
| En→Es | 34.50 | 34.25 | 34.40 | 34.77 | 34.70 |
| En→Pt | 38.40 | 37.35 | 37.42 | 37.80 | 37.92 |
| Es→En | 38.00 | 36.04 | 36.50 | 37.26 | 37.45 |
| Pt→En | 44.40 | 42.53 | 42.82 | 43.64 | 43.87 |
| En→De | 26.43 | 23.15 | 23.77 | 23.63 | 24.01 |
| En→Fr | 35.37 | 34.00 | 34.19 | 34.91 | 34.81 |
| De→En | 31.77 | 31.17 | 31.65 | 32.24 | 32.32 |
| Fr→En | 36.47 | 34.40 | 34.56 | 35.35 | 35.52 |
| ave diff | - | -1.72 | -1.43 | -0.95 | -0.76 |
| vs single | - | -5.6% | -4.7% | -3.1% | -2.5% |

Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

# Google's MNMT Zero-shot

- Bilingual pivot
- Multilingual joint
- What is missing in the table?
  - Multilingual pivot
- zero-shot

Table 5: Portuguese→Spanish BLEU scores using various models.

| | Model | Zero-shot | BLEU |
|---|---|---|---|
| (a) | PBMT bridged | no | 28.99 |
| (b) | NMT bridged | no | 30.91 |
| (c) | NMT Pt→Es | no | 31.50 |
| (d) | Model 1 (Pt→En, En→Es) | yes | 21.62 |
| (e) | Model 2 (En↔{Es, Pt}) | yes | 24.75 |
| (f) | Model 2 + incremental training | no | 31.77 |

no longer zero-shot, since additional Pt-Es pairs are used.

Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017

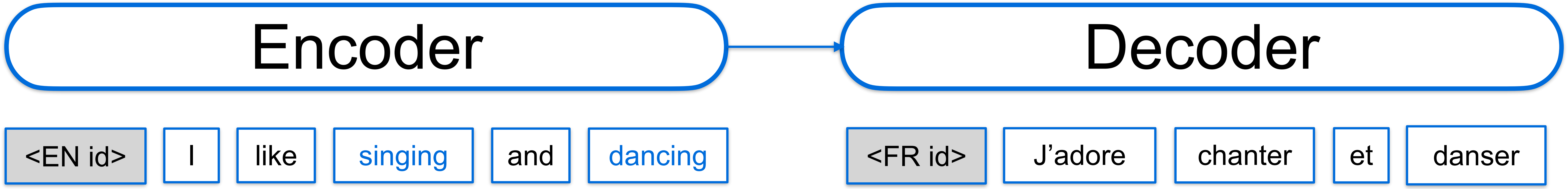
# Google's MNMT Zero-shot

- MNMT is worse than pivot on zero-shot directions

Table 6: Spanish→Japanese BLEU scores for explicit and implicit bridging using the 12-language pair large-scale model from Table 4.

| | Model | BLEU |
|---|---|---|
| | NMT Es→Ja explicitly bridged | 18.00 |
| zero-shot | NMT Es→Ja implicitly bridged | 9.14 |

# Source Language Tag or target Language Tag?

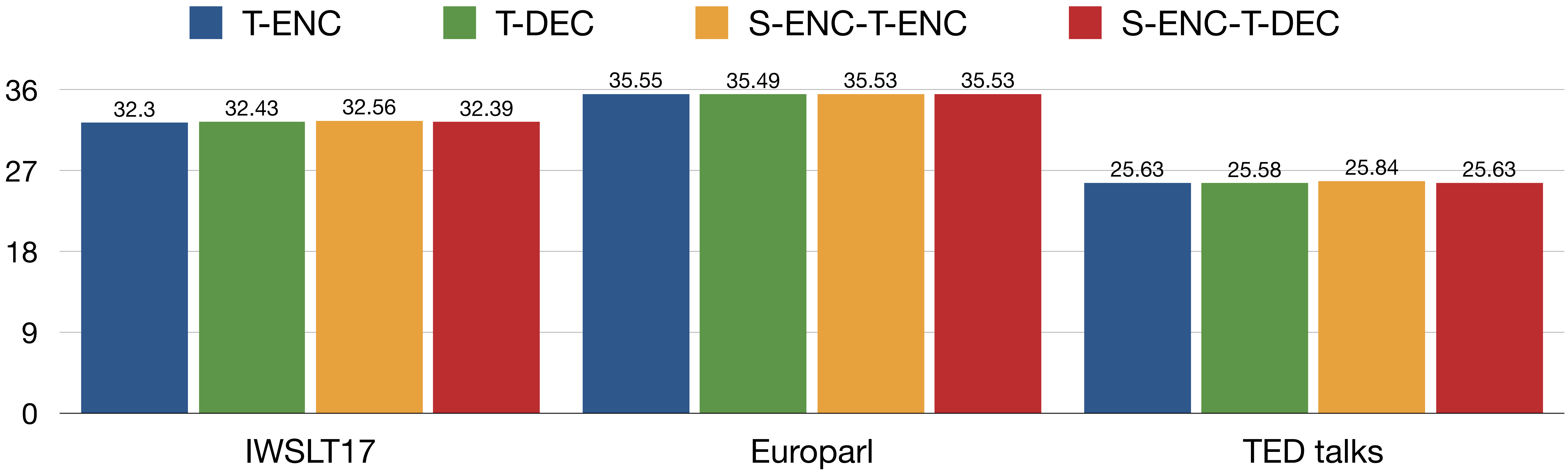



| Strategy | Source sentence | Target sentence |
|---|---|---|
| Original | Hello World! | ¡Hola Mundo |
| T-ENC | **__es__** Hello World! | ¡Hola Mundo |
| T-DEC | Hello World! | **__es__** ¡Hola Mundo |
| S-ENC-T-ENC | **__en__** **__es__** Hello World! | ¡Hola Mundo |
| S-ENC-T-DEC | **__en__** Hello World! | **__es__** ¡Hola Mundo |

Wu et al. Language Tags Matter for Zero-Shot Neural Machine Translation 2021.

# Language Tag Does not Affect Performance on Supervised Directions

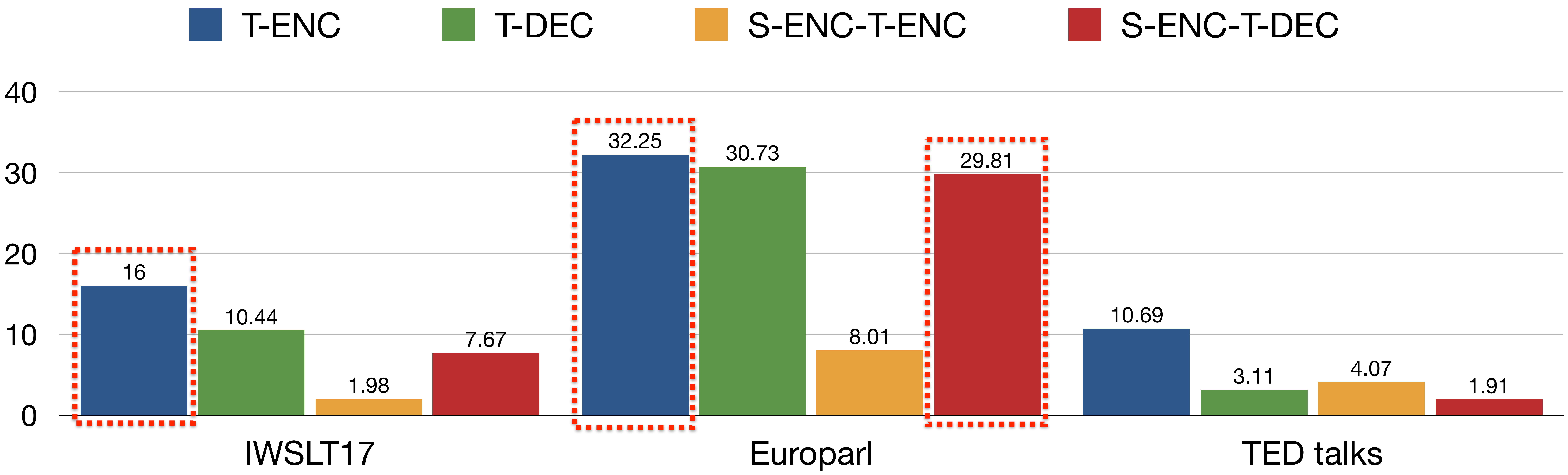
Supervised directions: The directions which has been seen together in the training time.




Wu et al. Language Tags Matter for Zero-Shot Neural Machine Translation 2021.

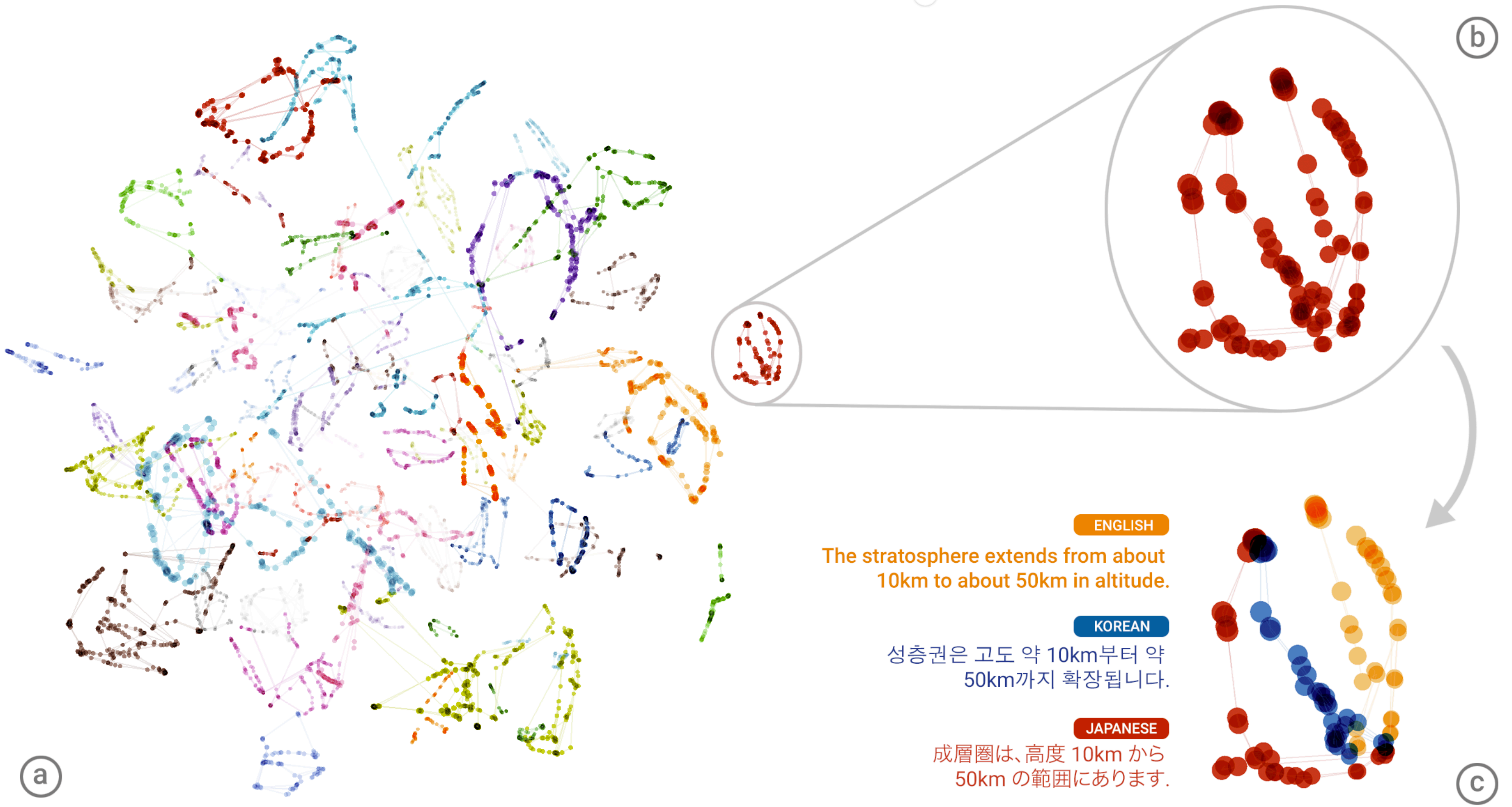
# Target Language Tag on Encoder Strategy Gets Best Zero-Shot Performance

Zero-shot directions: The directions between known languages that the model has never seen together at training time.




Wu et al. Language Tags Matter for Zero-Shot Neural Machine Translation 2021.

# Does sentence have similar emb. representation?



# Mixed Source Language can still be Translated

- {Ja, Ko} -> En
- Japanese: 私は東京大学の学生です。 → I am a student at Tokyo University.
- Korean: 나ㄴㄴㅡ ㅗㄷ쿄 ㅐㄷ학ㅢㅇ 학ㅐㅇㅅㅂ이니다. → I am a student at Tokyo University.
- Japanese/Korean: 私は東京大学ㅏㅎㄱㅇㅐㅅ입ㅣㄴ 다. → I am a student of Tokyo University.

