

Multilinguality

CSE 5525: Foundations of Speech and Natural Language
Processing

<https://shocheen.github.io/cse-5525-fall-2025/>



THE OHIO STATE UNIVERSITY

Agenda

- I. Languages of the World and Linguistic Diversity
- II. Multilingual LLMs
 - A. Pre-training
 - B. Instruction Fine-tuning
 - C. Alignment
- III. Challenges
- IV. Other Directions

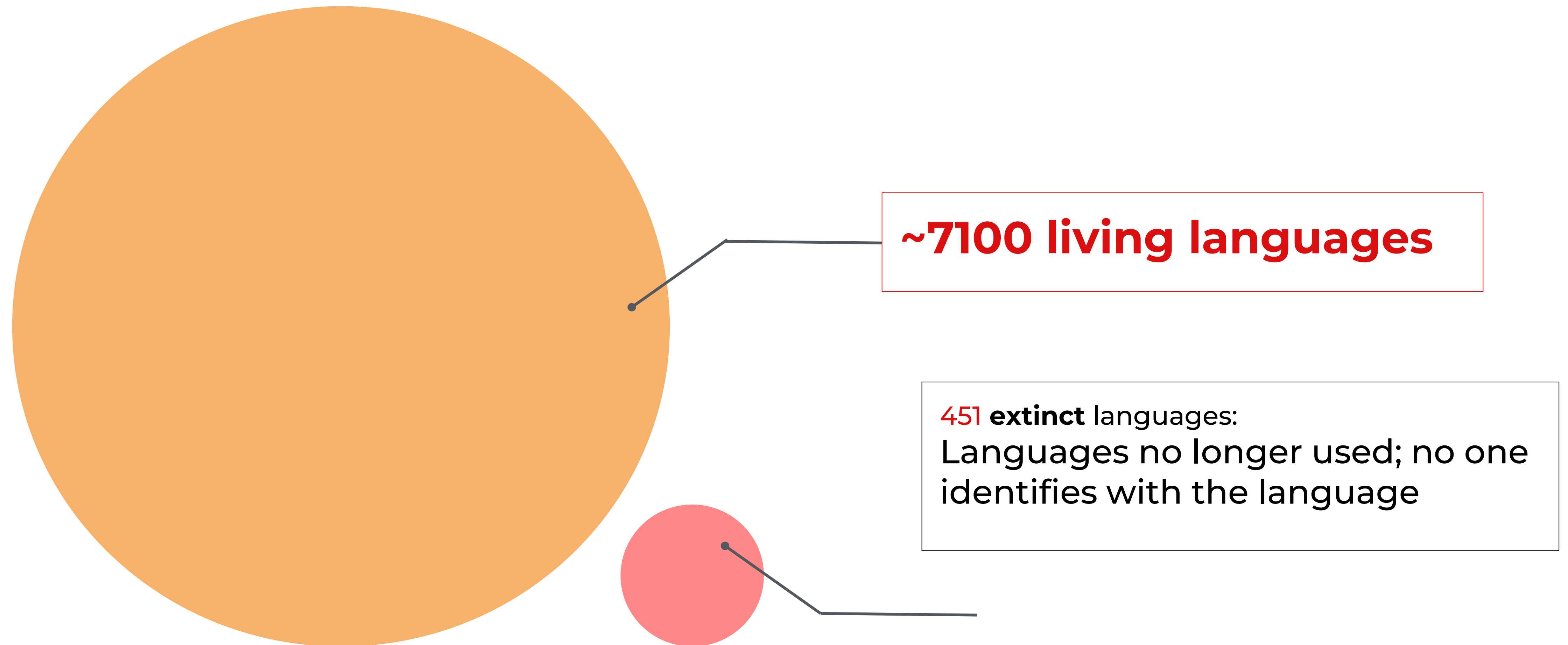
Languages of the World



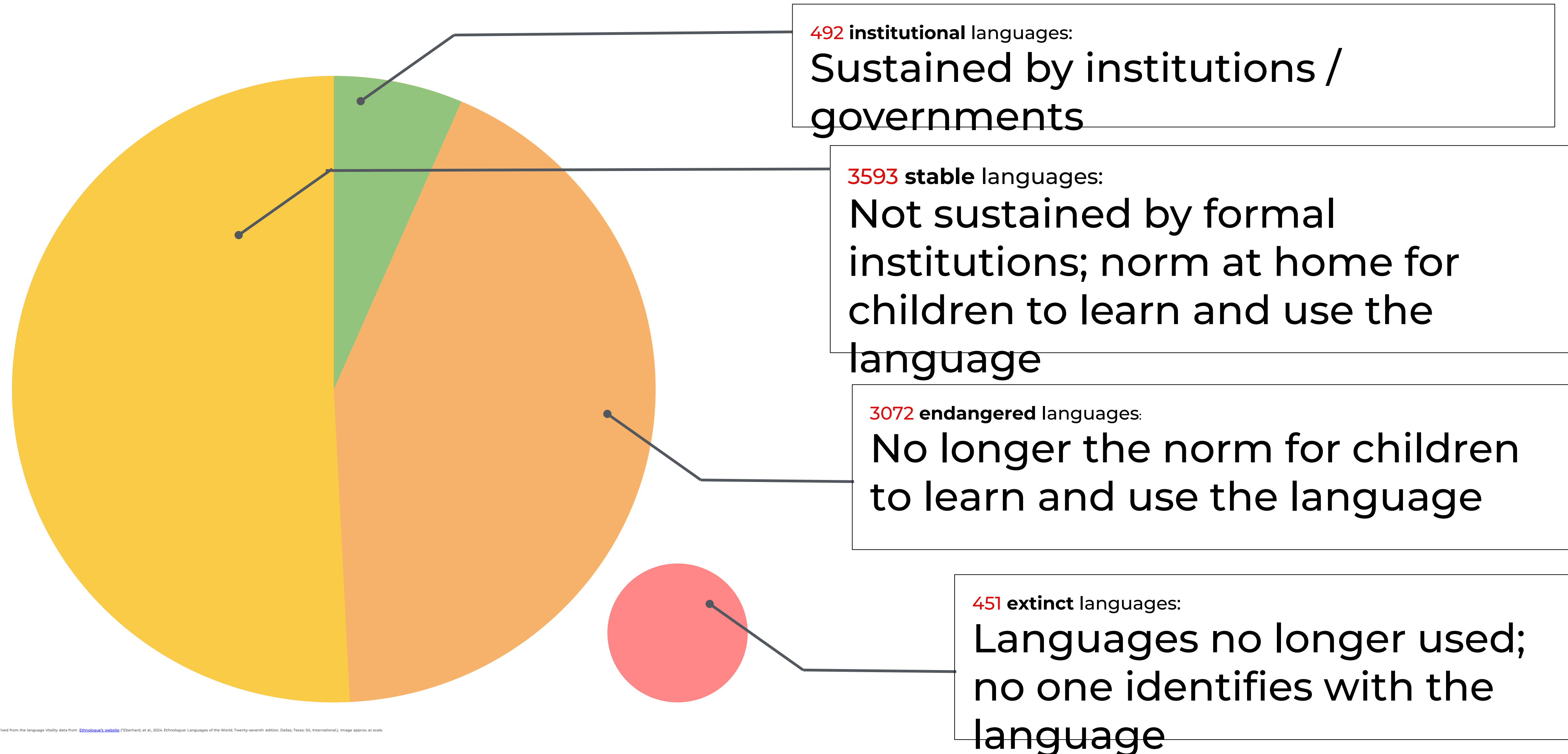
7164 languages
in use !!! (as of 2022)

