CS11-747 Neural Networks for NLP

Multilingual Learning

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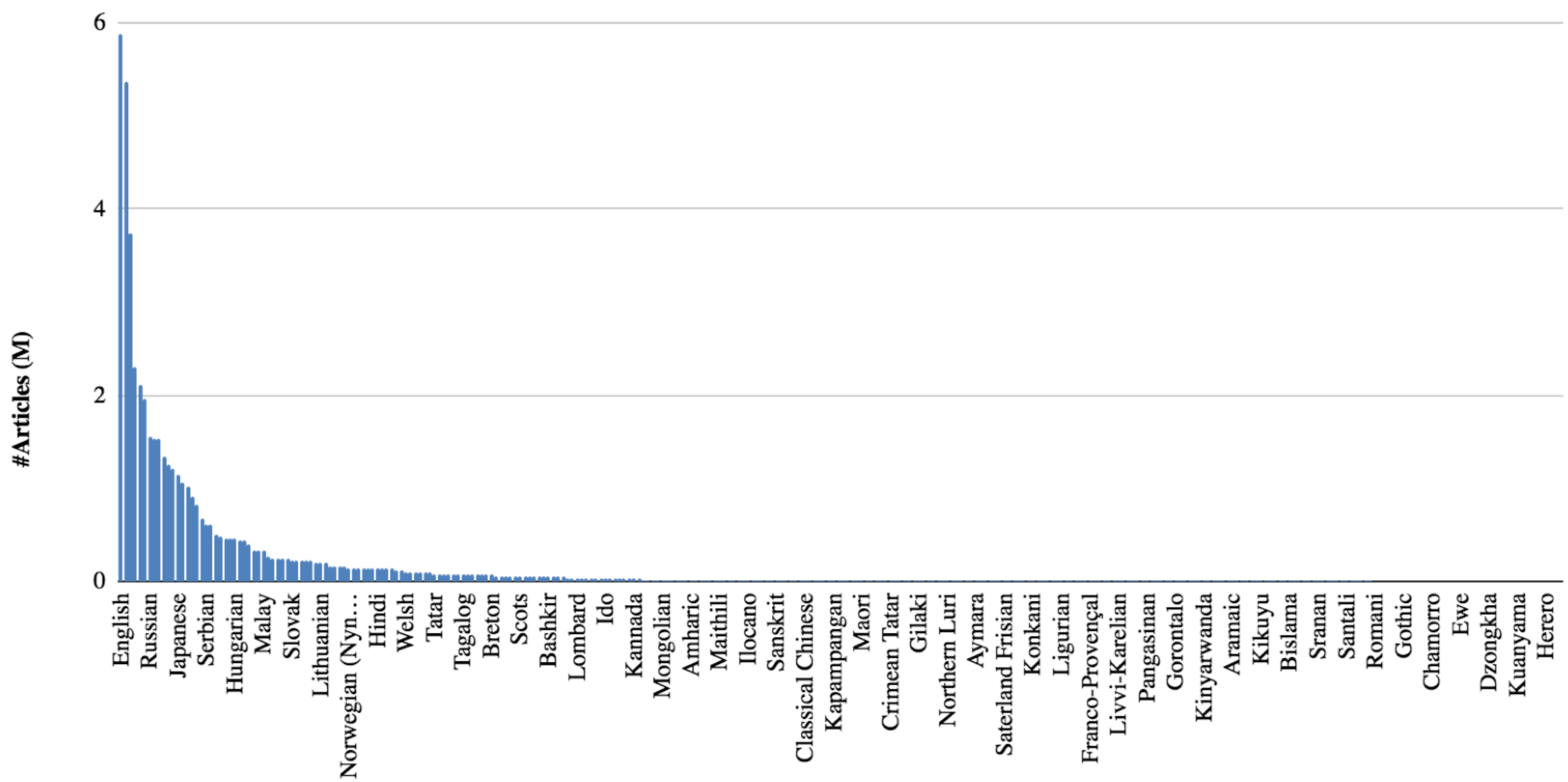
Site
https://phontron.com/class/nn4nlp2021/

w/ Slides by Aditi Chaudhary, Xinyi Wang

Many languages are left behind



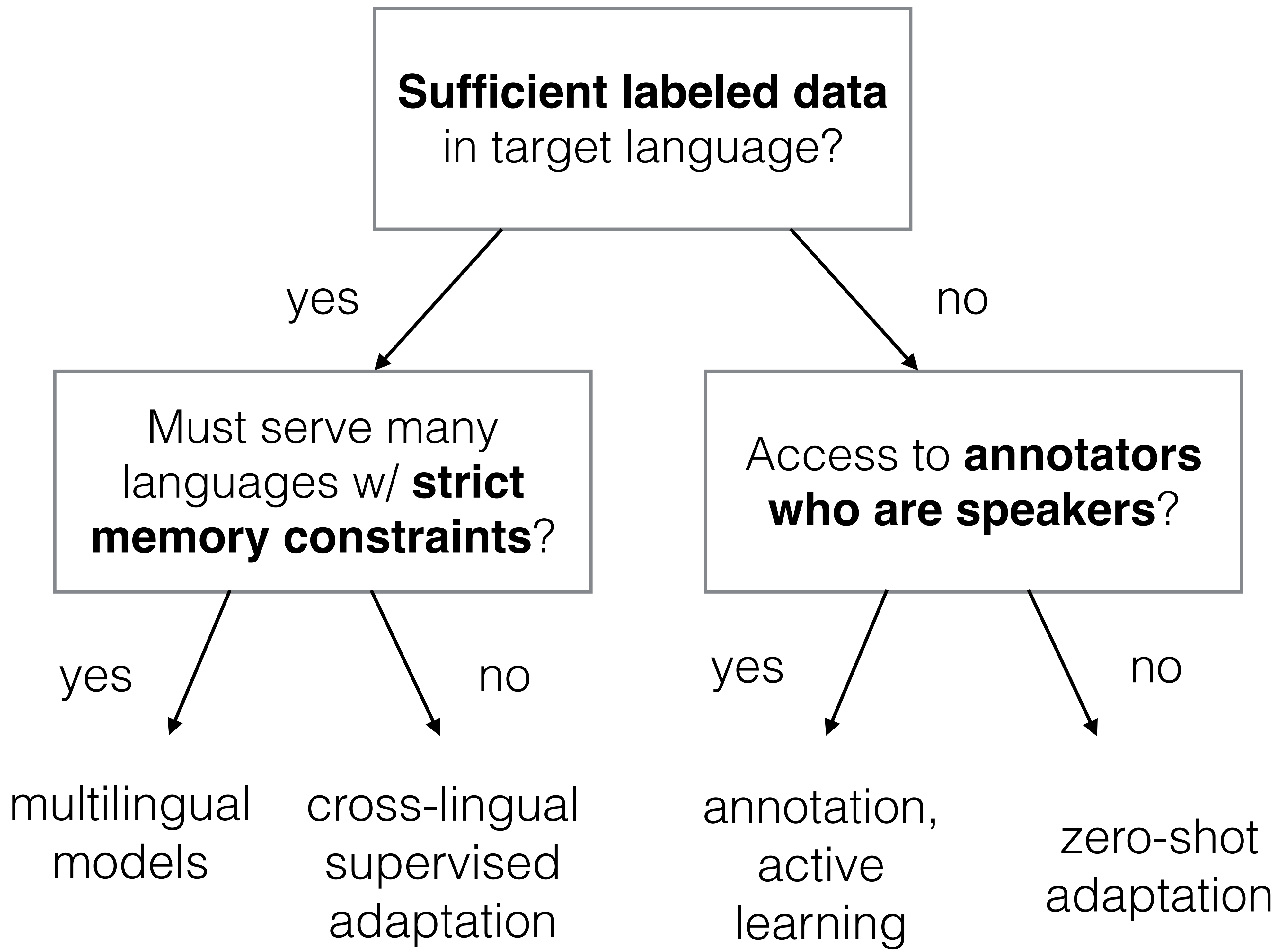
- There is not enough monolingual data for many languages
- Even less annotated data for NMT, sequence label, dialogue…

Data Source: Wikipedia articles from different languages

Multilingual Learning

- We would like to learn models that process **multiple languages**
- Why?
  - **Transfer Learning:** Improve accuracy on lower-resource languages by transferring knowledge from higher-resource languages
  - **Memory Savings:** Use one model for all languages, instead of one for each

High-level Multilingual Learning Flowchart



Multilingual Models

Multi-lingual Sequence-to-sequence Models

- It is possible to learn a single model that handles several languages
- Even as simple as adding a tag about the target language for generation (Johnson et al. 2016)

