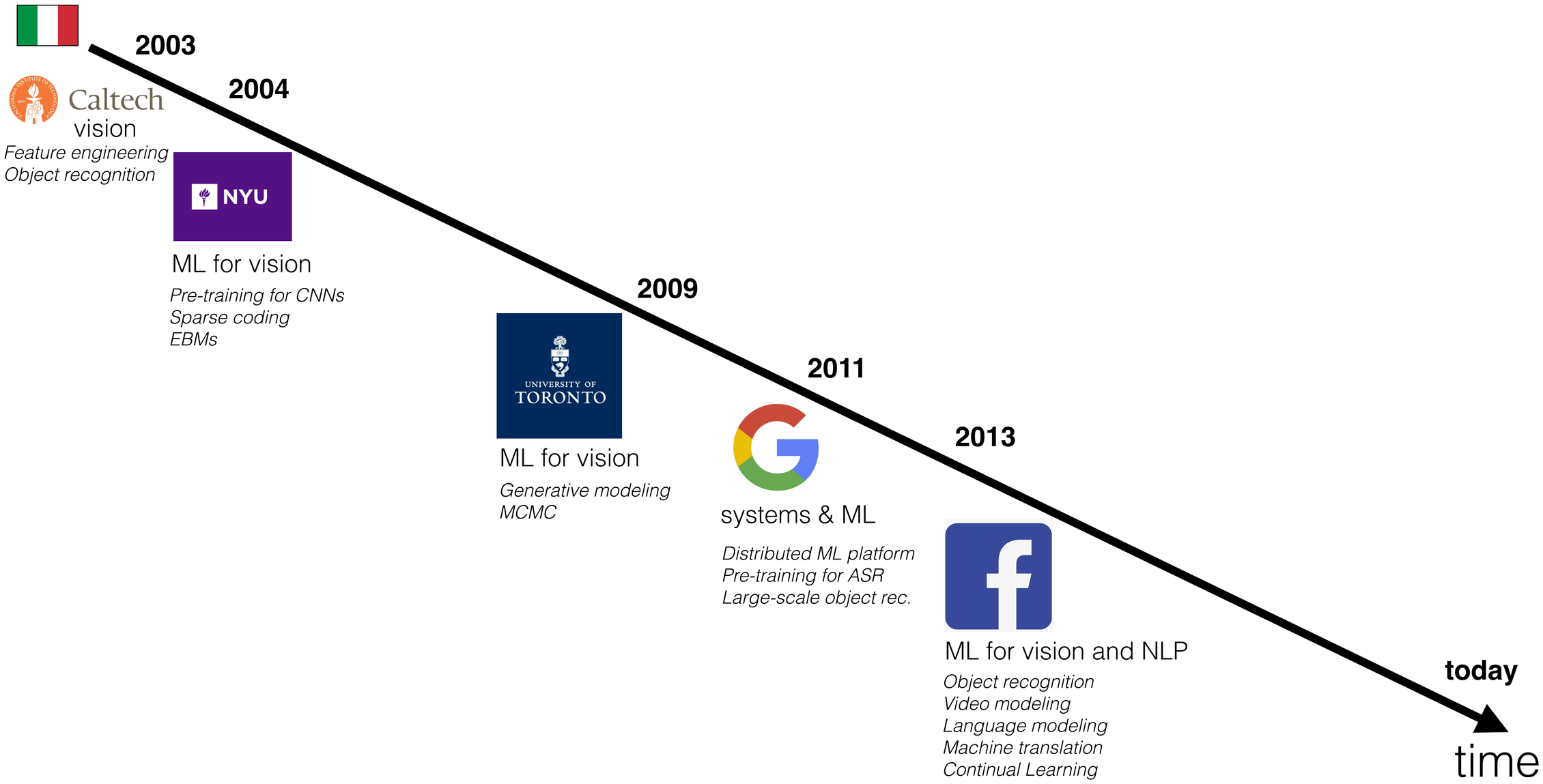
Low Resource Machine Translation

Marc'Aurelio Ranzato
Facebook AI Research - NYC
ranzato@fb.com

Mediterranean Machine Learning "Summer" School, 12 January 2021

$whoami


2003
2004
Caltech
vision
Feature engineering
Object recognition
NYU
ML for vision
Pre-training for CNNs
Sparse coding
EBMs
2009
UNIVERSITY OF TORONTO
ML for vision
Generative modeling
MCMC
2011
systems & ML
Distributed ML platform
Pre-training for ASR
Large-scale object rec.
2013
ML for vision and NLP
Object recognition
Video modeling
Language modeling
Machine translation
Continual Learning
today
time

$whoami

Goal: effective and efficient learning with limited supervision.

Phrase-Based & Neural Unsupervised Machine Translation

Guillaume Lample[†] Facebook AI Research, Sorbonne Universités, glample@fb.com
Myle Ott Facebook AI Research, myleott@fb.com
Alexis Conneau Facebook AI Research, Université Le Mans, aconneau@fb.com
Ludovic Denoyer[†] Sorbonne Universités, ludovic.denoyer@lip6.fr
Marc'Aurelio Ranzato Facebook AI Research, ranzato@fb.com

Leverage unlabeled data

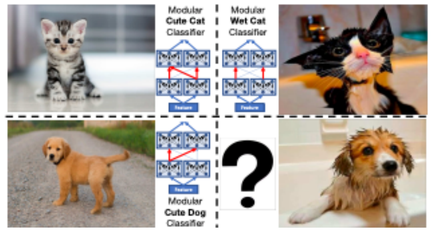
- unsupervised learning
- semi-supervised learning

Task-Driven Modular Networks for Zero-Shot Compositional Learning

Senthil Purushwalkam* Carnegie Mellon University, spurushw@andrew.cmu.edu
Maximilian Nickel Facebook AI Research, maxn@fb.com
Abhinav Gupta Facebook AI Research, gabhinav@fb.com
Marc'Aurelio Ranzato Facebook AI Research, ranzato@fb.com

Leverage inductive biases

- modularity
- compositionality



EFFICIENT CONTINUAL LEARNING WITH MODULAR NETWORKS AND TASK-DRIVEN PRIORS

Tom Veniat LIP6, Sorbonne Université, France, tom.veniat@lip6.fr
Ludovic Denoyer & Marc'Aurelio Ranzato Facebook Artificial Intelligence Research, {denoyer,ranzato}@fb.com

Leverage knowledge accrued on other tasks

- continual learning
- few-shot learning
- meta-learning

Machine Translation

Training data

English

Italian

Train NMT

NMT System

Ingredients:
- seq2seq with attention
- *SGD*

Test NMT

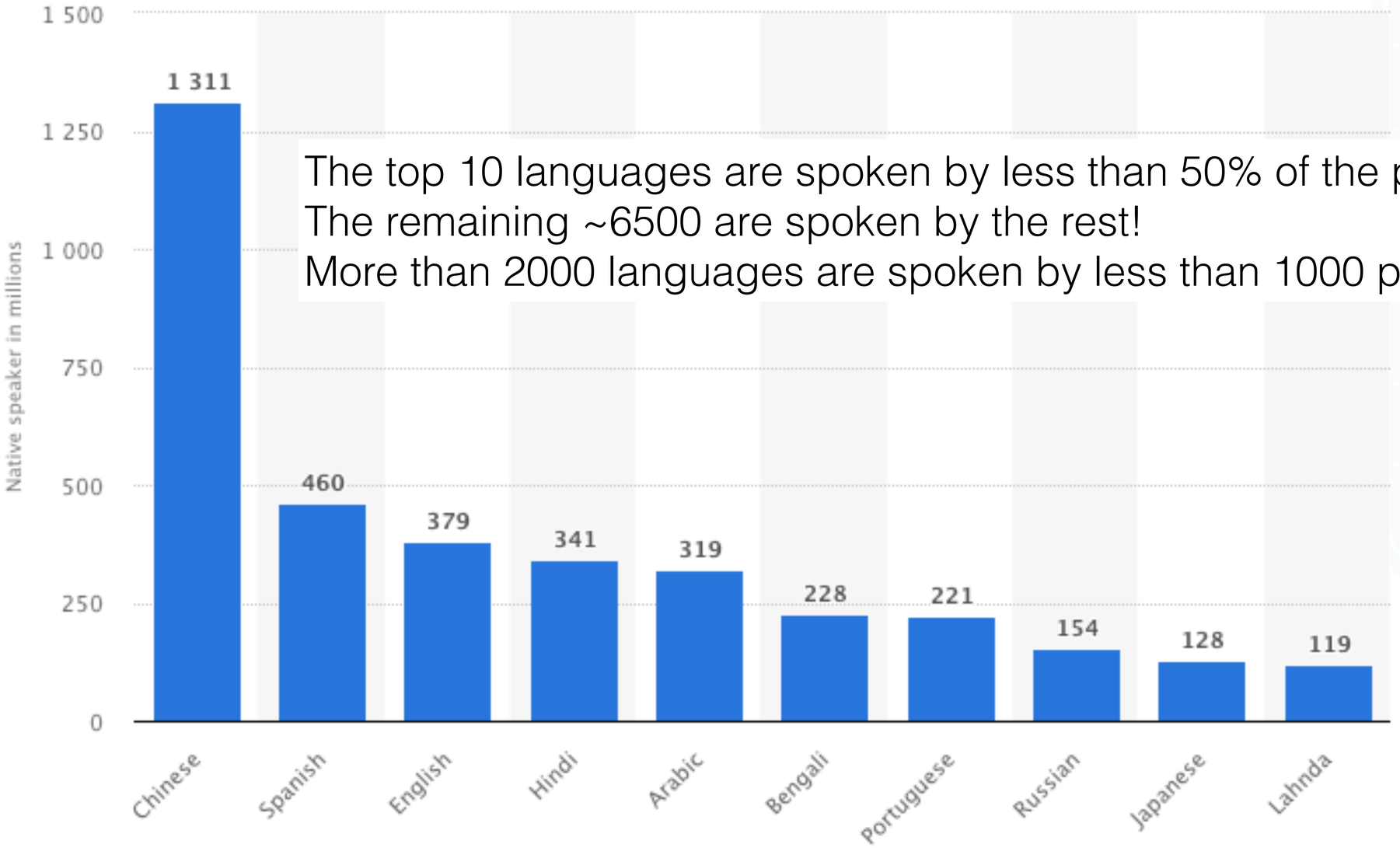
life is beautiful → **NMT System** → *La vita è bella*

Ingredient:
- beam decoding

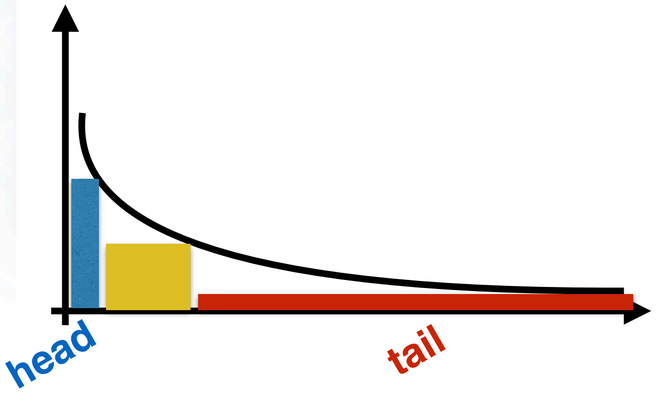
Some Stats

- 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.

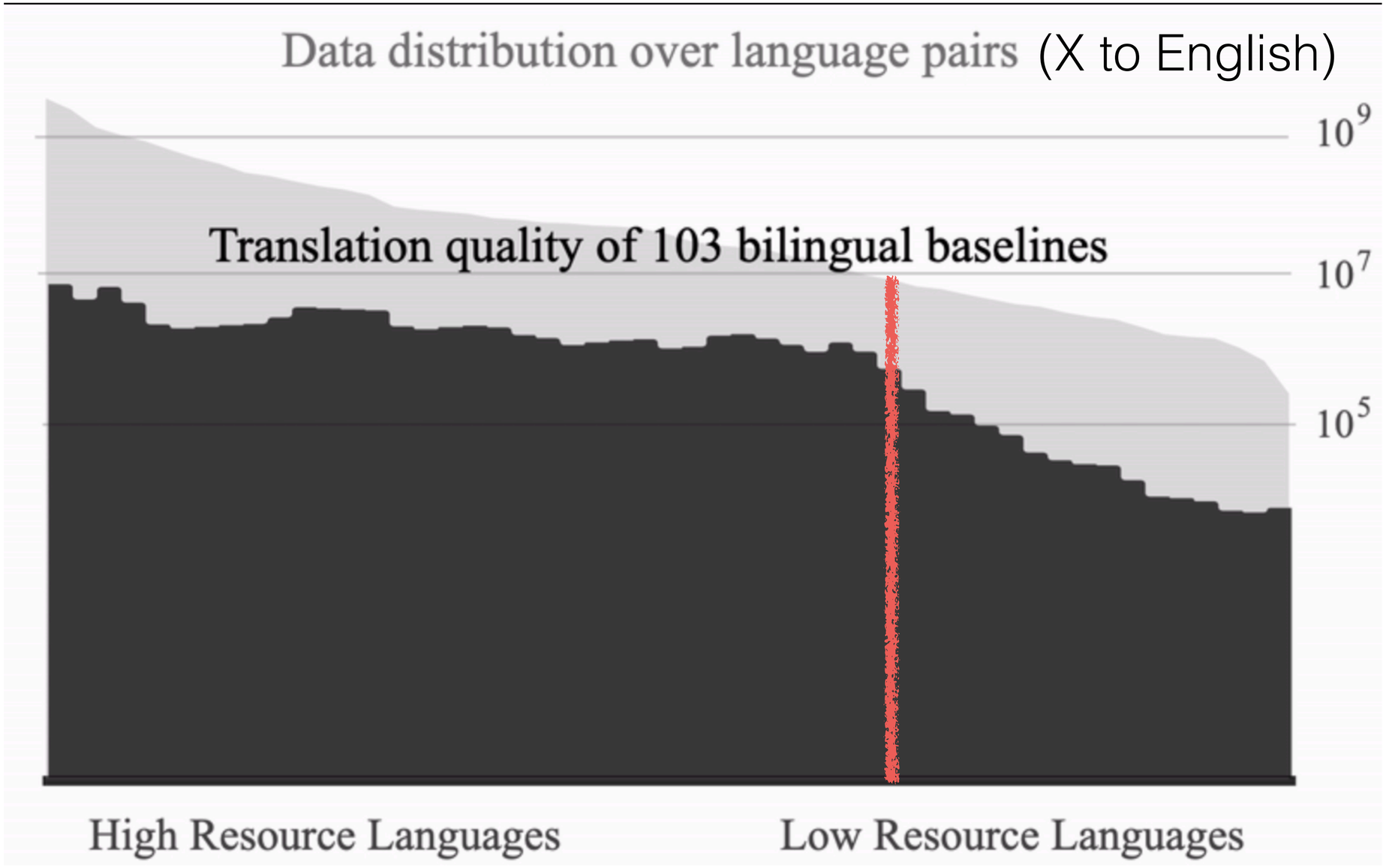
The Long Tail of Languages



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

Goal: Build MT system that can translate English news in Nepali.

