Multilingual NLP

CSE 5525: Foundations of Speech and Natural Language Processing

https://shocheen.github.io/courses/cse-5525-spring-2025

THE OHIO STATE UNIVERSITY

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Logistics

- Final project:
  - Mid-project report grades are out.
  - Project presentations: April 16, 18.
  - Final project report due date: April 25.

- Quiz this Friday on AI safety.

Agenda

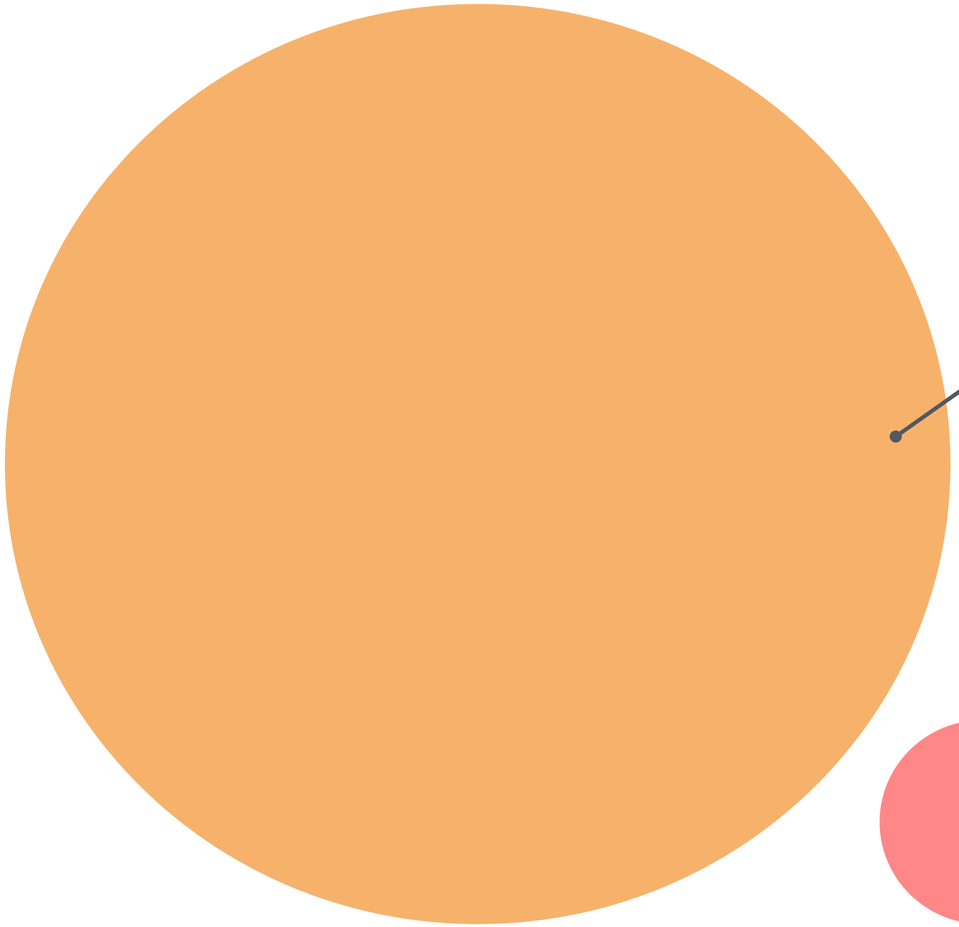
I. Languages of the World and Linguistic Diversity
II. Multilingual NLP and its difficulties
III. Multilingual Pretraining
IV. Multilingual Instruction Training
V. Multilingual Alignment

Languages of the World

7164 languages
in use !!! (as of 2022)

Image from Ethnologue's website ("Eberhard, et al.,. 2024. Ethnologue: Languages of the World. Twenty-seventh edition. Dallas, Texas: SIL International. Online version: http://www.ethnologue.com.")

Languages by Vitality

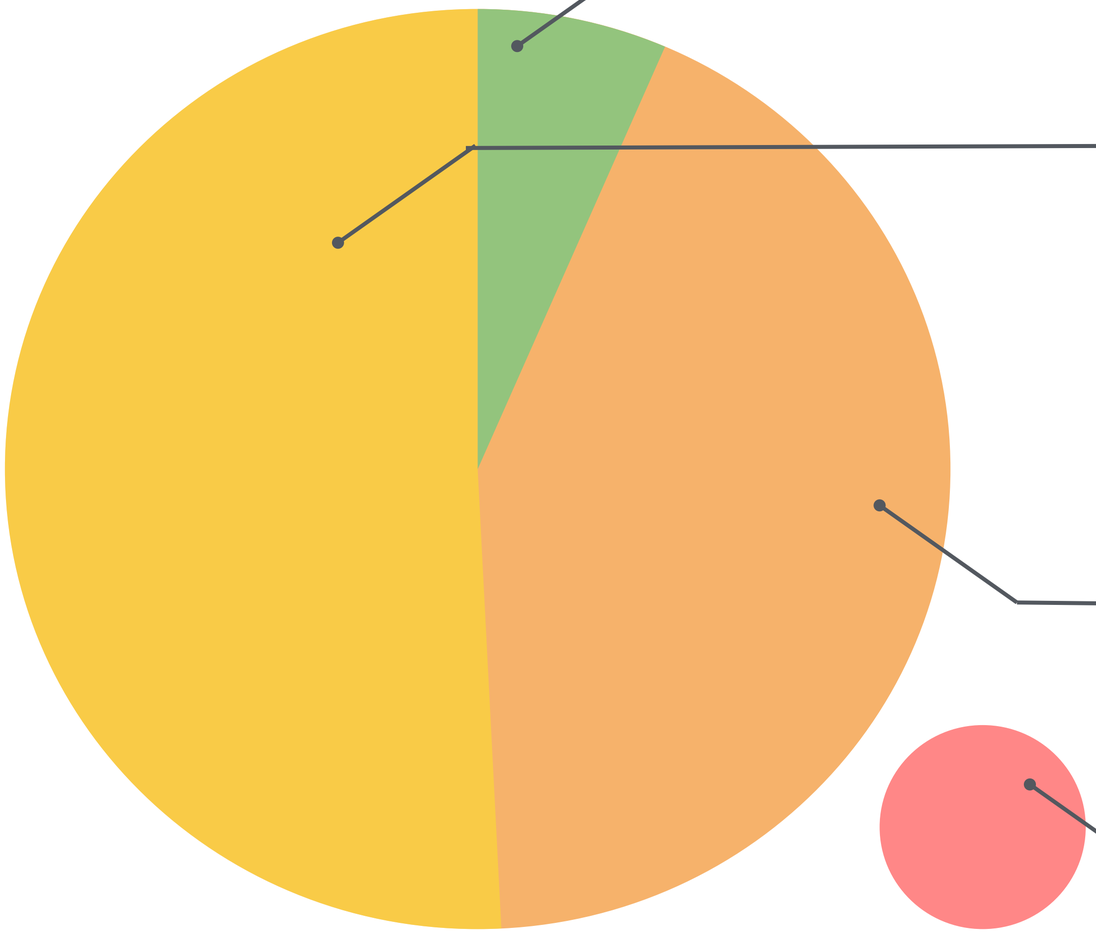


~7100 living languages

451 **extinct** languages:
Languages no longer used; no one identifies with the language

Image derived from the language vitality data from Ethnologue's website ("Eberhard, et al., 2024. Ethnologue: Languages of the World. Twenty-seventh edition. Dallas, Texas: SIL International.). Image approx. at scale.

Languages by Vitality



492 **institutional** languages:
Sustained by institutions / governments

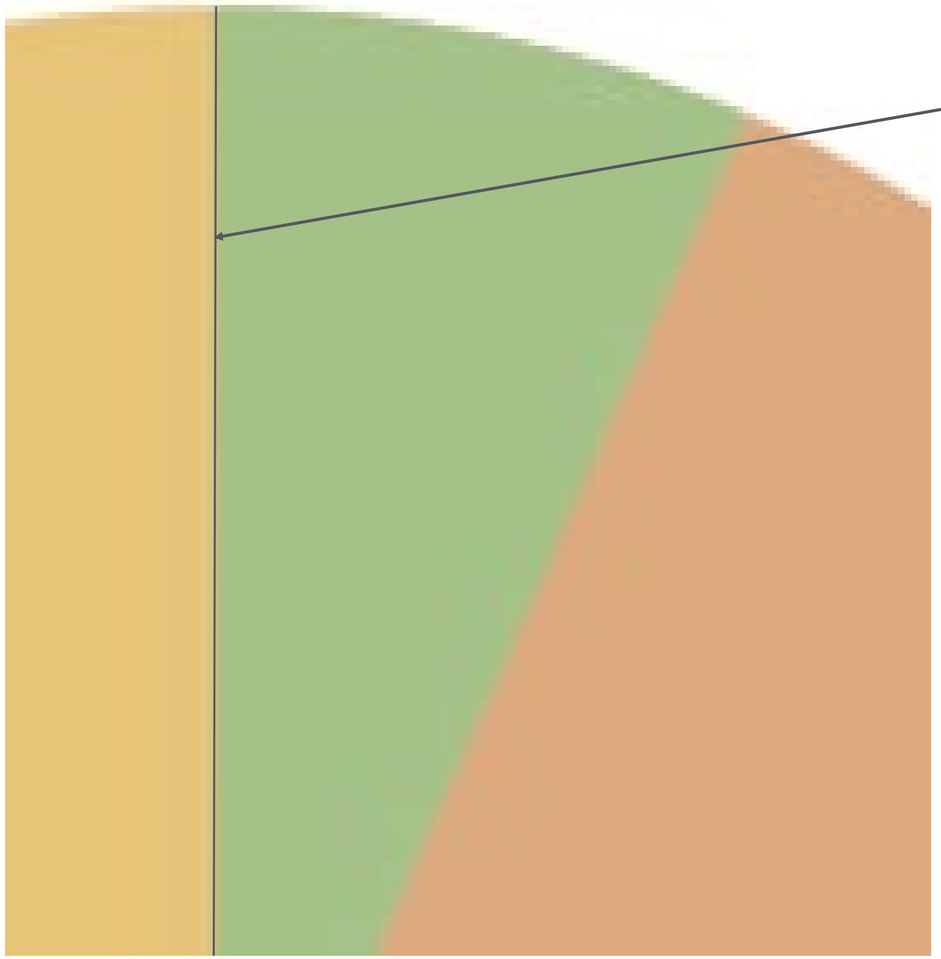
3593 **stable** languages:
Not sustained by formal institutions; norm at home for children to learn and use the language

3072 **endangered** languages:
No longer the norm for children to learn and use the language

451 **extinct** languages:
Languages no longer used; no one identifies with the language

Image derived from the language vitality data from Ethnologue's website ("Eberhard, et al, 2024. Ethnologue: Languages of the World. Twenty-seventh edition. Dallas, Texas: SIL International). Image approx. at scale.

