Low Resource Machine Translation

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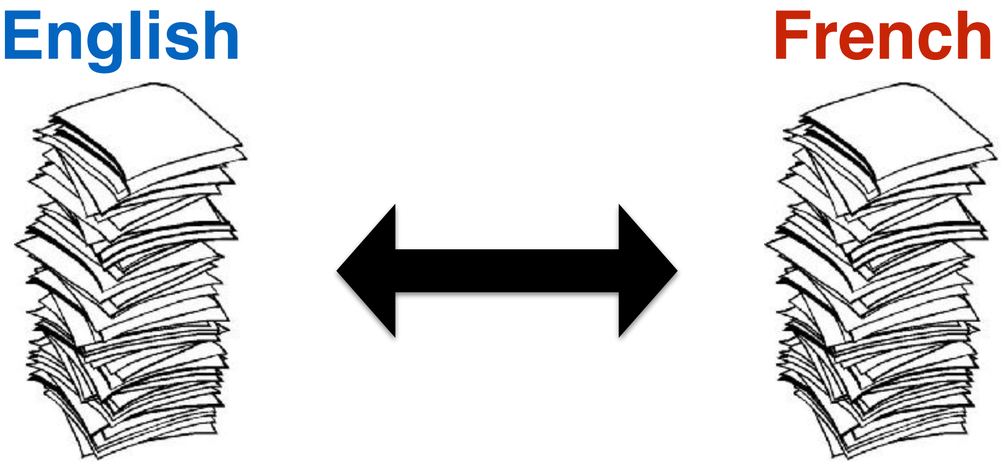
Stanford - CS224N, 10 March 2020

Machine Translation

For Large datasets

Training data



Train NMT

NMT System

Ingredients:
- seq2seq with attention
- *SGD*

Test NMT

life is beautiful → NMT System → *la vie est belle*

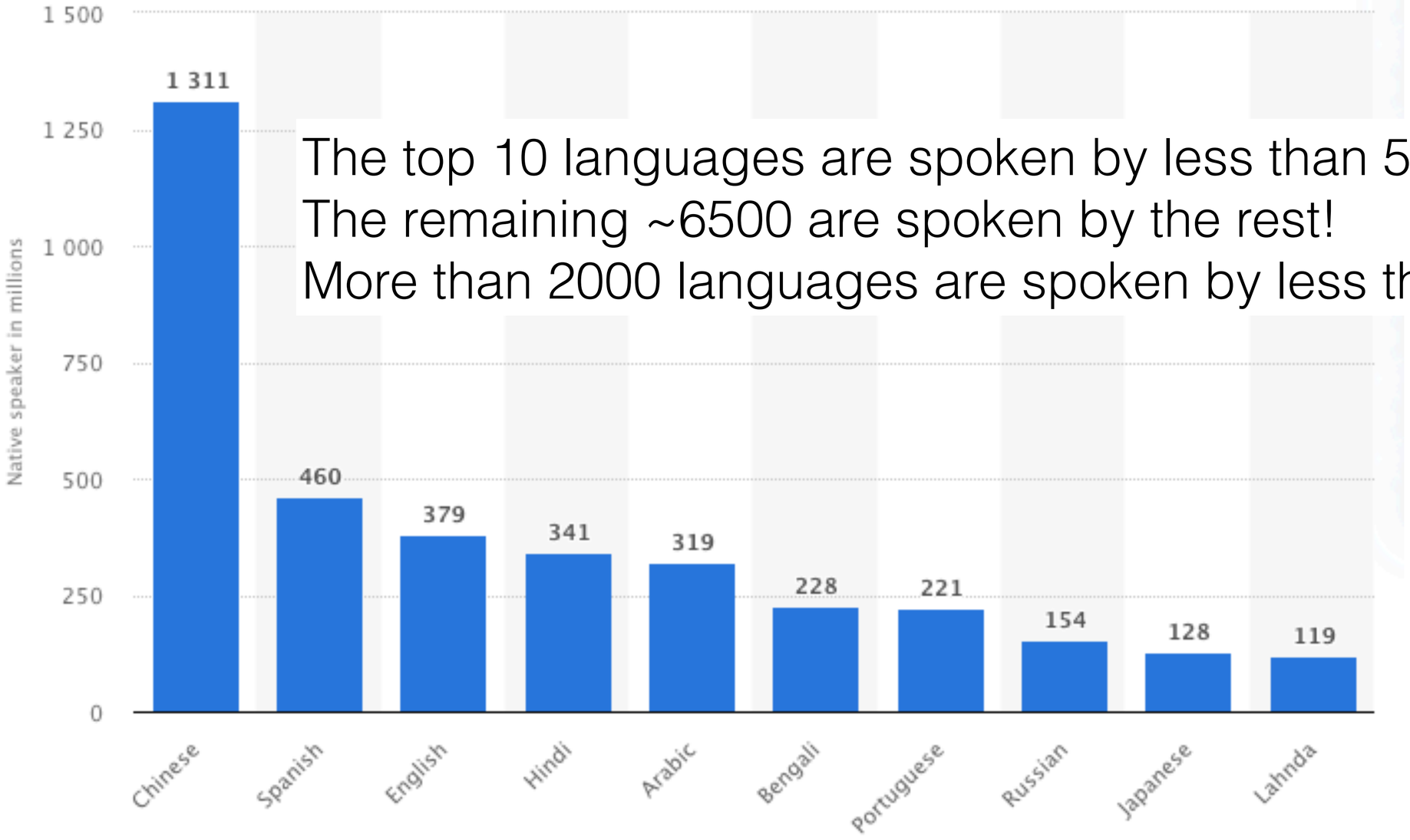
Ingredient:
- beam

Beam search to find the best result

Some Stats

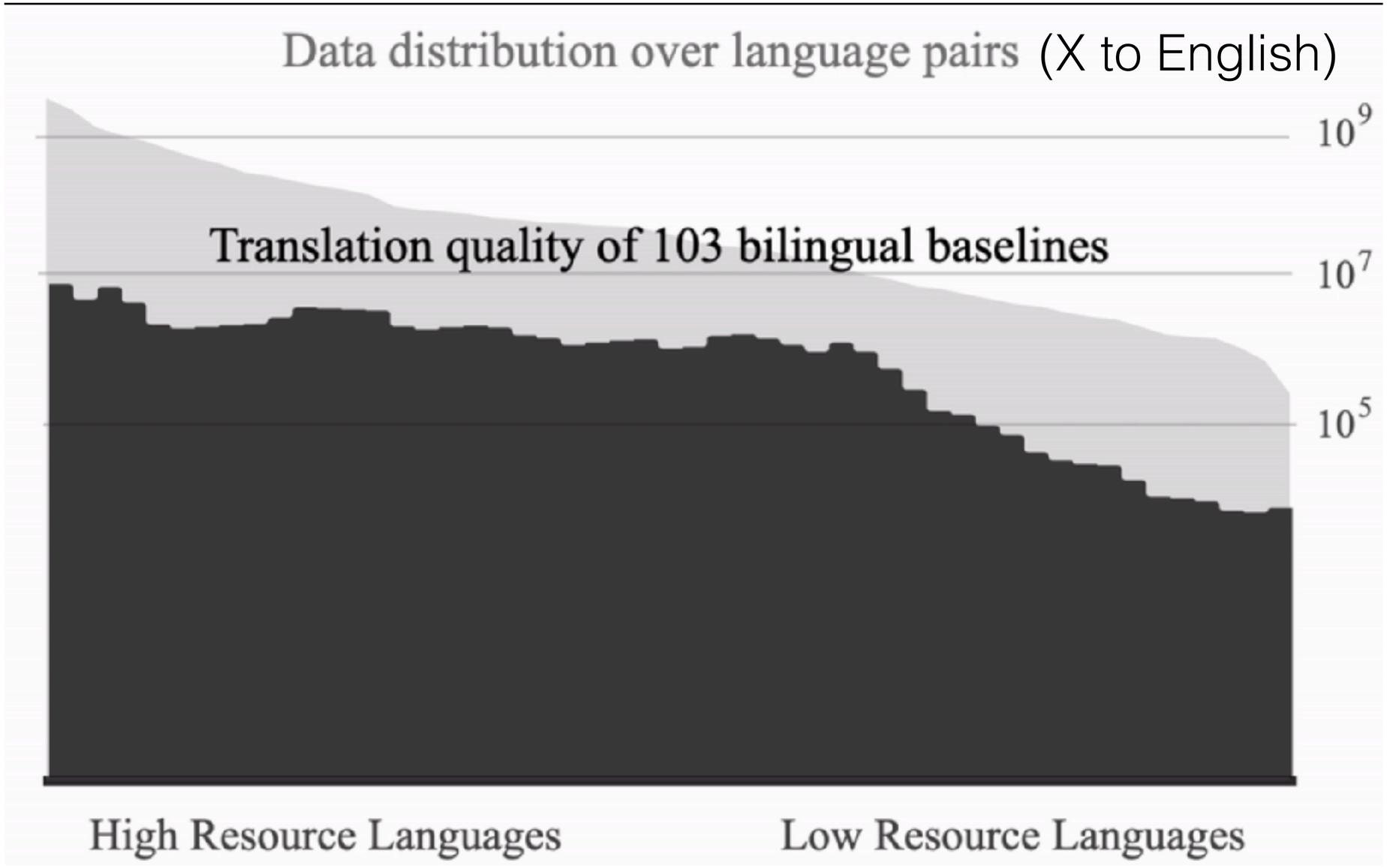
- 6000+ languages in the world
- 80% of the world population does not speak English
- Less than 5% of the people in the world are native English speakers.

The Long Tail of Languages



The top 10 languages are spoken by less than 50% of the people.
The remaining ~6500 are spoken by the rest!
More than 2000 languages are spoken by less than 1000 people.

source: https://www.statista.com/statistics/266808/the-most-spoken-languages-worldwide/



source: https://ai.googleblog.com/2019/10/exploring-massively-multilingual.html

Machine Translation in Practice

Training data

English

Nepali

25M people

Machine Translation in Practice

English **Nepali**

Training data

25M people

Parallel training data (collection of sentences with corresponding translation) is small!

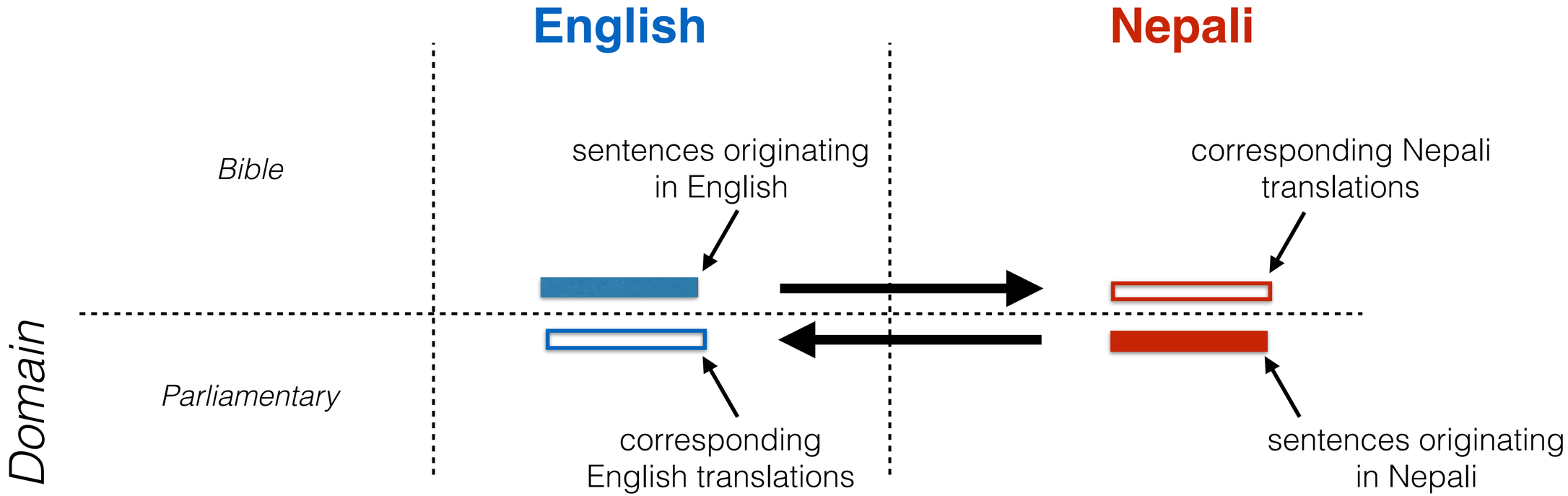
Machine Translation in Practice

English **Nepali**

Training data

Let’s represent data with rectangles. The color indicates the language.

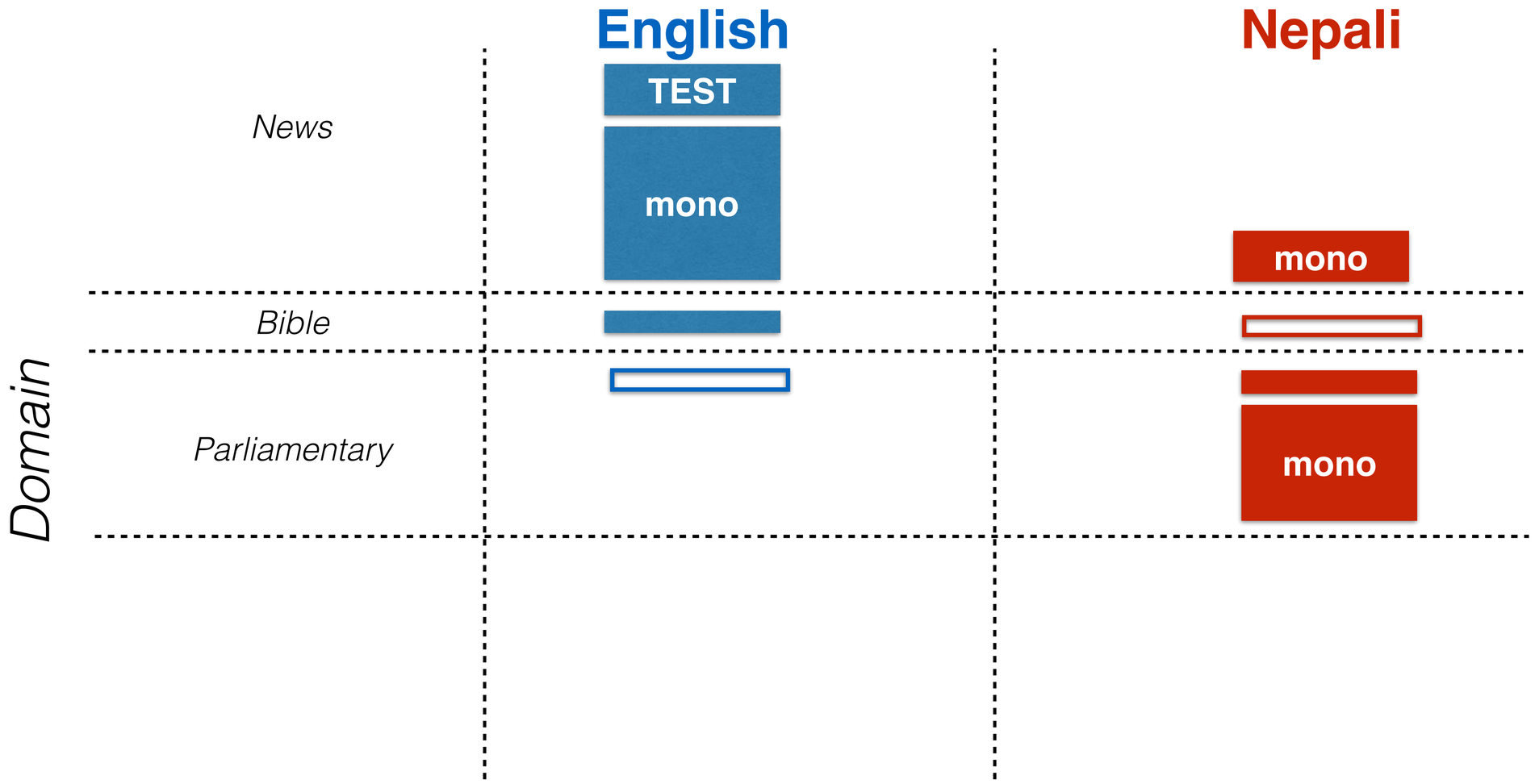
Machine Translation in Practice



Let's represent (human) translations with empty rectangles.

- Some parallel data originates in the source, some in the target language.
- Source and target domains may not match.

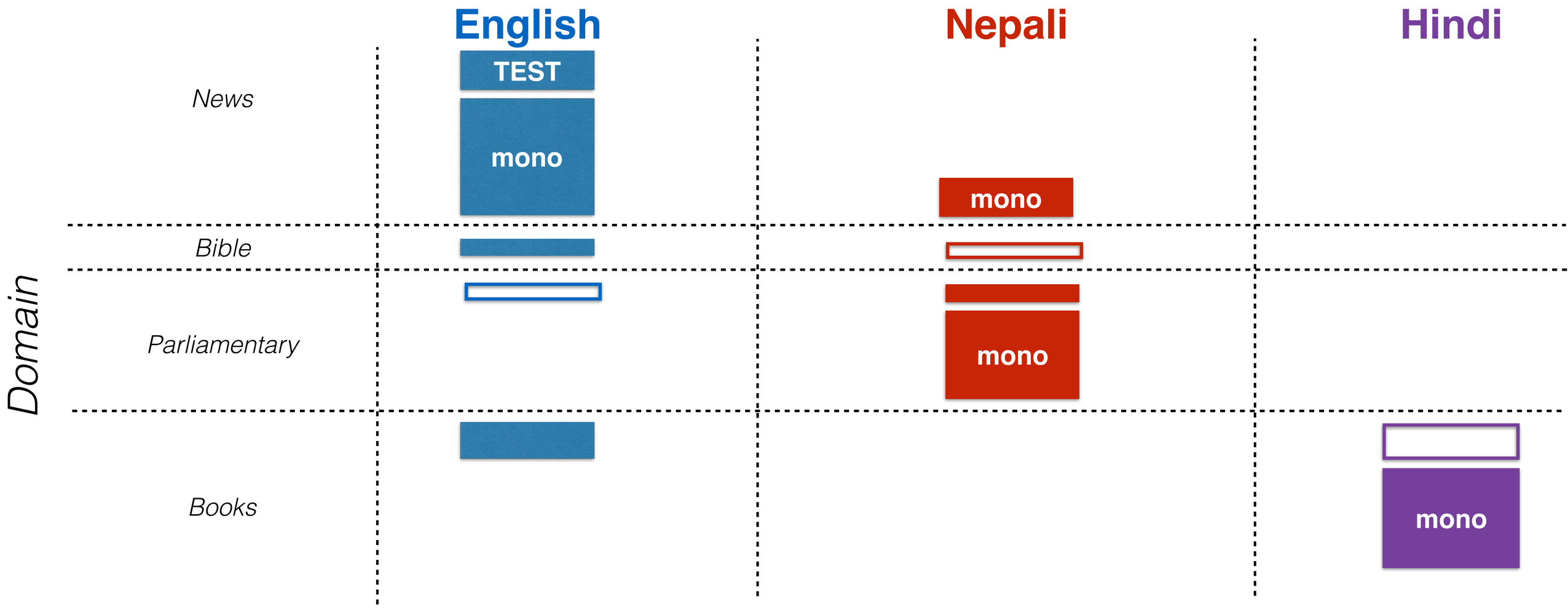
Machine Translation in Practice



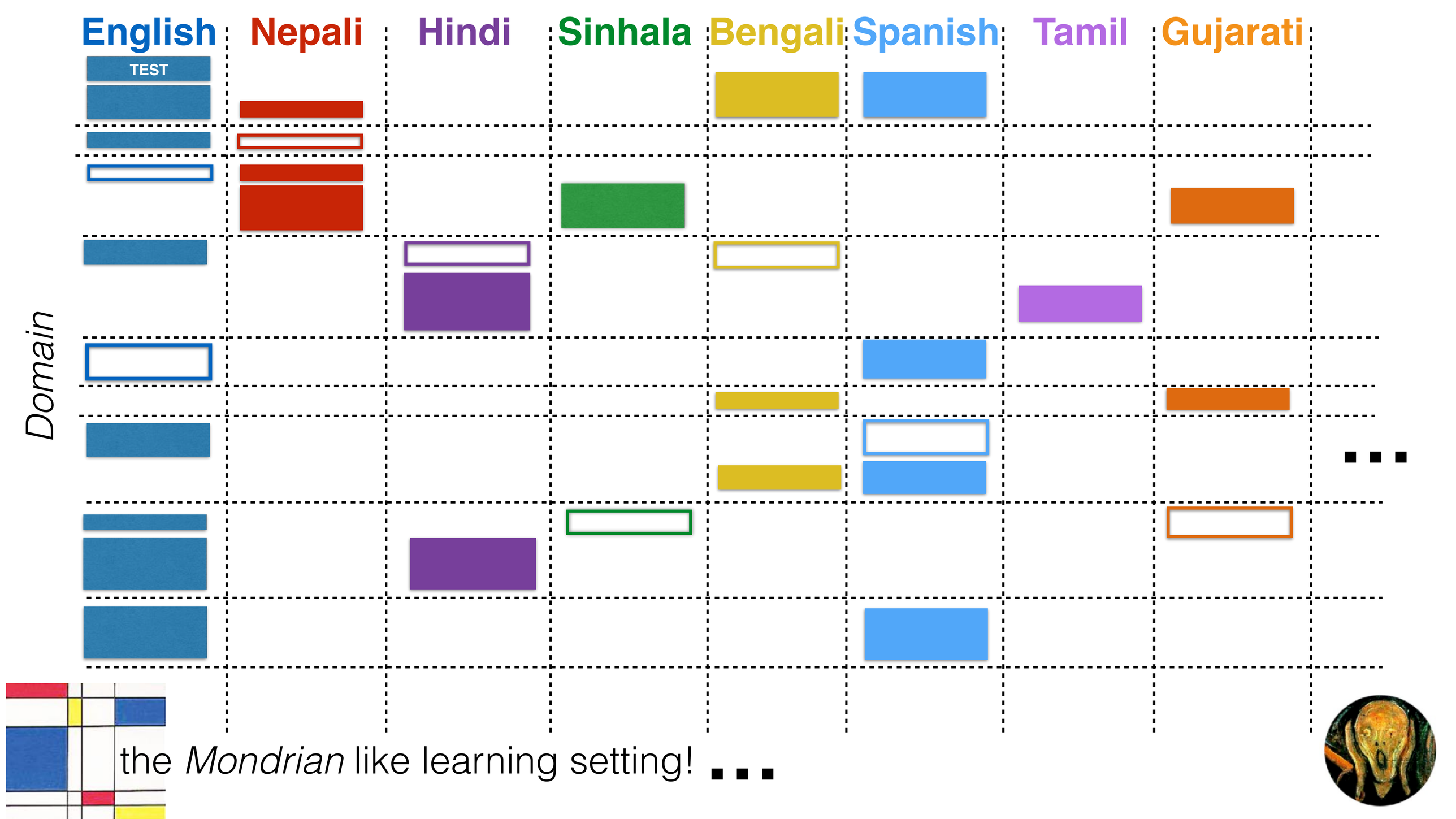
News is the test domain
it has monolingual data but not parallel data

- Test data might be in another domain.
- There might exist source side in-domain monolingual data.

