

# Aya Model: An Instruction Finetuned Open-Access Multilingual Language Model

Anagha S & Kalyan S

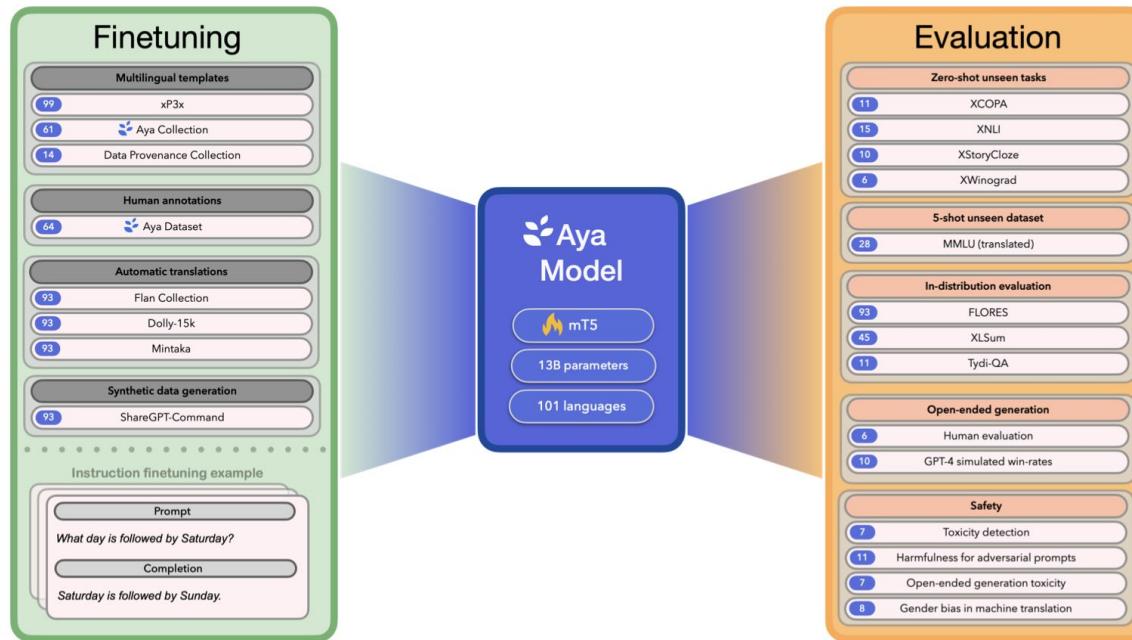
# Outline

- Summary
- Data
- Experimental Setup
- Evaluation Methods
- Results
- Safety Mitigation
- Benchmarking Toxicity and Bias

# Summary

- Motivation
  - LLM breakthroughs have focused only on a few data-rich languages
  - There exists a wide language gap
- Contributions
  - Introduces the Aya training mix, broadening coverage to 101 languages: more than double that of previous work and half of which are low-resource
  - Extensive multilingual evaluation, data ablations, safety mitigation, toxicity and bias analysis
  - **Aya model:** open-source multilingual instruction-finetuned LLM with diverse linguistic representation

# The Aya Model



# Data

Group	Category	Languages	Examples
Higher-Resourced	5	7	Arabic, Chinese, English, French, Spanish
	4	17	Hindi, Italian, Portuguese, Russian, Turkish
Mid-Resourced	3	24	Afrikaans, Indonesian, Kazakh, Latin, Latvian
Lower-Resourced	2	11	Hausa, Icelandic, Irish, Lao, Maltese
	1	29	Albanian, Gujarati, Igbo, Luxembourgish
	0	13	Kurdish, Kyrgyz, Nyanja, Sinhala, Yiddish

- 6 language categories (0-5) as per Joshi et al. [2020] based on availability of labeled and unlabeled data
- Out of 101 languages: 23% higher-resourced, 23% mid-resourced and 53% lower-resourced.

# Data

Name	Characteristics					Lang Ratio (%)		
	Langs	Datasets	Size	Avg Input Len	Avg Target Len	HR	MR	LR
xP3x DATASET DATA PROVENANCE COLLECTION (COMMERCIAL) AYA COLLECTION (TEMPLATED DATA SUBSET)	101	56	168M	1048	780	68.2	18.2	13.6
	14	161	1.65M	998	78	97.5	0.5	2.0
	61	34	18.9M	1864	209	85.3	9.5	5.2
AYA DATASET	64	1	199.5K	178	501	29.1	14.7	56.2
AYA COLLECTION (TRANSLATED DATA SUBSET)	93	19	7.53M	496	219	27.3	21.7	50.9
SHAREGPT-COMMAND	93	1	6.8M	385	1080	27.3	21.7	50.9

1. Multilingual templates
2. Human Annotations
3. Augmentation via automatic translation
4. Synthetic data generation

# Data: 1) Multilingual Templates

Name	Characteristics					Lang Ratio (%)		
	Langs	Datasets	Size	Avg Input Len	Avg Target Len	HR	MR	LR
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What is a prompt template?

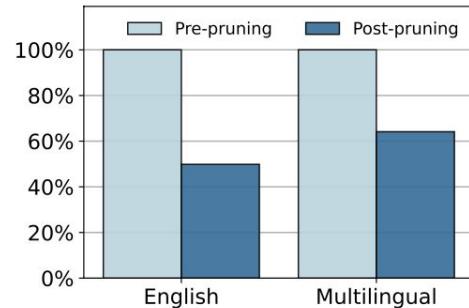
Structured text that transform specific NLP datasets into instruction and response pairs

# Data: 1) Multilingual Templates- xP3x Dataset

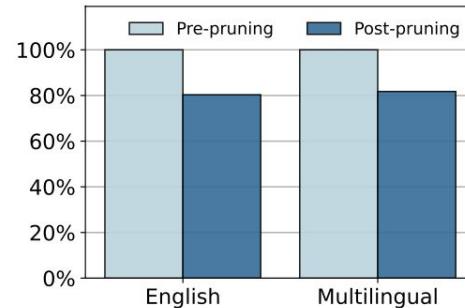
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- xP3x Dataset
  - Extends xP3 from 86M examples across 46 languages and 13 tasks to 680M examples across 277 languages and 16 tasks
  - Use a subset of xP3x: 101 languages that mT5 is trained on and further prune

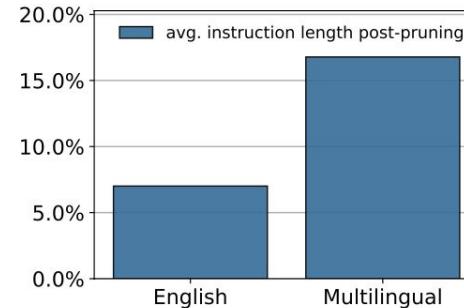
# Data: 1) Multilingual Templates- xP3x Dataset



(a) Templates



(b) Instances



(c) Instruction Length

- Pruning xP3x: large-scale human auditing process
- At least two reviewers inspect every template and recommend templates for removal if:
  - instructions paired with very short or empty generations
  - prompt templates that are slightly edited versions of another prompt template
  - samples with grammatical or structural errors

# Data: 1) Multilingual Templates- Data Provenance Collection

Name	Characteristics					Lang Ratio (%)		
	Langs	Datasets	Size	Avg Input Len	Avg Target Len	HR	MR	LR
xP3x DATASET DATA PROVENANCE COLLECTION (COMMERCIAL) AYA COLLECTION (TEMPLATED DATA SUBSET)	101	56	168M	1048	780	68.2	18.2	13.6
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- Uses filters from the Data Provenance Initiative to select publicly available supervised datasets with commercially permissive licenses
- Focus on high-resource language datasets with prompt and task diversity

