

# Multilinguality

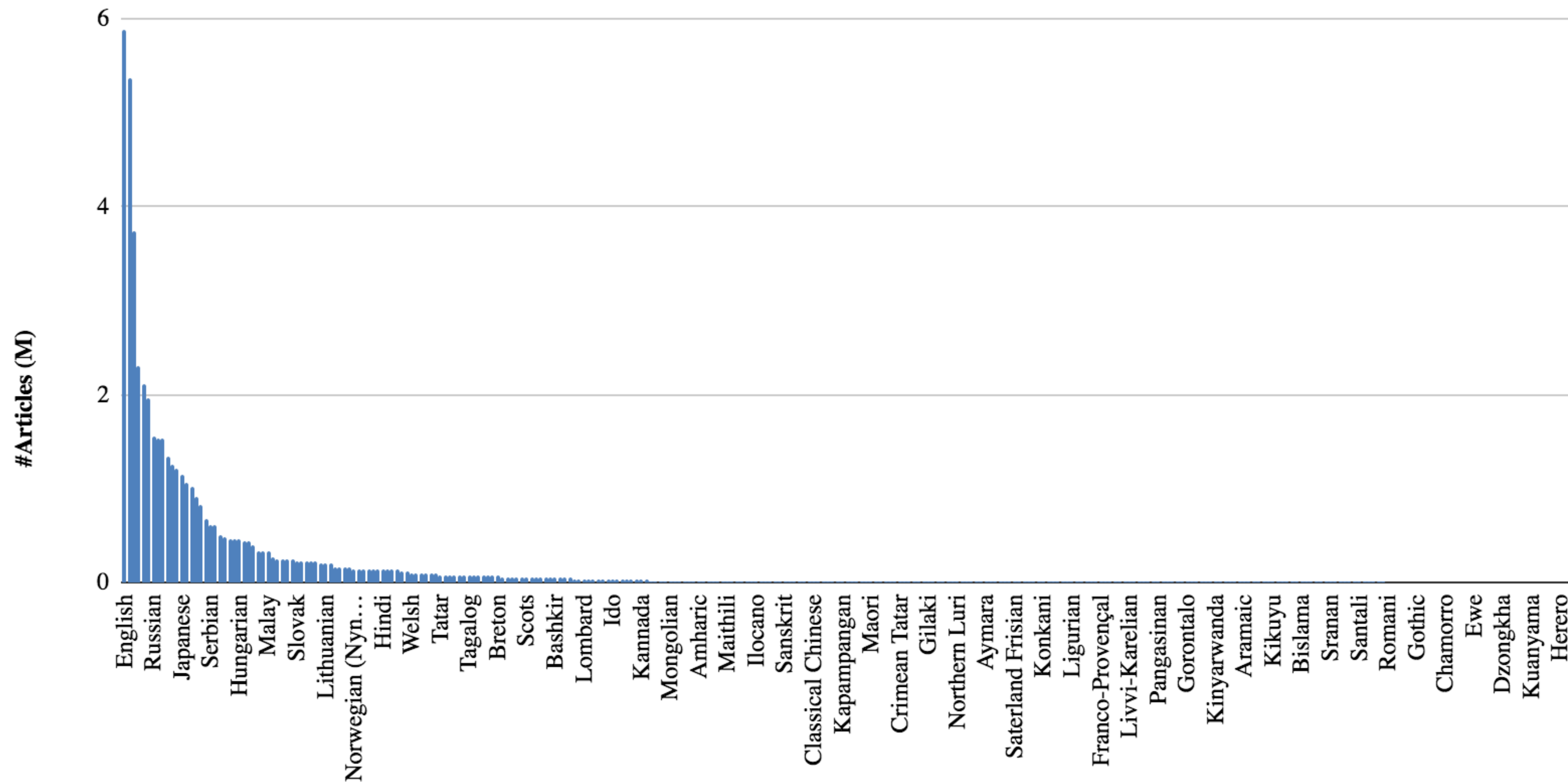
CS6120: Natural Language Processing  
Northeastern University

David Smith  
with slides from Graham Neubig

# Two varieties of multilingual NLP

- Monolingual NLP in Multiple Languages
  - QA, sentiment analysis, chatbots, code generation
  - in English, Chinese, Hindi, Japanese, Spanish, ...
- Cross-lingual NLP
  - Machine translation
  - Cross-language information retrieval
  - Cross-lingual QA

# Data are mostly sparse



Data Source: Wikipedia articles from different languages

- Big disparity in monolingual data available for training
- Even less annotated data for MT, sequence labeling, dialogue, etc., in many languages

# Linguistic peculiarities

- Most methods are tested first on English, but many languages differ from English in, e.g.,
  - Rich morphology (case, gender, mood, etc.)
  - Accents/diacritics
  - Different scripts
  - Variety and status of dialects
  - Lack of formal writing systems

# 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
  - **Time Savings:** We don't need to decide which language we're processing

# Code switching

Ulikuwa ukiongea **a lot of nonsense**. (Code-switching, English in bold)

"You were talking a lot of nonsense." (Translation)

Embedded language	Code-switched text
Latin	... die <i>fortitudo animi, magnitudo</i> (c. 5.) seinem Sohne schildert, ...
English	... die man das Westende nennt, <i>the west end of the town</i> , und wo die vornehmere und minder beschäftigte Welt lebt.
French	... eine frivole Laune, ein “ <i>car tel est notre plaisir</i> ” des Geistes ...
Greek	Diess ist das Spinnrad des <i>βᾶθος</i> ; diess ist das Spinnrad, welches die Gedanken spinnet, ...

