The Road Towards Massively Multilingual Large Language Models

François Yvon - ISIR (Sorbonne Université, CNRS, INSERM)

BUCC @ LREC 2024, Torino

Monolingual LLMs

Learning parameters on large monolingual corpora with auxiliary tasks and natural annotations

1. Predict next word given prefix: pure decoder

Longtemps je me suis couché [mask] - unmask='de', train $P_\theta(w_t | w_{<t})$

(eg. GPT*, OPT, GPTJ, PALM*, LLAMA*, Mistral*)

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(eg. BERT, Roberta, CamemBERT, FlauBERT, etc)

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3. Denoising sequence to sequence : encoder-decoder

Longtemts je couché suis de bnone heur || Longtemps je me suis couché de bonne heure

train $P_\theta(w | \tilde{w}) = \prod_t P(w_t | w_{<t}, \tilde{w})$ (eg. BART, T5, etc)

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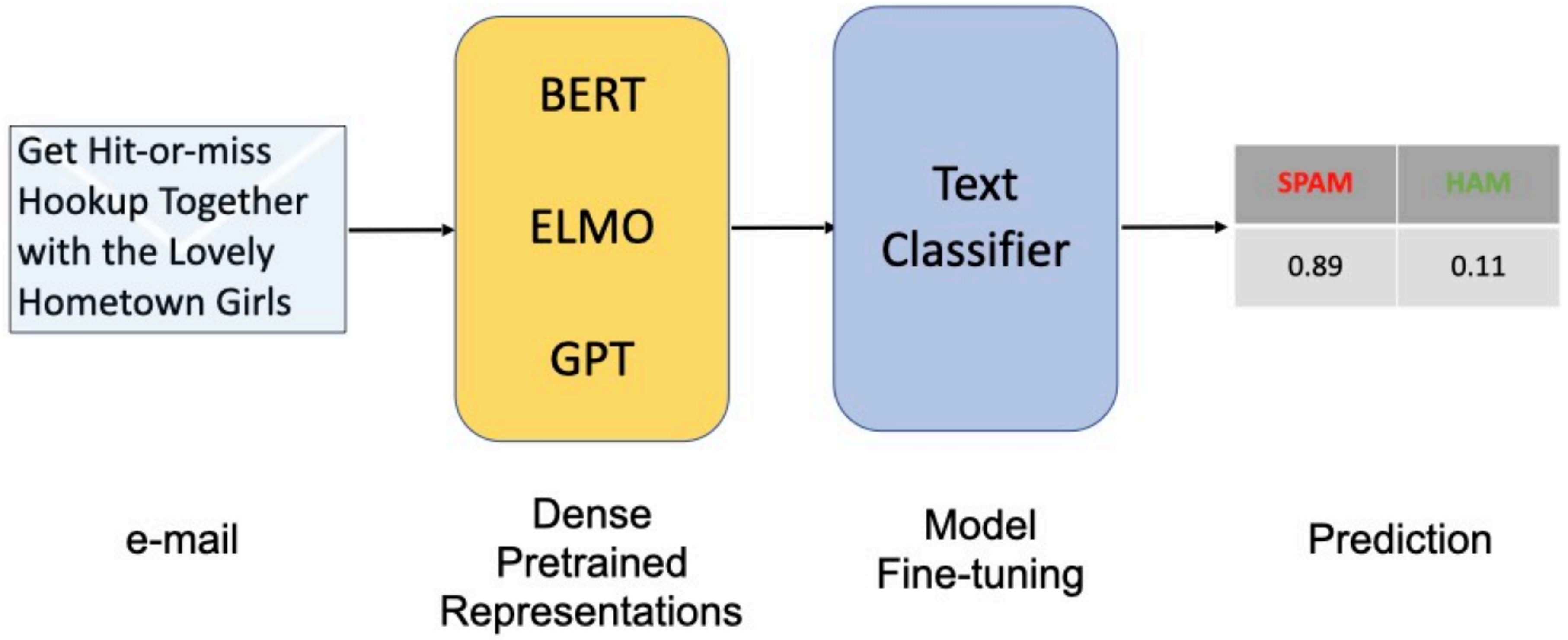
+Alt. auxiliary tasks

- NSP
- span prediction (eg. SpanBERT)
- corruption detection (eg. Electra)

Using Monolingual LLMs

1. **Fine-tuned task-adapted model:** $h_{\phi,\theta} = h_{\phi}(f_{\theta}(w); c)$