Machine Translation in Practice

English **Nepali**

25M people

Training data

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

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 annotat
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 s
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
WikiMatrix v1	1	40.5k	1.0G	4.3M	xces en ne	en ne	tmx	moses	en ne	en ne				en ne		sample	
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	
ParaCrawl v7.1	2	92.1k	3.5M	4.4M	xces en ne	en ne	tmx	moses	en ne	en ne				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	
GlobalVoices v2018q4	158	2.8k	0.1M	0.2M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt	dic	en ne		sample	
tico-19 v2020-10-28	1	3.1k	80.5k	0.1M	xces en ne	en ne	tmx	moses	en ne	en ne		alg smt		en ne		sample	
TED2020 v1	44	4.1k	73.9k	91.0k	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	**6352**	**1.1M**	**1.1G**	**22.9M**	**1.1M**		**0.7M**	**0.7M**									

http://opus.nlpl.eu/

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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	
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http://opus.nlpl.eu/

OPUS ... the open parallel corpus

OPUS linguistic annotat
with ackage. We used s
collec

The C
Contr

Searcl

Relative to the number of parameters O(100M+),
there are very few parallel sentences to learn from.
There are multiple domains and varying quality of translation.

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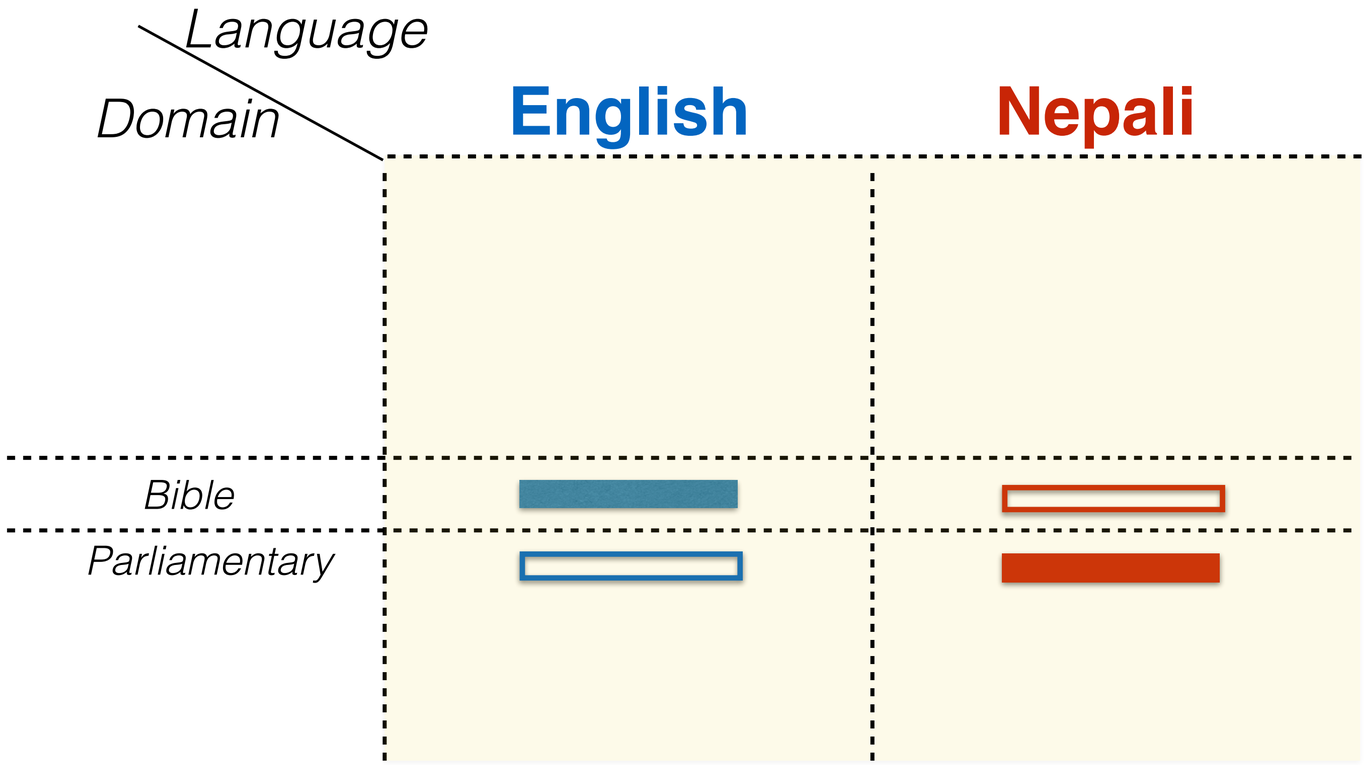
Machine Translation in Practice

English **Nepali**

Training data
(parallel sentences)

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

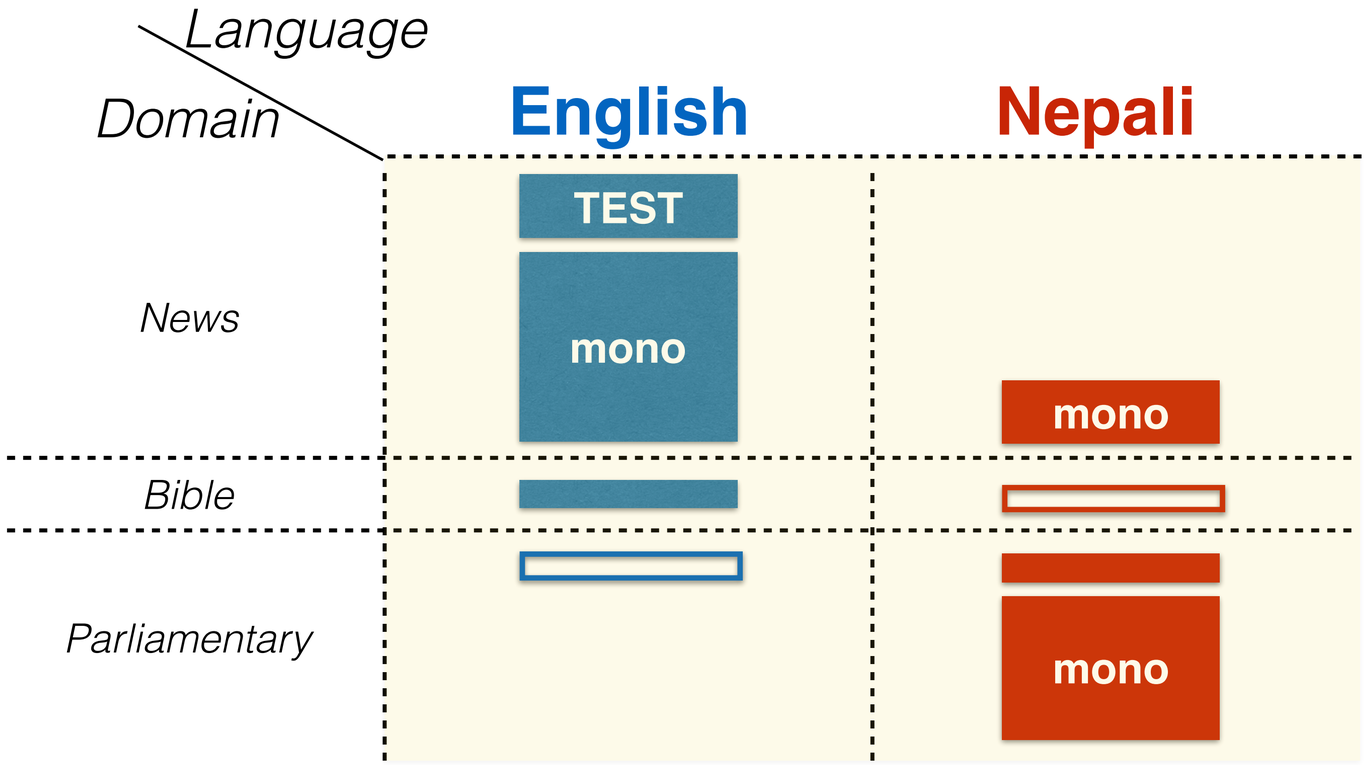
Machine Translation in Practice



Let's represent original text with filled boxes and (human) translations with empty rectangles.

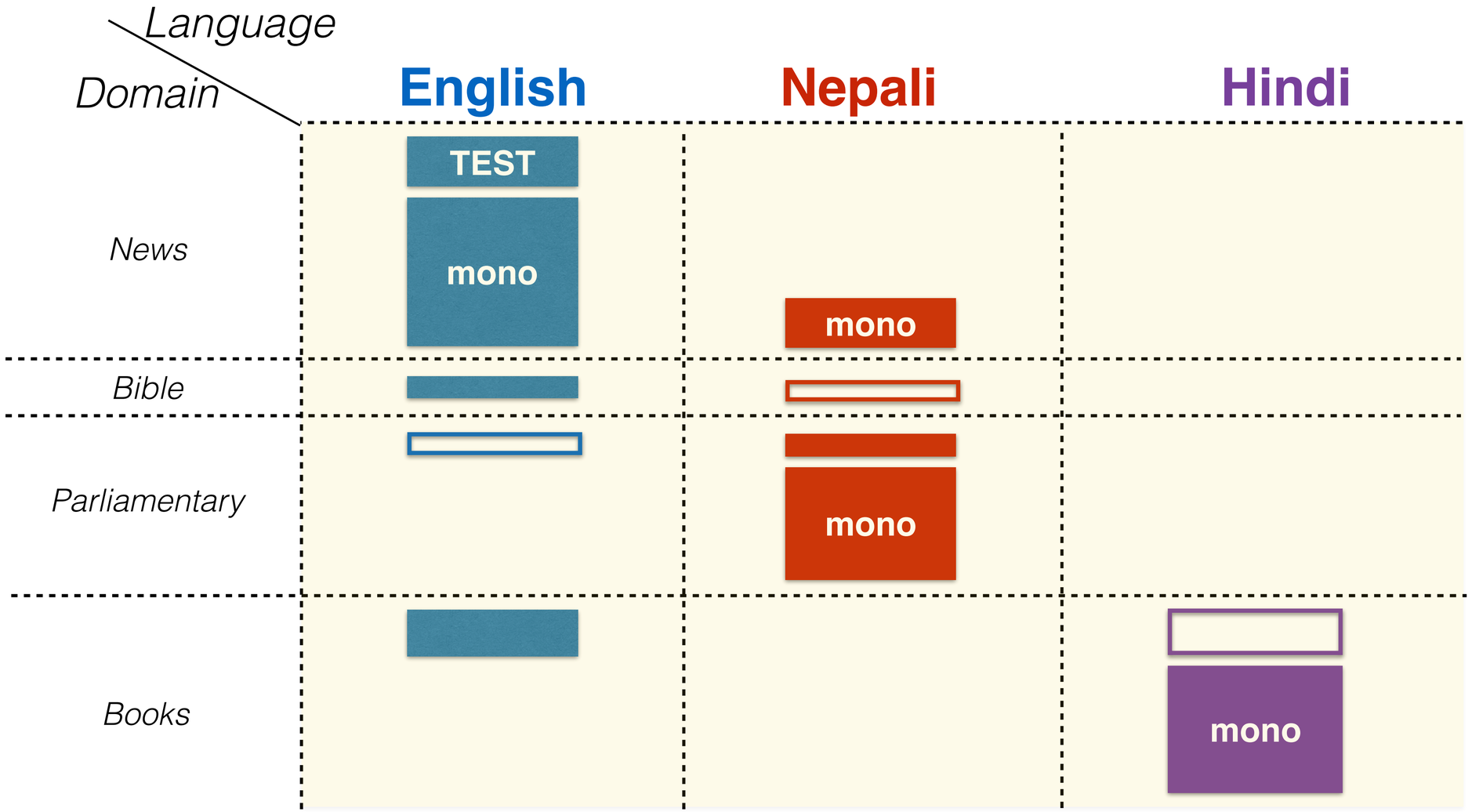
- Some parallel data originates in the source, some in the target language.
- Source and target domains may not match.

Machine Translation in Practice



- 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.

English Nepali Hindi Sinhala Bengali Spanish Tamil Gujarati

TEST

Domain

...

the *Mondrian* like learning setting! ...

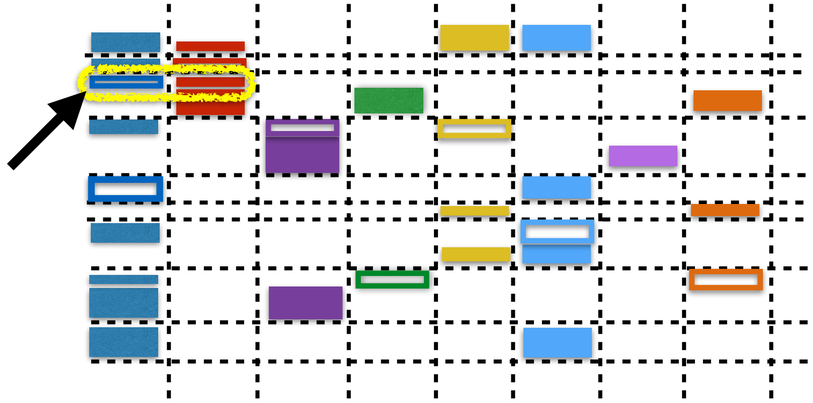
Low Resource Machine Translation

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.

Challenges:

- Datasets
  - Sourcing data to train on
  - High quality evaluation datasets
- Metrics
  - Human evaluation
  - Automatic evaluation
- Modeling
  - Learning paradigm
  - Domain adaptation
  - Generalization
- Scaling

Low-resource MT is about **large**-scale learning!

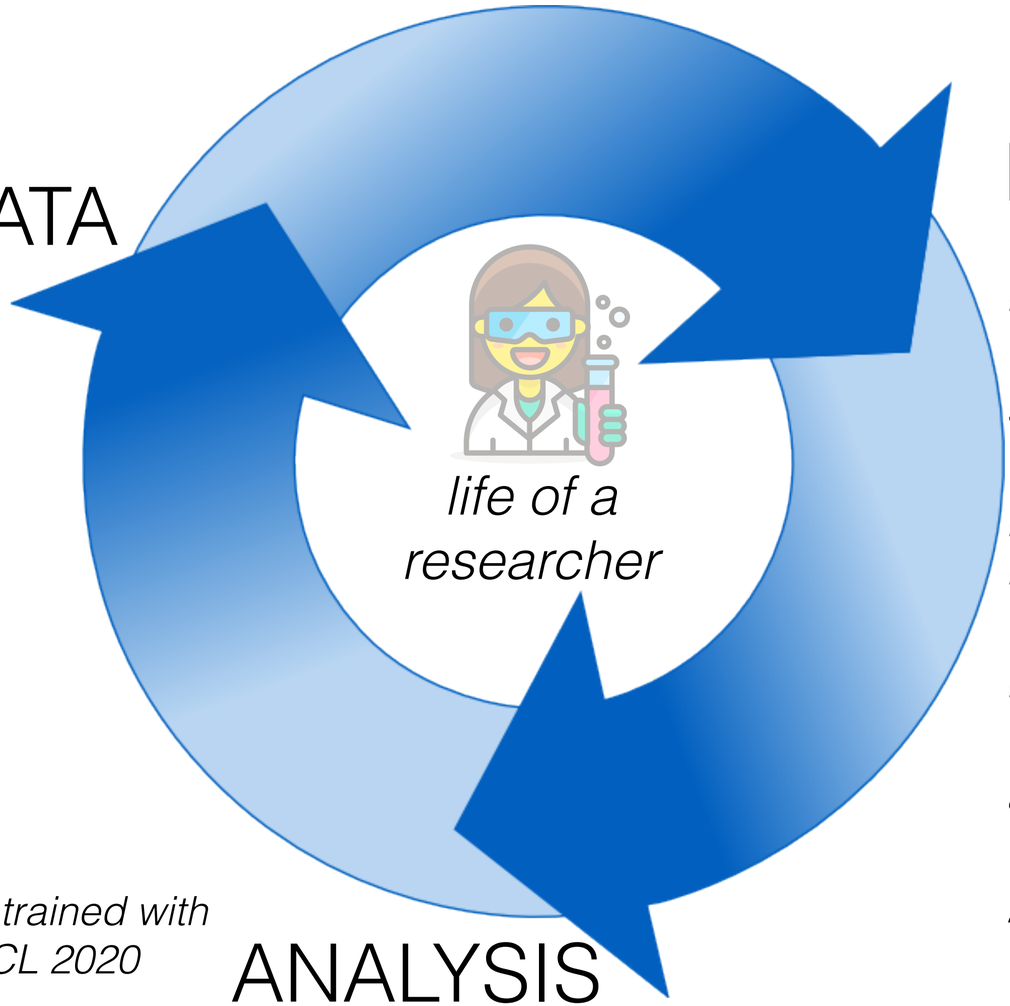


General ML Tip: whenever you lack supervised data, come up with auxiliary tasks or even fantasize it.