# Multilingual Language Modeling

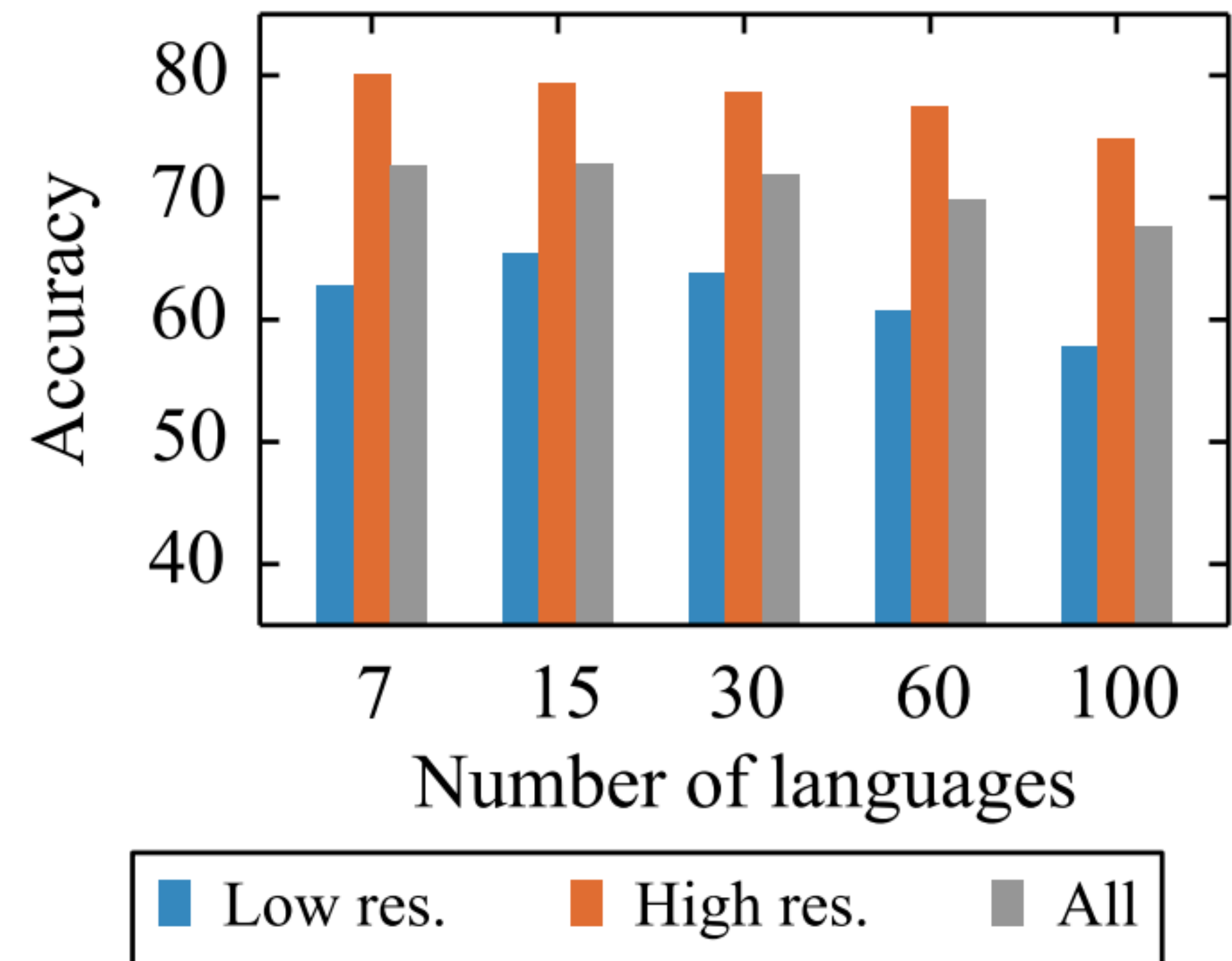
# Simple multilingual modeling

- It is possible to learn a single model that handles several languages
- **Multilingual Input:** Can just process different input languages using the same network (Wu and Dredze 2019)
  - ceci est un exemple → this is an example
  - これは例です → this is an example
- **Multilingual Output:** Add a tag or prompt 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



# Difficulties in fully multilingual learning

- “**Curse of Multilinguality**” 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**



# Tokenization disparities

English

GPT-3.5 & GPT-4 GPT-3 (Legacy)

OpenAI's large language models (sometimes referred to as GPT's) process text using tokens, which are common sequences of characters found in a set of text. The models learn to understand the statistical relationships between these tokens, and excel at producing the next token in a sequence of tokens.

Clear Show example

Tokens Characters  
58 301

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Text Token IDs

Burmese/Myanmar (Google Translated)

GPT-3.5 & GPT-4 GPT-3 (Legacy)

OpenAI ၏ကြီးမားသောဘာသာစကားမော်ဒယ်များ (တစ်ခါတစ်ရံ GPT များဟုရည်ညွှန်းသည်) စာသားအစုအဝေးတွင်တွေ့ရလေ့ရှိသောအက္ခရာများဖြစ်သည့် တိုက်ကပ်များကိုအသုံးပြု၍ စာသားလုပ်ဆောင်သည်။ မော်ဒယ်များသည် ဤတိုက်ကပ်များကြား ကိန်းဂဏန်းဆိုင်ရာ ဆက်နွယ်မှုများကို နားလည်ရန် သင်ယူကြပြီး တိုက်ကပ်၏ အတွဲလိုက် နောက်လာမည့် တိုက်ကပ်ကို ထုတ်လုပ်ရာတွင် ထူးချွန်သည်။

Clear Show example

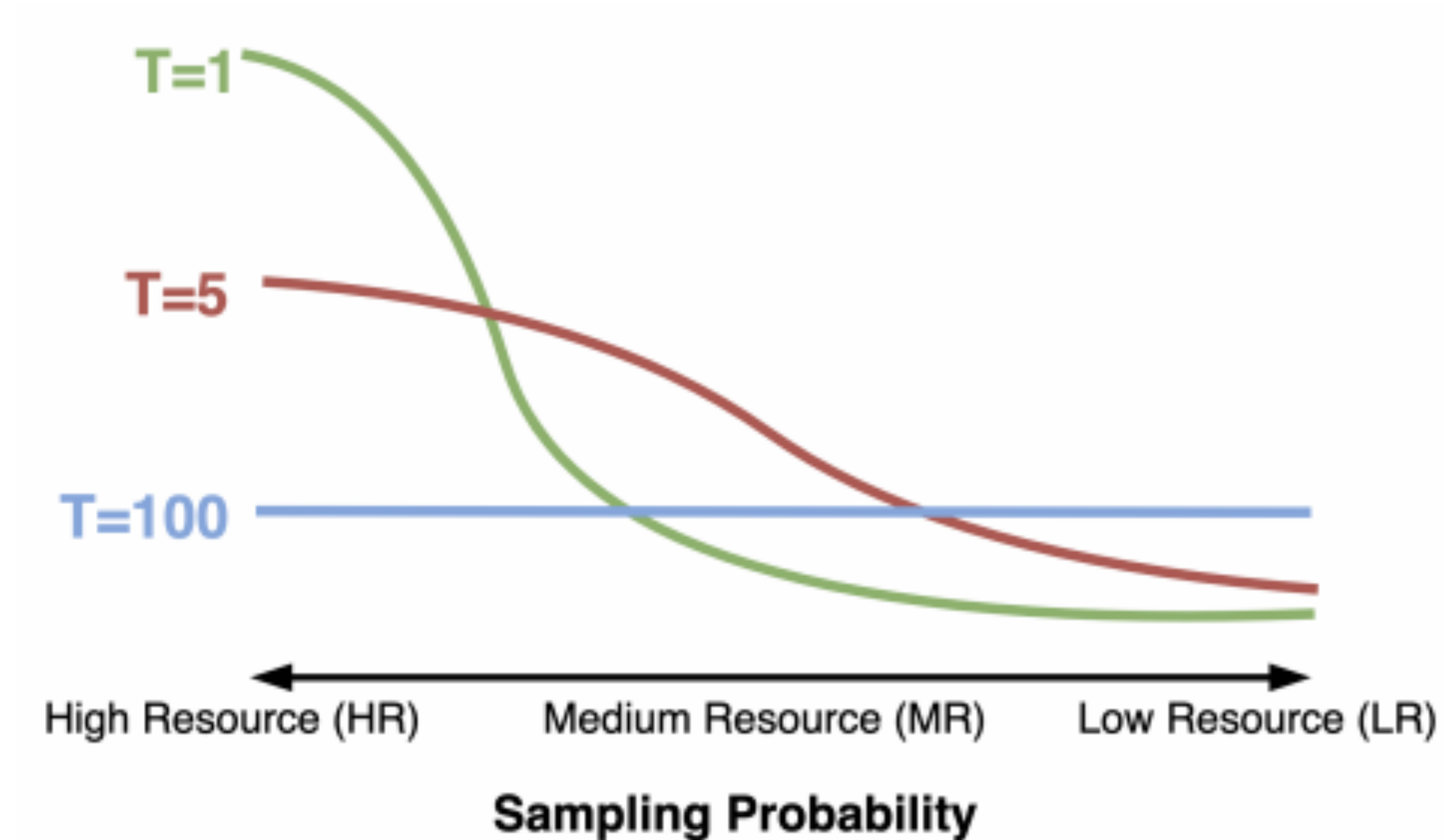
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Text Token IDs

Similar content, 10.6x the tokens!

