Multilingual NLP

Slides from S Sun, M Iyyer, G Neubig and many other sources

Multilingual transfer

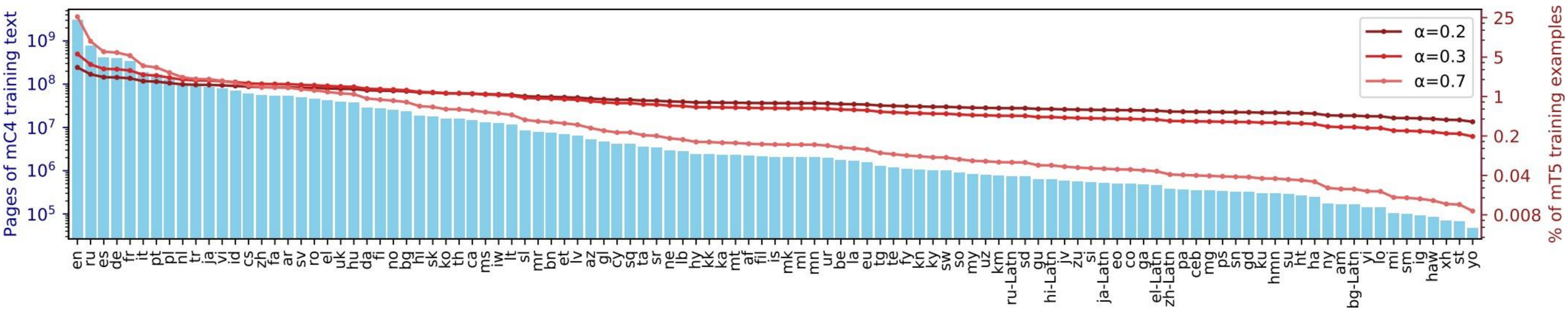
- So far, we've mainly talked about pretraining and fine-tuning models on English text.

- One approach: pretrain BERT-like models on *monolingual* data from a different language
  - "BERTje > Dutch, "FlauBERT" > French, "PhoBERT" > Vietnamese, etc.

- Another approach: pretrain models on a large mixture of many languages
  - mBERT, mBART, XLM-R, mT5, byT5, etc.
  - Allows for transfer learning *across* languages

mC4 dataset

- 107 languages, lower-resource languages upsampled based on their frequency in the dataset



Model	Architecture	Parameters	# languages	Data source
mBERT (Devlin, 2018)	Encoder-only	180M	104	Wikipedia
XLM (Conneau and Lample, 2019)	Encoder-only	570M	100	Wikipedia
XLM-R (Conneau et al., 2020)	Encoder-only	270M – 550M	100	Common Crawl (CCNet)
mBART (Lewis et al., 2020b)	Encoder-decoder	680M	25	Common Crawl (CC25)
MARGE (Lewis et al., 2020a)	Encoder-decoder	960M	26	Wikipedia or CC-News
mT5 (ours)	Encoder-decoder	300M – 13B	101	Common Crawl (mC4)

mT5 paper, Sue et al., ACL 2021

Cross-lingual zero-shot learning

- We are given labeled training data for task X only in language A. Can we build a model that can make predictions for task X in a different language B?

- **Idea**: leverage information from high-resource languages to help improve performance on low-resource languages.

- **Zero-shot** learning: no labeled data is available for the target task X in language B, although unlabeled data in language B might be available for pretraining

XNLI benchmark

Language	Premise / Hypothesis	Genre	Label
English	You don't have to stay there. You can leave.	Face-To-Face	Entailment
French	La figure 4 montre la courbe d'offre des services de partage de travaux. Les services de partage de travaux ont une offre variable.	Government	Entailment
Spanish	Y se estremeció con el recuerdo. El pensamiento sobre el acontecimiento hizo su estremecimiento.	Fiction	Entailment
German	Während der Depression war es die ärmste Gegend, kurz vor dem Hungertod. Die Weltwirtschaftskrise dauerte mehr als zehn Jahre an.	Travel	Neutral
Swahili	Ni silaha ya plastiki ya moja kwa moja inayopiga risasi. Inadumu zaidi kuliko silaha ya chuma.	Telephone	Neutral
Russian	И мы занимаемся этим уже на протяжении 85 лет. Мы только начали этим заниматься.	Letters	Contradiction
Chinese	让我告诉你，美国人最终如何看待你作为独立顾问的表现。 美国人完全不知道您是独立律师。	Slate	Contradiction