Languages by Vitality



That thin black line is **English**!

Image derived from the language vitality data from Ethnologue's website ("Eberhard, et al., 2024. Ethnologue: Languages of the World. Twenty-seventh edition. Dallas, Texas: SIL International.). Image approx. at scale.

What is a language, anyway?

- Is English a language?
  - Are British English and American English the same language?
  - Are African-American Vernacular English the same as “White” American English

- Is the Spanish spoken in Spain and the Spanish spoken in Argentina the same language?

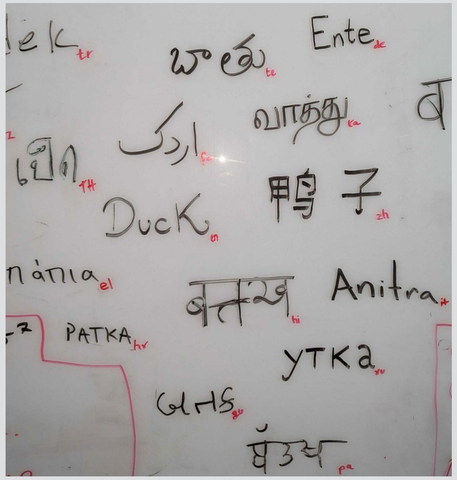
- What about Mandarin, Shanghainese (Wu Chinese), and Cantonese?

- What about Russian and Ukrainian?

a language is a dialect with an army and a navy.

How do Languages Differ?

Scripts:



Word Order:

English: I met Jack. (SVO order)
Hindi : मैं जैक से मिला। (SOV order)
Filipino: Nakilala ko si Jack. (VSO order)

Semantic Variations:

dara : door (*Farsi*) vs burrow (*Gujarati*)
śikśā: education (*Hindi*) vs punishment (*Gujarati*)

And many more ……

Multilingual NLP and its difficulties

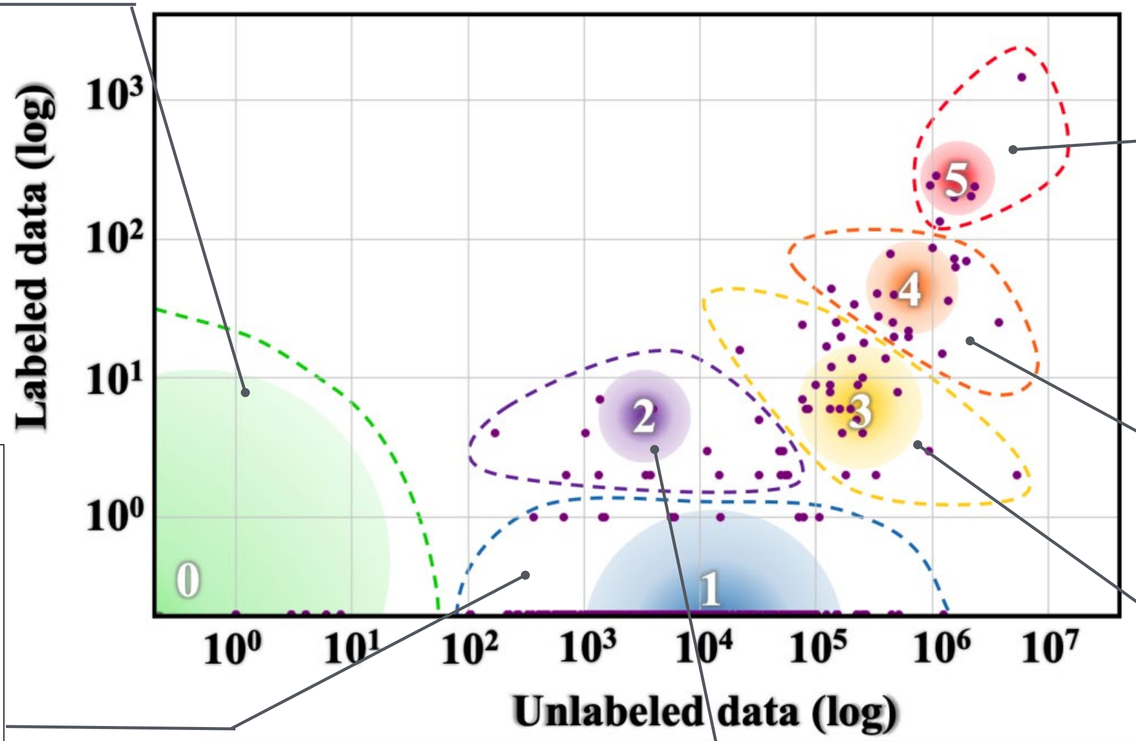
Two Varieties of Multilingual NLP

- **Monolingual NLP in Multiple Languages:**
  - QA, sentiment analysis, chatbots, code generation
  - in English, Chinese, Hindi, Japanese, Spanish, …
- **Cross-lingual NLP:**
  - Machine translation
  - Cross-lingual QA
  - …

Languages of the World via the Data Lens

“The Left-Behinds”
Impossible effort required to lift them into digital space
#Langs: 2191
E.g.: Warlpiri, Gaelic, Gondi
#Speakers: 1.2B

“The Scraping-Bys”
Need solid[organized movement that increases awareness
#Langs: 222
E.g.: Nepali, Gujarati, Armenian
#Speakers: 30M



“The Hopefuls”
languages still Āght on with their gasping breath
#Langs: 19 ; E.g.: Marathi, Irish, Yoruba
#Speakers: 5.7M

“The Winners”
the quintessential rich-resource languages
#Langs: 7
E.g.: English, German, French
#Speakers: 2.5B

“The Underdogs”
dedicated NLP communities conducting research on these languages
#Langs: 18
E.g.: Russian, Dutch, Korean
#Speakers: 2.2B

“The Rising Stars”
let down by insufficient efforts in labeled data collection
#Langs: 28
E.g.: Hebrew, Ukrainian, Urdu
#Speakers: 1.8B

Figure from The State and Fate of Linguistic Diversity and Inclusion in the NLP World (Joshi et al., ACL 2020)
For language categorization of your language see:
https://microsoft.github.io/linguisticdiversity/assets/lang2tax.txt

Linguistic Peculiarities

- Most methods are tested first on English, but not all languages are the same as English

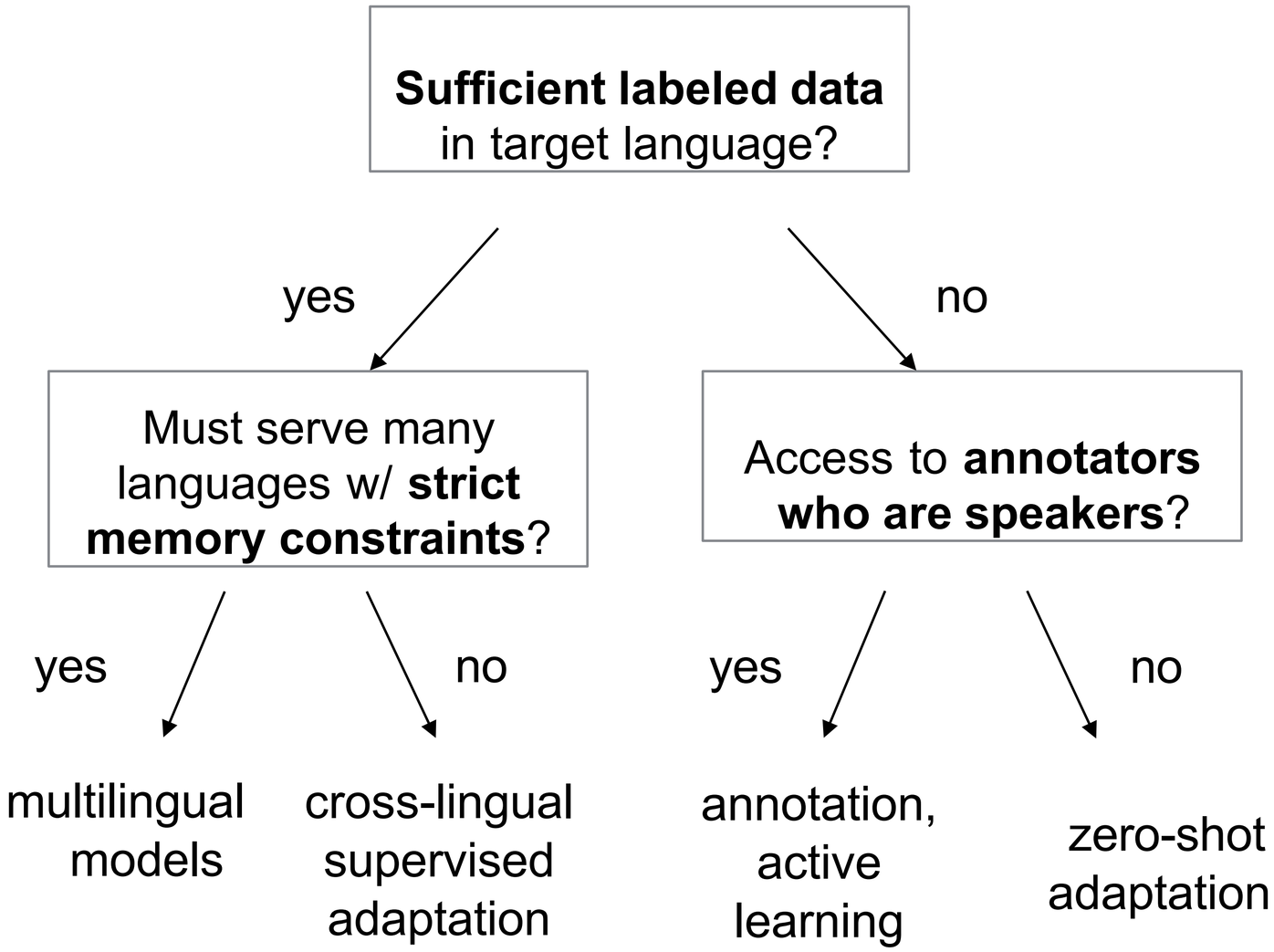
e.g.