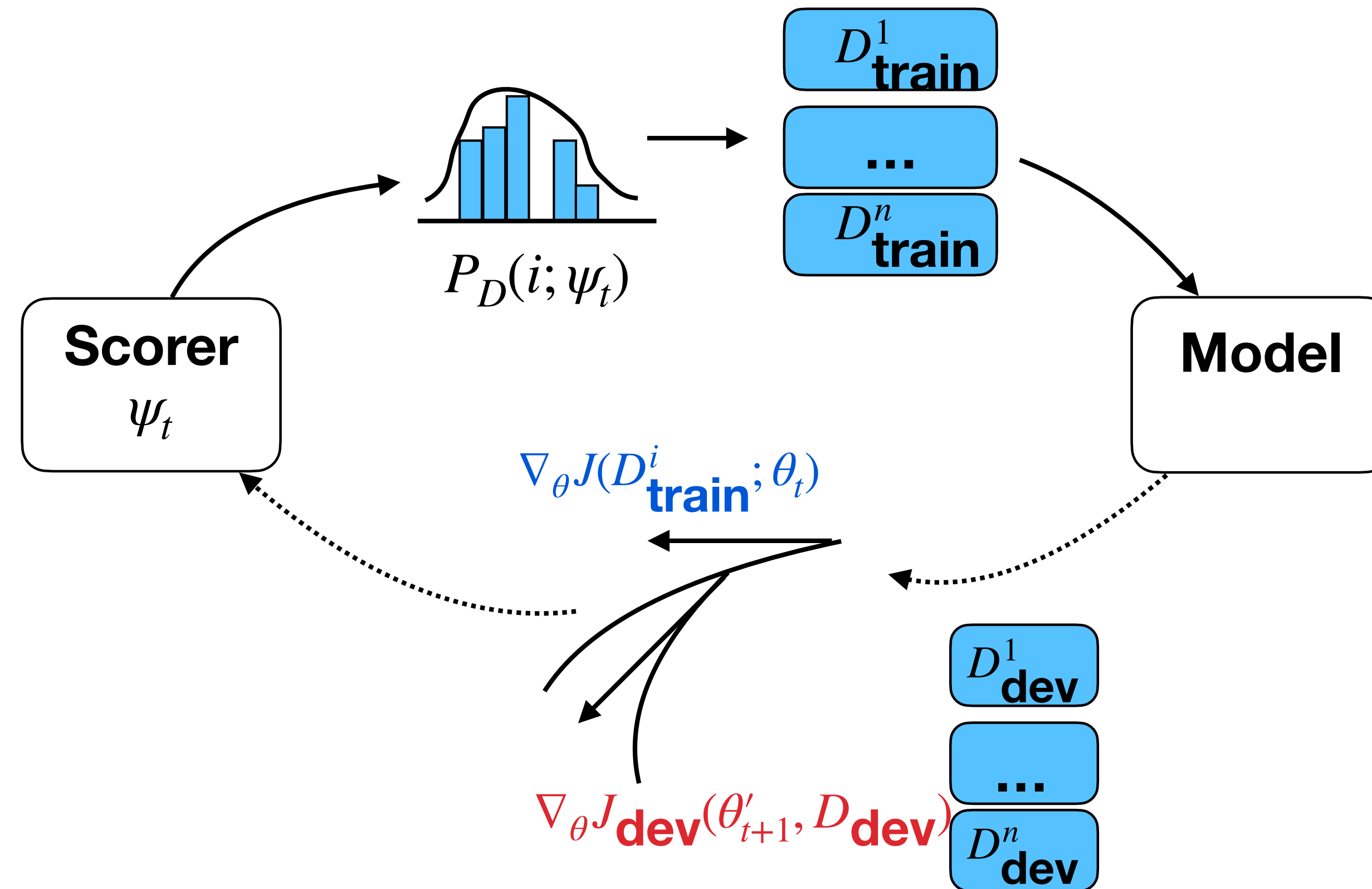
# Heuristic sampling



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

- Sample data based on dataset size scaled by a temperature term
- Sample at model training time, or vocabulary construction time

# Learning to balance data



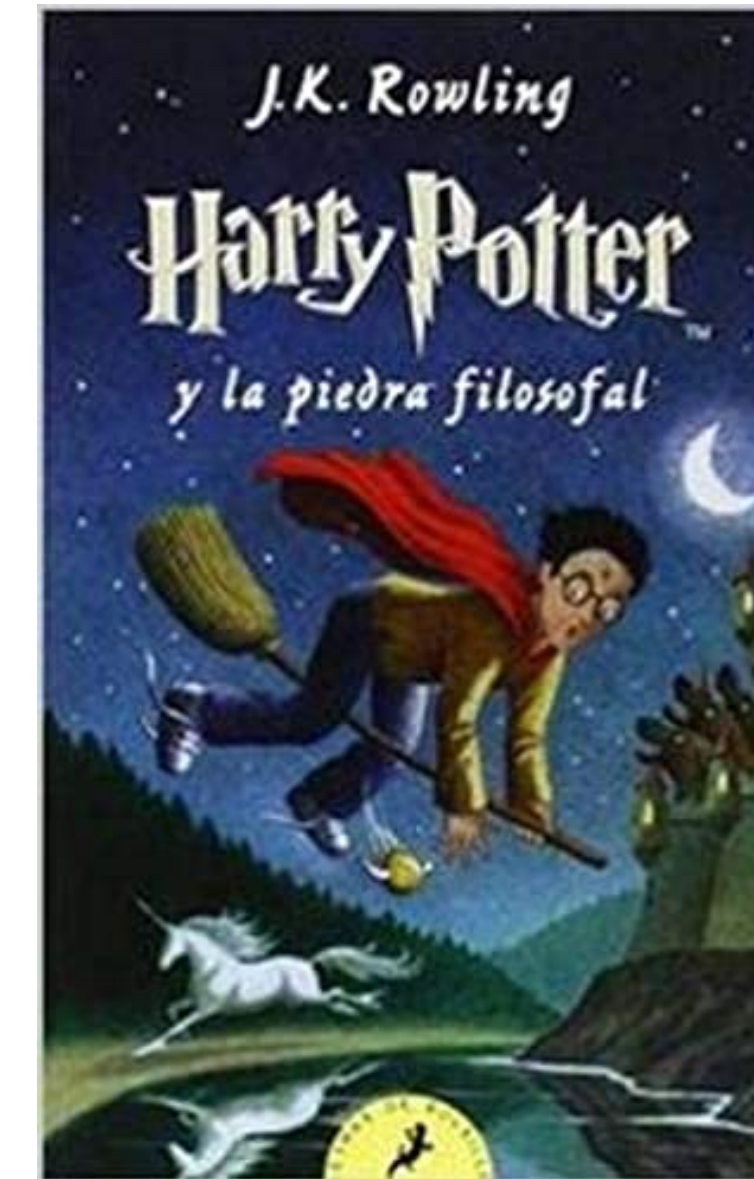
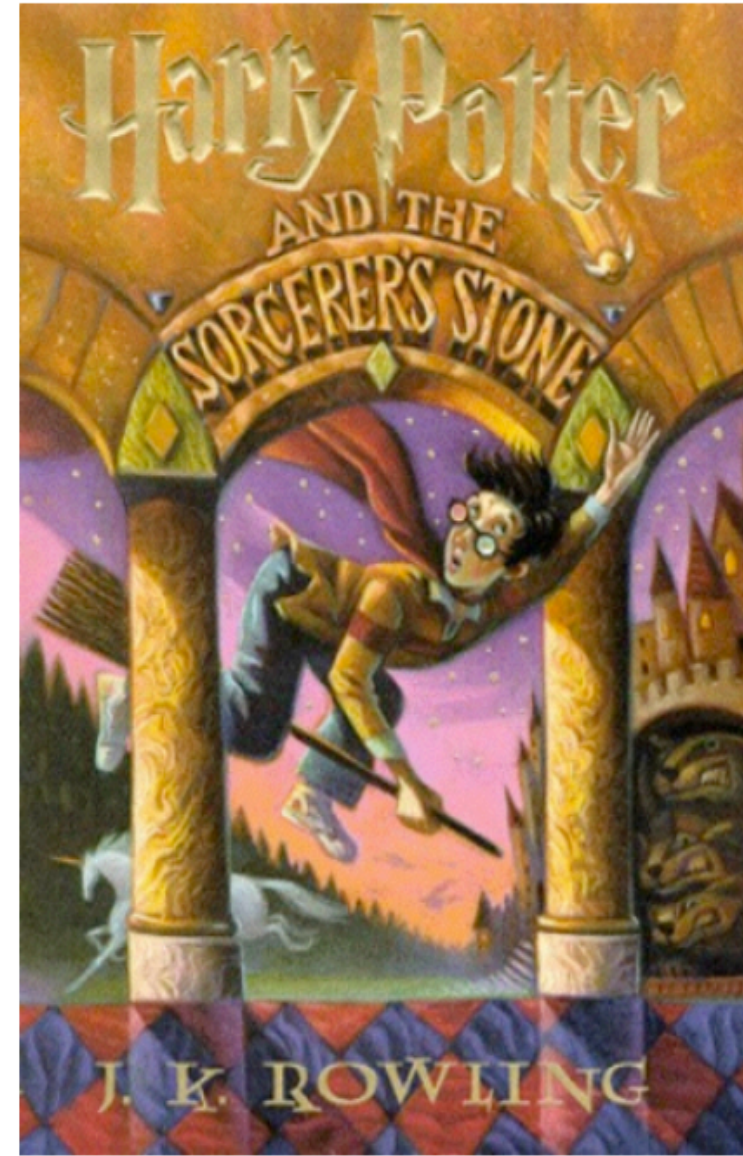
Balancing Training for multilingual neural machine translation. Wang et. al. 2020