XNLI dataset, Conneau et al., ACL 2018

XNLI given only English training data

Model	Sentence pair	
	XNLI	PAWS-X
Metrics	Acc.	Acc.
Cross-lingual zero-shot transfer (models fine-tu		
mBERT	65.4	81.9
XLM	69.1	80.9
InfoXLM	81.4	-
X-STILTs	80.4	87.7
XLM-R	79.2	86.4
VECO	79.9	88.7
RemBERT	80.8	87.5
mT5-Small	67.5	82.4
mT5-Base	75.4	86.4
mT5-Large	81.1	88.9
mT5-XL	82.9	89.6
mT5-XXL	**85.0**	**90.0**

What if we use a machine translation system to get more labeled data (e.g., translate all the labeled English text to other languages)?

Adding translations doesn't improve that much over the zero-shot setting!

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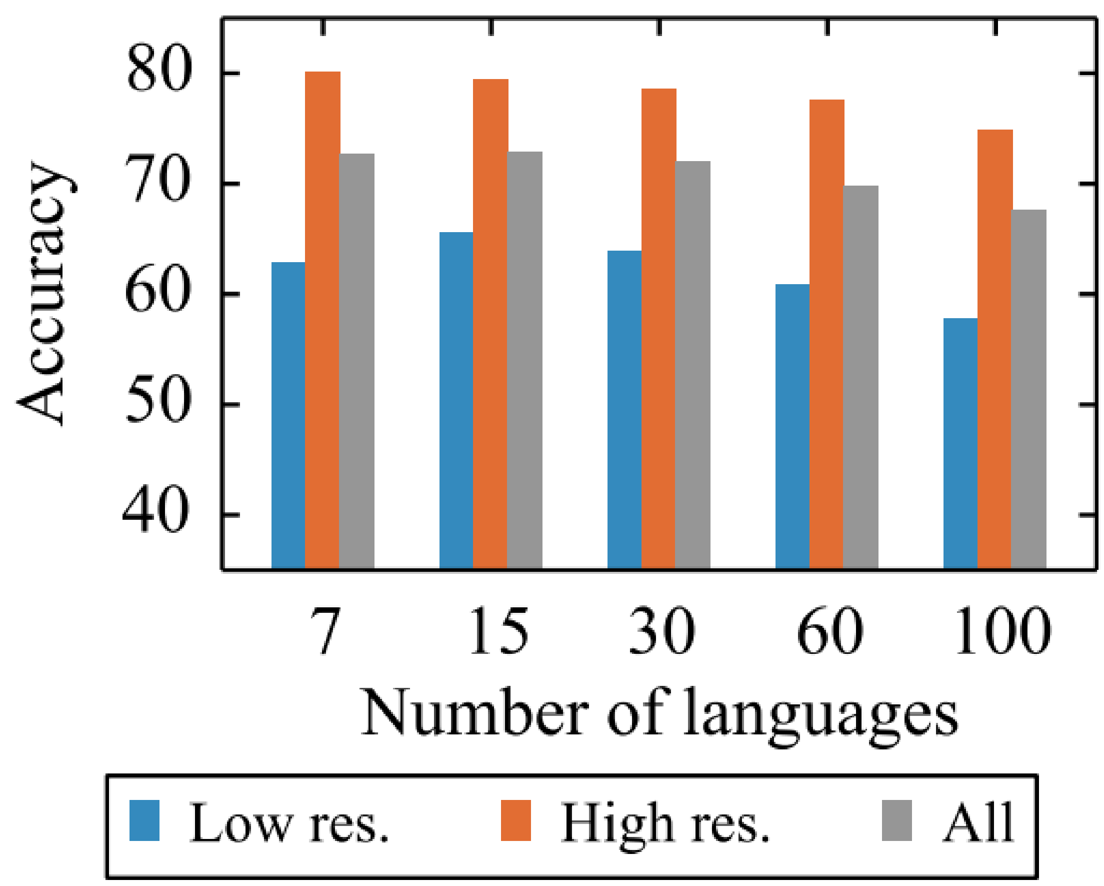
mT5-XXL	**85.0**	**90.0**
Translate-train (models fine-tuned on English		
XLM-R	82.6	90.4
FILTER + Self-Teaching	83.9	91.4
VECO	83.0	91.1
mT5-Small	64.7	79.9
mT5-Base	75.9	89.3
mT5-Large	81.8	91.2
mT5-XL	84.8	91.0
mT5-XXL	**87.8**	**91.5**