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

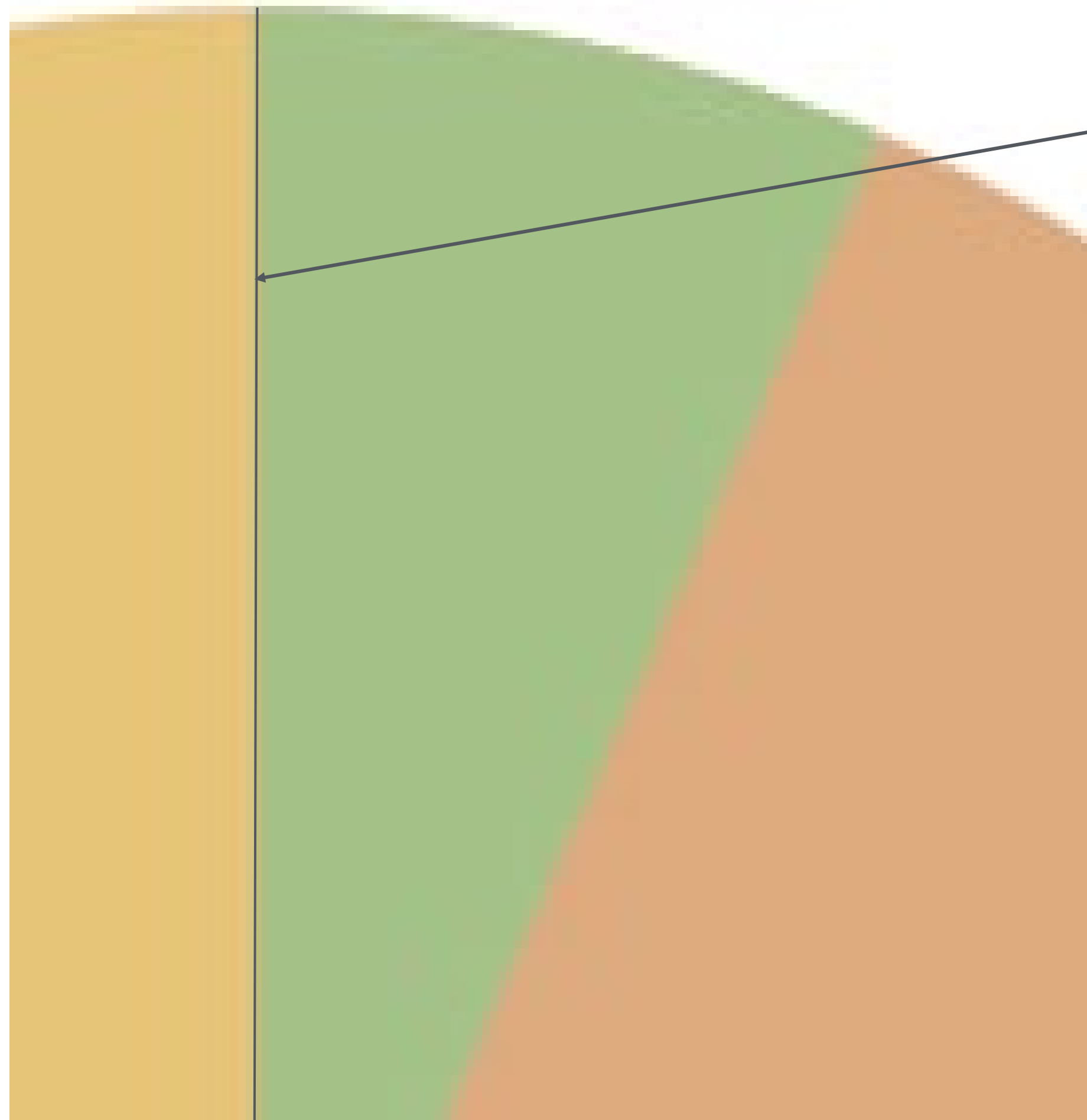
Languages by Vitality



Languages by Vitality



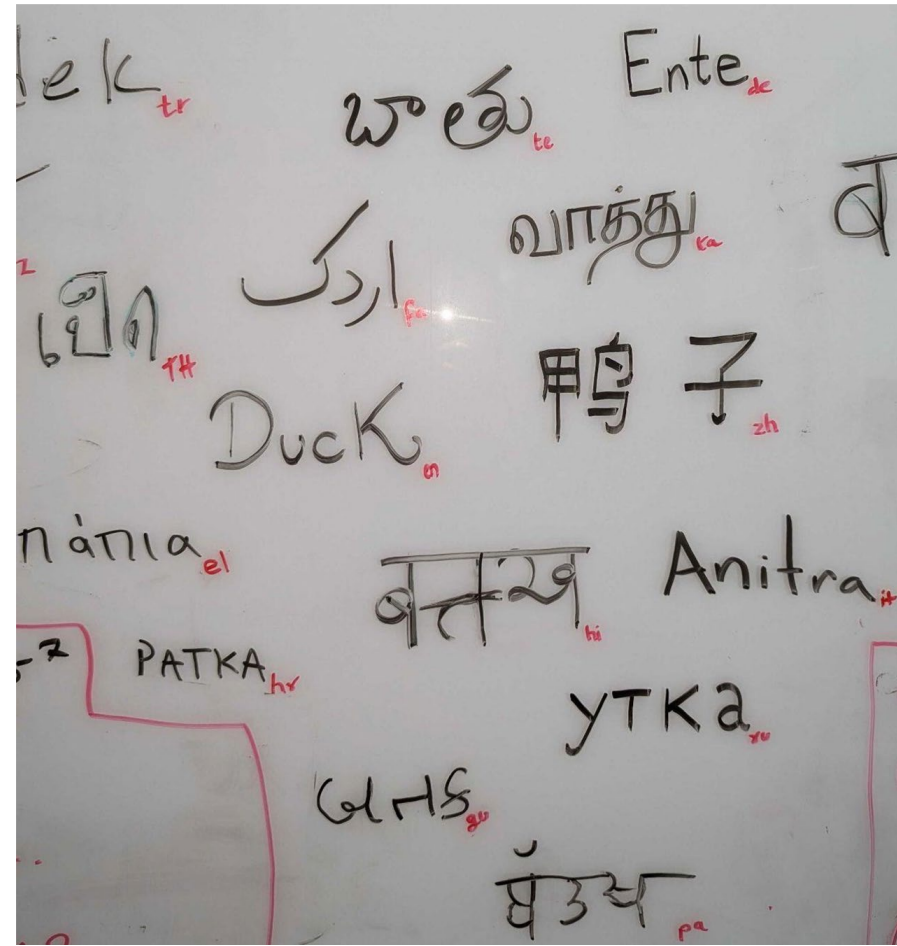
Languages by Vitality



That thin black line is English!

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 LLMs

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



Llama 2

 Meta AI

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Incidentally Multilingual Models

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Meta AI

Natively Multilingual Models

mT5