Machine Translation in Practice



- There might be parallel and monolingual data with a high resource language close to the low resource language of interest. This data may belong to a different domain.



the *Mondrian* like learning setting! ...

Low Resource Machine Translation

Loose definition: A language pair can be considered **low resource** when the number of parallel sentences is in the order of 10,000 or less.

Note: modern NMT systems have several hundred million parameters nowadays!

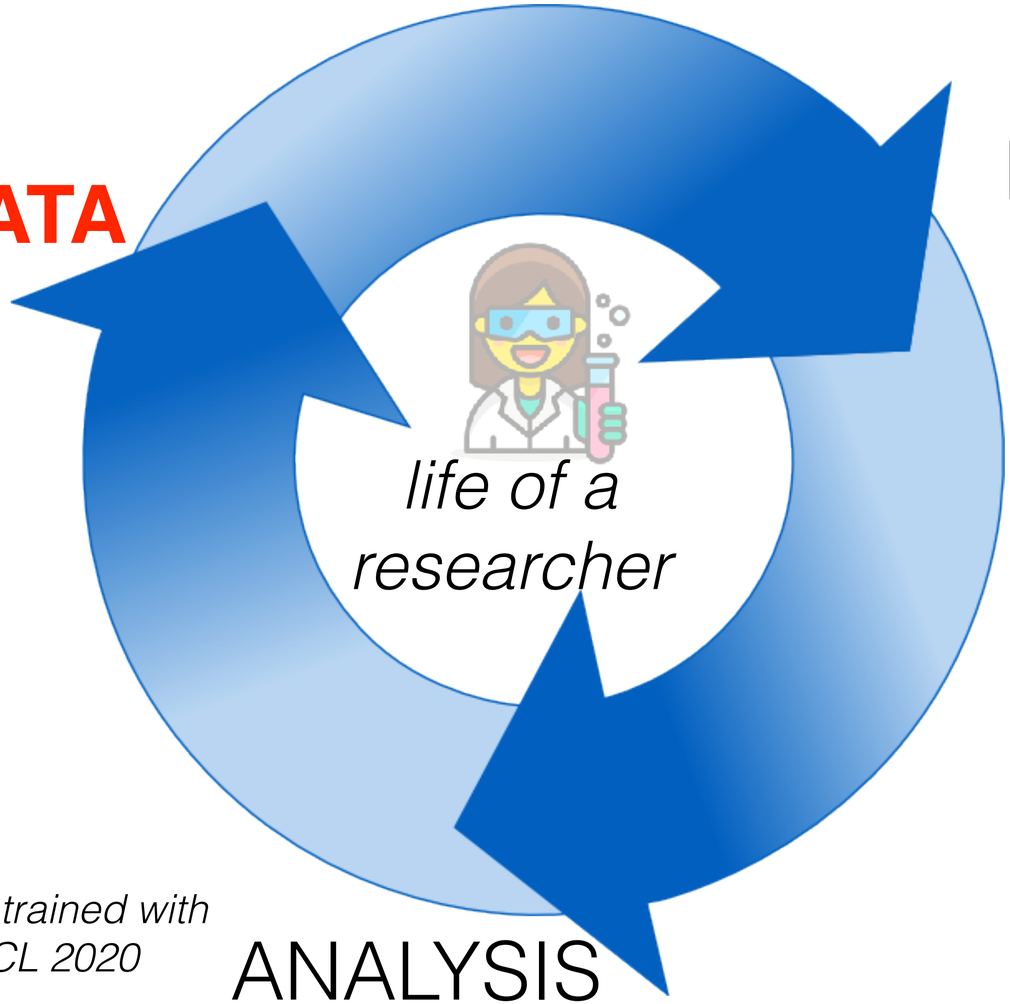
Challenges:

- data
  - sourcing data to train on
  - evaluation datasets
- modeling
  - unclear learning paradigm how to train
  - domain adaptation
  - generalization

Why Low Resource MT Is Interesting?

- It is about learning with less labeled data.
- It is about modeling structured outputs and compositional learning.
- It is a real problem to solve.

Outline



"The FLoRes evaluation for low resource MT:…" Guzmán, Chen et al. 'EMNLP 2019

"Phrase-based & Neural Unsup MT" Lample et al. EMNLP 2018

"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

"Investigating Multilingual NMT Representations at Scale" Kudugunta et al., EMNLP 2019

"Multilingual Denoising Pre-training for NMT" Liu et al., arXiv 2001:08210 2020

"Analyzing uncertainty in NMT" Ott et al. ICML 2018

"On the evaluation of MT systems trained with back-translation" Edunov et al. ACL 2020

"The source-target domain mismatch problem in MT" Shen et al. arXiv 1909.13151 2019

A Big “Small-Data” Challenge

OPUS ... the open parallel corpus

OPUS is a growing collection of translated texts from the web. In the OPUS project we try to convert and align free online data, to add linguistic annotation, a provide the community with a publicly available parallel corpus. OPUS is based on open source products and the corpus is also delivered as an open content package. We used several tools to compile the current collection. All pre-processing is done automatically. No manual corrections have been carried out.

The OPUS collection is growing! Check this page from time to time to see new data arriving ...
Contributions are very welcome! Please contact <jorg.tiedemann@helsinki.fi >

Search & download resources: en (English) | ne (Nepali) | all | show all versions

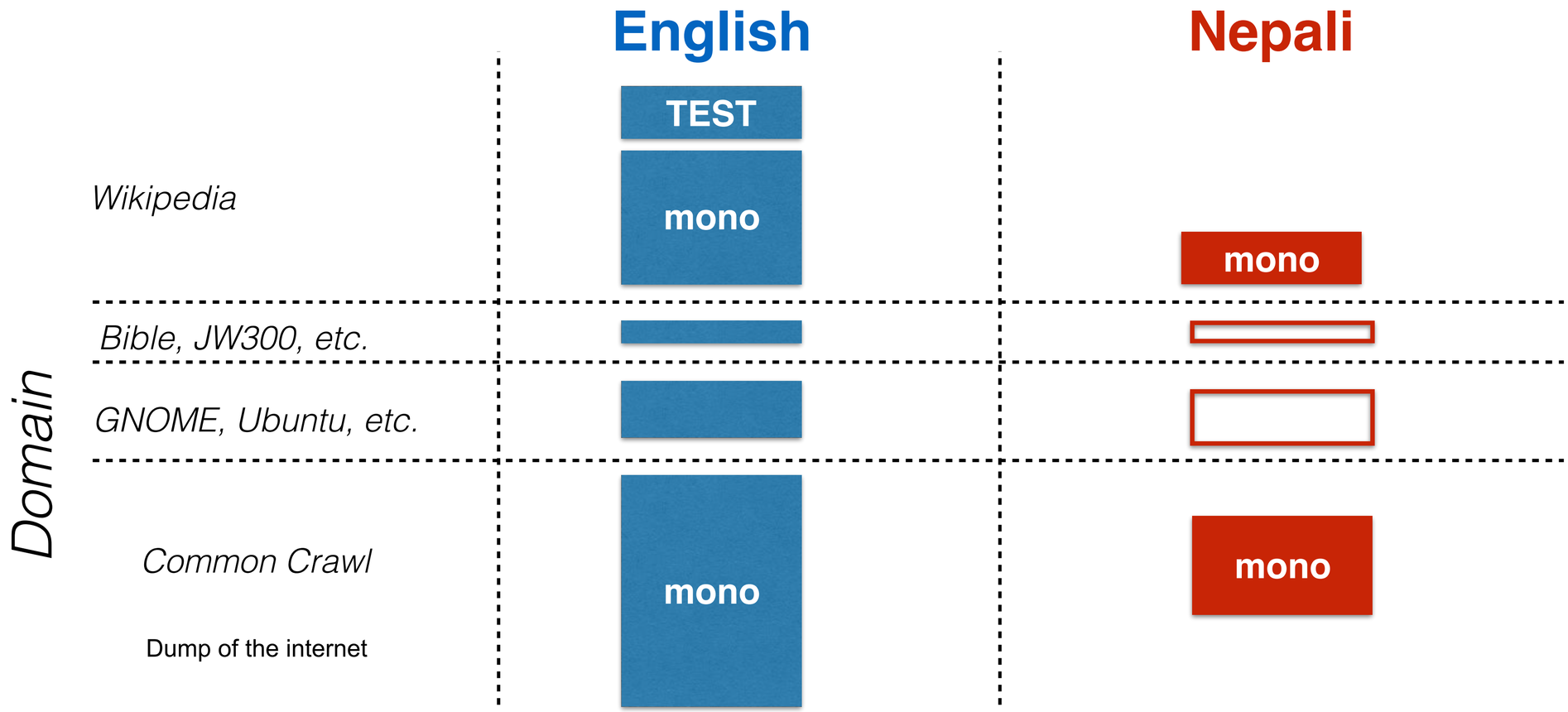
Language resources: click on [tmx | moses | xces | lang-id] to download the data! (raw = untokenized, ud = parsed with universal dependencies, alg = word alignments and phrase tables)

corpus	doc's	sent's	en tokens	ne tokens	XCES/XML	raw	TMX	Moses	mono	raw	ud	alg	dic	freq			other files
JW300 v1	4663	0.4M	6.5M	5.5M	xces en ne	en ne			en ne	en ne				en ne		sample	
wikimedia v20190628	1	2.8k	7.7M	1.2M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne		sample	
GNOME v1	830	0.4M	1.8M	4.7M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt		en ne		sample	
bible-uedin v1	2	61.1k	1.8M	1.6M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne		sample	
KDE4 v2	435	0.1M	0.6M	0.5M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne	query	sample	
Ubuntu v14.10	155	31.7k	0.3M	0.2M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne		sample	
QED v2.0a	60	4.3k	69.8k	41.7k	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne		sample	
total	**6146**	**1.0M**	**18.8M**	**13.7M**	**1.0M**		**0.6M**	**0.6M**									

Large but not useful

http://opus.nlpl.eu/

Case Study: En-Ne



In-domain data: no parallel, little monolingual.
Out-of-domain: little parallel, quite a bit monolingual
No translation originating from Nepali.

A Case Study: En-Ne

- Parallel Training data: versions of bible and ubuntu handbook (<1M sentences).
- Nepali Monolingual data: wikipedia (90K), common crawl (few millions).
- English Monolingual data: unlimited almost.
- Test data: ???

FLoRes Evaluation Benchmark

For Competition

- Validation, test and hidden test set, each with 3000 sentences in English-Nepali and English-Sinhala.
- Sentences taken from *Wikipedia* documents.

Data Collection Process:

- Very expensive and slow.
- Very hard to produce high-quality translations:
  - automatic checks (language model filtering, transliteration filtering, length filtering, language id filtering, etc), automated checks
  - human assessment.

Guzmàn, Chen et al. "The FLoRes evaluation datasets for low resource MT…" EMNLP 2019

Examples

Si-En

අධ්‍ය‍ාපනයෙන් පසු හෝ පවුලේ යුතුකම් ඉටු කරන්නට හෝ රෝග තත්වයන් නිසා සංඝයා උපසම්පදාවෙන් නිතරම ඉවත් වෙති .

original

After education priests leave ordination in order to fulfill duties to the family or due to sickness.

තර්ජන , ශාරීරික හිංසනය , දේපල හානිය , පහර දීම සහ මරාදැමීම මෙම දඩුවම්ය .

translation

Threatening, physical violence, property damage, assault and execution are these punishments.

En-Si

In Serious meets, the absolute score is somewhat meaningless.

සැබෑ තරඟ වලදී ලකුණු සැසඳීම තේරුමක් නැති ක්‍රියාවකි .

Wikipedia originating in Si has different topics than Wikipedia originating in En

Iphone users can and do access the internet frequently, and in a variety of places.

අයිෆෝන් භාවිත කරන්නන්ට නිතරම සහ විවිධ ස්ථානවලදී අන්තර්ජාලයට පිවිසිය හැකිය .

Guzmàn, Chen et al. “The FLoRes evaluation datasets for low resource MT…” EMNLP 2019

Examples

Ne-En

पुरानो समयमा राजालाई सल्लाह दिने सभा ' संसद ' कहलाउँथ्यो ।

In the past, the assembly that advised the king were called 'parliament'.

कार्यकर्ताका रुपमा अफ्रिकन नेशनल कंग्रेसमा आबद्ध भए ।

As a worker African Mandela joined the Congress party.

En-Ne

The academic research tended toward the improvement of basic technologies, rather than their specific applications.

शैक्षिक अनुसन्धानले उनीहरूको विशिष्ट अनुप्रयोगहरूको सट्टा आधारभूत प्रविधिको सुधारको पक्षमा जोड दिए ।

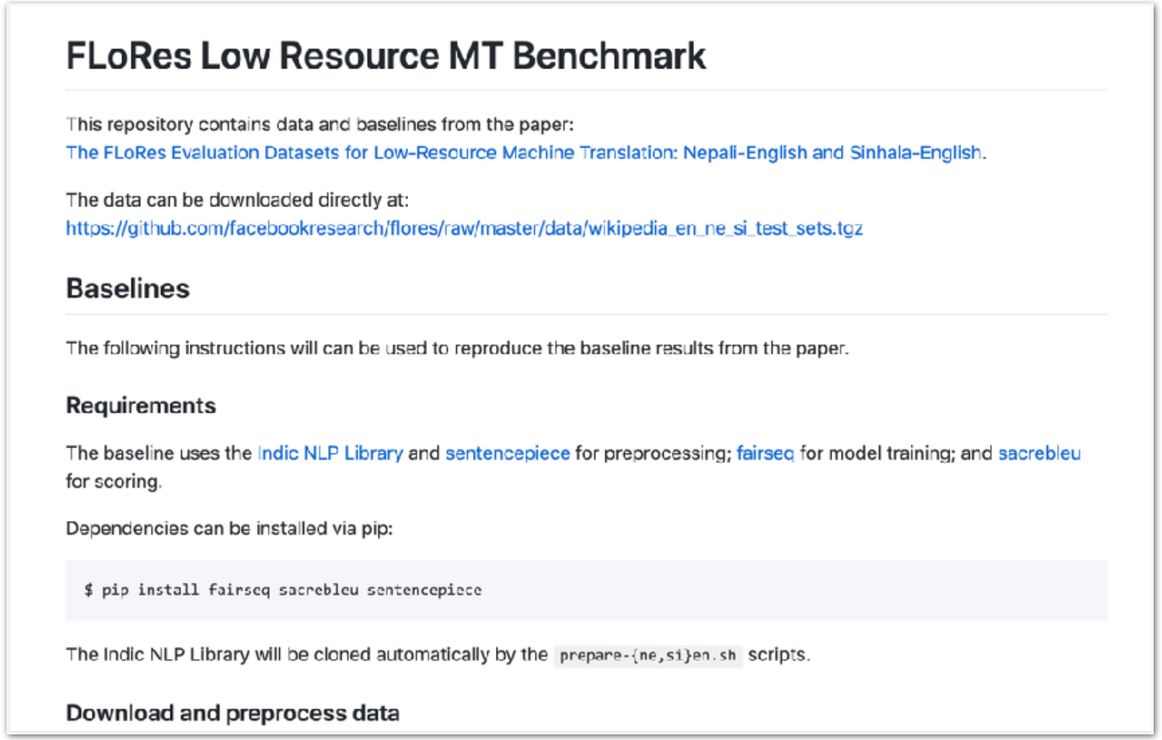
It has automatic spell checking and correction, predictive word capabilities, and a dynamic dictionary that learns new words.

यसमा स्वचालित हिज्जे जाँच र सुधार छ , भविष्यवाणी शब्द क्षमताहरू , र गतिशील शब्दकोश हुन्छ जसले नयाँ शब्दहरू सिक्छ ।

Guzmàn, Chen et al. “The FLoRes evaluation datasets for low resource MT…” EMNLP 2019

FLoRes

- Useful to evaluate truly low resource language pairs.
  - WMT 2019 and WMT 2020 shared filtering task.
  - Several publications.
- Sustained effort, more to come…



FLoRes Low Resource MT Benchmark

This repository contains data and baselines from the paper:
The FLoRes Evaluation Datasets for Low-Resource Machine Translation: Nepali-English and Sinhala-English.

The data can be downloaded directly at:
https://github.com/facebookresearch/flores/raw/master/data/wikipedia_en_ne_si_test_sets.tgz

Baselines

The following instructions will can be used to reproduce the baseline results from the paper.

Requirements

The baseline uses the Indic NLP Library and sentencepiece for preprocessing; fairseq for model training; and sacrebleu for scoring.

Dependencies can be installed via pip:

```
$ pip install fairseq sacrebleu sentencepiece
```

The Indic NLP Library will be cloned automatically by the `prepare-{ne,si}en.sh` scripts.

Download and preprocess data

https://github.com/facebookresearch/flores

data & baseline models

What Did We Learn?

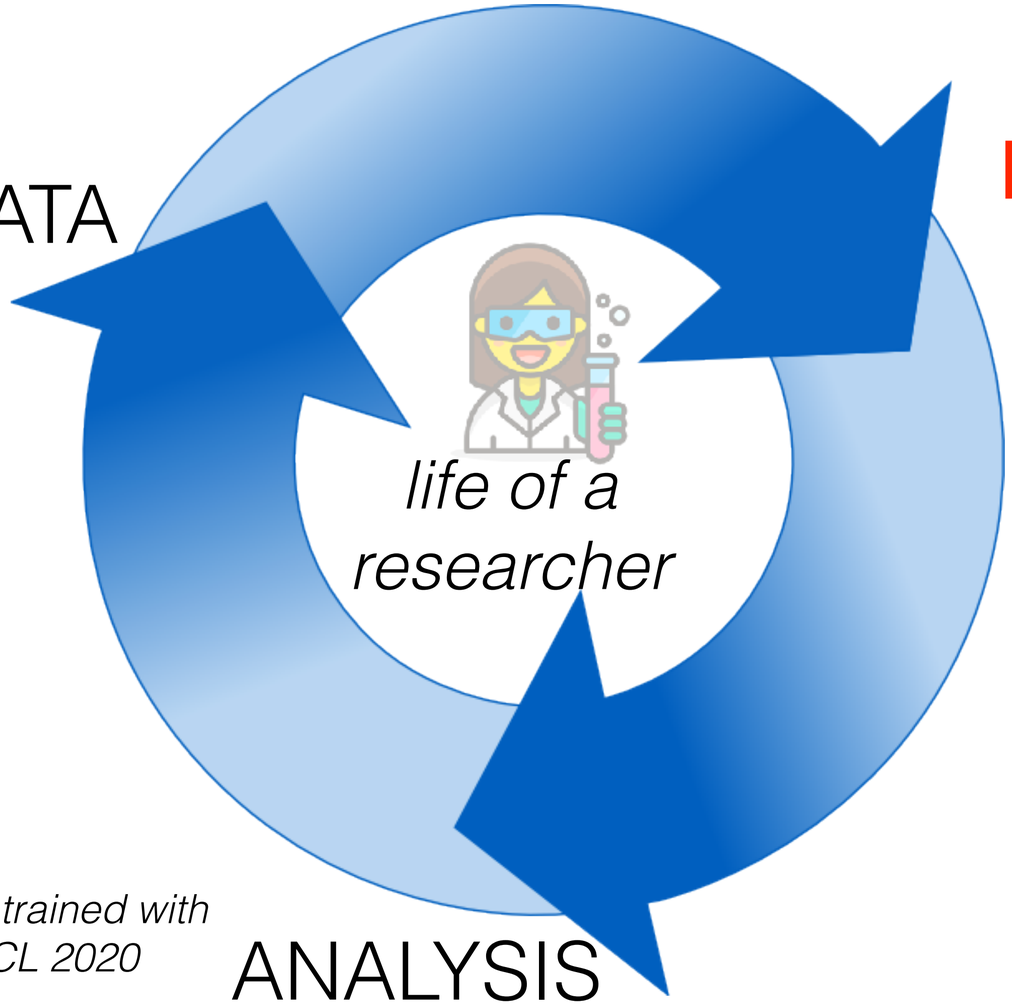
- Data is often as or more important than designing a model.
- Collecting data is not trivial.
- Look at the data!!