# Mixed Decoder for Target Language

- En -> {Ja, Ko}
- Either generate Japanese or Korean

Table 8: Gradually mixing target languages Ja/Ko.

| $w_{ko}$ | I must be getting somewhere near the centre of the earth. |
|---|---|
| 0.00 | 私は地球の中心の近くにどこかに行っているに違いない。 |
| 0.40 | 私は地球の中心近くのどこかに着いているに違いない。 |
| 0.56 | 私は地球の中心の近くのどこかになっているに違いない。 |
| 0.58 | 私は지구の中心의가까이에어딘가에도착하고있어야한다。 |
| 0.60 | 나는지구의센터의가까이에어딘가에도착하고있어야한다。 |
| 0.70 | 나는지구의중심근처어딘가에도착해야합니다。 |
| 0.90 | 나는어딘가지구의중심근처에도착해야합니다。 |
| 1.00 | 나는어딘가지구의중심근처에도착해야합니다。 |

# Multilingual NMT with mTransformer

- Model: Transformer-base (6e6d, 512) ==> mTransformer
- Data: TED-talk, 59 languages, 116 directions

| | Az-En | Be-En | Gl-En | Sk-En | Avg. |
|---|---|---|---|---|---|
| # of examples | 5.9k | 4.5k | 10k | 61k | 20.3k |
| Neubig & Hu 18 | | | | | |
| baselines | 2.7 | 2.8 | 16.2 | 24 | 11.42 |
| many-to-one | 11.7 | 18.3 | 29.1 | 28.3 | 21.85 |
| Wang et al. 18 | 11.82 | 18.71 | 30.3 | 28.77 | 22.4 |
| Ours | | | | | |
| many-to-one | 11.24 | 18.28 | 28.63 | 26.78 | 21.23 |
| many-to-many | **12.78** | **21.73** | **30.65** | **29.54** | **23.67** |

| | Ar-En | De-En | He-En | It-En | Avg. |
|---|---|---|---|---|---|
| # of examples | 213k | 167k | 211k | 203k | 198.5k |
| baselines | 27.84 | 30.5 | **34.37** | 33.64 | 31.59 |
| many-to-one | 25.93 | 28.87 | 30.19 | 32.42 | 29.35 |
| many-to-many | **28.32** | **32.97** | 33.18 | **35.14** | **32.4** |

Aharoni et al. Massively Multilingual Neural Machine Translation. 2019

# Unfortunate mTransformer does not work for Many-to-Many En-X

| | En-Az | En-Be | En-Gl | En-Sk | Avg. |
|---|---|---|---|---|---|
| # of examples | 5.9k | 4.5k | 10k | 61k | 20.3k |
| baselines | 2.16 | 2.47 | 3.26 | 5.8 | 3.42 |
| one-to-many | **5.06** | **10.72** | **26.59** | **24.52** | **16.72** |
| many-to-many | 3.9 | 7.24 | 23.78 | 21.83 | 14.19 |

| | En-Ar | En-De | En-He | En-It | Avg. |
|---|---|---|---|---|---|
| # of examples | 213k | 167k | 211k | 203k | 198.5k |
| baselines | 12.95 | 23.31 | 23.66 | 30.33 | 22.56 |
| one-to-many | **16.67** | **30.54** | **27.62** | **35.89** | **27.68** |
| many-to-many | 14.25 | 27.95 | 24.16 | 33.26 | 24.9 |

Table 3: En→X test BLEU on the TED Talks corpus

Aharoni et al. Massively Multilingual Neural Machine Translation. 2019

# Even More Languages

- mTransformer
  - 6e6d, 1024 -> 8192
  - 473m parameters
- 103 Languages (inc. En)
  - 64k vocab

| | |
|---|---|
| # of language pairs | 102 |
| examples per pair | |
| min | 63,879 |
| max | 1,000,000 |
| average | 940,087 |
| std. deviation | 188,194 |
| total # of examples | 95,888,938 |

| | Ar | Az | Be | De | He | It | Nl | Ro | Sk | Tr | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baselines | 23.34 | 16.3 | 21.93 | 30.18 | 31.83 | **36.47** | 36.12 | 34.59 | 25.39 | 27.13 | 28.33 |
| many-to-one | **26.04** | **23.68** | **25.36** | 35.05 | **33.61** | 35.69 | **36.28** | 36.33 | 28.35 | **29.75** | **31.01** |
| many-to-many | 22.17 | 21.45 | 23.03 | **37.06** | 30.71 | 35.0 | 36.18 | **36.57** | **29.87** | 27.64 | 29.97 |

Table 5: X→En test BLEU on the 103-language corpus

| | Ar | Az | Be | De | He | It | Nl | Ro | Sk | Tr | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baselines | 10.57 | 8.07 | 15.3 | 23.24 | 19.47 | 31.42 | 28.68 | 27.92 | 11.08 | 15.54 | 19.13 |
| one-to-many | **12.08** | **9.92** | **15.6** | **31.39** | **20.01** | **33** | **31.06** | **28.43** | **17.67** | **17.68** | **21.68** |
| many-to-many | 10.57 | 9.84 | 14.3 | 28.48 | 17.91 | 30.39 | 29.67 | 26.23 | 18.15 | 15.58 | 20.11 |

Table 6: En→X test BLEU on the 103-language corpus

Aharoni et al. Massively Multilingual Neural Machine Translation. 2019

# More language trained together, but

| | Ar-En | En-Ar | Fr-En | En-Fr | Ru-En | En-Ru | Uk-En | En-Uk | Avg. |
|---|---|---|---|---|---|---|---|---|---|
| 5-to-5 | **23.87** | **12.42** | **38.99** | **37.3** | 29.07 | **24.86** | **26.17** | 16.48 | **26.14** |
| 25-to-25 | 23.43 | 11.77 | 38.87 | 36.79 | **29.36** | 23.24 | 25.81 | **17.17** | 25.8 |
| 50-to-50 | 23.7 | 11.65 | 37.81 | 35.83 | 29.22 | 21.95 | 26.02 | 15.32 | 25.18 |
| 75-to-75 | 22.23 | 10.69 | 37.97 | 34.35 | 28.55 | 20.7 | 25.89 | 14.59 | 24.37 |
| 103-to-103 | 21.16 | 10.25 | 35.91 | 34.42 | 27.25 | 19.9 | 24.53 | 13.89 | 23.41 |

# mTransformer Zero-shot Performance

| | Ar-Fr | Fr-Ar | Ru-Uk | Uk-Ru | Avg. |
|---|---|---|---|---|---|
| 5-to-5 | 1.66 | 4.49 | 3.7 | 3.02 | 3.21 |
| 25-to-25 | 1.83 | **5.52** | **16.67** | 4.31 | 7.08 |
| 50-to-50 | **4.34** | 4.72 | 15.14 | **20.23** | **11.1** |
| 75-to-75 | 1.85 | 4.26 | 11.2 | 15.88 | 8.3 |
| 103-to-103 | 2.87 | 3.05 | 12.3 | 18.49 | 9.17 |

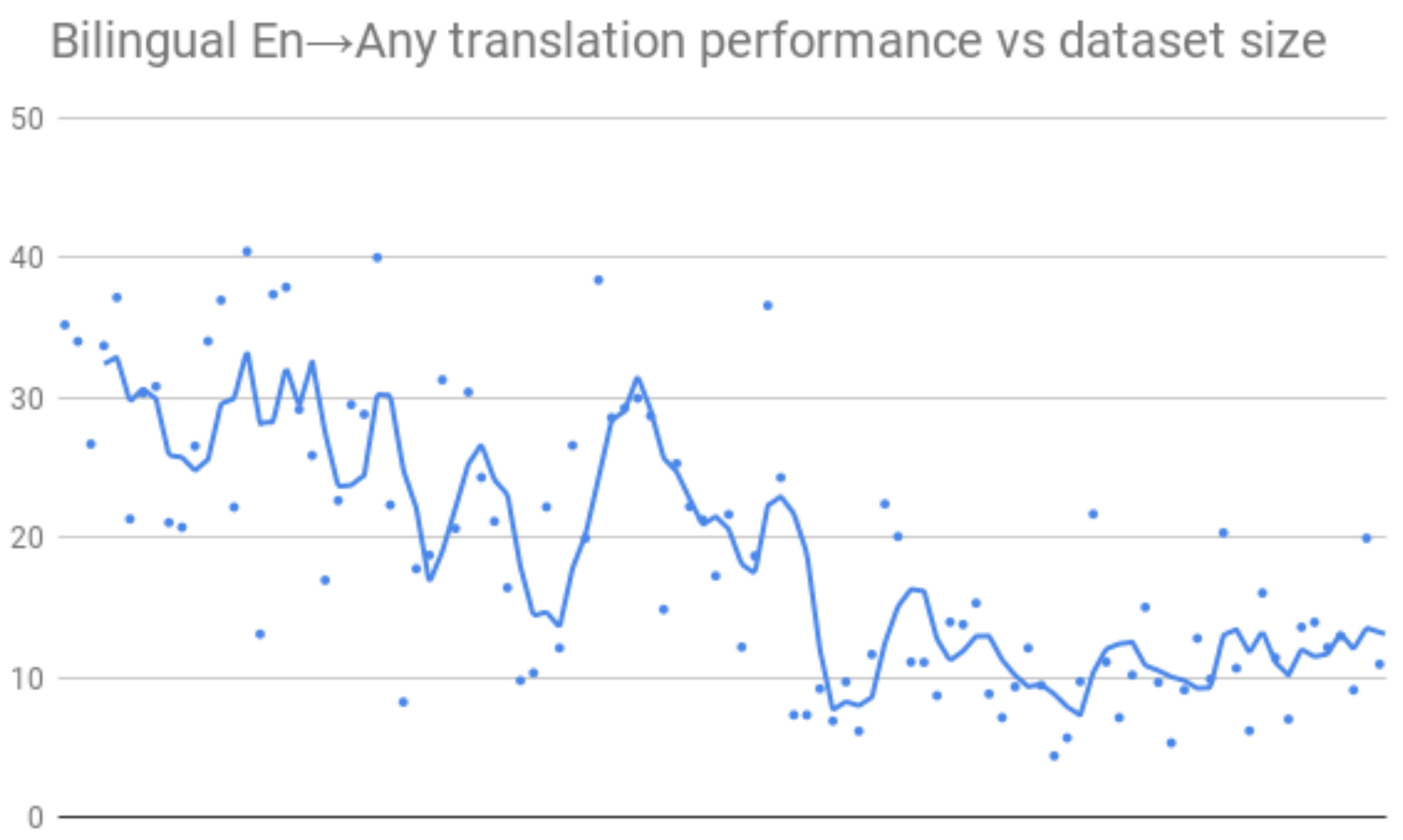
Table 8: Zero-Shot performance while varying the number of languages involved

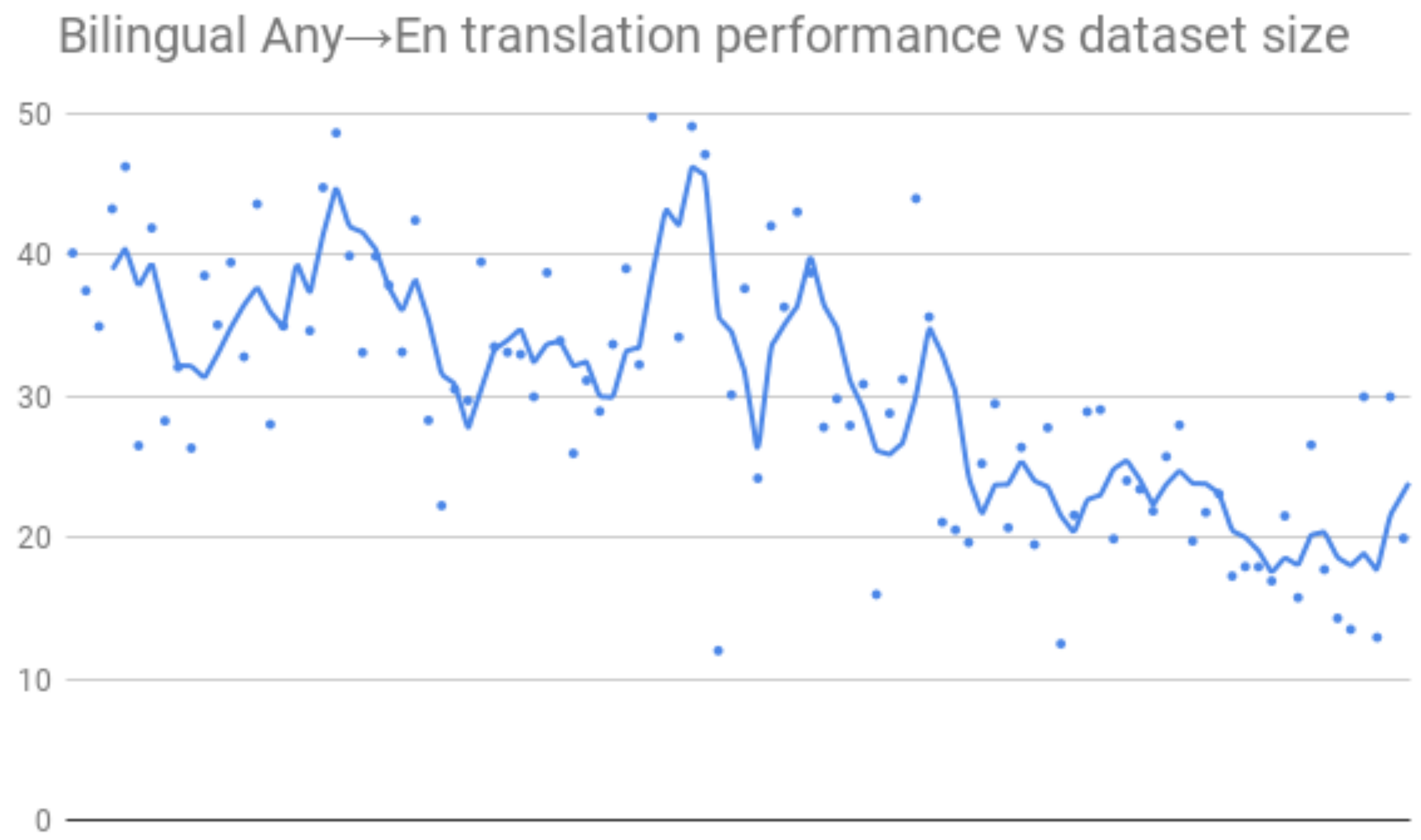
# Bigger Data

- Data: 25 billion sentence pairs in 103 languages
- Model: mTransformer with 375million params (larger than Transformer-big)

| *En→Any* | High 25 | Med. 52 | Low 25 |
|---|---|---|---|
| Bilingual | 29.34 | 17.50 | 11.72 |
| *All→All* | 28.03 | 16.91 | 12.75 |
| *En→Any* | 28.75 | 17.32 | 12.98 |

| *Any→En* | High 25 | Med. 52 | Low 25 |
|---|---|---|---|
| Bilingual | 37.61 | 31.41 | 21.63 |
| *All→All* | 33.85 | 30.25 | 26.96 |
| *Any→En* | 36.61 | 33.66 | 30.56 |



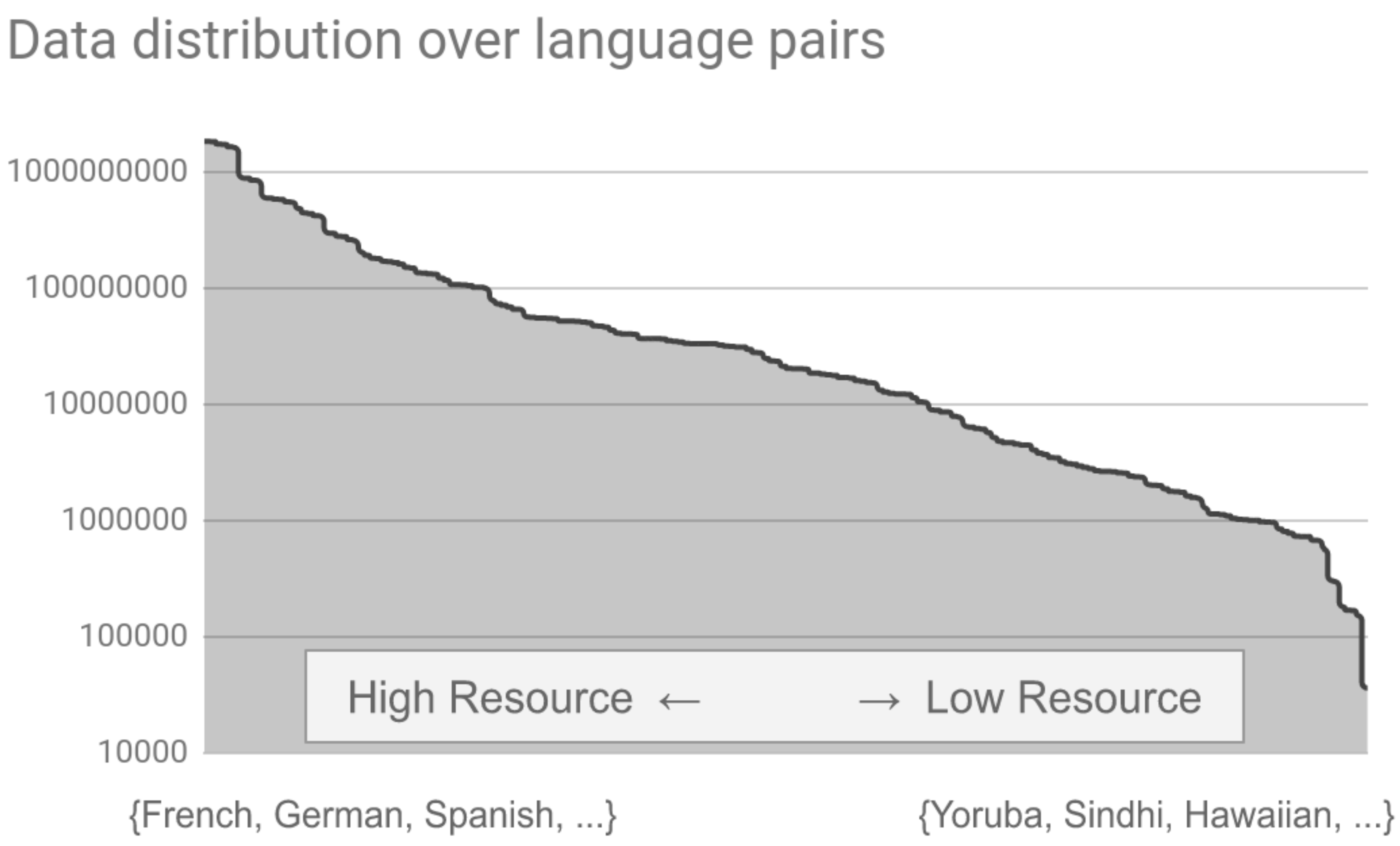




Arivazhagan et al. Massively Multilingual Neural Machine Translation in the Wild: Findings and Challenges. 2019