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.

The Cycle of Research



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

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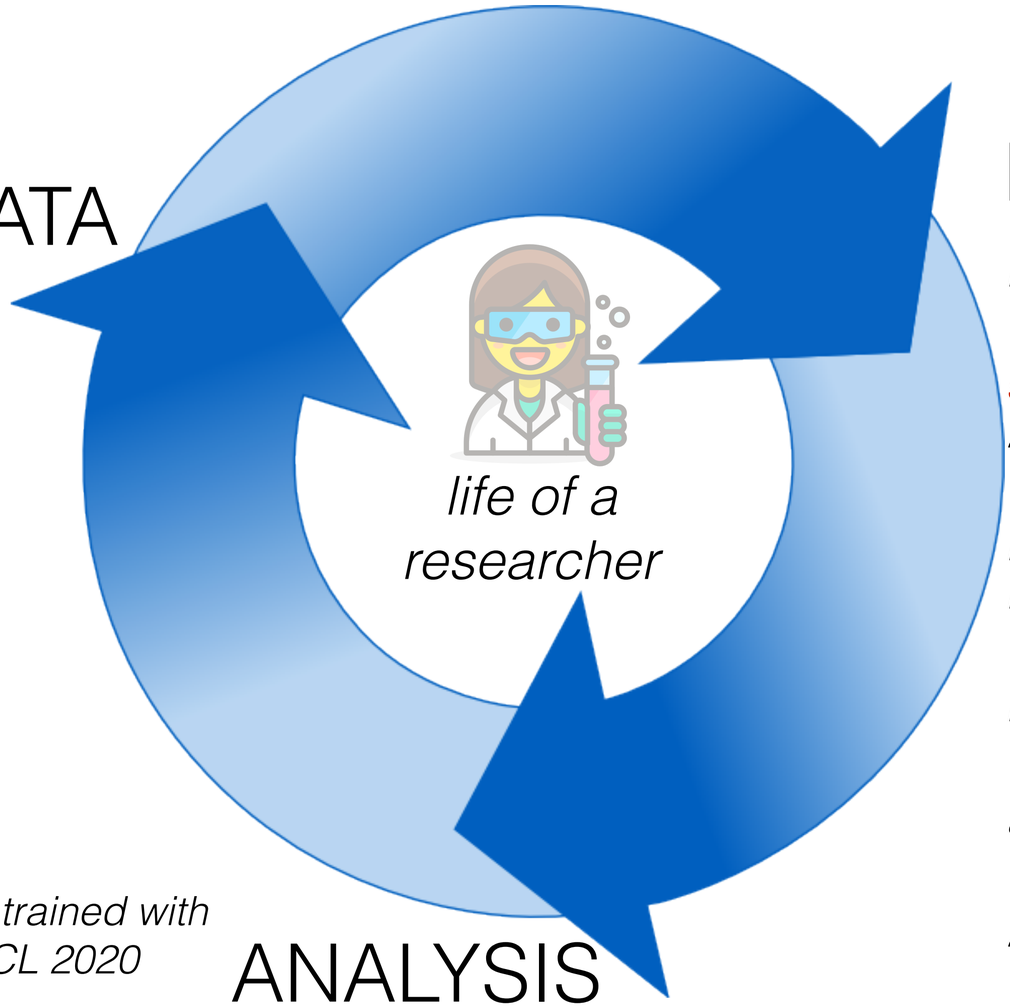
The Cycle of Research



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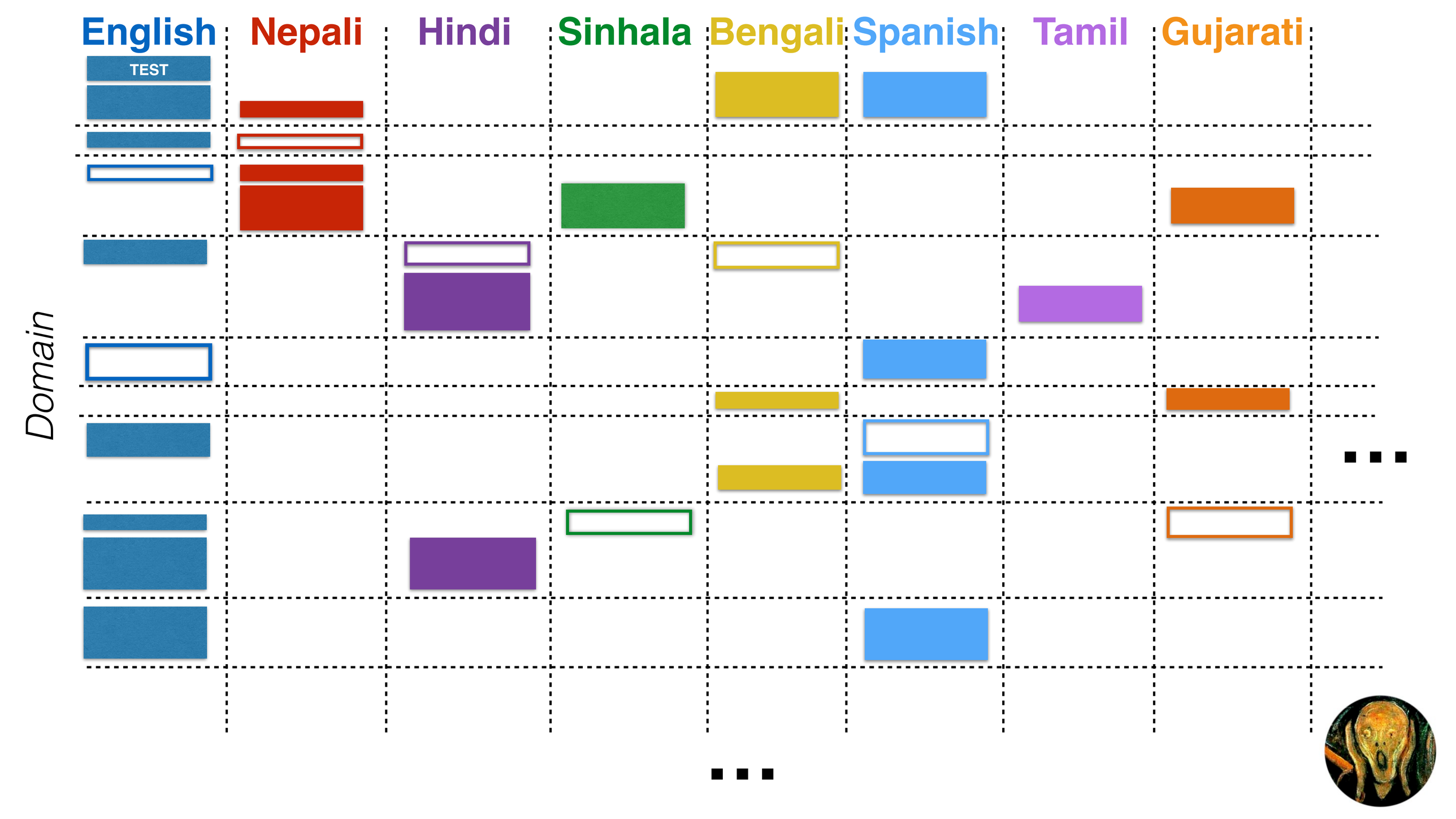
Outline

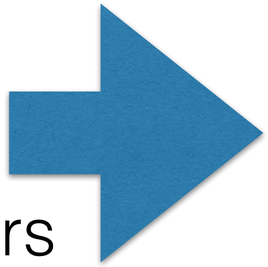
- What is low-resource MT and why is it important?
- **ML perspective on low resource MT**
- Case studies:
  - Unsupervised MT
  - En-Ne
  - En-My
- Perspectives


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

ML Perspective

NLP/MT

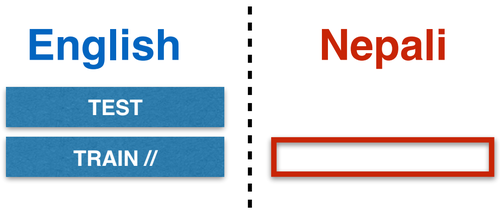
- Parallel dataset
- Monolingual data
- Multiple language pairs
- Multiple domains



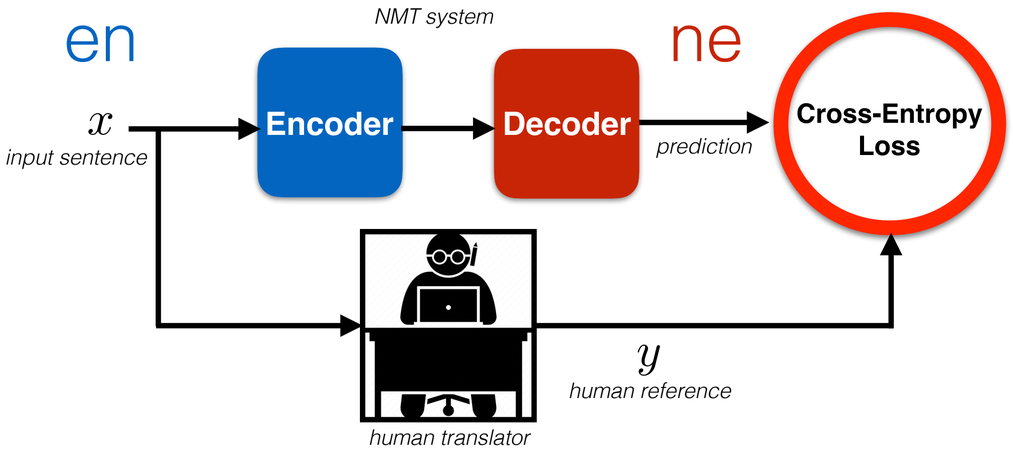
ML

- Supervised learning
- Semi-supervised learning
- Multi-task/multi-modal learning
- Domain adaptation

Supervised Learning



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



Per-sample loss: $\mathcal{L}(\theta) = -\log p(y|x;\theta)$

usual attention-based transformer

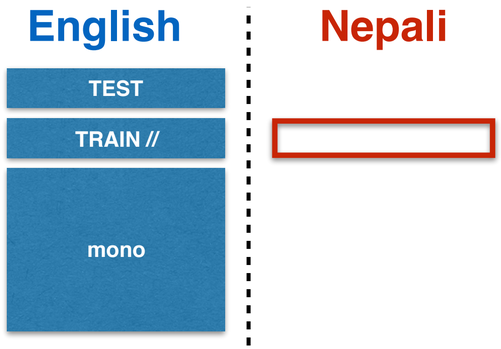
Regularize the model using:

- dropout [1]
- label smoothing [2]

[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

Semi-Supervised Learning (DAE)

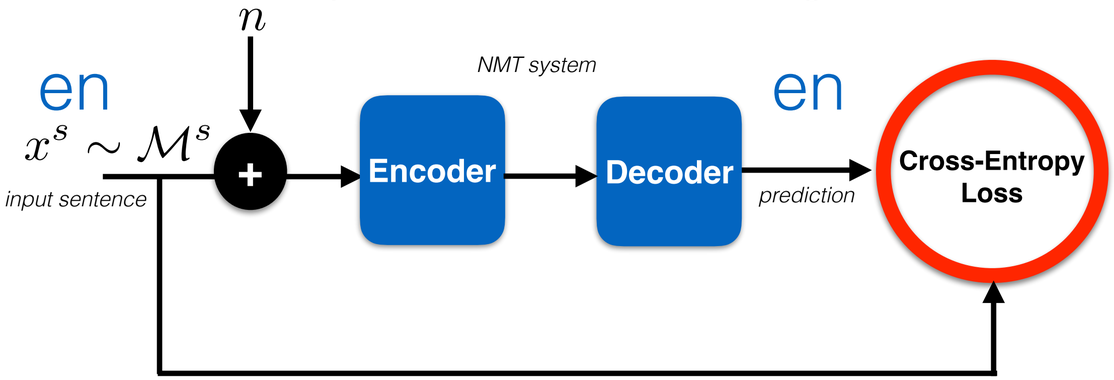


$$\mathcal{D} = \{(x, y)_i\}_{i=1,..,N}$$

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

Additional source side monolingual data.

Idea: model p(x) with a denoising auto-encoder.



Noise: word drop, swap, etc.

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

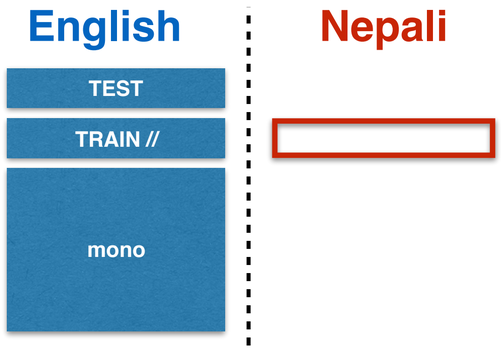
Learning Framework: DAE

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

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

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

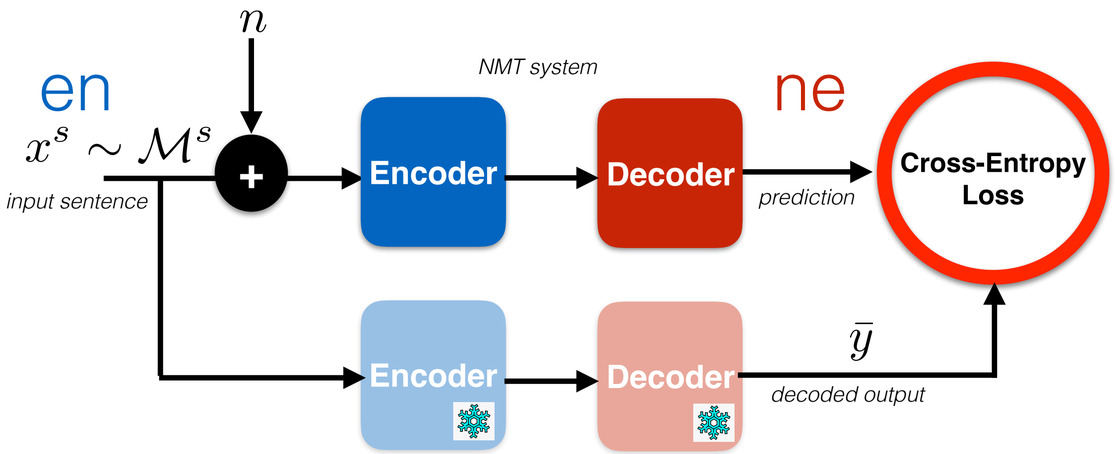
Semi-Supervised Learning (ST)



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

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

Idea: predict missing labels.