Language model for Nepali: Count based n-gram, prob of one word given context

Score: avg of log prob of words in a sentence

Threshold to determine if fluent or not.

Outline



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"Massively Multilingual NMT" Aharoni et al.,ACL 2019

"Multilingual Denoising Pre-training for NMT" Liu et al., arXiv 2001:08210 2020

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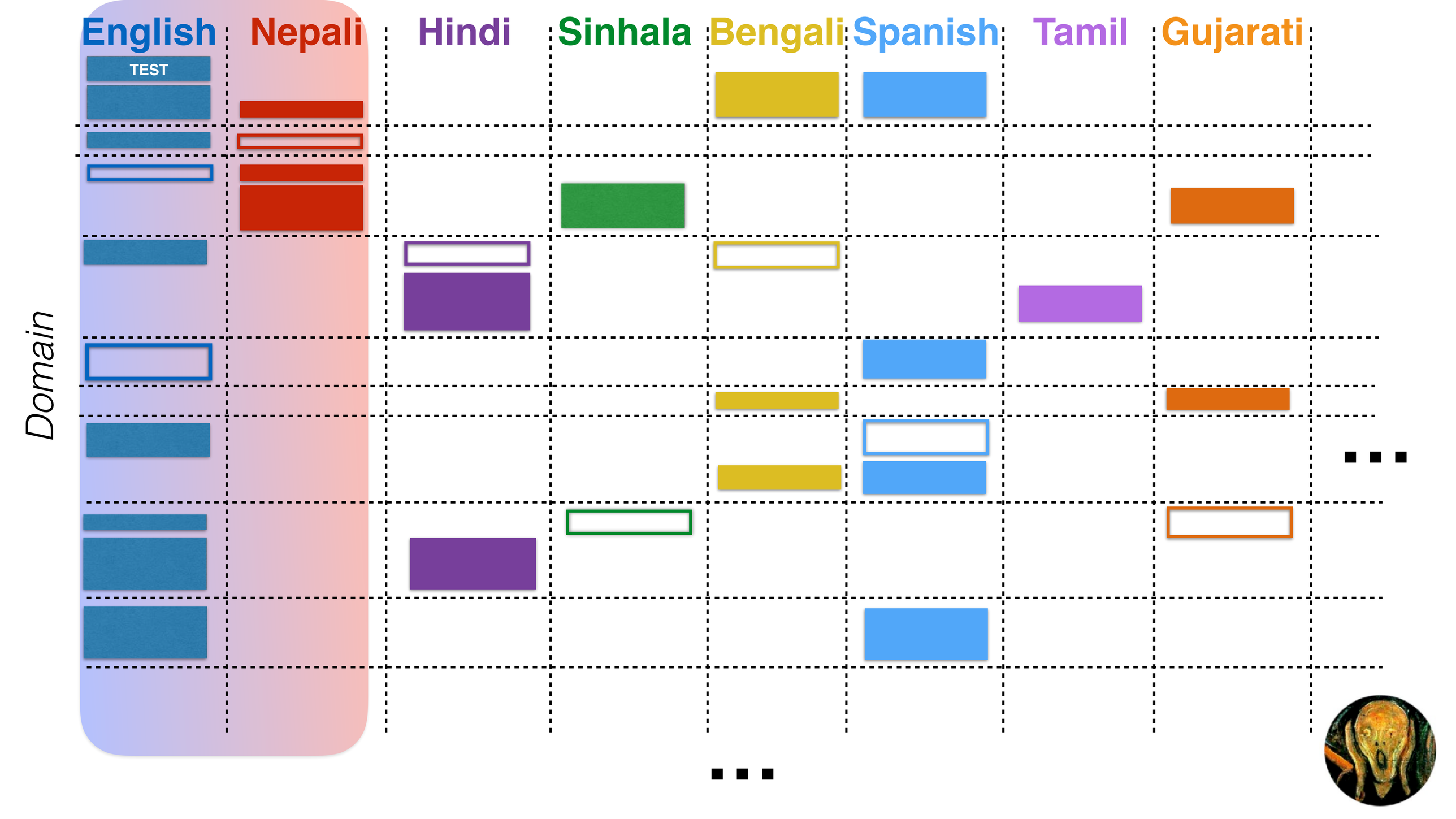
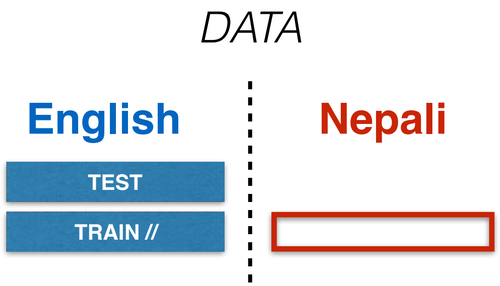
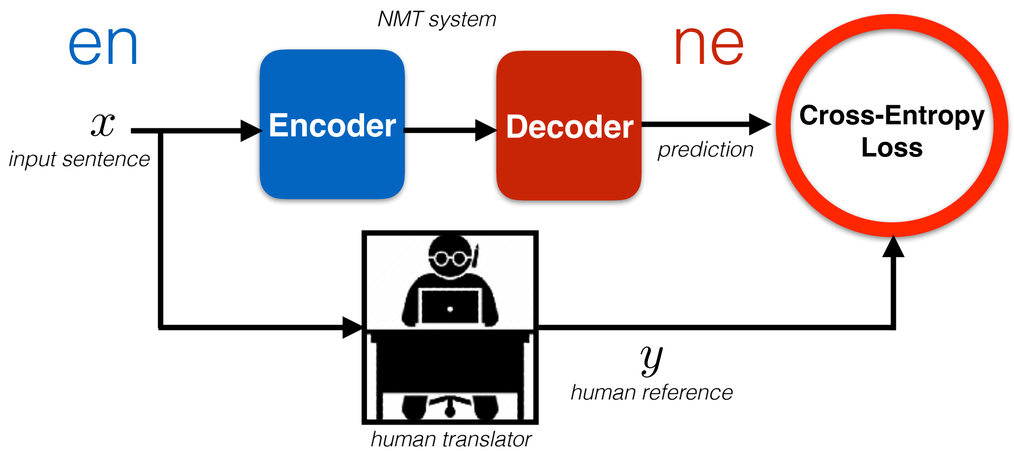

English
Nepali
Hindi
Sinhala
Bengali
Spanish
Tamil
Gujarati
TEST
Domain
...
...

ML Perspective: Supervised Learning



English and its translation in Nepali



Training Dataset

$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$

Learning Framework: Supervised Learning.

Per-sample loss:

$$\mathcal{L}(\theta) = -\log p(y|x)$$

usual attention-based transformer

If N is small, how can we further regularize the model?

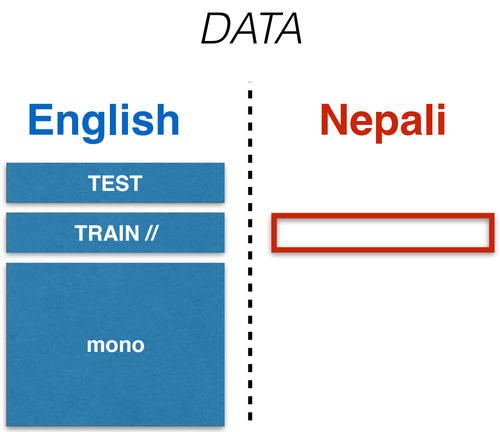
- dropout [1]
- label smoothing [2]

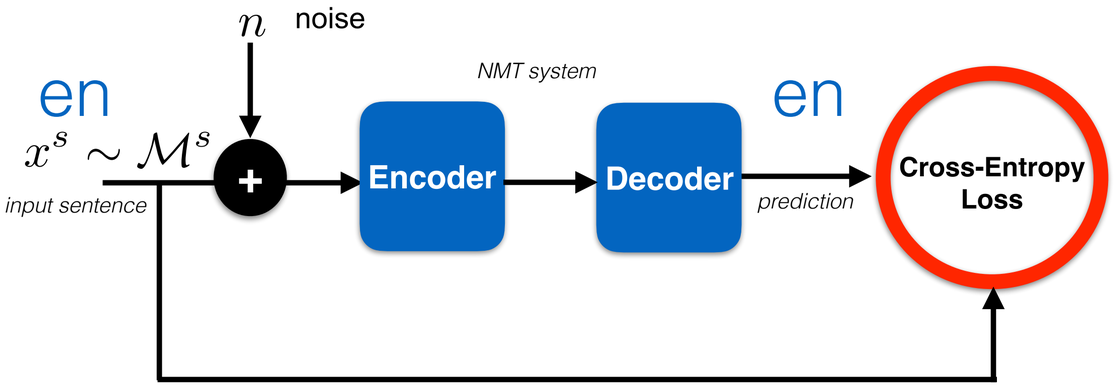
Label Smoothing is a regularization technique that introduces noise for the labels. Combat overconfidence and improve generalization in deep neural networks

[1] Srivastava et al. "Dropout: a simple way to prevent neural networks from overfitting" JMLR 2014

[2] Szegedy et al. "Rethinking the inception architecture for computer vision" CVPR 2016

ML Perspective: Semi-Supervised Learning





between actual and predicted

encoder parameters are shared between previous and this

Training Dataset

$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$

$$\mathcal{M}^s = \{x^s_j\}_{j=1,..,M_s}$$

Adding source-side monolingual data.
Idea: model p(x).

Noise: word drop, swap, etc.

E.g.: The cat the on sat mat.
The cat sat on the.

just enough noise to train the model

Learning Framework: DAE

Either pre-train or add a DAE loss to the supervised cross-entropy term.

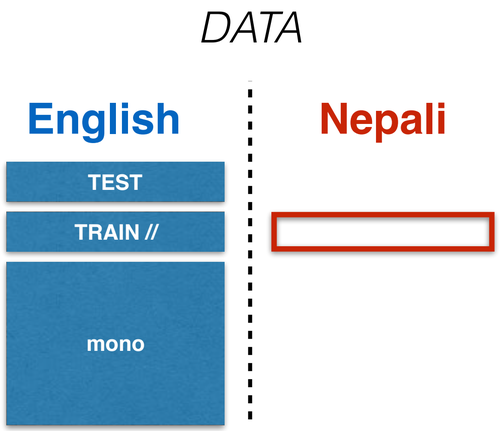
$$\mathcal{L}^{DAE}(\theta) = -\log p(x|x+n)$$

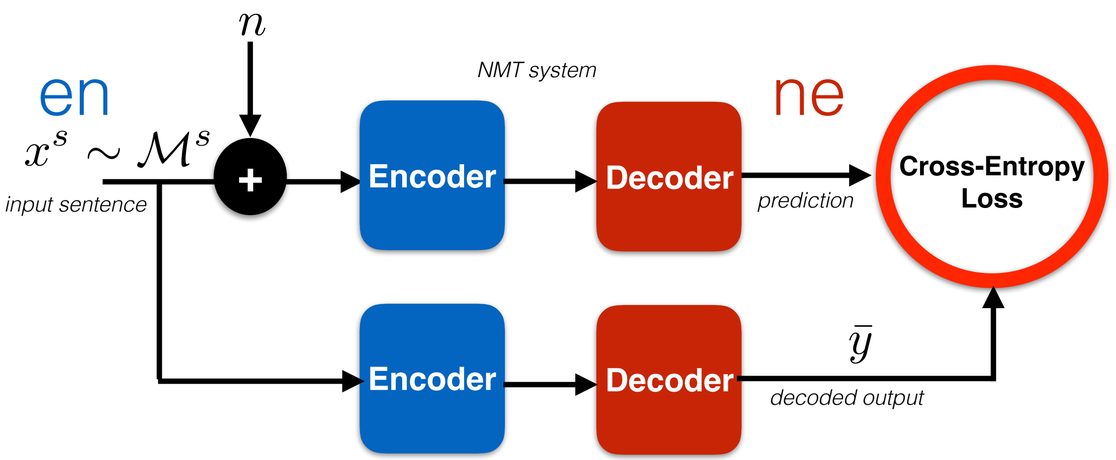
noised x

can also use this loss by adding with previous loss

Vincent et al. "Stacked denoising auto-encoders:…" JMLR 2010
Liu et al. "Multilingual denoising pretraining for NMT" arXiv:2001.08210 2020

ML Perspective: Semi-Supervised Learning





loss calculated between noise and without noise

Training Dataset

$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$

$$\mathcal{M}^s = \{x_j^s\}_{j=1,..,M_s}$$

Adding source-side monolingual data.
An alternative approach to DAE.

$$\mathcal{L}^{ST}(\theta) = -\log p(\bar{y}|x+n)$$

$$\mathcal{L}(\theta) = \mathcal{L}^{\text{sup}}(\theta) + \lambda \mathcal{L}^{\text{ST}}(\theta)$$

Learning Framework: Self-Training (ST).

ALGORITHM

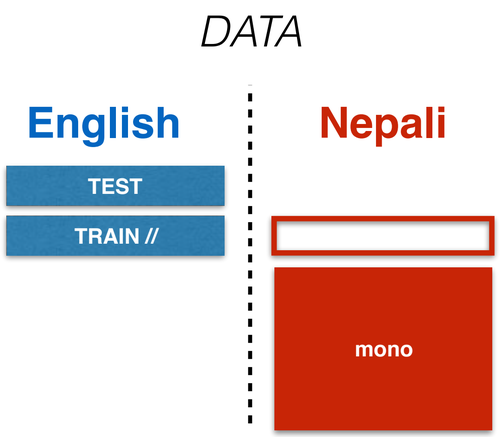
- train model $p(y|x)$ on $\mathcal{D}$
- repeat
  - decode $x^s \sim \mathcal{M}^s$ to $\bar{y}$ and create additional dataset $\mathcal{A}^s = \{(x_j^s, \bar{y}_j)\}_{j=1,..,M_s}$
  - retrain model on: $\mathcal{D} \cup \mathcal{A}^s$

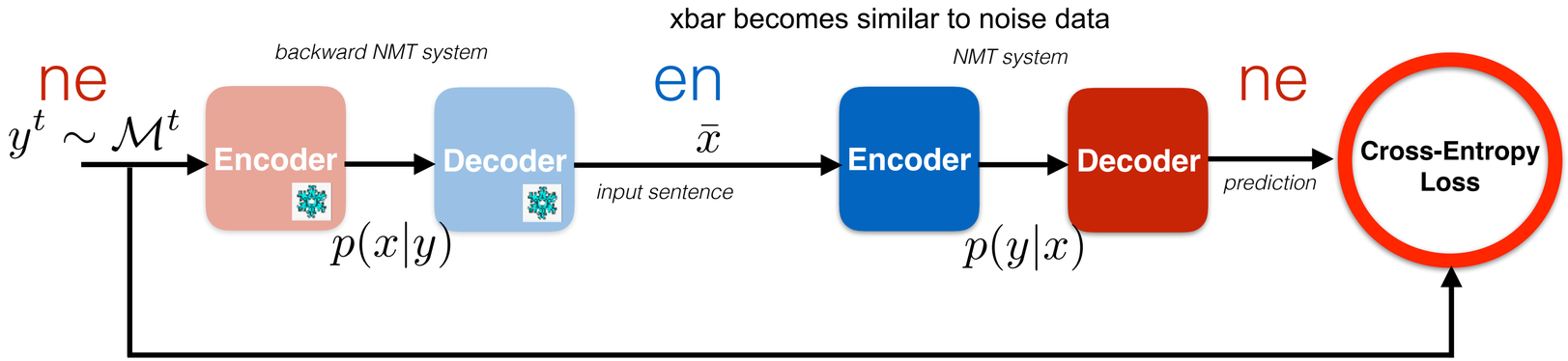
m+noise

Key elements: decoding and training noise.

He et al. "Revisiting self-training for neural sequence generation" ICLR 2020

ML Perspective: Semi-Supervised Learning





Training Dataset

$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$
$$\mathcal{M}^t = \{y_k^t\}_{k=1,..,M_t}$$

Adding target-side monolingual data.
Two benefits:

a) Decoder learns a good language model.
b) Better generalization via data augmentation.
c) Unlike ST, target is correct but input is not.

$$\mathcal{L}^{BT}(\theta) = -\log p(y|\bar{x})$$
$$\mathcal{L}(\theta) = \mathcal{L}^{\sup}(\theta) + \lambda \mathcal{L}^{\mathrm{BT}}(\theta)$$

Learning Framework: Back-Translation (BT).

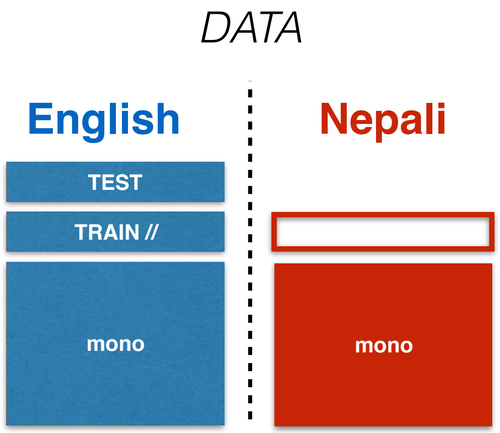
ALGORITHM

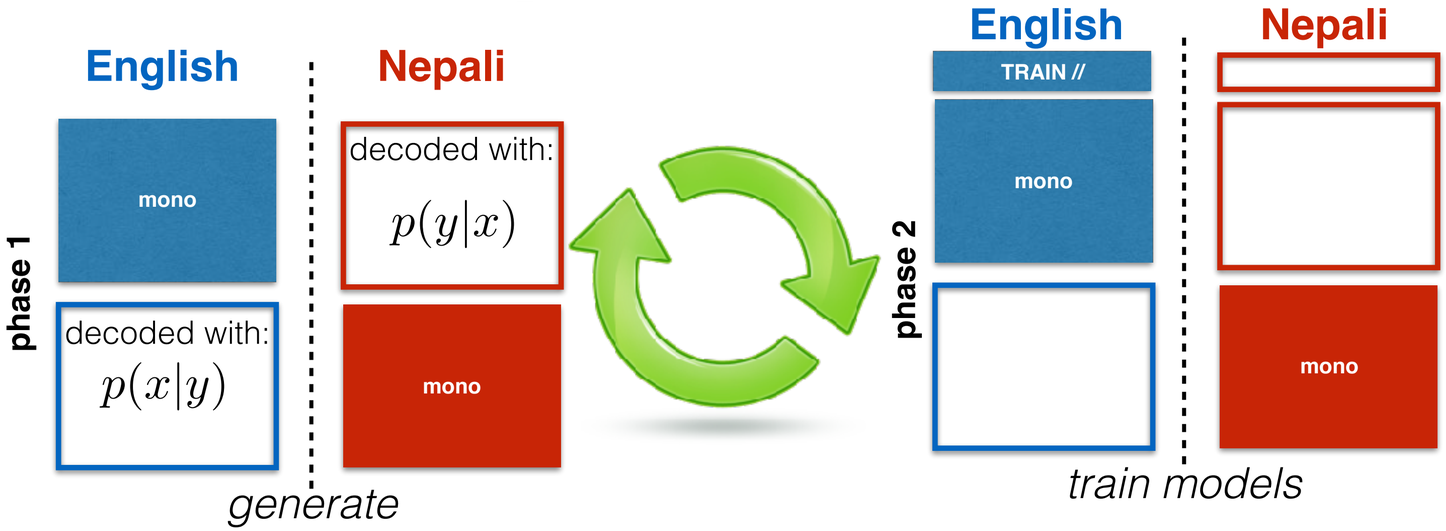
- train model $p(x|y)$ and $p(y|x)$ on $\mathcal{D}$
- decode $y^t \sim \mathcal{M}^t$ to $\bar{x}$ with $p(x|y)$, create additional dataset $\mathcal{A}^t = \{(\bar{x}_k, y_k^t)\}_{k=1,..,M_t}$
- retrain model $p(y|x)$ on: $\mathcal{D} \cup \mathcal{A}^t$

Initializing at random is also possible

Sennrich et al. "Improving NMT models with monolingual data" ACL 2016

ML Perspective: Semi-Supervised Learning





Training Dataset

$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$
$$\mathcal{M}^t = \{y_k^t\}_{k=1,..,M_t}$$
$$\mathcal{M}^s = \{x_j^s\}_{j=1,..,M_s}$$

Adding both source & target-side monolingual data.

$$\mathcal{L}^{\text{total}}(\theta) = -\log p(y|x) - \lambda_1 \log p(y^t|\bar{x}^t) - \lambda_2 \log p(\bar{y}^s|x^s)$$

Most Effective

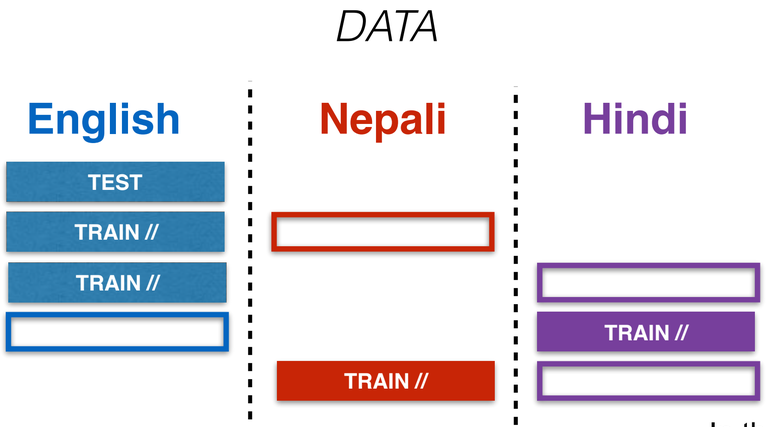
Learning Framework: Iterative ST & BT.