1+2. **Multi-task fine-tuning with prompts a.k.a instruction tuning**

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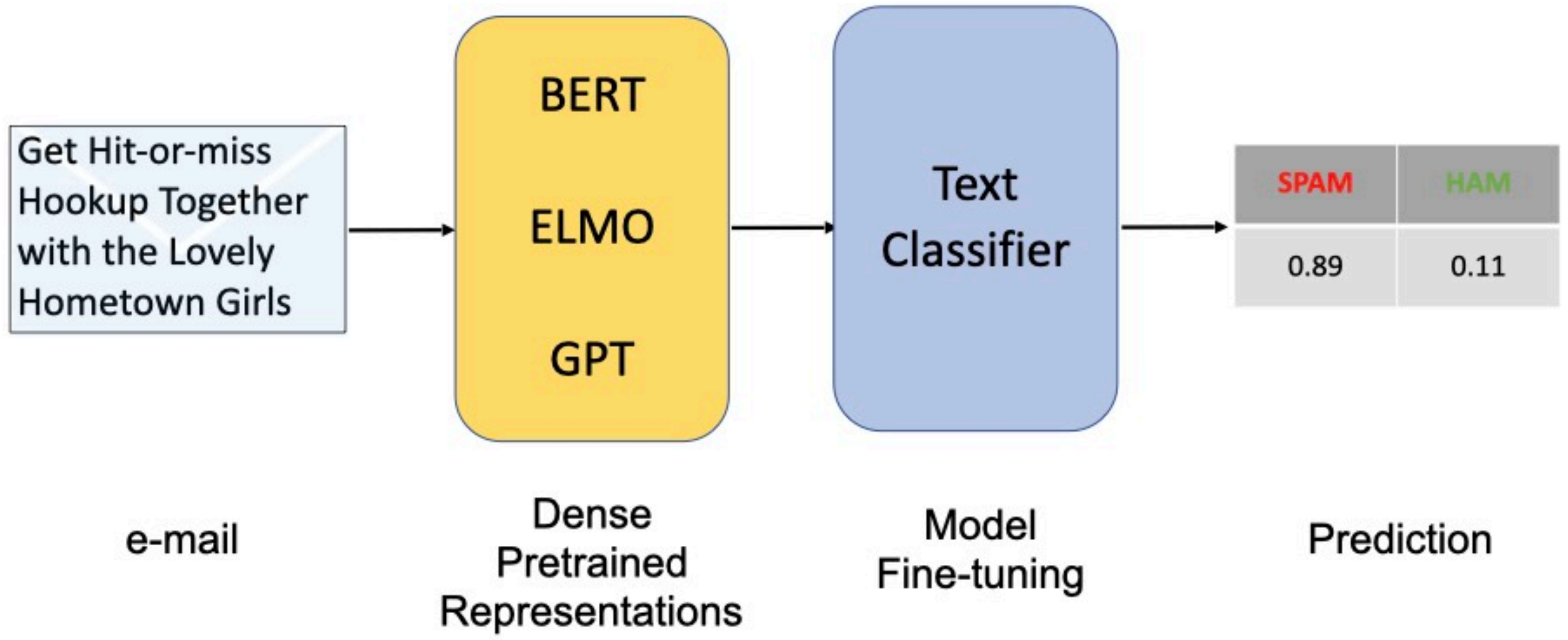


2. **Multi-purpose text generation via prompting**

GEN Of course. In Chorukor, Monday is ilopagar, Tuesday ilopager, . . .
Wednesday ilopagur, Thursday ilopagir ...

Q&A Answer this : What are the birth date and place of Ludvík Vaculík ? . . .
23 July 1926, in Brumov, Moravia

SA "This Czech writer has written some the most wonderful French novels."
is a positive comment ? . . . [Yes | No]

1+2. Multi-task fine-tuning with prompts a.k.a instruction tuning

"Holistic" evaluation

81 models

AI21 Labs / J1-Jumbo v1 (178B)
AI21 Labs / J1-Large v1 (7.5B)
AI21 Labs / J1-Grande v1 (17B)
AI21 Labs / J1-Grande v2 beta (17B)
AI21 Labs / Jurassic-2 Jumbo (178B)
AI21 Labs / Jurassic-2 Grande (17B)
AI21 Labs / Jurassic-2 Large (7.5B)
Aleph Alpha / Luminous Base (13B)
Aleph Alpha / Luminous Extended (30B)
Aleph Alpha / Luminous Supreme (70B)
neurips / Local service
Anthropic / Anthropic-LM v4-s3 (52B)
Anthropic / Anthropic Claude 2.0
Anthropic / Anthropic Claude v1.3
Anthropic / Anthropic Claude Instant V1
UC Berkeley / Koala (13B)
BigScience / BLOOM (176B)
BigScience / BLOOMZ (176B)
BigScience / T0pp (11B)
BigCode / SantaCoder (1.1B)
BigCode / StarCoder (15.5B)
Cerebras / Cerebras GPT (6.7B)
Cerebras / Cerebras GPT (13B)
Cohere / Cohere xlarge v20220609 (52.4B)
Cohere / Cohere large v20220720 (13.1B)
Cohere / Cohere medium v20220720 (6.1B)
Cohere / Cohere small v20220720 (410M)
Cohere / Cohere xlarge v20221108 (52.4B)
Cohere / Cohere medium v20221108 (6.1B)
Cohere / Cohere Command beta (6.1B)
Cohere / Cohere Command beta (52.4B)

73 scenarios

Question answering
- MMLU
- BoolQ
- NarrativeQA
- NaturalQuestions (closed-book)
- NaturalQuestions (open-book)
- QuAC
- HellaSwag
- OpenbookQA
- TruthfulQA

Information retrieval
- MS MARCO (regular)
- MS MARCO (TREC)

Summarization
- CNN/DailyMail
- XSUM

Sentiment analysis
- IMDB

Toxicity detection
- CivilComments

Text classification
- RAFT

Aspirational scenarios
- Data-to-text generation
- Fact verification
- Copywriting
- Story generation

65 metrics

Accuracy
- none
- Quasi-exact match
- F1
- Exact match
- RR@10
- NDCG@10
- ROUGE-2
- Bits/byte
- Exact match (up to specified indicator)
- Absolute difference
- F1 (set match)
- Equivalent
- Equivalent (chain of thought)
- pass@1

Calibration
- Max prob
- 1-bin expected calibration error
- 10-bin expected calibration error
- Selective coverage-accuracy area
- Accuracy at 10% coverage
- 1-bin expected calibration error (after Platt scaling)
- 10-bin Expected Calibration Error (after Platt scaling)
- Platt Scaling Coefficient
- Platt Scaling Intercept