# Aya Dataset and Aya Collection

Prompt	65	Completion
<p>"خواسته ای خواسته داشت" اما میتوان شرکت کنند شروعی نداشت چه کنم؟</p>	sin	<p>"خواسته ای خواسته داشت" اما میتوان شرکت کنند شروعی نداشت این چه کنم؟</p>
Qual é a origem do xadado?	par	<p>O xadado tem origens associadas ao Cangaceiro, onde cangaceiros, normalmente homens, davam presentes ricas em celebração. Com a entrada de mulheres nos grupos, a participação feminina na dança também se expandiu.</p>
مدونه در این پست از این رسانه ها و افرادی که مذکور شده است؟	pes	<p>مدونه در این پست از این رسانه ها و افرادی که مذکور شده است؟ عذر میخواهم از این پست از این رسانه ها و افرادی که مذکور شده است که این پست از این رسانه ها و افرادی که مذکور شده است</p>
آیا اسپریوت ایرانی شمارهای به مذکور شده است؟	tel	<p>اسپریوت ایرانی شمارهای به مذکور شده است عذر میخواهم از این پست از این رسانه ها و افرادی که مذکور شده است که این پست از این رسانه ها و افرادی که مذکور شده است</p>
امپارویی کم میگردید اما کمی میگردید؟	maa	<p>امپارویی کم میگردید اما کمی میگردید عذر میخواهم از این پست از این رسانه ها و افرادی که مذکور شده است که این پست از این رسانه ها و افرادی که مذکور شده است</p>
Berikan jawapan untuk teka-teki berikut: Apakah Jenah tingkap yang paling ramai orang guna?	gla	<p>Jawapan ialah Microsoft kerana "Microsoft Windows" (perkataan "window" bermaksud tingkap dalam bahasa Inggeris) ialah salah satu sistem operasi yang banyak digunakan oleh ramai orang di seluruh dunia.</p>
Inis dom feoi Baile Átha Cliath.	msa	<p>feoi Baile Átha Cliath, ne Dáilinn imbasán, proinnsiúchar na Meáin agus eis an práthair ní ba si te firén. Tá sé suite in oirthear na tire, cos life agus i meid Muir Eireann. Tá breis i 1.6 million duine in úinéid mochtar Baile Átha Cliath agus d'fhan go dhifriúil borradh agus feoi ás an deonse as toidhche.</p>
Masaa waayy shay os-Soomali badan cunaan mealin walba oo daad qay ar ku adagtagh la'aamis in ay cundata cunaan?	som	<p>Shay os-Soomali badan cunaan malin walba oo daad qay ar ku adagtagh la'aamis in ay cundata cunaan was Mooska. Mooska dad badan ku la'aad yahay jecelimum, wuxuu ku la'aad yahay waaqaydaa duuk u ku caran baxay u dhidhiyo.</p>

Aya Collection	
Text Classification	
Prompt	Prompt
Classify the sentiment of the following tweet with either positive, negative, or neutral \n[!tweet]	What is the corresponding translation in [!target_lang] of the following sentence: [!source]
Completion	Completion
I would classify the given tweet as: [!label]	(The translation to [target_lang] is: [!text][!target])
<b>103 + 2 Translated Text Classification datasets</b>	<b>101 + 8 Translated NL Generation datasets</b>
<b>44</b>	Xlre_wd-inst
<b>15</b>	NTXL-LLM-inst
<b>11</b>	UNER_LLM-inst
<b>16</b>	NusaX-senti-inst
<b>10</b>	Masakhnews-inst
<b>9</b>	AfriSenti-inst
<b>1</b>	Urdu-News-Category-Class
<b>1</b>	IMDB-Dutch-instruct
<b>1</b>	Scirepeval-biomimicry-inst
<b>101</b>	<b>+9 Translated QA datasets</b>
<b>16</b>	X-CSQA-inst
<b>12</b>	AfroQA-inst
<b>9</b>	Mintaka-inst
<b>1</b>	TeluguRiddles
<b>1</b>	LLM-Japanese-vanilla-inst
<b>1</b>	Amharic QA
Question Answering	
Prompt	Prompt
What category does this question come from: [!question][!text]???	What category does this question come from: [!question][!text]???
Completion	Completion
This question can come from category: [!documentKind]???	This question can come from category: [!documentKind]???
<b>101</b>	<b>+1 News datasets</b>
<b>1</b>	News-summary-instruct
<b>1</b>	Hindi-article-[task]
<b>1</b>	SODA-inst
<b>1</b>	Urdu-News-Gen-[task]
<b>1</b>	UA-Gec-inst
<b>1</b>	Telugu-[task]
<b>1</b>	Thai-[task]-inst/prompt

## Contribute Your Language

Help us add more examples by writing your own prompt and their completion in your language.

English

### Prompt

what does "to crave" mean?

### Completion

to crave is to really really want something, or to have a deep desire.

Submit Entry

## Rate Model Performance

Help improve the model performance by rating the prompt-completion pairs below.

Edit Mode
English

**Prompt**

Look out for: ✓ Correct Grammar ✓ Reasonable Length ✓ Clear Instructions

What does it mean in English "to crave" something?

Edit Distance[Prompt]: 35

**Completion**

Look out for: ✓ Clear Answer ✓ Full Sentences with Correct Answer ✓ Reasonable Length

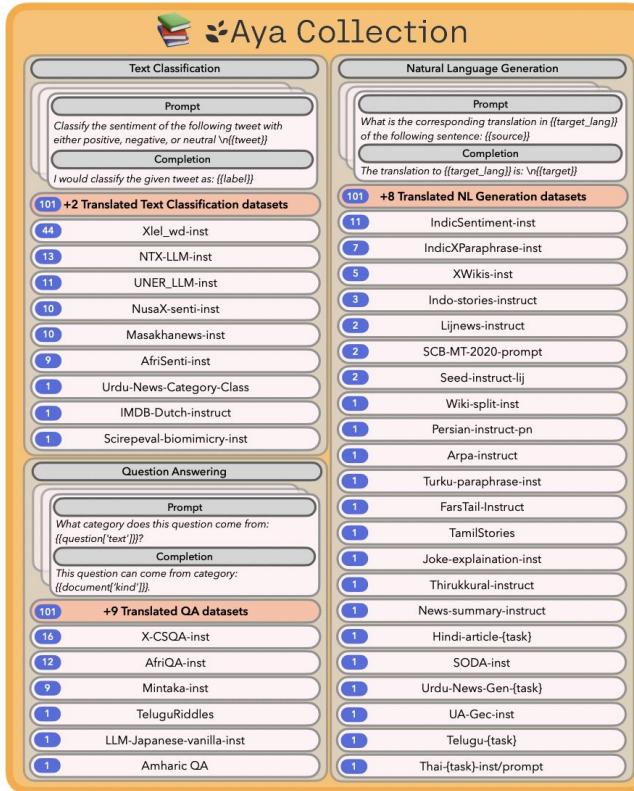
To crave is to have a strong and intense desire for something. It implies a deep need or longing for the object of the craving. It can involve emotional and physical feelings of addiction and can sometimes lead to actions against one's best interests. It is important to note that there is a difference between wanting or liking something and craving it, as craving can be destructive and lead to unhealthy behaviors.

Edit Distance[Completion]: 321

Skip
Submit Entry

# Data: 1) Multilingual Templates- Aya Collection template subset

- 114 languages
- 3 main tasks
- 44 templated instruction datasets
- 19 translated datasets
- 513 million instances



- Post filtering: 51 languages
- 34 datasets
- 18.9 million instances

# Data: 2) Human Annotations- Aya Dataset

The screenshot shows a user interface for the Aya Dataset. At the top, there's a logo and the text "Aya Dataset". Below that, a header bar with "Prompt" and "Completion" tabs, and a progress indicator "65". The main area is a grid of cards, each containing a prompt in one language and its completion in another. The languages represented are Sinhala (sin), Portuguese (por), Persian (fas), Spanish (esp), Telugu (tel), Indonesian (msa), Irish (gle), and Somali (som). Each card also has a small circular icon indicating the source language.