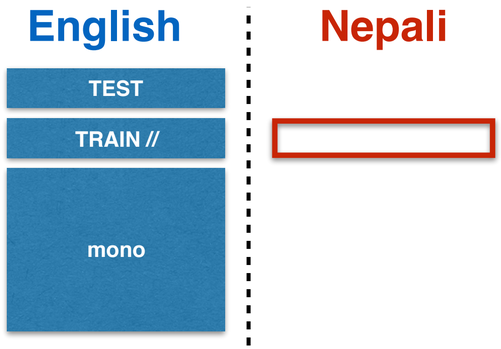
$$\mathcal{L}^{ST}(\theta) = -\log p(\bar{y}|x+n)$$

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

Key elements: decoding and training noise.

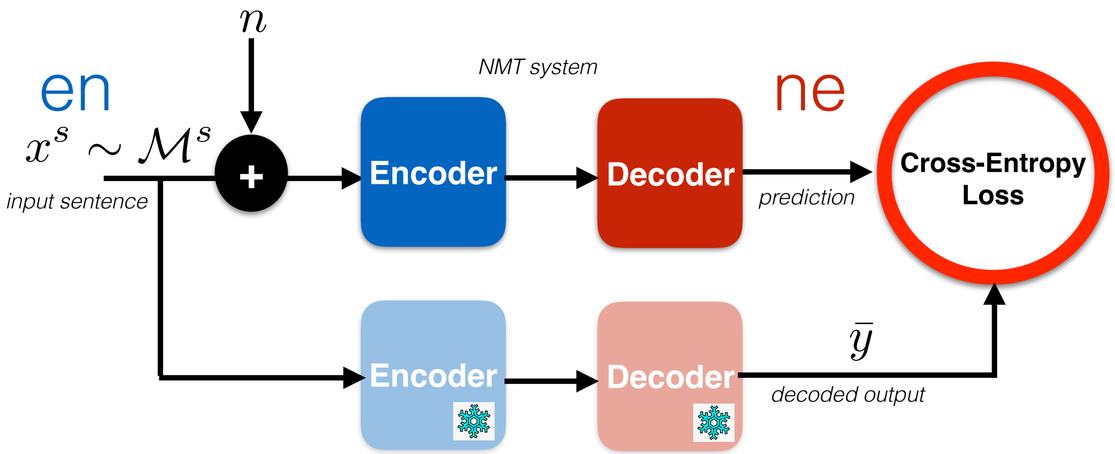
He et al. "Revisiting self-training for neural sequence generation" ICLR 2020

Semi-Supervised Learning (ST)



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

Idea: predict missing labels.



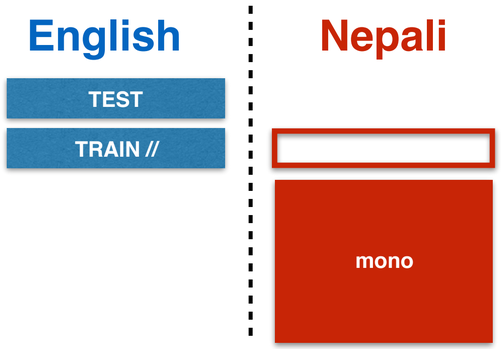
ALGORITHM

- 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: $\mathcal{D} \cup \mathcal{A}^s$

Key elements: decoding and training noise.

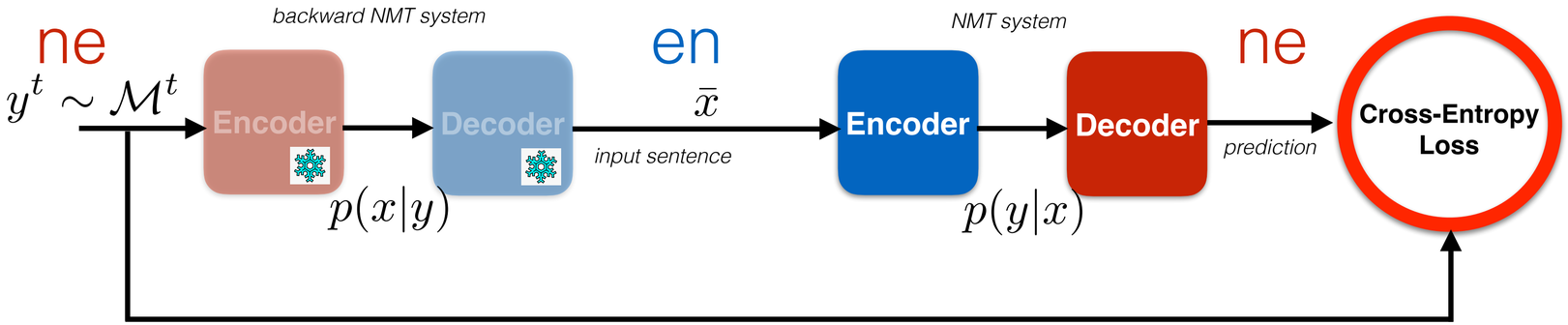
He et al. "Revisiting self-training for neural sequence generation" ICLR 2020

Semi-Supervised Learning (BT)



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

Additional target side monolingual data.



Learning Framework:
Back-Translation (BT).

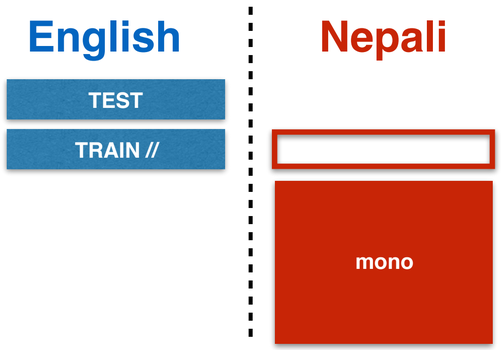
$$\mathcal{L}^{BT}(\theta) = -\log p(y|\bar{x})$$
$$\mathcal{L}(\theta) = \mathcal{L}^{\text{sup}}(\theta) + \lambda \mathcal{L}^{\text{BT}}(\theta)$$

Adding target-side monolingual data.
Two benefits:

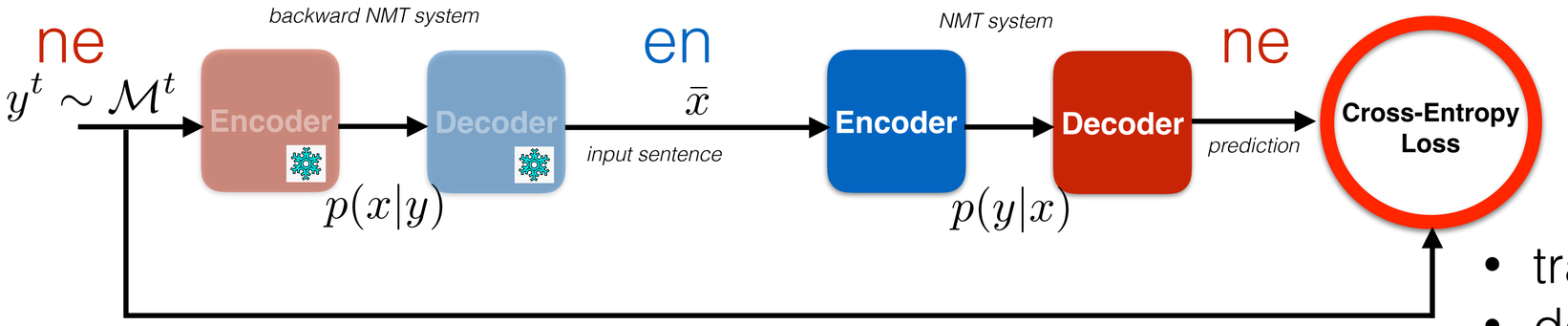
a) Decoder learns a good language model.
b) Better generalization via data augmentation.
c) Unlike ST, target is correct but input is not.

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

Semi-Supervised Learning (BT)



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



Adding target-side monolingual data.
Two benefits:

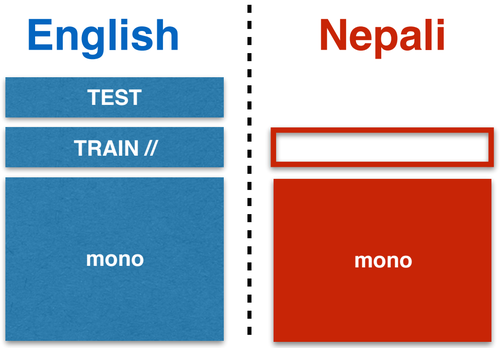
a) Decoder learns a good language model.
b) Better generalization via data augmentation.
c) Unlike ST, target is correct but input is not.

ALGORITHM

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

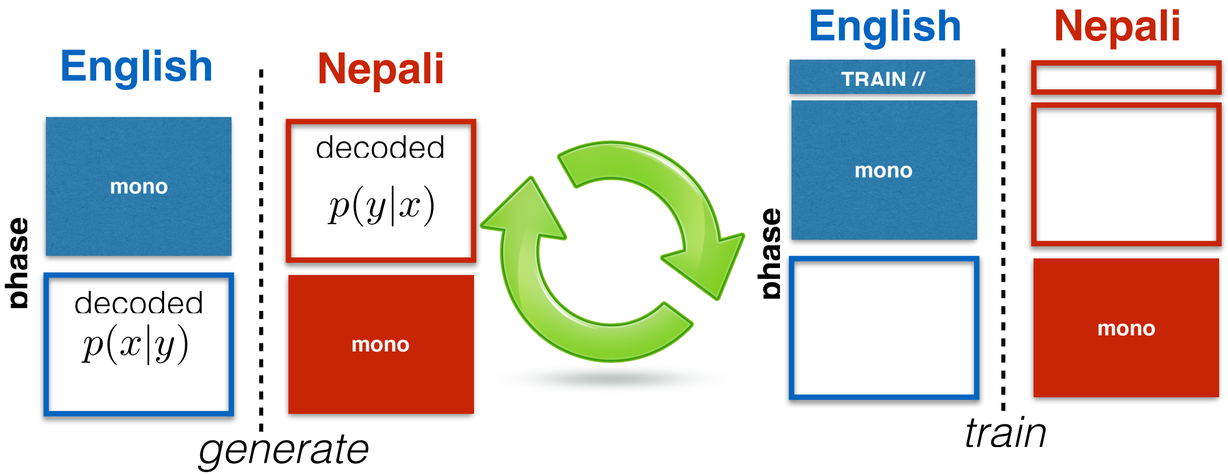
Sennrich et al. "Improving NMT models with monolingual data" ACL 2016

Semi-Supervised Learning (ST+BT)



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

Additional source & target side monolingual data.



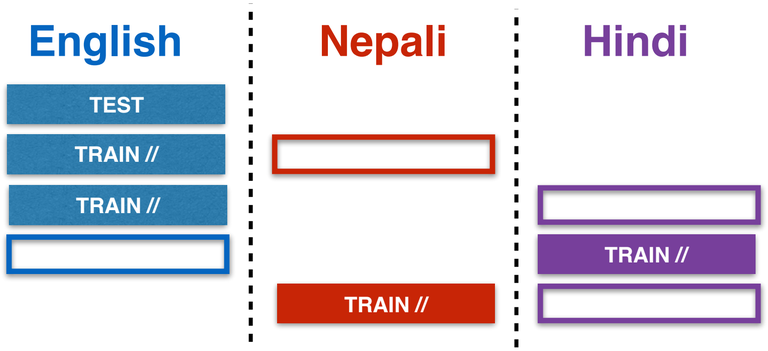
ALGORITHM

- train model $p(x|y)$ and $p(y|x)$ on $\mathcal{D}$
- repeat
  - **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 $\mathcal{A}^s = \{(x_j^s, \bar{y}_j)\}_{j=1,..,M_s}$
  - **phase 2**
    - retrain both $p(y|x)$ and $p(x|y)$ on: $\mathcal{D} \cup \mathcal{A}^t \cup \mathcal{A}^s$

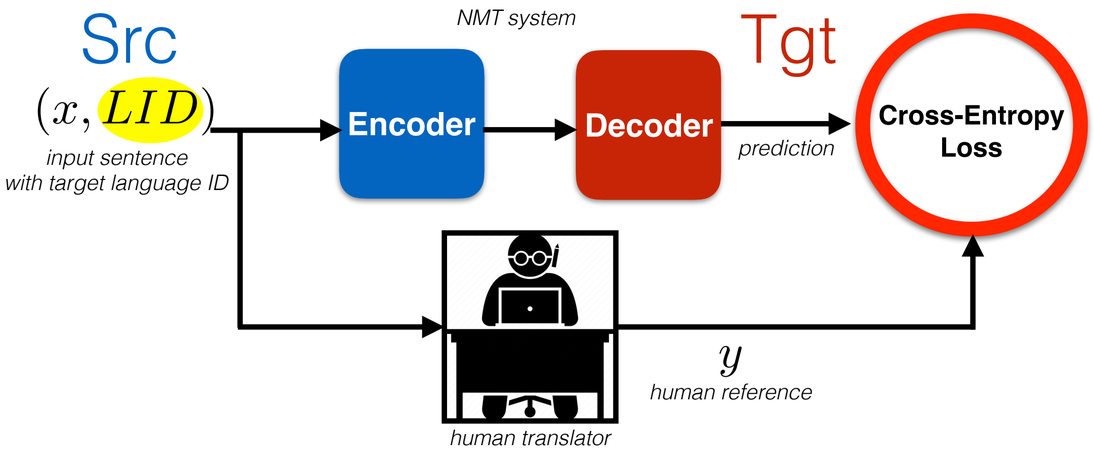
$$\mathcal{L}^{\text{total}}(\theta) = -\log p(y|x) - \lambda_1 \log p(y^t|\bar{x}^t) - \lambda_2 \log p(\bar{y}^s|x^s)$$

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

Multi-Task/Multi-Modal Learning



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



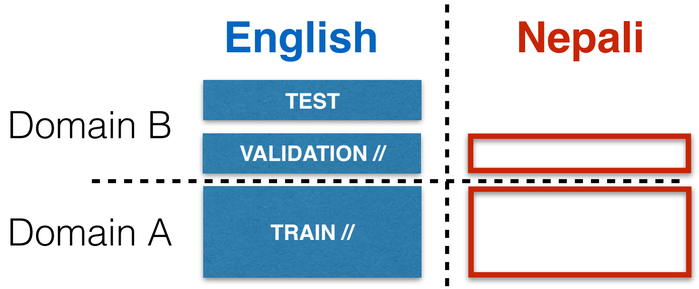
Learning Framework: Multilingual Training

Share encoder and decoder across 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.

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

Johnson et al. "Google's multilingual NMT system…" ACL 2017
Aharoni et al. "Massively multilingual NMT" ACL 2019
Fan et al. "Beyond English centric MMT" arXiv 2020

Domain Adaptation



Learning Framework: Fine-tuning.

Train on domain A.
Finetune on domain B by continuing training for a little bit on the validation set.

Several basic learning approaches can be used and combined to tackle low-resource MT, thanks to the end-to-end learning based approach (there is nothing too specific to the task and language pair).

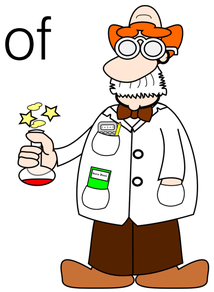
General ML Tip #1: keep architecture and learning algorithm as general as possible, let the model learn from data what the task is about.

General ML Tip #2: data augmentation is often a very powerful way to improve generalization.