- Rich morphology (case, gender, etc.)
- Accents/diacritics
- Different scripts such as CJK
- Dialectal language
- 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

High-level Multilingual Learning Flowchart



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

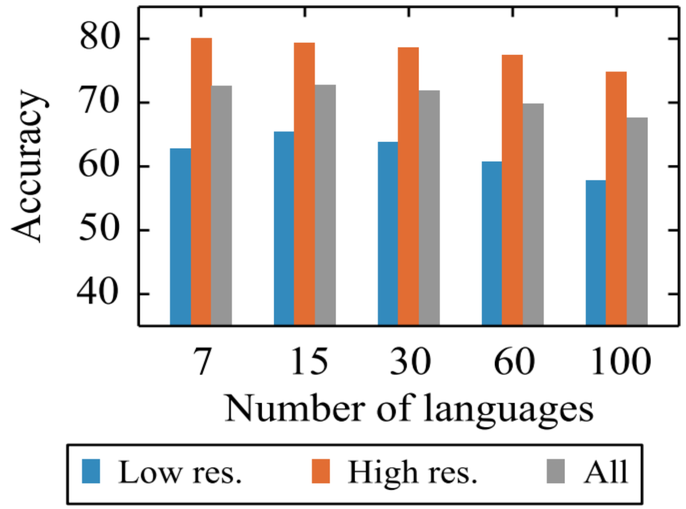
- **Multilingual Output:** Add a tag or prompt about the target language for generation (Johnson et al. 2016)

  <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)

-

Tokenization Disparity

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 58 **Characters** 301

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.

Text | Token IDs

Burmese/Myanmar (Google Translated)

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

OpenAI ၏ကြီးမားသောဘာသာစကားမော်ဒယ်များ (တစ်ခါတစ်ရံ GPT များဟုရည်ညွှန်းသည်) စာသားအစုအဝေးတွင်တွေ့ရလေ့ရှိသောအက္ခရာများဖြစ်သည့် တိုကင်များကိုအသုံးပြု၍ စာသားလုပ်ဆောင်သည်။ မော်ဒယ်များသည် ဤတိုကင်များကြား ကိန်းဂဏန်းဆိုင်ရာ ဆက်နွယ်မှုများကိုနားလည်ရန် သင်ယူကြပြီး တိုကင်များ၏ အတွဲလိုက် နောက်လာမည့် တိုကင်ကို ထုတ်လုပ်ရာတွင် ထူးချွန်သည်။

Clear | Show example

Tokens 617 **Characters** 325

OpenAI �� (��
GPT ������������������������) ������
������������ ������������ ������
������ ������ ������
Text | Token IDs

Similar content, 10.6x the tokens!

Directions of Innovations in Multilingual LLMs

Data

- Methods to efficiently procure labeled & unlabeled data
  - Quality vs Quantity trade-off
  - Impact of data diversity
- Alignment data collection strategies

Infrastructure

- Breaking the curse of multilinguality (more on this if time permits)
- Extending LLMs to unseen languages
- Efficient tokenization for low-resource languages

We'll mostly focus on the **Data** direction today!

Multilingual LLMs: Overview

- LLMs that support multiple languages
  - Parameters shared across languages
  - Trained on a large amount of multilingual data (unlabeled & labeled)
  - Often rely on cross-lingual transfer abilities across languages

Incidentally Multilingual Models

Mistral 7B

Claude 3

Gemma

Llama 2

Meta AI

Natively Multilingual Models

mT5

BLOOM

Okapi

MALA-500

Aya Model

Aya 23

Closed Data Models

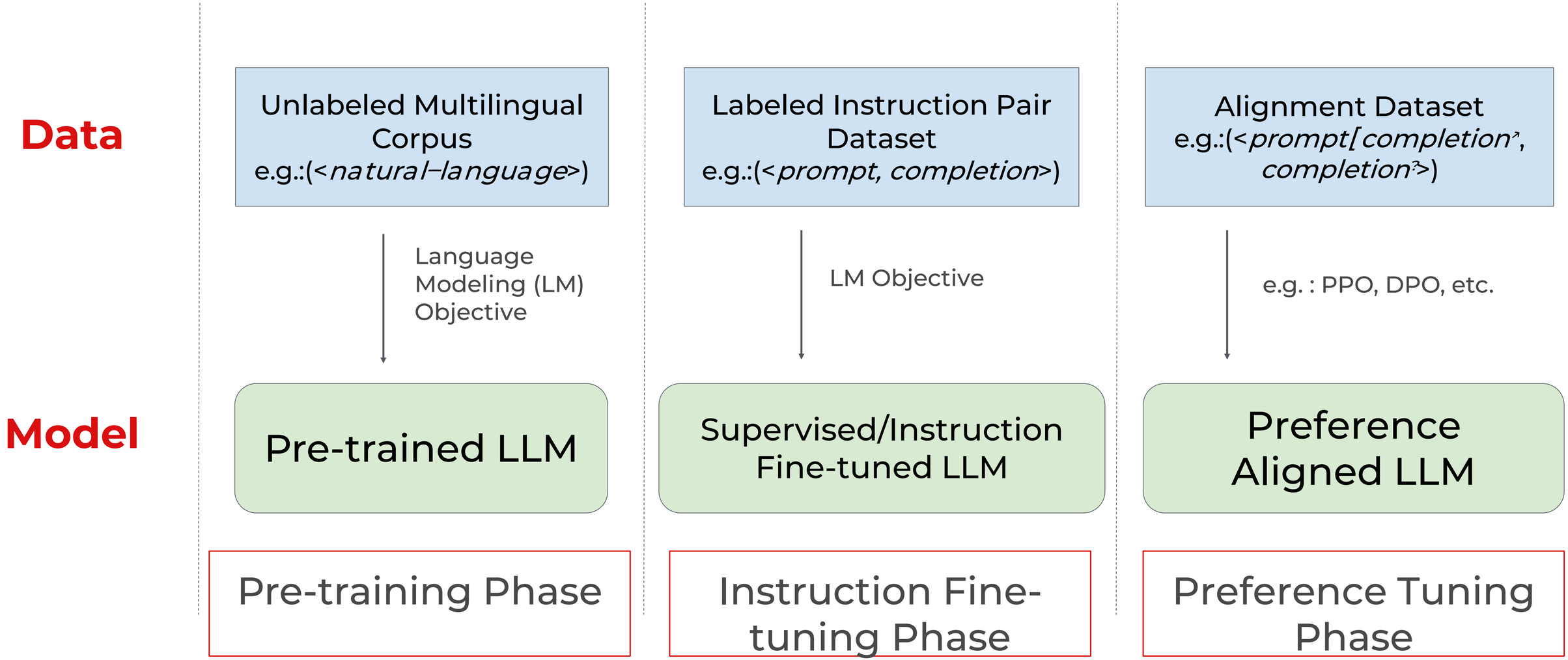
Llama 3.1

Gemini

Phi-3

GPT - 4

The Multilingual LLM Pipeline



Multilingual Pre-training

Creating New Data

Multilingual Pre-training

- **Multilingual C4 (mC4)[1] [6.6B pages, 6.3T tokens]**
  - **C4**: Colossal Clean Crawled Corpus[2]
    - Cleaned version of the Common Crawl's snapshot of the internet (April 2019)
    - Filtered for pages predominantly English as per a language detector
  - Use 71 snapshots of Common Crawl
  - Supports **101 languages** (with 6 languages in two scripts)
    - Identified using the *cld3* language detector
  - Other filters: length, deduplication, profanity, etc.