<fr> this is an example → ceci est un exemple

<ja> this is an example → これは例です

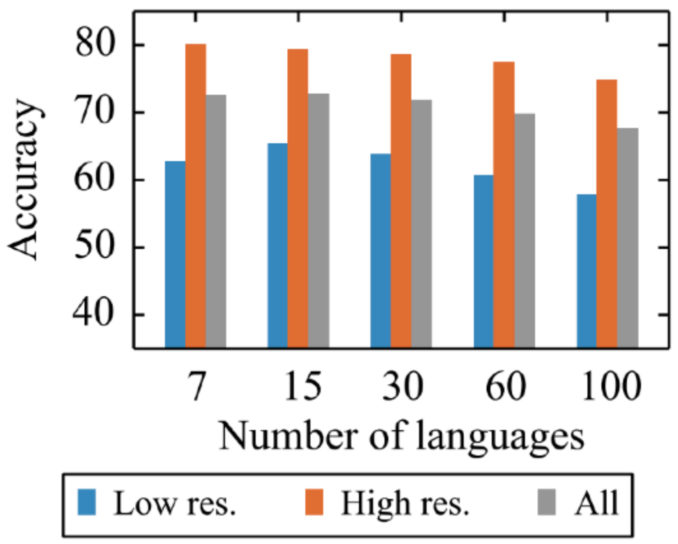
- Or even just processing different input languages using the same network (Wu and Dredze 2019)

ceci est un exemple

これは例です

Difficulties in Fully Multi-lingual Learning

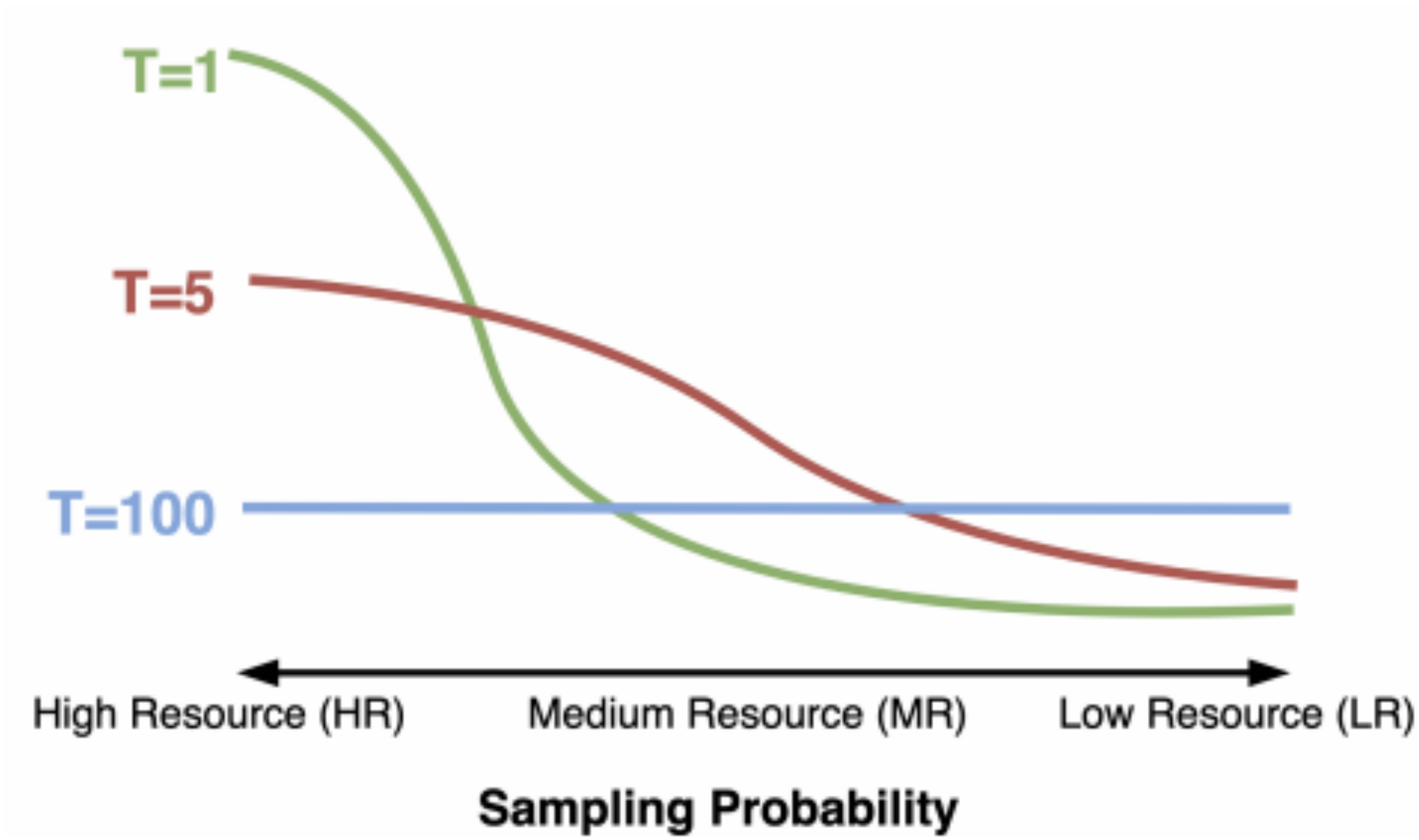
- For a fixed sized model, the per-language capacity decreases as we increase the number of languages. (Conneau et al, 2019)



- Increasing the number of low-resource languages —> decrease in the quality of high-resource language translations (Aharoni et al, 2019)

- How to mitigate? **Better data balancing, better parameter sharing**

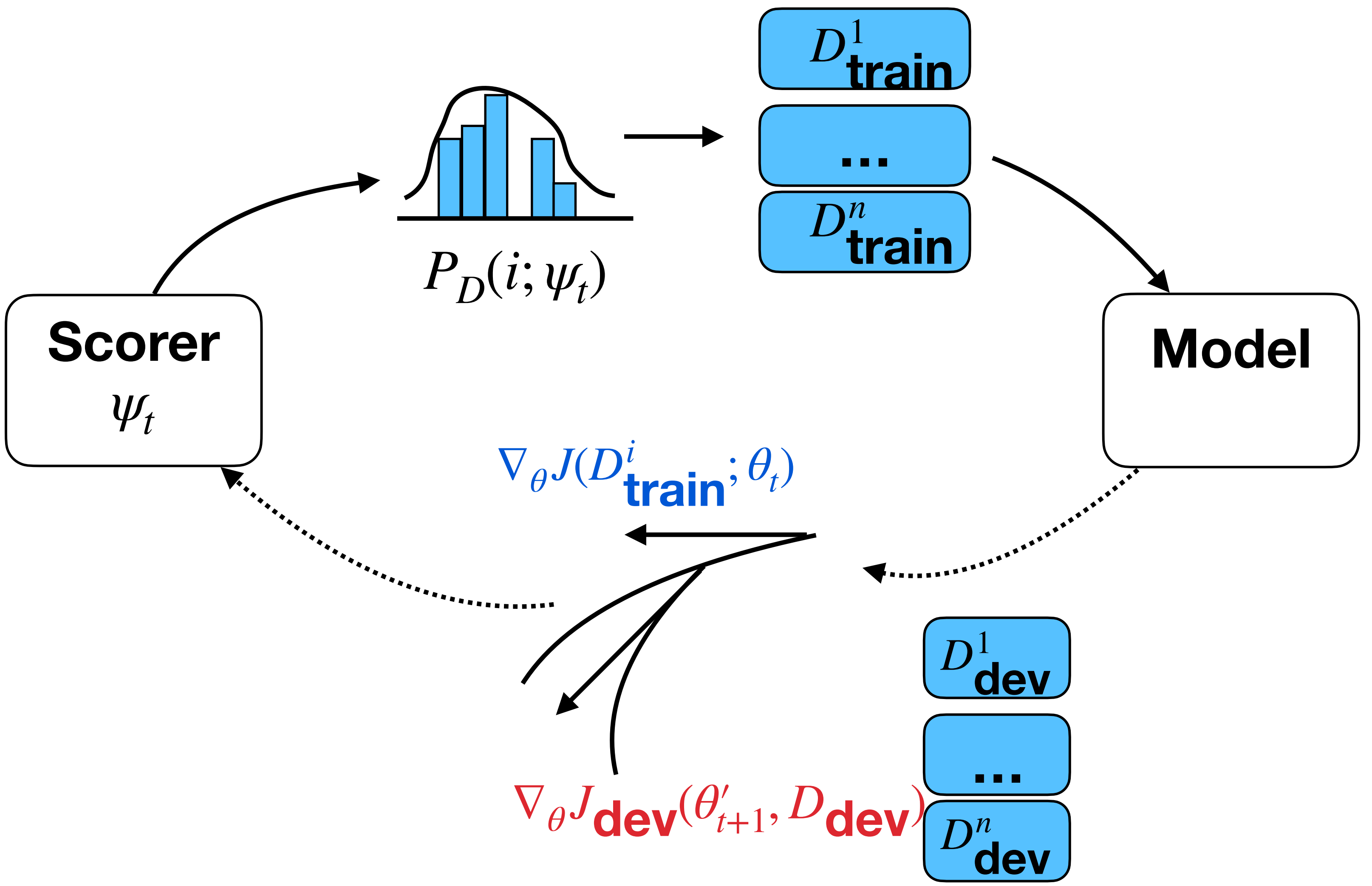
Heuristic Sampling of Data



- Sample data based on dataset size scaled by a temperature term
- Easy control of how much to upsample low-resource data