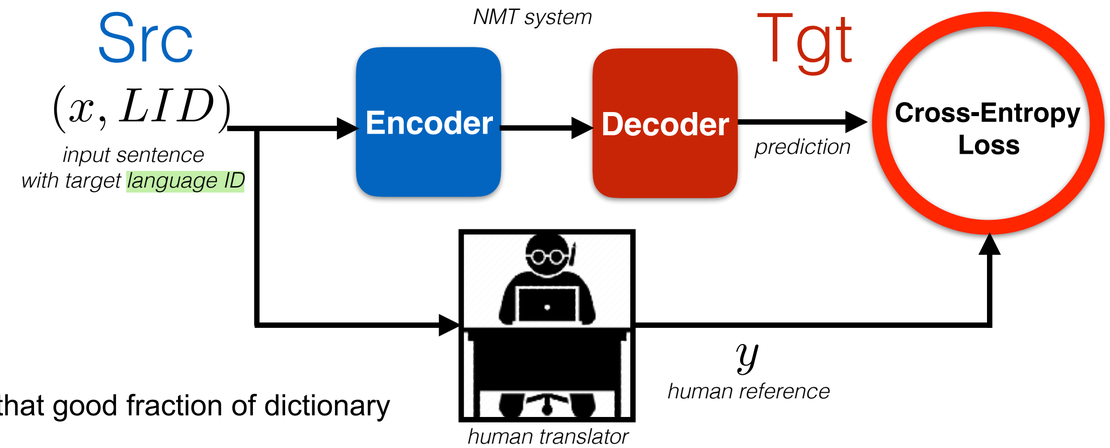
ALGORITHM

- train model $p(x|y)$ and $p(y|x)$ on $\mathcal{D}$
- repeat
  - phase 2 phase 1
    - decode $y^t \sim \mathcal{M}^t$ to $\bar{x}$ with $p(x|y)$, create additional dataset $\mathcal{A}^t = \{(\bar{x}_k, y_k^t)\}_{k=1,..,M_t}$
    - decode $x^s \sim \mathcal{M}^s$ to $\bar{y}$ with $p(y|x)$, create additional dataset $\mathcal{A}^s = \{(x_j^s, \bar{y}_j)\}_{j=1,..,M_s}$
  - retrain both $p(y|x)$ and $p(x|y)$ on: $\mathcal{D} \cup \mathcal{A}^t \cup \mathcal{A}^s$

Shen et al. "The source-target domain mismatch problem in MT" arXiv:1909.13151 2019
Chen et al. "FBAI WAT'19 Myanmar-English translation task submission" WAT@EMNLP 2019

ML Perspective: Multi-Task/Multi-Modal





In this scenario it is also possible that good fraction of dictionary that is shared

Training Dataset

$$\mathcal{D}_{\text{en,ne}} \cup \mathcal{D}_{\text{en,hi}} \cup \mathcal{D}_{\text{hi,en}} \cup \mathcal{D}_{\text{ne,hi}}$$

Adding parallel data in other languages.

$$\mathcal{L}(\theta) = -\sum_{s,t} \mathbb{E}_{(x,y)\sim\mathcal{D}_{s,t}} [\log p(y|x;t)]$$

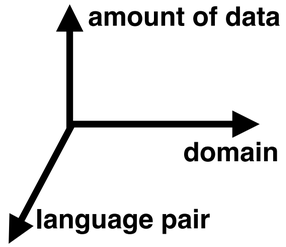
Learning Framework: Multilingual Training

Share the same encoder and the same decoder with all the language pairs.
Prepend a target language identifier to the source sentence to inform decoder of desired language.
Concatenate all the datasets together.
Train using standard cross-entropy loss.

Johnson et al. "Google's multilingual NMT system…" ACL 2017
Aharoni et al. "Massively multilingual NMT" ACL 2019

Conclusion so far…

- Assuming no domain effect, there are lots of training paradigms depending on the available data.



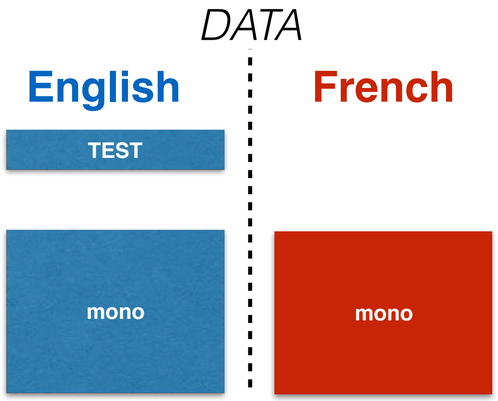
- It is hard to predict what works best.
- In general, DAE pretraining, (iterative) BT and multi-lingual training perform strongly on low resource languages.
- All these methods can be combined together, but it requires some level of craftsmanship…

- Final touch: ensembling, fine-tuning, distillation, etc.

Open Challenges

- Diversity of domains and varying translation quality.
- Wildly varying dataset sizes.
- Diversity of language pairs.
- Training large models to handle large datasets, as soon as we put together lots of language pairs and monolingual data.

Case Study #1: Unsupervised MT



$$\mathcal{M}^t = \{y_k^t\}_{k=1,..,M_t}$$
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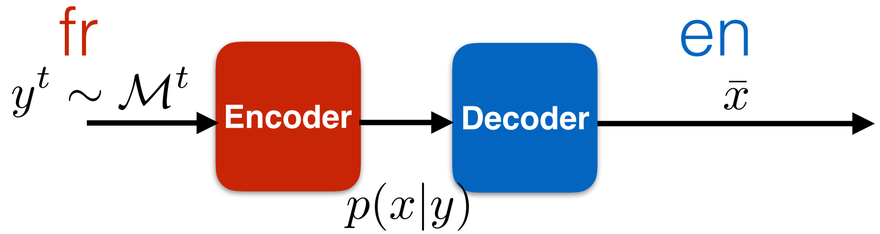
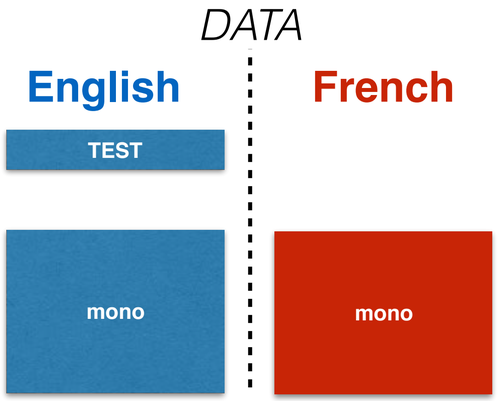


Lample et al. "Phrase-based and neural unsupervised MT" EMNLP 2018
Artetxe et al. "An effective approach to unsupervised MT" ACL 2019

Case Study #1: Unsupervised MT



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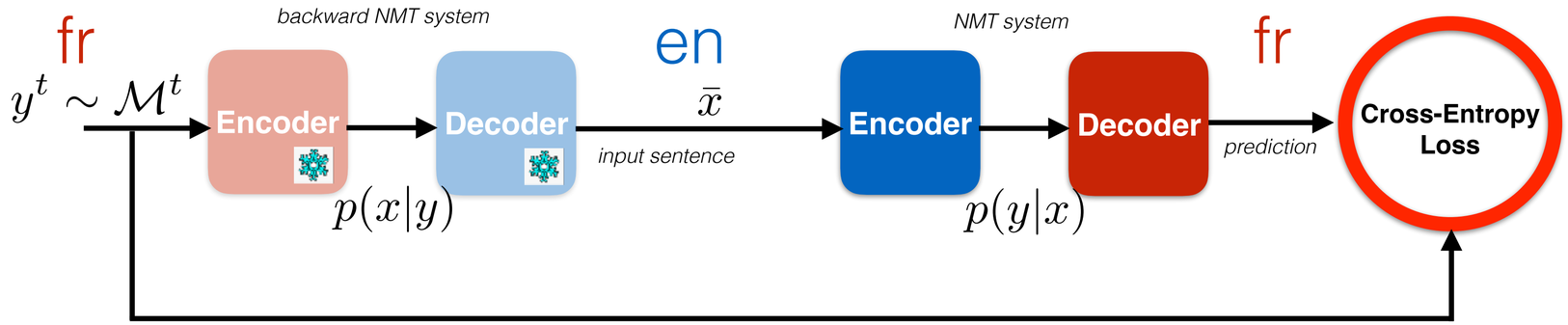
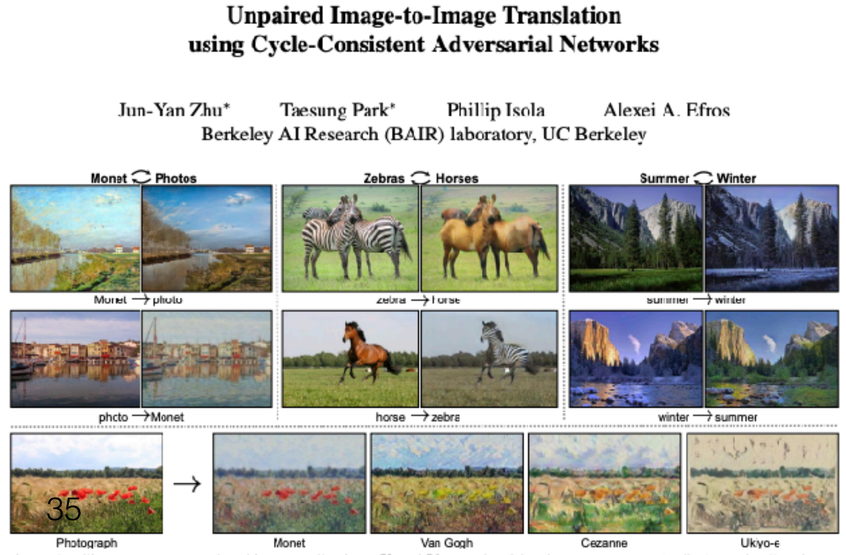


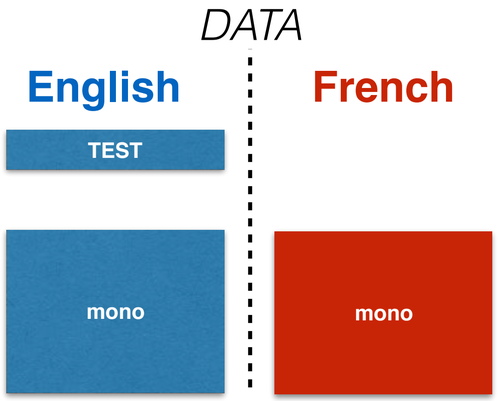
…and vice versa starting from English.

This is an example of auto-encoding or cycle consistency.

Problem: lack of constrained on $\bar{x}$



Case Study #1: Unsupervised MT



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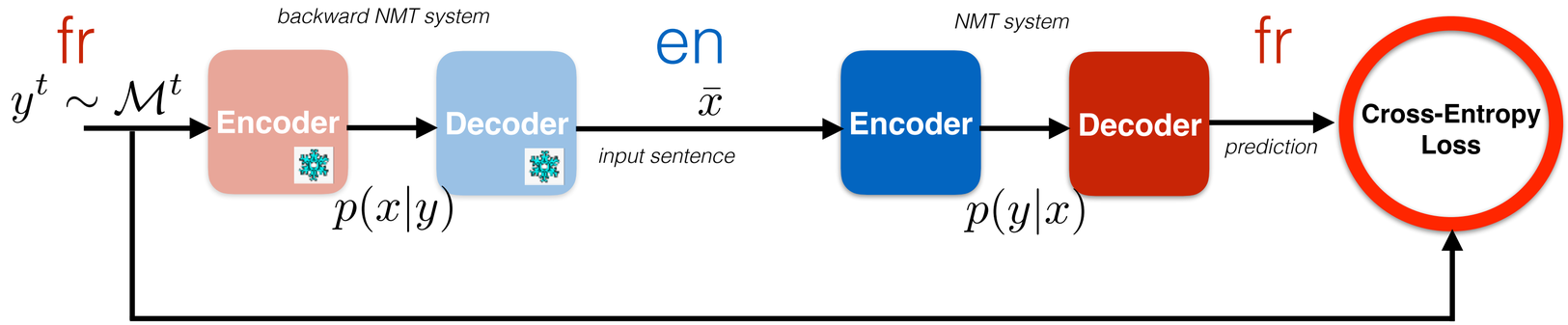
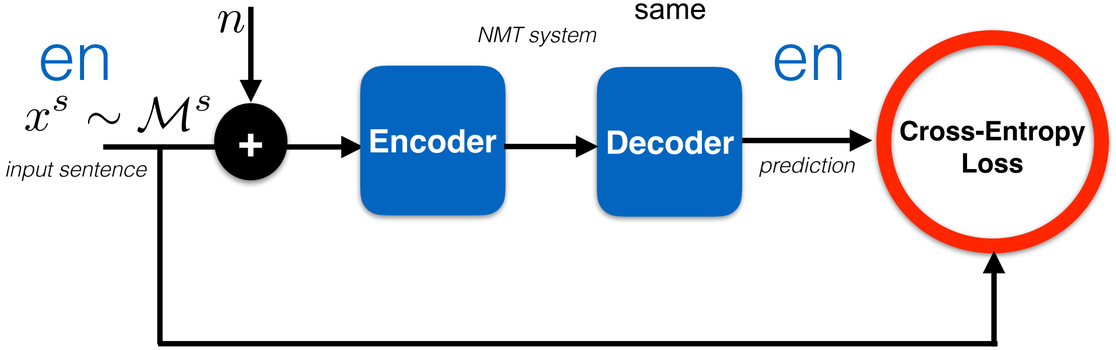


this decoder and one above generating english anguages are same



Denoising autoencoding

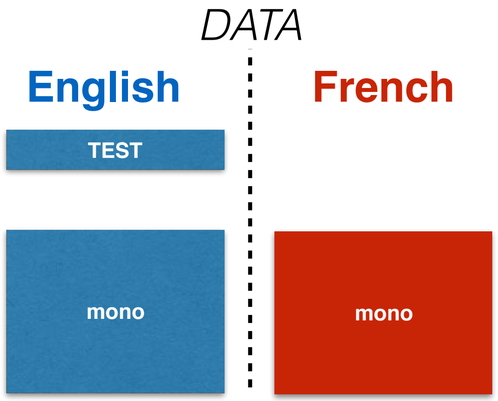
DAE makes sure decoder outputs fluently in the desired language.

Problem: lack of modularity.

Decoder may behave differently when fed with representations from French encoder VS English encoder.

Lample et al. "Phrase-based and neural unsupervised MT" EMNLP 2018
Artetxe et al. "An effective approach to unsupervised MT" ACL 2019

Case Study #1: Unsupervised MT



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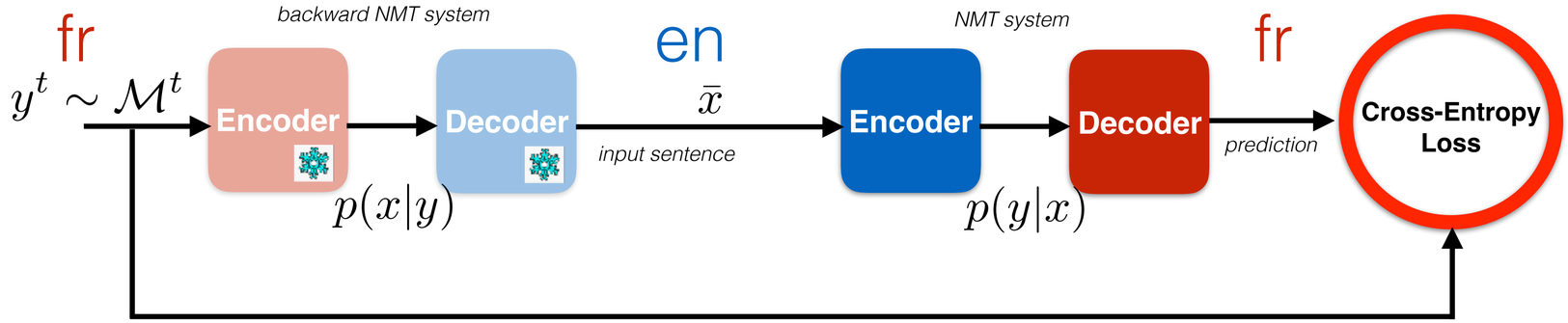

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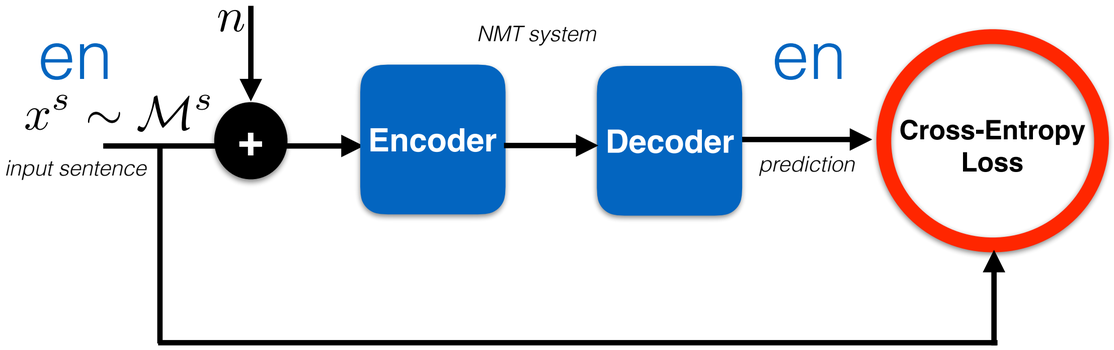
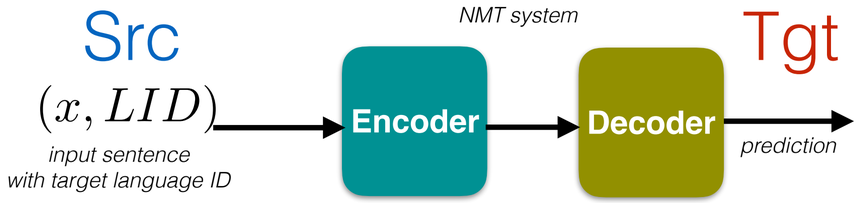
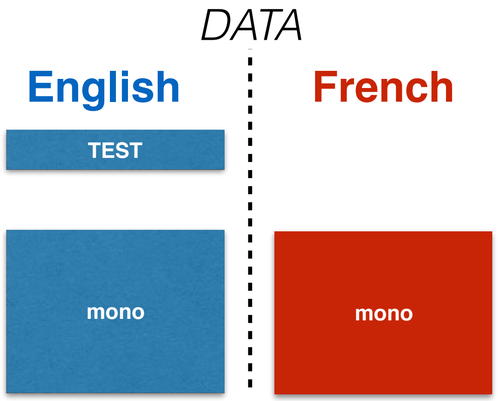


Like in multilingual NMT, share encoder and decoder parameters. Encoder is encouraged to produce shared representations (particularly if pre-trained).