# Sampling of Data

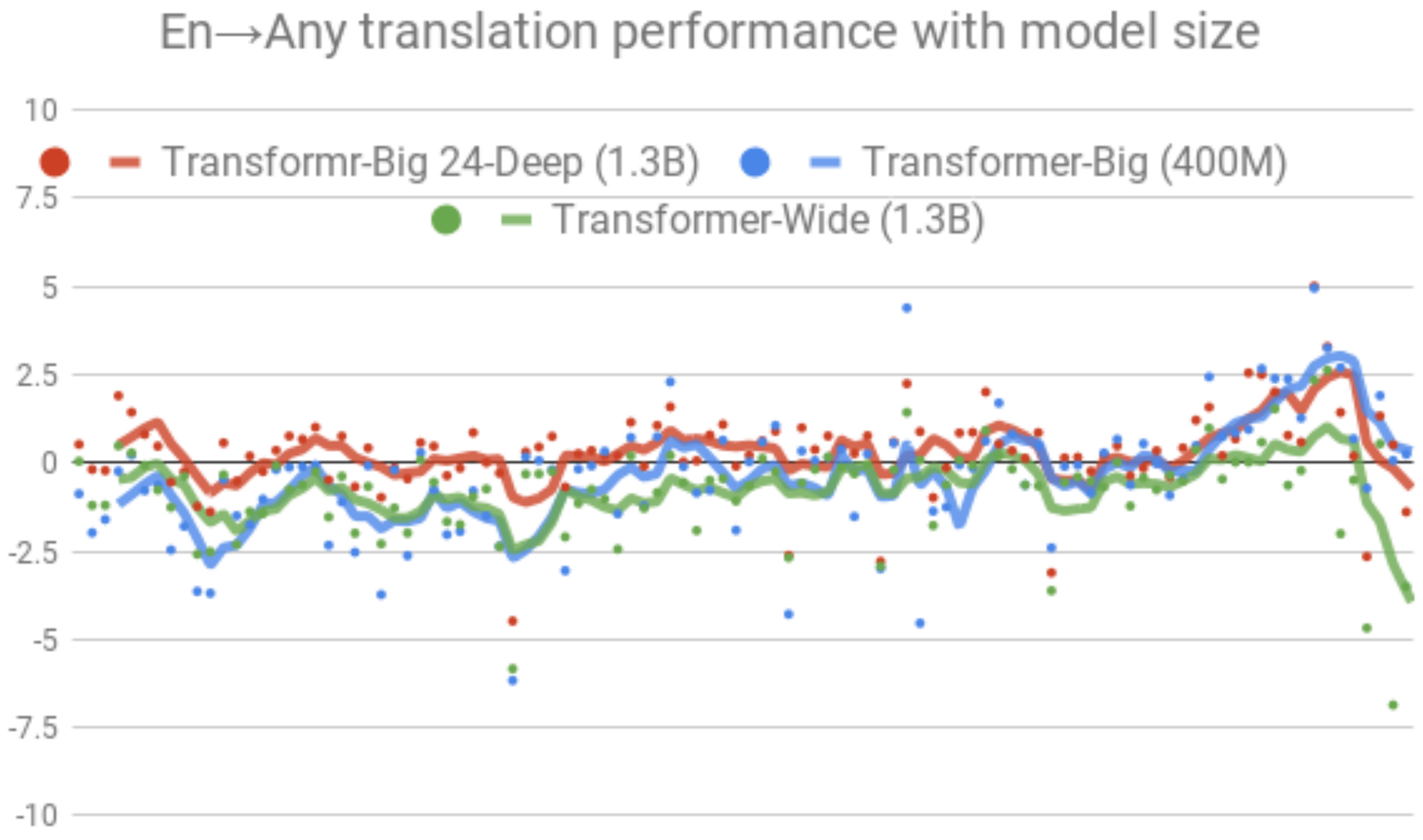
- sample data prob w.r.t $p^{\frac{1}{T}}$
-

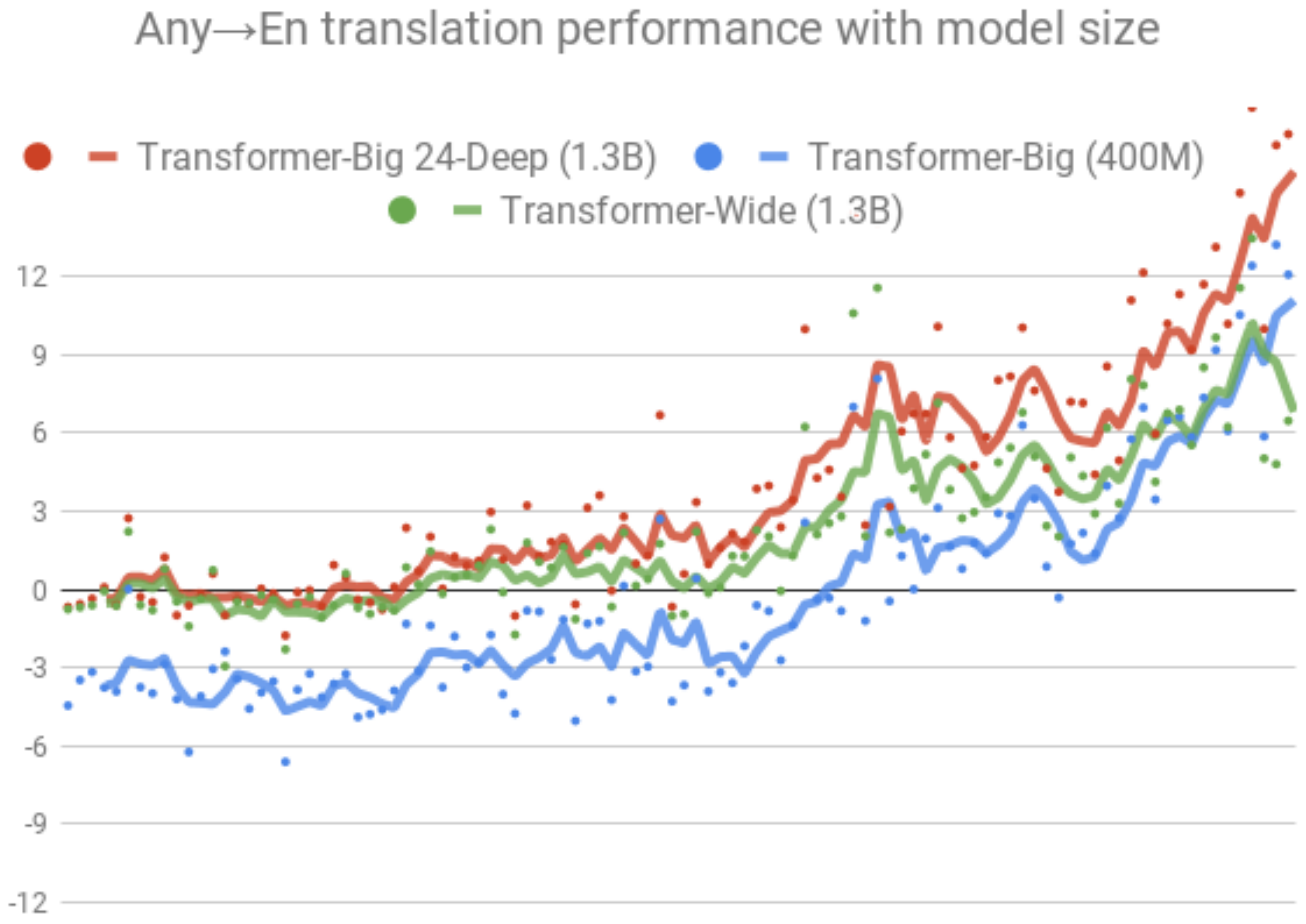
| *En*→*Any* | High 25 | Med. 52 | Low 25 |
|---|---|---|---|
| $T_V = 1$ | 27.81 | 16.72 | 12.73 |
| $T_V = 100$ | 27.83 | 16.86 | 12.78 |
| $T_V = 5$ | 28.03 | 16.91 | 12.75 |
| *Any*→*En* | High 25 | Med. 52 | Low 25 |
| $T_V = 1$ | 33.82 | 29.78 | 26.27 |
| $T_V = 100$ | 33.70 | 30.15 | 26.91 |
| $T_V = 5$ | 33.85 | 30.25 | 26.96 |



# Bigger Model

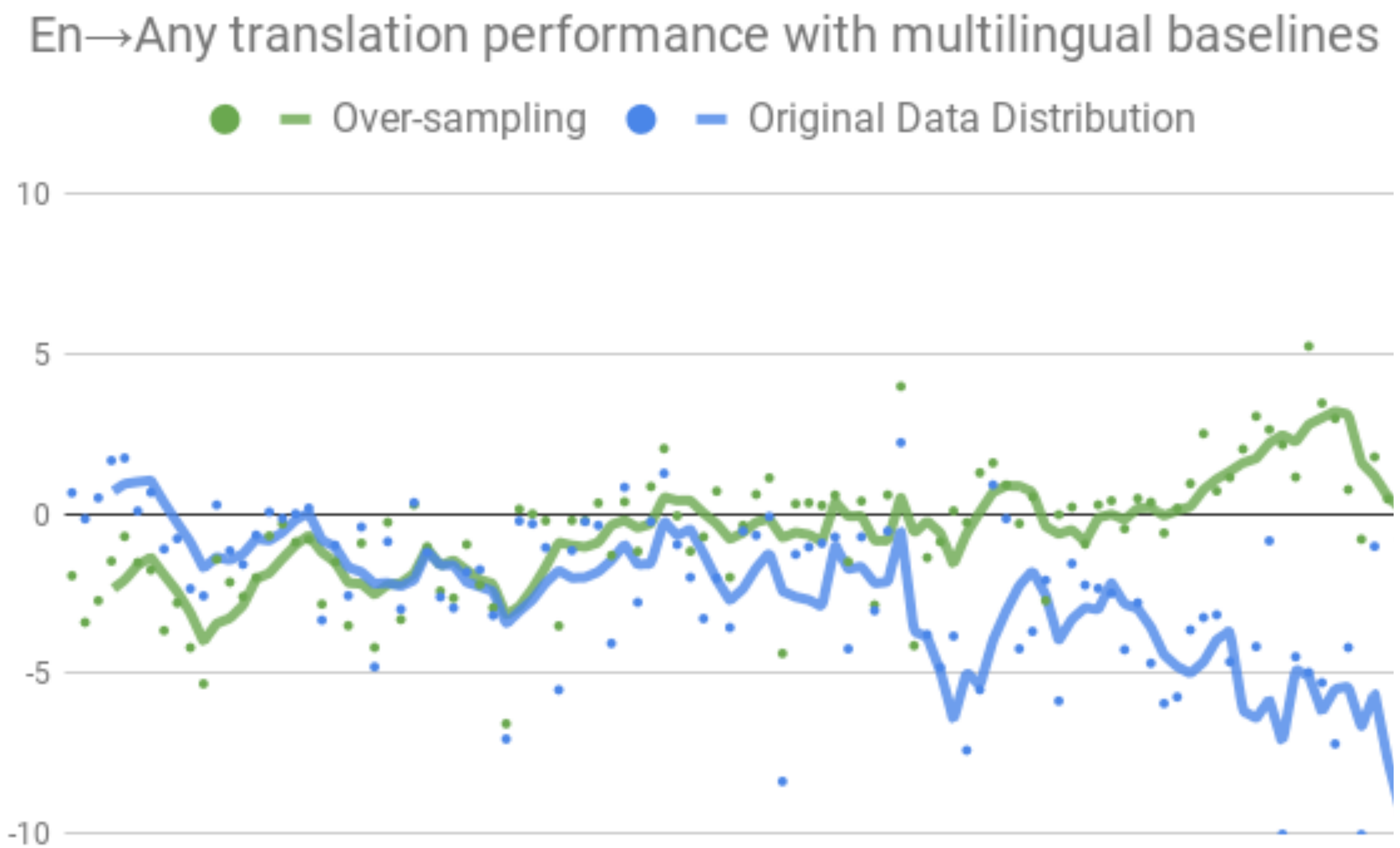
- mTransformer:
  - 400m, 1.3B wide (12e12d), 1.3B deep (24e24d)
  - Deep is better than wide!