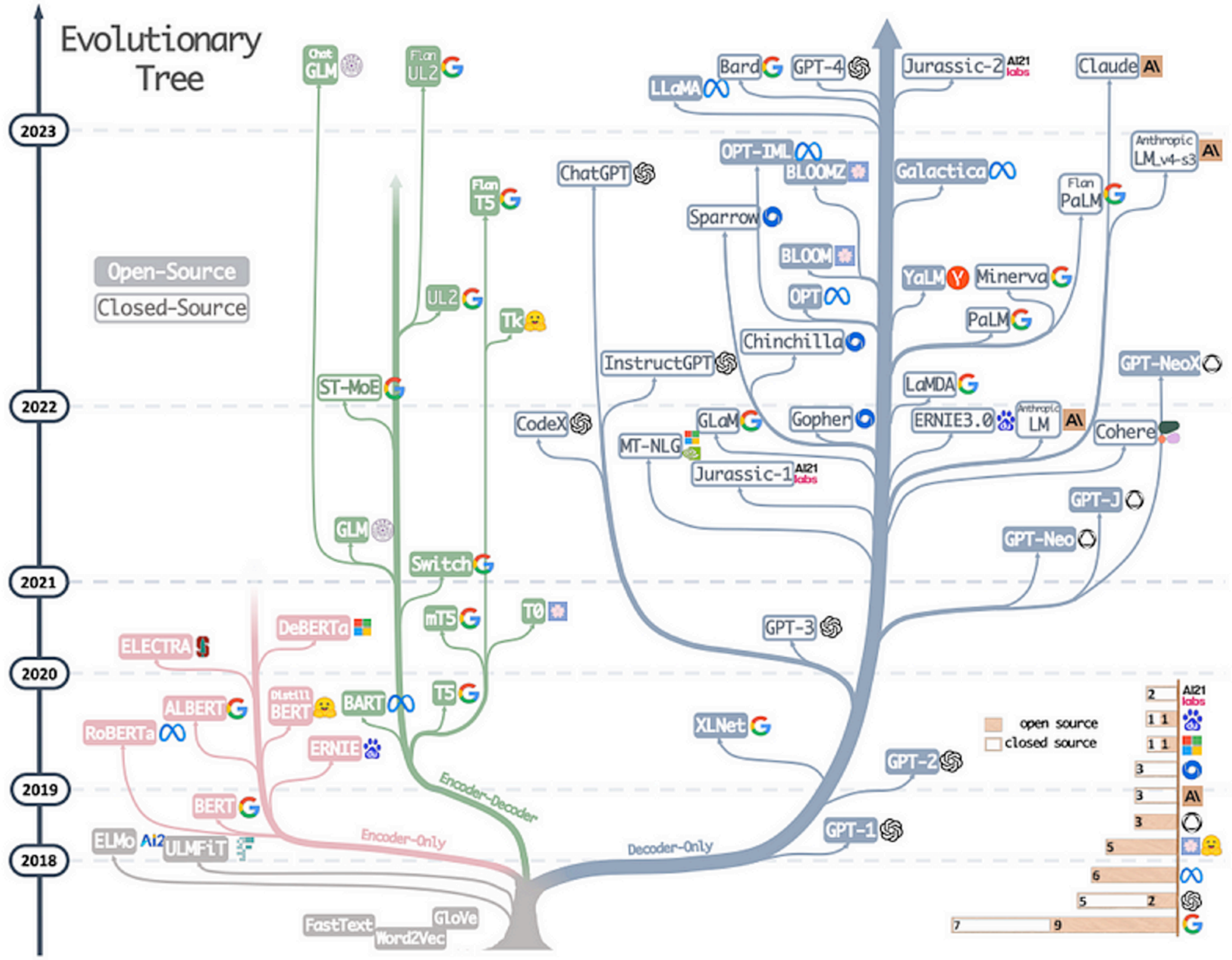
Robustness
- Quasi-exact match (perturbation: typos)
- F1 (perturbation: typos)
- Exact match (perturbation: typos)
- RR@10 (perturbation: typos)

Multifacet Evaluation

- tasks, bias, fairness, openness, etc.

Holistic Evaluation of Large Language Models (Liang et al, 2022)

Types of LLMs



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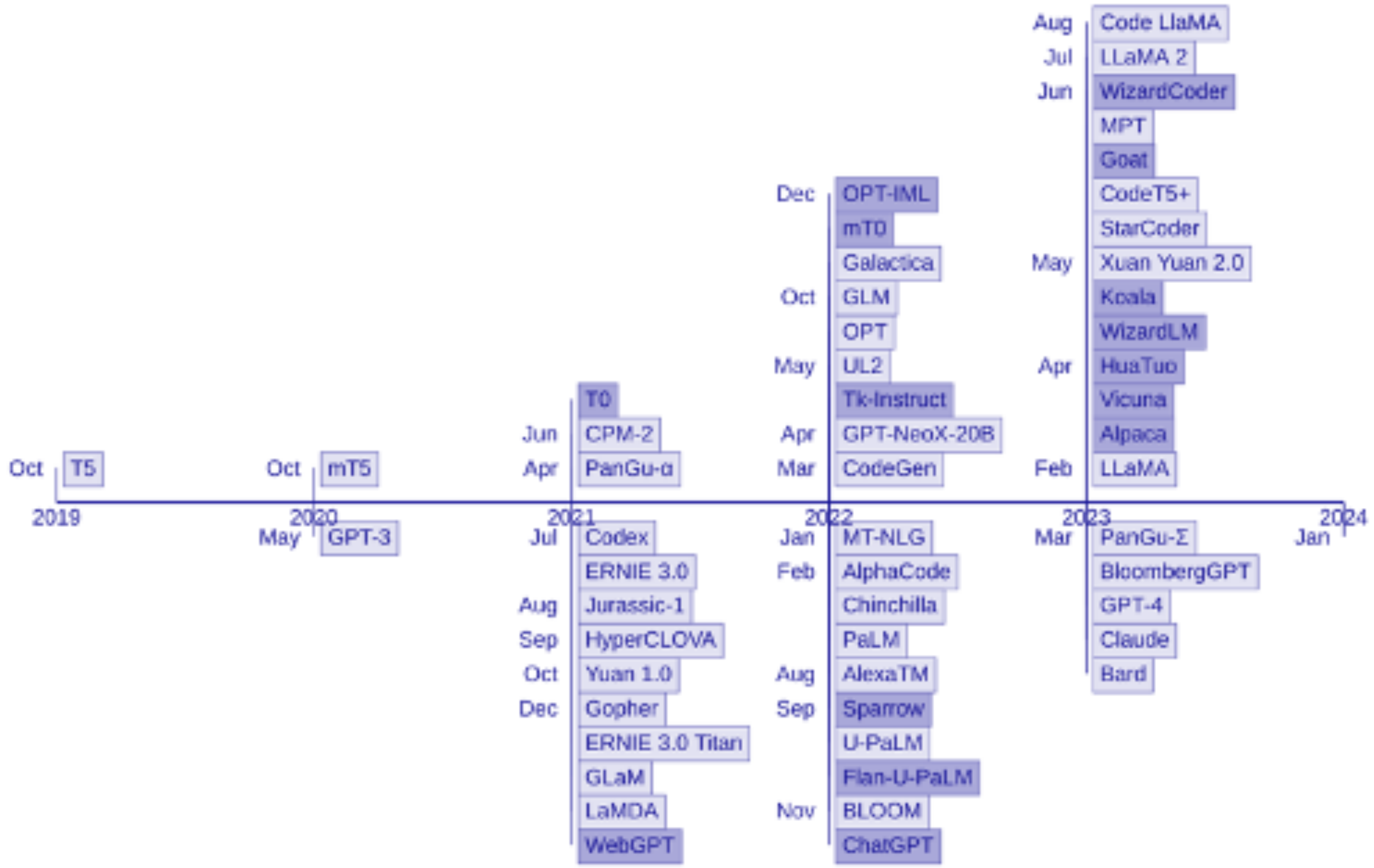