What's so special about MT? The symmetry of the prediction task. This is what is exploited to fantasize data in BT.

Conclusion so far…

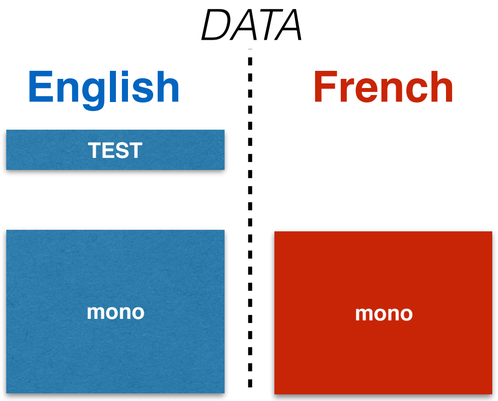
- Even assuming no domain effect, there are lots of training paradigms depending on the available data.
- Complex interaction: generalization, domain, language pair, capacity, amount of parallel and monolingual data, etc.
- In general, DAE pretraining, (iterative) BT and multi-lingual training perform 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.



Outline

- What is low-resource MT and why is it important?
- ML perspective on low resource MT
- **Case studies:**
  - Unsupervised MT
  - En-Ne
  - En-My
- Perspectives

Case Study #1: Unsupervised MT



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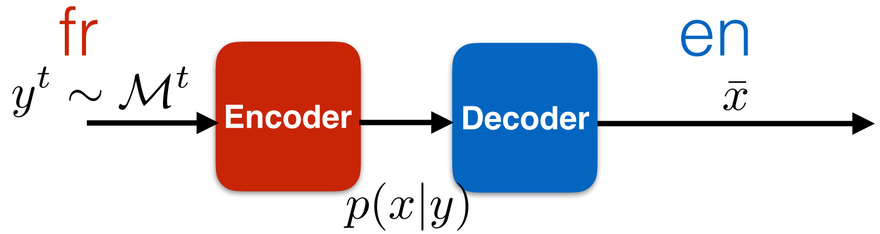
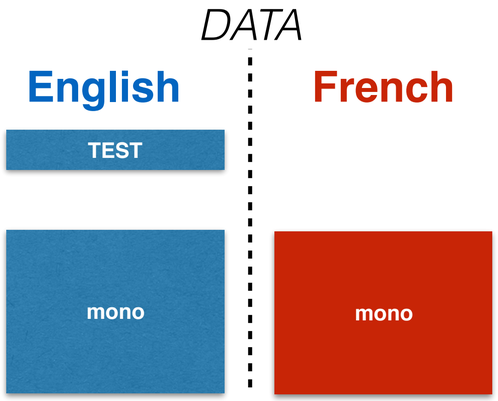


Lample et al. "Phrase-based and neural unsupervised MT" EMNLP 2018
Artetxe et al. "An effective approach to unsupervised MT" ACL 2019

Case Study #1: Unsupervised MT



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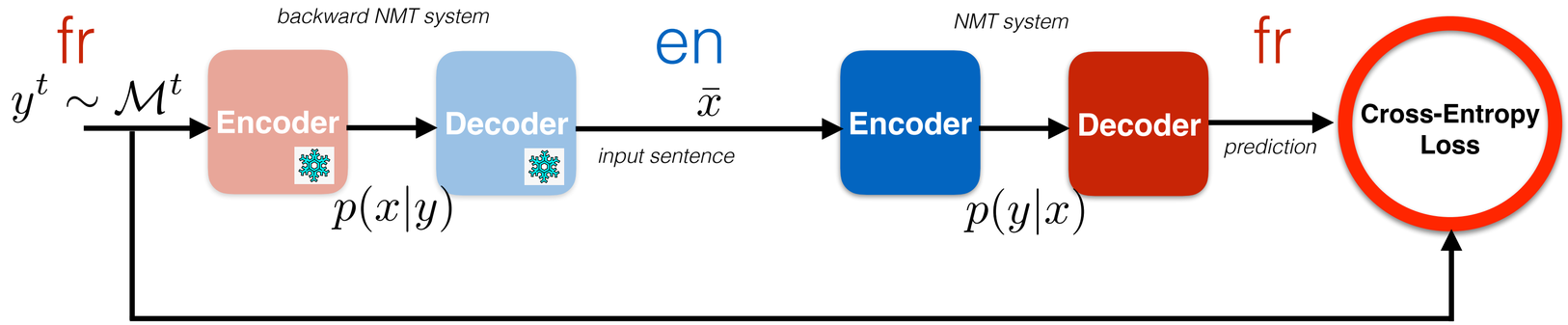
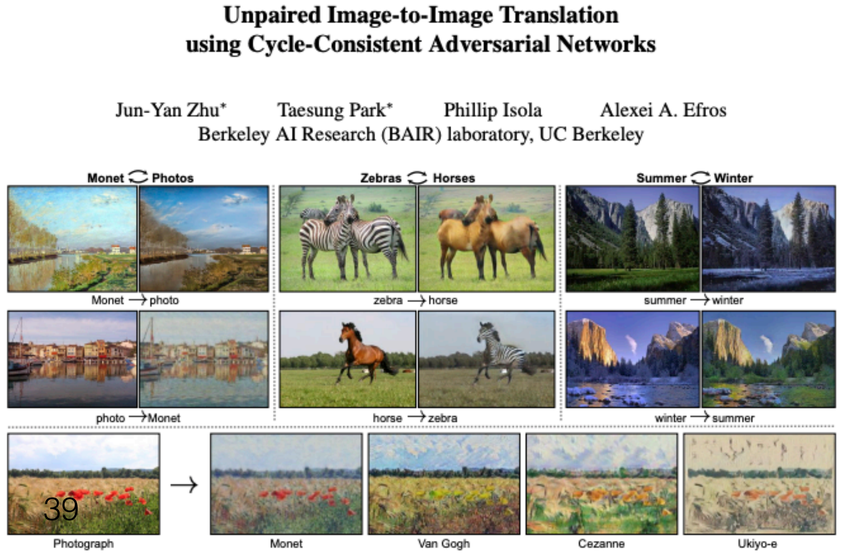


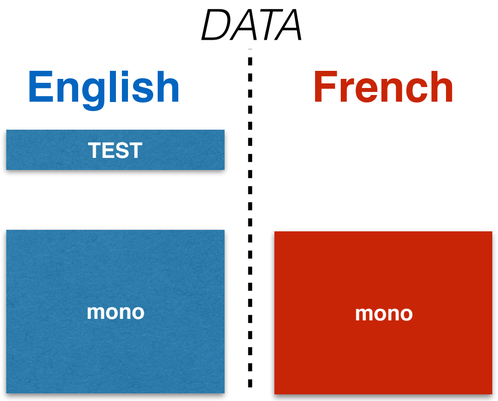
…and vice versa starting from English.

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

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



Case Study #1: Unsupervised MT



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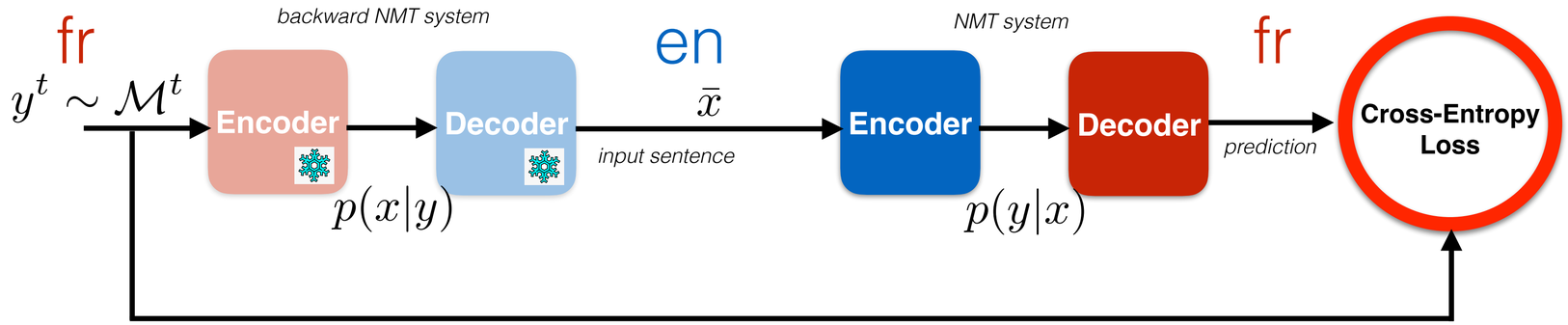
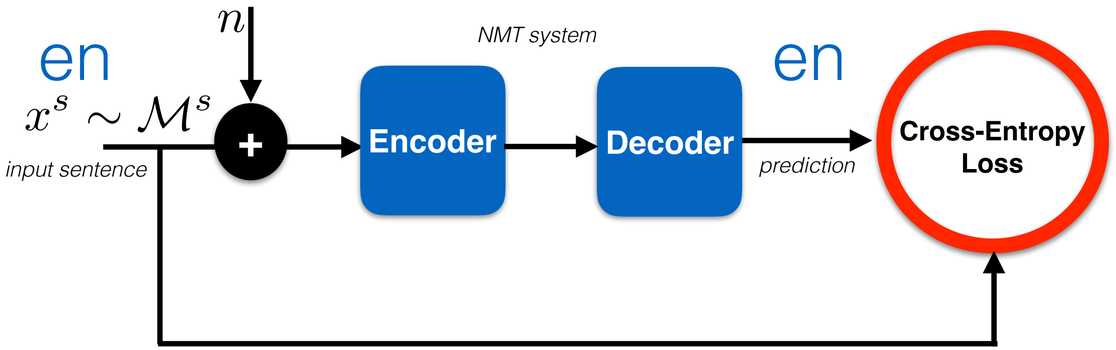




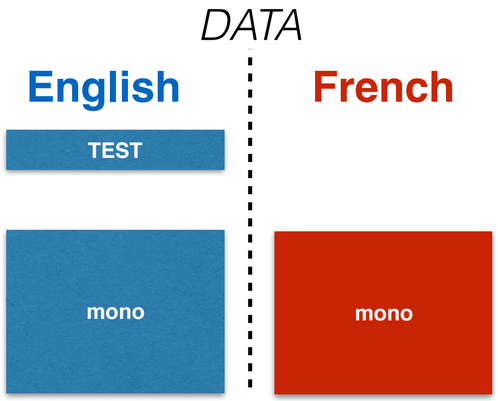
DAE makes sure decoder outputs fluently in the desired language.

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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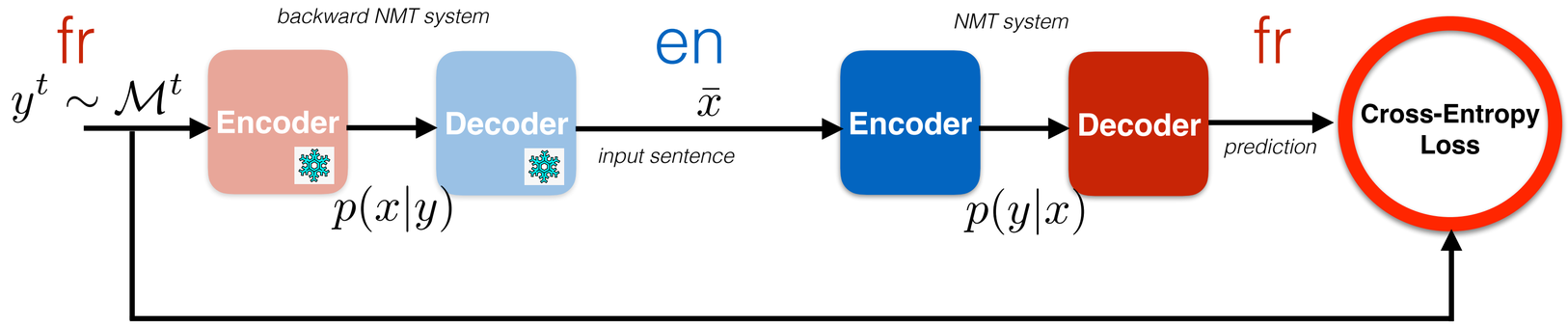

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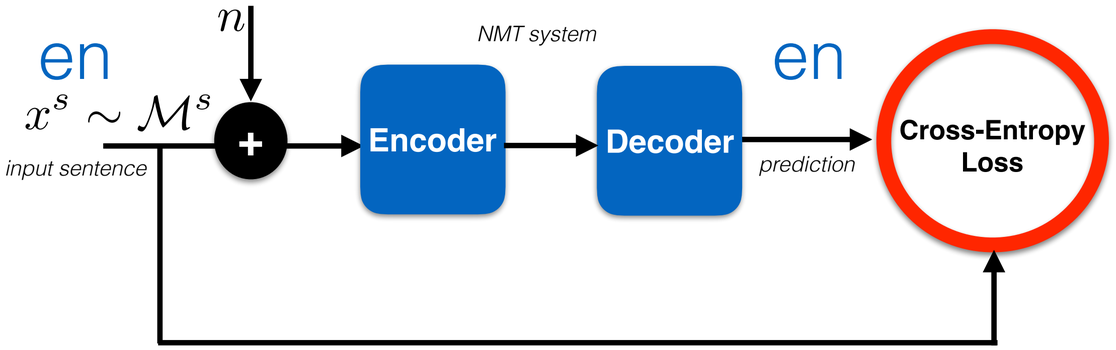
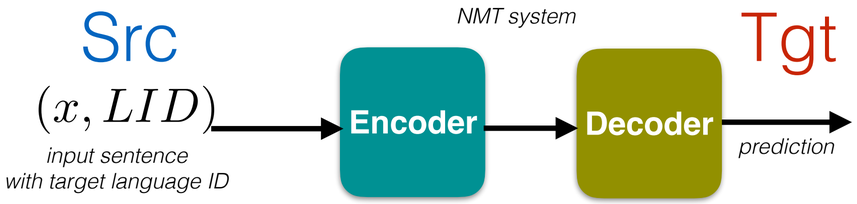
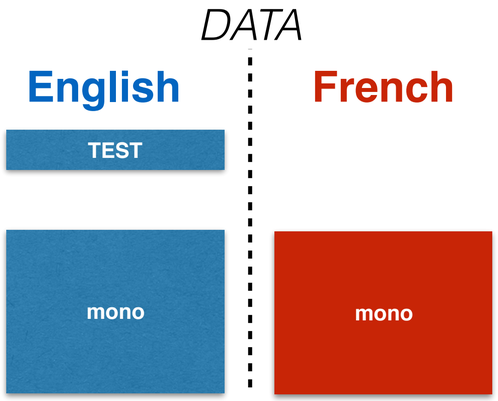


Like in multilingual NMT, share encoder and decoder parameters. Encoder is encouraged to produce shared representations (particularly if pre-trained).



Case Study #1: Unsupervised MT



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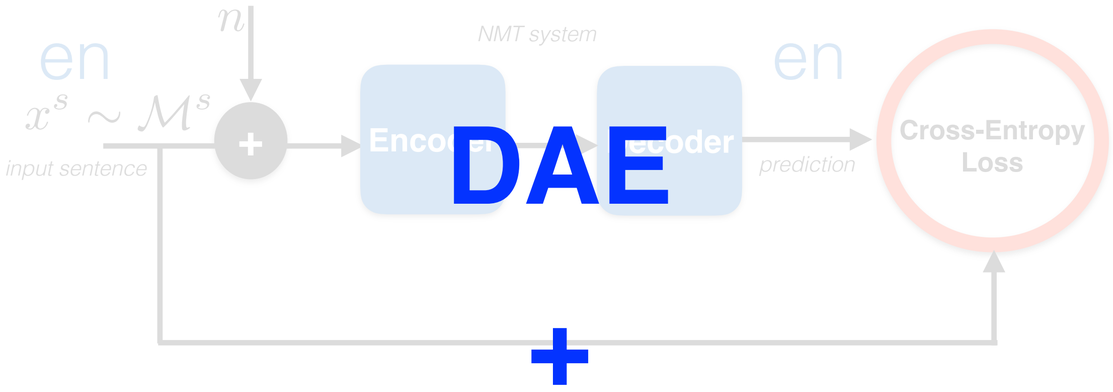

DAE makes sure decoder outputs fluently in the desired language.