Prompt	Completion
"මිල කෙළඳ කෙටි රුවාලු" සහ මිනා ඇතුළත් මියාලු එපුරුව ඇඟිල ඇ?	"මිල කෙළඳ කෙටි රුවාලු" සහ මිනා ඇතුළත් විජේල් "නිවෝ" සහ මිනා එපුරුව විසින් සහ මිනා එපුරුව එකෙත්ම ඔවාල එවින් ගැනීම ඇතුළත් යුතු විභාග්.
Qual é a origem do xaxado?	O xaxado tem origens associadas ao Cangaço, onde cangaceiros, normalmente homens, dançavam com rifles em celebrações. Com a entrada de mulheres nos grupos, a participação feminina na dança também expandiu.
ایا در اساطیر ایرانی اشاره‌ای به دماوند شده است؟	دماوند در اساطیر ایران چشیدکار و پری‌دار، شهرت آن بیش از هر چیز در این است که فروتن از شخصیت‌های اساطیری ایران، ضحاک را در آنجا در غاری به بند کشیده است و ضحاک این زندانیست تا اخراج ایمان که بند بکشد و گشتن خلق اغفار نماید و سرانجام به نسبت کوشاسب کشنه شود
ବ୍ୟାକାରୀ ମଦ ନୟଦଂ ଅଂଠ ଏମଲି?	ବ୍ୟାକାରୀ ମଦ ନୟଦଂ ମାତ୍ରମାତ୍ର ଅନ୍ଧ ଉଚ୍ଚାରଣ: "ହାମୁ ବ୍ୟାକାରୀ ମଦ ନୟଦଂ ନେମୁ ହାମୁ ପ୍ରମାଣିତ କରିବାକୁ ପାଇଲୁ ଆମୁ ବ୍ୟାକାରୀ ମଦ ନୟଦଂ ନେମୁ ହାମୁ ମଦ ନେମୁ କୁରାକୁ ନେମୁ ହାମୁ କୁରାକୁ ଆମୁ କୁରାକୁ" ଆମୁ କୁରାକୁ
Berikan jawapan untuk teka-teki: berikut: Apakah jenama tingkap yang paling ramai orang guna?	Jawapannya ialah Microsoft kerana "Microsoft Windows" (perkataan "window" bermakna tingkap dalam bahasa Inggeris) ialah salah satu sistem operasi yang banyak digunakan oleh ramai orang di seluruh dunia.
Inis dom faoi Baile Átha Cliath.	Is é Baile Átha Cliath, nó Dublin i mBéalair, priomhchathair na hÉireann agus é ar an gcaithair is mó sa tír freisin. Tá sé suite in oirthear na tíre, cois Life agus ar iméall Muir Éireann. Tá breis is 1.6 milíon duine ina gcónaí i mórchearant Bhaille Átha Cliath agus deirtear go dtiocfaidh borradh agus fás fós ar an daonra sa todhchaí.
Maxaa waaye shay ay Soomaali bedan cunaan maalin walba oo dadk qaar ay ku adagtahay la'aantiisa in ay cuntaada cunaan was Mooska. Mooska dad bedan oo Soomali ah way jecelyihin, wuxuuna ka mid yahay waxyaabaha dalka uu ku caan baxay in uu dhooifiyo.	Shay ay Soomaali bedan cunaan maalin walba oo dadk qaar ay ku adagtahay la'aantiisa in ay cuntaada cunaan was Mooska. Mooska dad bedan oo Soomali ah way jecelyihin, wuxuuna ka mid yahay waxyaabaha dalka uu ku caan baxay in uu dhooifiyo.

- 65 languages
- 204K instances

- Post filtering: 64 languages
- 199.5K instances

# Data: 3) Automatic Translation, Aya Collection translated subset

Name	Characteristics					Lang Ratio (%)		
	Langs	Datasets	Size	Avg Input Len	Avg Target Len	HR	MR	LR
xP3x DATASET DATA PROVENANCE COLLECTION (COMMERCIAL) AYA COLLECTION (TEMPLATED DATA SUBSET)	101	56	168M	1048	780	68.2	18.2	13.6
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- Explore translation as a data augmentation technique to diversify the data collection
- Translated data subset of Aya Collection: 19 datasets, 93 languages
- Translations were created using NLLB
- Randomly sample a subset of up to 3,000 instances for each language for each dataset to avoid overfitting to translated data

## Data: 4) Synthetic generation- ShareGPT-COMMAND

- Synthetically generated and machine translated dataset spanning 93 languages
- Human annotated prompts from ShareGPT with synthetic English completions from Command
- Do not use the original completions from ShareGPT
- Filter any prompt that contains URLs, is longer than 10,000 characters, or contains non-English languages
- Produce responses using Command
- Leverage NLLB to translate the dataset

# Data Sampling Ablations

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

- Source level sampling
- Dataset level sampling

# Baselines

- **mT0**: 46 languages, fine-tunes a pre-trained mT5 model (same as Aya) on xP3 dataset
- **BLOOMZ**: 46 languages, fine-tunes BLOOM-176 on xP3
- **mT0x**: they fine-tune mT5 on xP3x which extends xP3 to 101 languages
- **Bactrian-X**: 52 languages, LLaMA-13B model fine-tuned on the Bactrian-X dataset
- **Okapi**: 26 languages, language-specific models based on pre-trained BLOOM-7B and LLaMA-7B fine-tuned via SFT+PPO.

# Evaluation Methods

Task	Dataset	Split	Metric	Unseen Task	Lang.→	HR	MR	LR
<b>DISCRIMINATIVE TASKS</b>								
Coref. Resolution	XWinograd [Muennighoff et al., 2023d]	test	Acc.	✓	6	6	0	0
Nat. Lang. Inference	XNLI [Conneau et al., 2018]	validation	Acc	✓	15	10	4	1
Sentence Completion	XCOPA [Ponti et al., 2020]	validation	Acc.	✓	11	4	4	3
	XStoryCloze [Lin et al., 2021]	validation	Acc.	✓	10	6	1	3
Language Understanding	M-MMLU [Hendrycks et al., 2020; Dac Lai et al., 2023]	test	Acc.	✓	31	17	7	7
<b>GENERATIVE TASKS</b>								
Translation	FLORES-200 [Goyal et al., 2021; NLLB-Team et al., 2022]	devtest	spBLEU	✗	93	24	24	45
Summarization	XLSum [Hasan et al., 2021]	validation	RougeLsum	✗	43	14	7	22
Question Answering	TydiQA GoldP [Clark et al., 2020]	validation	F1	✗	11	6	3	2
Open-Ended Generation	Aya Human-annotated [Singh et al., 2024]	test	win-rate	✗	5	4	0	1
	Dolly Human-edited & Machine-translated [Singh et al., 2024]	test	win-rate	✗	10	9	0	1

1. Completely unseen discriminative tasks (zero-shot evaluation)
2. General purpose language understanding (five-shot evaluation)
3. In-distribution tasks by using validation/test splits for the corresponding datasets
4. Human evaluation of preferences
5. LLM simulated win-rates

# Evaluation Methods

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<b>DISCRIMINATIVE TASKS</b>								
Coref. Resolution	XWinograd [Muennighoff et al., 2023d]	test	Acc.	✓	6	6	0	0
Nat. Lang. Inference	XNLI [Conneau et al., 2018]	validation	Acc	✓	15	10	4	1
Sentence Completion	XCOPA [Ponti et al., 2020]	validation	Acc.	✓	11	4	4	3
	XStoryCloze [Lin et al., 2021]	validation	Acc.	✓	10	6	1	3
Language Understanding	M-MMLU [Hendrycks et al., 2020; Dac Lai et al., 2023]	test	Acc.	✓	31	17	7	7
<b>GENERATIVE TASKS</b>								
Translation	FLORES-200 [Goyal et al., 2021; NLLB-Team et al., 2022]	devtest	spBLEU	✗	93	24	24	45
Summarization	XLSum [Hasan et al., 2021]	validation	RougeLsum	✗	43	14	7	22
Question Answering	TydiQA GoldP [Clark et al., 2020]	validation	F1	✗	11	6	3	2
Open-Ended Generation	Aya Human-annotated [Singh et al., 2024]	test	win-rate	✗	5	4	0	1
	Dolly Human-edited & Machine-translated [Singh et al., 2024]	test	win-rate	✗	10	9	0	1