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

# Machine Translation



# Translation



Mr. and Mrs. Dursley, who lived at number 4 on Privet Drive, were proud to say they were very normal, fortunately.

El señor y la señora Dursley, que vivían en el número 4 de Privet Drive, estaban orgullosos de decir que eran muy normales, afortunadamente.

Even if you don't know Spanish, can you find the correspondences between them?

# Difficulties of translation: Syntactic divergences

The development of artificial intelligence is a really big deal.

El desarrollo de la inteligencia artificial es un asunto realmente importante.

The development of artificial intelligence is a really big deal.

人工知能の発展は本当にすごいことです。

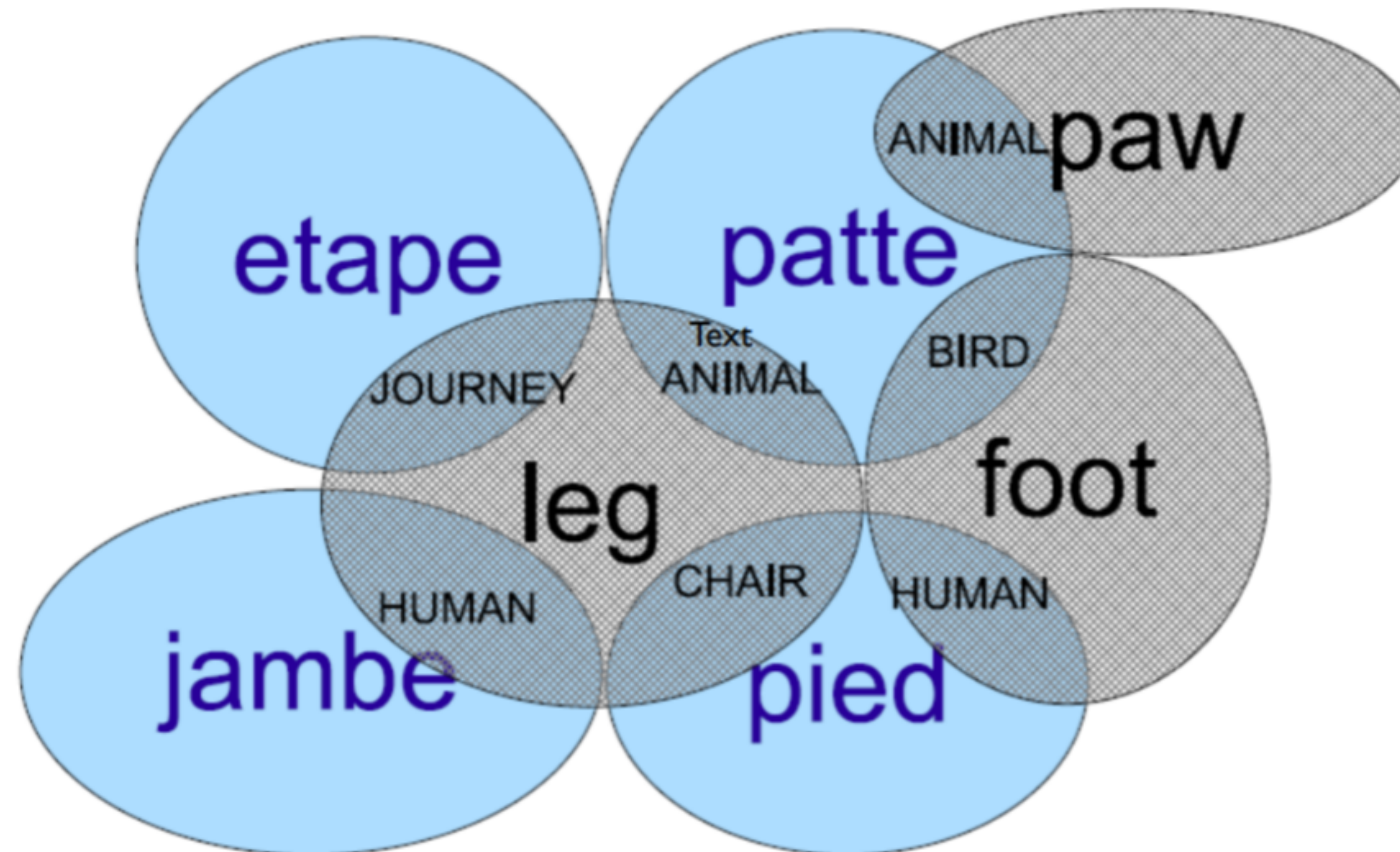
# Difficulties of translation: Syntactic divergences

- [illegible]