Massively Multilingual Neural Machine Translation in the Wild. Arivazhagan et. al. 2019

Learning to Balance Data



- Optimize the data sampling distribution during training
- Upweight languages that have similar gradient with the multilingual dev set

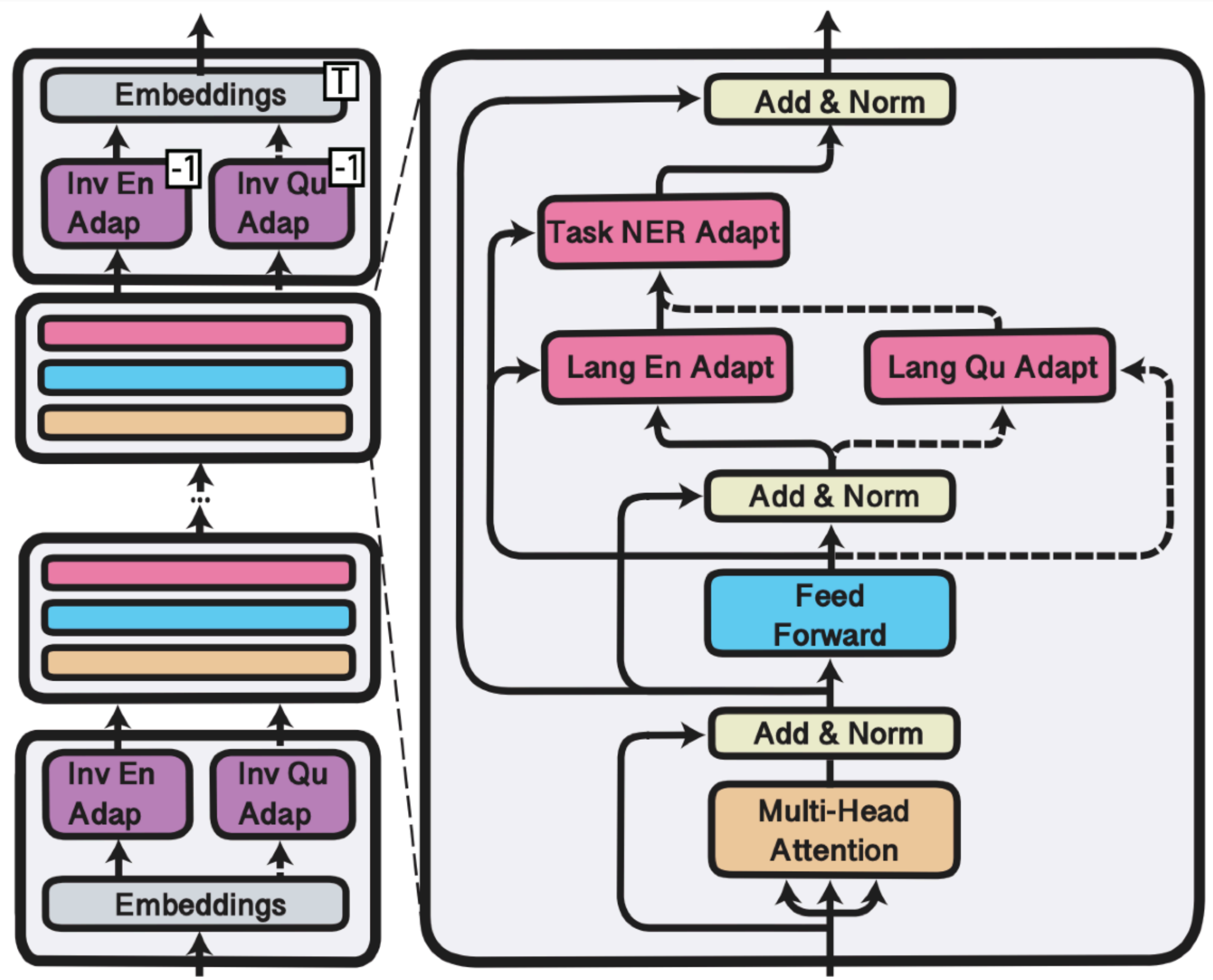
Balancing Training for multilingual neural machine translation. Wang et. al. 2020

How to Share Parameters?

- Share all parameters (e.g. Johnson et al. 2016)
- Share only the encoder or or attention mechanism (Dong et al. 2015, Firat et al. 2016)
- Share some matrices of the Transformer model (Sachan and Neubig 2018)
- Use a parameter generator to generate parameters per language (Platonios et al. 2018)

Adapters

- Adapters are small sub-networks that can be added post-hoc to train downstream models
- Can be used for multi-task or multi-lingual learning (e.g. Pfeiffer et al. 2020)

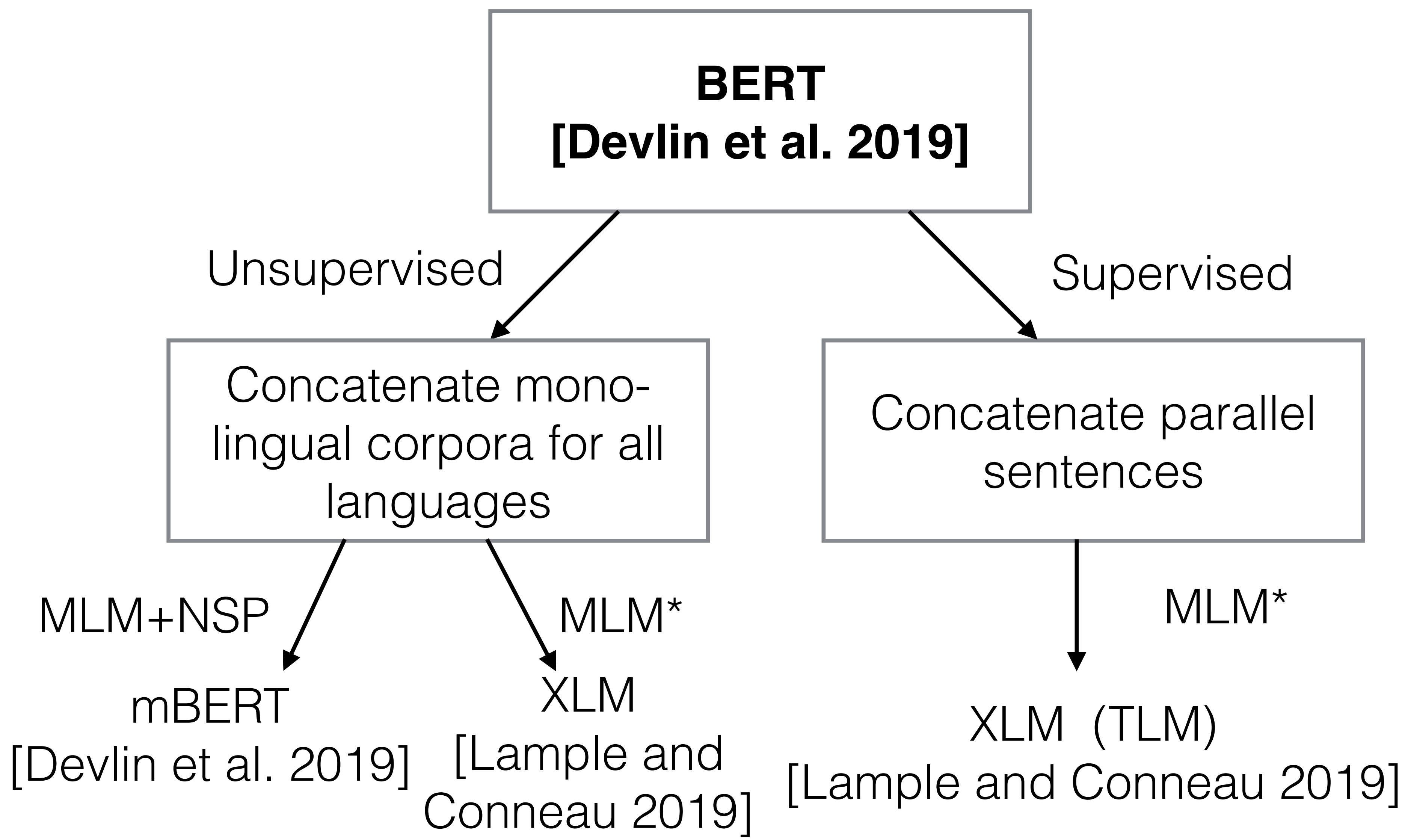


Multilingual Pre-trained Models

Multi-lingual Pre-training

- Language model pre-training has shown to be effective for many NLP tasks, eg. BERT
- BERT uses masked language model (MLM) and next sentence prediction (NSP) objective.
- Models such as mBERT, XLM, XLM-R extend BERT for multi-lingual pre-training.