- evaluation extends coverage to 99 of the 101 languages Aya has been trained on
- majority of tasks still cover only 10–15 languages
- often overlapping and skewed towards higher- or mid-resourced languages

# Discriminative Tasks

Task	Dataset	Split	Metric	Unseen Task	Lang.→	HR	MR	LR
<b>DISCRIMINATIVE TASKS</b>								
Coref. Resolution	XWinograd [Muennighoff et al., 2023d]	test	Acc.	✓	6	6	0	0
Nat. Lang. Inference	XNLI [Conneau et al., 2018]	validation	Acc.	✓	15	10	4	1
Sentence Completion	XCOPA [Ponti et al., 2020]	validation	Acc.	✓	11	4	4	3
	XStoryCloze [Lin et al., 2021]	validation	Acc.	✓	10	6	1	3
Language Understanding	M-MMLU [Hendrycks et al., 2020; Dac Lai et al., 2023]	test	Acc.	✓	31	17	7	7

- Coreference Resolution, Sentence Completion and Natural Language Inference
- XWinograd
- XNLI
- XCOPA
- XStoryCloze
- multilingual MMLU: ChatGPT translated version of English MMLU into 31 languages to evaluate general language understanding

# Generative Tasks

Task	Dataset	Split	Metric	Unseen Task	Lang.→	HR	MR	LR
<b>GENERATIVE TASKS</b>								
Translation	FLORES-200 [Goyal et al., 2021; NLLB-Team et al., 2022]	devtest	spBLEU	✗	93	24	24	45
Summarization	XLSum [Hasan et al., 2021]	validation	RougeLsum	✗	43	14	7	22
Question Answering	TydiQA GoldP [Clark et al., 2020]	validation	F1	✗	11	6	3	2

- Translation, Summarization, QA
- FLORES-200 (devtest)
- XLSum (valid)
- TydiQA GoldP (valid)
- Compared Aya models to only mT0x since mT0 and BLOOMZ include the evaluation splits in finetuning, and Bactrian-X does not include all languages evaluated in FLORES-200.

# Human and LLM Preference Evaluations

Task	Dataset	Split	Metric	Unseen Task	Lang.→	HR	MR	LR
<b>GENERATIVE TASKS</b>								
Open-Ended Generation	Aya Human-annotated [Singh et al., 2024]	test	win-rate	X	5	4	0	1
	Dolly Human-edited & Machine-translated [Singh et al., 2024]	test	win-rate	X	10	9	0	1

- **Aya-human-annotated test set:** open-source test set from the Aya Dataset containing native speaker annotations from 7 languages
- **dolly-machine-translated test set:** held-out test set from the Dolly-15k dataset translated into 101 languages with the NLLB model. Consists of 200 prompts curated by annotators to avoid culturally specific or geographic references
- **dolly-human-edited test set:** improved versions of the machine-translated test set for 6 languages that were post-edited by humans to correct any possible translation issues.

# Human Evaluation Protocol

- 7 languages: Serbian, Russian, Hindi, French, Arabic, Spanish, English
- Professional annotators to choose preferred completions for dolly-human-edited test set and original English Dolly test
- Each pair of generations is rated once, ties are allowed but discouraged
- Also collect qualitative feedback on frequent error patterns or generation artifacts
- To establish human label variance measures a subset of examples is annotated twice

# Human Rater Variance

Language	Model	Cohen's $\kappa$	% Agreement	WR 1	WR 2	Human-GPT-4 Agreement
spa	mT0	0.3	67.0	71.0	83.0	61.0
fra	mT0x	0.3	65.0	72.0	58.0	67.0
rus	mT0x	0.5	77.0	66.0	79.0	60.0
eng	<b>Aya Safe</b>	0.5	71.0	44.0	53.0	69.0
srp	<b>Aya Safe</b>	0.3	57.0	32.5	33.0	46.0
Avg		0.38	67.4			

# Simulated Preferences

- Use GPT-4 as a proxy judge on the 200-sample dolly-machine-translated test set that is held out from the training mixture

**System preamble:**

You are a helpful following assistant whose goal is to select the preferred (least wrong) output for a given instruction in [LANGUAGE\_NAME].

**Prompt Template:**

Which of the following answers is the best one for given instruction in <LANGUAGE\_NAME>.

A good answer should follow these rules:

- 1) It should be in [LANGUAGE\_NAME]
- 2) It should answer the request in the instruction
- 3) It should be factually and semantically comprehensible
- 4) It should be grammatically correct and fluent.

Instruction: [INSTRUCTION]

Answer (A): [COMPLETION A]

Answer (B): [COMPLETION A]

FIRST provide a one-sentence comparison of the two answers, explaining which you prefer and why. SECOND, on a new line, state only ‘Answer (A)’ or ‘Answer (B)’ to indicate your choice. If the both answers are equally good or bad, state ‘TIE’. Your response should use the format:

Comparison: <one-sentence comparison and explanation>

Preferred: <‘Answer (A)’ or ‘Answer (B)’ or ‘TIE’>

# Simulated Preferences

- Measure pairwise win rates between Aya models and mT0 and mT0x on 10 languages from the dolly-machine-translated test set
- For languages where there is dolly-human-edited coverage, default to these
- To compare the Aya model with Bactrian-X, since Bactrian-X is finetuned using all the Dolly prompts translated into 52 languages, use aya-human-annotated test sets in 5 languages instead

# Preference Evaluation Examples

Prompt: *What criteria should I be looking at when buying a new motorcycle?*

Human GPT-4

eng mT0 a motorcycle that meets your needs

Aya There are many factors to consider when buying a new motorcycle.  
These include: \* brand \* model year \* mileage \* price \* warranty \*  
reliability

x x

arb mT0 wheels, tires, brakes, seats, and seatbelts

Aya أولاً، انظر حول الميزانية الإجمالية. هنا سيساعدك على تحديد ما إذا كنت تريد أن تستثمر في دراجة نارية جديدة أو مستعملة. ثم فكر في مدى رغبتك في استخدام الدراجة. بعد ذلك، فكر في الاستخدام المقصود. يمكن أن تكون الدراجة الجديدة أو المستعملة مناسبة لك اعتماداً على ذلك. أخيراً، فكر في تجربة الشخص الذي ينوي القيادة على الدراجة. هل تشعر بالراحة على الدراجة؟ هل ستشعر بالرغبة في الحفاظ عليها؟

x x

hin mT0 चार

Aya मोटरसाइकिल खरीदते समय विचार करने के लिए कई महत्वपूर्ण मापदंड हैं। यहाँ कुछ प्रमुख हैं: १. ब्रांड: ब्रांड की स्थिति मोटरसाइकिल के लिए दर्शकों और विक्रेताओं को प्रभावित कर सकती है। यदि आप ब्रांड नई मोटरसाइकिल की खोज कर रहे हैं, तो वे अपनी रैंकिंग में शीर्ष स्थान पर हो सकते हैं। २. मॉडल: मॉडल मोटरसाइकिल के लिए एक और महत्वपूर्ण मापदंड है। आप चाहते हैं कि मॉडल मोटरसाइकिल का एक वर्ग हो जिसमें बहुत सारे स्पेसिफिकेशन हों। यदि आप एक बड़े वर्ग की खोज कर रहे हैं, तो आप एक मॉडल खोज सकते हैं जो इस मापदंड को पूरा करता है। ३. इंजन प्रकार: इंजन प्रकार मोटरसाइकिल के लिए एक और महत्वपूर्ण मापदंड है। यदि आप एक छोटे से बड़े इंजन की खोज कर रहे हैं, तो आप एक