BLOOM

Okapi

MALA-500

 Aya Model

 Aya 23

Closed Data Models



Directions of Innovations in Multilingual LLMs

Data

Infrastructure

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

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- Methods to efficiently procure labeled & unlabeled data
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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 focus on the **Data** direction today!

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

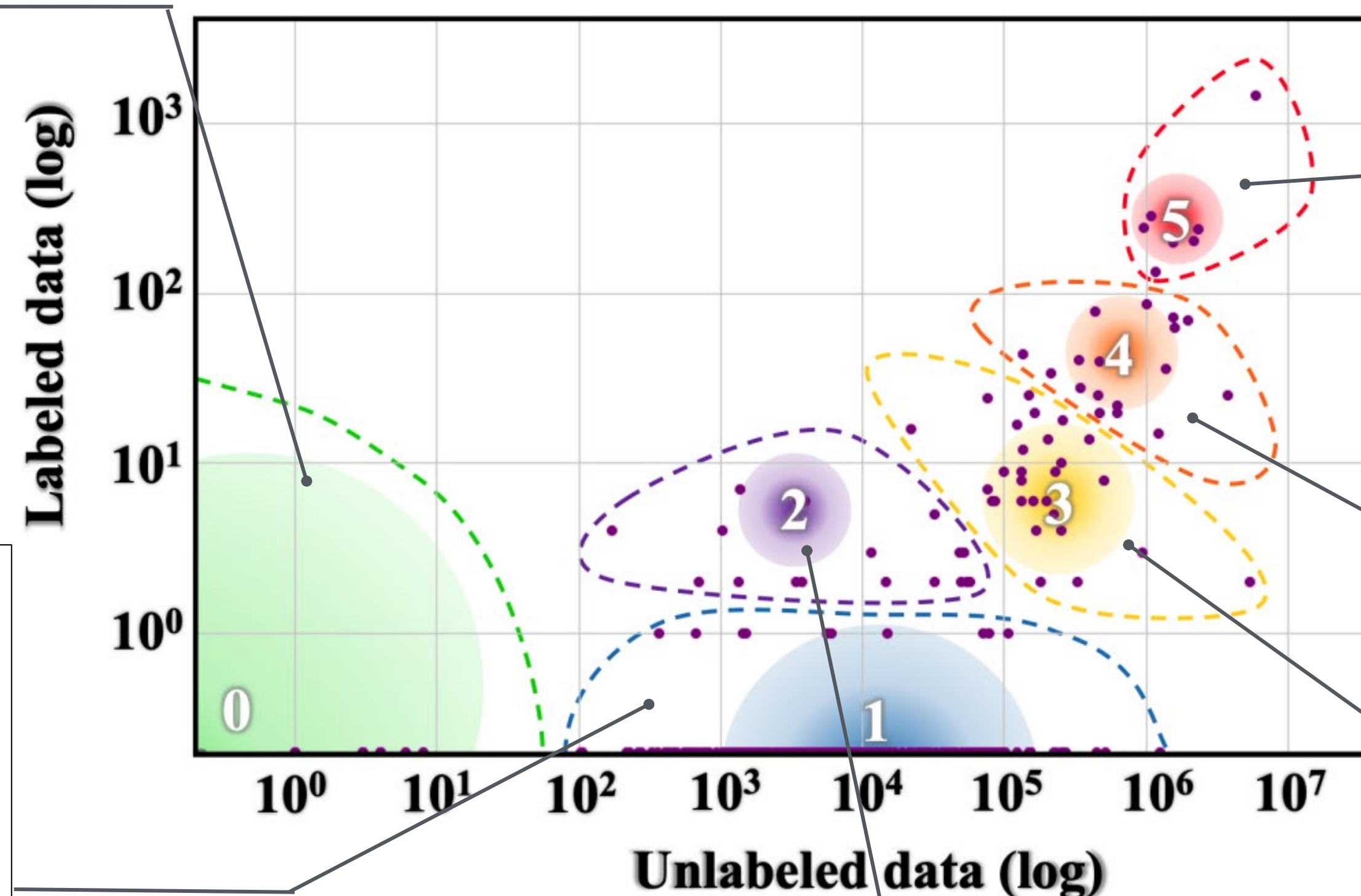
“The Scraping-Bys”