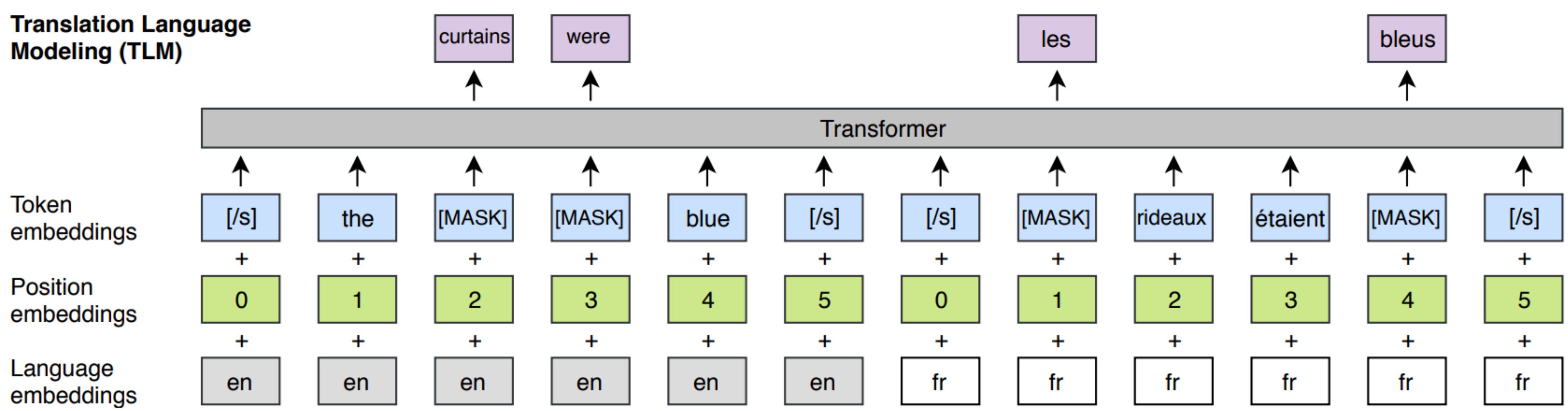
Multi-lingual Pre-training



MLM: Masked language modeling with word-piece
MLM* : MLM + byte-pair encoding

Multilingual Masked Language Modeling

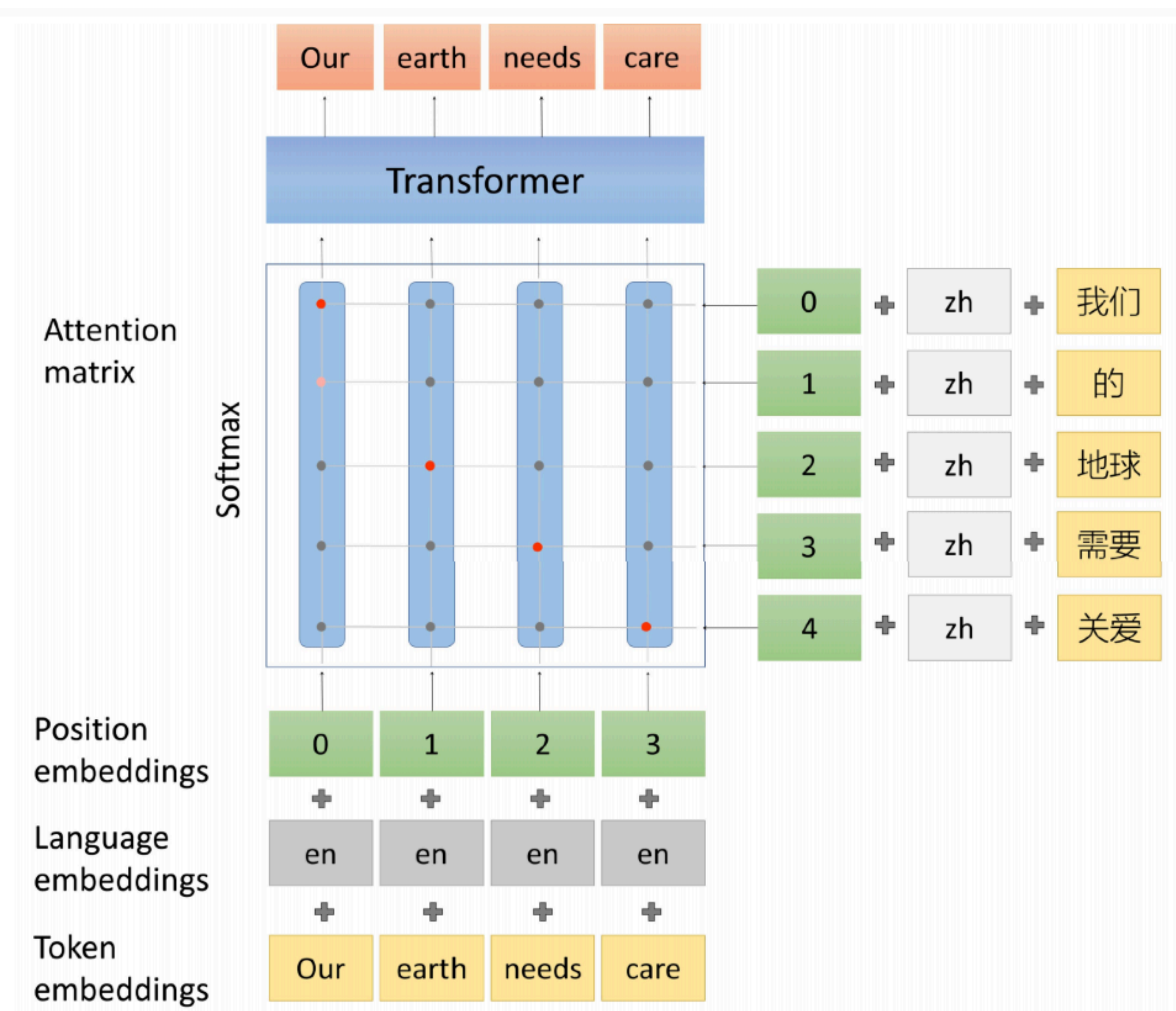
- Also called translation language modeling (Lample and Conneau 2019)



More Explicit Alignment Objectives

Unicoder (Huang et al. 2019)

"cross-lingual word recovery"



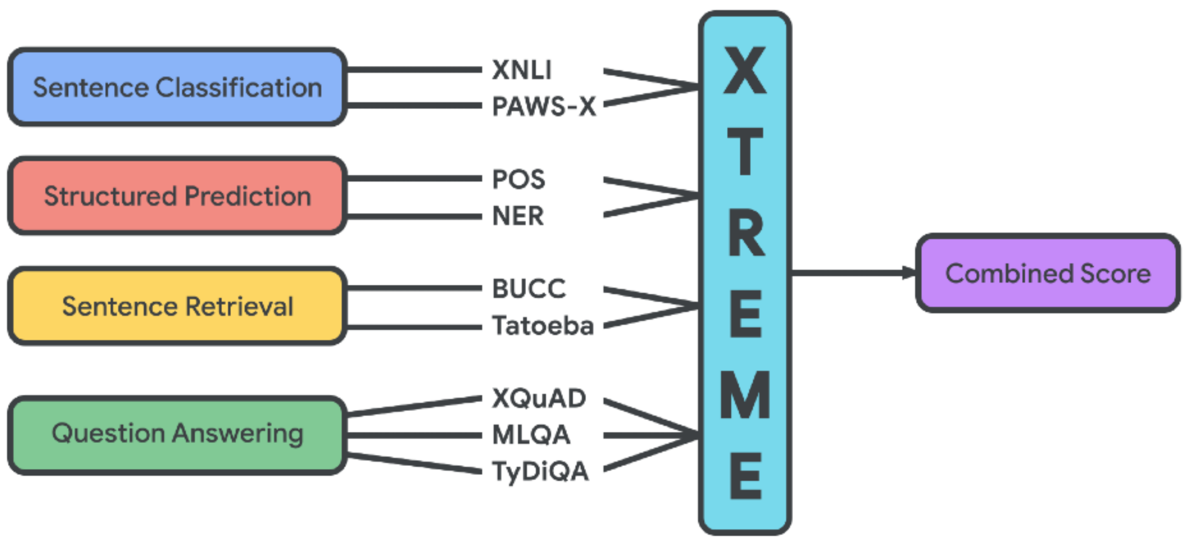
AMBER (Hu et al. 2020)

bidirectional explicit alignment objective

$$\ell_{\mathrm{WA}}(x, y) = 1 - \frac{1}{H} \sum_{h=1}^{H} \frac{\operatorname{tr}\left(\mathbf{A}_{y \to x}^{h}{}^{T} \mathbf{A}_{x \to y}^{h}\right)}{\min(|x|, |y|)}$$

Multilingual Representation Evaluation

- Large-scale benchmarks that cover many tasks
- **XTREME:** 40 languages, 9 tasks (Hu et al. 2020)