What if a language is unseen or poorly represented during *pretraining*?

- The "curse of multilinguality" (Conneau et al., 2020): *For a fixed-size model, the per-language capacity decreases as we increase the number of languages…*

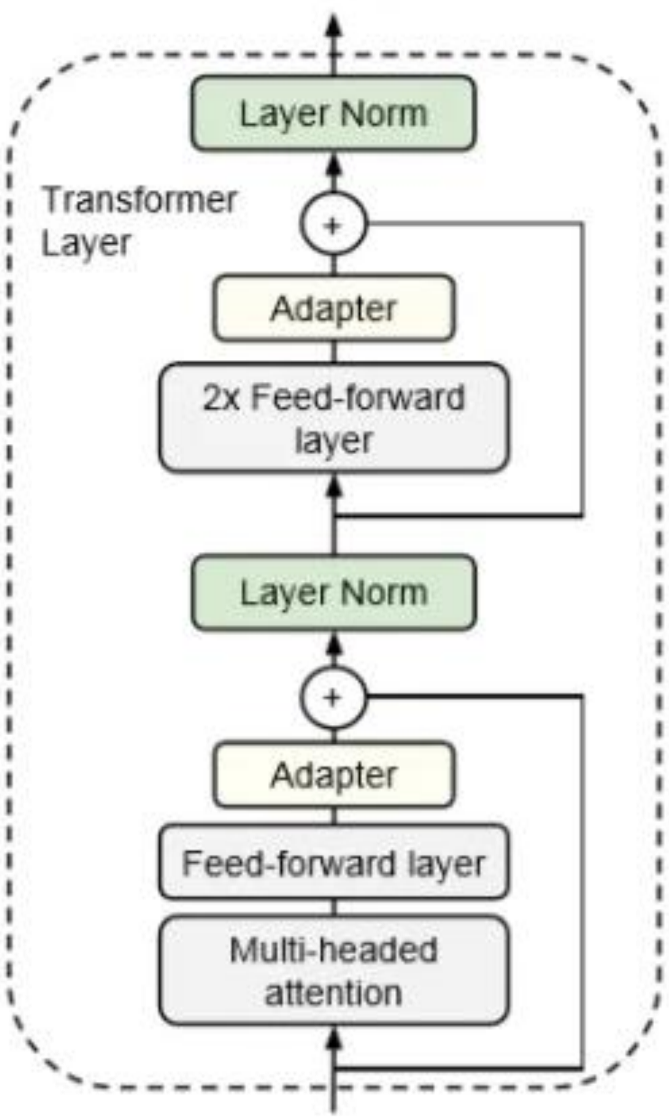


Target language adaptation

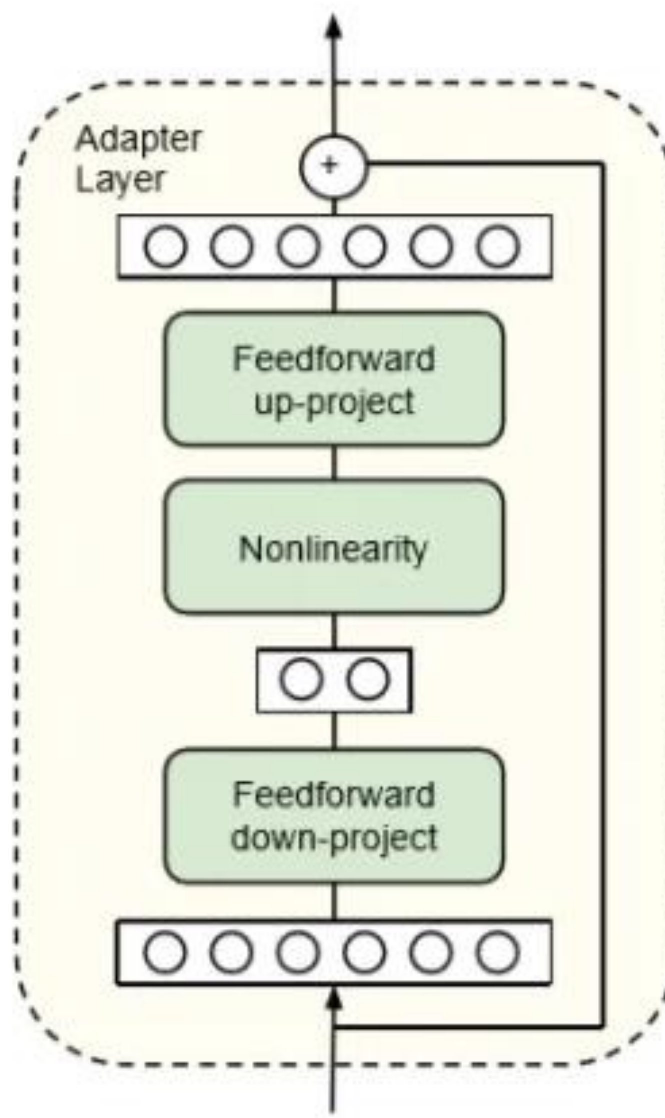
- If you only care about transferring to a specific target language B, then after normal pretraining on many languages, you can perform a second phase of fine-tuning on only unlabeled data from language B

- However, doing this might result in *catastrophic forgetting* of multilingual knowledge learned during the first stage of pretraining.

One solution: just train a small number of parameters in the second phase!



Transformer with Adopters



An Adopter Block

MAD-X paper, Pfeiffer et al., EMNLP 2020

This research is still in early stages, but it’s very exciting! Let’s move on to machine translation

Do we have enough parallel data?

Parallel Corpus	Sentences	Parallel Corpus	Sentences
Romanian-English	399,375	Greek-English	1,235,976
Bulgarian-English	406,934	Swedish-English	1,862,234
Slovene-English	623,490	Italian-English	1,909,115
Hungarian-English	624,934	German-English	1,920,209
Polish-English	632,565	Finnish-English	1,924,942
Lithuanian-English	635,146	Portuguese-English	1,960,407
Latvian-English	637,599	Spanish-English	1,965,734
Slovak-English	640,715	Danish-English	1,968,800
Czech-English	646,605	Dutch-English	1,997,775
Estonian-English	651,746	French-English	2,007,723

Europarl parallel data: http://www.statmt.org/europarl/

What if we don’t have parallel data?

https://arxiv.org/pdf/1804.07755.pdf

Phrase-Based & Neural Unsupervised Machine Translation

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https://arxiv.org/pdf/1711.00043.pdf

UNSUPERVISED MACHINE TRANSLATION
USING MONOLINGUAL CORPORA ONLY

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https://arxiv.org/pdf/1901.07291.pdf

Cross-lingual Language Model Pretraining

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https://arxiv.org/pdf/1710.11041.pdf