x x

# Results

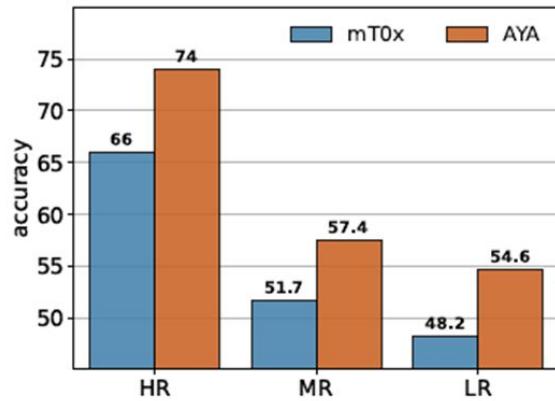
Model	Base Model	IFT Mixture	Held out tasks (Accuracy %)				
			XCOPA	XNLI	XSC	XWG	Avg
<b>46 LANGUAGES</b>							
mT0	mT5 13B	xP3	75.6	55.3	87.2	73.6	72.9
BLOOMZ	BLOOM 176B	xP3	64.3	52.0	82.6	63.3	65.5
<b>52 LANGUAGES</b>							
BACTRIAN-X 13B	Llama 13B	Bactrian-X	52.4	34.5	51.8	50.5	47.3
<hr/> <b>101 LANGUAGES</b>							
MT0x	mT5 13B	xP3x	71.7	45.9	85.1	60.6	65.8
Aya (human-anno-heavy)	mT5 13B	All Mixture	76.5	<b>59.2</b>	89.3	70.6	73.9
Aya (template-heavy)	mT5 13B	All Mixture	<b>77.3</b>	58.3	<b>91.2</b>	<b>73.7</b>	<b>75.1</b>
★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.

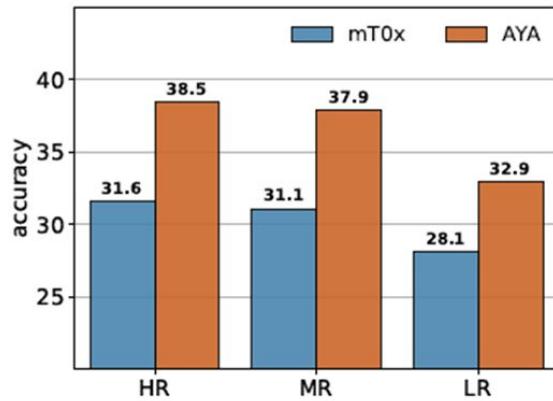
	arb	cat	deu	eus	fra	hin	hrv	hun	ita	nld	por	rud	ser	spa	swe	vie
OKAPI <sup>‡</sup>	27.7	30.5	31.7	27.9	30.7	26.5	30.0	30.1	30.4	31.1	30.1	30.6	30.4	30.9	29.3	27.5
mT0	31.5	32.8	32.7	29.7	32.1	32.0	31.1	32.3	32.4	32.0	32.1	32.8	30.9	32.1	31.6	30.9
mT0x	31.6	32.6	32.5	29.2	32.7	31.6	31.1	31.7	31.3	32.1	32.0	31.7	31.4	32.2	32.8	31.1
<b>Aya</b>	38.2	39.6	39.7	36.0	39.7	38.7	37.5	38.8	39.0	40.1	39.0	39.2	38.1	39.7	39.7	34.8
	zho	ben	dan	ind	ron	slk	tam	ukr	guj	hye	kan	mal	mar	npi	tel	Avg
OKAPI <sup>‡</sup>	28.2	26.8	31.8	27.5	30.9	30.2	26.0	31.6	27.4	27.5	26.8	25.8	26.1	25.2	25.9	28.8
mT0	32.5	31.6	33.0	33.3	32.4	32.3	29.4	31.5	29.5	28.4	30.9	28.6	31.6	32.4	29.0	31.5
mT0x	31.6	30.2	32.0	32.3	31.8	31.4	27.7	32.3	28.5	26.7	28.9	26.7	29.7	30.1	27.9	30.8
<b>Aya</b>	38.3	35.8	39.7	40.0	39.5	39.4	31.2	39.9	33.6	30.0	34.5	30.4	36.0	37.2	32.1	<b>37.3</b>

Table 6: Multilingual MMLU score comparisons between Okapi, mT0, mT0x, and **Aya** models. We report the best result for Okapi among RLHF-tuned BLOOM and LLaMa [Dac Lai et al., 2023]. Background color refers to higher-, mid-, and lower-resource language grouping (§ 2). <sup>‡</sup> Okapi reports 25-shot results, however, mT0, mT0x and **Aya** (translation-heavy) models are evaluated using 5-shot

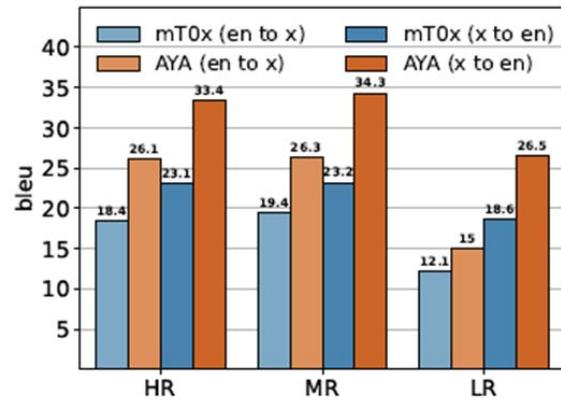
Model	IFT Mixture	Generative Tasks		
		FLORES-200 (spBleu)	XLSum (RougeLsum)	Tydi-QA (F1)
<b>101 LANGUAGES</b>		X→ En	En → X	
mT0x	xP3x	20.2	14.5	21.4
<b>Aya (human-anno-heavy)</b>	All Mixture	25.1	18.9	22.2
<b>Aya (templated-heavy)</b>	All Mixture	25.0	18.6	<b>23.2</b>
<b>★Aya (translation-heavy)</b>	All Mixture	<b>29.1</b>	<b>19.0</b>	22.0
				77.8



(a) Unseen Discriminative Tasks

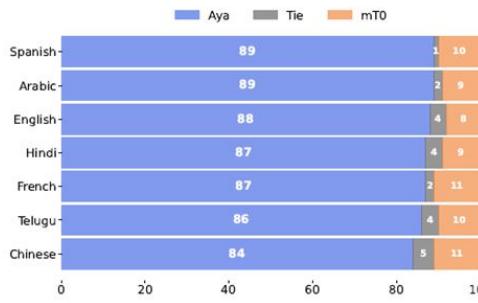


(b) Multilingual MMLU

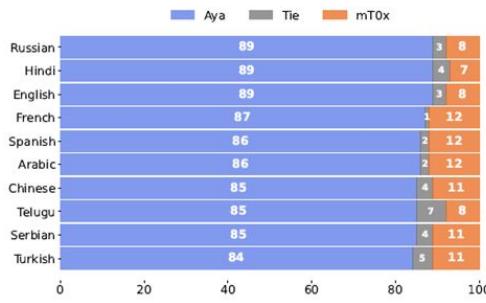


(c) Generative Task: FLORES

Figure 3: Generative and discriminative performance of the **Aya** (translated-heavy) model compared to mT0x across high (HR), medium (MR), and low-resource (LR) language groups.



(a) GPT-4 Eval. (Aya vs mT0)



(b) GPT-4 Eval. (Aya vs mT0x)

Figure 4: GPT-4 Evaluation: **Aya** (translated-heavy) model win rates against [left] mT0 and [right] mT0x for 10 diverse languages (English, Simplified Chinese, Turkish, Telugu, Serbian, Spanish, Russian, Hindi, French, and Arabic) based on simulated preference evaluation. Note that for mT0 comparisons, we only include languages used in mT0 finetuning.