+

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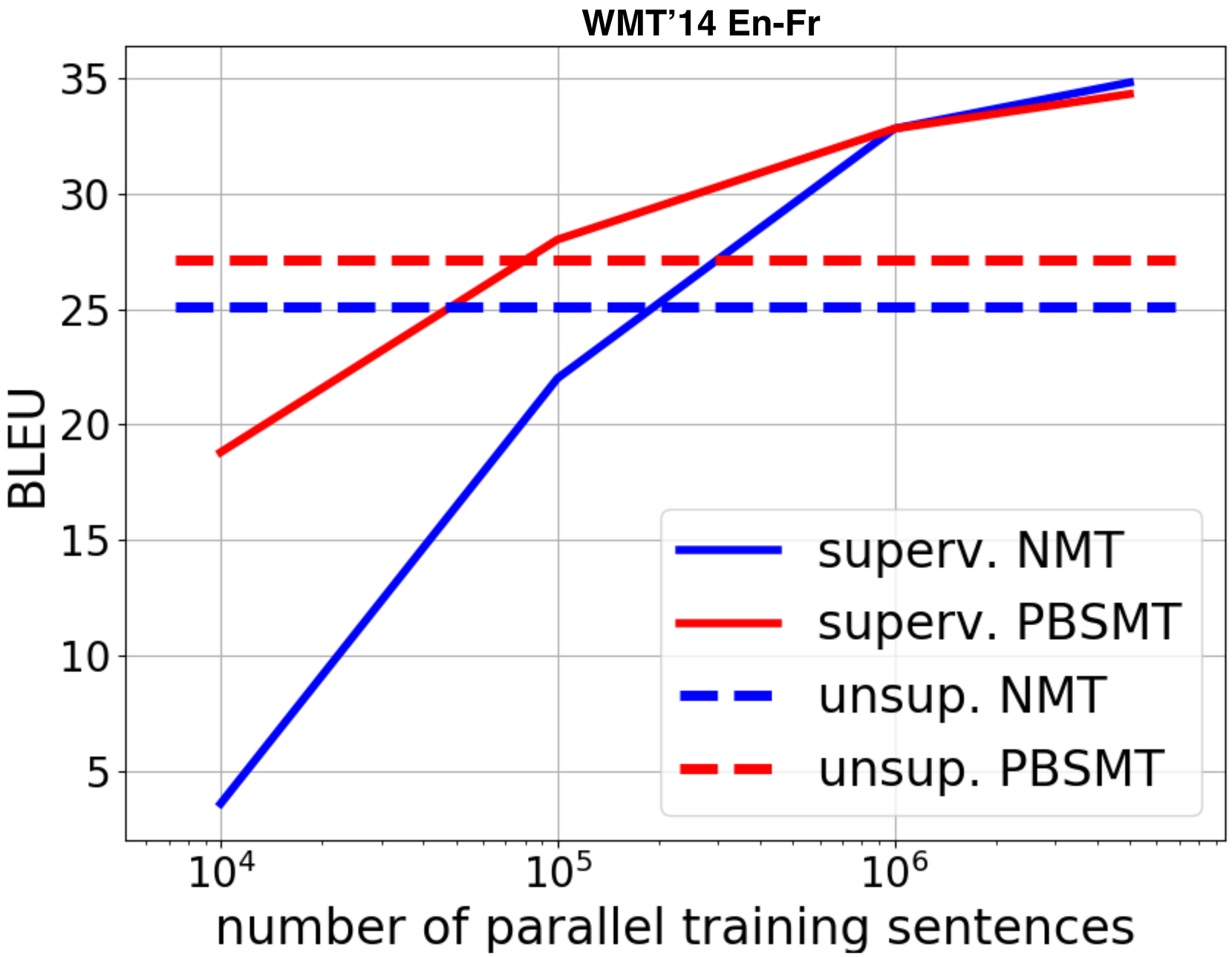


Same ideas can be applied to phrase-based statistical MT systems (PBSMT). NMT and PBSMT can be combined for even better results.

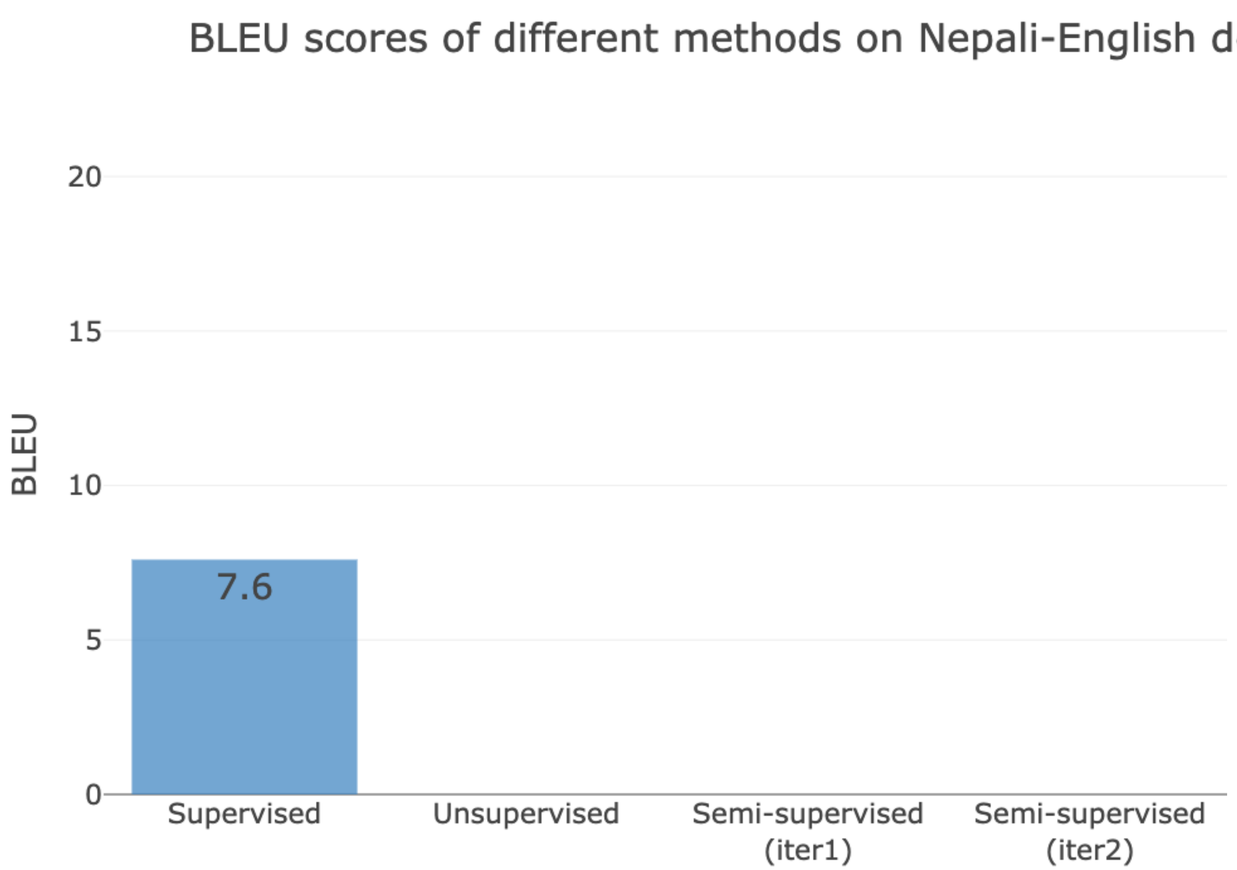
Since unsupMT was trained on about 10M sentences, each parallel sentence is worth 100 monolingual sentences (for this dataset and language pair).

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

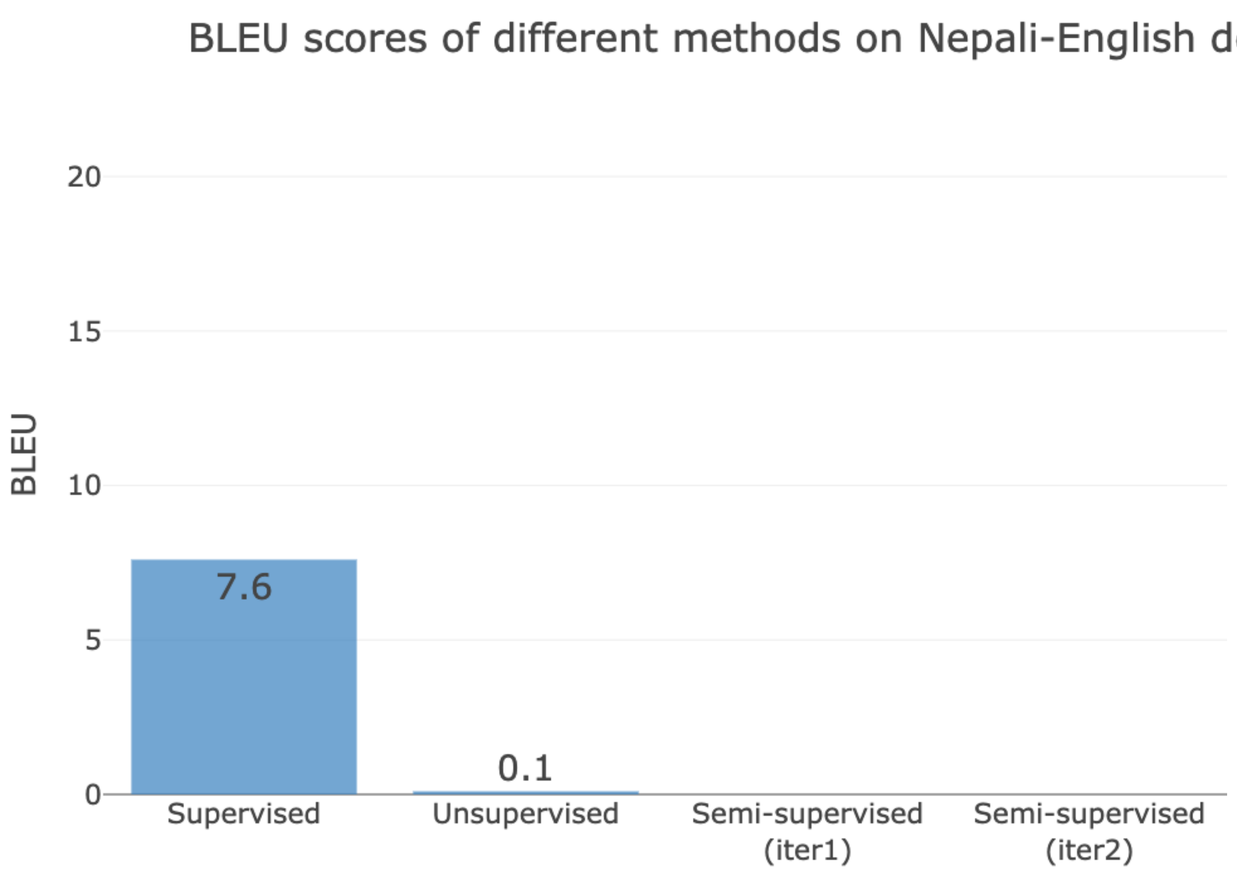
Case Study #2: FLoRes Ne-En

	In-domain (Wikipedia)	**Out-of-domain**
Parallel	None	500K sentences (Bible, GNOME/Ubuntu, OpenSubtitle, ...) *Hindi: 1.5M
Monolingual	Ne: 100K sentences En: 70M	~5M sentences (CommonCrawl) *Hindi: 45M