UNSUPERVISED NEURAL MACHINE TRANSLATION

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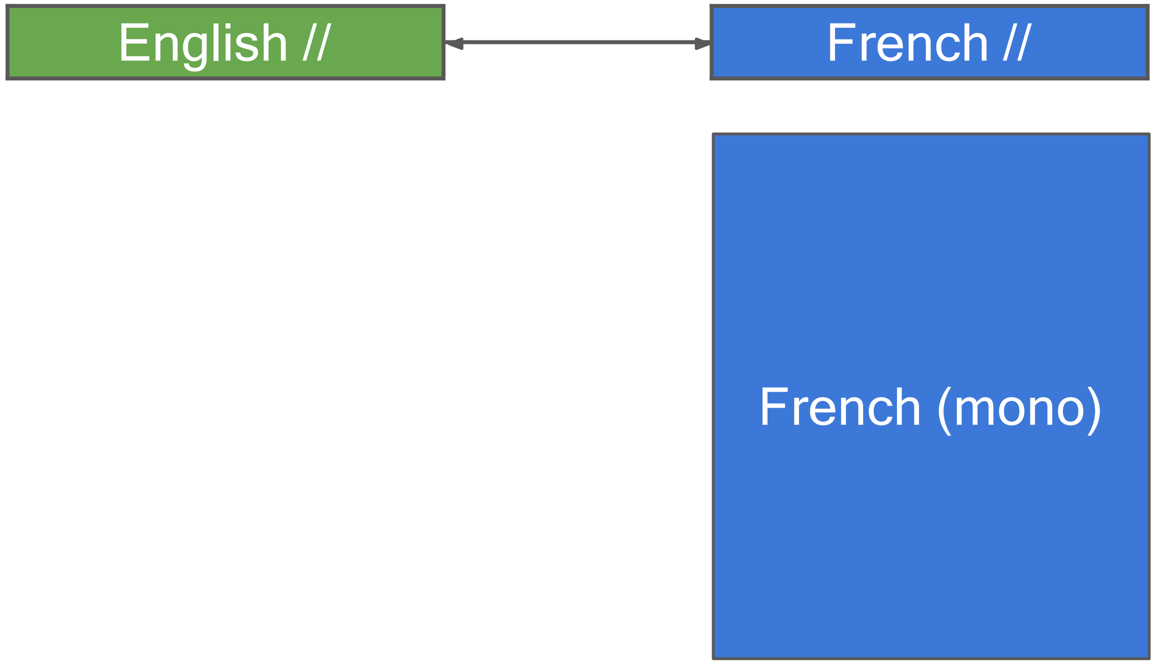
Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