Share encoder and decoder wi

Case Study #1: Unsupervised MT



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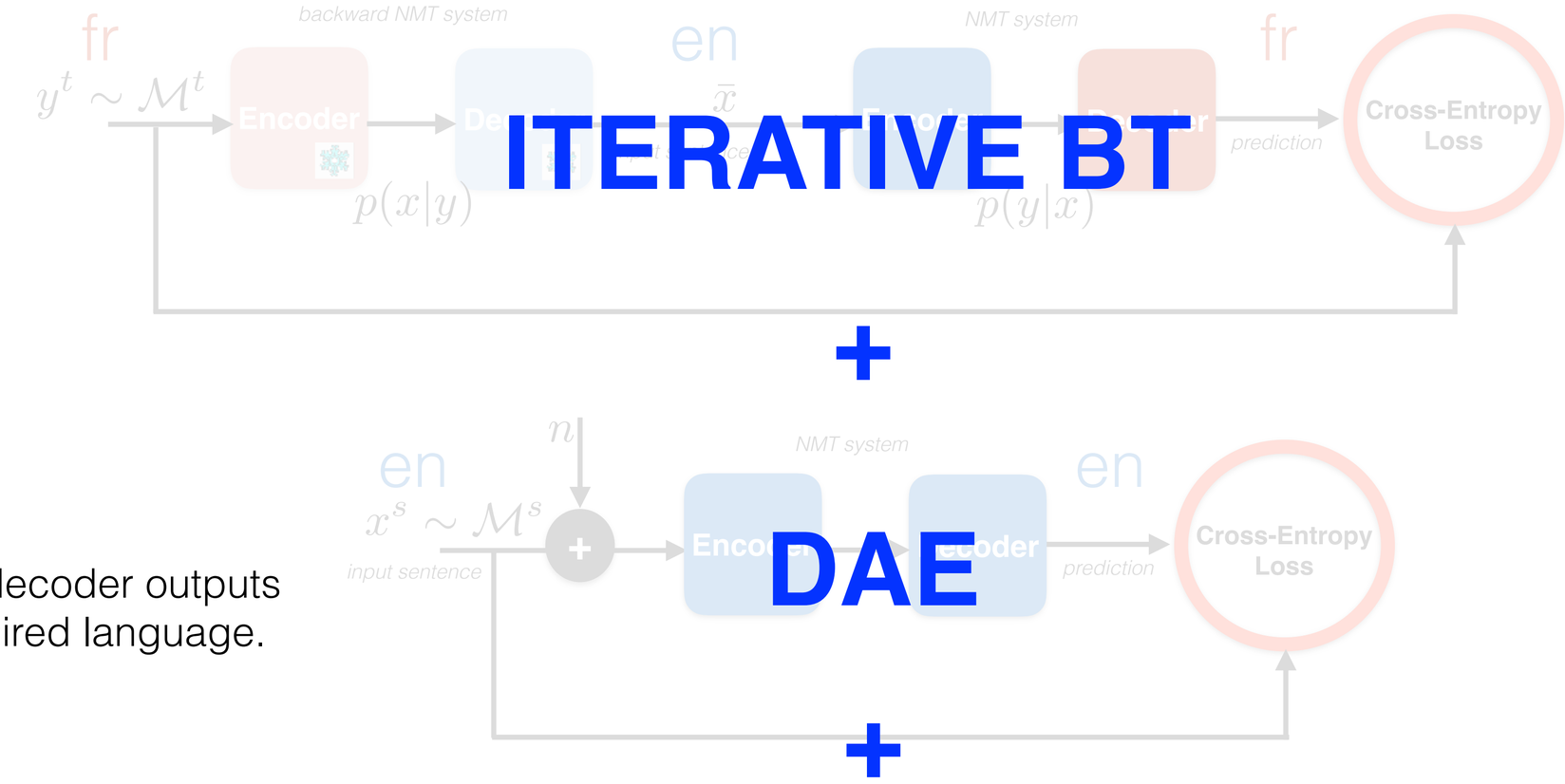
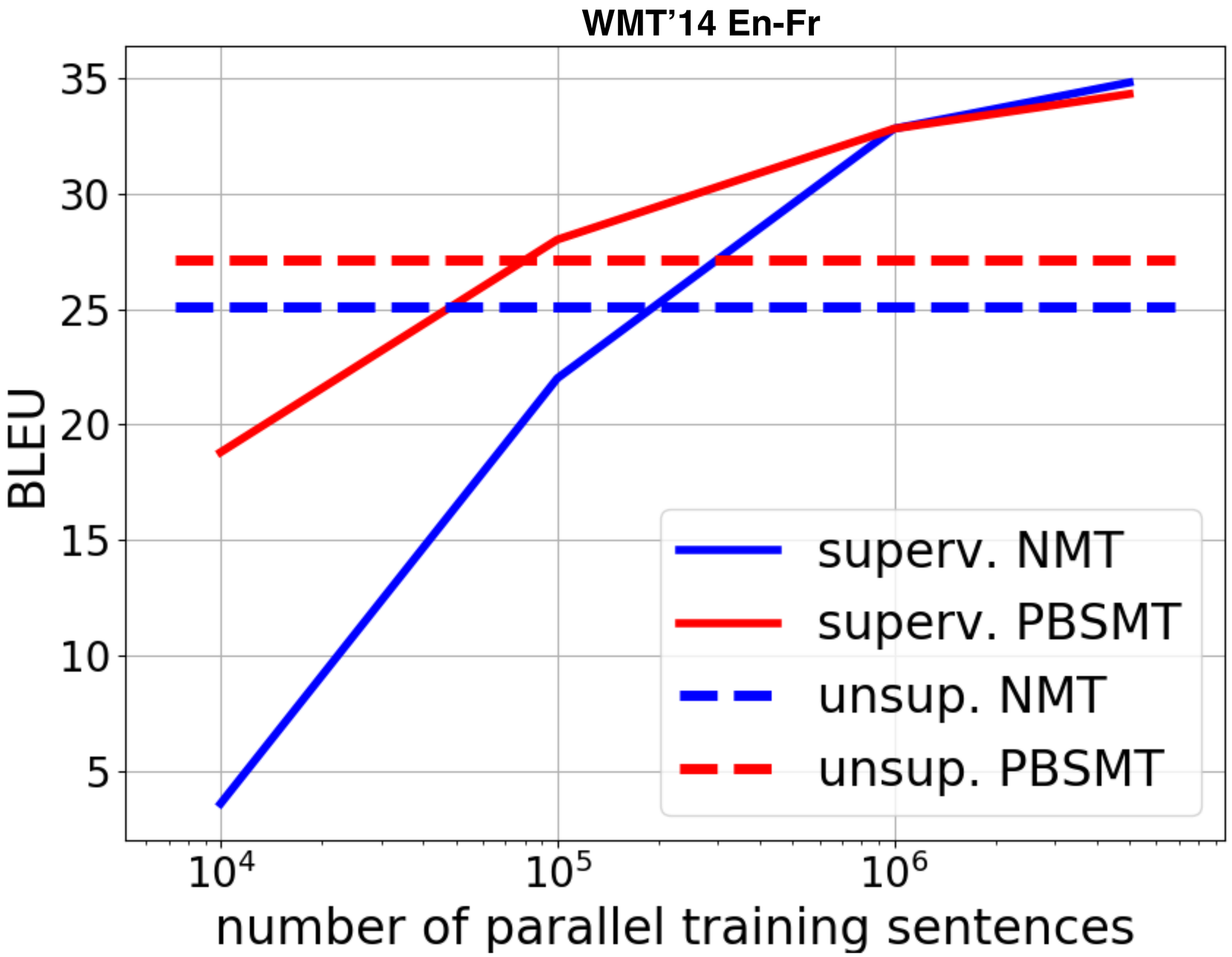




Same ideas can be applied to phrase-based statistical MT systems (PBSMT). NMT and PBSMT can be combined for even better results.

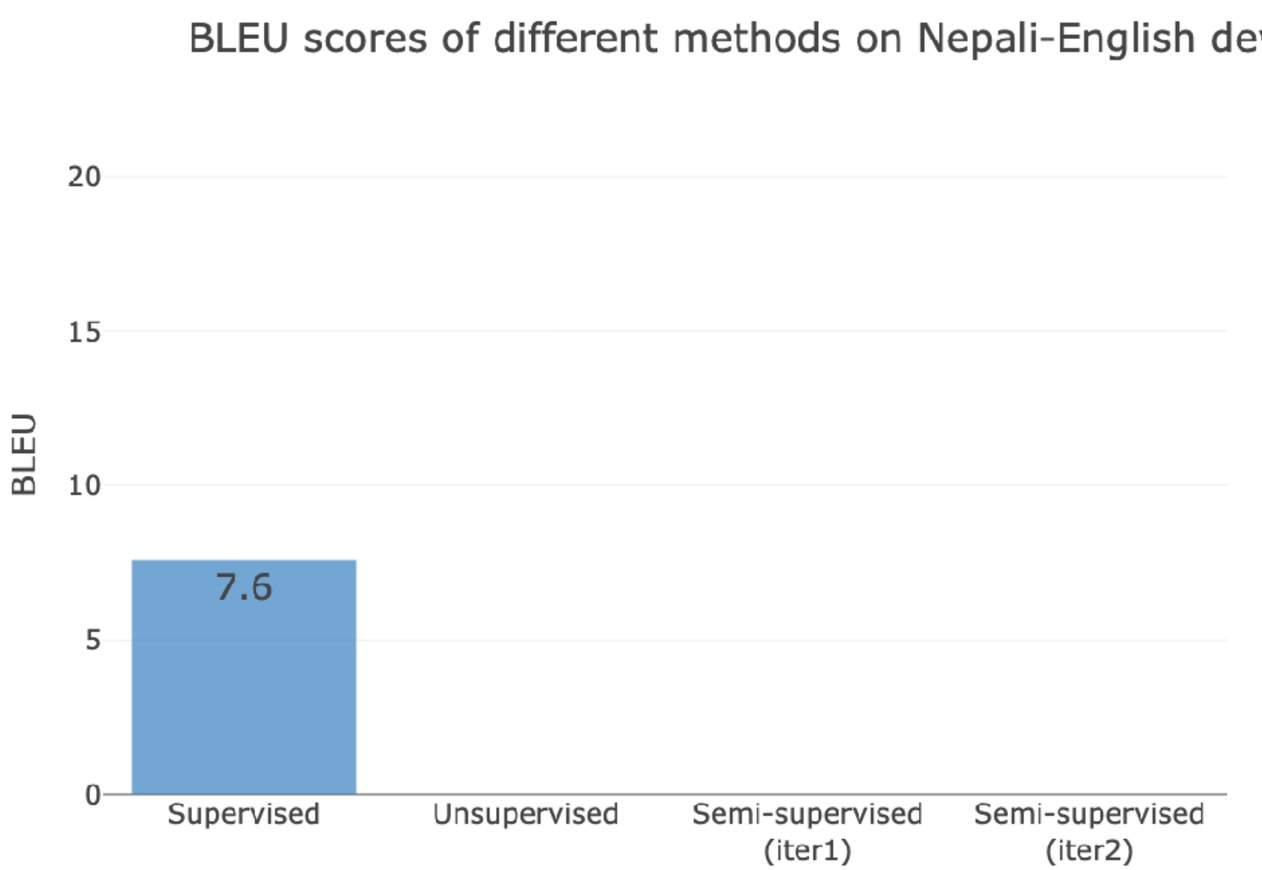
Since unsupMT was trained on about 10M sentences, each parallel sentence is worth 100 monolingual sentences (for this dataset and language pair).

Lample et al. "Phrase-based and neural unsupervised MT" EMNLP 2018

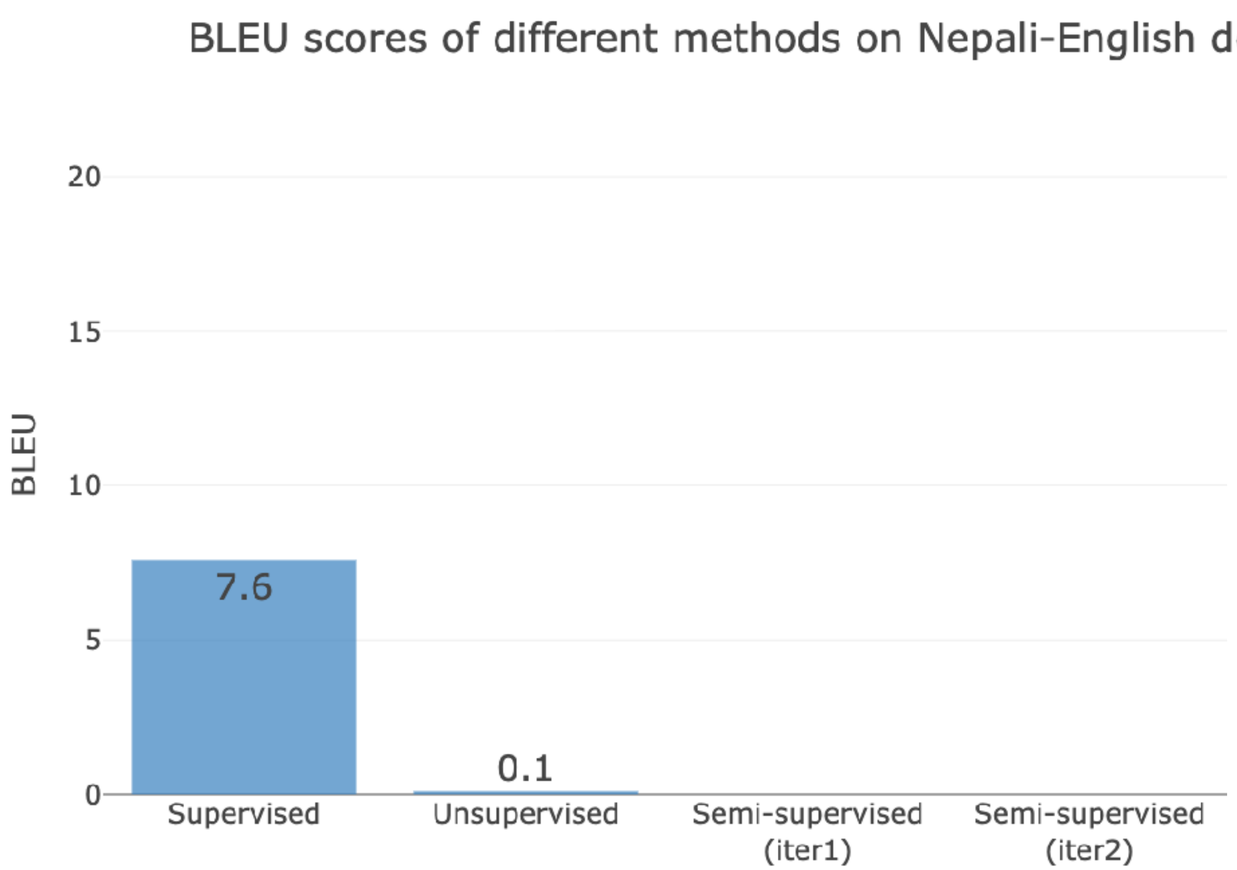
Case Study #2: FLoRes Ne-En

	In-domain (Wikipedia)	**Out-of-domain**
Parallel	None	500K sentences (Bible, GNOME/Ubuntu, OpenSubtitle, ...) *Hindi: 1.5M
Monolingual	100K sentences	~5M sentences (CommonCrawl) *Hindi: 45M

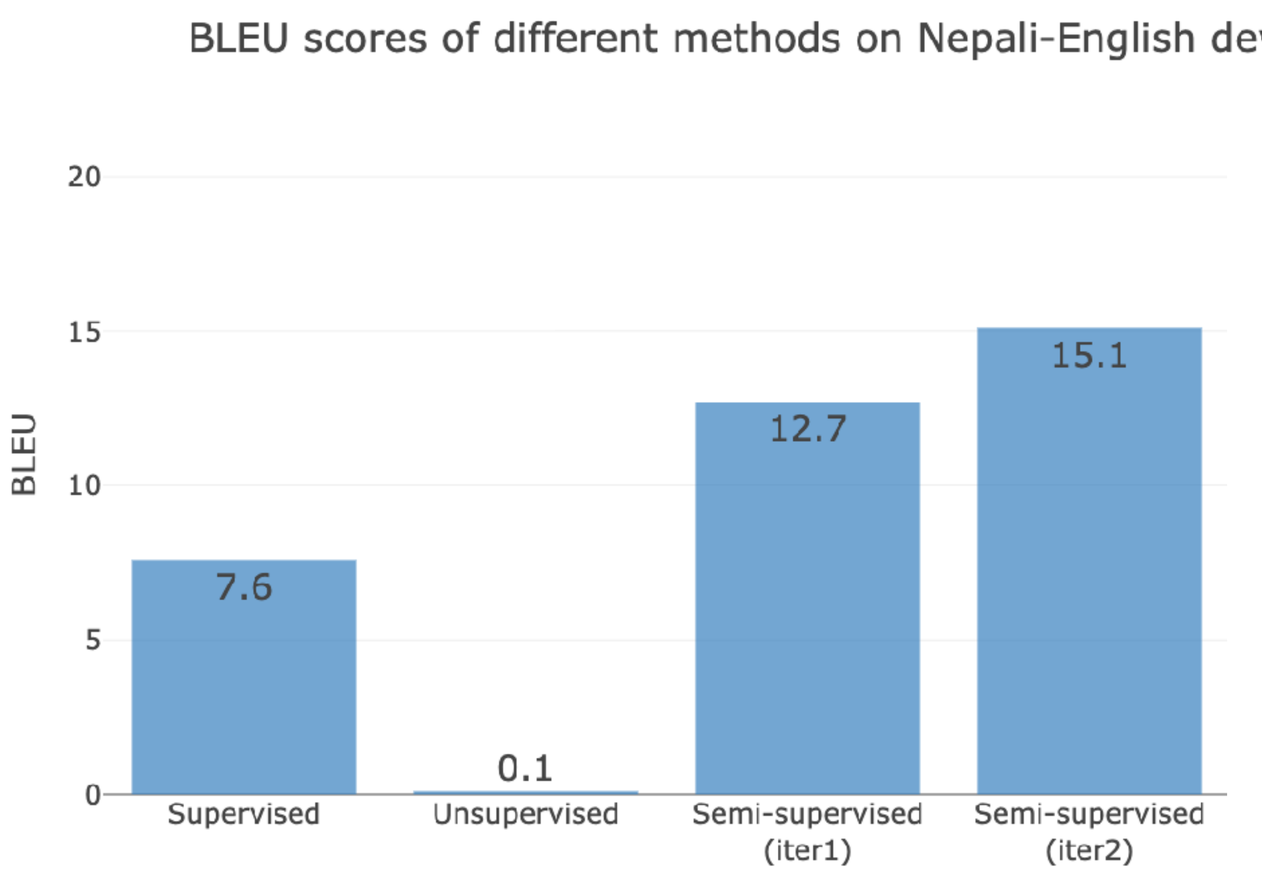
Results on FLoRes: Ne-En



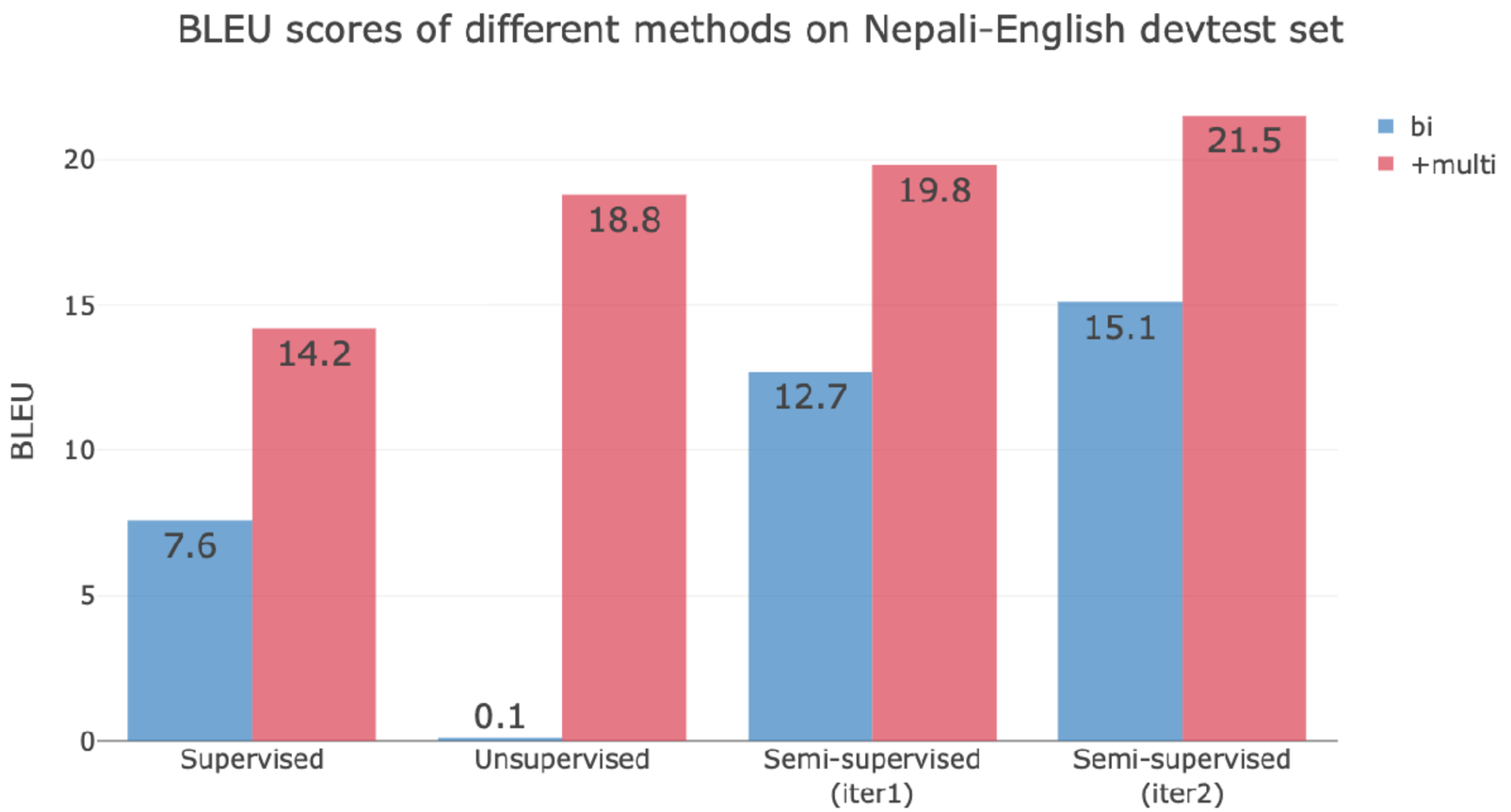
Results on FLoRes: Ne-En



Results on FLoRes: Ne-En



Results on FLoRes: Ne-En



Case-Study #3: English-Burmese

ဗဟိုစာမျက်နှာ ဆွေးနွေးချက် ဖတ်ရန် ရင်းမြစ်ကို ကြည့်ရန် ရာဇဝင်ကြည့်ရန် ဝီကီပီးဒီးယား တွင် ရှာဖွေရန်