# Difficulties of translation: Lexical divergences

- Lexical ambiguities and divergences across languages

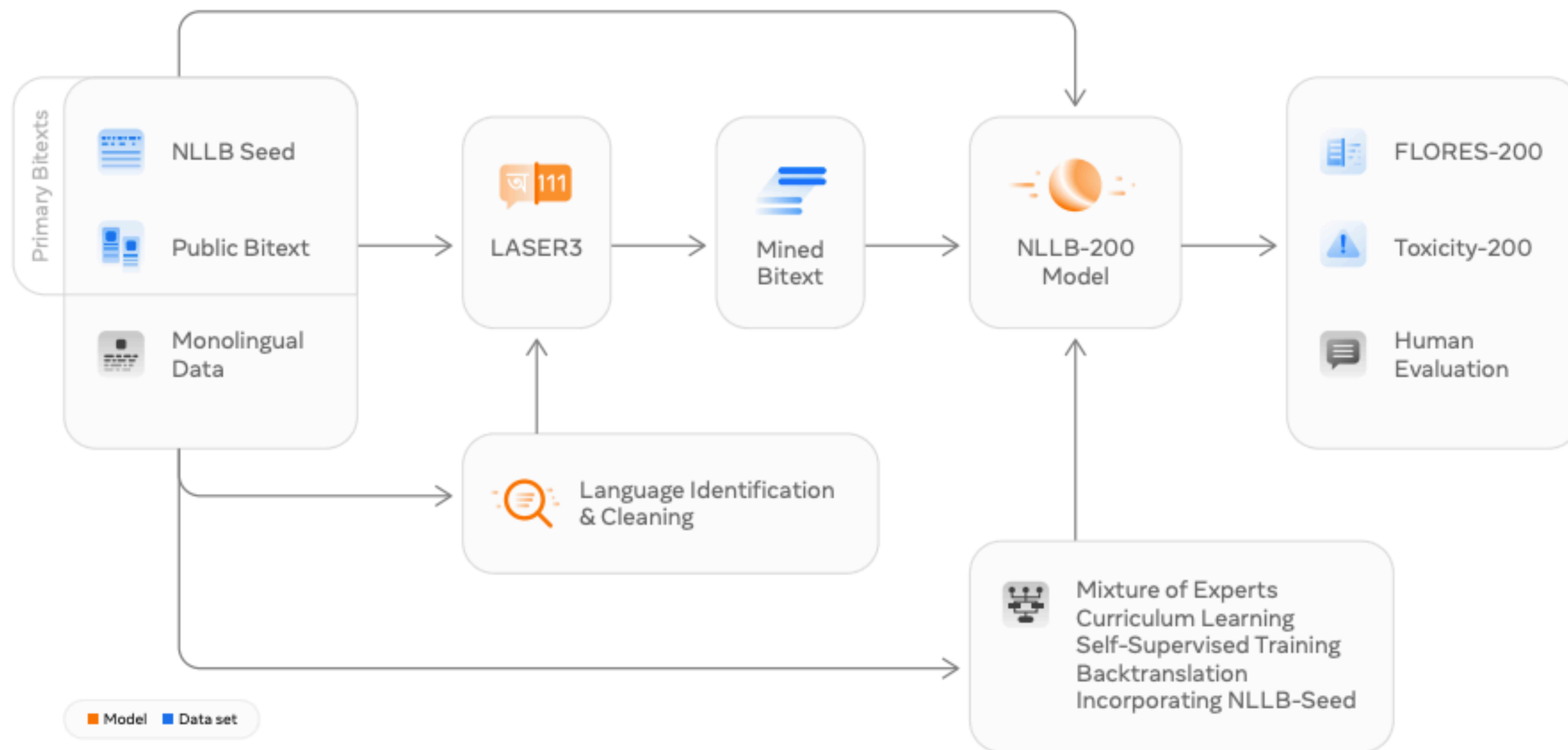


[Example from Jurafsky & Martin Speech and Language Processing 2nd ed.]

# Translation tasks

- **WMT (the Conference on Machine Translation)** shared tasks—run every year for translation, evaluation, etc.
- **FLORES**: a dataset in 200 languages translated from English Wikipedia
- **IWSLT**: tasks on speech translation

# No Language Left Behind (2022)



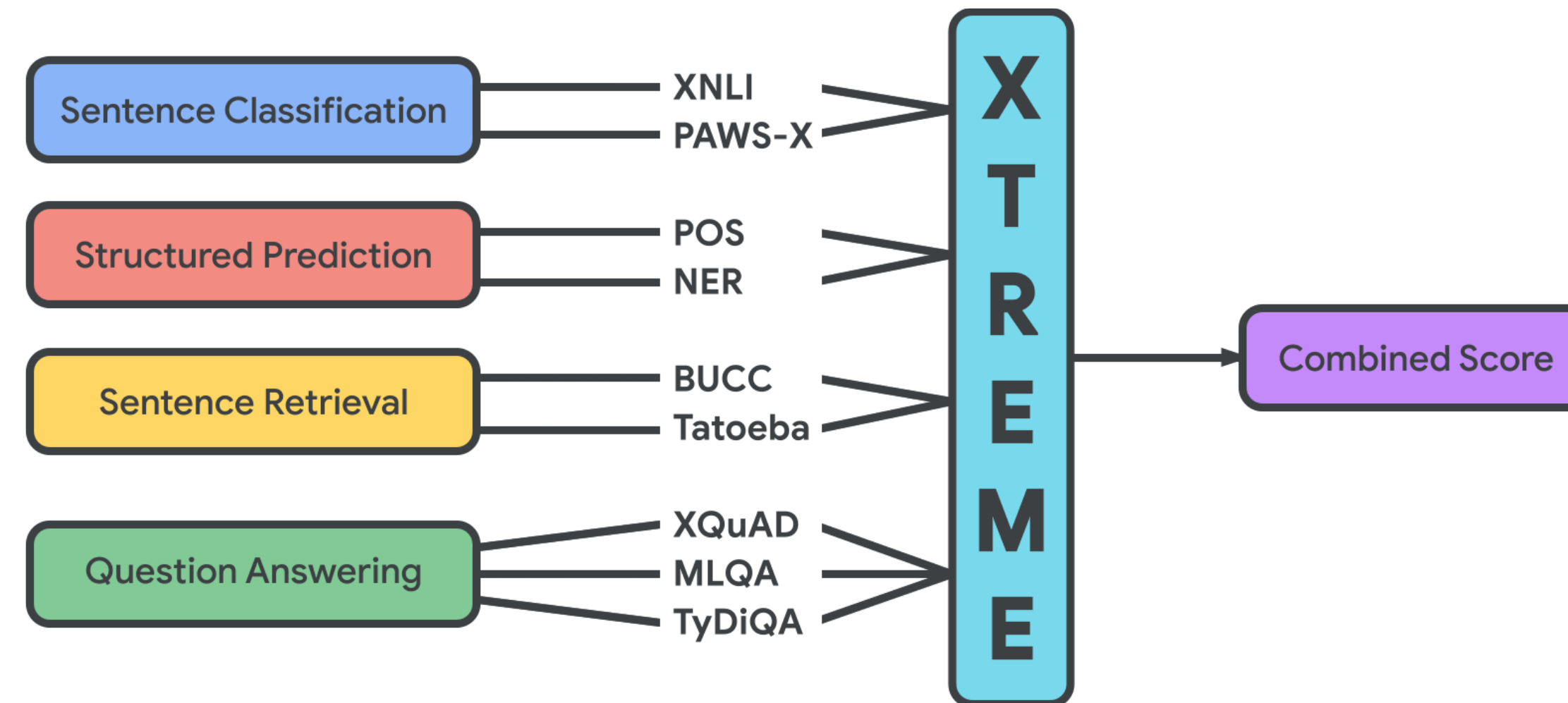
# Multilingual Pre-trained Models

# Multilinguality of general LLMs

- Closed LLMs such as GPT-4 are typically incidentally multilingual due to large training data
- Open LLMs (e.g., OLMo) often do data filtering to allow for good performance on English, and can be less multilingual
- Models such as mBERT, XLM, XLM-R extend BERT for multi-lingual pre-training

# Multilingual representation evaluation

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



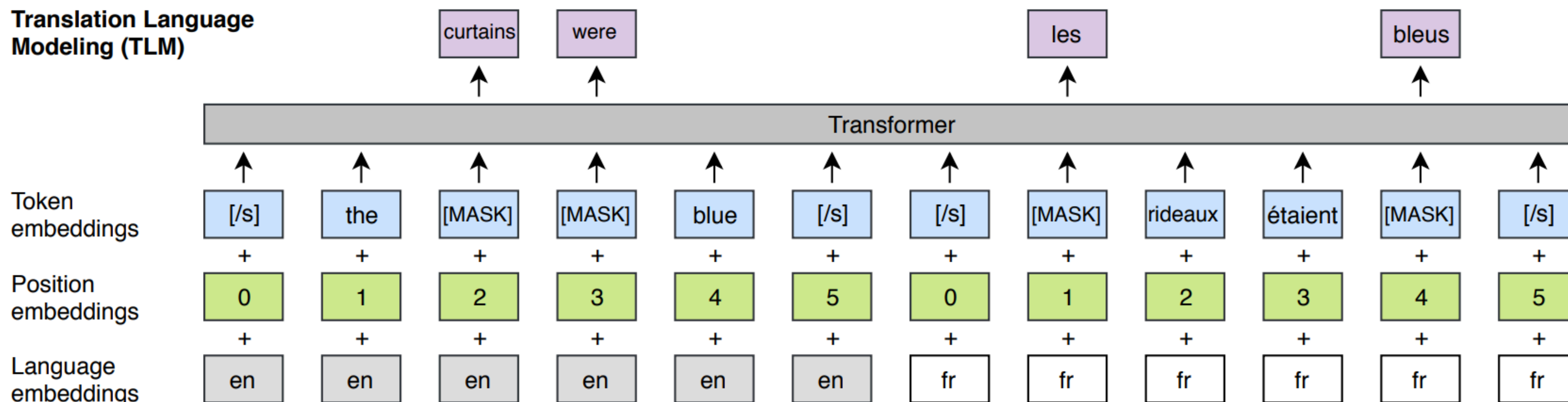
- **XGLUE**: less typologically diverse but contains generation (Liang et al. 2020)
- **XTREME-R** harder version based on XTREME (Ruder et al. 2021)