- Small parallel dataset
- Huge monolingual corpus in target language



Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

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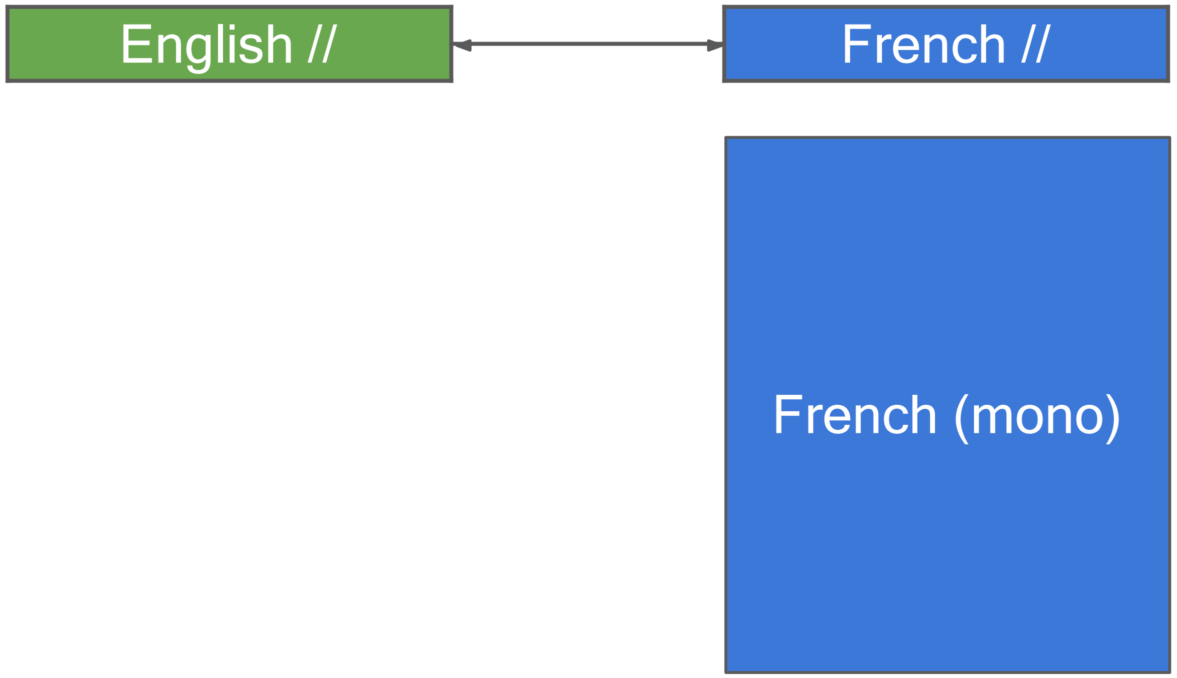
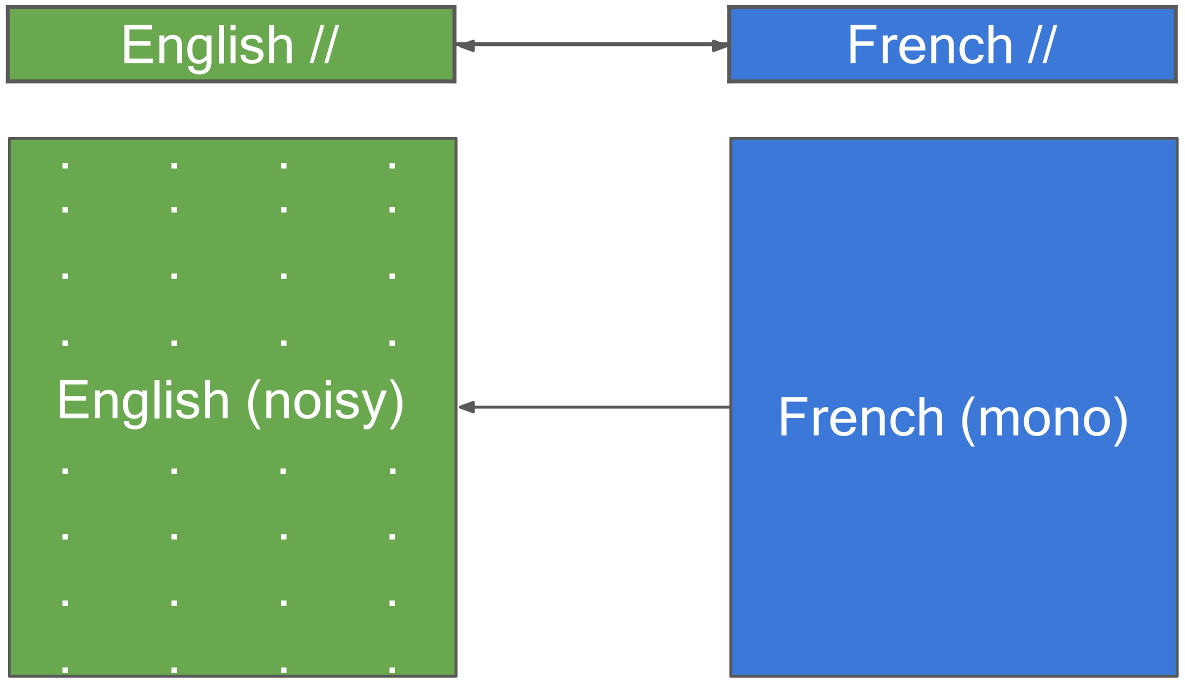
- Train a (target → source) model $\mathbf{M}_{t2s}$



Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

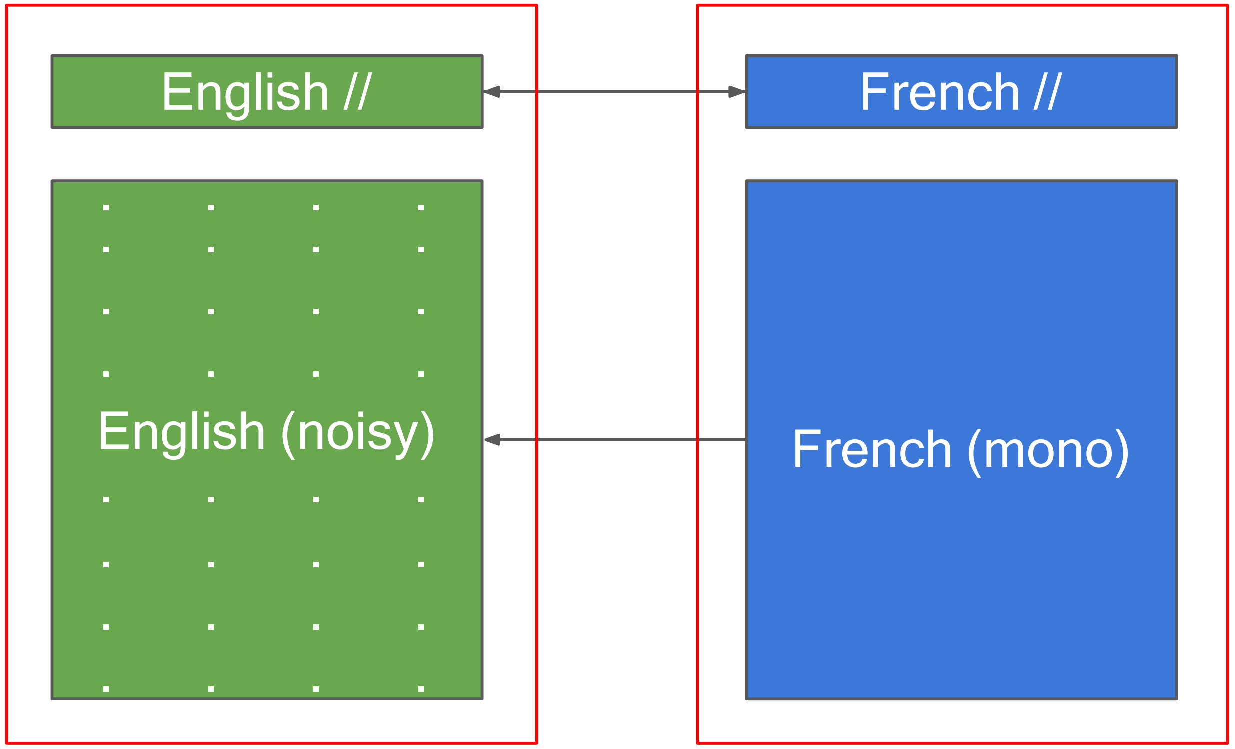
- Small parallel dataset
- Huge monolingual corpus in target language
- Train a (target → source) model $\mathbf{M}_{t2s}$
- Use $\mathbf{M}_{t2s}$ to translate target monolingual corpus



Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

- Small parallel dataset
- Huge monolingual corpus in target language
- Train a (target → source) model $\mathbf{M}_{t2s}$
- Use $\mathbf{M}_{t2s}$ to translate target monolingual corpus
- Use the two parallel datasets to train $\mathbf{M}_{s2t}$



Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

- en-->de WMT14
  - Parallel only: 20.4
  - + back-translation: 23.8
- en-->de WMT15
  - Parallel only: 23.6
  - + back-translation: 26.5

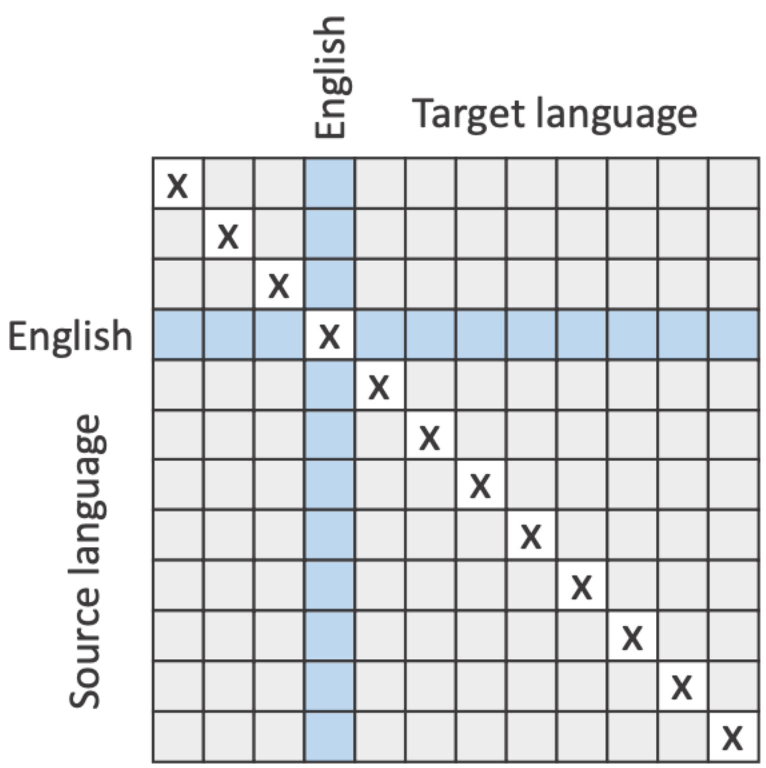
Back-translation (Sennrich et al. 2016)