ဗဟိုစာမျက်နှာ

ဝီကီပီးဒီးယားမှ ကြိုဆိုပါသည်။

မည်သူမဆို ကြည့်ရှုပြင်ဆင်နိုင်သော အခမဲ့လွတ်လပ်စွယ်စုံကျမ်း ဖြစ်ပါသည်။

အကြောင်းအရာပေါင်း ၄၄၈၁၄ ခုကို မြန်မာဘာသာဖြင့် ဖတ်ရှုနိုင်ပါသည်။

- အနုပညာ
- အတ္ထုပ္ပတ္တိ
- ပထဝီဝင်
- သမိုင်း
- သချိုင်္ဂ
- သိပ္ပံ
- လူမှုရေး
- နည်းပညာ
- မုခ်ဦးအားလုံး

အထူးအကြောင်းအရာ

သိန္နီနယ် သည် ယခင် ရှမ်းပဒေသရာဇဖြည်နယ်များတွင် ပါဝင်ခဲ့သော ပြည်နယ်တစ်ခု ဖြစ်သည်။ သိန္နီနယ်ကို ခရစ် ၁၈၈၈ ခုနှစ် အင်္ဂလိပ်တို့ ဝင်ရောက်သိမ်းပိုက်ပြီးနောက်မှ မြောက်သိန္နီနယ် (သိန္နီနယ်)နှင့် တောင်သိန္နီနယ်(မိုင်းရယ်နယ်)ဟု ခွဲခြားအုပ်ချုပ်ခဲ့သည်။ ရှေးအခါသမယက သိန္နီနယ်ကြီးသည် အစိတ် စိတ်ကွဲပြားခြင်းမရှိဘဲ ရှမ်းပြည်နယ်တဝှမ်းလုံးတွင် အာဏာအလွှမ်းမိုးဆုံးသော နယ်ကြီးဖြစ်ခဲ့သည်။ သို့သော် မြန်မာဘုရင်များ ဝင်ရောက်တိုက်ခိုက် သိမ်းပိုက်ပြီးသည့်နောက် အုပ်ချုပ်ရေးဝါဒအရ ရာထူးလုသည့်နယ်ရှင် စော်ဘွားတို့ကြောင့် သိန္နီနယ်ကြီးသည် ငါးနယ်အထိ အစိတ်စိတ် ကွဲပြားခဲ့လေသည်။ ထို အတွင်း စော်ဘွားအချင်းချင်း စိတ်ဝမ်းကွဲကာ တစ်ဦးနှင့်တစ်ဦးတိုက်ခိုက်၍ ဆိုင်ရာ နယ်ပယ်များကို အုပ်ချုပ်ကြသည်။ နောက်ဆုံးခရစ် ၁၈၈၈ ခုနှစ်၊ အင်္ဂလိပ်တို့ဝင်ရောက်လာမှ အထက်ပါ အတိုင်းနှစ်နယ်ခွဲ၍ အုပ်ချုပ်ခဲ့သည်။ နှစ်နယ်ခွဲ၍ အုပ်ချုပ်စက ခွန်ဆိုင်တုံဟမ်းအား မြောက်သိန္နီနယ်အတွက် စော်ဘွားအဖြစ်လည်းကောင်း၊ ဆိုင်နော်ဖဈီသား နော်မိုင်းအား တောင်သိန္နီနယ် စော်ဘွားအဖြစ်လည်းကောင်း၊ ခန့်အပ်ခဲ့လေသည်။ ၁၉၂၅ ခုနှစ် တွင် မြောက်သိန္နီနယ်ကို စဝ်ဟုံဖက စော်ဘွားအဖြစ် ဆောင်ရွက်ခဲ့လေသည်။

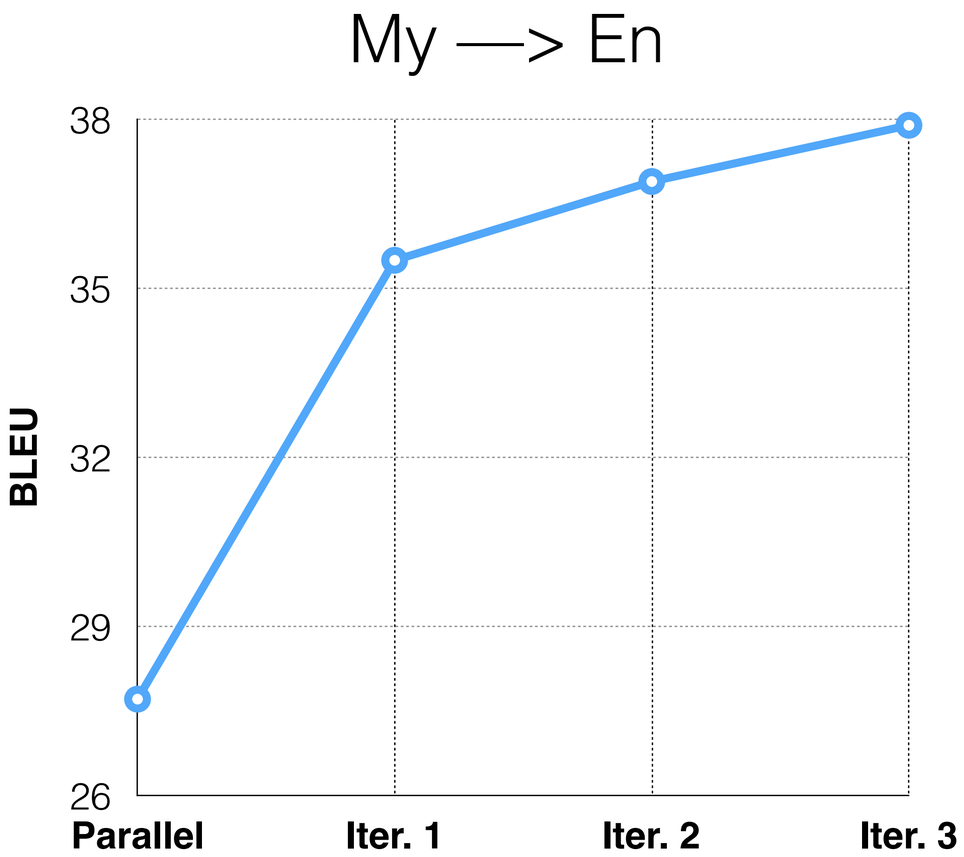
https://my.wikipedia.org/wiki/ဗဟိုစာမျက်နှာ

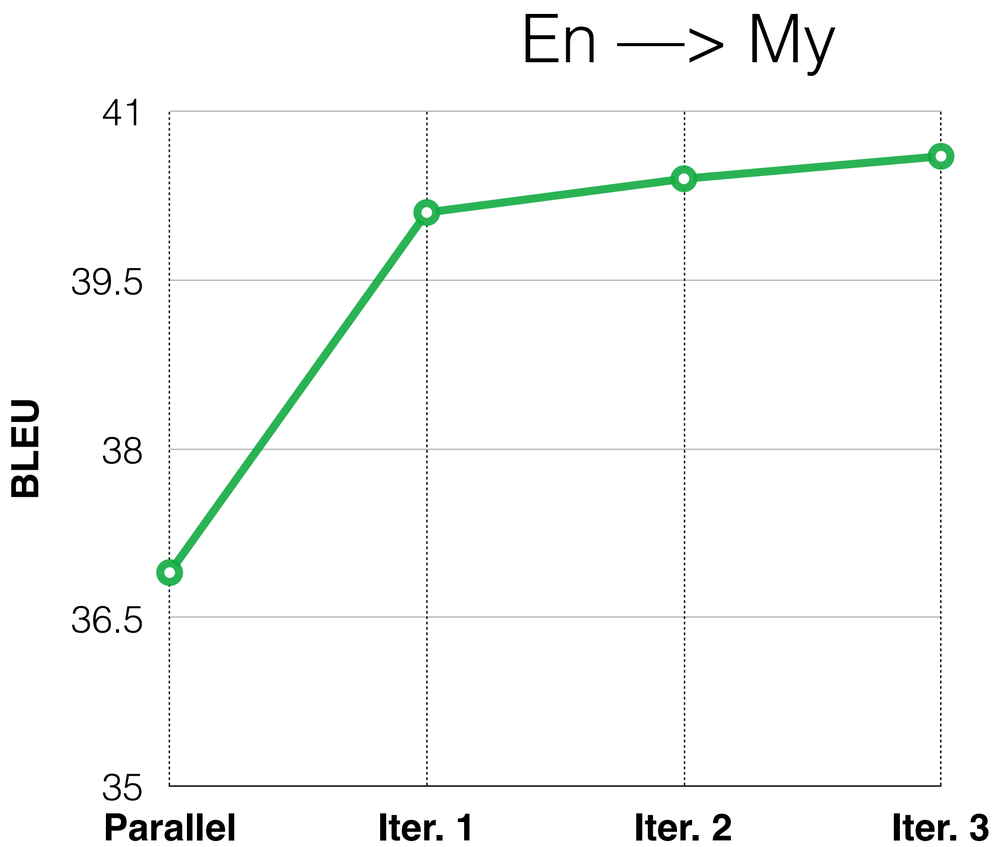
Workshop on Asian Translation 2019: English-Burmese

	In-domain (News)	**Out-of-domain**
Parallel	20K sentences	200K sentences
Monolingual	~79M sentences (En only)	~23M sentences (My only)

"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

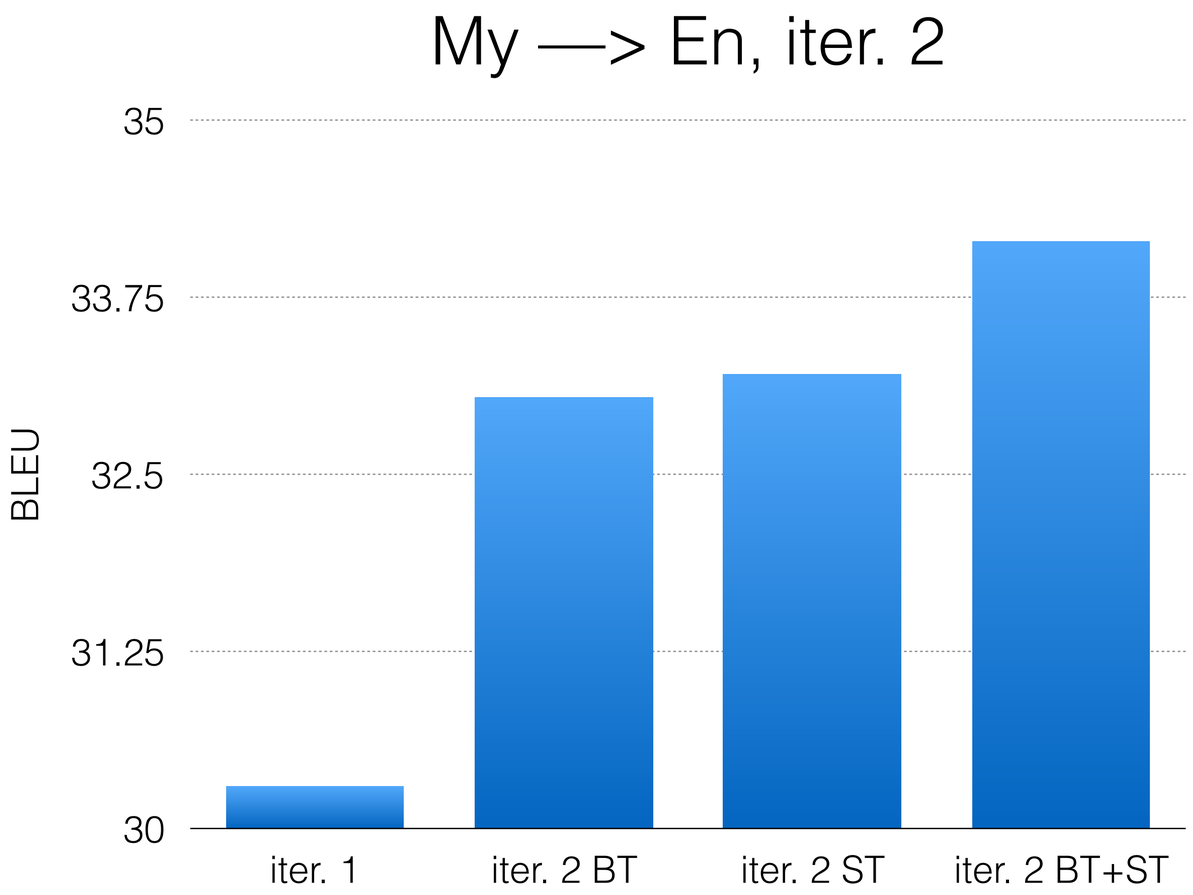
Results: Iterative ST+BT





"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

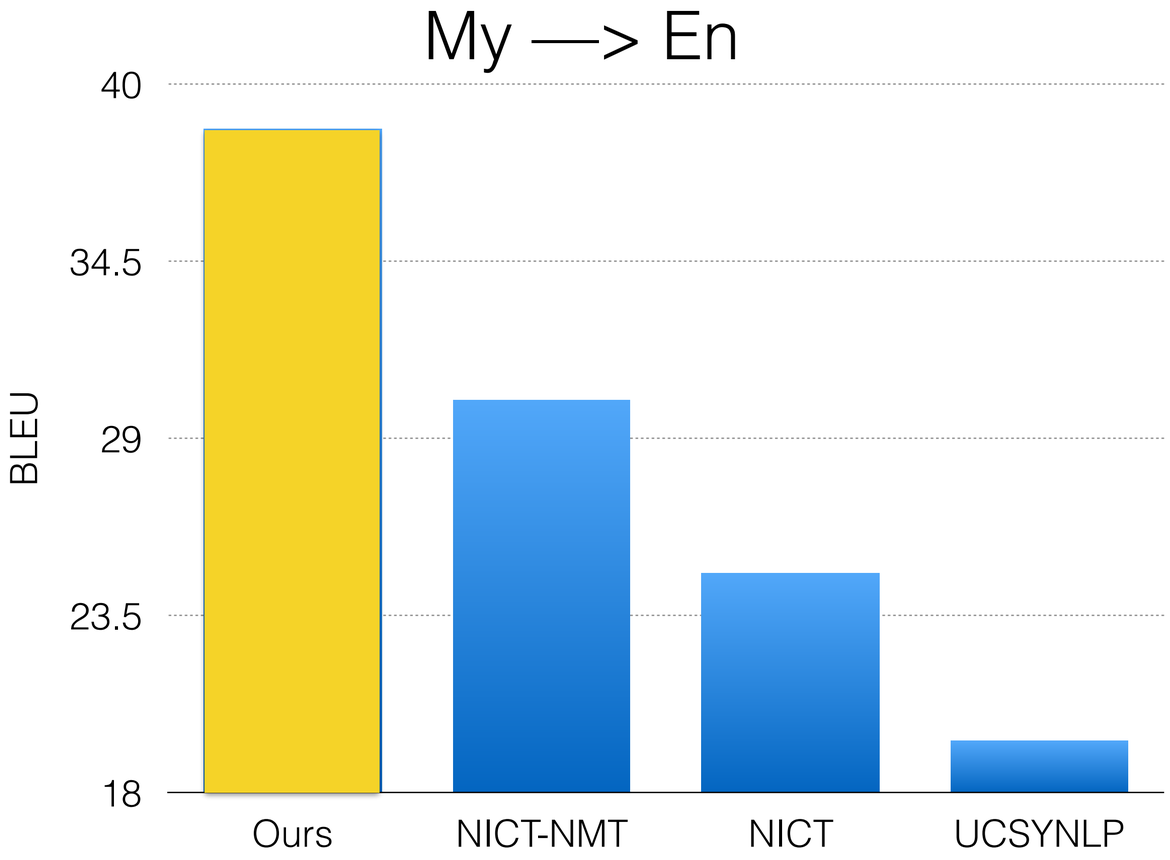
Results: BT vs ST vs BT+ST

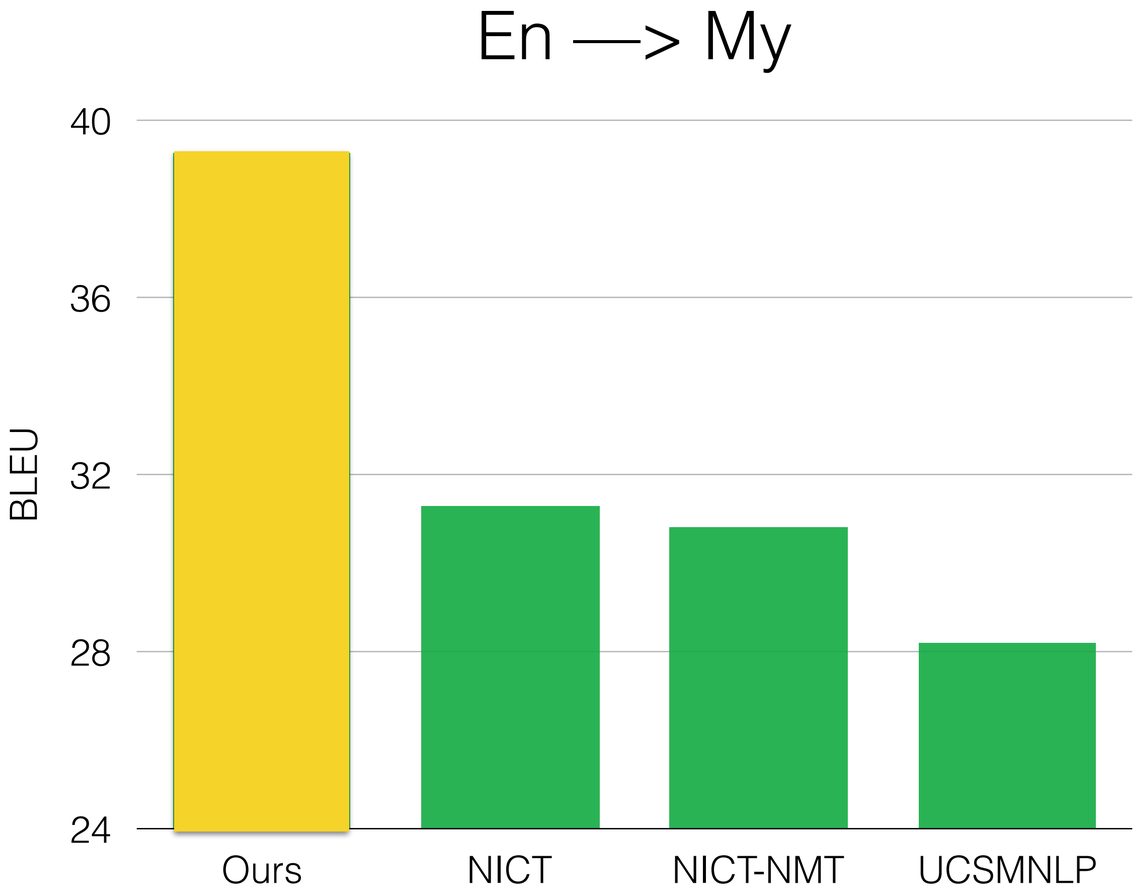


"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

Final Results of 2019 Competition

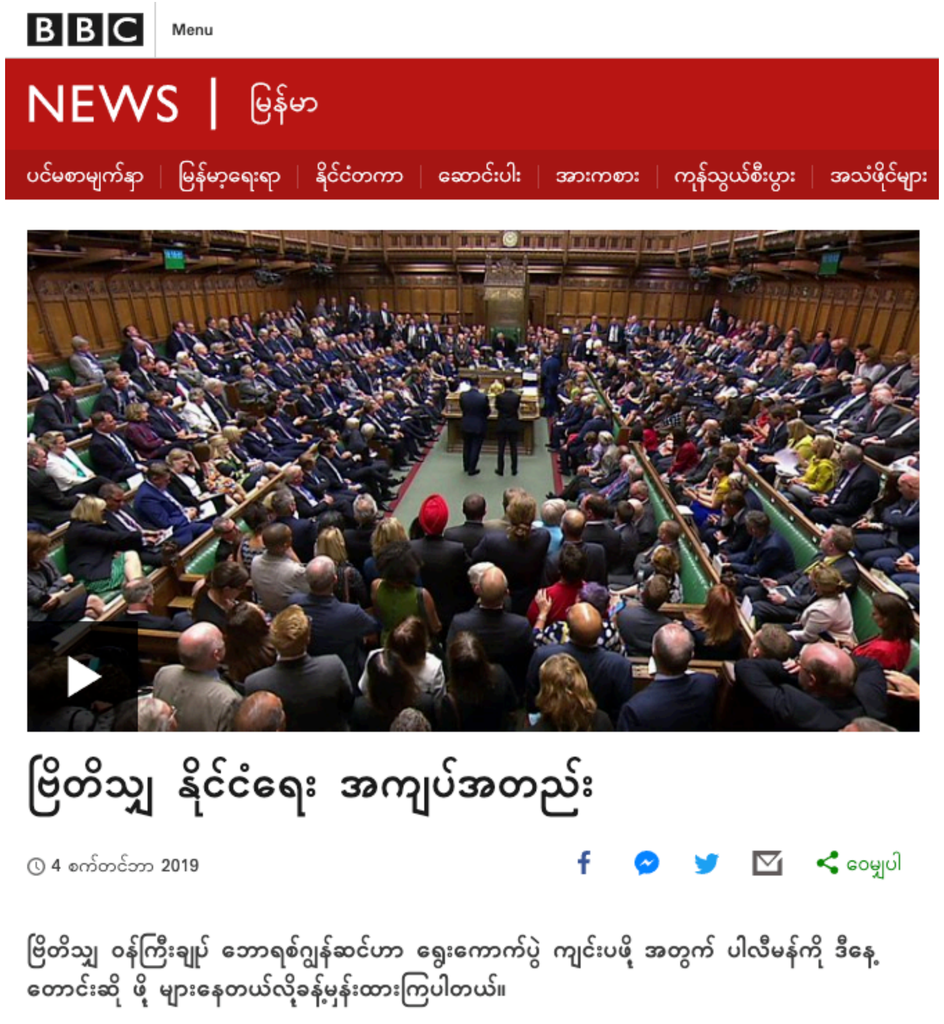
+8 BLEU compared to second best





"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

Demo (Burmese —> English)