# Multilingual masked language modeling

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

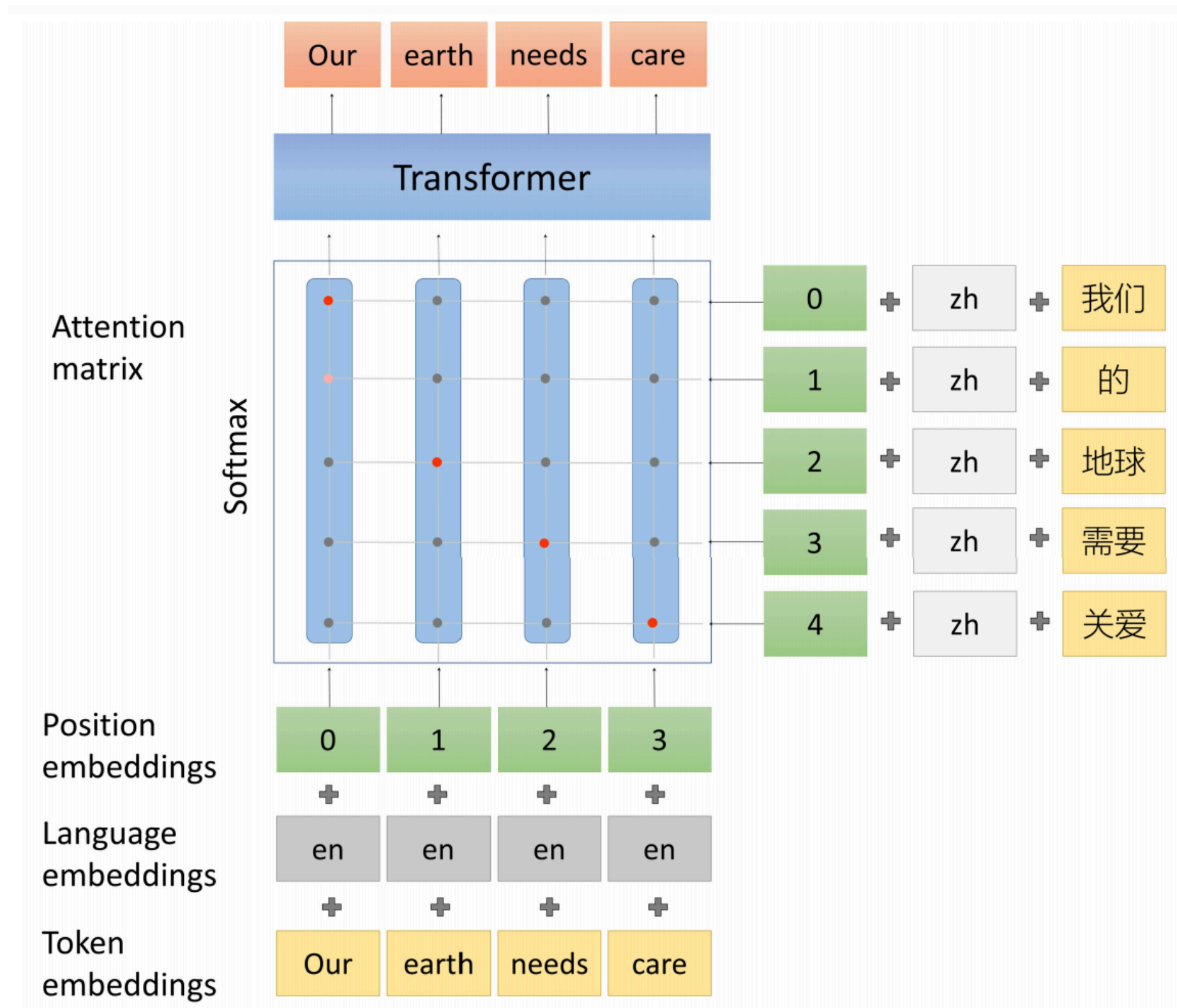
Translation Language Modeling (TLM)



# More explicit alignment objectives

**Unicoder** (Huang et al. 2019)

"cross-lingual word recovery"



**AMBER** (Hu et al. 2020)

bidirectional explicit alignment objective

$$\ell_{\text{WA}}(x, y) = 1 - \frac{1}{H} \sum_{h=1}^H \frac{\text{tr}(\mathbf{A}_{y \rightarrow x}^h \mathbf{A}_{x \rightarrow y}^h)}{\min(|x|, |y|)}$$



# Multilingual encoder-decoder

- mT5 (Xue et al., 2020) is a multilingual encoder-decoder
- Trained on many languages, high performance

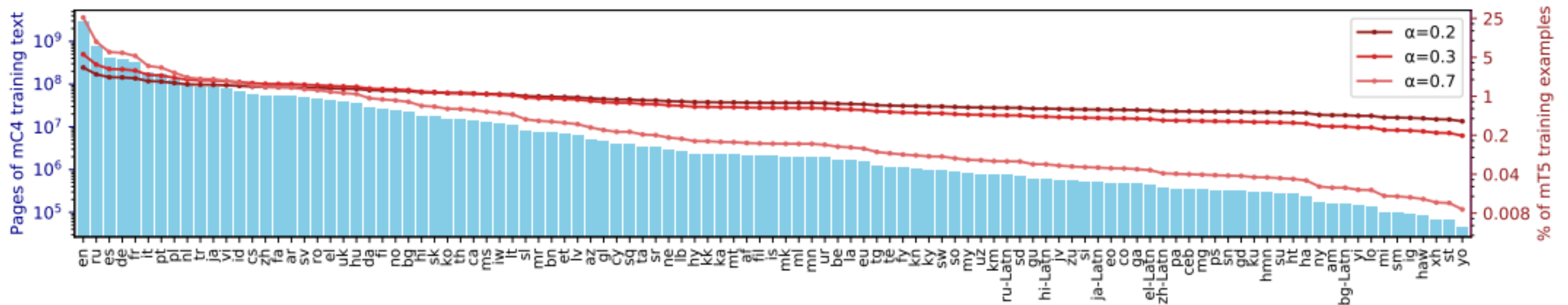
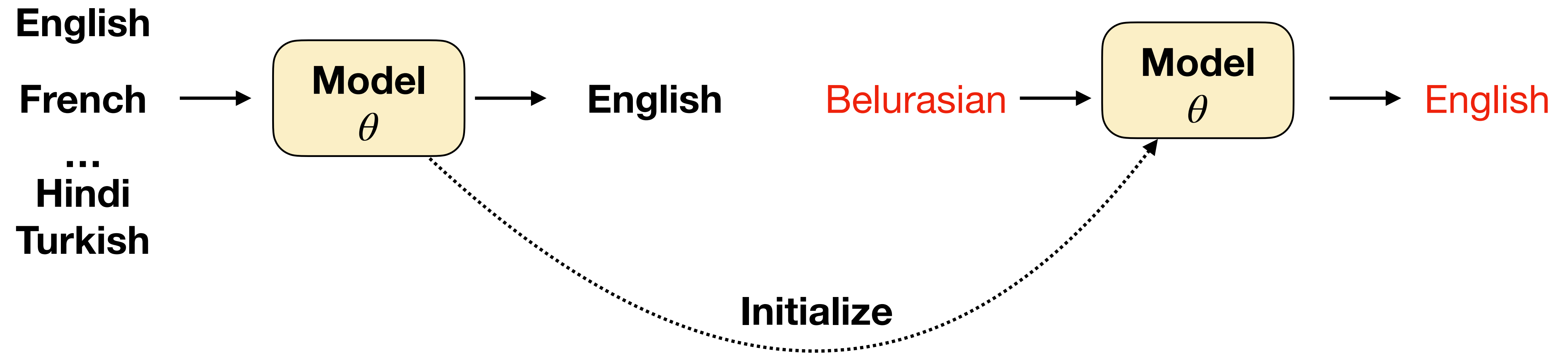