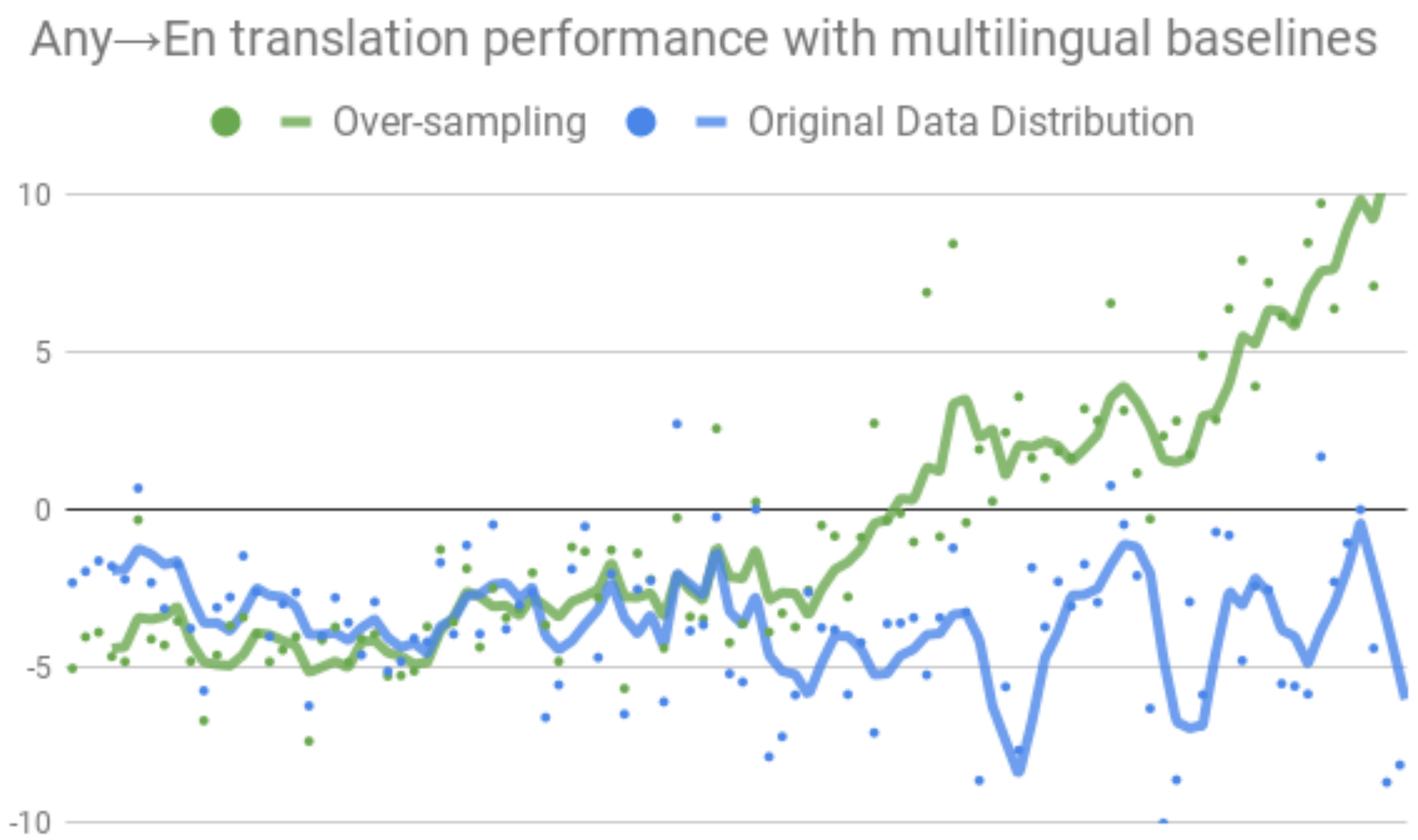


# Limitation

- mTransformer boosts performance on low-resource languages but not high-resource
- Zero-shot directions are not usable yet.




Arivazhagan et al. Massively Multilingual Neural Machine Translation in the Wild: Findings and Challenges. 2019

# MT w/ Adapter

# Parameter Interference issue for MNMT

- Insufficient model capacity
  - the sharing model capacity has to be split for different translation directions

Bilingual

Multilingual

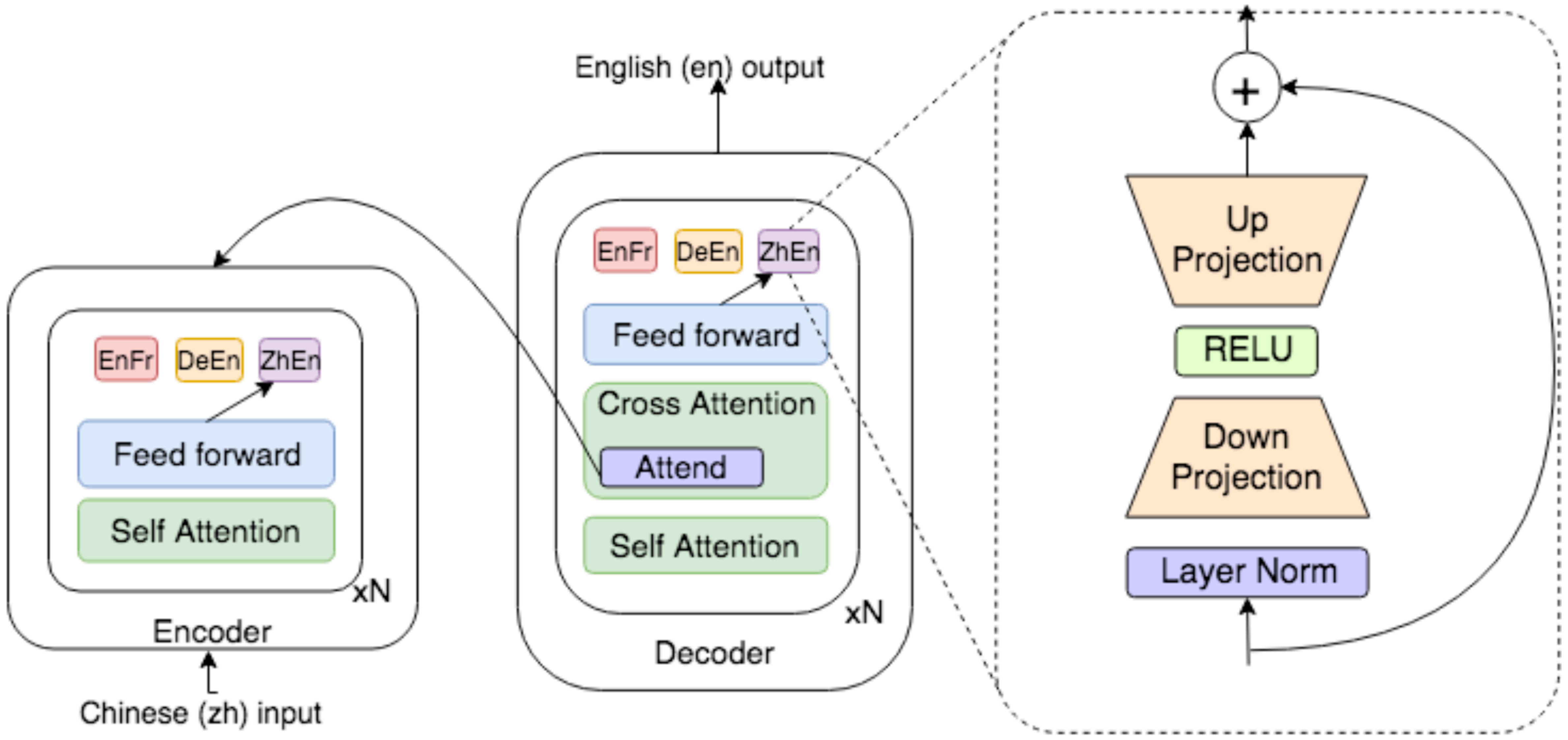
# Language Aware mTransformer

- deep mTransformer
  - 12e12d +2BLEU
- language-aware layer normalization +2~3BLEU
  - each language has its own normalization
- language-aware linear transformation
  - the output of encoder is transformed with a language-specific matrix
- Online back translation (+up to 10BLEU)
- Evaluated on OPUS100: 55M sentence pairs

Zhang et al. Improving Massively Multilingual Neural Machine Translation and Zero-Shot Translation. 2020

# Multilingual NMT with Serial Adapter

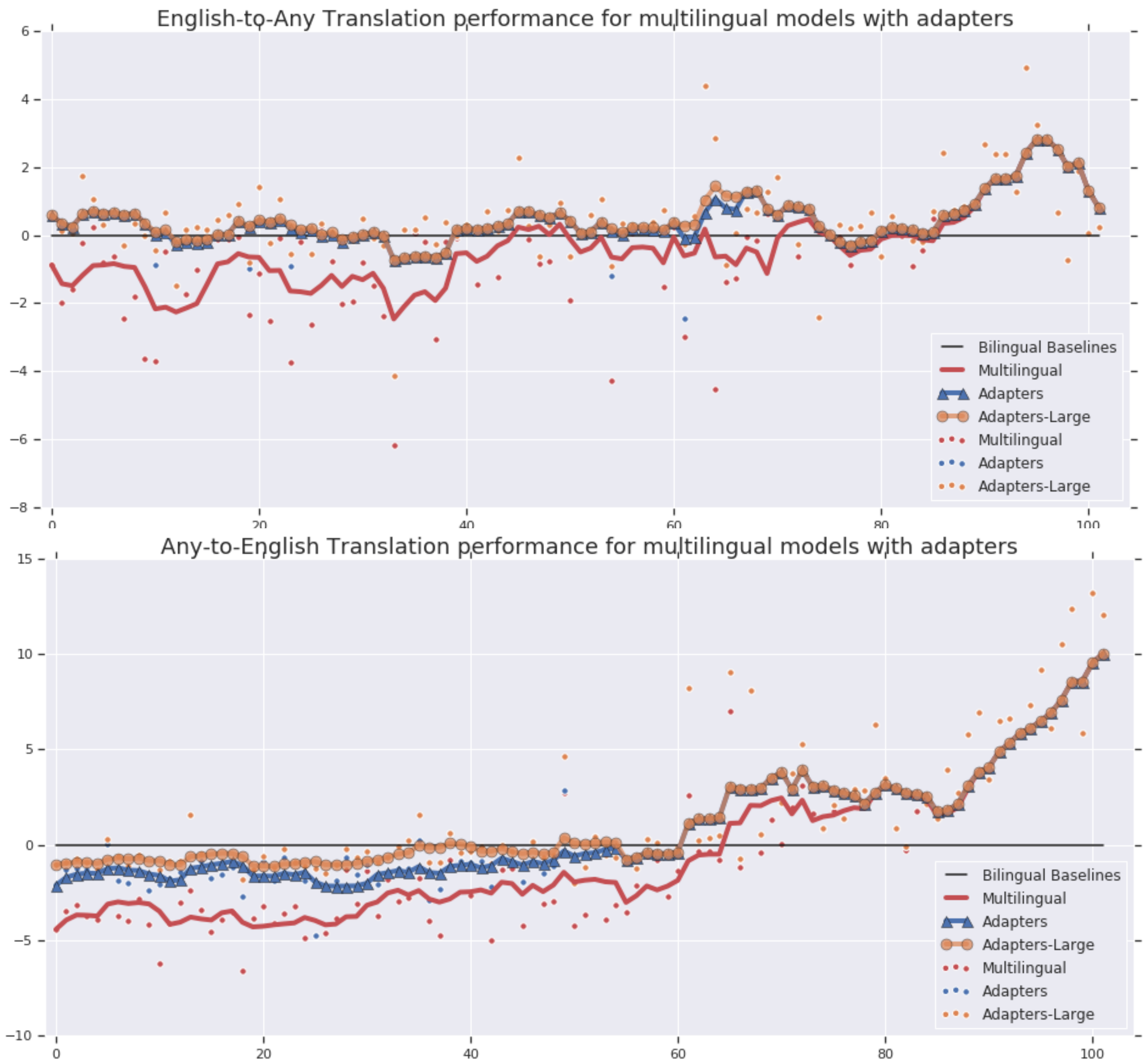
- For each layer, adding language-specific module
- $\tilde{z} = \mathrm{LNT}(z_i)$.
- $h = \mathrm{relu}(W \tilde{z})$
- $x = Wh + z$
- Could be used for both domain adaptation and MNMT
- Joint training the whole architecture




Bapna & Firat, Simple, Scalable Adaptation for Neural Machine Translation, 2019

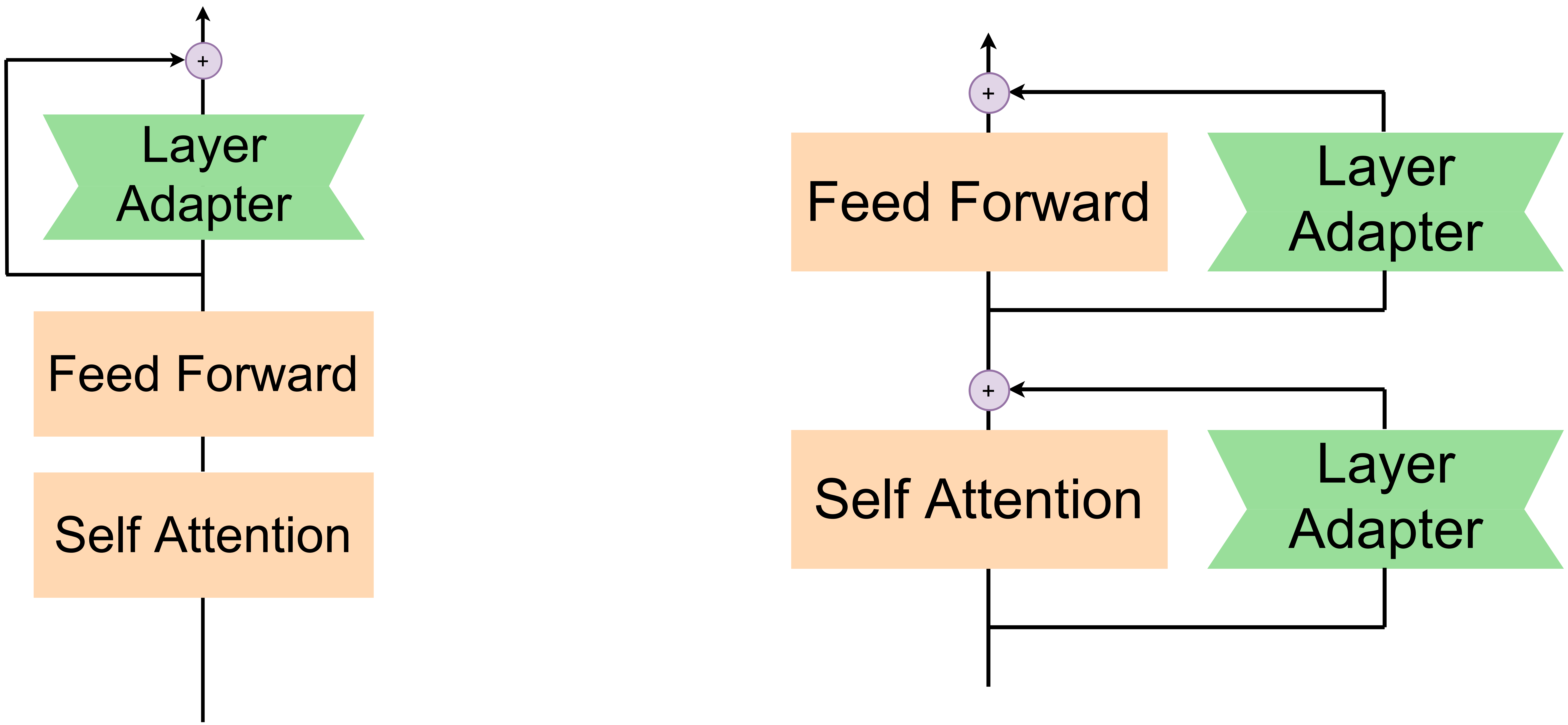
# Serial Adapter improves Multilingual Translation

- on rich-resource lang.
- But serial-adapter is not plug-and-play
  – Joint training mTransformer+SA will be better than training mTransformer, fix, and train adapter.
  – Adapter has tight integration with the main architecture.