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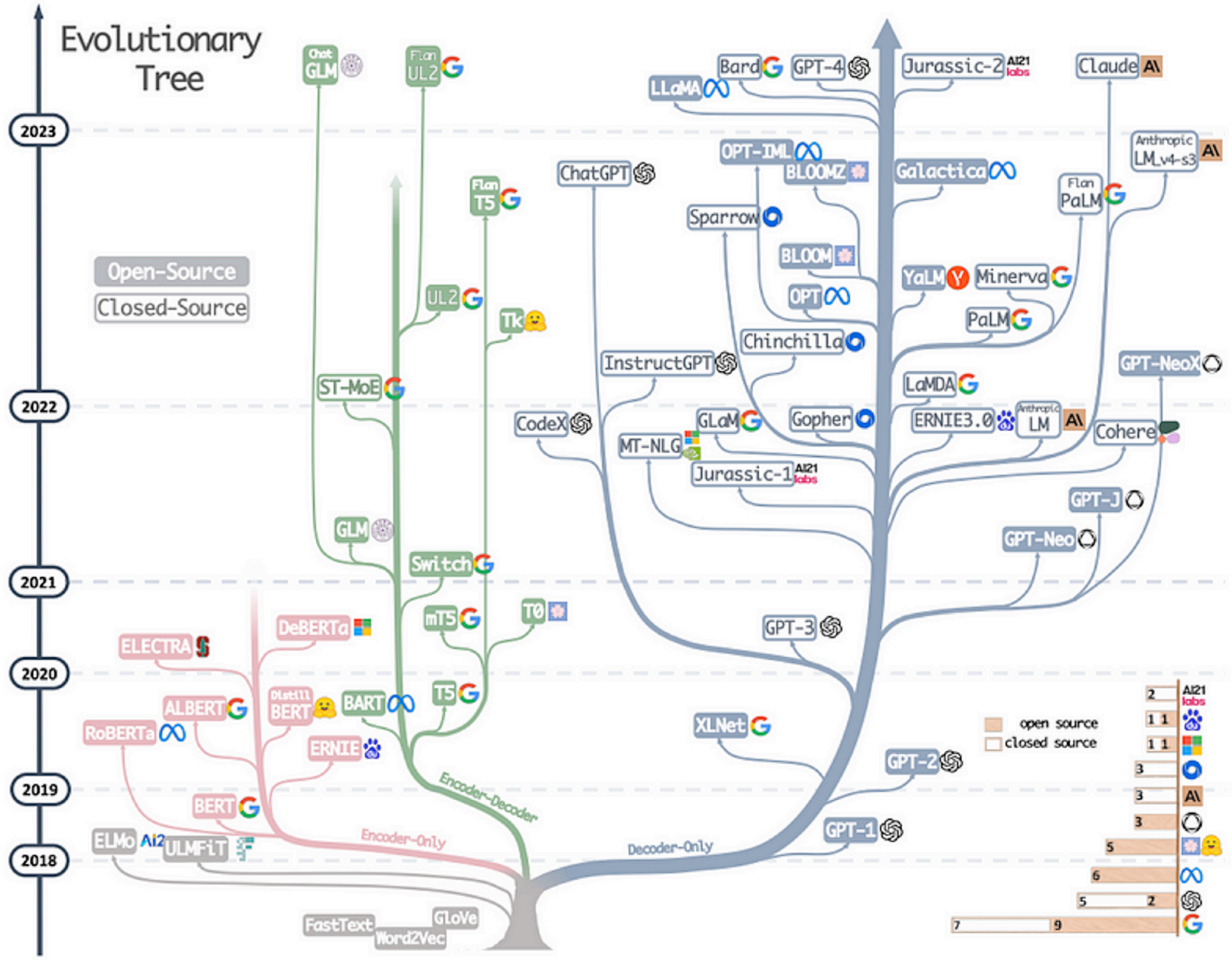