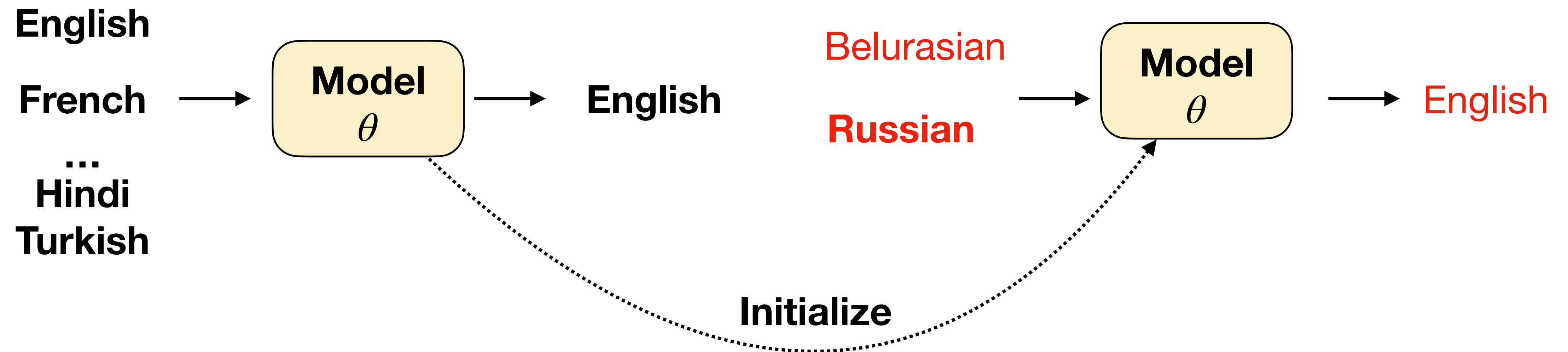
Figure 1: Page counts per language in mC4 (left axis), and percentage of mT5 training examples coming from each language, for different language sampling exponents  $\alpha$  (right axis). Our final model uses  $\alpha=0.3$ .

# 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

# Similar language regularization



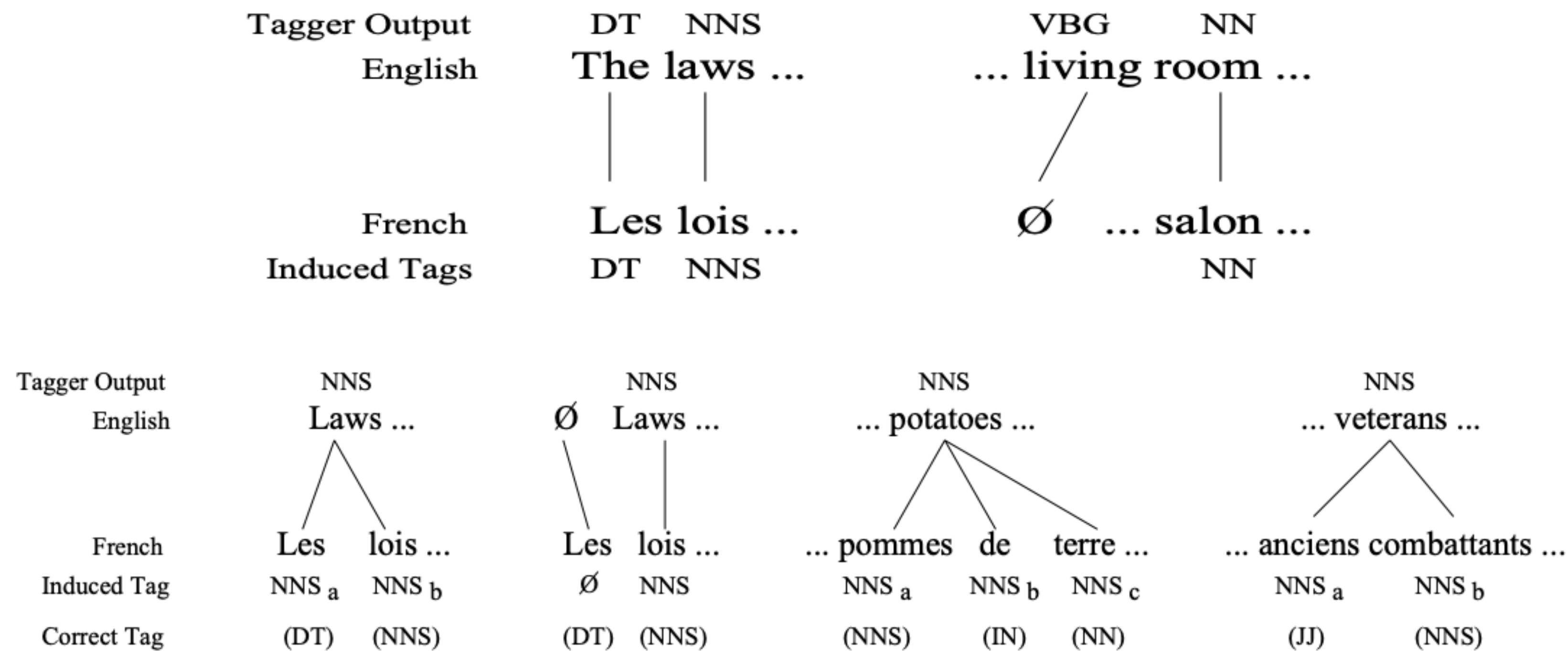
- Regularized fine-tuning: fine-tune on low-resource language and its related high-resource language to avoid overfitting

# Zero-shot transfer for pretrained representations

- Pretrain: large language model using **monolingual data** from many different languages
- Fine-tune: using **annotated data** in a given language (e.g., English)
- Test: test the fine-tuned model on a **different language** from the fine-tuning language (e.g., 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).