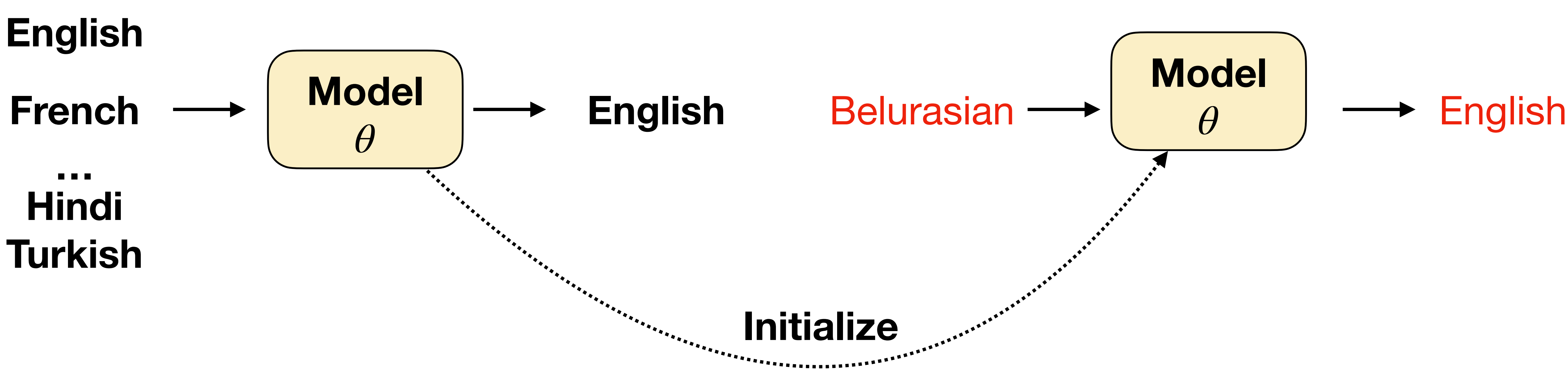
- **XGLUE:** less typologically diverse but contains generation (Liang et al. 2020)
- **XTREME-R** harder version based on XTREME (Ruder et al. 2021)

Cross-lingual Transfer Learning

Cross-lingual Transfer Learning

- CLTL leverages data from one or more high-resource source languages.
- **Popular strategies:**
  - Multilingual learning (above)
  - Pre-train and fine-tune
  - Zero-shot transfer
  - Annotation projection

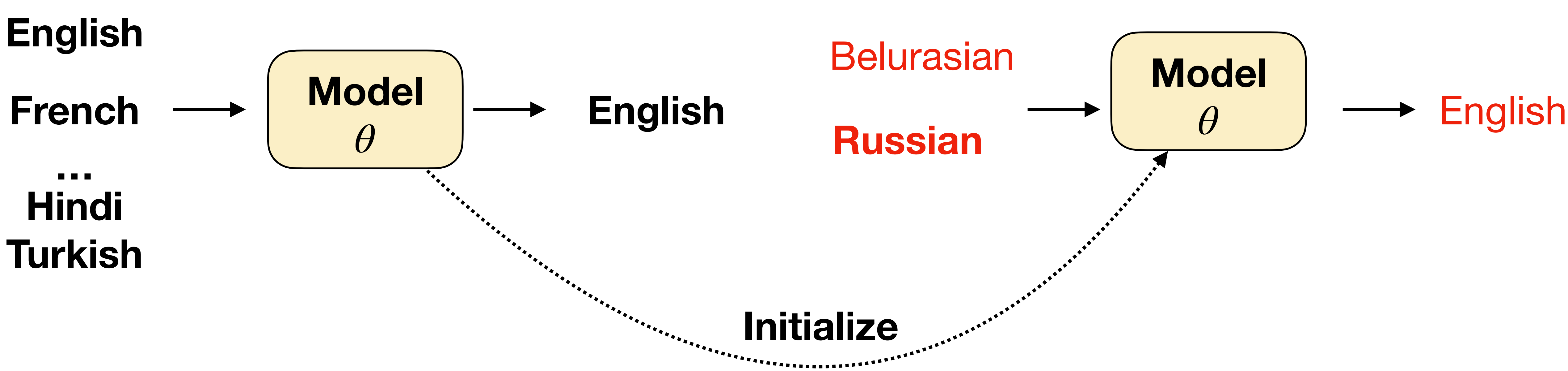
Pre-train and Fine-tune



- First, do multilingual training on many languages (eg. 58 languages in the paper)
- Next fine-tune the model on a new low-resource language

Rapid adaptation of Neural Machine Translation to New Languages. Neubig et. al. 2018

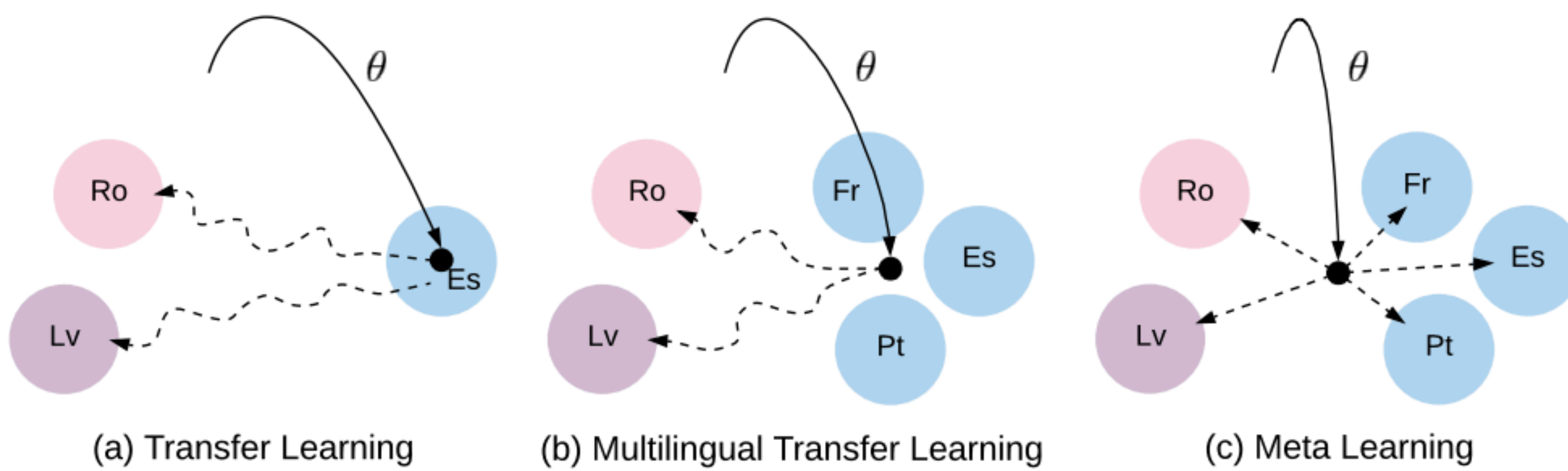
Similar Language Regularization



- Regularized fine-tuning: fine-tune on low-resource language and its related high-resource language to avoid overfitting

Rapid adaptation of Neural Machine Translation to New Languages. Neubig et. al. 2018

Meta-learning for multilingual training



- Learning a good initialization of model for fast adaptation to all languages
- Meta-learning: learn how to learn
  - Inner loop: optimize/learn for each language
  - Outter loop (meta objective): learn how to quickly optimize for each language

Meta-learning for low-resource neural machine translation. Gu et. al. 2018

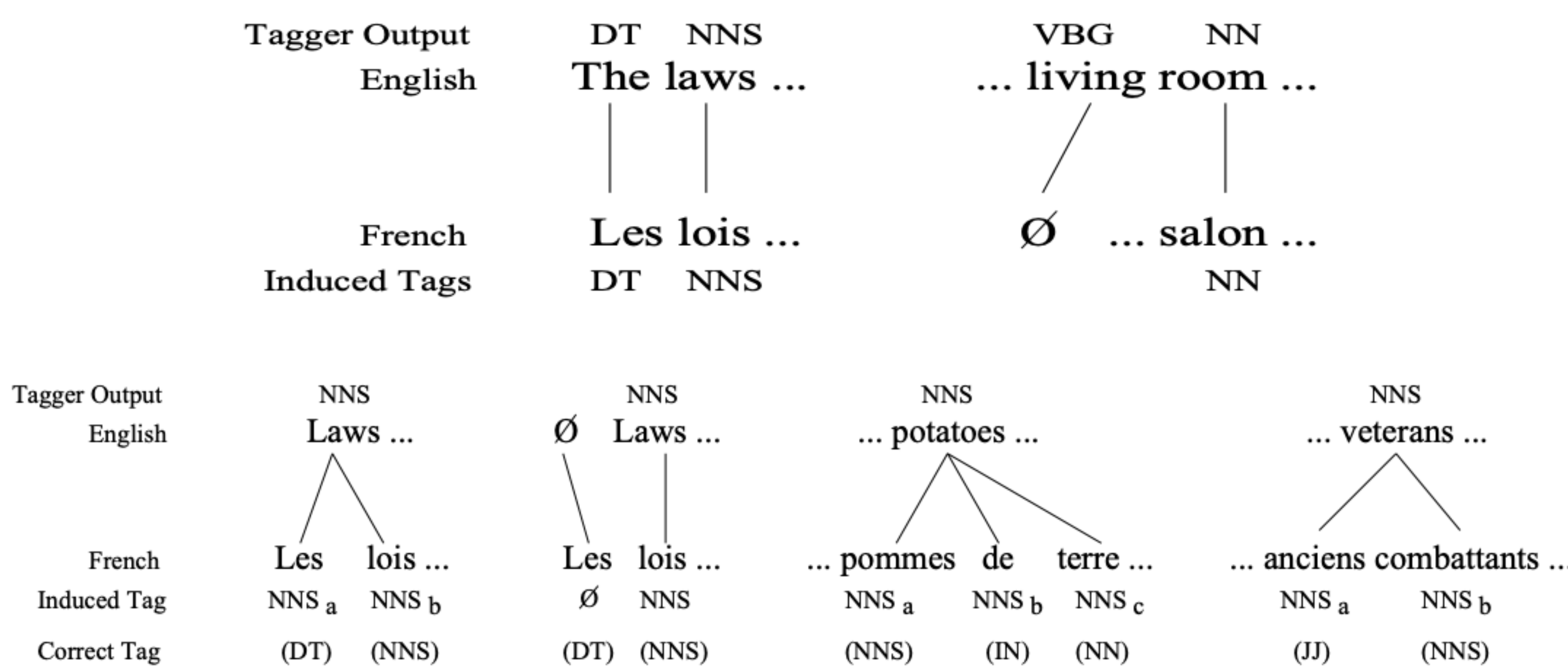
Zero-shot transfer for pretrained representations