Need solid, organized movement that increases awareness

#Langs: 222

E.g.: Nepali, Gujarati, Armenian

#Speakers: 30M



“The 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

“The Hopefuls”

languages still fight on with their gasping breath

#Langs: 19 ; E.g.: Marathi, Irish, Yoruba

#Speakers: 5.7M

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>

The Multilingual LLM Pipeline

Data

Unlabeled Multilingual
Corpus
e.g.:(<*natural_language*>)

Language
Modeling (LM)
Objective

Model

Pre-trained LLM

Pre-training Phase



The Multilingual LLM Pipeline

Data

Unlabeled Multilingual
Corpus
e.g.:(<*natural_language*>)

Labeled Instruction Pair
Dataset
e.g.:(<*prompt*[*completion*>)

Language
Modeling (LM)
Objective

LM Objective

Model

Pre-trained LLM

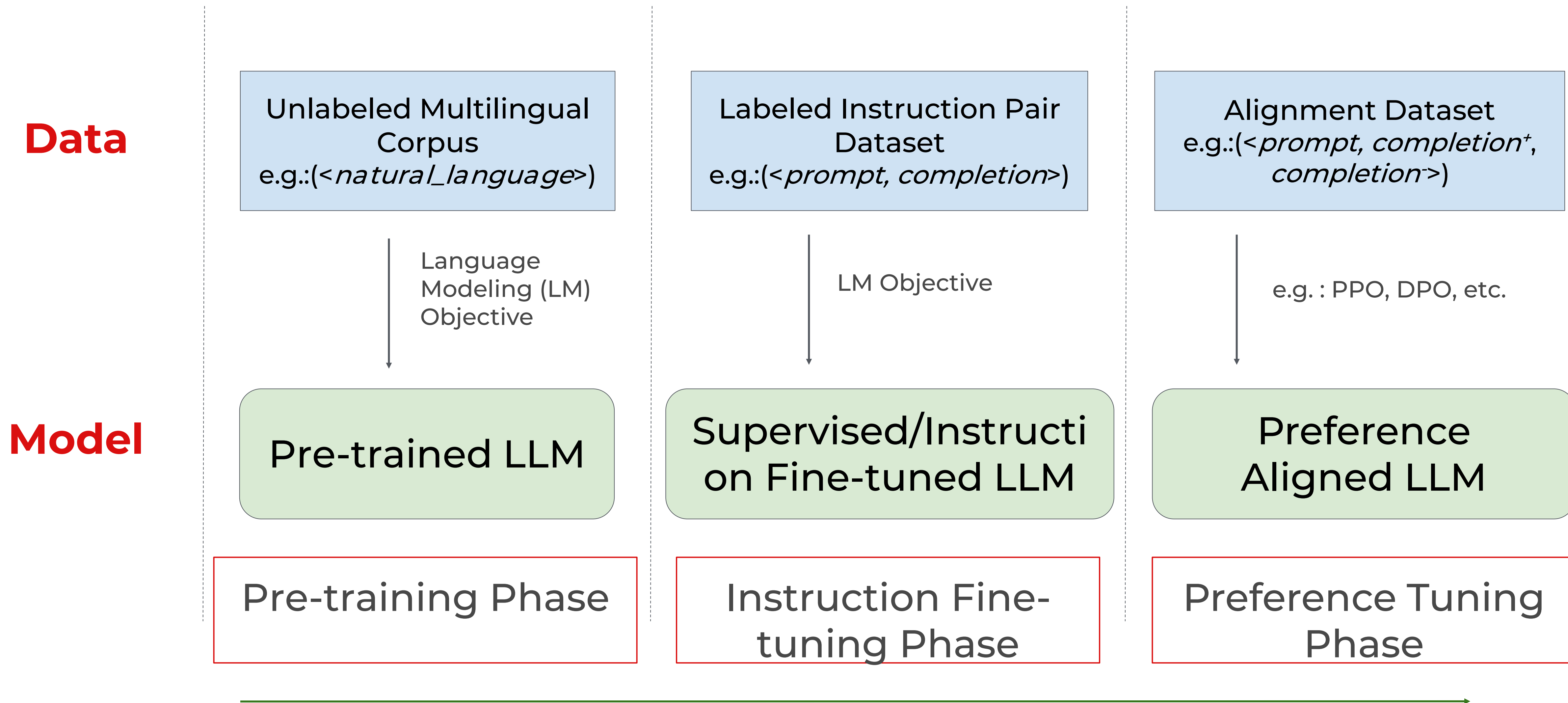
Supervised/Instruction
on Fine-tuned LLM

Pre-training Phase

Instruction Fine-
tuning Phase



The Multilingual LLM Pipeline



Multilingual Pre-training

Multilingual Pre-training: mC4

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

[1] [mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer](#) (Xue et al., NAACL 2021)

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 - 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.

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 - Other filters: length, deduplication, profanity, etc.
- Models trained on mC4: mT5, mTo, Aya-101

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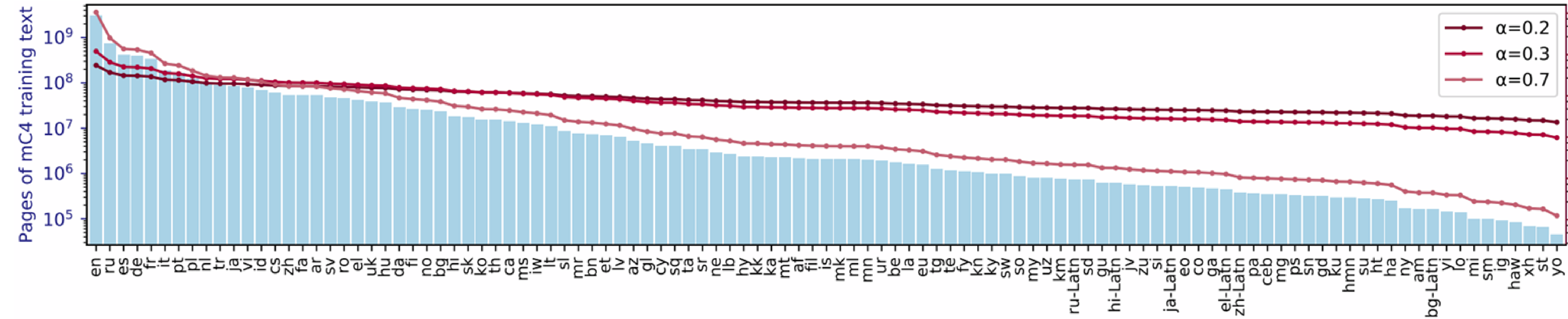