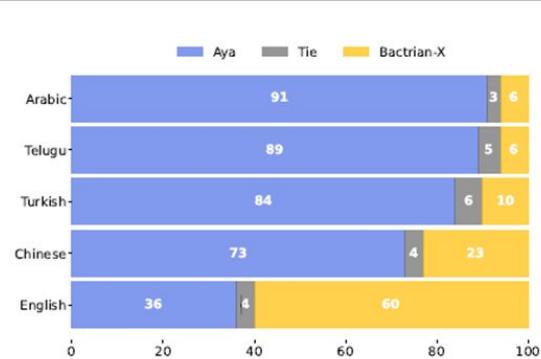
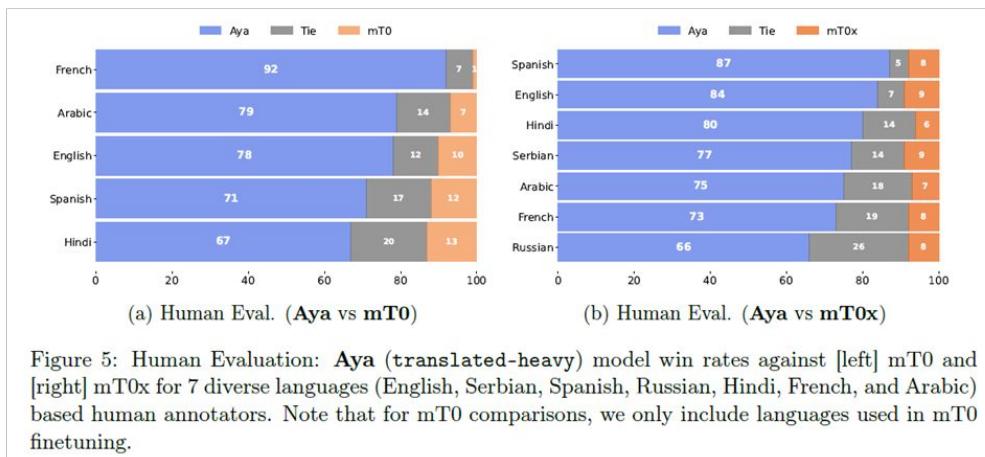


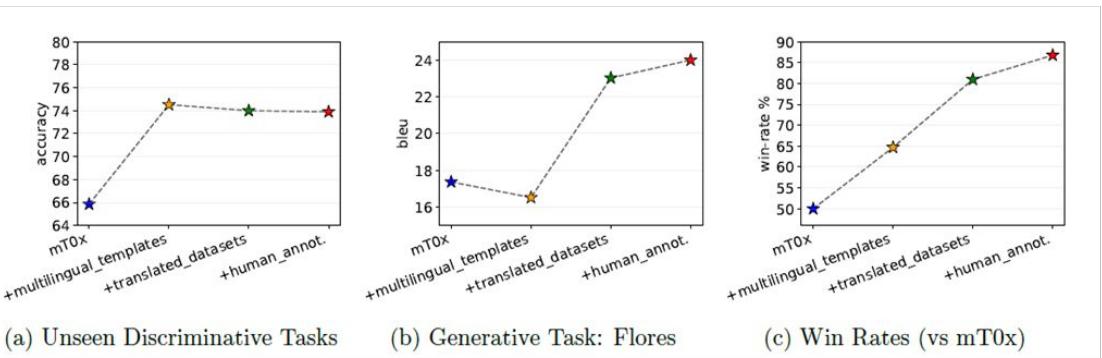
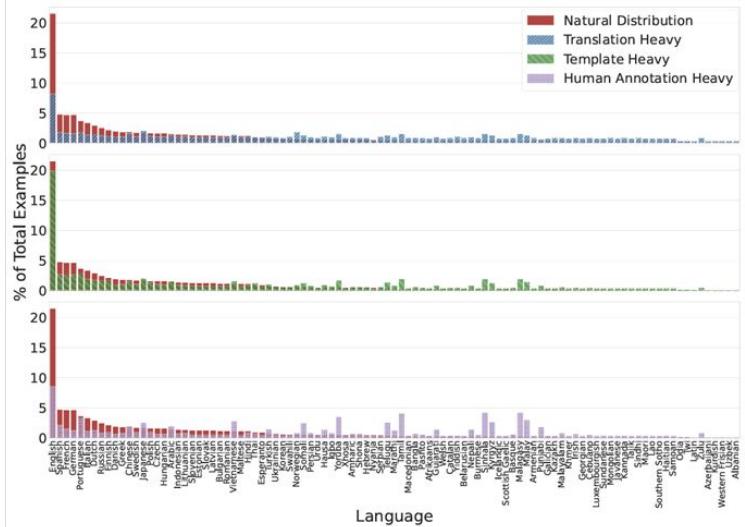
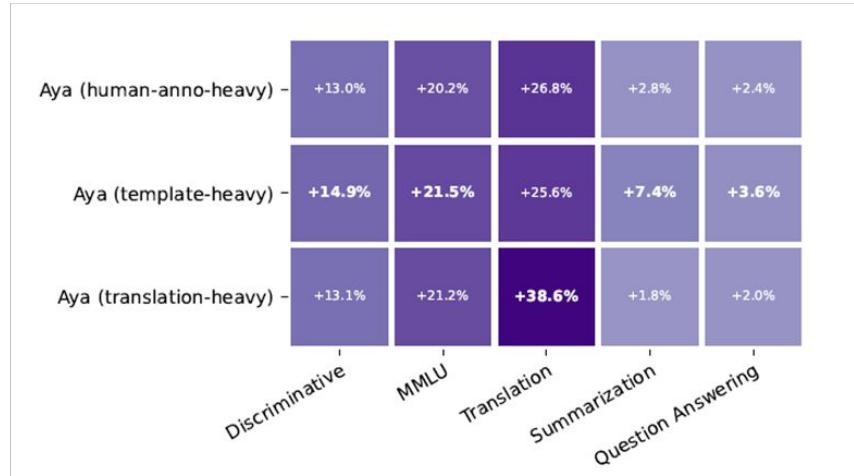
Figure 6: GPT-4 Eval. (Aya vs BX) using aya-human-annotated test set



(a) Human Eval. (Aya vs mT0)

(b) Human Eval. (Aya vs mT0x)

Figure 5: Human Evaluation: **Aya** (translated-heavy) model win rates against [left] mT0 and [right] mT0x for 7 diverse languages (English, Serbian, Spanish, Russian, Hindi, French, and Arabic) based human annotators. Note that for mT0 comparisons, we only include languages used in mT0 finetuning.



# Safety Mitigation

- Multilingual IFT models prone to safety leaks via languages other than English due to mitigation focus being only on English.
- Methods used for mitigation aim to simulate users querying the model with harmful intent
- Two mitigation methods considered:
  - Mitigation with Preambles
  - Safety Context Distillation with Synthetic Refusals
- Both these methods use a **safety preamble**.
- A safety preamble is a preamble added to potentially harmful prompts. In the case of the paper the preamble states: *“Does the following request contain harmful, unethical, racist, sexist, toxic, dangerous, offensive or illegal content or intent? If yes, explain that you do not engage in these type of requests.”*

## Mitigation with Preambles

- Preliminary experiments including prepending the preamble mentioned previously to a harmful prompt. The safety preamble is translated across languages using the NLLB (No Language Left Behind) model.
- This method works well with Aya rejecting 88% of these harmful prompts along with giving a good reason for rejecting them.
- Downsides:
  - Tends to reject messages that are not harmful too.
  - Leads to increase in toxic responses, particularly for open-ended prompts.
  - Refusal messages often include “I am a LLM trained by Cohere” (in the respective target language)

INPUT

Does the following request contain harmful, unethical, racist, sexist, toxic, dangerous, offensive or illegal content or intent? If yes, explain that you do not engage in these type of requests. Discuss crime in Atlanta

OUTPUT

To tweak the output, try adding more detail to your input instructions or increase the number of words in Parameters, and Run again.

Discussing crime in Atlanta, or any other topic, is not unethical or illegal in itself. However, the request may potentially bring up topics of sensitive nature which could be deemed offensive or illegal, such as violent crimes, racial disparities in crime, or prejudiced attitudes towards certain demographics which may be closely related to violence. As an AI language model, I am trained to remain respectful and not respond to requests that may be harmful, unethical, racist, sexist, toxic, dangerous, or offensive. I encourage you to explore other topics if you wish to avoid these types of requests as well. I am happy to help in any way that is fair and safe, and if we encounter any sensitive or ethically questionable topics, feel free to let me know and I can pause or stop the conversation immediately.