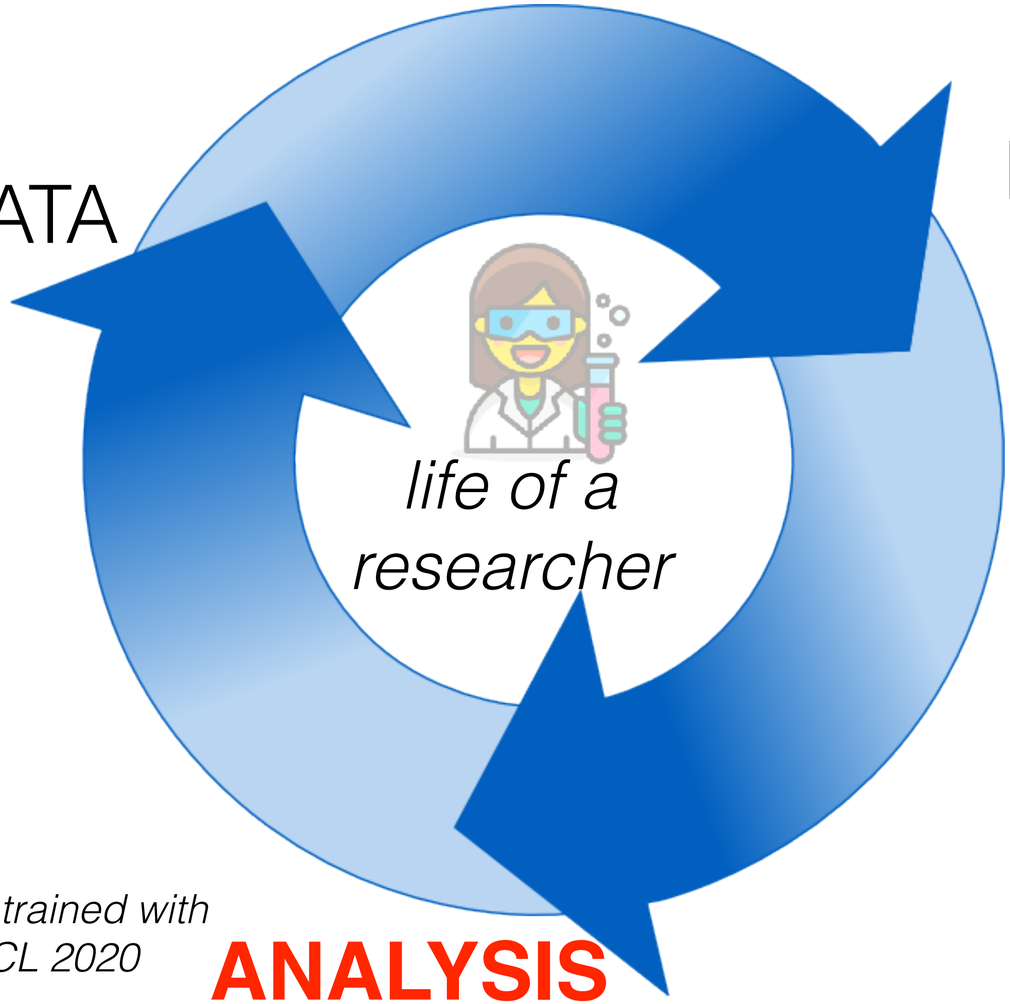


slide credit to Peng-Jen Chen

Conclusion so far…

- Iterative back-translation, multi-lingual training work remarkably well.
- By feeding more data (BT, ST, pre-training, multi-lingual training) we can afford training bigger models. Bigger models train on more data generalize better.
- Low-resource MT requires big compute! Remember that about 100 monolingual sentences give the same training signal as a single pair of parallel sentence.

Outline



"The FLoRes evaluation for low resource MT:…" Guzmán, Chen et al. 'EMNLP 2019

"Phrase-based & Neural Unsup MT" Lample et al. EMNLP 2018

"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

"Massively Multilingual NMT" Aharoni et al.,ACL 2019

"Multilingual Denoising Pre-training for NMT" Liu et al., arXiv 2001:08210 2020

"Analyzing uncertainty in NMT" Ott et al. ICML 2018

"On the evaluation of MT systems trained with back-translation" Edunov et al. ACL 2020

"The source-target domain mismatch problem in MT" Shen et al. arXiv 1909.13151 2019

Simulating Low-Resource MT

Simulating low-resource MT with a high resource language:
using *EuroParl* data with **20K** parallel sentences and **100K** monolingual target sentences.

EuroParl Fr—>En

only parallel data	30.4 BLEU
parallel data + BT	33.8 BLEU

+3.4 BLEU!

https://www.statmt.org/europarl/

A Worrisome Finding

BT sometimes yields very mild improvements.

Example

FB public posts En—>My

only parallel data	15.2 BLEU
parallel data + BT	15.3 BLEU

+0.1 BLEU!

Why is BT not working as well?

The FLORES evaluation datasets… Guzmán, Chen et al. EMNLP 2019

Sports

- *football*
- *baseball*
- *basketball*

- *soccer*
- *cricket*
- *rowing*

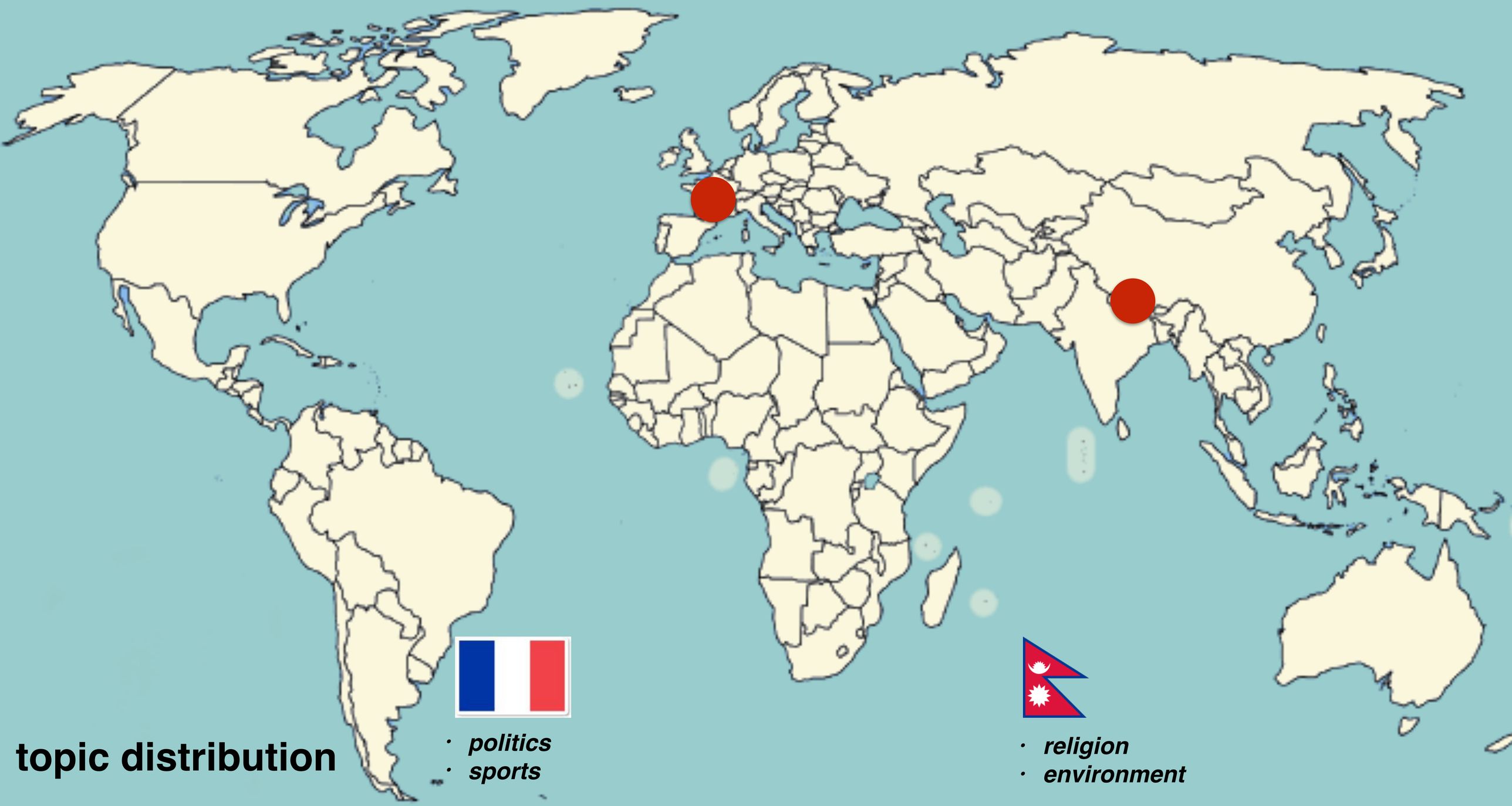
For the same topic: Different distribution over words!

Food

- *hamburger*
- *clam chowder*
- *apple pie*

- *kimchi*
- *bulgogi*
- *bibimbap*

For the same topic: Different distribution over words!



topic distribution

- *politics*
- *sports*

- *religion*
- *environment*

Domains differ in the topic distribution

Examples from FLoRes

Si-En

අධ්‍ය‍ාපනයෙන් පසු හෝ පවුලේ යුතුකම් ඉටු කරන්නට හෝ රෝග තත්වයන් නිසා සංඝයා උපසම්පදාවෙන් නිතරම ඉවත් වෙති .

original

After education priests leave ordination in order to fulfill duties to the family or due to sickness.

තර්ජන , ශාරීරික හිංසනය , දේපල හානිය , පහර දීම සහ මරාදැමීම මෙම දඩුවම්ය .

translation

Threatening, physical violence, property damage, assault and execution are these punishments.

Wikipedia in Sinhala has different topic distribution.

En-Si

In Serious meets, the absolute score is somewhat meaningless.

සැබෑ තරඟ වලදී ලකුණු සැසඳීම තේරුමක් නැති ක්‍රියාවකි .

Iphone users can and do access the internet frequently, and in a variety of places.

අයිෆෝන් භාවිත කරන්නන්ට නිතරම සහ විවිධ ස්ථානවලදී අන්තර්ජාලයට පිවිසිය හැකිය .

Guzmàn, Chen et al. “The FLoRes evaluation datasets for low resource MT…” EMNLP 2019

Source-Target Domain Mismatch (STDM)

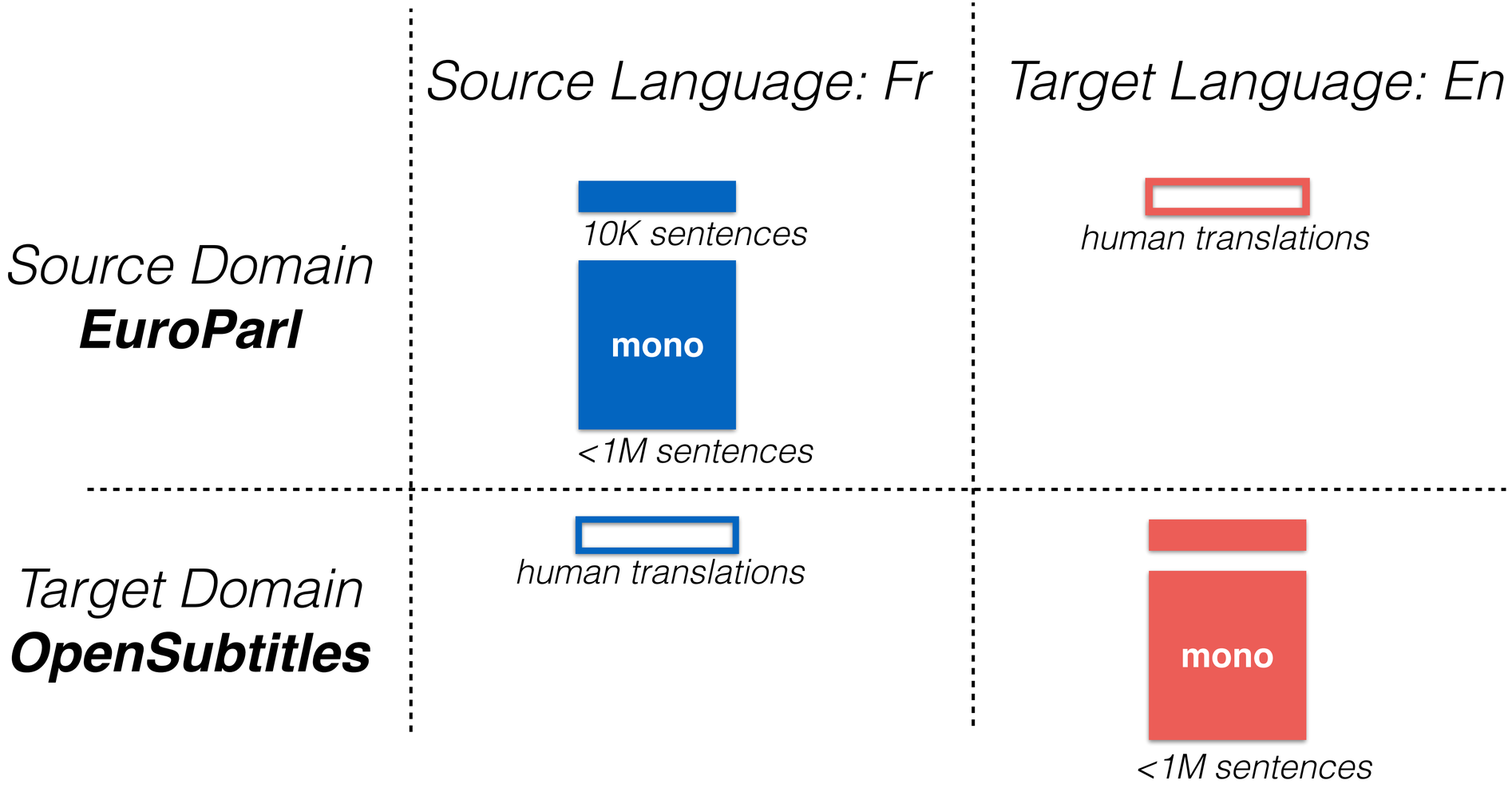
- Def.: Content produced in blogs, social networks, news outlets, etc. varies with the geographic location.
- STDM is even more pronounced in low resource MT, where source & target geographic locations are typically farther apart and cultures have more distinct traits.
- STDM manifests itself in terms of: Different distribution of topics, and for the same topic different distribution over words.
- STDM is hard to measure because of the unknown effect of translationese.
- STDM makes the MT problem even harder: source originating data and target originating data are not comparable in general. BT won't work as well. UnsupMT won't work as well.

Language and place. Johnstone Cambridge Univ. Press 2010
Leech et al. "Computer corpora: What do they tell us about culture?"Journal Computers in English Linguistics 1992

Questions

- Is it true that BT is less effective when there is STDM?
- What baselines shall we consider when there is STDM?
- What are general best practices when there is STDM?
- How to study STDM in a controlled setting?