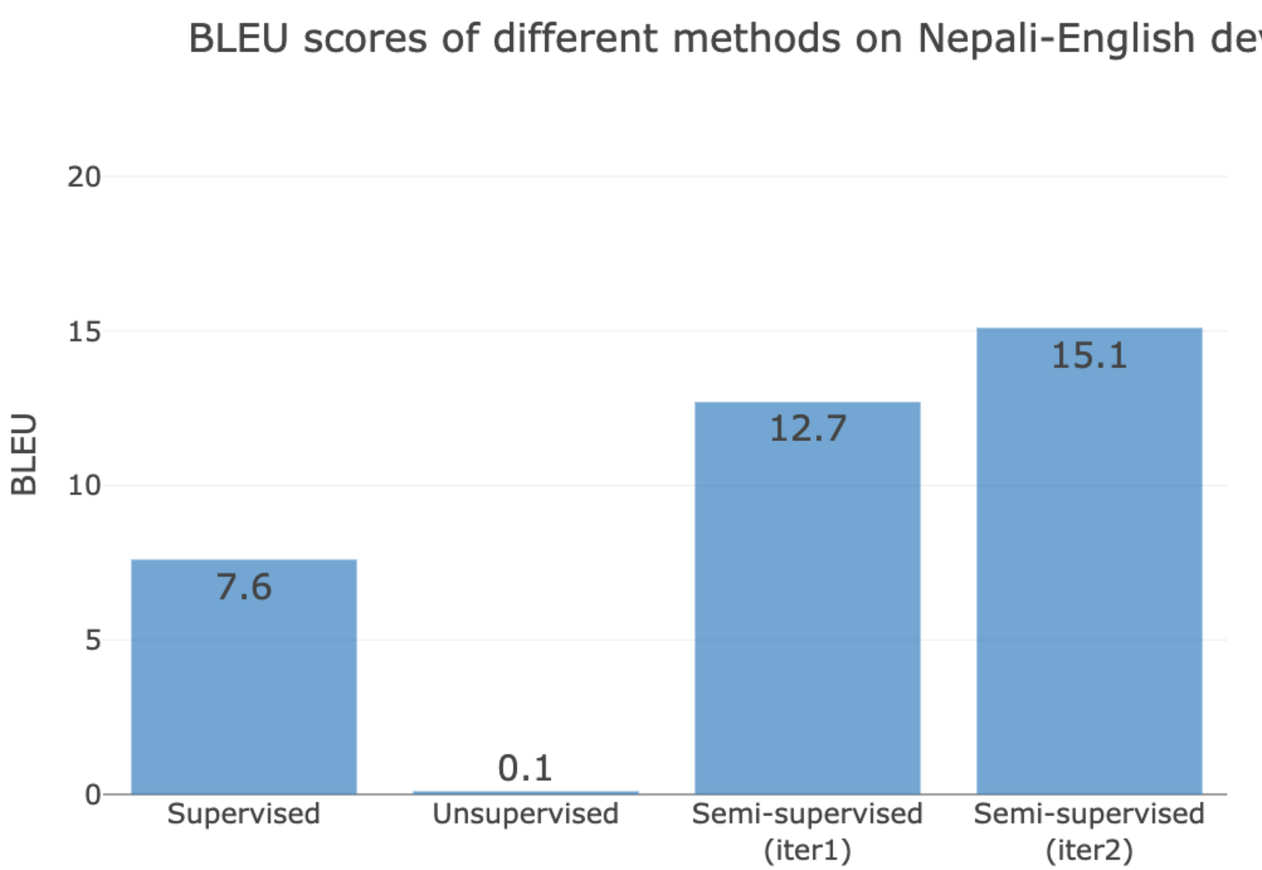
Results on FLoRes: Ne-En



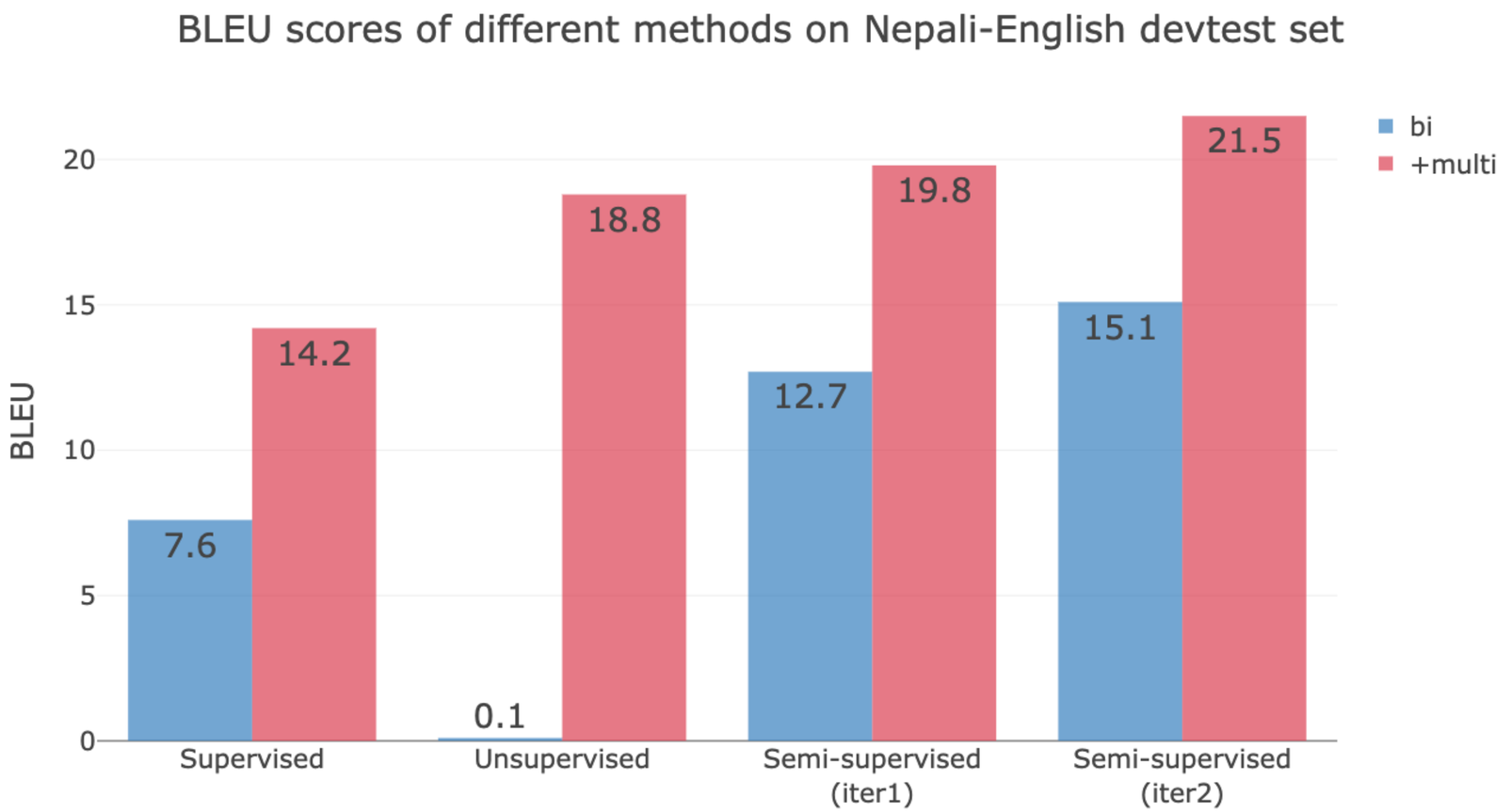
Results on FLoRes: Ne-En



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

သိန္ဒီနယ် သည် ယခင် ရှမ်းပဒေသရာဇ်ပြည်နယ်များတွင် ပါဝင်ခဲ့သော ပြည်နယ်တစ်ခု ဖြစ်သည်။ သိန္ဒီနယ်ကို ခရစ် ၁၈၈၈ ခုနှစ် အင်္ဂလိပ်တို့ ဝင်ရောက်သိမ်းပိုက်ပြီးနောက်မှ မြောက်သိန္ဒီနယ် (သိန္ဒီနယ်)နှင့် တောင်သိန္ဒီနယ်(မိုင်းရယ်နယ်)ဟု ခွဲခြားအုပ်ချုပ်ခဲ့သည်။ ရှေးအခါသမယက သိန္ဒီနယ်ကြီးသည် အစိတ် စိတ်ကွဲပြားခြင်းမရှိဘဲ ရှမ်းပြည်နယ်တဝှမ်းလုံးတွင် အာဏာအလွှမ်းမိုးဆုံးသော နယ်ကြီးဖြစ်ခဲ့သည်။ သို့သော် မြန်မာဘုရင်များ ဝင်ရောက်တိုက်ခိုက် သိမ်းပိုက်ပြီးသည့်နောက် အုပ်ချုပ်ရေးဝါဒအရ ရာထူးလု သည့်နယ်ရှင် စော်ဘွားတို့ကြောင့် သိန္ဒီနယ်ကြီးသည် ငါးနယ်အထိ အစိတ်စိတ် ကွဲပြားခဲ့လေသည်။ ထို အတွင်း စော်ဘွားအချင်းချင်း စိတ်ဝမ်းကွဲကာ တစ်ဦးနှင့်တစ်ဦးတိုက်ခိုက်၍ ဆိုင်ရာ နယ်ပယ်များကို အုပ်ချုပ်ကြ သည်။ နောက်ဆုံးခရစ် ၁၈၈၈ ခုနှစ်၊ အင်္ဂလိပ်တို့ဝင်ရောက်လာမှ အထက်ပါ အတိုင်းနှစ်နယ်ခွဲ၍ အုပ်ချုပ်ခဲ့သည်။ နှစ်နယ်ခွဲ၍ အုပ်ချုပ်စက ခွန်ဆိုင်တုံဟမ်းအား မြောက်သိန္ဒီနယ်အတွက် စော်ဘွားအဖြစ်လည်းကောင်း၊ ဆိုင် နော်ဖ၏သား နော်မိုင်းအား တောင်သိန္ဒီနယ် စော်ဘွားအဖြစ်လည်းကောင်း၊ ခန့်အပ်ခဲ့လေသည်။ ၁၉၂၅ ခုနှစ် တွင် မြောက်သိန္ဒီနယ်ကို စဝ်ဟုံဖက စော်ဘွားအဖြစ် ဆောင်ရွက်ခဲ့လေသည်။

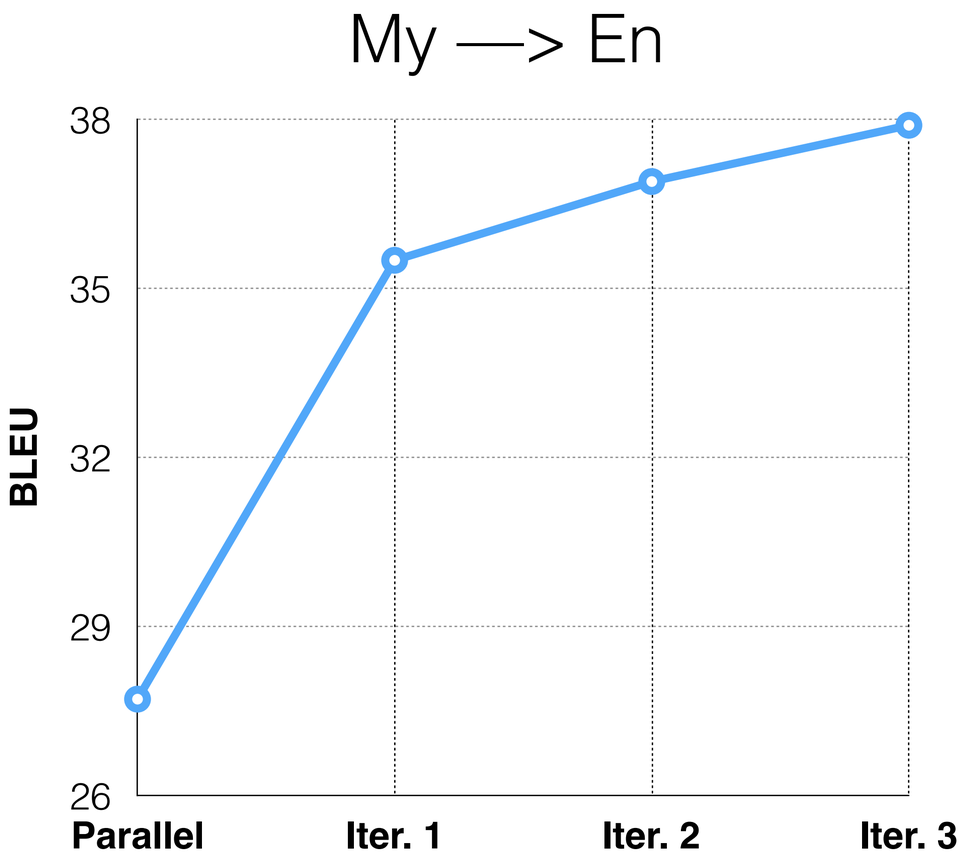
https://my.wikipedia.org/wiki/ဗဟိုစာမျက်နှာ

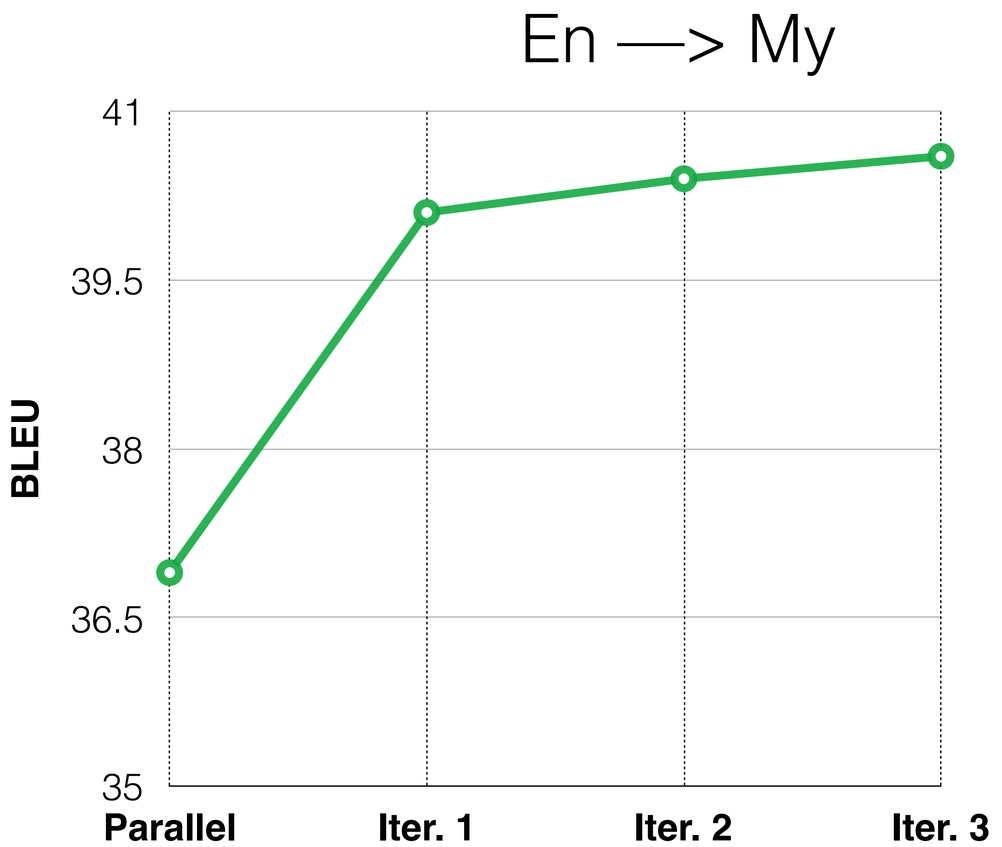
Workshop on Asian Translation 2019: English-Myanmar