Improving Neural Machine Translation Models with Monolingual Data

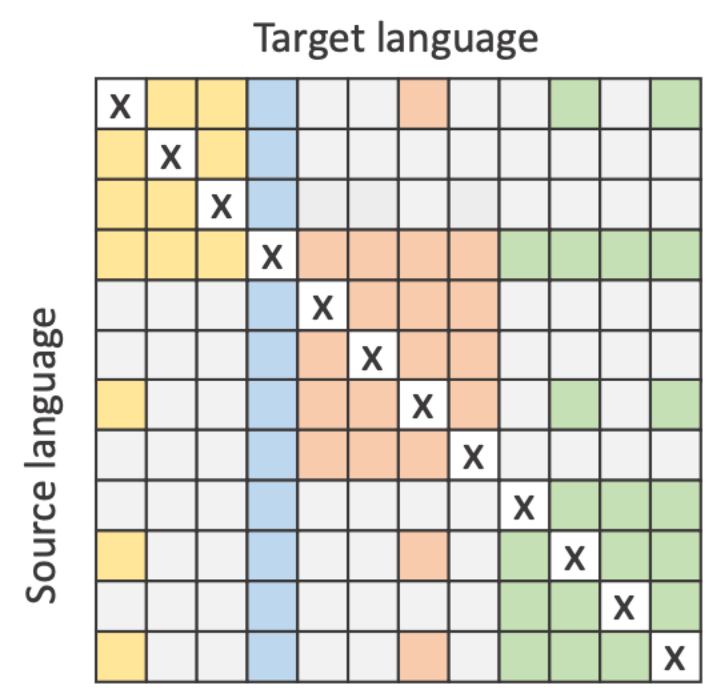
- Back-translation can be used for
    - Semi-supervised machine translation
    - Style transfer
    - Domain transfer
    - (small parallel, large unlabeled data)

Many-to-Many Translation

- A *single model* capable of translating between 100 languages (any of them can be source or target)



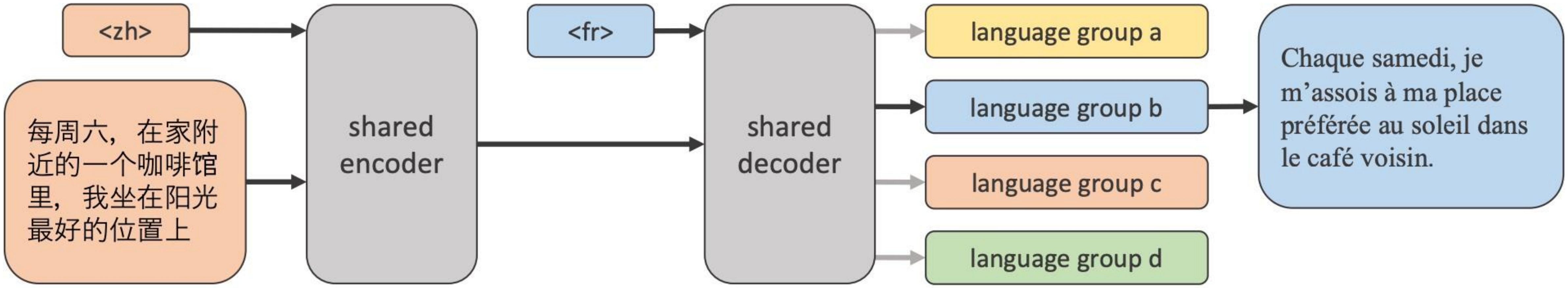
(a) English-Centric Multilingual



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

Beyond English-Centric Multilingual MT paper, Fan et al., arXiv 2021

Adding language-specific params can improve further



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

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**