- Pretrain: large language model using **monolingual data** from many different langauges
- Fine-tune: using **annotated data** in a given language (eg. English)
- Test: test the fine-tuned model on a **different** language from the fine-tuned language (eg. French)
- **Multilingual pretraining** learns a language-universal representation!

How multilingual is multilingual BERT? Pires et. al. 2019

Annotation Projection

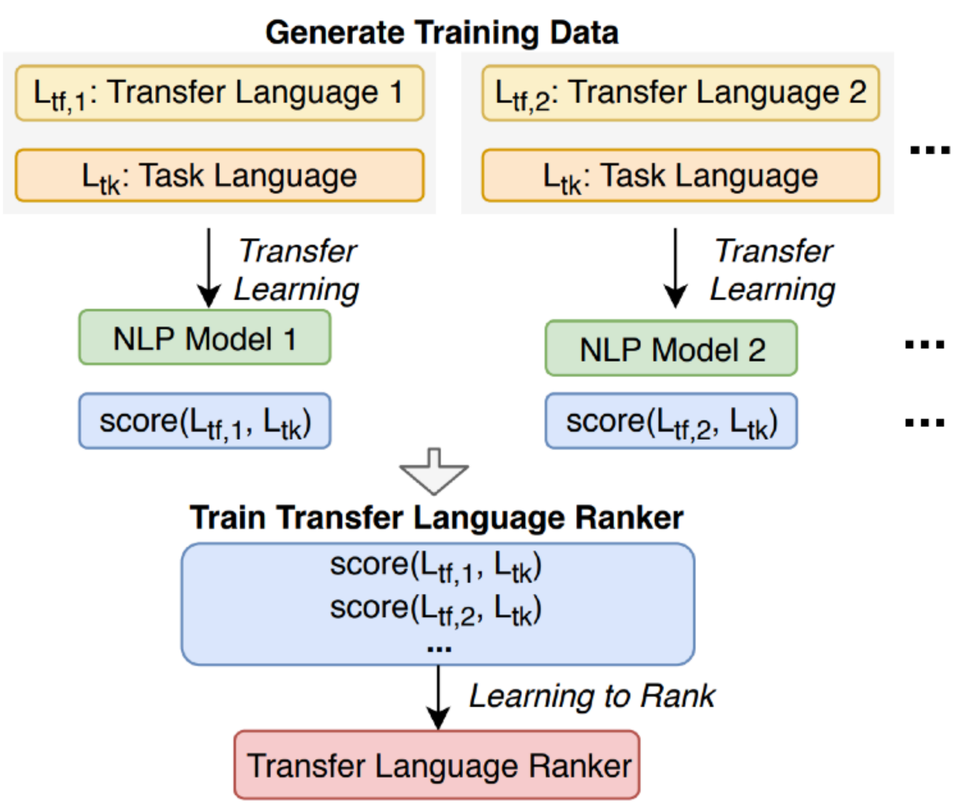
- Induce annotations in the target language using parallel data or bilingual dictionary (Yarowsky et al, 2001).



Transfer Peculiarities

Which Language to Use?

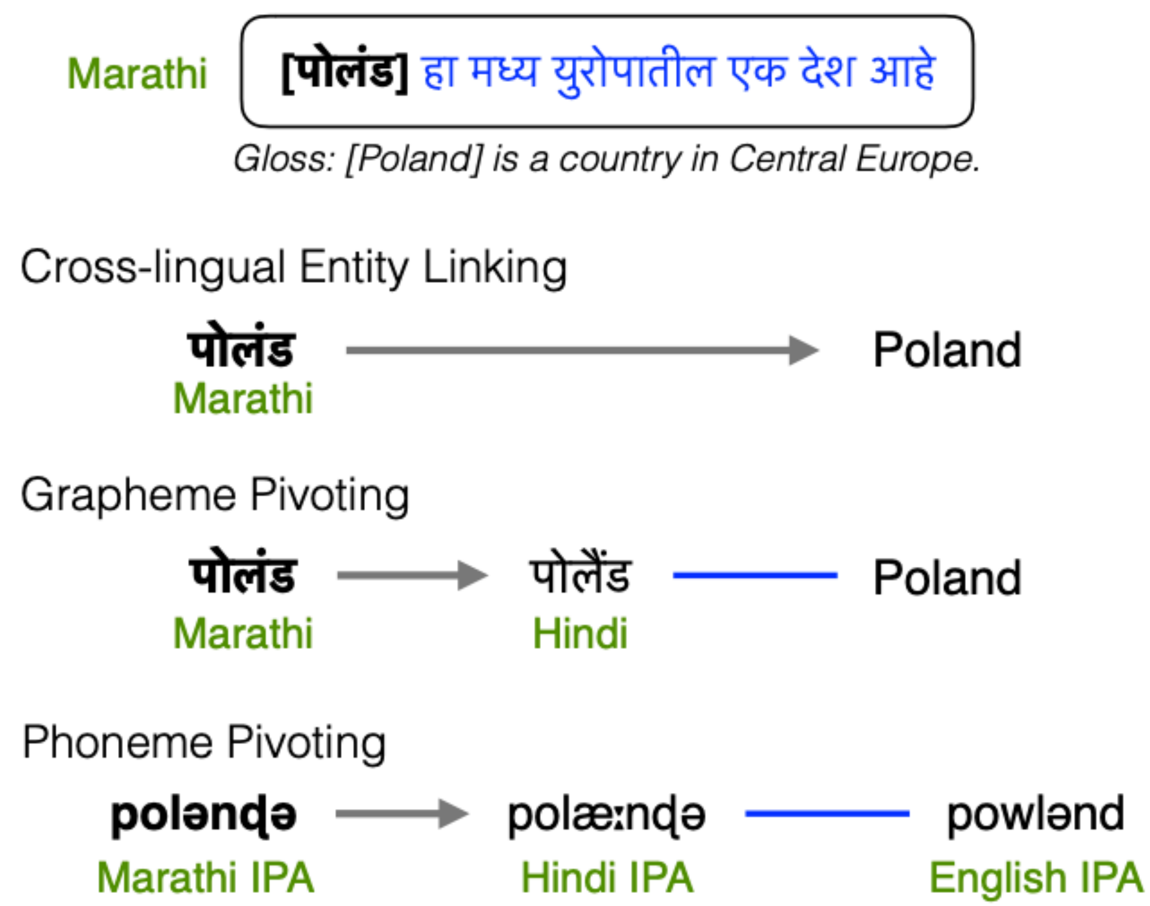
- When transferring from another language, it is ideal that it is
  - **Similar** to the target language
  - **Data-rich**
- Lin et al. (2019) examine how to identify better transfer languages



	Method	MT	EL	POS	DEP
dataset	word overlap o_w	28.6	30.7	13.4	52.3
	subword overlap o_{sw}	29.2	–	–	–
	size ratio s_{tf}/s_{tk}	3.7	0.3	9.5	24.8
	type-token ratio d_{ttr}	2.5	–	7.4	6.4
ling. distance	genetic d_{gen}	24.2	50.9	14.8	32.0
	syntactic d_{syn}	14.8	46.4	4.1	22.9
	featural d_{fea}	10.1	47.5	5.7	13.9
	phonological d_{pho}	3.0	4.0	9.8	43.4
	inventory d_{inv}	8.5	41.3	2.4	23.5
	geographic d_{geo}	15.1	49.5	15.7	46.4
	LangRank (all)	51.1	**63.0**	**28.9**	**65.0**
	LangRank (dataset)	**53.7**	17.0	26.5	**65.0**
	LangRank (URIEL)	32.6	58.1	16.6	59.6