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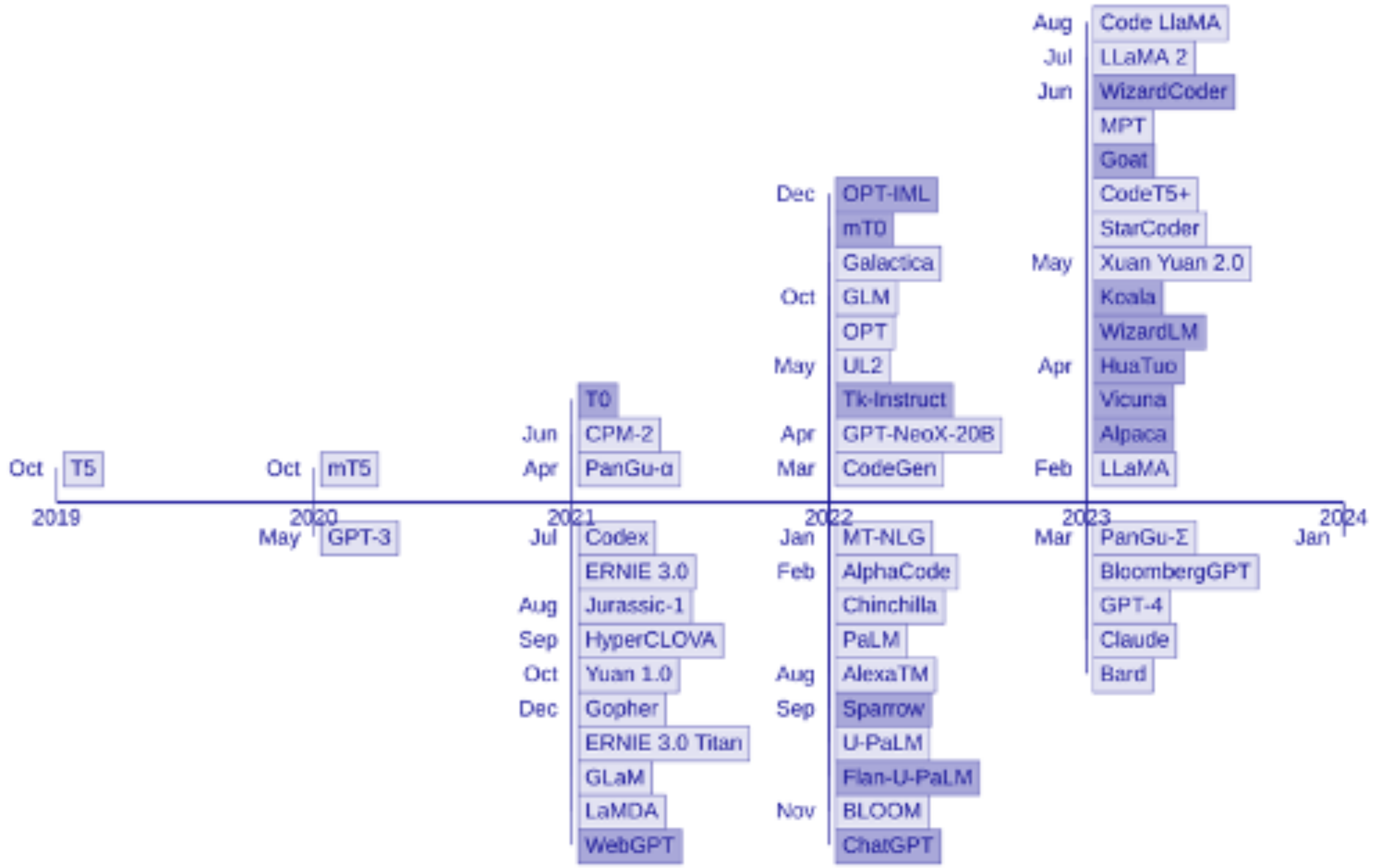

Also

- derivatives (fine-tuned, aligned)
- augmented (RAG, Tools, KBs)
- speech, image, video
- multimodal (text+image, +video)
- code, bio-chem, material, actions, …

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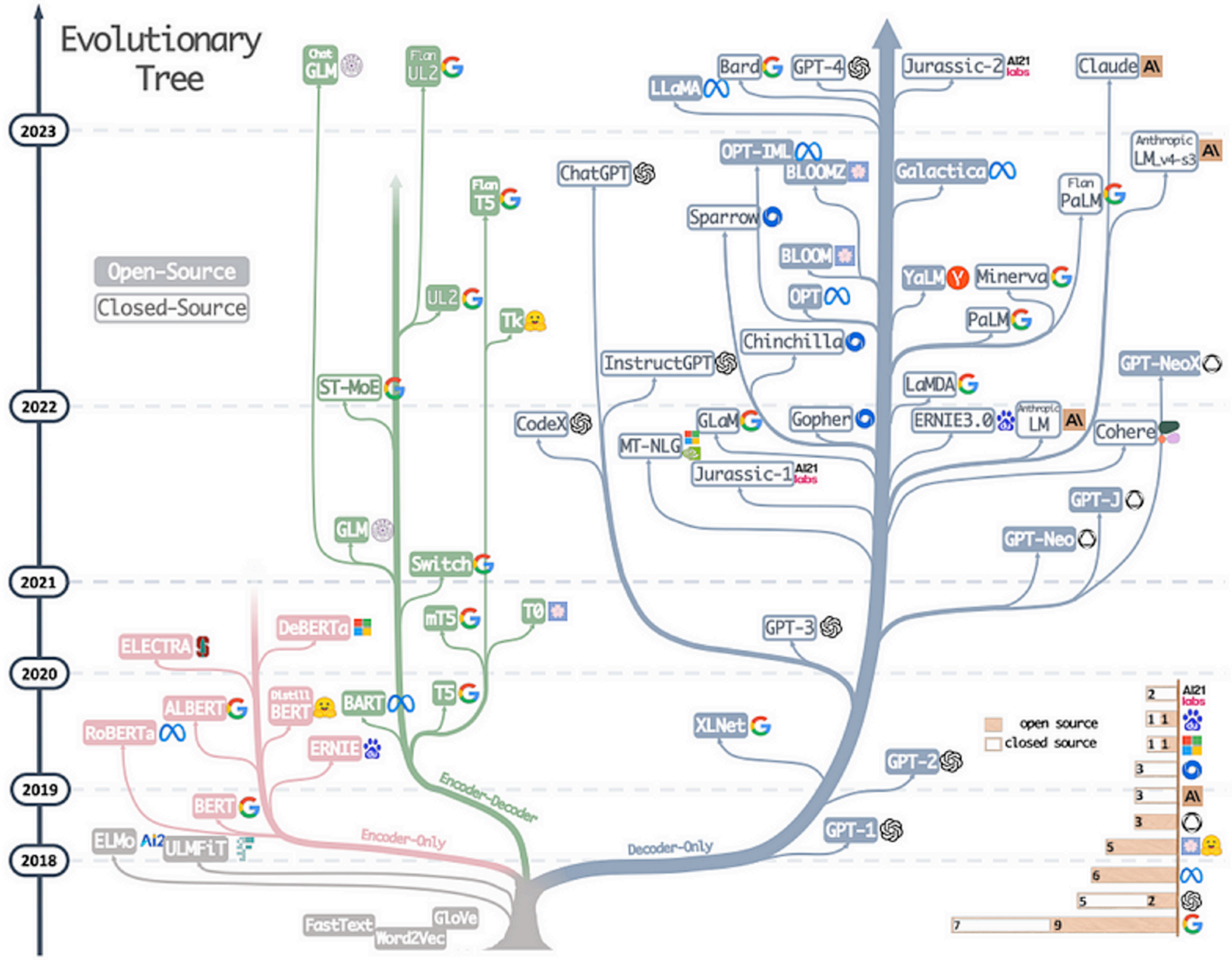