Figure 1: Page counts per language in mC4 (left axis) from mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer (Xue et al., NAACL 2021)

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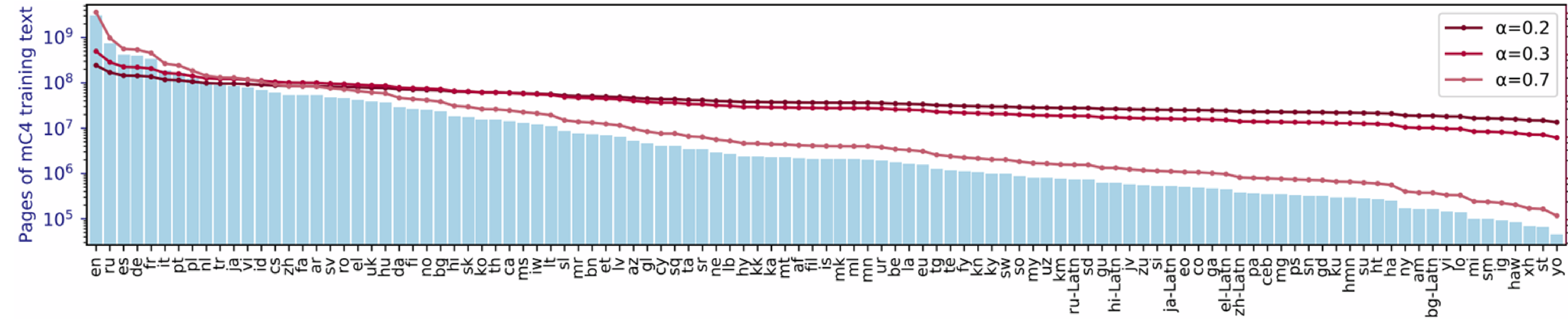


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Sampling affects model performance*:

- 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] Explor

[2] mT5: A

* - <https://>

\$ - <https://>

Multilingual Pre-training: Glot500-c

- **Glott500-c^[1] [1.5B sentences, 600 GB]**

[1] [Glott500: 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

- **Glott500-c^[1] [1.5B sentences, 600 GB]**
 - Subset of **Glott2000-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

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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.

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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.

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- Models trained on Glott500-c: Glott500-m, MALA-500

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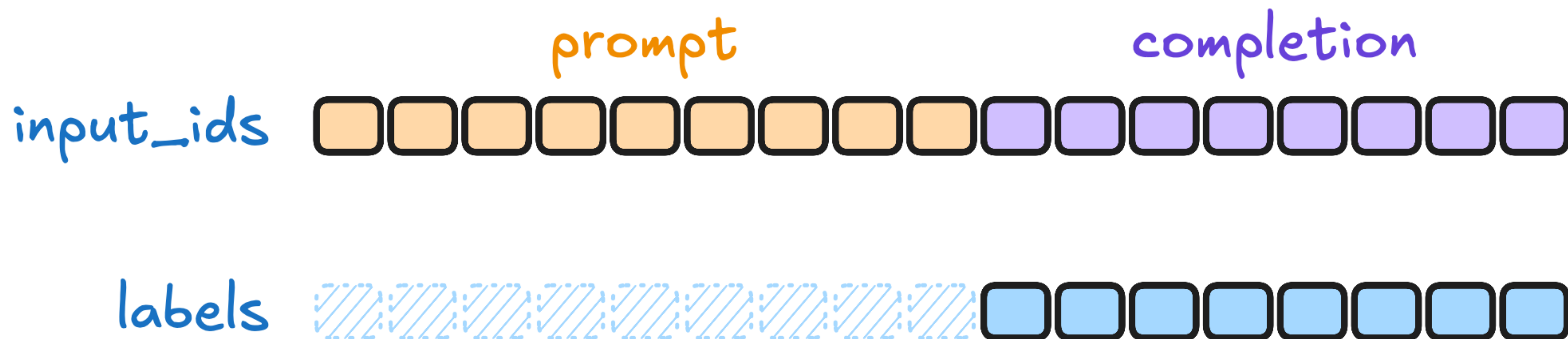
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Multilingual Instruction Fine-tuning

Template-based



Template-based

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

Template-based

Input	Output
Jim, I had a lot of fun at dinner ...	Not spam
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...	

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
Congratulations! You just won ...Indicate if this mail is spam or not. This mail is	spam
...	

Template-based

- Convert existing multilingual datasets to prompt-completion pairs
- Instructions can be English or multilingual
- Easy to scale

[1] [Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks](#) (Wang et al., EMNLP 2022) (largely collected via class-sourcing and public invitation)

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Template-based

- Convert existing multilingual datasets to prompt-completion pairs
- Instructions can be English or multilingual
- Easy to scale
- Drawback?

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Template-based

- Convert existing multilingual datasets to prompt-completion pairs
- Instructions can be English or multilingual
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- Low in diversity

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Template-based

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- 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

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Do Translated Instructions over English Ones Help?

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

Unseen
Tasks

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

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- Easy to scale
- **Low in diversity**
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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 ...

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Translation-based

- Templates lack diversity
- Translate diverse English instructions into other languages
 - Popular machine translation models^[1,2] to the rescue!

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 - Introduction of translation artefacts known as translationese

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 - Popular machine translation models^[1,2] to the rescue!
- Bottleneck?
 - Translation quality in lower resourced languages
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- 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

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Human Annotations

. **Gold** standard

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- Expensive to collect
 - **Technological factors:** Support of languages on annotation platforms
 - **Sociological factors:**
 - Access to language technology^[1]
 - Dialectical and other biases^[2]

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 - 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

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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

% of the training budget

Model	Base Model	IFT Mixture	Held out tasks (Accuracy %)				
			XCOPA	XNLI	XSC	XWG	<u>Avg</u>
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

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 %)				
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101 LANGUAGES							
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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
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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