# Counter Interference

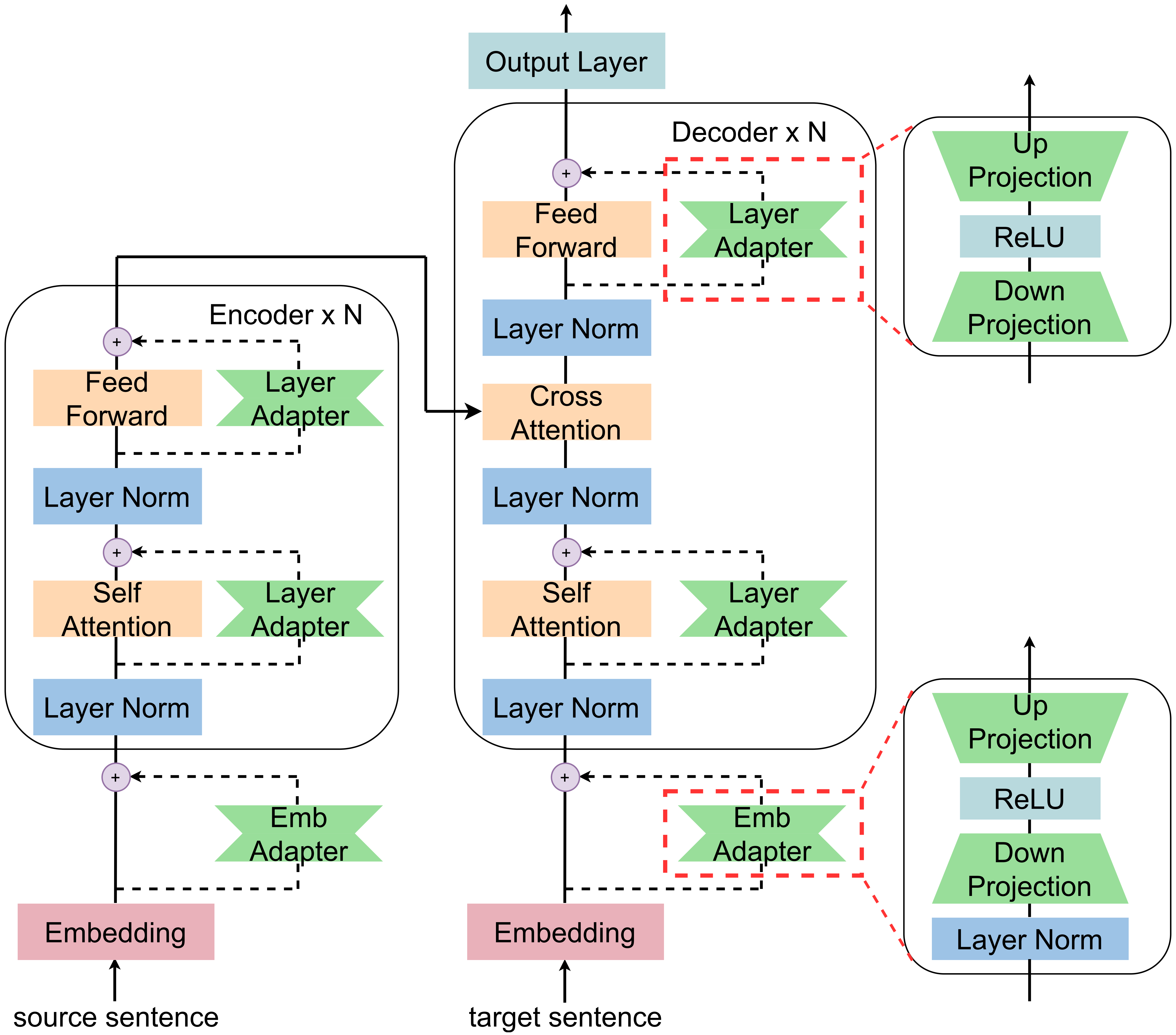
- Which adapter will remove noise?




Zhu et al. Counter-Interference Adapter for Multilingual Machine Translation. 2021

# Parallel Adapter - CIAT

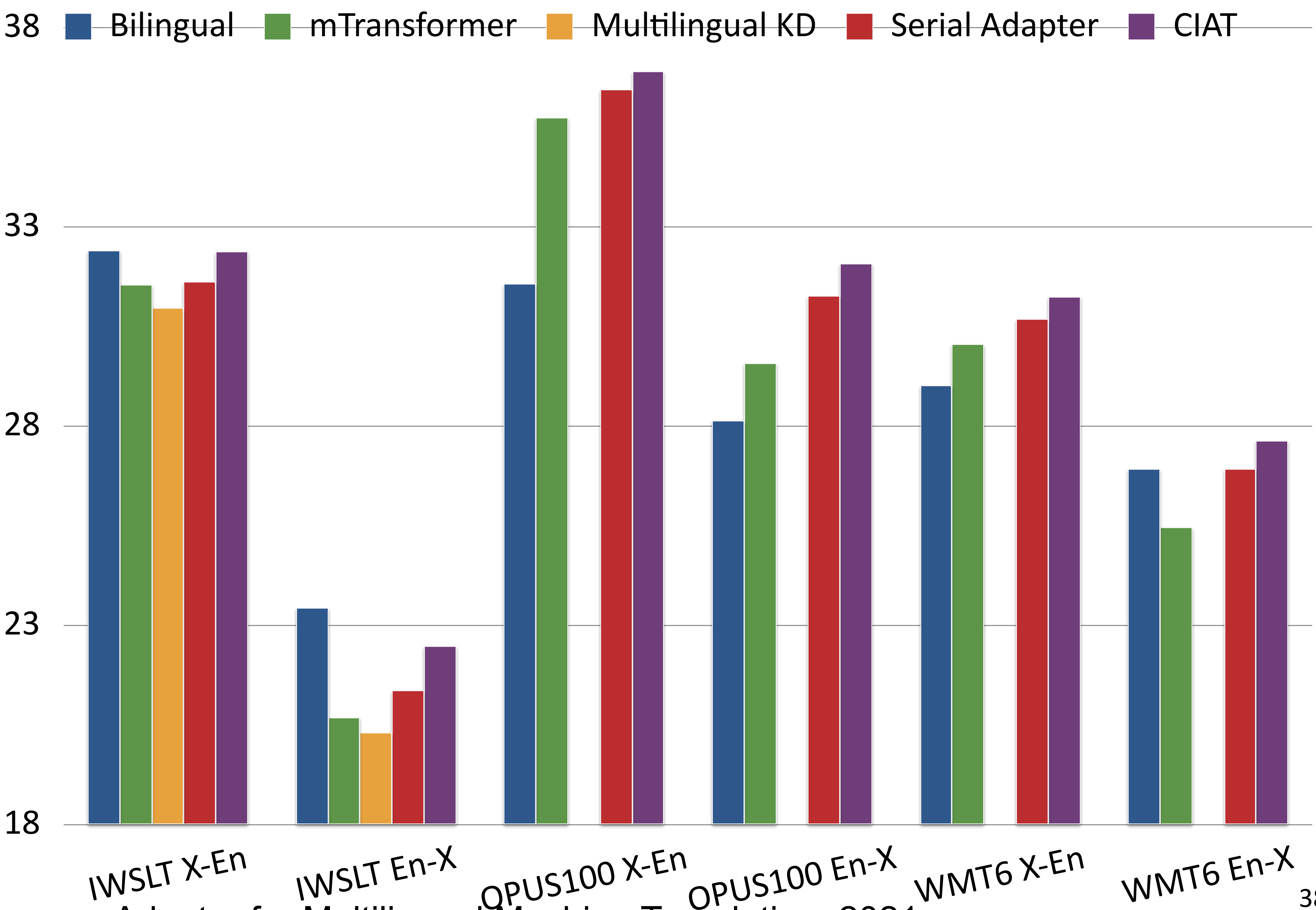
- Design rationale:
  - process before multilingual interference is introduce in each layer
- Embedding adapter
- Parallel layer adapter
- Training:
  - Pretrain mTransformer on multilingual data
  - Fix mTransformer and train parallel adapters on specific language pairs




Zhu et al. Counter-Interference Adapter for Multilingual Machine Translation. 2021

# Comparing MNMT w/ Adapters

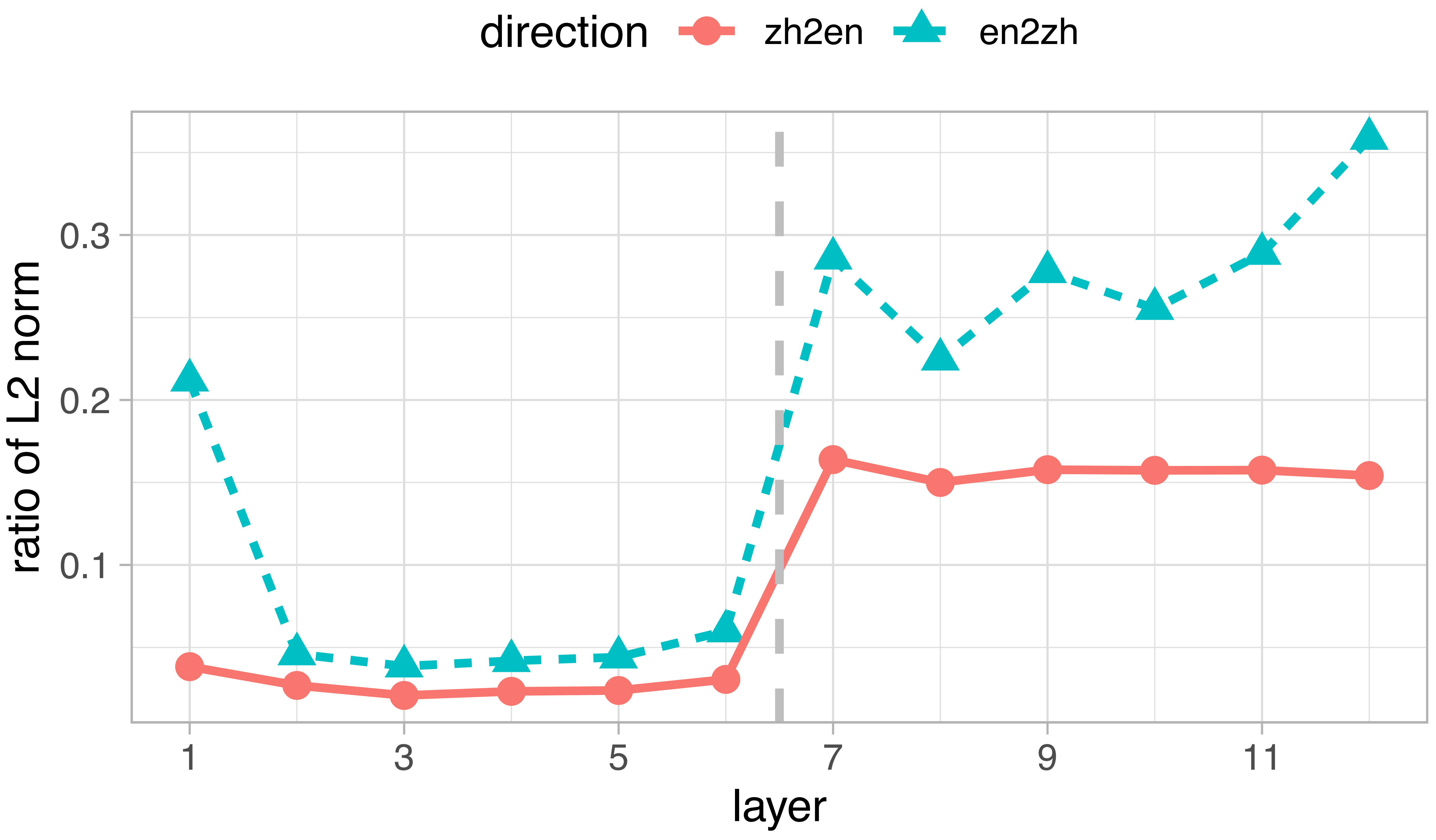
- mTransformer could be worse than bilingual Transformer
- Both serial adapter and parallel adapter (CIAT) improves mTransformer
- Parallel even beat bilingual Transformer! Serial adapter does not.



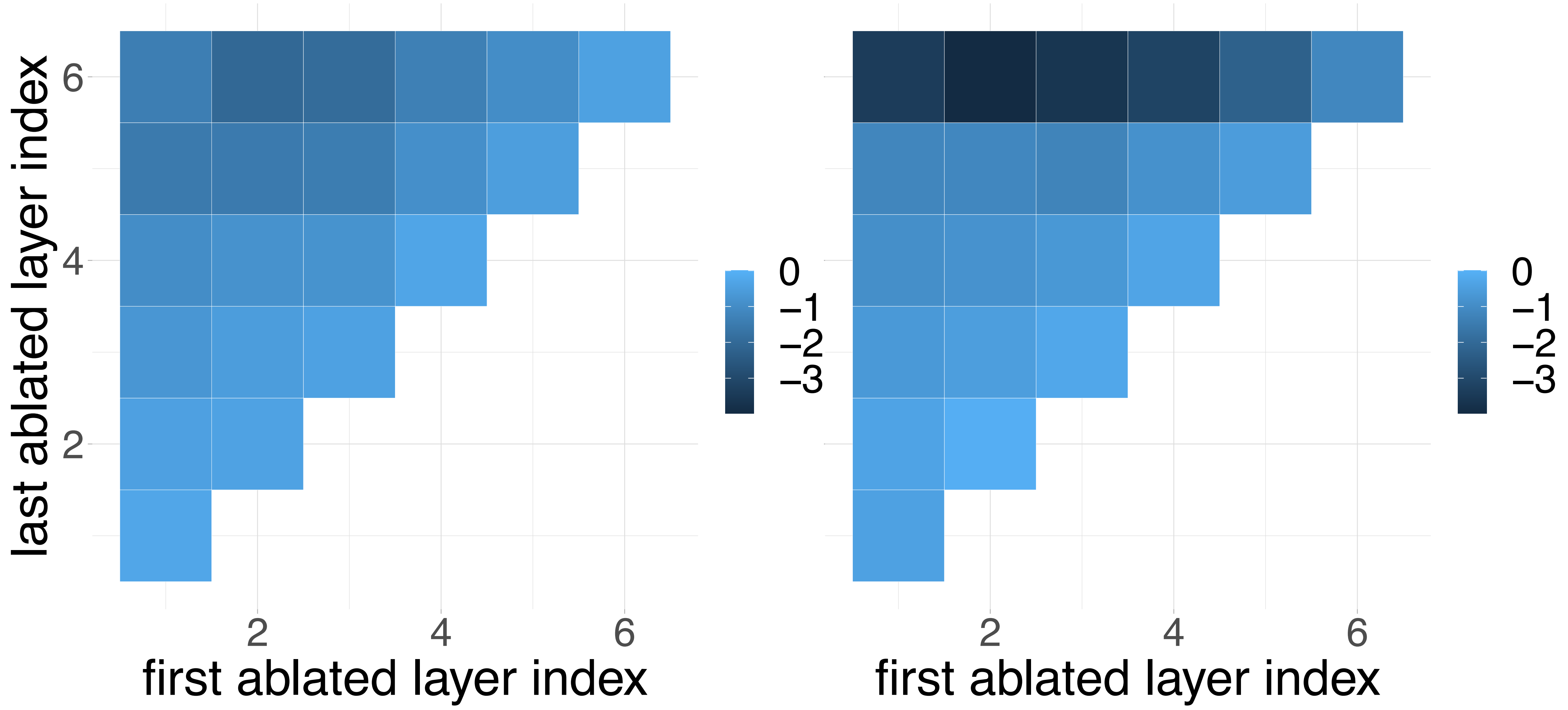

Zhu et al. Counter-Interference Adapter for Multilingual Machine Translation. 2021