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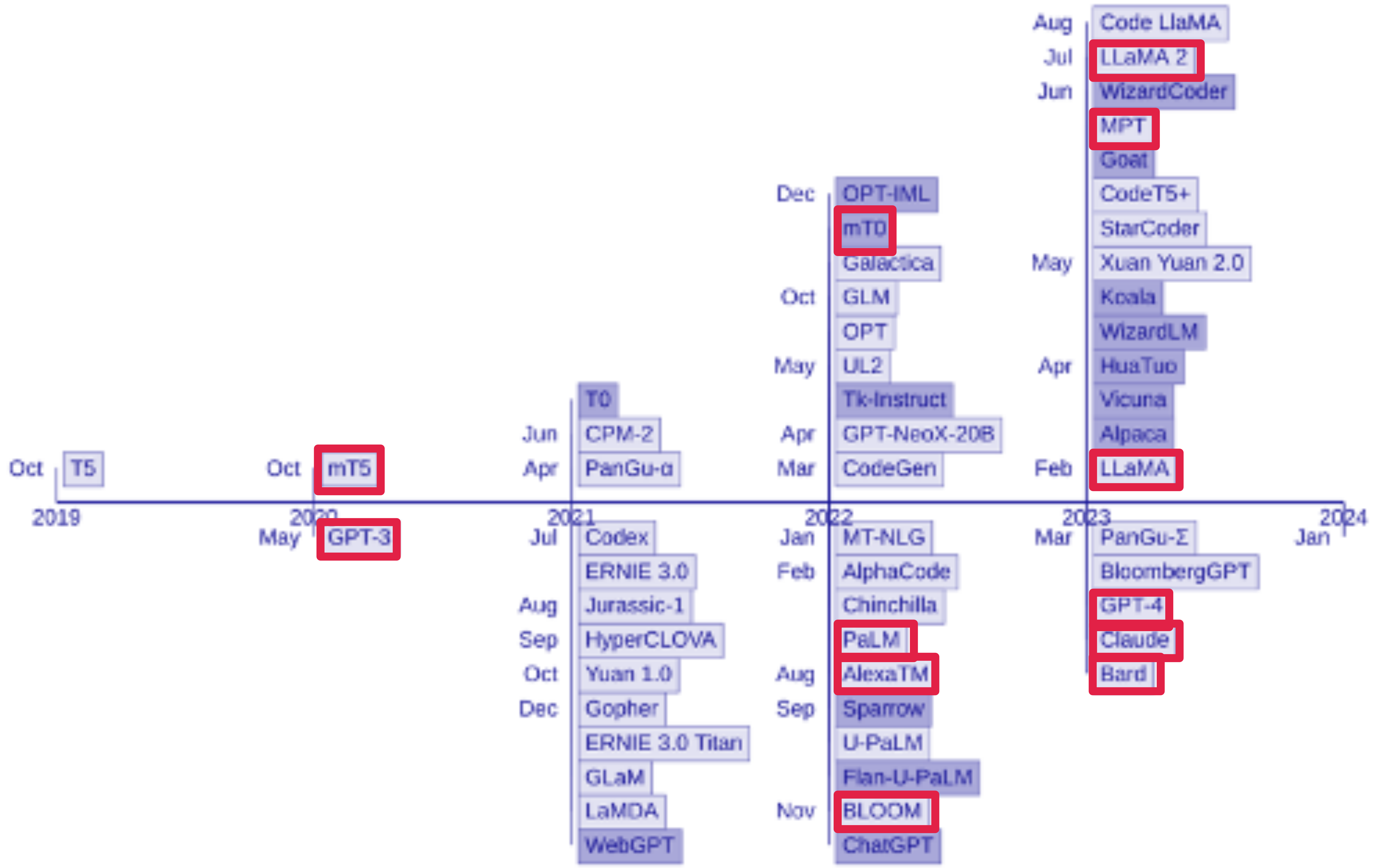

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This talk: multilingual (texts)

Multilingual LLMs: mLLMs

Learning parameters with large multilingual corpora, auxiliary tasks and natural annotations

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+ Complementary objectives to align languages

- parallel corpora (TLM loss, MT loss)
- bilingual dictionaries
- synthetic mixed-language data
- script normalization (romanization, transliteration)

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Using Multilingual LLMs

1. Fine-tune task-adapted models on L1 and process L2 with zero-shot model transfer

Only requires annotations in L1

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Translate into English

" By the end of the year, we will have seven new pharmacists. " :

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mLLMs are a blessing
- hardly more difficult than mLLMs
- excel in multilingual tasks
- enable X-lingual transfer

mLLMs need multilingual texts

_Tous _les _être s _humain s _na issent _libre s _et _ég aux _en _digni té _et _en _droits . _Ils _sont _do u és _de _raison _et _de _conscience _et _doivent _agir _les _uns _en vers _les _autres _dans _un _ esprit _de _frater n ité .