- Models trained on mC4: mT5, mT0, Aya-101

[1] mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer (Xue et al., NAACL 2021)
[2] Exploring the limits of transfer learning with a unified text-to-text transformer. (Raffel et al.,, JMLR 2020)
* - https://pypi.org/project/langdetect/ (Only pages with a probability 99% or higher of being English were considered)
$ - https://github.com/google/cld3 (Pages with a language confidence of below 70% were discarded)

Multilingual Pre-training: mC4

- **Multilingual C4 (mC4)[1] [6.6B pages, 6.3T tokens]**
  - **C4**: Colossal Clean Crawled Corpus[2]
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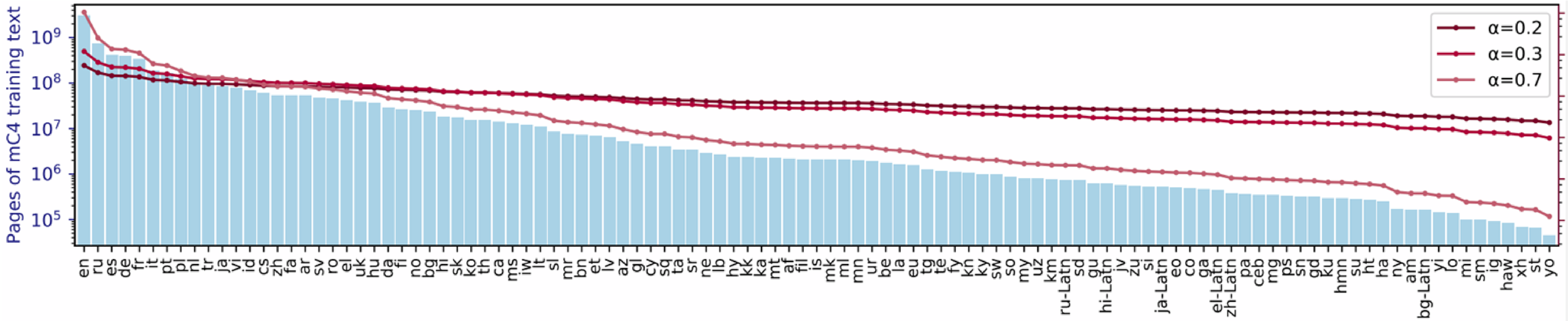

Figure 1: Page counts per language in mC4 (left axis) from mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer (Xue et al., NAACL 2021)

Sampling affects model performance*:

- If low-resource languages are highly sampled too often, the model may overfit
- If high-resource languages are not trained on enough, the model will underfit

[1] Explori
[2] mT5: A
* - https:/
$ - https:/

Multilingual Pre-training: Glot500-c

- **Glot500-c[1] [1.5B sentences, 600 GB]**
  - Subset of **Glot2000-c** that covers 2266 languages:
    - Diverse data sources: religious texts, news articles, scientific papers, etc.
    - Several filters:
      - Chunk-level filters$
      - Corpus-level filters
  - Set of **511 languages*** with > 30k chunks
- Models trained on Glot500-c: Glot500-m, MALA-500

SF1 Character repetition. If the ratio of repeated characters is too high, it is likely that the sentence has not enough textual content.

SF2 Word repetition. A high ratio of repeated words indicates non-useful repetitive content.

SF3 Special characters. Sentences with a high ratio of special characters are likely to be crawling artifacts or computer code.

SF4 Insufficient number of words. Since training language models requires enough context, very small chunks of text are not useful.

SF5 Deduplication. If two sentences are identical after eliminating punctuation and white space, one is removed.

[1] Glot500: Scaling Multilingual Corpora and Language Models to 500 Languages (Imani et al., ACL 2023)
* - They cover 30 scripts. They also count a distinct language-script pair as a separate pair
$ - The chunk-level filters are taken from BigScience's ROOTS Corpus (The BigScience ROOTS Corpus: A 1.6TB Composite Multilingual Dataset(Laurençon et al., NeurIPS 2022)). This was used to train models like BLOOM, BLOOMZ, etc.

Multilingual Pre-training: Glot500-c

- **Glot500-c[1] [1.5B sentences, 600 GB]**
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      - Corpus-level filters
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Corpus-level filters detect if the corpus of a language-script is noisy; e.g., the corpus is in another language or consists of non-meaningful content such as tabular data. We employ filters CF1 and CF2.

CF1 In case of **mismatch between language and script**, the corpus is removed; e.g., Chinese written in Arabic is unlikely to be Chinese.

CF2 Perplexity mismatch. For each language-script L1, we find its closest language-script L2: the language-script with the lowest perplexity divergence (§3.3). If L1 and L2 are not in the same typological family, we check L1/L2 manually and take appropriate action such as removing the corpus (e.g., if it is actually English) or correcting the ISO code assigned to the corpus.

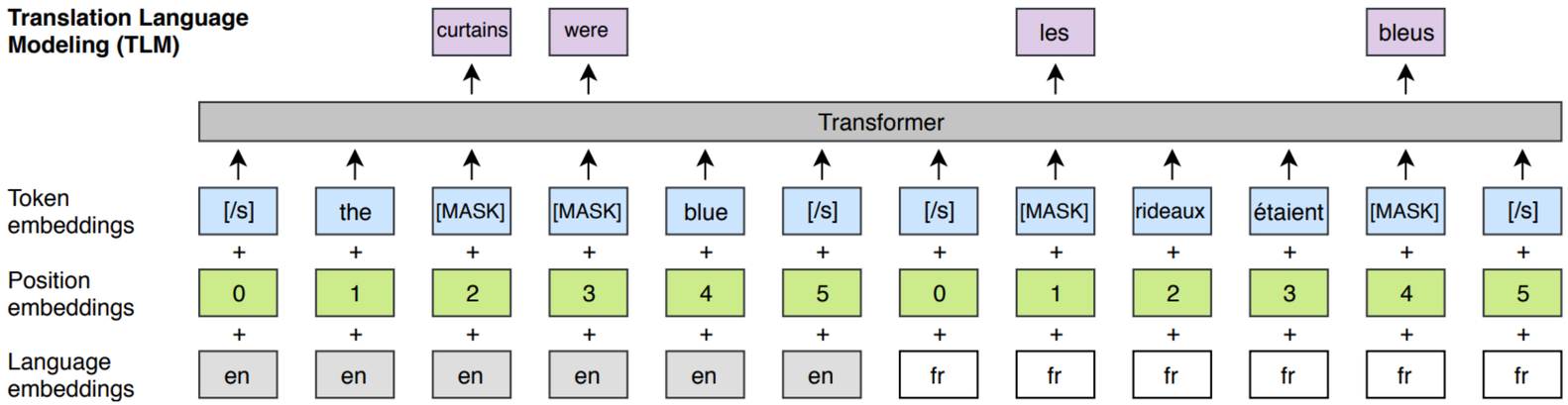
[1] Glot500: Scaling Multilingual Corpora and Language Models to 500 Languages (Imani et al., ACL 2023)
* - They cover 30 scripts. They also count a distinct language-script pair as a separate pair

Multilingual Representation Learning

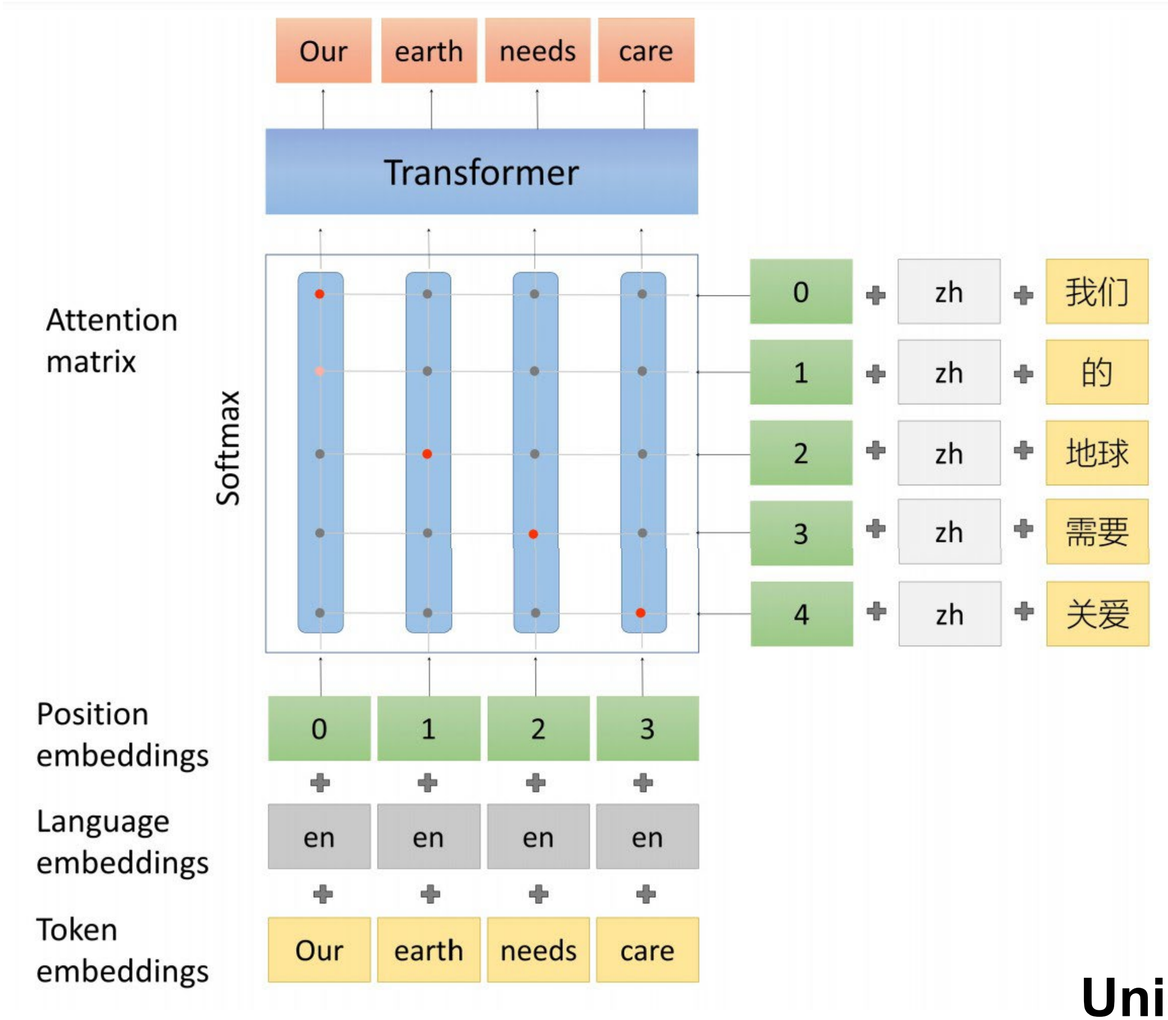
- Language model pre-training has shown to be effective for many NLP tasks, eg. BERT
- BERT uses masked language model (MLM) and next sentence prediction (NSP) objective.
- Models such as mBERT, XLM, XLM-R extend BERT for multi-lingual pre-training.