Multilingual Alignment

Online vs Offline Alignment Methods

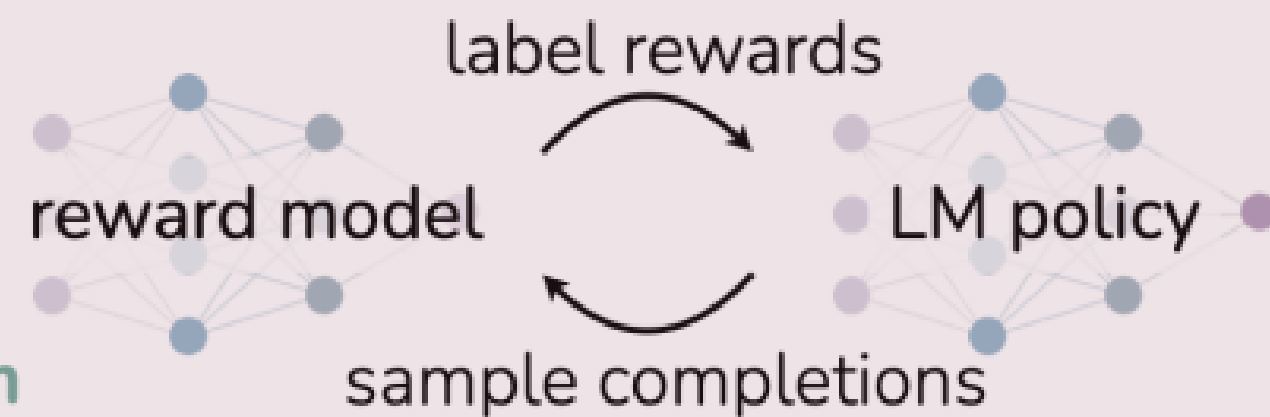
Reinforcement Learning from Human Feedback (RLHF)

x : "write me a poem about
the history of jazz"



preference data

maximum
likelihood



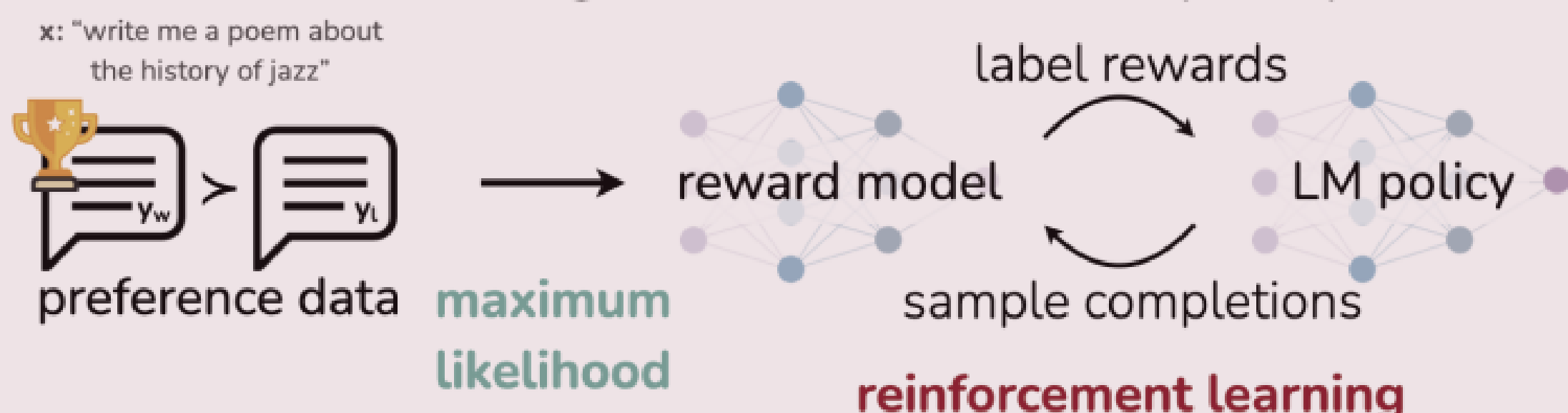
reinforcement learning

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

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

Online vs Offline Alignment Methods

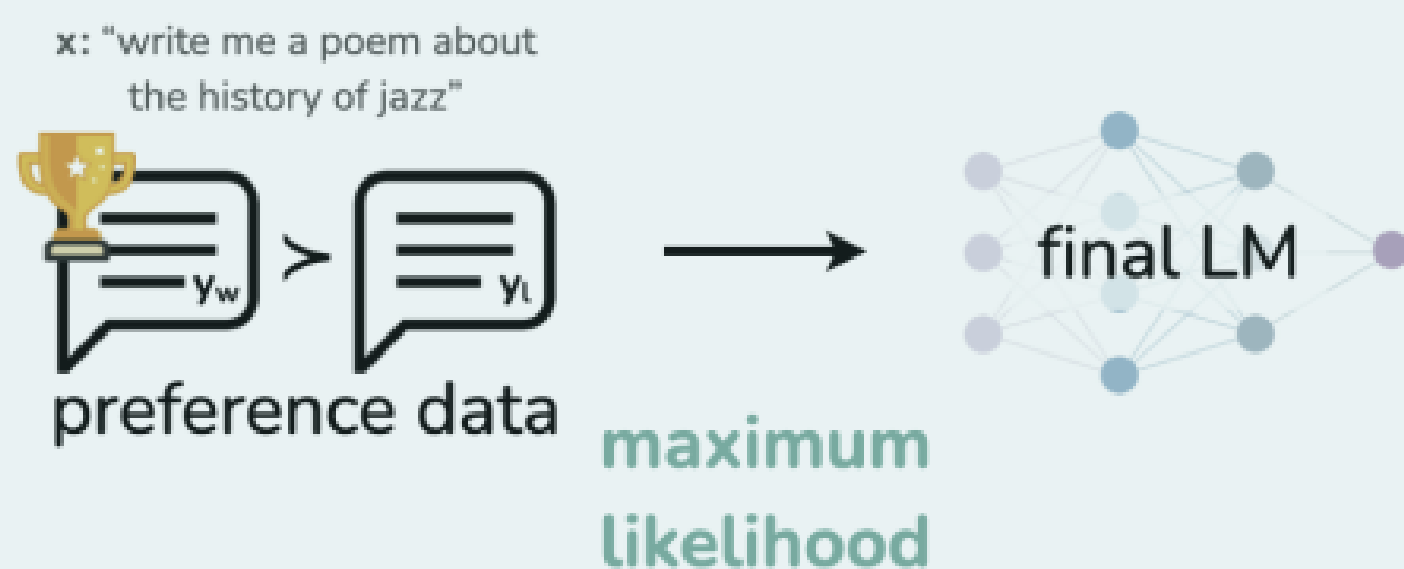
Reinforcement Learning from Human Feedback (RLHF)