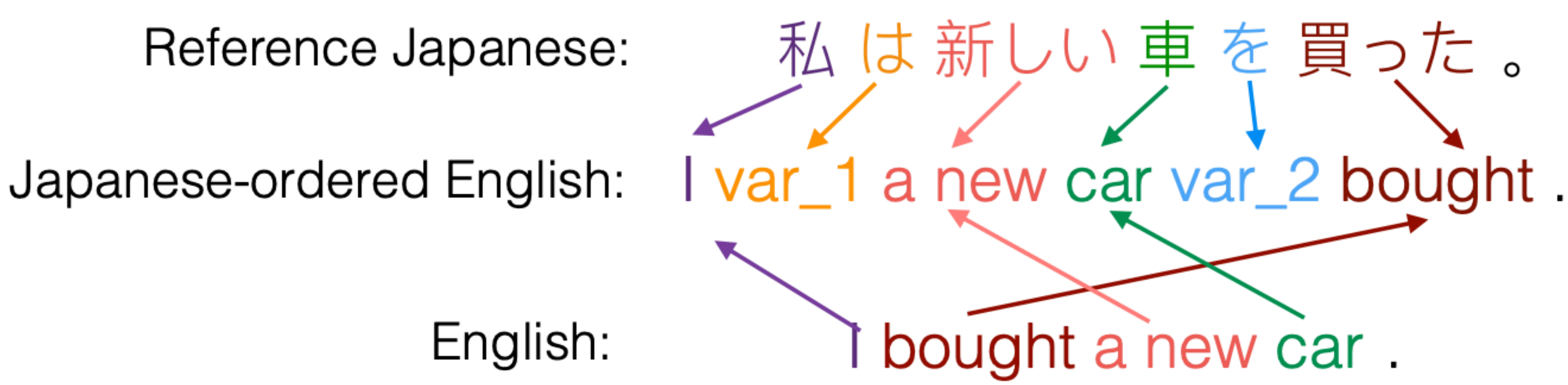
What if languages don't share the same script?

- Use phonological representations to make the similarity between languages apparent.
- e.g.: Rijhwani et al (2019) use a pivot-based entity linking system for low-resource languages.



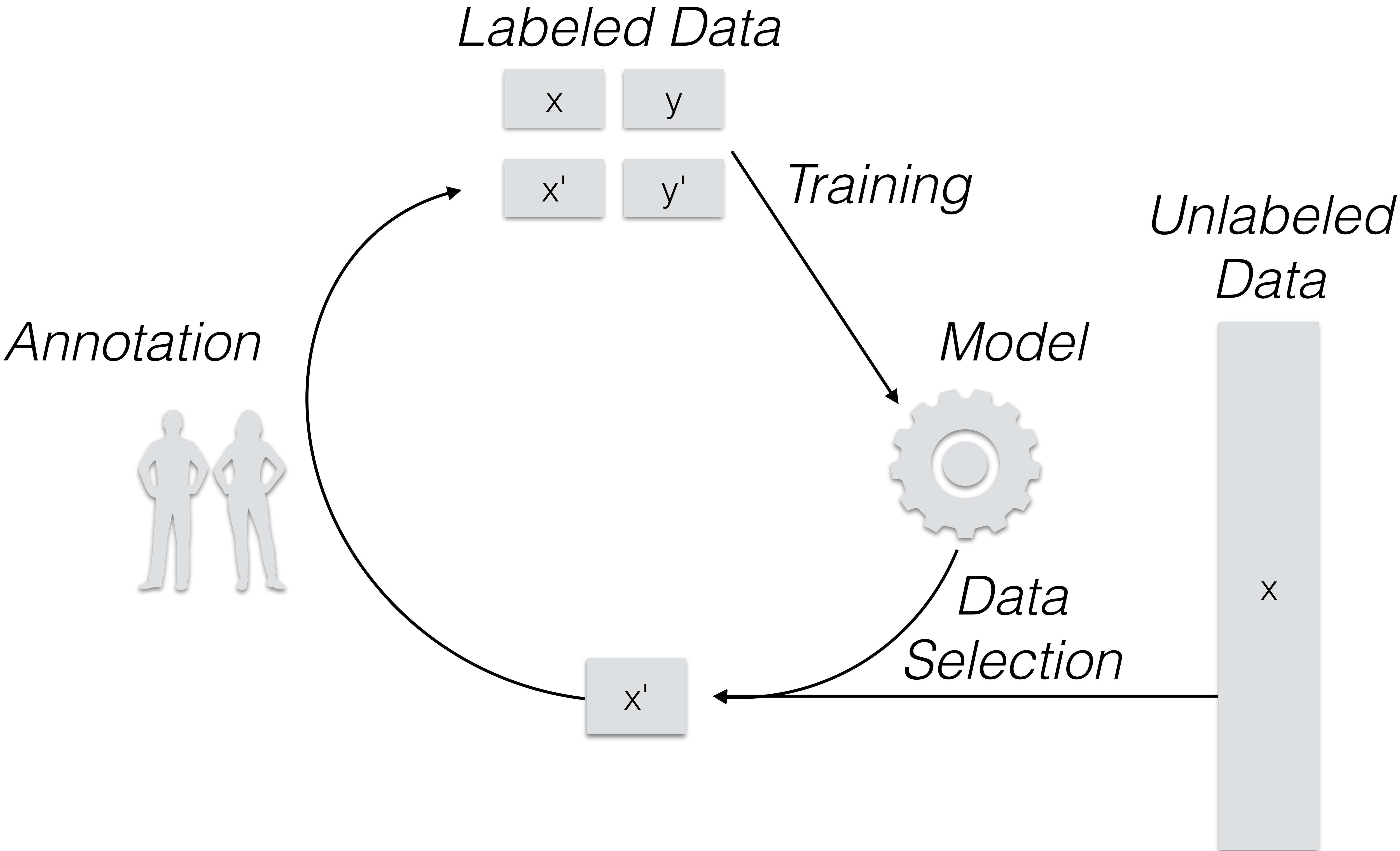
What if languages don't share the same syntax?

- Can use syntax-based data augmentation to try to reduce syntactic divergences (Zhou et al. 2019)

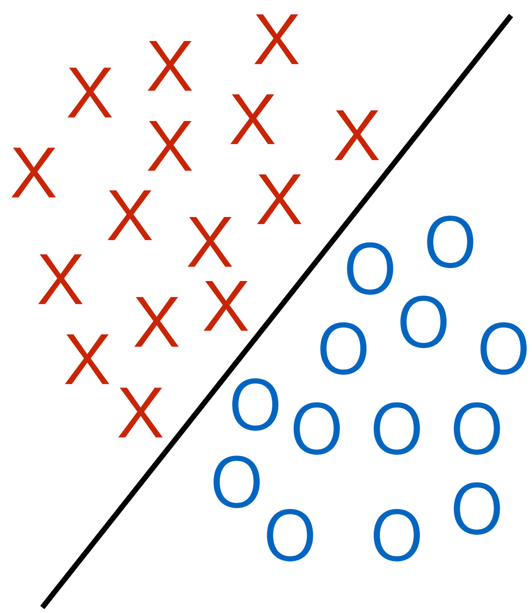


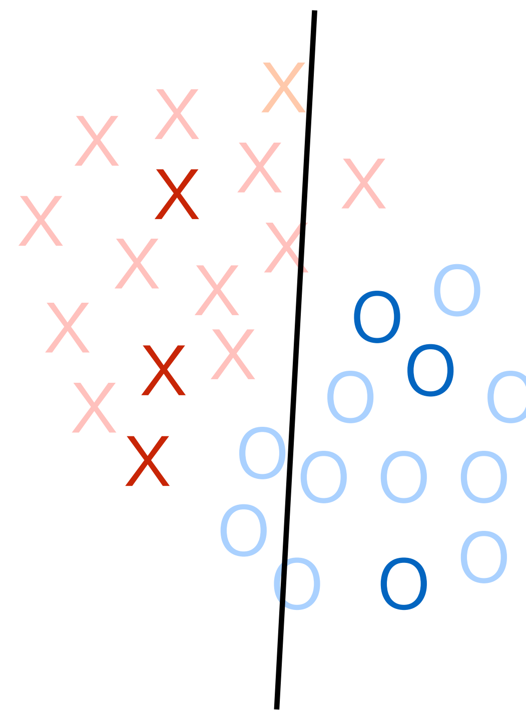
Creating New Data

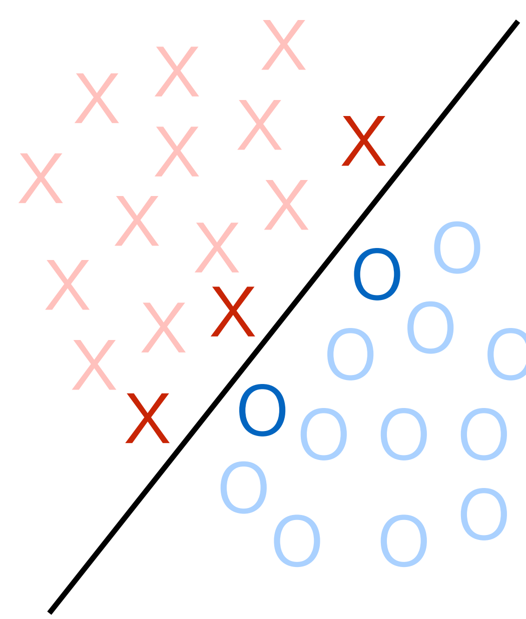
Active Learning Pipeline



Why Active Learning?