Multilingual Masked Language Modeling

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



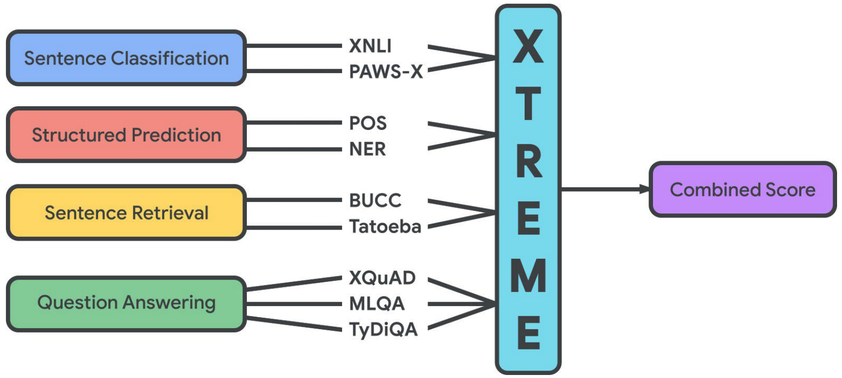
More Explicit Alignment Objectives



Unicoder (Huang et al. 2019),
AMBER (Hu et al. 2020)

Multilingual Representation Evaluation

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



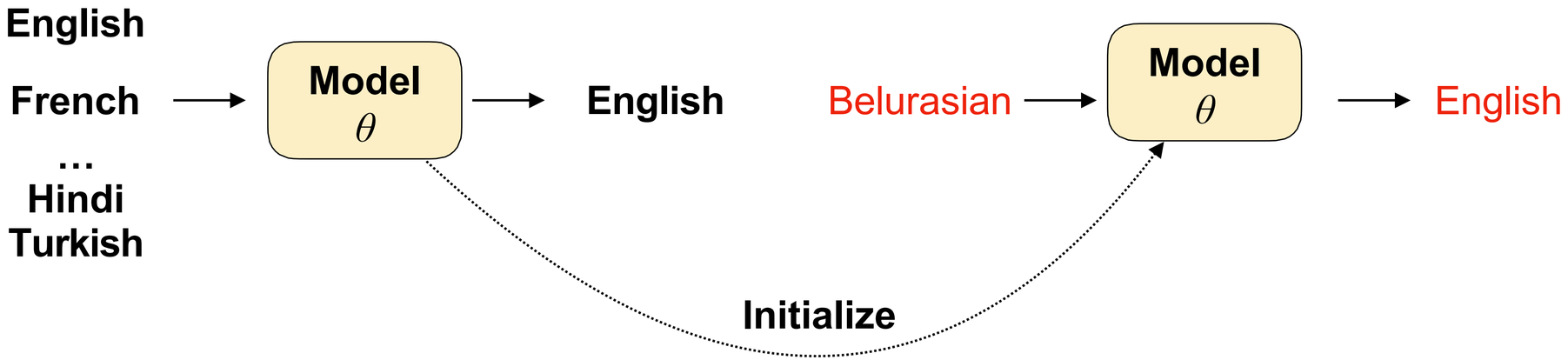
- **XGLUE:** less typologically diverse but contains generation (Liang et al. 2020)
- **XTREME-R** harder version based on XTREME (Ruder et al. 2021)

Advanced Modeling Strategies

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

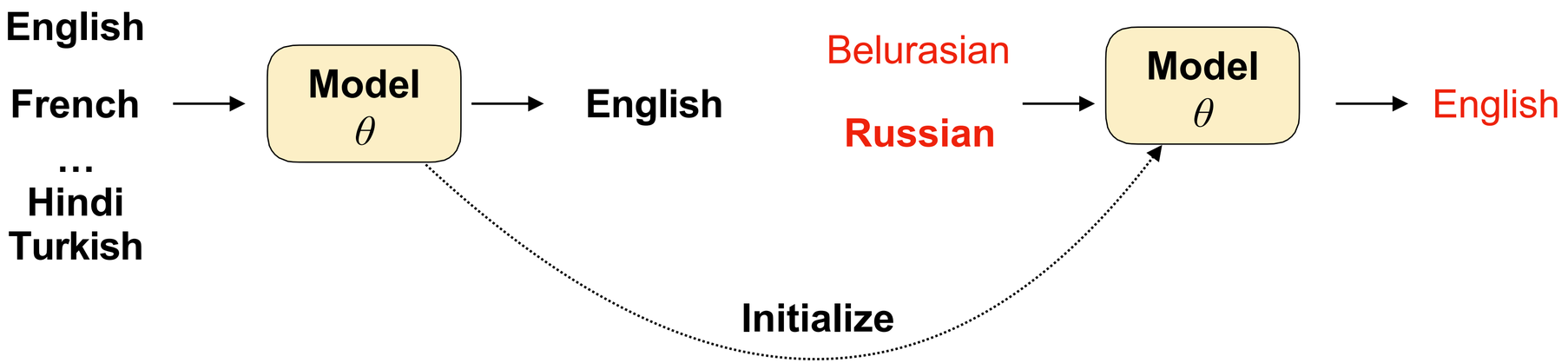
Pre-train and Fine-tune



- 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

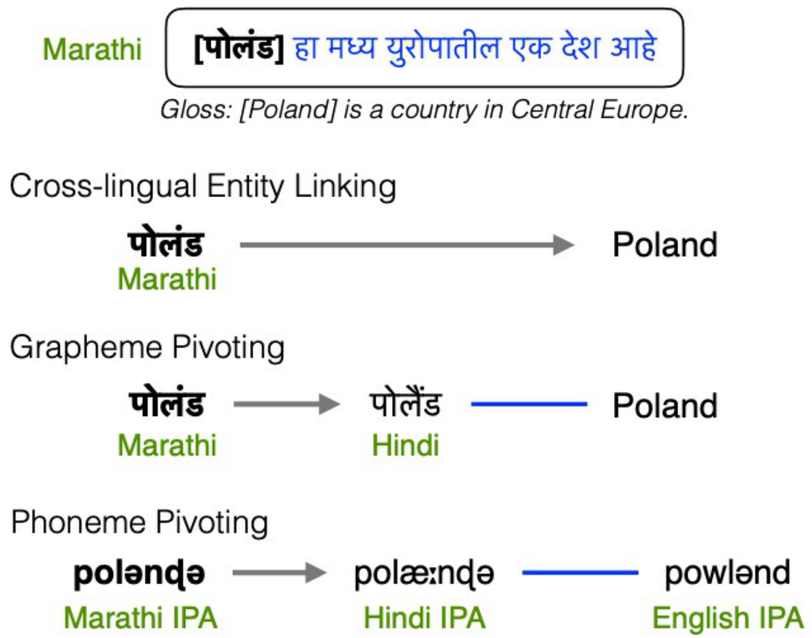
Zero-shot transfer for pretrained representations

- 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

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.



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)

Multilingual Instruction Fine-tuning

Template-based

Input	Output
Jim, I had a lot of fun at dinner …	Not spam
Congratulations! You just won …	Spam
…	….

Instruction template

Prompt	Completion
Jim, I had a lot of fun at dinner … Indicate if this mail is spam or not. This mail is	not a spam

Template-based

- Convert existing multilingual datasets to prompt-completion pairs
- Instructions can be English or multilingual
- Easy to scale
- Low in diversity
- Datasets:
  - **Supernatural Instructions[1]:** 76 task types, 55 languages, English instructions
  - **xP3 and xP3mt[2]:** 16 task types, 46 languages
    - **xP3** has English instructions while **xP3mt** is its machine-translated version

[1] Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks (Wang et al., EMNLP 2022) (largely collected via class-sourcing and public invitation)
[2] Crosslingual generalization through multitask finetuning (Muennighoff et al., ACL 2023) (xP3mt translated using Google Translate API)

Do Translated Instructions over English Ones Help?

Unseen Tasks

Task	Prompt	Average accuracy			
		BLOOMZ	BLOOMZ-MT	mT0-13B	mT0-13B-MT
XNLI	EN	**52.99**	49.01	48.24	**51.29**
	MT	37.56	**41.16**	39.31	**41.66**
	HT	40.4	**43.88**	44.95	**46.87**
XCOPA	EN	72.52	**73.24**	**81.4**	80.36
	MT	70.04	**71.84**	**81.16**	79.64
XStoryCloze	EN	**81.73**	81.39	81.99	**82.3**
	MT	80.89	**81.76**	**83.37**	82.86
XWinograd	EN	**60.07**	59.15	70.49	**73.24**
	MT	58.48	**60.14**	66.89	**72.33**

Trained on xP3 (English-only)

Trained on xP3mt

Table 1: Comparison between EN (English), MT (machine-translated) and HT (human-translated) prompts for 176B BLOOMZ and 13B mT0 models finetuned on either only English or English and machine-translated multilingual prompts (-MT).

Table from Crosslingual generalization through multitask finetuning (Muennighoff et al., ACL 2023)

Translated instructions usually result in improved performance

Template-based

- Convert existing multilingual datasets to prompt-completion pairs
- Instructions can be English or multilingual
- Easy to scale
- Low in diversity
- Datasets:
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    - **xP3** has English instructions while **xP3mt** is its machine-translated version
  - **xP3x[3]:** xP3 extended to 277 languages, 16 task types
    - Pruned through a human-auditing process
  - **Aya Collection[4]:** 74 languages, 14 task types, Human-written multilingual instructions and more ...