	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

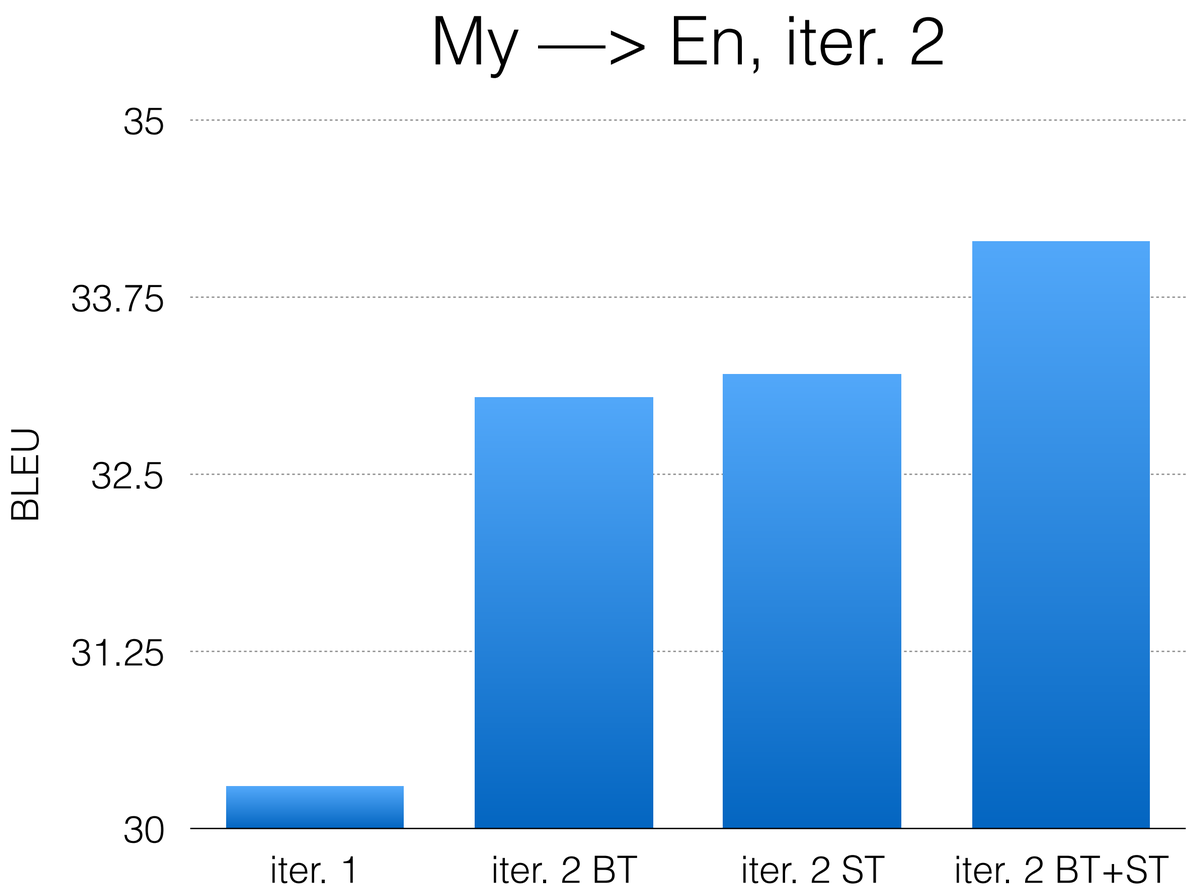
Results: Iterative ST+BT





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

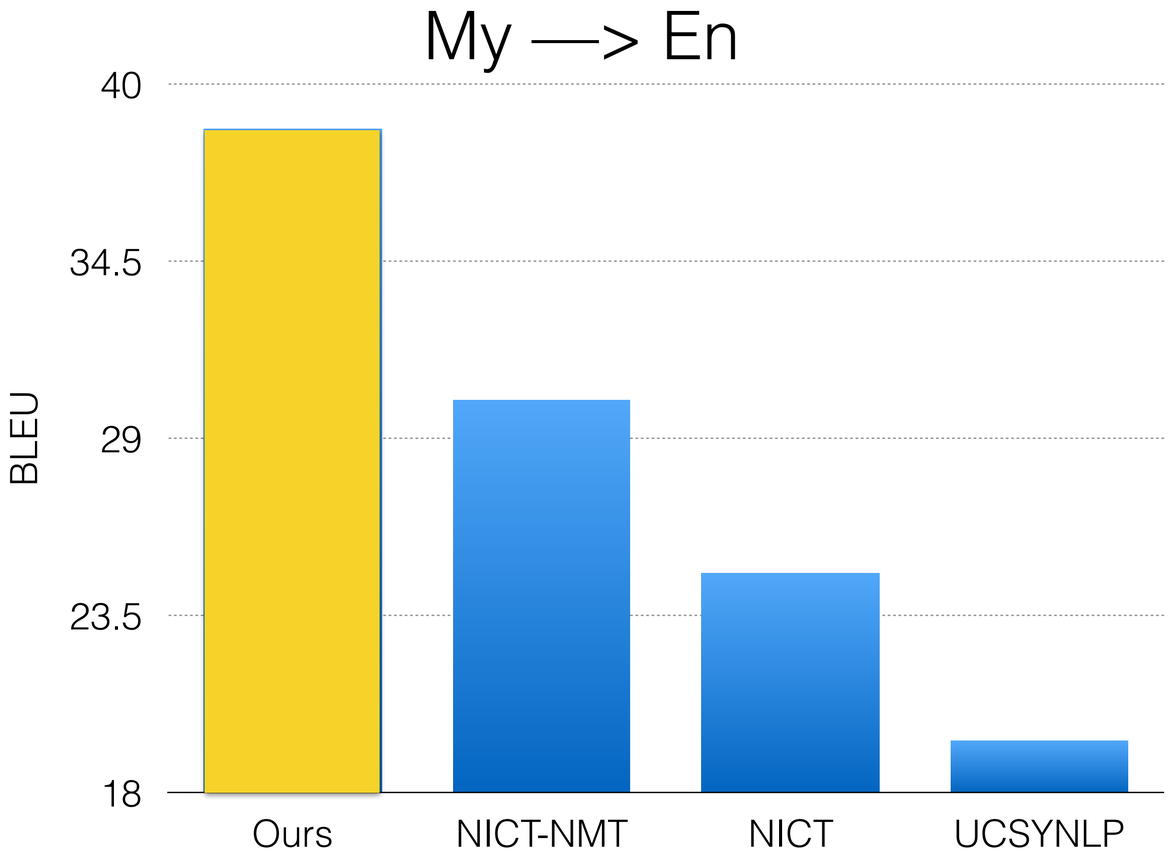
Results: BT vs ST vs BT+ST

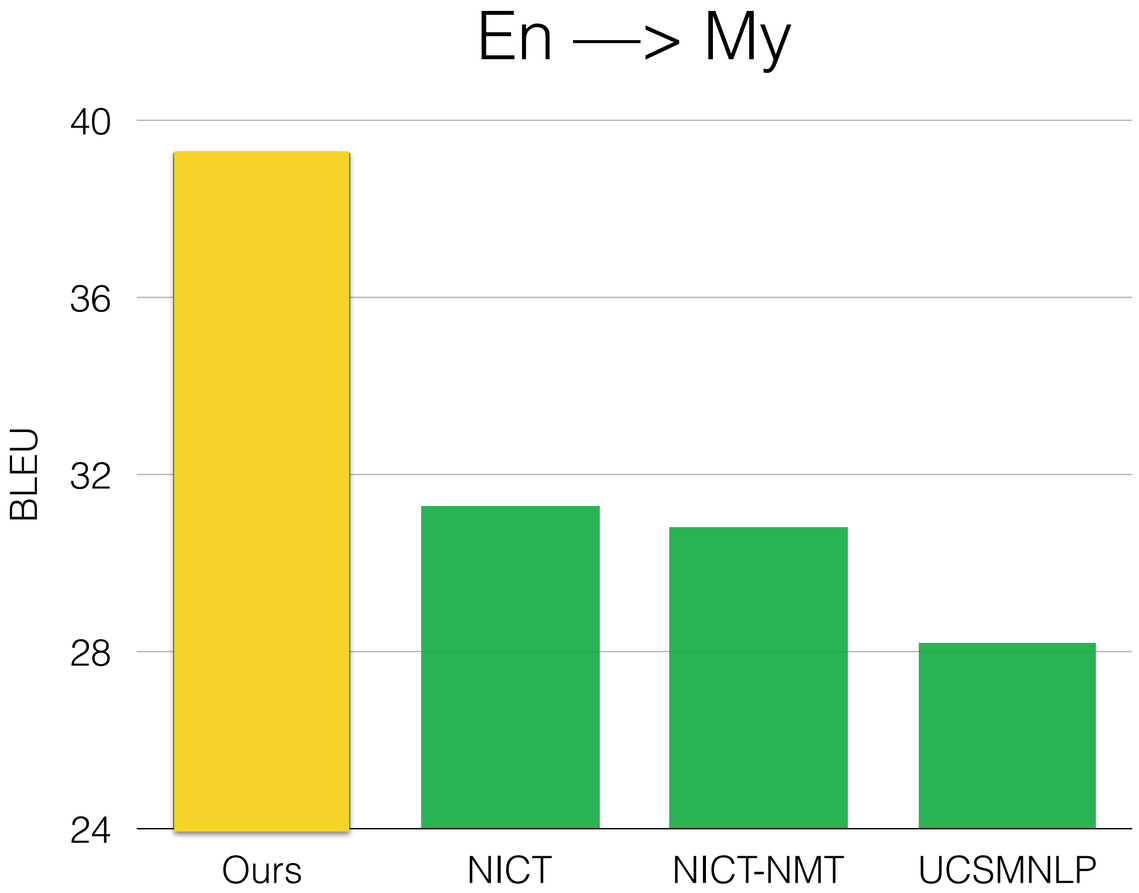


"FBAI WAT'19 My-En translation task submission" Chen et al., WAT@EMNLP 2019

Final Results of 2019 Competition

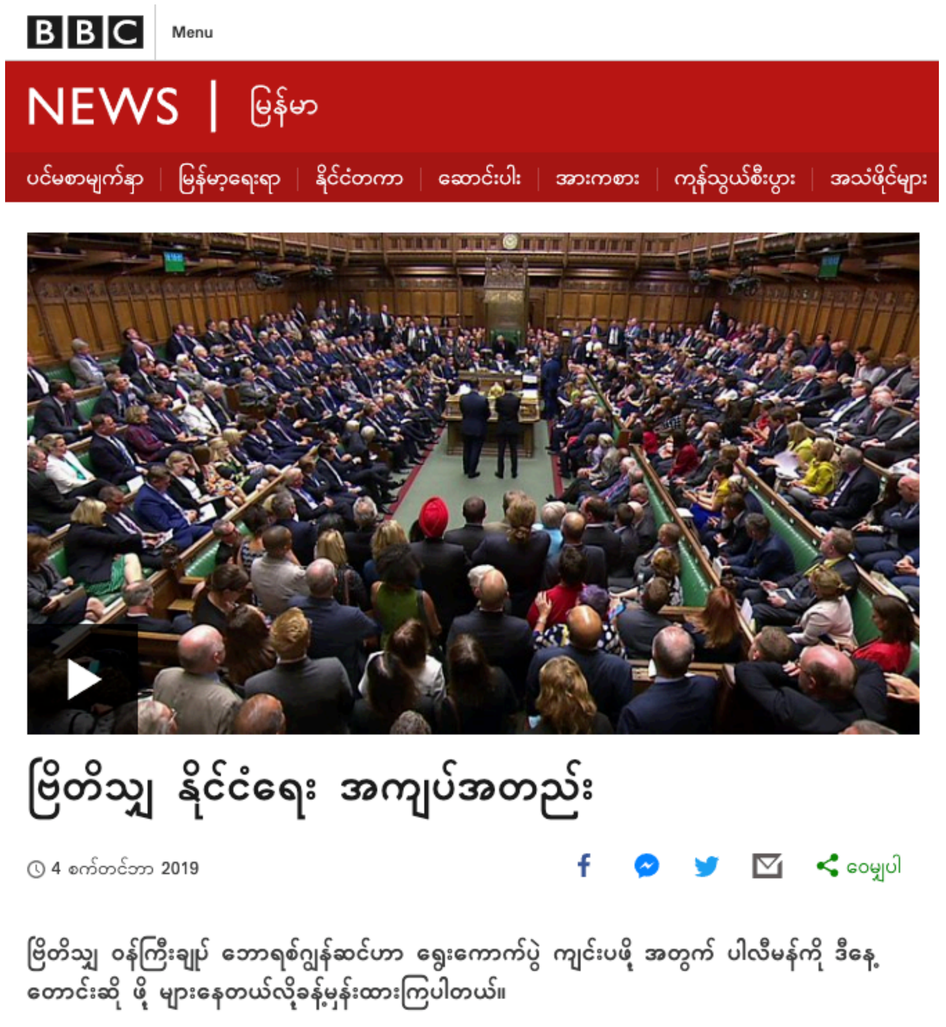
+8 BLEU compared to second best





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

Demo (Myanmar —> English)



slide credit to Peng-Jen Chen

Conclusion so far…

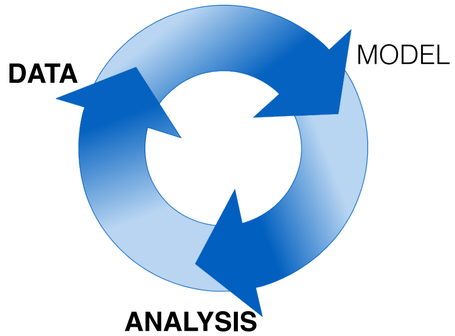
- Iterative back-translation, multi-lingual training work remarkably well.
- By feeding more data (BT, ST, pre-training, multi-lingual training) we can afford training bigger models. Bigger models train on more data generalize better.
- Low-resource MT requires big data and big compute!

Outline

- What is low-resource MT and why is it important?
- ML perspective on low resource MT
- Case studies:
  - Unsupervised MT
  - En-My
- **Perspectives**

What I did not talk about…

- The other two pillars



- Filtering (*)

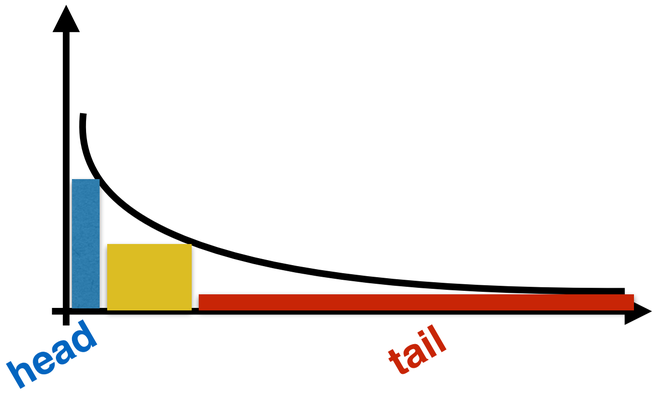
- Context: document level, multimodal, … MT
- Scaling & Efficient prediction

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

Fan et al. "Beyond English centric MMT" arXiv 2020

What I did not talk about…

- The long tail of languages



- Bias

Example: the director decided to proceed with the acquisition -> ITA “director” is translated with male gender.

- Metrics and long tail of mistakes
- Idiomatic and fluid use of language

- Limited supervision is very common in practical applications.
- It usually does not pay off to scale down the model when there is little supervision.
- It is better to use more data and to scale-up the model instead. Model will learn lots of things, hopefully some of these will be relevant to the task of interest.
- The less direct supervision the more data (from auxiliary tasks) is needed.
- When dealing with lots of similar tasks (translation of various language pairs), it is better to be as language-pair agnostic as possible.
- Key techniques:
  - Data augmentation
  - Sharing a big model across several tasks
  - Iterative refinement
  - Domain adaptation

Debugging NMT

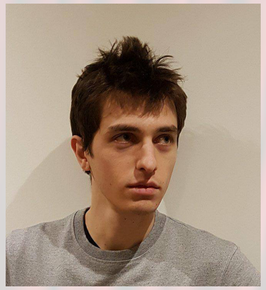
- **Data**: plot basic statistics (sentence length, token frequency).
    - Deduplicate sets, make sure there is no overlap between training/validation/test sets. Do not use test set ever.
- **Reproducibility**: Start simple and build on top of what is known to work. First reproduce then create something new. Be systematic and force yourself to come up with reproducible approaches. Releasing code does not suffice, if code is full of dataset-dependent hacks.
- **Analysis**: what do generation look like?
    - Sort generations by sentence level BLEU and observe if there is any pattern (repetitions, excessively long/short sentences, etc.).
    - Often, your method encompasses some previous method as special case. Check things work as expected in that case. Adopt bottom-up approach to research.

Debugging NMT

- **Optimization**: does the training loss decrease on the training set?
    - If not, check initialization, normalization layers and optimizer hyper-parameters.
- **Overfitting**: plot training and validation loss over time.
    - If overfitting is an issue, check dropout rate, label smoothing, input noise, add back-translation, do multilingual training, etc.
- **Domain adaptation**: does performance on held out portion of training set differ from validation set? Is the training set composed of several datasets? What's the statistics of sentence lengths and token frequency in each dataset?
    - Tagging, finetuning, example/dataset weighting methods.

Opportunities @fb

- Internships
- Postdocs
- Full time positions
- Visiting scholar positions
- Scholarships



Guillaume Lample

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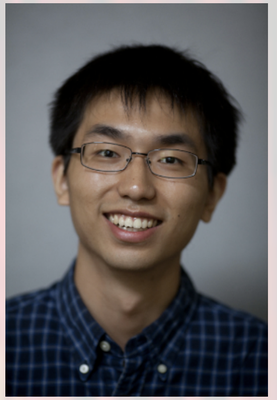


Jiajun Shen

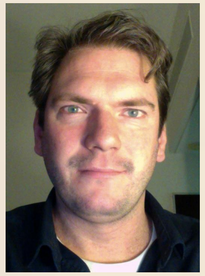
Questions?
Вопросы?
¿Preguntas?
Domande?

Jiatao Gu

Xian Li

Naman Goyal

Matt Le



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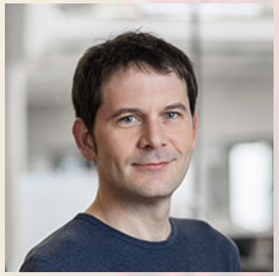

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