Fundamental Ideas

- **Uncertainty:** we want data that are *hard* for our current models to handle

- **Representativeness:** we want data that are *similar* to the data that we are annotating

Uncertainty Sampling Criteria

- **Entropy:** larger entropy = more uncertain

$$H(x) = -\sum_y P(y|x) \log P(y|x)$$

- **Top-1 confidence:** lower top-1 confidence = more uncertain

$$\hat{y} = \operatorname*{argmax}_y \log P(y|x)$$

$$\mathrm{top1}(x) = \log P(\hat{y}|x)$$

- **Margin:** smaller difference between first and second candidates = more uncertain

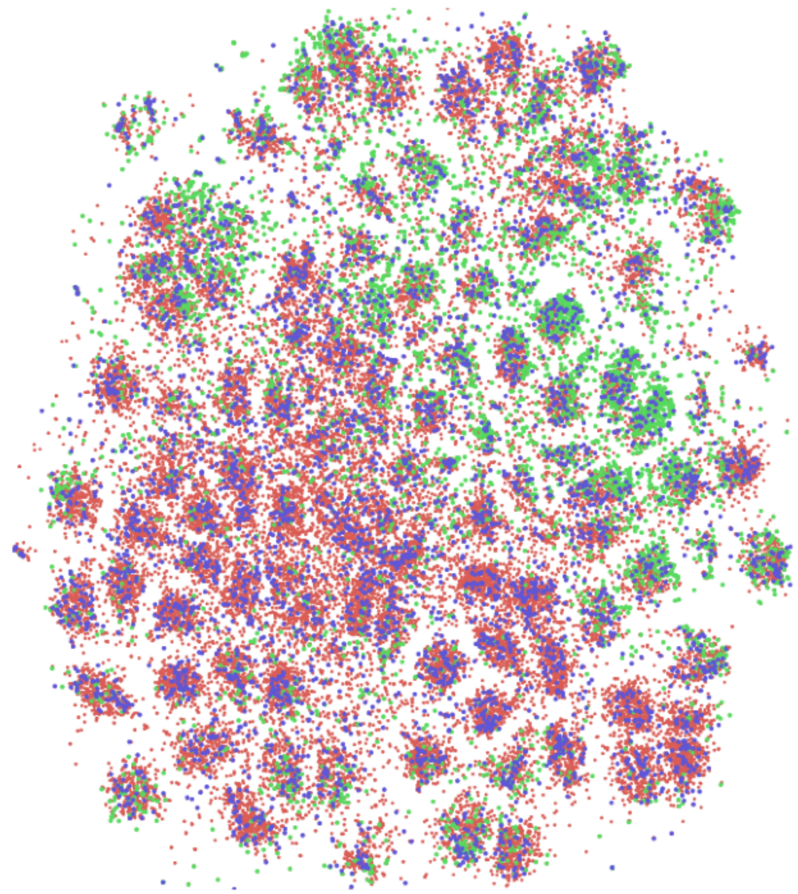
$$\mathrm{margin}(x) = \log P(\hat{y}|x) - \max_{y \neq \hat{y}} \log P(y|x)$$

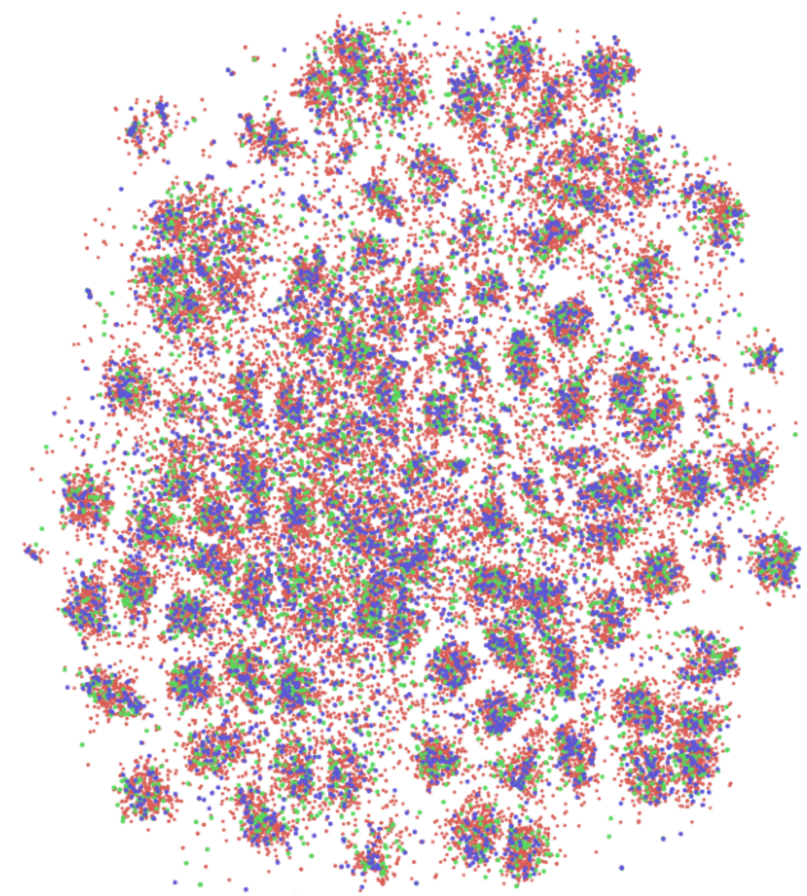
Tong, Simon, and Daphne Koller. "Support vector machine active learning with applications to text classification." *Journal of machine learning research* 2.Nov (2001): 45-66.

Culotta, Aron, and Andrew McCallum. "Reducing labeling effort for structured prediction tasks." *AAAI*. Vol. 5. 2005.

Representativeness

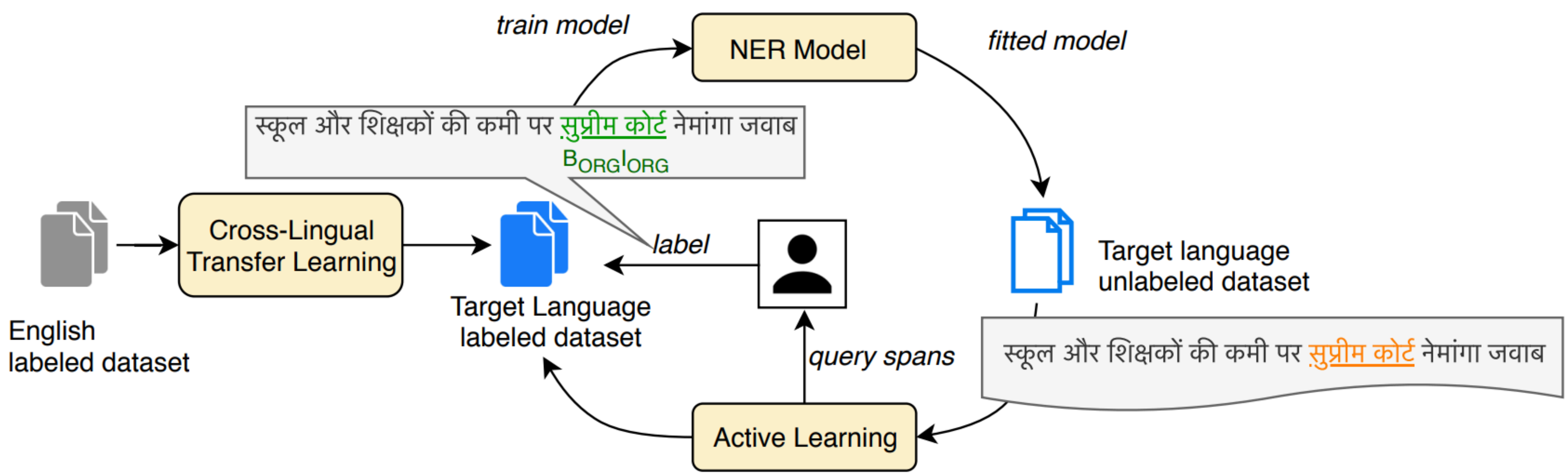
- How can we classify examples as being "similar to many others"?
- In simple feature vectors: high overlap in vector space


(a) Uncertainty Oracle


(b) Our Method

Sener, Ozan, and Silvio Savarese. "Active learning for convolutional neural networks: A core-set approach." *arXiv preprint arXiv:1708.00489* (2017).

Cross-lingual Learning + Active Learning



- Both perform better than either in isolation

Chaudhary, Aditi, et al. "A little annotation does a lot of good: A study in bootstrapping low-resource named entity recognizers." *EMNLP 2019*.

Questions?