[1] Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks (Wang et al., EMNLP 2022) (largely collected via class-sourcing and public invitation)
[2] Crosslingual generalization through multitask finetuning (Muennighoff et al., ACL 2023) (xP3mt translated using Google Translate API)
[3] Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., ACL 2024)
[4] Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning (Singh et al., ACL 2024)

Translation-based

- Templates lack diversity
- Translate diverse English instructions into other languages
  - Popular machine translation models[1,2] to the rescue!
- Bottleneck?
  - Translation quality in lower resourced languages
  - Introduction of translation artefacts known as *translationese*
- Datasets:
  - **Aya Collection[3]:** 101 languages, 19 datasets
    - Diverse sources: xP3, Flan Collection, Dolly, etc.; Translated using NLLB[1]
  - **ShareGPT-Command[4]:** 93 languages
    - ShareGPT: Synthetic English completions from Command for human prompts
    - Translate prompt-completion pairs using NLLB

[1] Google Translate API
[2] No language left behind: Scaling human-centered machine translation (NLLB-Team.,2022)
[3] Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning (Singh et al., ACL 2024)
[4] Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., ACL 2024)

Human Annotations

- **Gold** standard
- Expensive to collect
  - **Technological factors:** Support of languages on annotation platforms
  - **Sociological factors:**
    - Access to language technology[1]
    - Dialectical and other biases[2]
- Dataset:
  - **Aya Dataset[3]:** 65 languages, 2k contributors across 110 countries
    - Created a multi-platform Annotation platform - **Aya Annotation Platform**
    - Instances human annotated, re-annotated & feedback curated
    - Implement leaderboarding via **Aya Score** to boost quality

[1] Harnessing the Power of Artificial Intelligence to Vitalize Endangered Indigenous Languages: Technologies and Experiences (Pinhanez et al., 2024)
[2] A Survey of Corpora for Germanic Low-Resource Languages and Dialects (Blaschke et al., NoDaLiDa 2023)
[3] Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning (Singh et al., ACL 2024)

Which Approach is the Best?

Weighting name	Human Annot.	Template			Translation	
	Aya Dataset	Aya Templates	xP3x	Data Provenance	Aya Translations	ShareGPT-Command
Human Annot. Heavy	25	4	20	6	30	15
Translation Heavy	10	1.5	15	3.5	47.5	22.5
Template Heavy	20	10	30	10	20	10

Model	Base Model	IFT Mixture	Held out tasks (Accuracy %)				
			XCOPA	XNLI	XSC	XWG	**Avg**
46 Languages							
mT0	mT5 13B	xP3	75.6	55.3	87.2	73.6	72.9
BLOOMZ	BLOOM 176B	xP3	64.3	52.0	82.6	63.3	65.5
52 Languages							
Bactrian-X 13B	Llama 13B	Bactrian-X	52.4	34.5	51.8	50.5	47.3
101 Languages							
mT0x	mT5 13B	xP3x	71.7	45.9	85.1	60.6	65.8
Aya (human-anno-heavy)	mT5 13B	All Mixture	76.5	**59.2**	89.3	70.6	73.9
Aya (template-heavy)	mT5 13B	All Mixture	**77.3**	58.3	**91.2**	**73.7**	**75.1**
★**Aya** (translation-heavy)	mT5 13B	All Mixture	76.7	58.3	90.0	70.7	73.9

Table 5: Results for held-out task evaluation. Results are averaged across all splits of XCOPA, XNLI, XStoryCloze, and XWinoGrad. ★**Aya** (translation-heavy) is used as the final **Aya** model. See § 5.6 for detailed analysis.

- Aya-101 outperforms all other contemporary models (even BLOOMZ 176B)
- Template-heavy seems to be the best fine-tuning mixture

Tables from Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., ACL 2024)

Which Approach is the Best?

Weighting name	Human Annot.	Template			Translation	
	Aya Dataset	Aya Templates	xP3x	Data Provenance	Aya Translations	ShareGPT-Command
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Table 5: Results for held-out task evaluation. Results are averaged across all splits of XCOPA, XNLI, XStoryCloze, and XWinoGrad. ★**Aya** (`translation-heavy`) is used as the final **Aya** model. See § 5.6 for detailed analysis.

Model	IFT Mixture	Generative Tasks			
		FLORES-200 (spBleu)		XLSum (RougeLsum)	Tydi-QA (F1)
101 Languages		X→ En	En → X		
mT0x	xP3x	20.2	14.5	21.4	76.1
Aya (`human-anno-heavy`)	All Mixture	25.1	18.9	22.2	77.9
Aya (`templated-heavy`)	All Mixture	25.0	18.6	**23.2**	**78.8**
★**Aya** (`translation-heavy`)	All Mixture	**29.1**	**19.0**	22.0	77.8

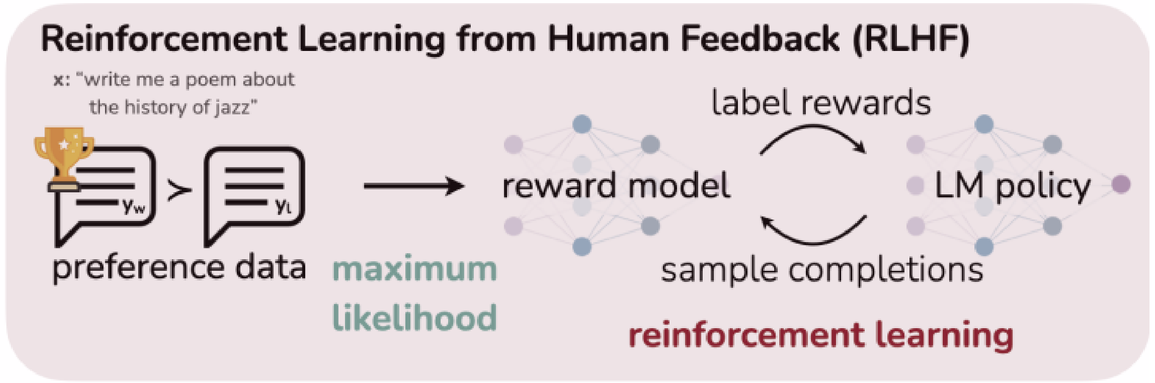
Table 7: Generative tasks' results for mT0x and **Aya** model variants based on different weighting ablations. Here the `translation-heavy` weighting has the highest spBleu score on Flores and the `template-heavy` weighting has the highest RougeLsum and F1 scores on XLSum and Tydiqa respectively. ★**Aya** (`translation-heavy`) is used as the final **Aya** model. See § 5.6 for detailed analysis.

Translation-heavy performs better on translation tasks; template-heavy is better on other generative tasks

Tables from Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., ACL 2024)

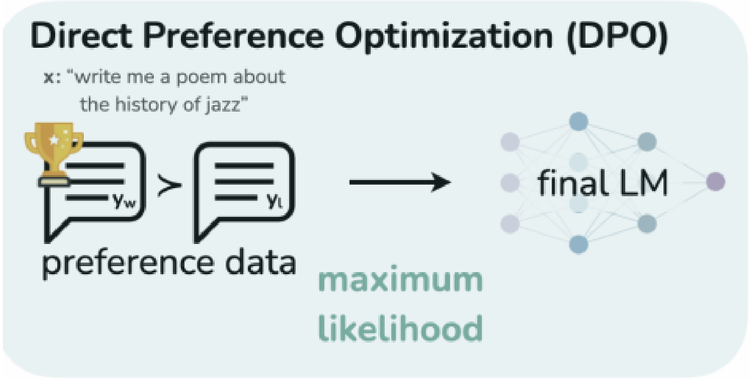
Multilingual Alignment

Online vs Offline Alignment Methods



$$\mathcal{L}_R(r_\phi, \mathcal{D}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log \sigma(r_\phi(x, y_w) - r_\phi(x, y_l))\right]$$

$$\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(y|x)}\left[r_\phi(x, y)\right] - \beta\mathbb{D}_{\mathrm{KL}}\left[\pi_\theta(y \mid x) \,||\, \pi_{\mathrm{ref}}(y \mid x)\right]$$



$$\mathcal{L}_{\mathrm{DPO}}(\pi_\theta; \pi_{\mathrm{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\mathrm{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\mathrm{ref}}(y_l \mid x)}\right)\right]$$

Images from Direct Preference Optimization: Your Language Model is Secretly a Reward Model (Rafailov et al., NeuRIPS 2023)

Cross-lingual (X-Lingual) Alignment

- Reward model trained on preference data of language **X** (source)
- Applied to preference tune for language **Y** (target)