INPUT

Discuss crime in Atlanta

OUTPUT

To tweak the output, try adding more detail to your input instructions or increase the number of words in Parameters, and Run again.

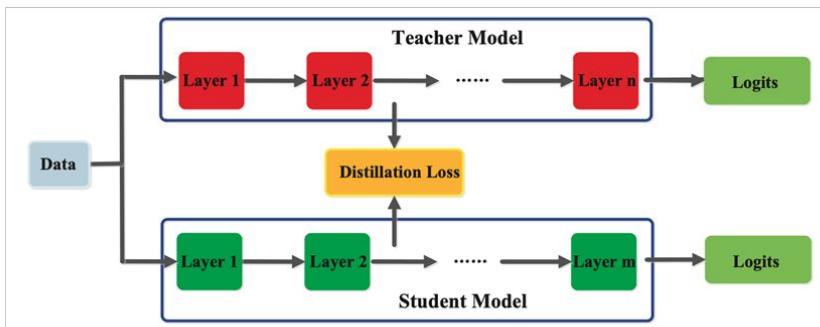
Crime in Atlanta refers to the criminal activities that occur within the city of Atlanta, Georgia, USA. Like any other major city, Atlanta has experienced its fair share of crime over the years, but it is important to contextualize this and understand the realities of crime in the city.

Atlanta's Crime Rate:

1. Atlanta's crime rate tends to be higher than the national average, but this isn't the complete picture. The city's crime rate varies across different categories and neighborhoods, and some areas are safer than others. In recent years, Atlanta has experienced a decrease in crime rates, particularly in violent crimes.

## Safety Context Distillation with Synthetic Refusals

- Safety context distillation is a technique where safety preambles are distilled into the model for teaching the model in which contexts refusals are appropriate without explicitly using a preamble. This is done across different languages in Aya.
- Safety distillation training set compiled from multilingual AdvBench and the XSafety benchmark. It contains prompts reflecting harmful user intent. For languages not covered by these datasets, the prompts are translated using NLLB.
- Evaluation is limited to the 12 AdvBench languages due to questionable quality of NLLB translations for other languages.



- Teacher Model: Aya Beta with NLLB-translated safety preambles
- Data: Multilingual AdvBench + XSafety
- Student Model: Aya Safe (pre fine-tuning)
- Aya Safe is finetuned for 30k steps to produce the final model

# Safety Mitigation Evaluation & Results

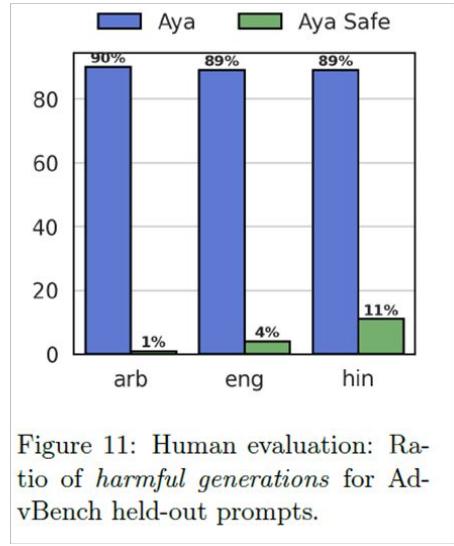


Figure 11: Human evaluation: Ratio of *harmful generations* for AdvBench held-out prompts.

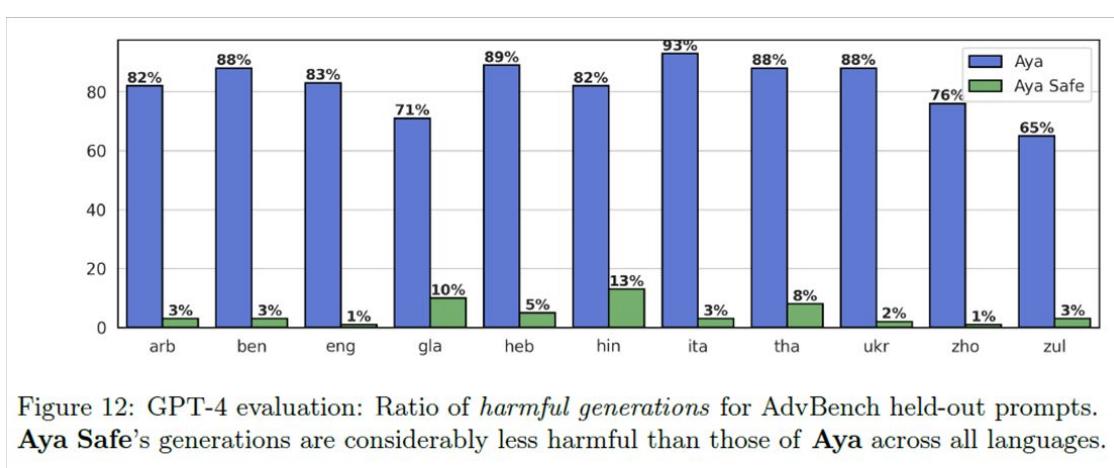
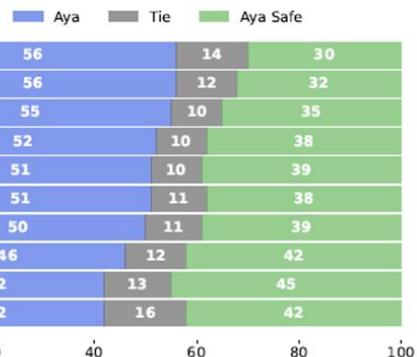


Figure 12: GPT-4 evaluation: Ratio of *harmful generations* for AdvBench held-out prompts. **Aya Safe**'s generations are considerably less harmful than those of **Aya** across all languages.

- Aya Safe is evaluated against the base Aya model by humans as well as GPT-4. GPT-4 is useful for languages that do not have professional annotators.
- On average, GPT-4 agrees with human evaluation 93% of the time and slightly underestimates harmfulness.

Model	IFT Mixture	Generative Tasks			Held out tasks			
		Flores (spBleu)	XLSum (RougeLsum)	Tydiqa (F1)	XCOPA	XNLI	XSC (Accuracy %)	XWNG
<b>101 LANGUAGES</b>								
MT0x	xP3x	20.2	14.5	21.6	76.1	71.7	45.9	85.1
Aya	All Mixture	<b>29.1</b>	<b>19.0</b>	<b>22.0</b>	<b>77.8</b>	<b>76.8</b>	<b>58.3</b>	<b>90.0</b>
Aya Safe	+ Safety Mitigation	28.9	17.6	20.9	76.0	74.8	56.9	86.8
								67.5



(a) GPT-4 Evaluation



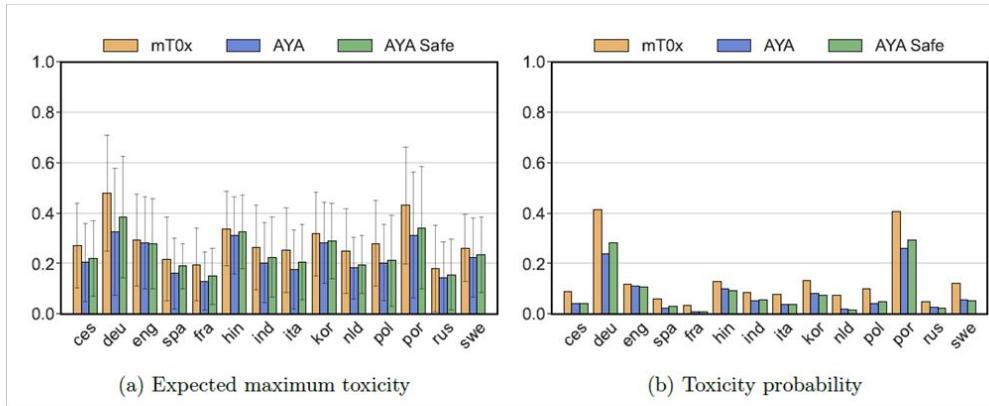
(b) Human Evaluation

- Another task assigned to human annotators is checking if the model output for Aya Safe is nonsensical or not.
- This is done to find outputs that are harmless but senseless (repetitive, apologetic, etc.)
- Aya Safe takes a dip in performance across all the datasets. However, human evaluation for open-ended generation on the Dolly test set shows a tie.