# Which layer-adapter are more important?

- Upper decoder layer adapter is more important

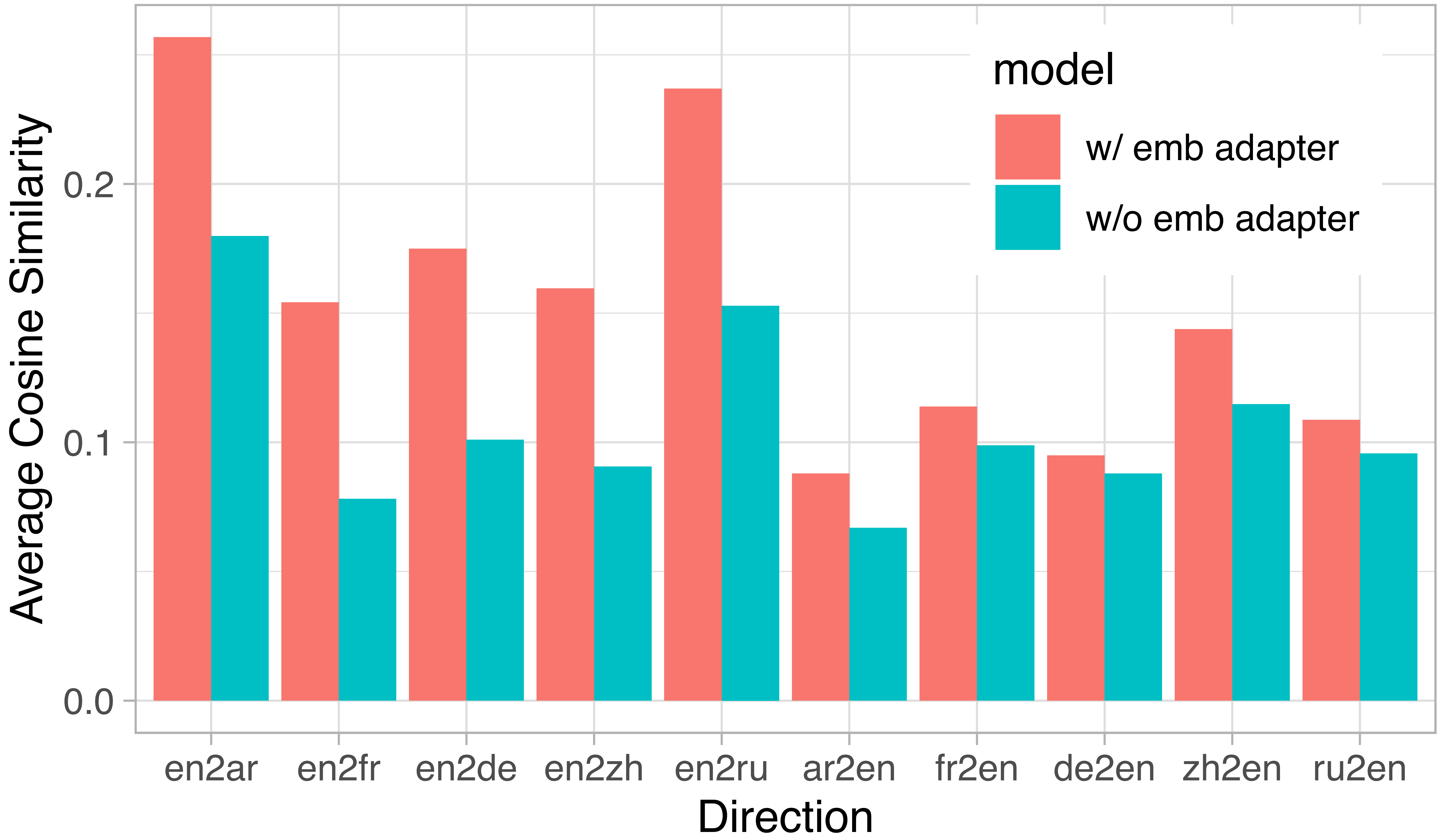



Drop in perf. removing enc/dec adapters



# Embedding Adapter is also important!

- Embedding adapter enhance the word embedding similarity between language pairs



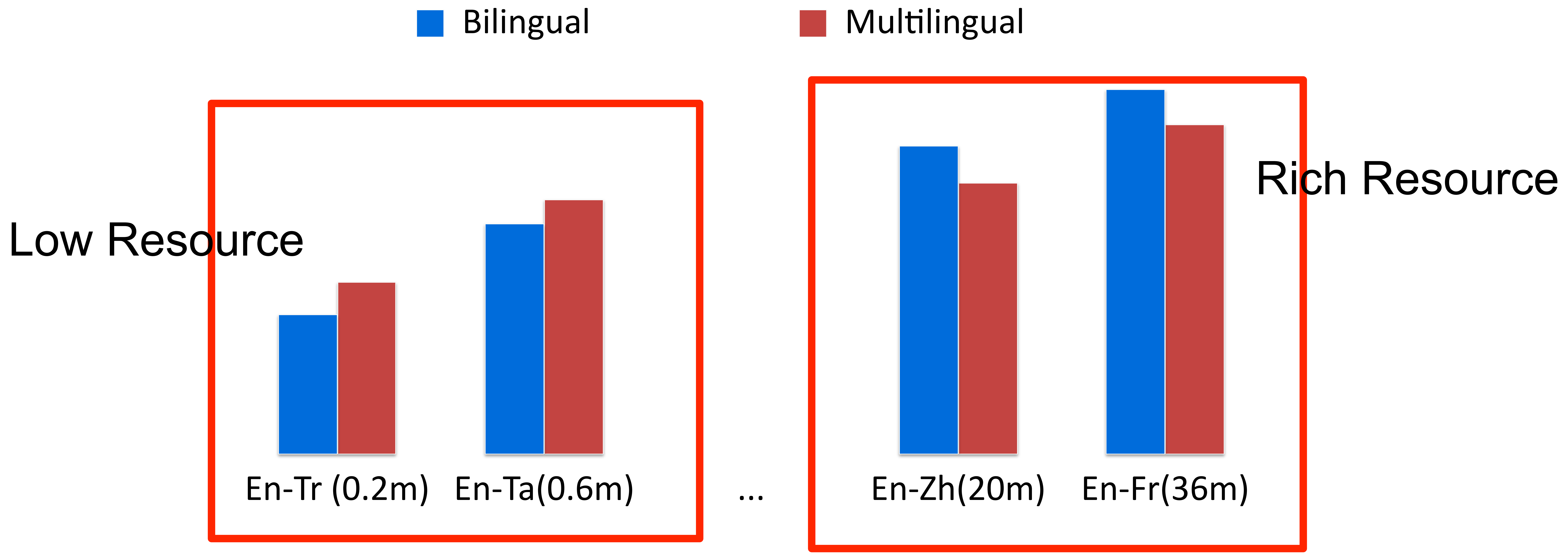
# Benefit of MNMT w/ Adapter

- Improve the performance on MNMT, even beat Bilingual NMT
  - Reducing interference among large languages
  - Boost performance on zero-shot setting
- With a fraction of overhead
  - Bilingual Transformer-big: N x 242m
  - mTransformer: 242m
  - mTransformer+Serial Adapter: 242m + N x 12.6m
  - mTransformer+parallel adapter (CIAT): 242m + N x 12.6~27.3m
- Plug-and-play: CIAT only needs to finetune adapter

# Exploiting Model Capacity with Language-specific Subnet

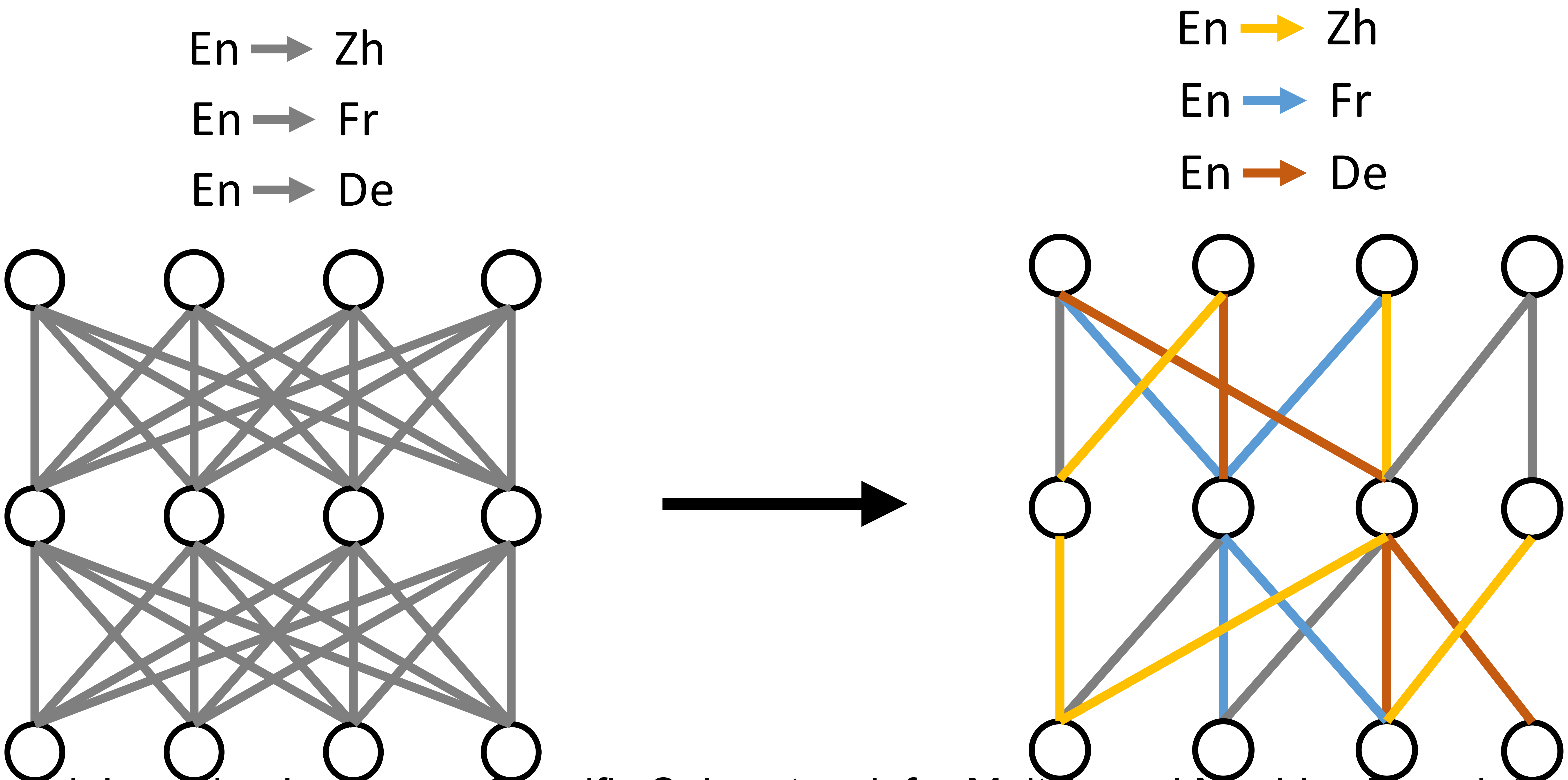
# Challenge of Multilingual NMT

- Challenge: Performance degradation for rich-resource
  - caused by Parameter Interference



# Language-Specific Sub-network (LaSS)

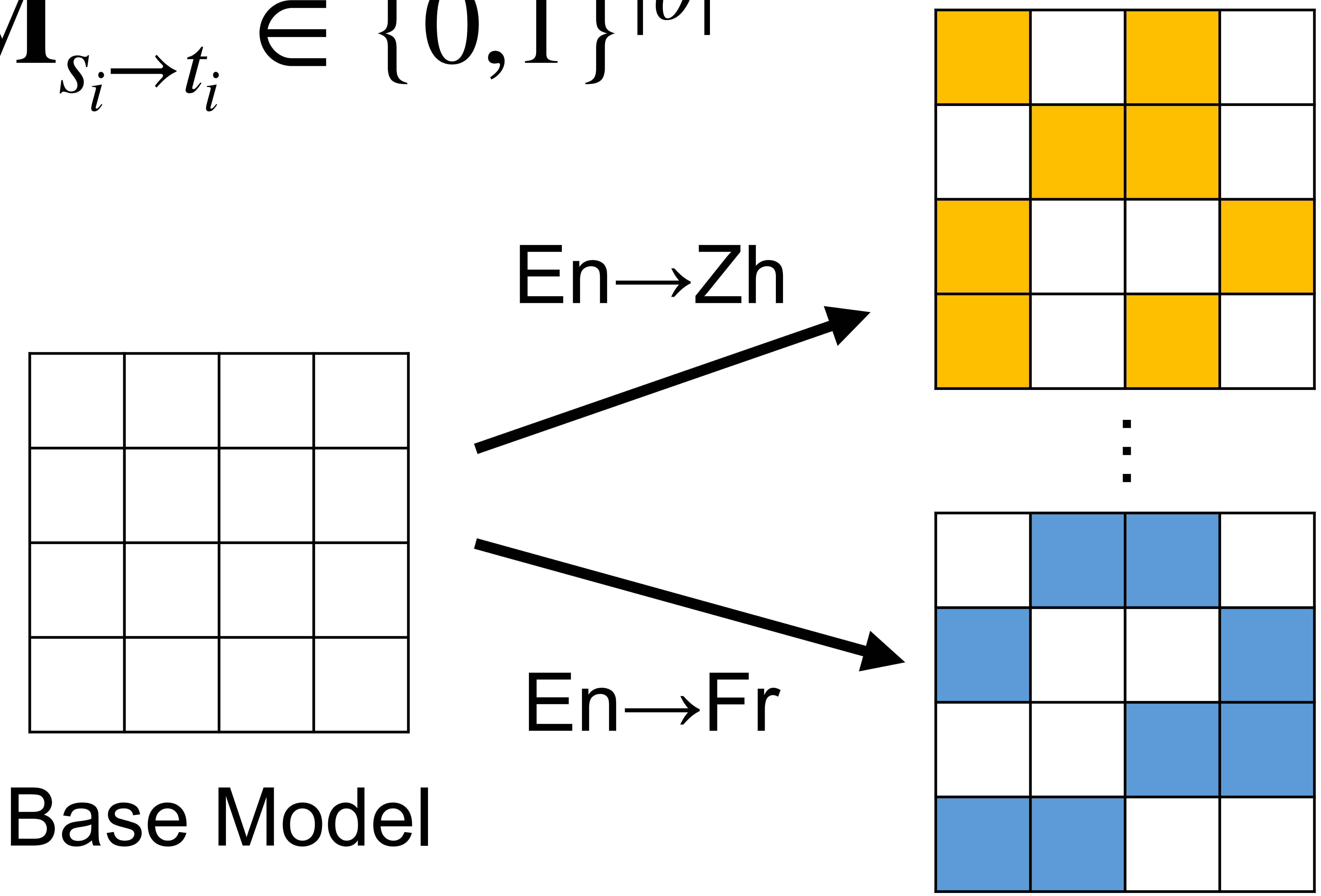
- Each direction has
  - shared parameters with other directions
  - preserves its language-specific parameters




Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation, 2021

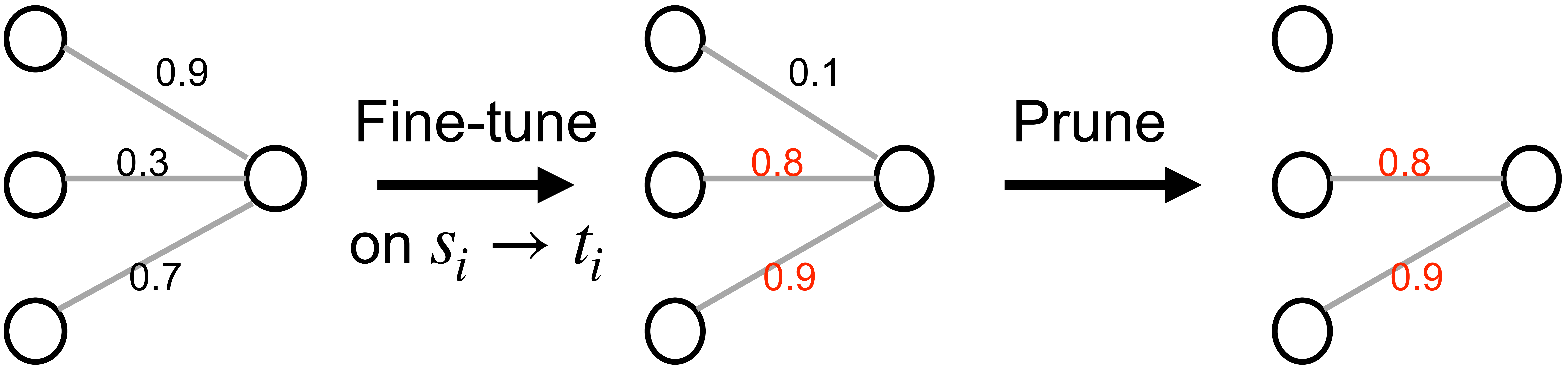
# LaSS overall framework

- For each language pair $s_i \rightarrow t_i$, a sub-network is selected from base model $\theta_0$ indicated by a binary mask $\mathbf{M}_{s_i \rightarrow t_i} \in \{0,1\}^{|\theta|}$



# How to find language-specific sub-network: Intuition

- Fine-tuning and pruning
  - Fine-tuning on $s_i \rightarrow t_i$ **amplifies** important weights and **diminishes** the unimportant weights.






Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation, 2021

# How to find language-specific masks

- Start with a vanilla multilingual model $\theta_0$ jointly trained on $\left\{\mathscr{D}_{s_i \rightarrow t_i}\right\}_{i=1}^{N}$
- For each language pair $s_i \rightarrow t_i$, fine-tuning $\theta_0$ on $\mathscr{D}_{s_i \rightarrow t_i}$, respectively
- Rank the weights in fine-tuned model and prune the lowest α percent to obtain $\mathbf{M}_{s_i \rightarrow t_i}$

Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021

# Structure-aware Joint Training

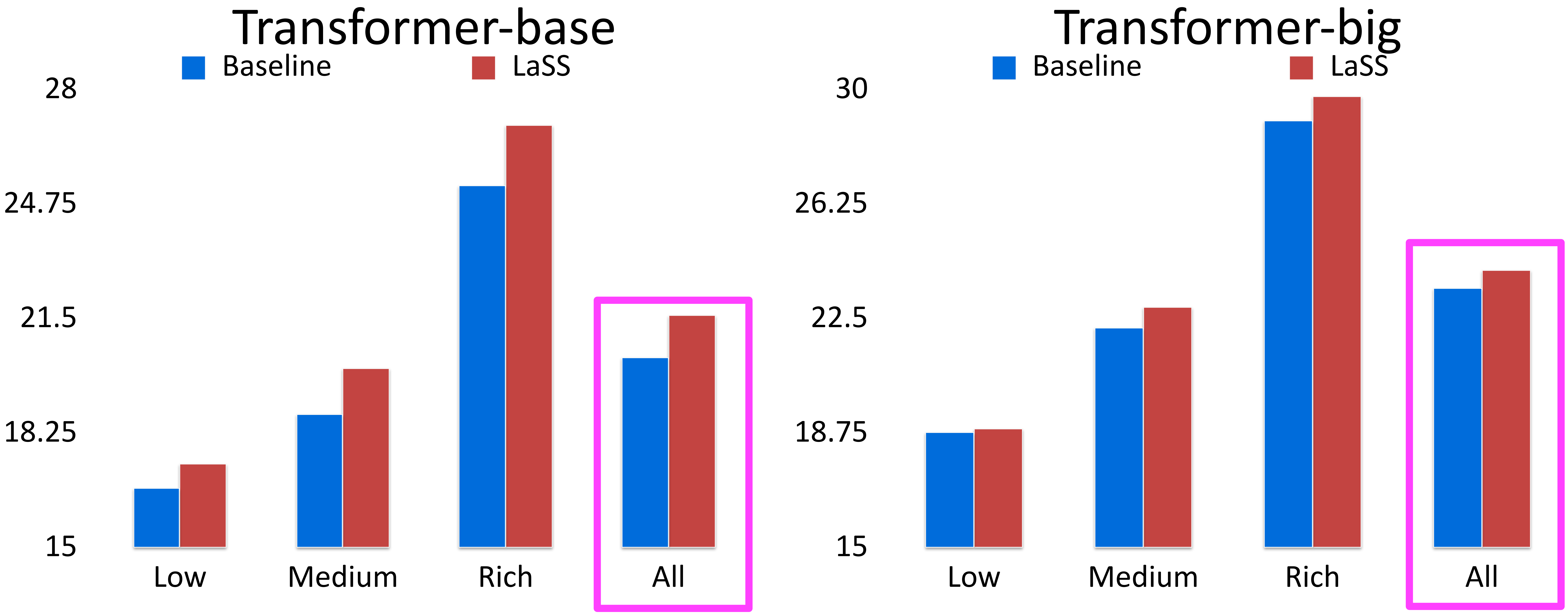
- Further continue to train $\theta_0$ through structure-aware updating after obtaining $\mathbf{M}_{s_i \to t_i}$
  - Create batch $\mathscr{B}_{s_i \to t_i}$ full of samples from $s_i \to t_i$
  - Forward and backward with sub-network

$$\theta_{s_i \to t_i} = \left\{ \theta_0^j \mid \mathbf{M}_{s_i \to t_i}^j = 1 \right\}$$

Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021

# Efficacy in alleviating Parameter Interference

- LaSS obtains consistent gains for both Transformer-base and Transformer-big

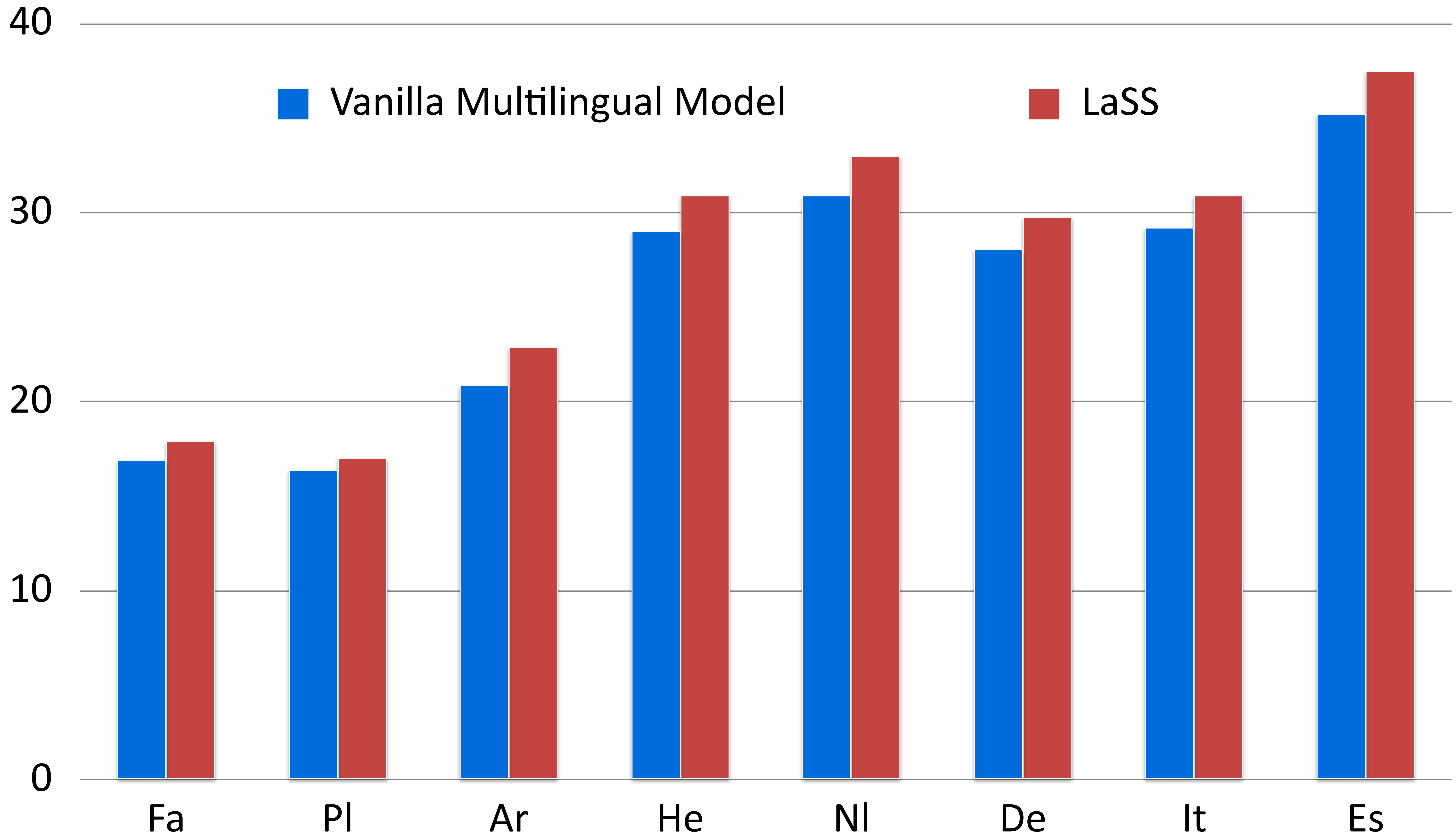





Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021

# Efficacy in alleviating Parameter Interference

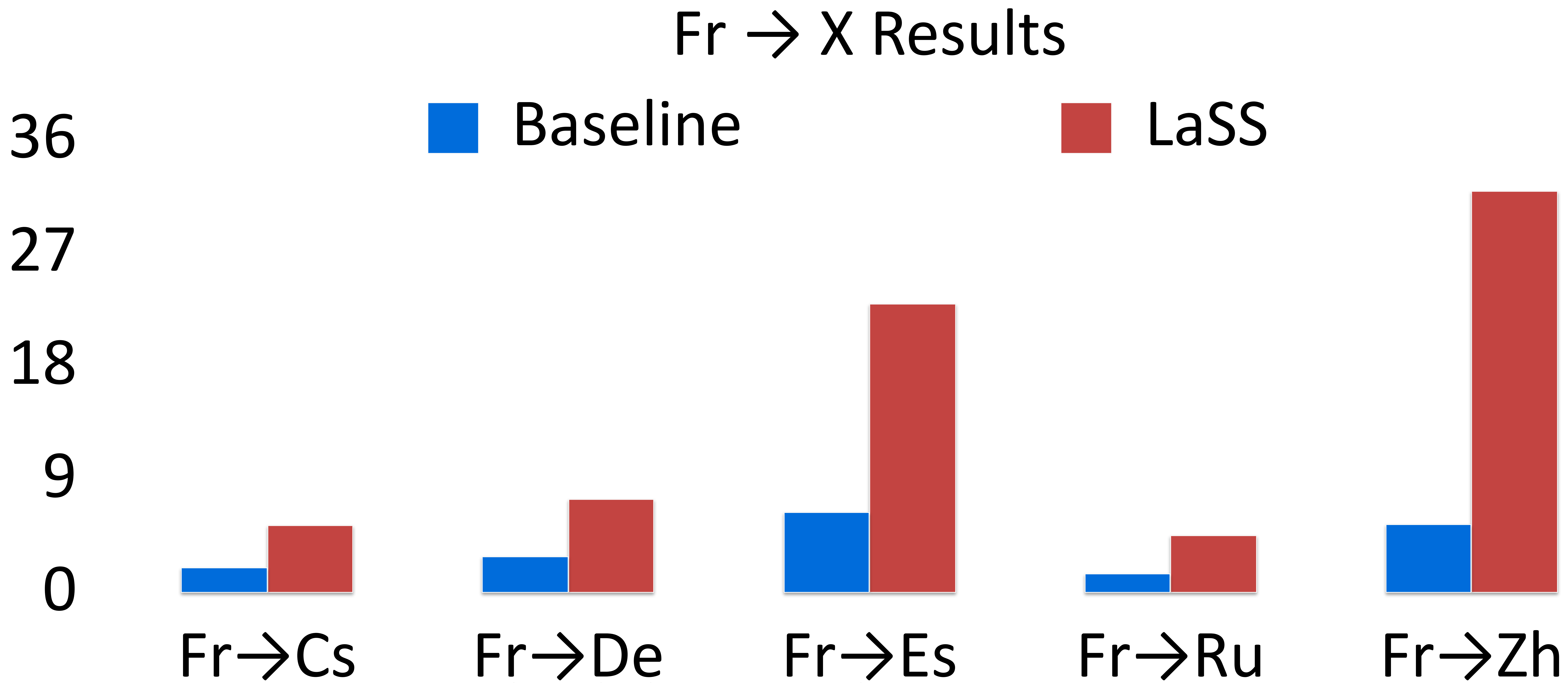
- LaSS obtains consistent performance gains.
  - IWSLT




Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021

# LaSS obtains large gains in zero-shot translation

- An average of 8.3 BLEU gains on 30 language pairs
- 26.5 BLEU gains for Fr→Zh




Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021

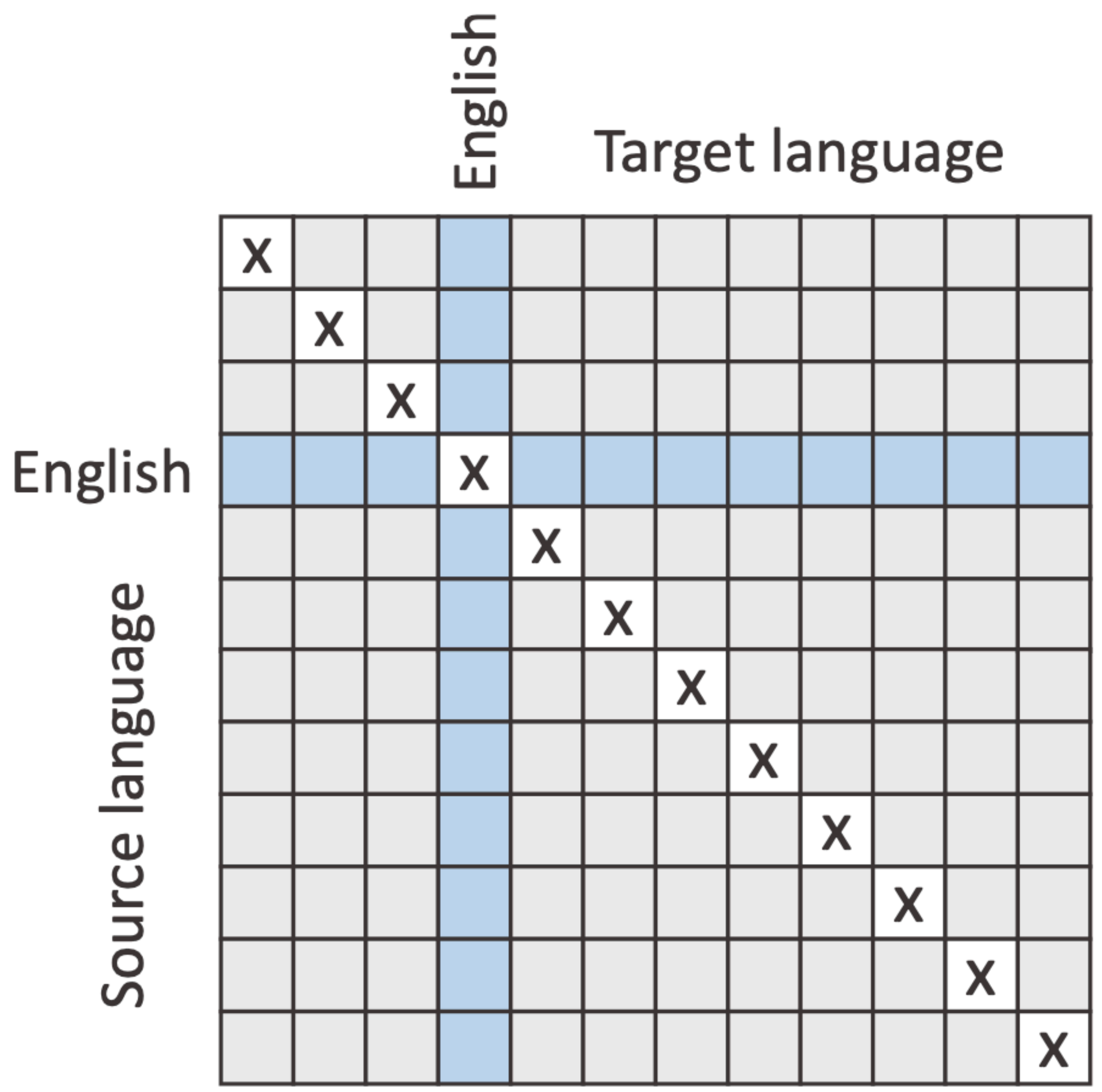
# Benefits of Language-specific Subnet

- The same number of parameters, no extra parameter
- Improved performance on both rich-resource and zero-shot translation directions.