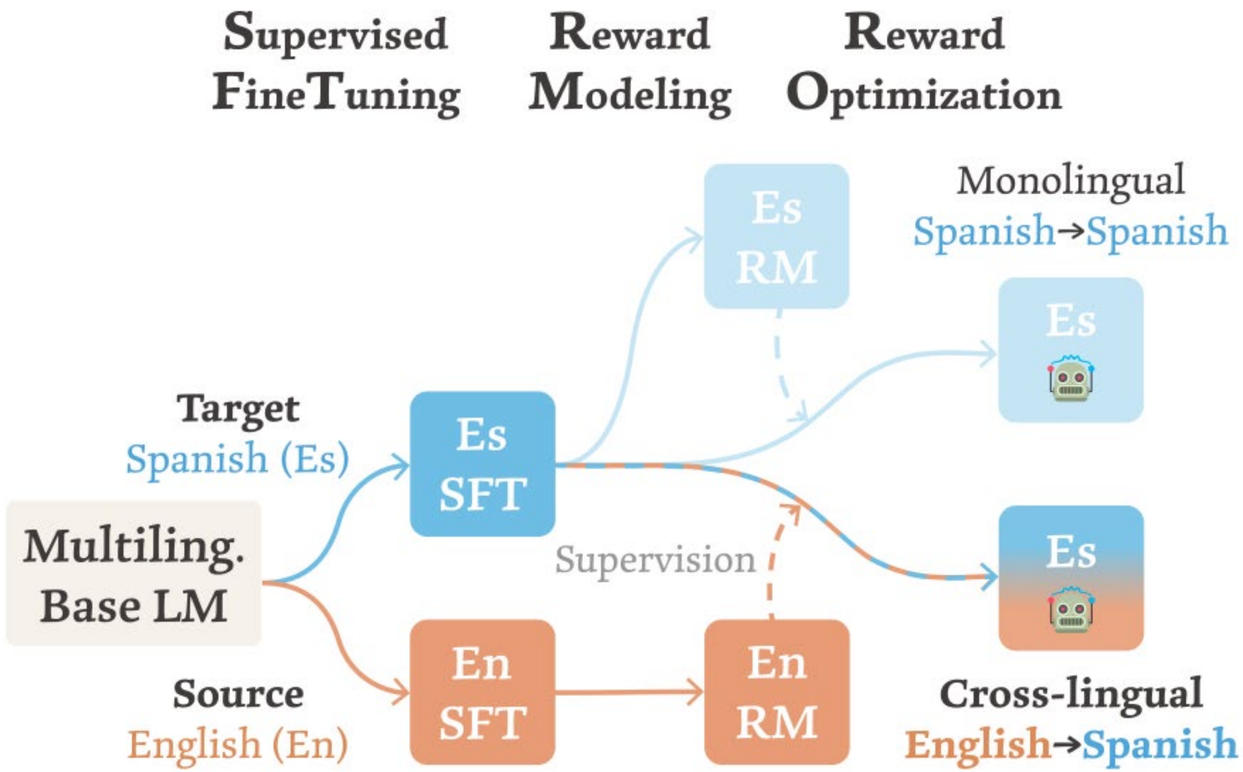
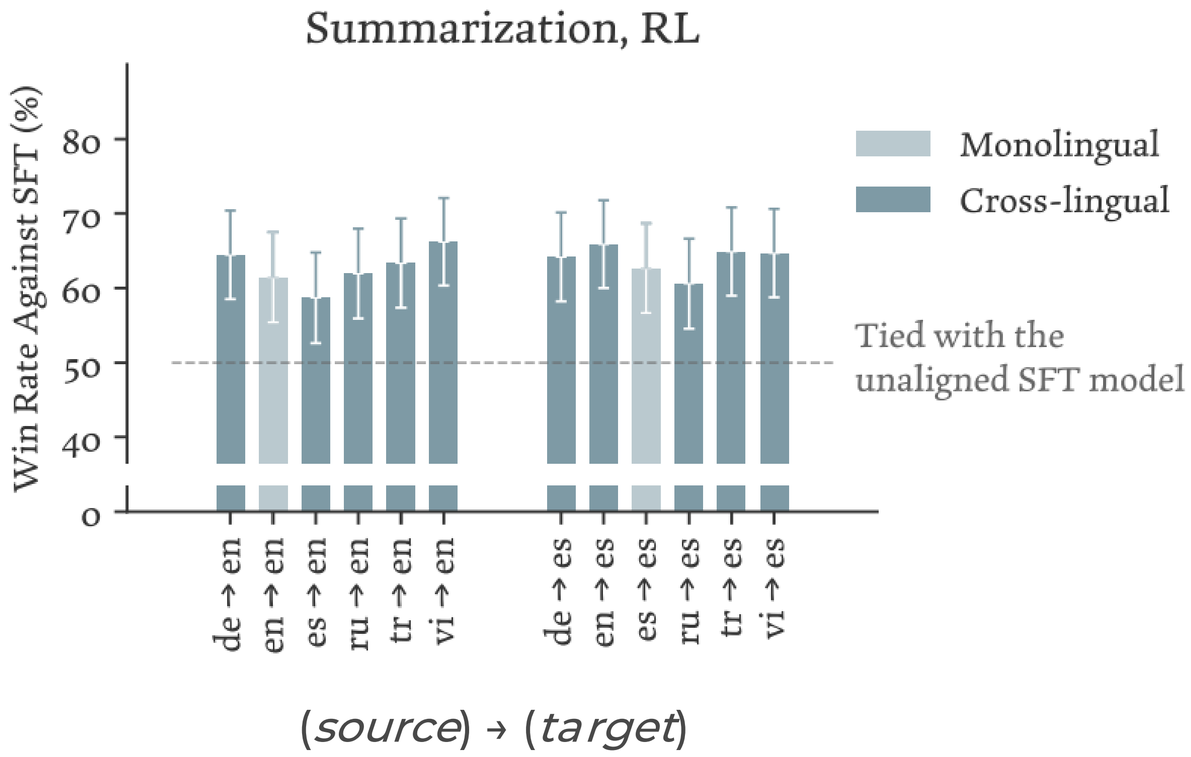


Image from [Reuse Your Rewards: Reward Model Transfer for Zero-Shot Cross-Lingual Alignment](#)(Wu et al., 2024)

Cross-lingual Alignment: Does it Work?



- **Evaluation:** Head-to-head win-rates as judged by humans
- **Base SFT model:** mT5-XL
- **Optimization:** Online (PPO)

Cross-lingual alignment sometimes outperforms in-language alignment

Image from [Reuse Your Rewards: Reward Model Transfer for Zero-Shot Cross-Lingual Alignment](#) (Wu et al., 2024)

Can’t I Just Translate Source Preference Data

Cross-lingual

Src \ Tgt	De	En	Es	Ru	Tr	Vi
De	52.3	50.8	63.0	66.7	63.0	60.4
En	56.4	55.5	66.1	70.7	67.2	63.1
Es	51.9	51.2	62.4	66.0	64.4	57.5
Ru	48.1	46.5	59.2	63.6	59.0	56.3
Tr	53.3	52.9	62.6	66.6	60.4	59.0
Vi	46.5	48.2	60.0	65.6	62.1	58.0

Table 6: Cross-lingual alignment results using **best-of-n** with $n = 64$, for the **summarization** task, measured in win rate (%) against the target-language SFT model as judged by **PaLM-2-L** (Figure 4).

Translation > Cross-lingual

Translation

Src \ Tgt	De	En	Es	Ru	Tr	Vi
De	–	50.0	61.9	66.1	66.1	54.6
En	47.9	–	63.3	64.9	64.5	53.1
Es	50.6	52.9	–	64.1	64.5	59.0
Ru	47.4	51.2	60.3	–	63.3	57.7
Tr	50.6	52.5	61.8	65.6	–	50.8
Vi	42.0	50.8	59.1	64.4	63.6	–

Table 17: Alignment quality using RM trained by translating the source language data into the target language using best-of-n with $n = 64$, for the summarization task, measured in win rate (%) against the target-language SFT model as judged by PaLM-2-L (§5.1).

Can’t say much!!

- English benefits from translation
- Russian (different script) doesn’t transfer well

Cross-lingual Alignment with N languages?

- Cross-lingual works with a language (well mostly!!)
- What if we transfer from more source languages?

- Testbed with various preference mixtures[1]:
  - **En-1:** English-only preference data (50k samples)
  - **ML-5:** 5 language set (en, vi, de, tr & pt) (50k samples, 10k per language)
  - **ML-23:** 23 language set (50k samples, ~2.2k per language)
  - **ML-23*:** 23 language set (230k samples, 10k per language)
- For "*ML*" data:
  - Prompts translated from ShareGPT into 22 languages via NLLB
  - Positive Response: Generated multilingual responses to translated prompts via Command R+[2]
  - Negative Response: Generate English response to English prompt via Command and translate
- Tested with offline and online alignment strategies

[1] RLHF Can Speak Many Languages: Unlocking Multilingual Preference Optimization for LLMs (Dang et al., 2024)
[2] Command R+ (supports the 23 languages considered for the experiments)

Challenges

Challenges (The Ones that Made the Cut)

Curse of multilinguality[1,2]

Packing more languages into a model decreases per language performance

Cost of Technology[3]

- GPT* models are behind paid APIs; cost∝input & generation tokens
- Poor tokenization in non-English languages → more tokens
- More tokens → more latency & money
- Efforts made but far from parity[4,5]

Dialectal Biases[6]

- Whose dialect matters the most?[7,8]
- Whose English?[9,10]

and many more .....

[1] Unsupervised Cross-lingual Representation Learning at Scale (Conneau et al., ACL 2020)
[2] When Is Multilinguality a Curse? Language Modeling for 250 High- and Low-Resource Languages (Chang et al., 2023))
[3] Do All Languages Cost the Same? Tokenization in the Era of Commercial Language Models (Ahia et al., EMNLP 2023)
[4] https://cohere.com/blog/command-r-plus-microsoft-azure
[5] https://openai.com/index/hello-gpt-4o/
[6] A Survey of Corpora for Germanic Low-Resource Languages and Dialects (Blaschke et al., NoDaLiDa 2023)
[7] Decolonizing NLP for “Low-resource Languages” (Ògúnrẹ̀mí et al., AI Frameworks Discussion of Abeba Birhane's "Algorithmic Injustice" and Social Impact Articles 2023)
[8] Which Humans? (Atari et al., 2023)
[9] What to do about non-standard (or non-canonical) language in NLP (Plank, KONVENS 2016)
[10] AI makes racist decisions based on dialect (Science, 24 August 2024)

Other Directions

Other Interesting Directions

Multilingual Architectures

- Efficient solutions for the curse of multilinguality
- Adding some language-specific parameters
- E.g.: Adapters[1], Cross-lingual expert models[2]

Tokenization and Vocabulary

- Efficient tokenization methods to reduce costs and latency
- E.g.: Vocab budgeting[6], allocation[7]