Controlled Setting



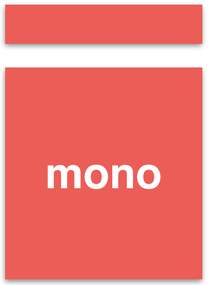
Controlled Setting

Source Language: Fr

Target Language: En

Source Domain
EuroParl

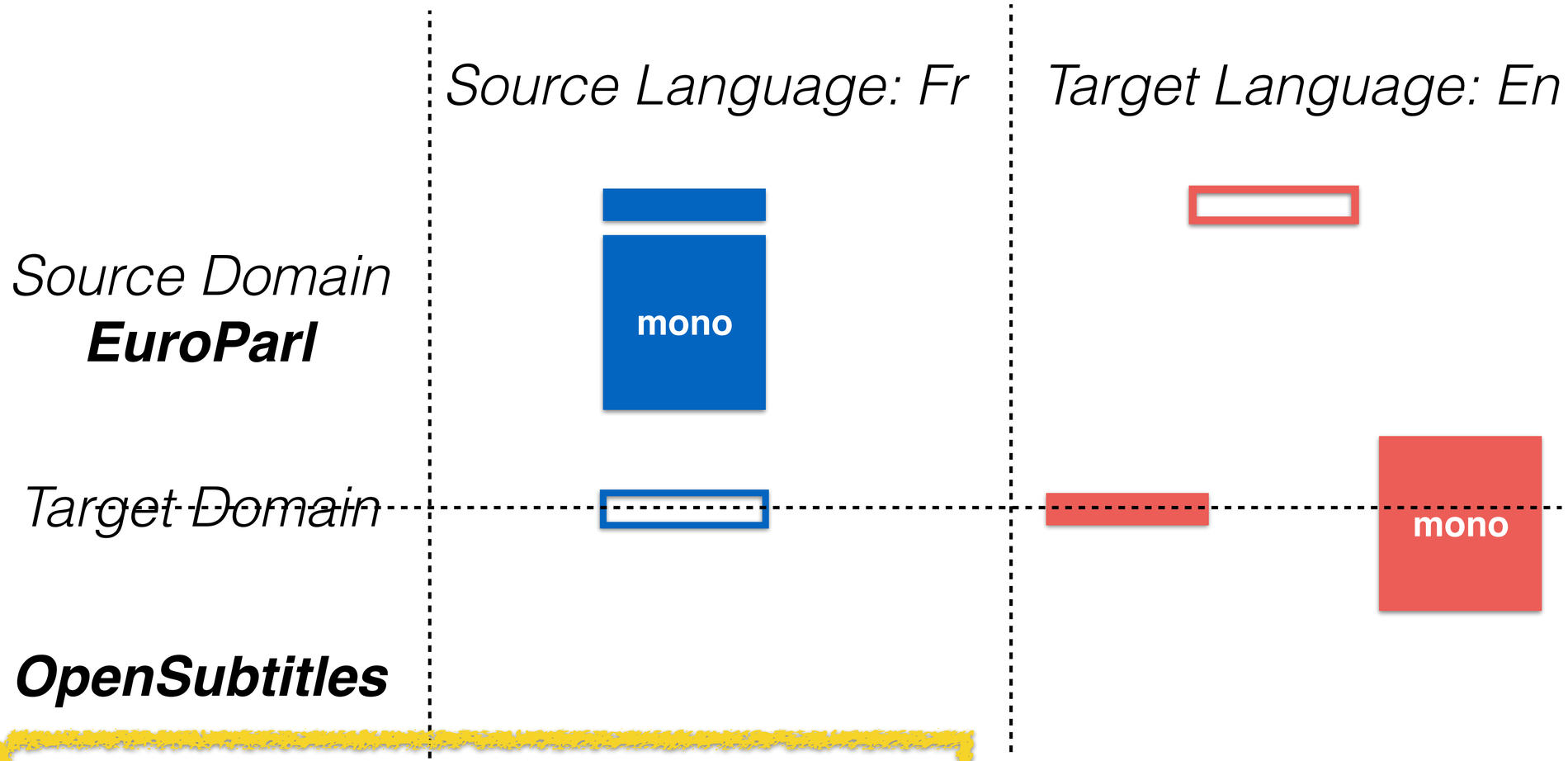
Target Domain
OpenSubtitles



$\alpha\, EuroParl + (1-\alpha)\, OpenSubtitles$

$\alpha = 0$

Controlled Setting



α *EuroParl* $+(1-\alpha)$ *OpenSubtitles*
intermediate value of α

Targetdomain as a mixture of Euro parl and opensubtitles

Controlled Setting

Source Language: Fr

Target Language: En

Source Domain &
Target Domain
EuroParl

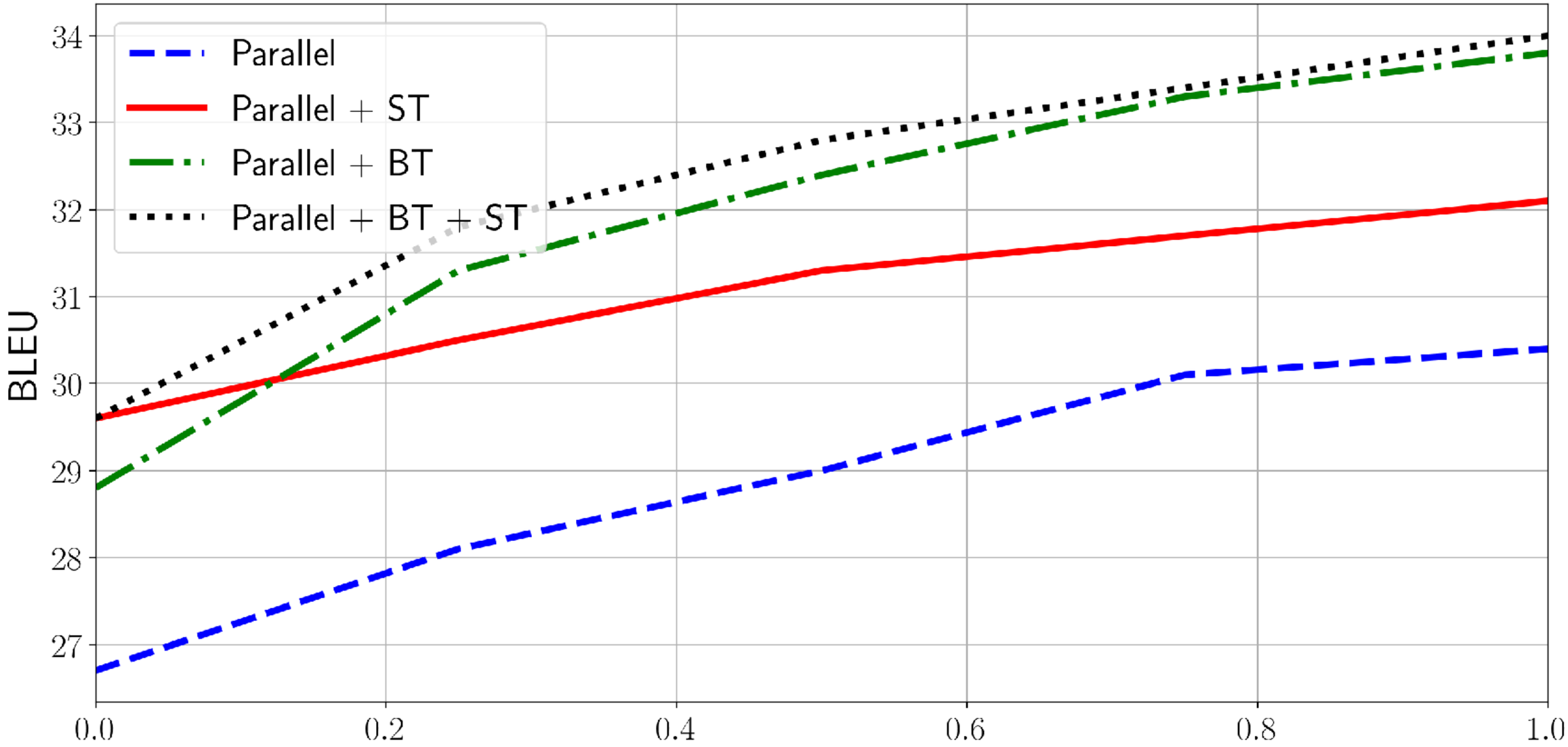
α *EuroParl* $+(1-\alpha)$ *OpenSubtitles*
$\alpha = 1$

	target mono data	*source mono data*	*in-domain mono data*
• Back-Translation:			
• Self-Training:			

Q.: Is it better to have clean targets but out-of-domain data, or noisy targets but in-domain data?
Q.: What's the effect of amount of parallel/monolingual data?
Q.: What's the effect of the quality of the model forward model when training with ST?

Varying Domain of Target Originating Data

Self training, works better than BT for alpha = 0



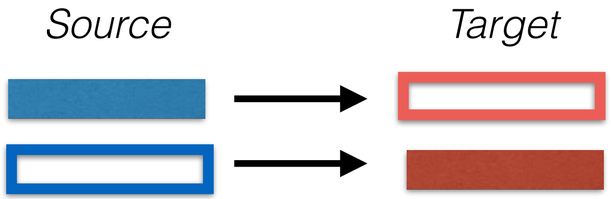
Target originating data is out-of-domain

Target originating data is in-domain

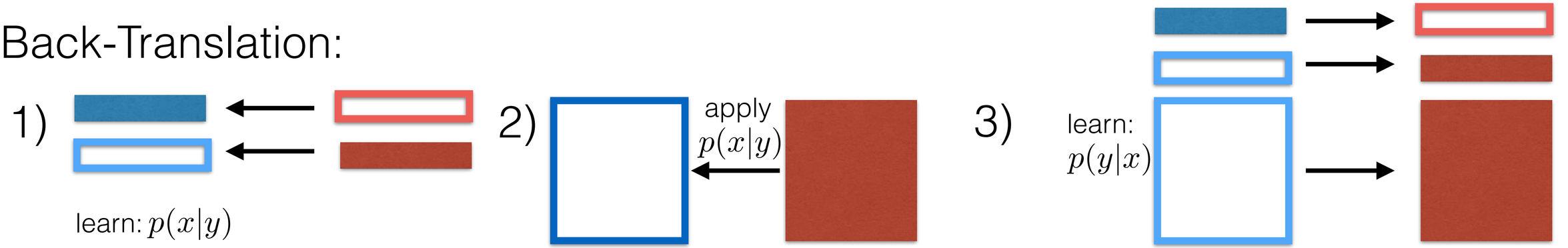
$$\alpha\, EuroParl + (1-\alpha)\, OpenSubtitles$$

Baseline Approaches

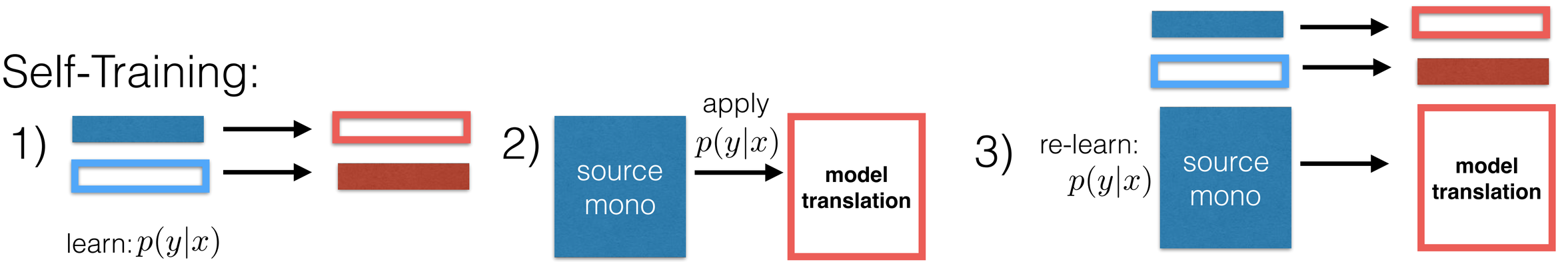
- Bitext only:



- Back-Translation:

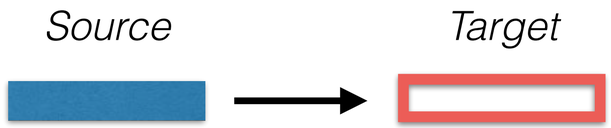


- Self-Training:

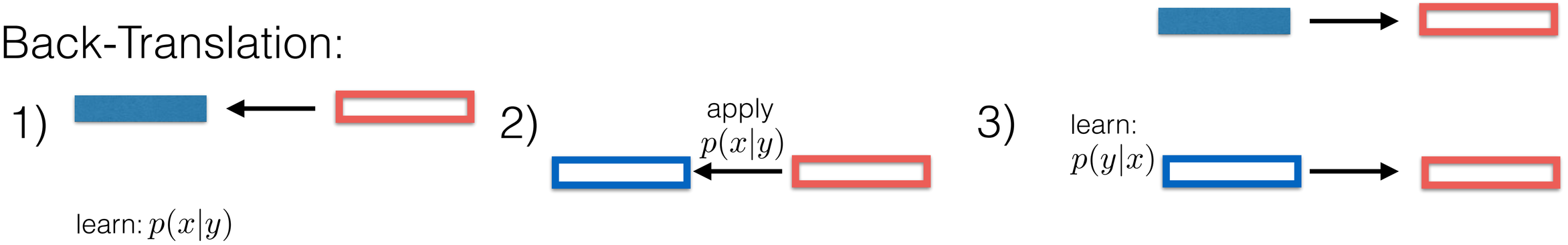


Baseline Approaches: Only In-Domain Data

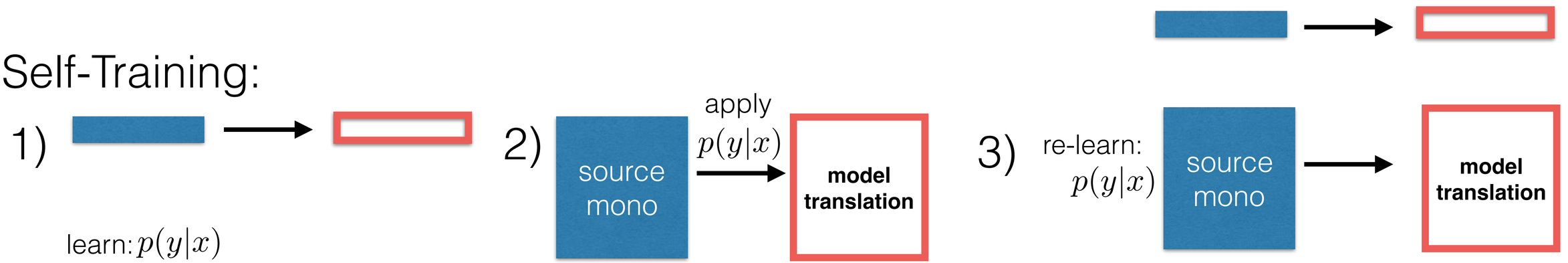
- Bitext only:



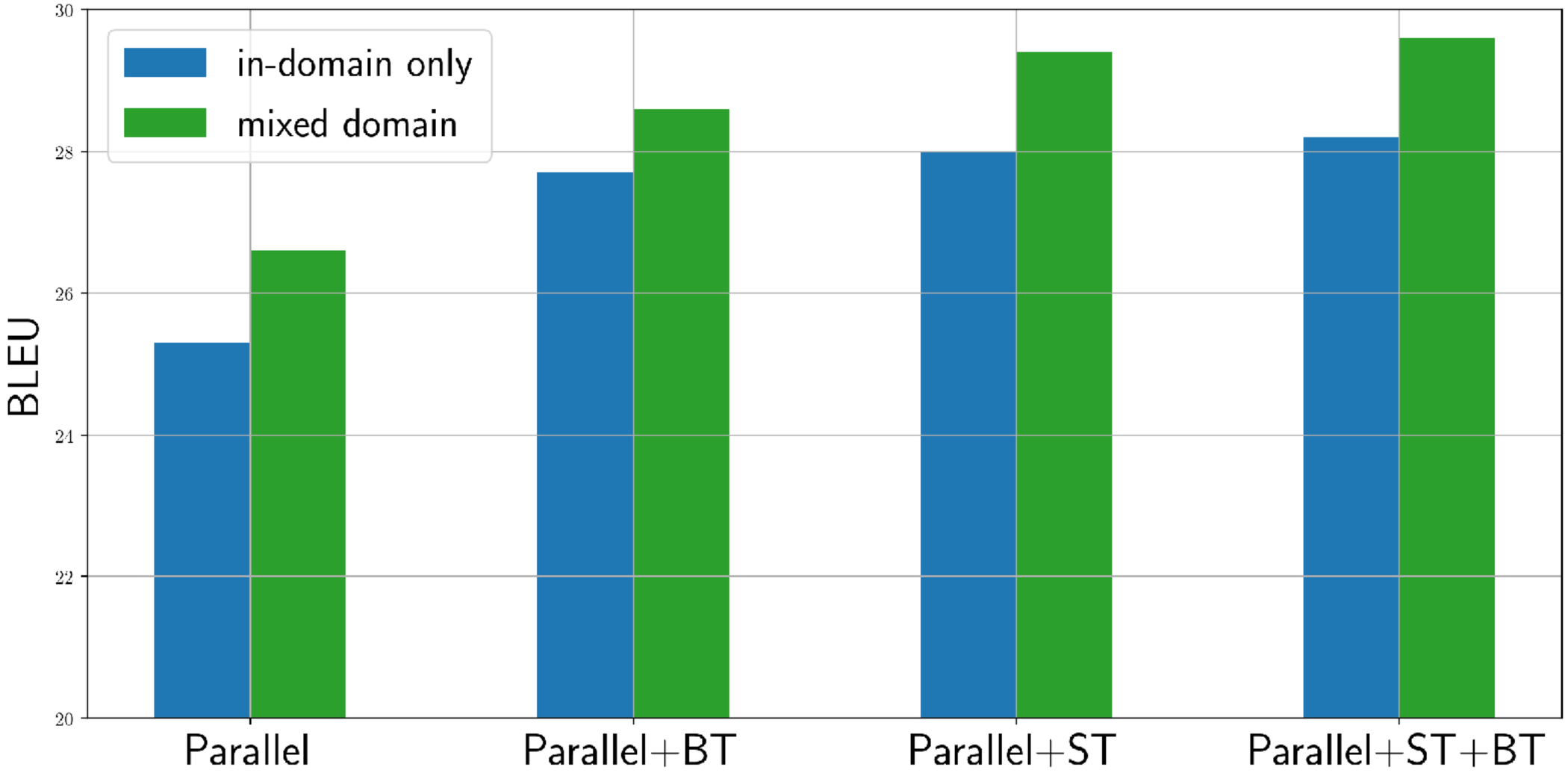
- Back-Translation:



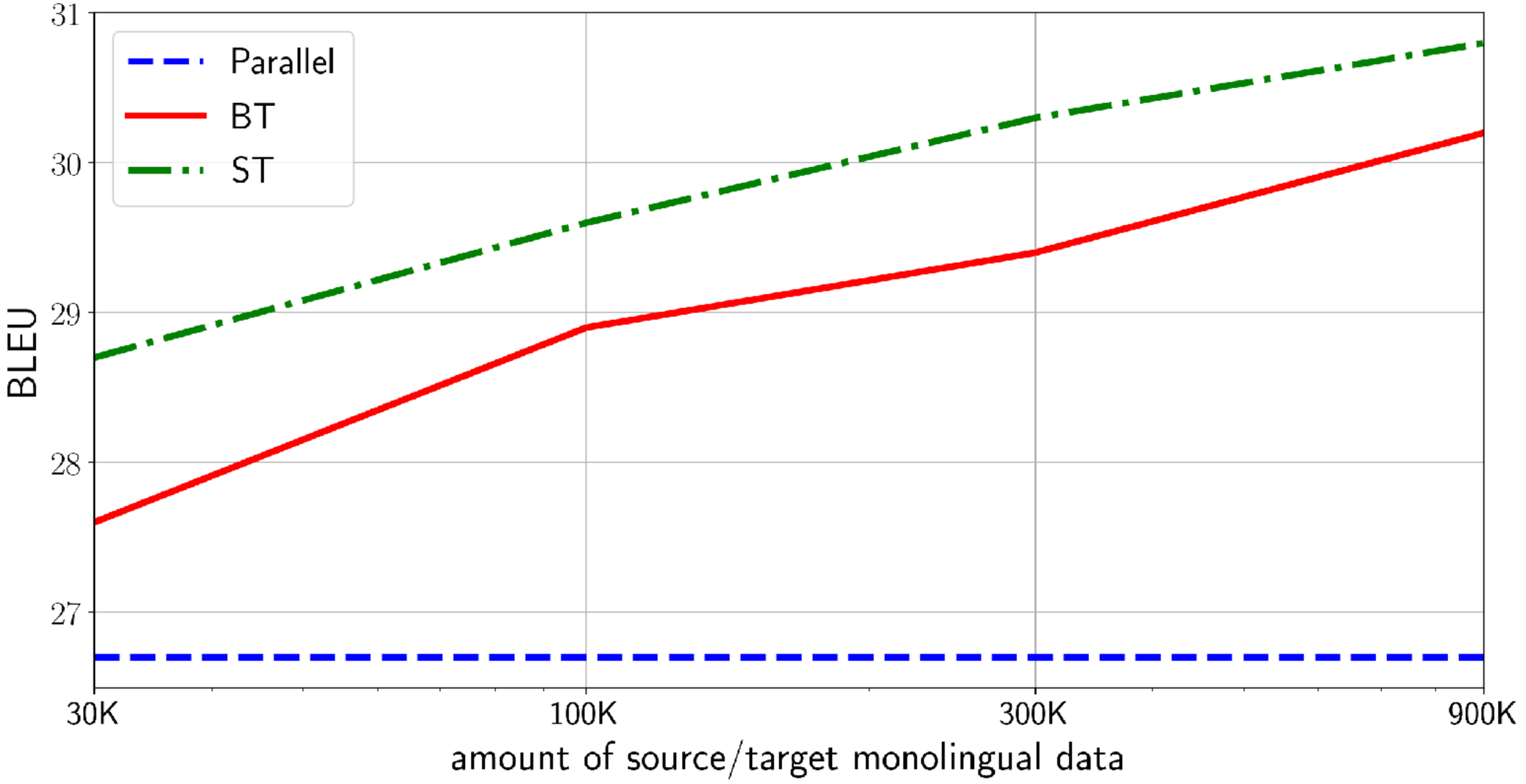
- Self-Training:



In-Domain Only VS. Mixed Domain



Varying Amount of Monolingual Data ($\alpha = 0$)

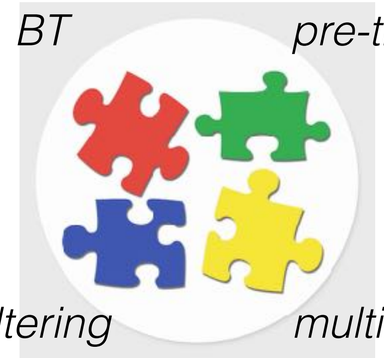


Conclusion

- STDM is particularly significant in low resource language pairs.
- Controlled setting helps studying STDM in isolation.
- ST is more robust than BT to STDM. We have already seen that combining ST & BT worked best in En-My.
- In practice, the influence of STDM depends on several factors, such as the amount of parallel and monolingual data, the domains, etc. In particular, if domains are not too distinct, STDM may even help regularizing!

What I did not talk about: Filtering

- Data: extract clean version of common crawl.
- Learn a joint embedding space. by training multilingual system on lots of training data
- Use approximate nearest neighbor methods to find closest matching sentence in embedding space.
- Translation quality on several languages is even higher than using actual existing bilingual + mono data!



for high resource data like english french

Schwenk et al. "CCMatrix: mining billions of high-quality parallel sentences on the WEB" arXiv:1911.04944 2019

Back translation tasks work a lot better for symmetric tasks like MT, but not for tasks like summarization

Final Remarks

- Low resource MT is a good use case applications of several long standing ML problems: aligning domains, learning with less supervision, leveraging compositionality, etc.
- The importance and difficulty of data collection should not be under-estimated.
- A healthy cycle of research: data, modeling, analysis.
- Low resource MT key idea: use as many auxiliary tasks and data.
- Low resource MT requires lots of data and compute.
- Lots of open challenges.
  - Specific to low resource: dealing with all sorts of domain mismatch, learning from little data, quality of evaluation sets…
  - General of text generation: better use of context, common sense, striking a good trade-off between accuracy and speed, controllability, safety, biases…

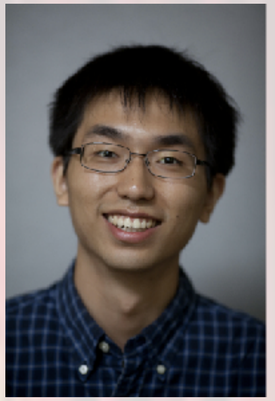
Guillaume Lample

Ludovic Denoyer

Myle Ott

Peng-Jen Chen

Paco Guzmán



Jiajun Shen

Questions?
Вопросы?
¿Preguntas?
Domande?

Jiatao Gu

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Hervé Jegou

Michael Auli

Junxian He

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