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Direct Preference Optimization (DPO)



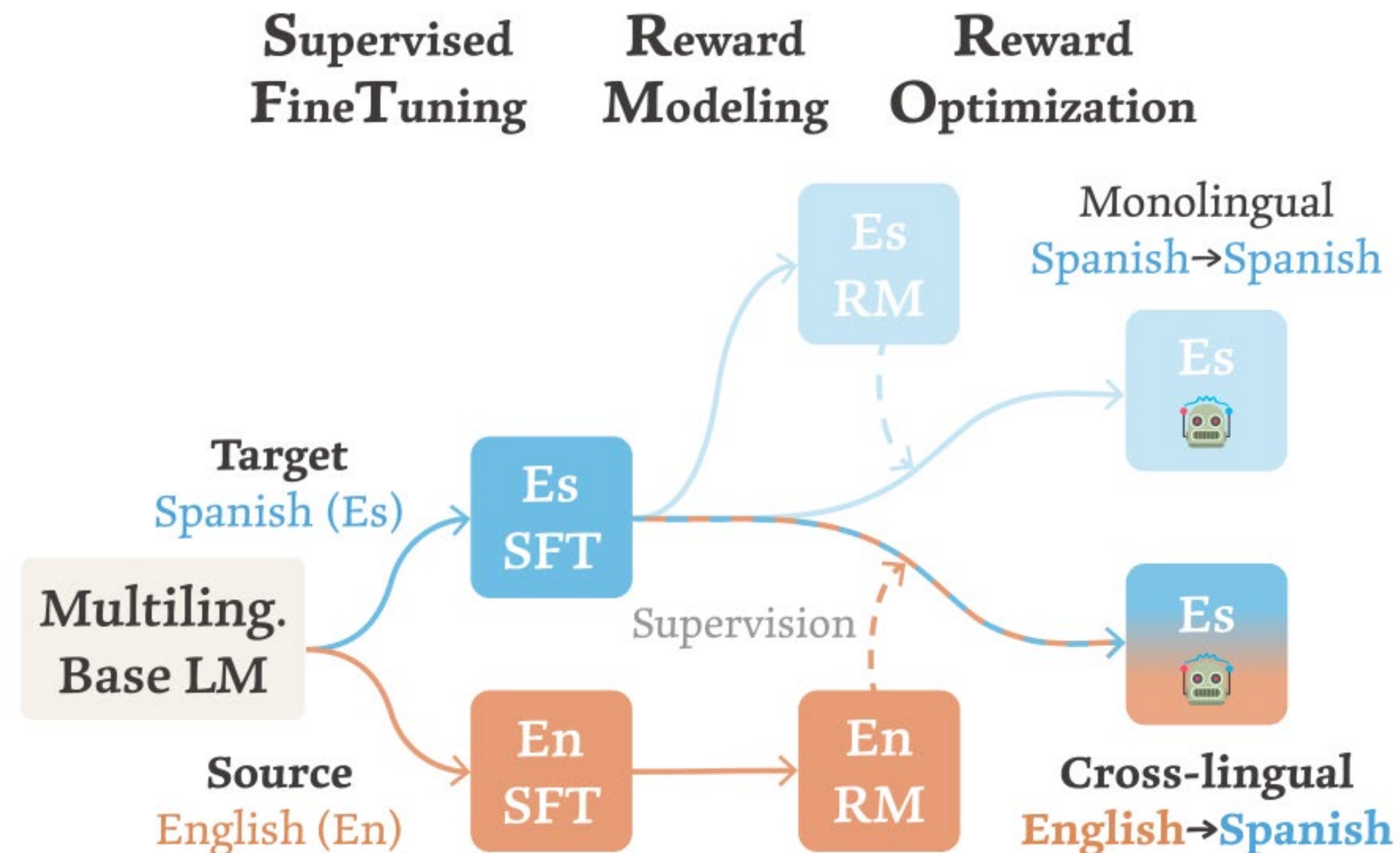
$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(y_w | x)}{\pi_{\text{ref}}(y_w | x)} - \beta \log \frac{\pi_\theta(y_l | x)}{\pi_{\text{ref}}(y_l | x)} \right) \right]$$

Cross-lingual (X-Lingual) Alignment

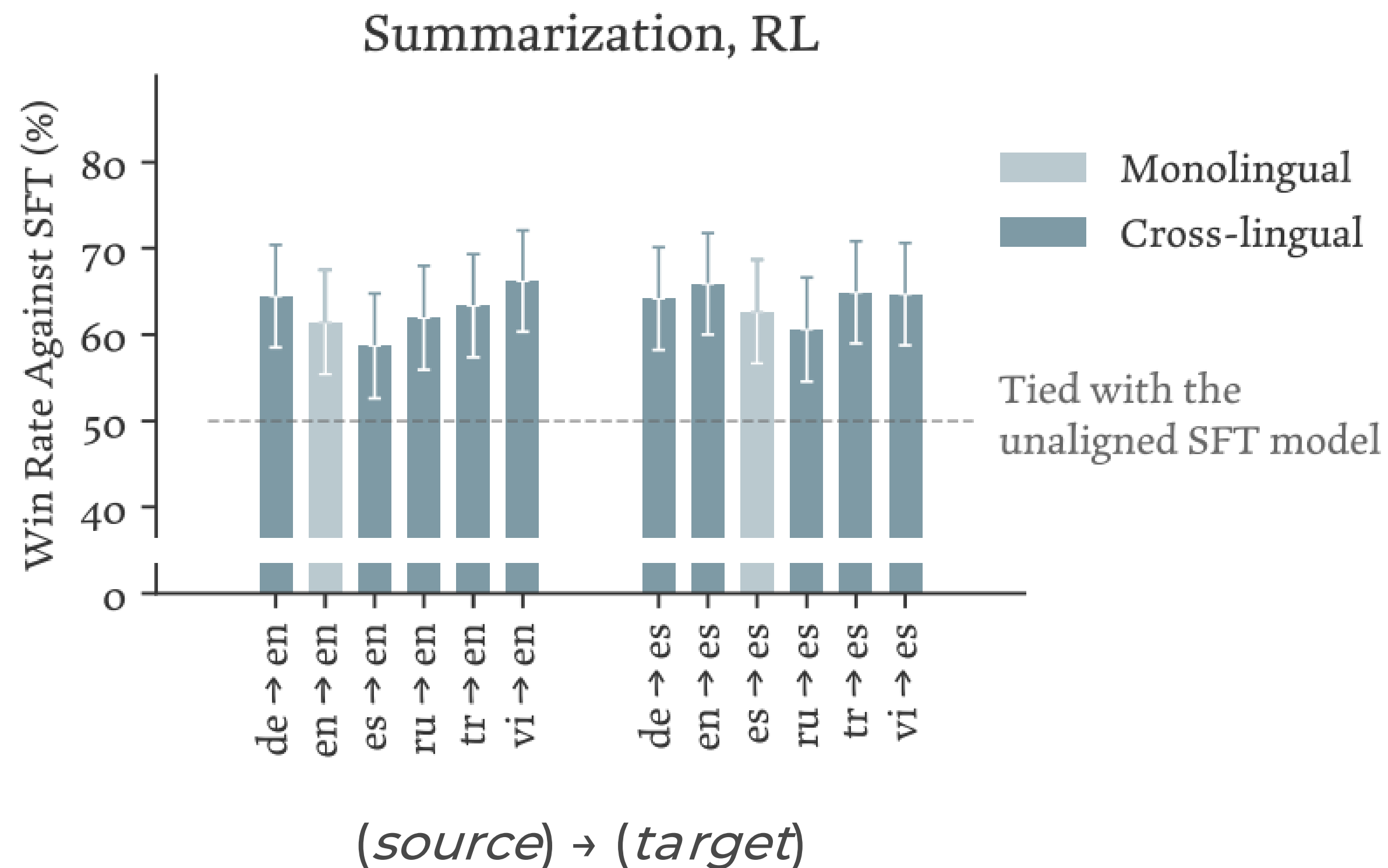
- Reward model trained on preference data of language **X** (source)
- Applied to preference tune for language **Y** (target)