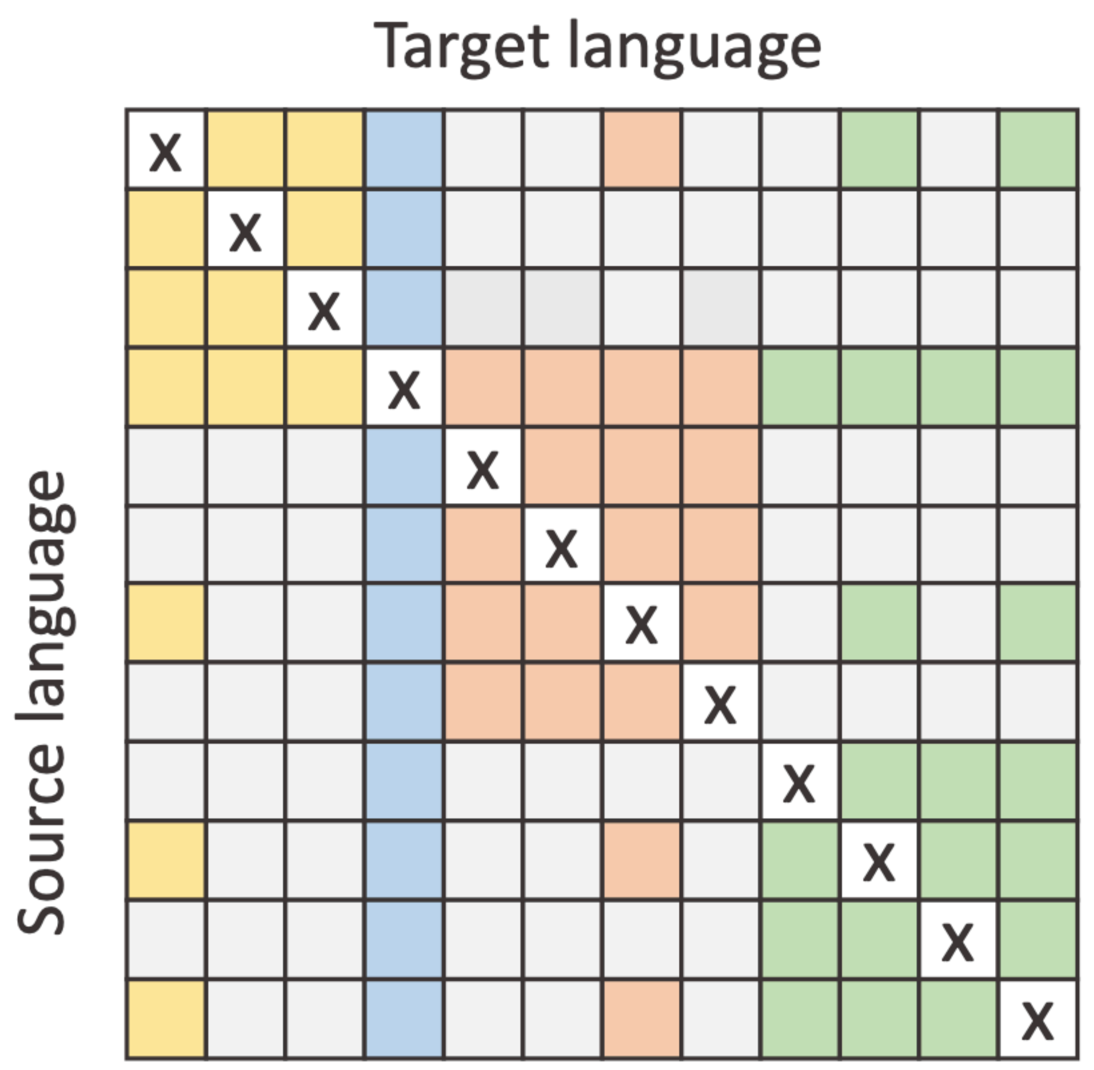
# What do we need for larger scale?

# Full Many-to-Many MNMT

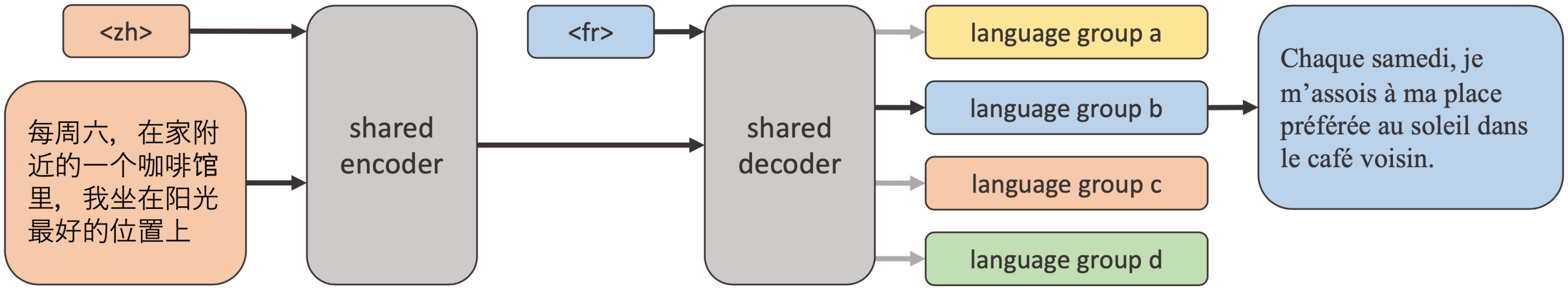
- Previous many-to-many MNMT does not work well on non-English pairs
-




(a) English-Centric Multilingual




(b) M2M-100: Many-to-Many Multilingual Model




(c) Translating from Chinese to French with Dense + Language-Specific Sparse Model

Fan et al. Beyond English-Centric Multilingual Machine Translation. 2021

# 100 Langauge Benchmark

- WMT — 13 languages
- WAT — Burmese-English
- IWSLT — 4 languages
- FLORES— Sinhala and Nepali <—> English
- TED—The TED Talks data set4 (Ye et al., 2018) contains translations between more than 50 languages; most of the pairs do not include English. The evaluation data is n-way parallel and contains thousands of directions.
- Autshumato— 11-way parallel data set comprising 10 African languages and English from the government domain. Half-half split.
- Tatoeba— 692 test pairs from mixed domains where sentences are contributed and translated by volunteers online. The evaluation pairs we use from Tatoeba cover 85 different languages.

# Data mining for parallel corpus

- CCAligned [El-Kishky et al 2020]
  - use LASER encoder to produce sentence embedding
  - for every Eng sentence, use vector search engine (e.g. FAISS) to search candidate aligned sentence by comparing sentence embedding
  - parallel or comparable web-document pairs in 137 languages aligned with English.
- Use language family as bridge to mine
  - non-English pairs
- Total Training Data: 7.5B parallel sentences, corresponding to 2200 directions.

# The power of non-English parallel data

- Not necessarily fair performance.

| **Setting** | **To English** | **From English** | **Non-English** |
|---|---|---|---|
| Bilingual baselines | 27.9 | **24.5** | 8.3 |
| English-Centric | 31.0 | 24.2 | 5.7 |
| English-Centric with Pivot | — | — | 10.4 |
| Many-to-Many | **31.2** | 24.1 | **15.9** |

Fan et al. Beyond English-Centric Multilingual Machine Translation. 2021

| | Source | Target | Test Set | BLEU | | |
|---|---|---|---|---|---|---|
| | | | | English-Centric | M2M-100 | Δ |
| India | Hindi | Bengali | TED | 3.9 | 8.7 | +4.8 |
| | Hindi | Marathi | TED | 0.4 | 8.4 | +8.0 |
| | Hindi | Tamil | TED | 1.1 | 7.5 | +6.4 |
| South Africa | Afrikaans | Xhosa | Autshumato | 0.1 | 3.6 | +3.5 |
| | Afrikaans | Zulu | Autshumato | 0.3 | 3.6 | +3.3 |
| | Afrikaans | Sesotho | Autshumato | 0.0 | 2.1 | +2.1 |
| | Xhosa | Zulu | Autshumato | 0.1 | 3.6 | +3.5 |
| | Sesotho | Zulu | Autshumato | 0.1 | 1.2 | +1.1 |
| Chad | Arabic | French | TED | 5.3 | 20.8 | +15.5 |
| DR Congo | French | Swahili | Tatoeba | 1.8 | 5.7 | +3.9 |
| Kazakhstan | Kazakh | Russian | TED | 0.5 | 4.5 | +4.0 |
| Singapore | Chinese | Tamil | TED | 0.2 | 8.0 | +7.8 |

| | Source | Target | Test Set | BLEU | | |
|---|---|---|---|---|---|---|
| | | | | English-Centric | M2M-100 | $\Delta$ |
| Austria | German | Croatian | TED | 9.6 | 21.3 | +11.7 |
| | German | Hungarian | TED | 11.3 | 17.4 | +6.1 |
| Belgium | Dutch | French | TED | 16.4 | 25.8 | +9.4 |
| | Dutch | German | TED | 18.1 | 26.3 | +8.2 |
| Belarus | Belarusian | Russian | TED | 10.0 | 18.5 | +8.5 |
| Croatia | Croatian | Serbian | TED | 22.4 | 29.8 | +7.4 |
| | Croatian | Hungarian | TED | 12.4 | 17.5 | +5.1 |
| | Croatian | Czech | TED | 15.2 | 22.5 | +7.3 |
| | Croatian | Slovak | TED | 13.8 | 24.6 | +10.8 |
| Cyprus | Greek | Turkish | TED | 4.8 | 12.6 | +7.8 |
| Czechia | Czech | Slovak | TED | 9.5 | 28.1 | +18.6 |
| Finland | Finnish | Swedish | TED | 7.9 | 19.2 | +11.3 |
| Italy | Italian | French | TED | 18.9 | 28.8 | +9.9 |
| | Italian | German | TED | 18.4 | 25.6 | +7.2 |
| Moldova | Romanian | Russian | TED | 8.0 | 19.0 | +11.0 |
| | Romanian | Ukrainian | TED | 8.7 | 17.3 | +8.6 |
| Montenegro | Albanian | Croatian | TED | 3.0 | 20.7 | +17.7 |
| | Albanian | Serbian | TED | 7.8 | 20.6 | +12.8 |
| Romania | Romanian | German | TED | 15.0 | 24.7 | +9.7 |
| | Romanian | Hungarian | TED | 11.0 | 16.3 | +4.3 |
| | Romanian | Turkish | TED | 5.1 | 12.0 | +6.9 |
| | Romanian | Armenian | TED | 0.4 | 8.2 | +7.8 |
| Russia | Bashkir | Russian | Tatoeba | 0.1 | 4.3 | +4.2 |

| Direction | Test Set | BLEU Published | BLEU M2M-100 | BLEU Δ |
|---|---|---|---|---|
| **Without Improvement** | | | | |
| English-Chinese (Li et al., 2019) | WMT'19 | 38.2 | 33.2 | -5.0 |
| English-Finnish (Talman et al., 2019) | WMT'17 | 28.6 | 28.2 | -0.4 |
| English-Estonian (Pinnis et al., 2018) | WMT'18 | 24.4 | 24.1 | -0.3 |
| Chinese-English (Li et al., 2019) | WMT'19 | 29.1 | 29.0 | -0.1 |
| **With Improvement** | | | | |
| English-French (Edunov et al., 2018) | WMT'14 | 43.8 | 43.8 | 0 |
| English-Latvian (Pinnis et al., 2017) | WMT'17 | 20.0 | 20.5 | +0.5 |
| German-English (Ng et al., 2019) | WMT'19 | 39.2 | 40.1 | +0.9 |
| Lithuanian-English (Pinnis et al., 2019) | WMT'19 | 31.7 | 32.9 | +1.2 |
| English-Russian (Ng et al., 2019) | WMT'19 | 31.9 | 33.3 | +1.4 |
| English-Lithuanian (Pinnis et al., 2019) | WMT'19 | 19.1 | 20.7 | +1.6 |
| Finnish-English (Talman et al., 2019) | WMT'17 | 32.7 | 34.3 | +1.6 |
| Estonian-English (Pinnis et al., 2018) | WMT'18 | 30.9 | 33.4 | +2.5 |
| Latvian-English (Pinnis et al., 2017) | WMT'17 | 21.9 | 24.5 | +2.6 |
| Russian-English (Ng et al., 2019) | WMT'19 | 37.2 | 40.5 | +3.3 |
| French-English (Edunov et al., 2018) | WMT'14 | 36.8 | 40.4 | +3.6 |
| English-German (Ng et al., 2019) | WMT'19 | 38.1 | 43.2 | +5.1 |
| English-Turkish (Sennrich et al., 2017) | WMT'17 | 16.2 | 23.7 | +7.5 |
| Turkish-English (Sennrich et al., 2017) | WMT'17 | 20.6 | 28.2 | +7.6 |
| | Average | 30.0 | 31.9 | **+1.9** |

# Language Presentation

# Reading

- Johnson et al. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. 2017
- Aharoni et al. Massively Multilingual Neural Machine Translation. 2019
- Arivazhagan et al. Massively Multilingual Neural Machine Translation in the Wild: Findings and Challenges. 2019
- Bapna & Firat, Simple, Scalable Adaptation for Neural Machine Translation, 2019
- Zhu et al. Counter-Interference Adapter for Multilingual Machine Translation. 2021
- Lin et al. Learning Language Specific Sub-network for Multilingual Machine Translation. 2021