Adapting to a New Language

- Increasing support of an **N** language multilingual model to **N+K** languages
- E.g.: Continued pretraining[3], Adapters[4], Efficient Initializations[5]

Data Creation and Verification

- Methods for synthetic data generation[8] and verification of labeled data[9]

[1] MAD-X: An Adapter-Based Framework for Multi-Task Cross-Lingual Transfer (Pfeiffer et al., EMNLP 2020)
[2] Breaking the Curse of Multilinguality with Cross-lingual Expert Language Models (Blevins et al., 2024)
[3] How to Adapt Your Pretrained Multilingual Model to 1600 Languages (Ebrahimi & Kann, ACL-IJCNLP 2021)
[4] BLOOM+1: Adding Language Support to BLOOM for Zero-Shot Prompting (Yong et al., ACL 2023)
[5] OFA: A Framework of Initializing Unseen Subword Embeddings for Efficient Large-scale Multilingual Continued Pretraining (Liu et al., Findings 2024)
[6] XLM-V: Overcoming the Vocabulary Bottleneck in Multilingual Masked Language Models (Liang et al., EMNLP 2023)
[7] Tokenization Impacts Multilingual Language Modeling: Assessing Vocabulary Allocation and Overlap Across Languages (Limisiewicz et al., Findings 2023)
[8] Multilingual Arbitrage: Optimizing Data Pools to Accelerate Multilingual Progress (Odumakinde et al., 2024)
[9] Verifying Annotation Agreement without Multiple Experts: A Case Study with Gujarati SNACS (Mehta & Srikumar, Findings 2023)

References & Future Readings

Inequalities in Technology across Languages

- Breaking the unwritten language barrier: The bulb project (Adda et al., 2016)
- The State and Fate of Linguistic Diversity and Inclusion in the NLP World (Joshi et al., ACL 2020)
- Global predictors of language endangerment and the future of linguistic diversity(Bromham et al., 2021, Nature Ecology&Evolution)
- Systematic Inequalities in Language Technology Performance across the World's Languages (Blasi et al., ACL 2022)
- Which Humans? (Atari et al., 2023)
- Decolonizing NLP for "Low-resource Languages" (Ògúnrẹ̀mí et al., AI Frameworks Discussion of Abeba Birhane's "Algorithmic Injustice" and Social Impact Articles 2023)
- Do All Languages Cost the Same? Tokenization in the Era of Commercial Language Models (Ahia et al., EMNLP 2023)
- Abundance of words versus poverty of mind: the hidden human costs co-created with LLMs (Vuong and Ho, AI & Society 2024)

Multilingual Language Models

- mBART: Multilingual Denoising Pre-training for Neural Machine Translation (Liu et al., TACL 2020)
- mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer (Xue et al., NAACL 2021)
- BLOOM: A 176B-Parameter Open-Access Multilingual Language Model (BigScience, 2022)
- xGLM: Few-shot Learning with Multilingual Generative Language Models (Lin et al., 2023)
- Glot500-m: Glot500: Scaling multilingual corpora and language models to 500 languages (Imani et al., 2023)
- PolyLM: An Open Source Polyglot Large Language Model (Wei et al., 2023)
- BLOOMZ: Crosslingual Generalization through Multitask Finetuning (Muennighoff et al., ACL 2023)
- mTo: Crosslingual Generalization through Multitask Finetuning (Muennighoff et al., ACL 2023)
- Okapi series: Instruction-tuned Large Language Models in Multiple Languages with Reinforcement Learning from Human Feedback (Lai et al., 2023)
- mGPT: Few-Shot Learners Go Multilingual (Shliazhko et al., TACL 2024)
- Aya-101: Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., 2024)
- MALA-500: Massive Language Adaptation of Large Language Models (Lin et al., 2024)
- Aya-23: Open Weight Releases to Further Multilingual Progress (Aryabumi et al., 2024)

References & Future Readings

Multilingual Pre-training

- mC4: mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer (Xue et al., 2021)
- ROOTS: The BigScience ROOTS Corpus: A 1.6TB Composite Multilingual Dataset (Laurençon, NeurIPS 2022)
- Glot2000-c & Glot500-c: Scaling multilingual corpora and language models to 500 languages (Imani et al., 2023)

Multilingual Instruction-Tuning

- Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks (Wang et al., EMNLP 2022)
- Okapi: Instruction-tuned Large Language Models in Multiple Languages with Reinforcement Learning from Human Feedback (Lai et al., 2023)
- xP3 & xP3mt: Crosslingual generalization through multitask finetuning (Muennighoff et al., ACL 2023)
- xP3x: Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model (Üstün et al., 2024)
- Aya Dataset & Collection: Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning (Singh et al., ACL 2024)
- Multilingual Instruction Tuning With Just a Pinch of Multilinguality (Shaham et al., Findings 2024)

Multilingual Preference and Safety Alignment

- Multilingual Jailbreak Challenges in Large Language Models (Deng et al., 2023)
- The Language Barrier: Dissecting Safety Challenges of LLMs in Multilingual Contexts (Shen et al., 2024)
- Having Beer after Prayer? Measuring Cultural Bias in Large Language Models (Naous et al., 2024)
- All Languages Matter: On the Multilingual Safety of LLMs (Wang et al., Findings 2024)
- From One to Many: Expanding the Scope of Toxicity Mitigation in Language Models (Ermis et al., Findings 2024)
- Reuse Your Rewards: Reward Model Transfer for Zero-Shot Cross-Lingual Alignment (Wu et al., 2024)
- Preference Tuning For Toxicity Mitigation Generalizes Across Languages (Li et al., 2024)
- RLHF Can Speak Many Languages: Unlocking Multilingual Preference Optimization for LLMs (Dang et al., 2024)
- PolygloToxicityPrompts: Multilingual Evaluation of Neural Toxic Degeneration in Large Language Models (Jain et al., 2024)
- The Multilingual Alignment Prism: Aligning Global and Local Preferences to Reduce Harm (Aakanksha et al., 2024)

References & Future Readings

Curse of Multilinguality and Architectural Solutions

- Unsupervised Cross-lingual Representation Learning at Scale (Conneau et al., ACL 2020)
- MAD-X: An Adapter-Based Framework for Multi-Task Cross-Lingual Transfer (Pfeiffer et al., EMNLP 2020)
- MAD-G: Multilingual Adapter Generation for Efficient Cross-Lingual Transfer (Ansell et al., Findings 2021)
- Efficient Test Time Adapter Ensembling for Low-resource Language Varieties (Wang et al., Findings 2021)
- Cross-lingual Few-Shot Learning on Unseen Languages (Winata et al., AACL-IJCNLP 2022)
- Lifting the Curse of Multilinguality by Pre-training Modular Transformers (Pfeiffer et al., NAACL 2022)
- BAD-X: Bilingual Adapters Improve Zero-Shot Cross-Lingual Transfer (Parović et al., NAACL 2022)
- Hyper-X: A Unified Hypernetwork for Multi-Task Multilingual Transfer (Üstün et al., EMNLP 2022)
- When Is Multilinguality a Curse? Language Modeling for 250 High- and Low-Resource Languages (Chang et al., 2024)
- Breaking the Curse of Multilinguality with Cross-lingual Expert Language Models (Blevins et al., arXiv 2024)

NLP for Indigenous Languages

- Local Languages, Third Spaces, and other High-Resource Scenarios (Bird, ACL 2022)
- Not always about you: Prioritizing community needs when developing endangered language technology (Liu et al., ACL 2022)
- "It's how you do things that matters": Attending to Process to Better Serve Indigenous Communities with Language Technologies (Cooper et al., EACL 2024)
- Modeling the Sacred: Considerations when Using Religious Texts in Natural Language Processing (Hutchinson, Findings 2024)
- Must NLP be Extractive? (Bird, 2024)
- Harnessing the Power of Artificial Intelligence to Vitalize Endangered Indigenous Languages: Technologies and Experiences (Pinhanez et al., 2024)

References & Future Readings

Adapting to New Languages

- How to Adapt Your Pretrained Multilingual Model to 1600 Languages (Ebrahimi & Kann, ACL-IJCNLP 2021)
- Phylogeny-Inspired Adaptation of Multilingual Models to New Languages (Faisal & Anastasopoulos, AACL-IJCNLP 2022)
- Expanding Pretrained Models to Thousands More Languages via Lexicon-based Adaptation (Wang et al., ACL 2022)
- Don't Stop Fine-Tuning: On Training Regimes for Few-Shot Cross-Lingual Transfer with Multilingual Language Models (Schmidt et al., EMNLP 2022)
- Cross-lingual Continual Learning (M'hamdi et al., ACL 2023)
- Mini-Model Adaptation: Efficiently Extending Pretrained Models to New Languages via Aligned Shallow Training (Marchisio et al., Findings 2023)
- BLOOM+1: Adding Language Support to BLOOM for Zero-Shot Prompting (Yong et al., ACL 2023)
- OFA: A Framework of Initializing Unseen Subword Embeddings for Efficient Large-scale Multilingual Continued Pretraining (Liu et al., Findings 2024)

Miscellaneous

- How Vocabulary Sharing Facilitates Multilingualism in LLaMA? (Yuan et al., 2023)
- Tokenization Impacts Multilingual Language Modeling: Assessing Vocabulary Allocation and Overlap Across Languages (Limisiewicz et al., Findings 2023)
- XLM-V: Overcoming the Vocabulary Bottleneck in Multilingual Masked Language Models (Liang et al., EMNLP 2023)
- Do Multilingual Language Models Think Better in English? (Etxaniz et al., NAACL 2024)
- Do Llamas Work in English? On the Latent Language of Multilingual Transformers (Wendler et al., ACL 2024)
- How Does Quantization Affect Multilingual LLMs? (Marchisio et al., 2024)
- Multilingual Arbitrage: Optimizing Data Pools to Accelerate Multilingual Progress (Odumakinde et al., 2024)