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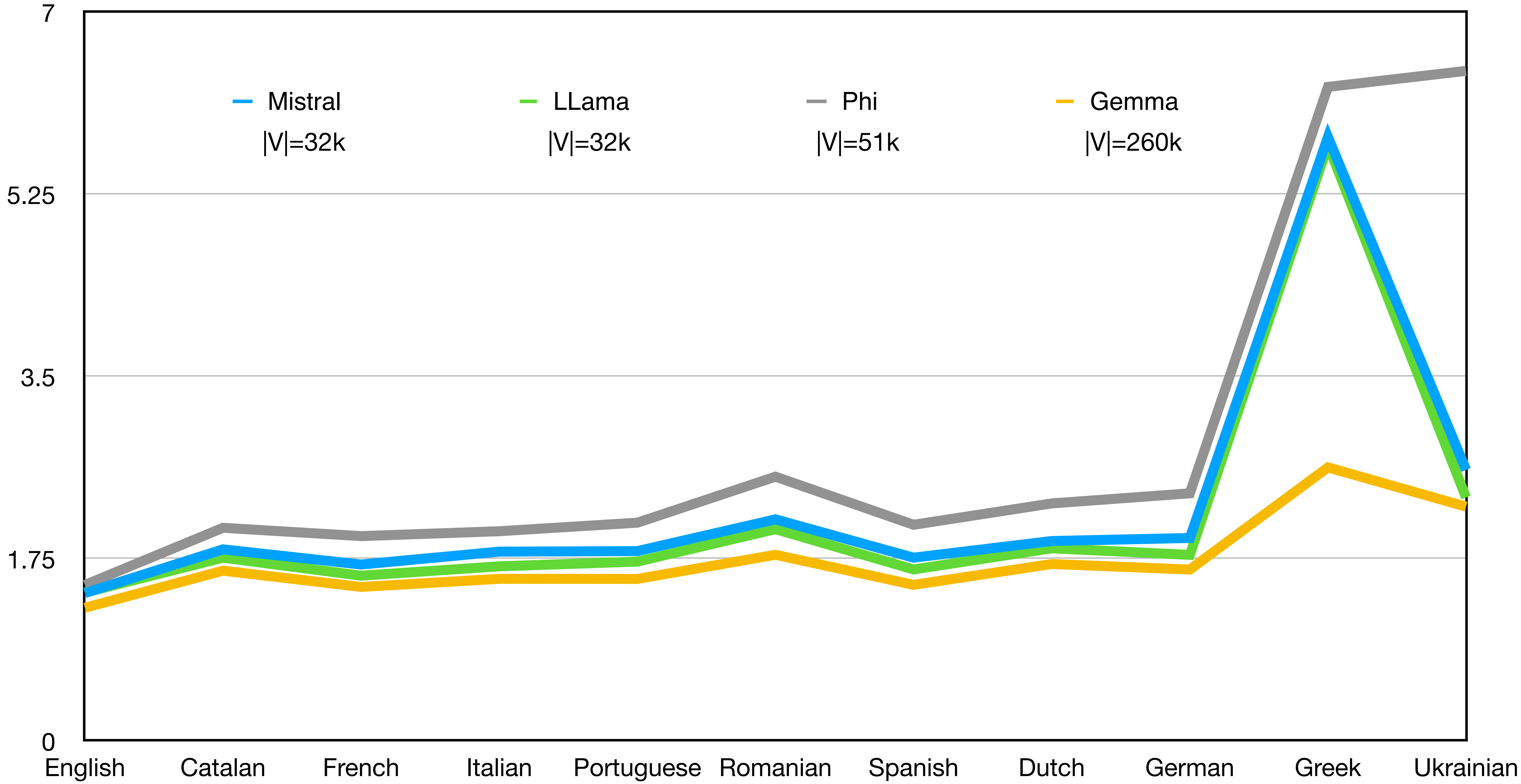
Subword tokenizers are trainable

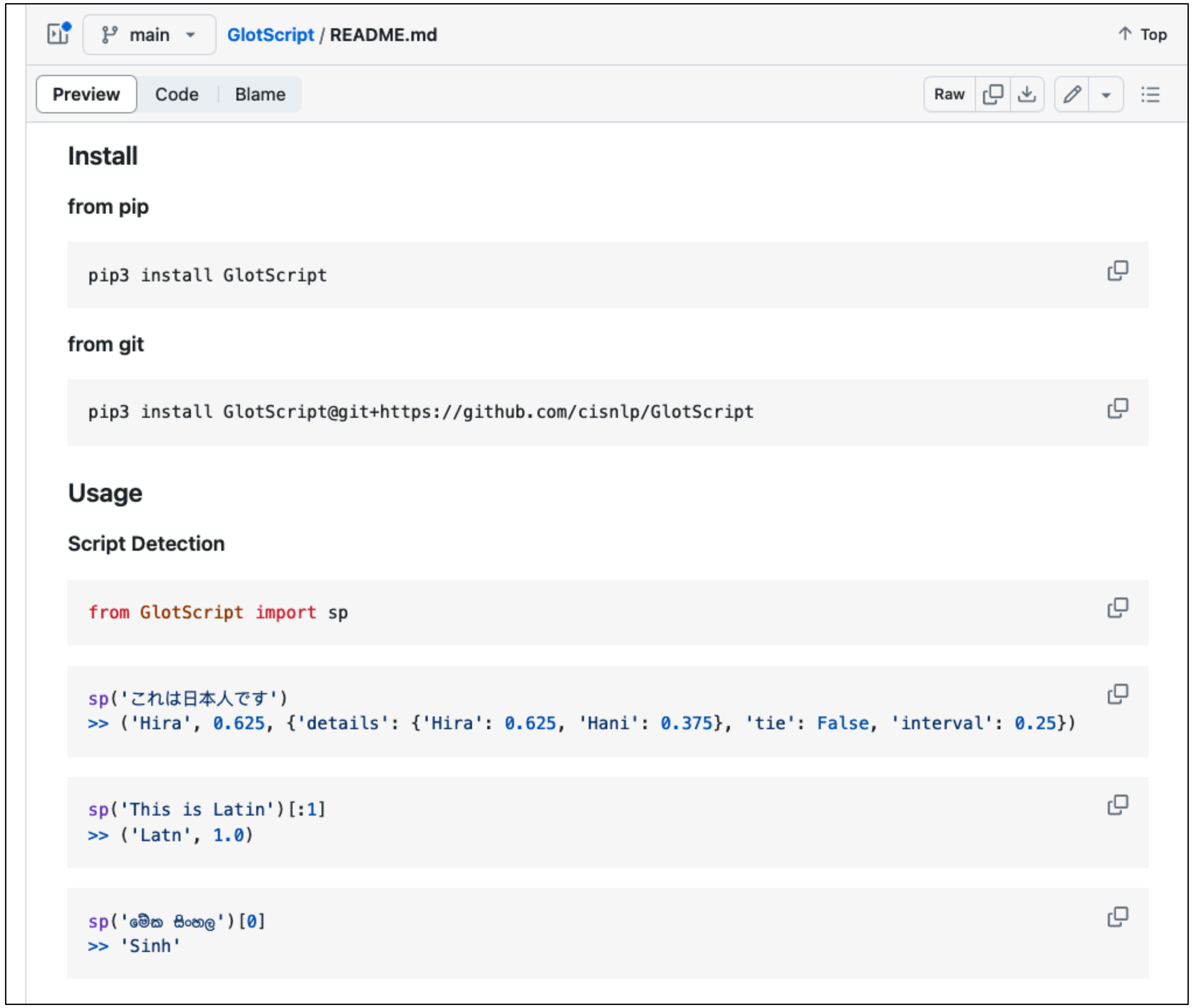
- require mixed-language, mixed-script training corpora
- parameter sharing for same-script languages
- larger language get more units, are better segmented, perform better