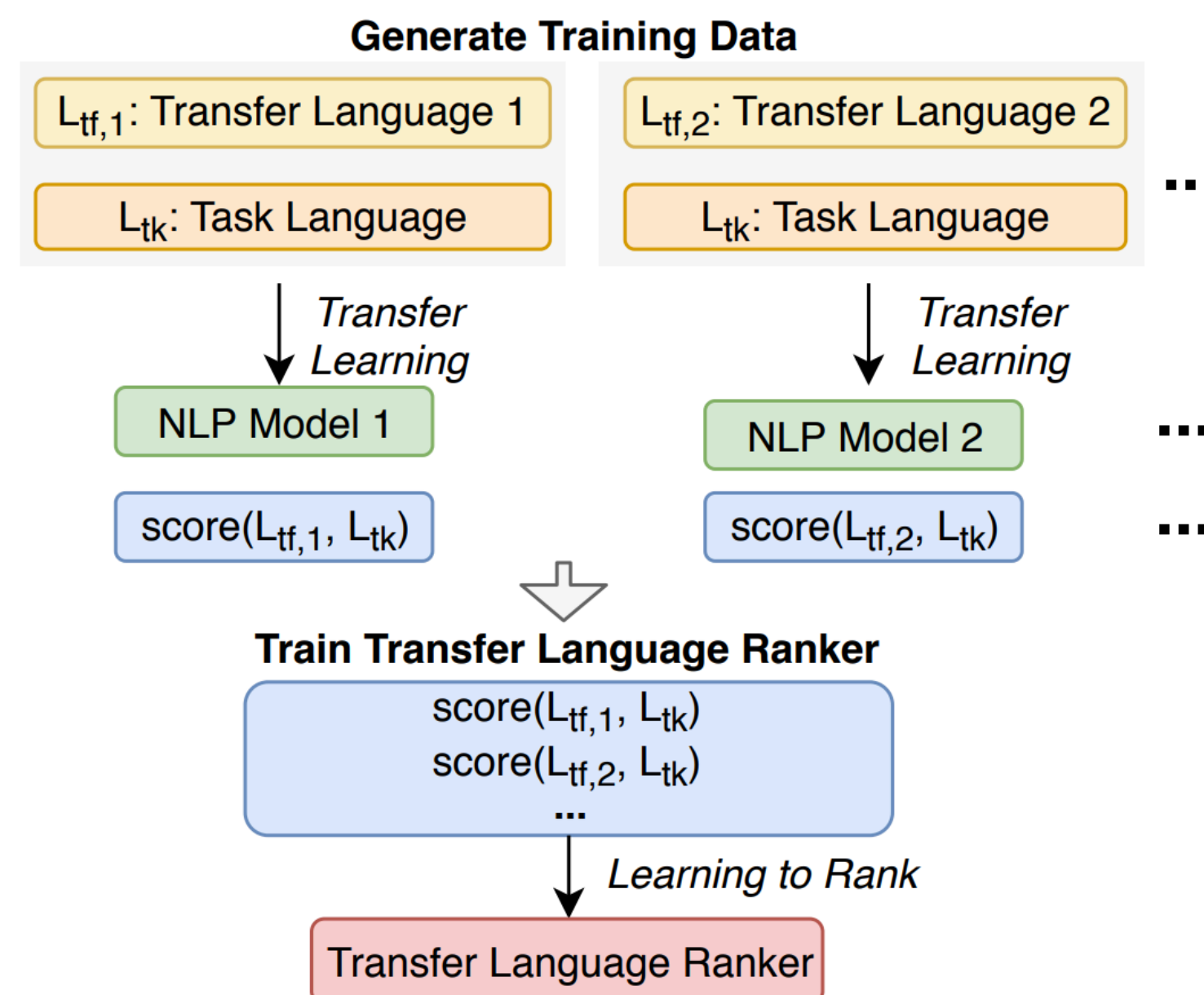


# Which language to use for transfer?

When transferring from another language, it is ideal that it is

- **Similar** to the target language
- **Data-rich**

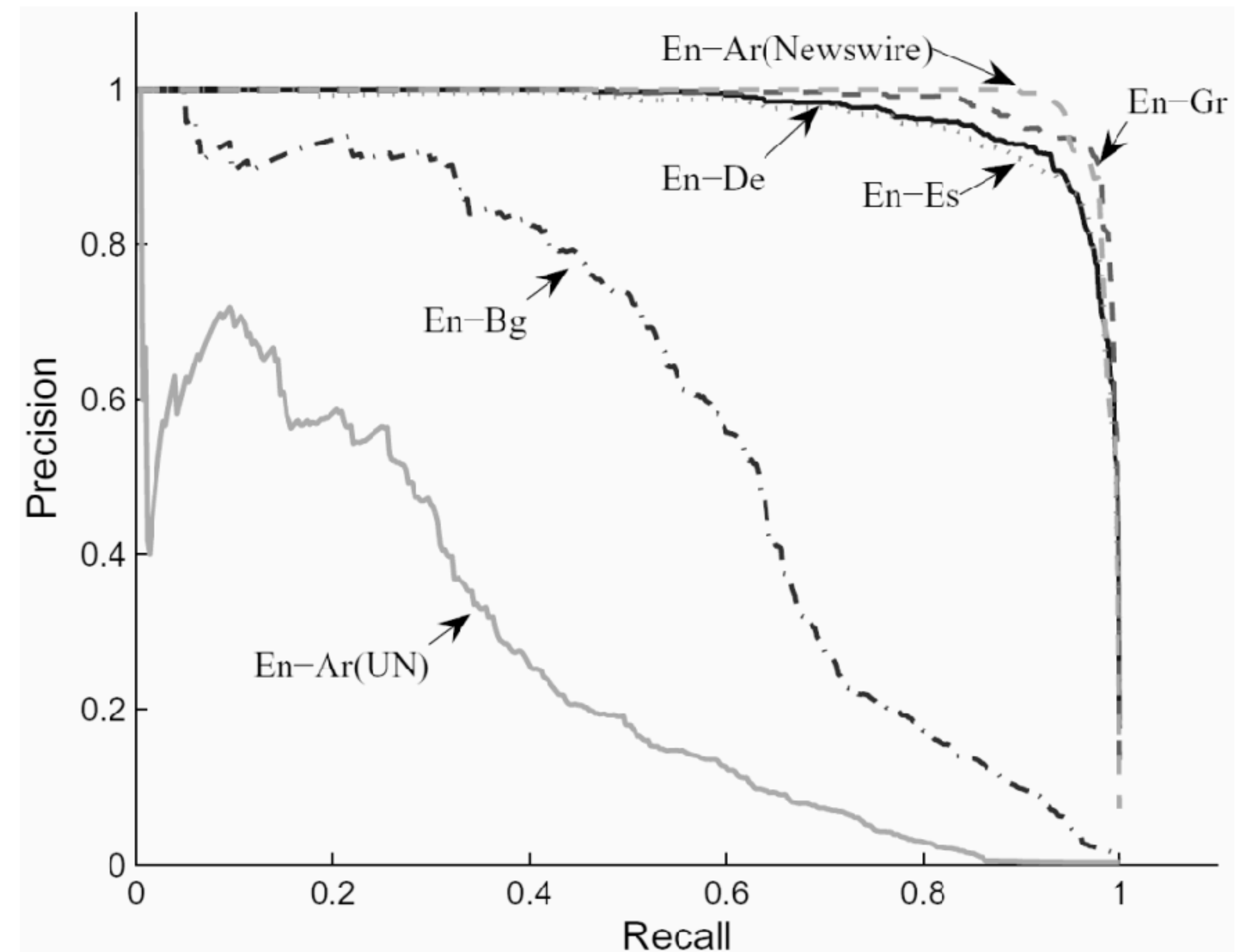
Lin et al. (2019) examine how to identify better transfer languages



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	<b>63.0</b>	<b>28.9</b>	<b>65.0</b>
LANGRANK (dataset)		<b>53.7</b>	17.0	26.5	<b>65.0</b>
LANGRANK (URIEL)		32.6	58.1	16.6	59.6

# What if languages don't share a script?

- Some tokens (e.g., numerals, dates) can still be shared
- Can get high accuracy at the document level
- High variance depending on orthography (Krstovski et al., 2011)



# What if languages don't share a 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.

Marathi

[पोलंड] हा मध्य युरोपातील एक देश आहे

Gloss: [Poland] is a country in Central Europe.

Cross-lingual Entity Linking

पोलंड  
Marathi

Poland

Grapheme Pivoting

पोलंड  
Marathi

पोलैंड  
Hindi

Poland

Phoneme Pivoting

poləndə  
Marathi IPA

polæ:ndə  
Hindi IPA

powlənd  
English IPA



# Multilingual summary

- LLMs can work with more languages than any human!
- But the “curse of multilinguality” imposes tradeoffs
- How to balance depends on our goals
  - Perform tasks independently in multiple languages?
    - Eventually specialize for important languages
  - Perform cross-language tasks?
    - Source-target asymmetry
      - Cf. speech→text and text→speech
- Much more with Terra Blevins on Tuesday!