Cross-lingual (X-Lingual) Alignment

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



Cross-lingual Alignment: Does it Work?



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

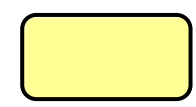
Cross-lingual alignment sometimes **outperforms** in-language alignment

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)

[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)

Cross-lingual Alignment with N languages?

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 - **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)

Does Language Diversity help X-lingual Alignment?

- Simulated win-rates with a GPT-4-Turbo

Not always for English

		Win%	English Loss%	ΔW-L%
DPO	EN-1	52.0	33.5	18.5
	ML-5	50.5	28.5	22.0
	ML-23	44.5	36.5	8.0
	ML-23*	57.5	31.0	26.5
RLOO	EN-1	47.5	38.5	9.0
	ML-5	55.5	30.5	25.0
	ML-23	53.0	37.0	16.0
	ML-23*	53.0	35.0	18.0

		Average 23 Languages		
		Win%	Loss%	ΔW-L%
DPO	EN-1	43.3	40.6	2.7
	ML-5	43.8	39.1	4.7
	ML-23	47.0	37.1	9.9
	ML-23*	50.2	39.0	11.2
RLOO	EN-1	46.4	38.9	7.5
	ML-5	54.4	35.8	18.6
	ML-23	54.0	38.0	16.0
	ML-23*	53.4	37.0	16.4

Almost always on average across multiple languages

Table 3: Open-ended generation (Dolly) win-rates for DPO/RLOO preference optimized Aya models against the original Aya 23 8B on **English** (left) and **averaged over 23 languages** (right). We report average win-rates on 23 languages for multiple training data mixtures: EN-1 (English Only), ML-5 (5 Languages), and ML-23 (23 Languages). All the data mixtures consist of 50K total training examples with the exception of ML-23*, which includes 230K total training examples. We report results for the best checkpoint across 2 epochs.

Does More Preference Data Help?

- Simulated win-rates with a GPT-4-Turbo

Yes, it
does!

		Win%	English		Average 23 Languages				
			Loss%	$\Delta W-L\%$	Win%	Loss%	$\Delta W-L\%$		
DPO	EN-1	52.0	33.5	18.5	DPO	EN-1	43.3	40.6	2.7
	ML-5	50.5	28.5	22.0		ML-5	43.8	39.1	4.7
	ML-23	44.5	36.5	8.0		ML-23	47.0	37.1	9.9
	ML-23*	57.5	31.0	26.5		ML-23*	50.2	39.0	11.2
RLOO	EN-1	47.5	38.5	9.0	RLOO	EN-1	46.4	38.9	7.5
	ML-5	55.5	30.5	25.0		ML-5	54.4	35.8	18.6
	ML-23	53.0	37.0	16.0		ML-23	54.0	38.0	16.0
	ML-23*	53.0	35.0	18.0		ML-23*	53.4	37.0	16.4

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What about Languages not in Preference Data?

		Avg. Win %	Unseen Loss %	Langs. $\Delta W-L\%$
EN-1	DPO	42.9	40.9	2.0
	RLOO	46.3	39.3	7.3
ML-5	DPO	43.3	39.5	3.8
	RLOO	54.9	35.5	19.4

Table 4: Win-rates for the 22 and 18 languages that are not included in the training data (“unseen”) for EN-1 and ML-5 respectively. We observe cross-lingual transfer from preference optimization, with an increased degree of transfer enhanced by multilingual training.

Offline vs Online Alignment

		Average 23 Languages		
		Win%	Loss%	$\Delta W-L\%$
DPO	EN-1	43.3	40.6	2.7
	ML-5	43.8	39.1	4.7
	ML-23	47.0	37.1	9.9
	ML-23*	50.2	39.0	11.2
RLOO	EN-1	46.4	38.9	7.5
	ML-5	54.4	35.8	18.6
	ML-23	54.0	38.0	16.0
	ML-23*	53.4	37.0	16.4

		Avg. Unseen Langs.		
		Win %	Loss %	$\Delta W-L\%$
EN-1	DPO	42.9	40.9	2.0
	RLOO	46.3	39.3	7.3
ML-5	DPO	43.3	39.5	3.8
	RLOO	54.9	35.5	19.4

Online method
is better!

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 $\propto$ input & generation tokens
- Poor tokenization in non-English languages $\rightarrow$ more tokens
- More tokens $\rightarrow$ 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”](#) (Ògúnremí 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"](#) (Ògúnremí 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)

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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)