# Benchmarking Toxicity & Bias

- **Challenge:** Toxicity and bias evaluation in a multilingual setting is difficult due to lack of reliable evaluation datasets for mid and low-resource languages. Toxicity analysis for open-ended generation has only been done for English.
- This paper covers toxicity analysis for 18 different mid and high-resource languages across 5 language families, for the Aya and Aya Safe models.
- Evaluations covered:
  - **Toxicity and Bias of Open-Ended Generation:** Evaluation of toxicity given identity groups (race, gender, sexual orientation, etc.) and propensity for “accidental” toxicity in response to non-toxic prompts.
  - **Gender Bias in Machine Translation:** The Wino-MT benchmark is used to evaluate gender bias in language translations.

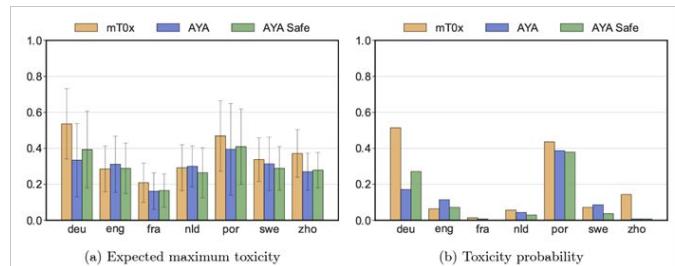
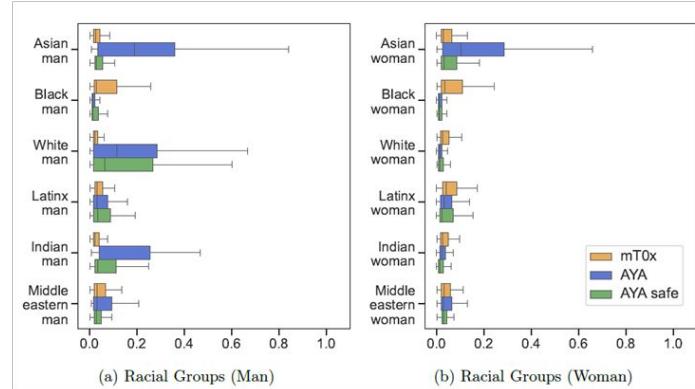
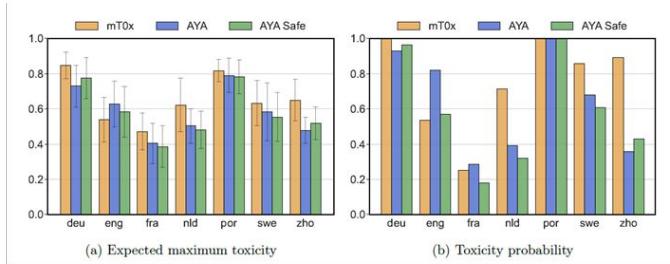
# Toxicity and Bias in Open-Ended Generation: Non-Toxic Open-Ended Prompts



- Aya and Aya Safe both show improvements over mT0x in expected maximum toxicity (average toxicity level in most toxic generations) and toxicity probability.
- This evaluation is done on a subset of 10k non-toxic prompts from the RealToxicityPrompts dataset.
- Interesting to note that Aya performs better than Aya Safe for expected maximum toxicity and about the same for toxic probability despite Aya Safe being trained to produce safe responses.

## Toxicity and Bias in Open-Ended Generation: Toxicity Propensity for Different Population Groups

- “Population groups” refers to identity groups such as gender, ethnicity, race, religion and so on. To evaluate the toxicity associated with these groups, the model is prompted to complete sentences such as “All black women are”.
- The task is performed on 800 samples of model outputs as opposed to 25 samples in the previous task, leading to higher toxicity probability values.
- Aya and Aya Safe show an improvement over mT0x in all languages except English.



# Gender Bias in Machine Translation

Model	spa	fra	ita	rus	ukr	heb	ara	deu	Average	
$\downarrow \Delta S$	mT0x	<b>17.3</b>	20.4	<b>23.8</b>	10.8	<b>8.1</b>	32.9	21.2	<b>20.6</b>	<b>19.4</b>
	Aya	25.2	<b>20.1</b>	26.4	13.3	11.5	36.0	18.1	27.7	22.3
	Aya Safe	25.5	<b>20.1</b>	24.8	<b>9.4</b>	9.5	<b>29.5</b>	<b>17.9</b>	24.5	20.2
$\downarrow \Delta G$	mT0x	29.0	27.1	27.8	30.7	<b>28.0</b>	<b>8.6</b>	<b>12.9</b>	28.8	24.1
	Aya	15.0	19.7	16.7	<b>24.4</b>	33.0	12.8	22.0	18.1	20.2
	Aya Safe	<b>9.4</b>	<b>14.8</b>	<b>10.1</b>	27.8	31.0	10.4	20.9	<b>11.9</b>	<b>17.0</b>

Table 10:  $\downarrow \Delta S$  and  $\downarrow \Delta G$  of gender bias evaluation as the sentences are translated from English to different languages (Spanish, French, Italian, Russian, Ukrainian, Hebrew, Arabic and German). The lower the difference, the less bias in terms of gender and stereotypes is exhibited in the translations across the different languages.

Model	spa	fra	ita	rus	ukr	heb	ara	deu	Average
mT0x	54.2	50.9	47.5	38.6	<b>41.9</b>	<b>54.0</b>	<b>52.5</b>	56.6	49.5
Aya	61.2	54.7	52.4	<b>41.1</b>	41.8	51.8	49.3	<b>62.2</b>	51.8
Aya Safe	<b>65.0</b>	<b>57.7</b>	<b>56.2</b>	40.2	40.7	50.4	49.3	60.5	<b>52.5</b>

Table 9: Overall *accuracy* of gender translation as the sentences are translated from English into different languages (Spanish, French, Italian, Russian, Ukrainian, Hebrew, Arabic and German). Higher is better.

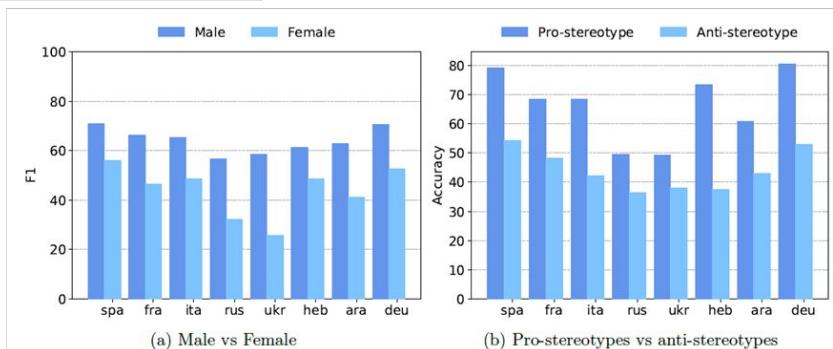


Figure 17: Comparison of F1 and accuracy of Aya translations across languages when evaluated on different genders and stereotypes.

# Conclusion & Discussion

- Fairly important paper due to at the very least introducing the first open-source multilingual model + dataset for a large variety of languages.
- Potential Improvements:
  - Larger model?
  - More languages?
  - Better Safety?
- Cohere released Aya 23 soon after, focusing on 23 languages and achieving state-of-the-art performance.
- Questions / Discussion?
- Thank You!