LMM tokenization: fertility



Tokenizer evaluation on European Langauges (Occiglot 2024)

Multilingualism in tokenizers


GlotScript / README.md

main

Top

Preview Code Blame

Raw

Install

from pip

```
pip3 install GlotScript
```

from git

```
pip3 install GlotScript@git+https://github.com/cisnlp/GlotScript
```

Usage

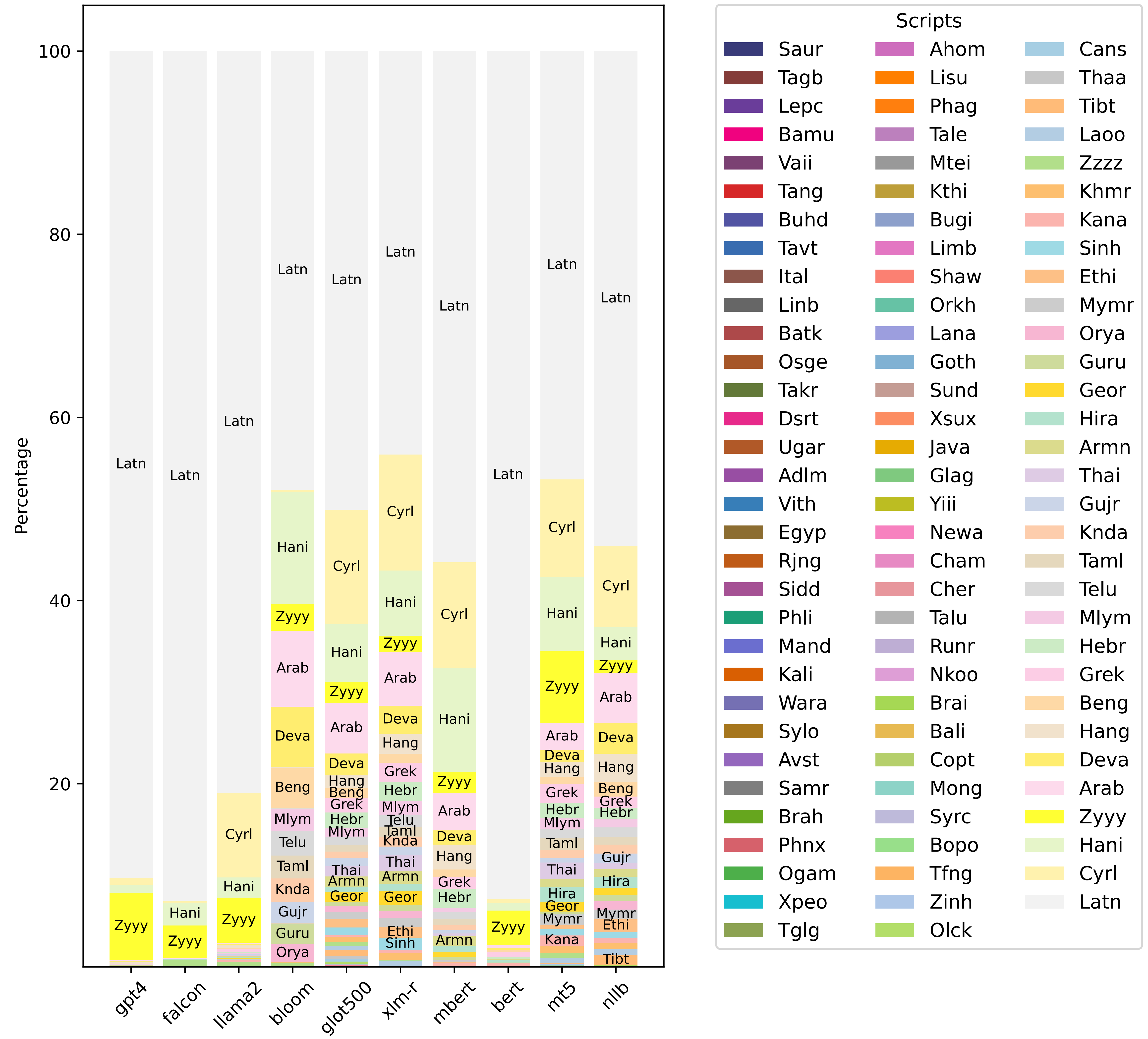
Script Detection

```
from GlotScript import sp
```

```
sp('これは日本人です')
>> ('Hira', 0.625, {'details': {'Hira': 0.625, 'Hani': 0.375}, 'tie': False, 'interval': 0.25})
```

```
sp('This is Latin')[:1]
>> ('Latn', 1.0)
```

```
sp('මෙක සිංහල')[0]
>> 'Sinh'
```



GlotScript: A Resource and Tool for Low Resource Writing System Identification (Kargaran et al, proc LREC COLING 2024)

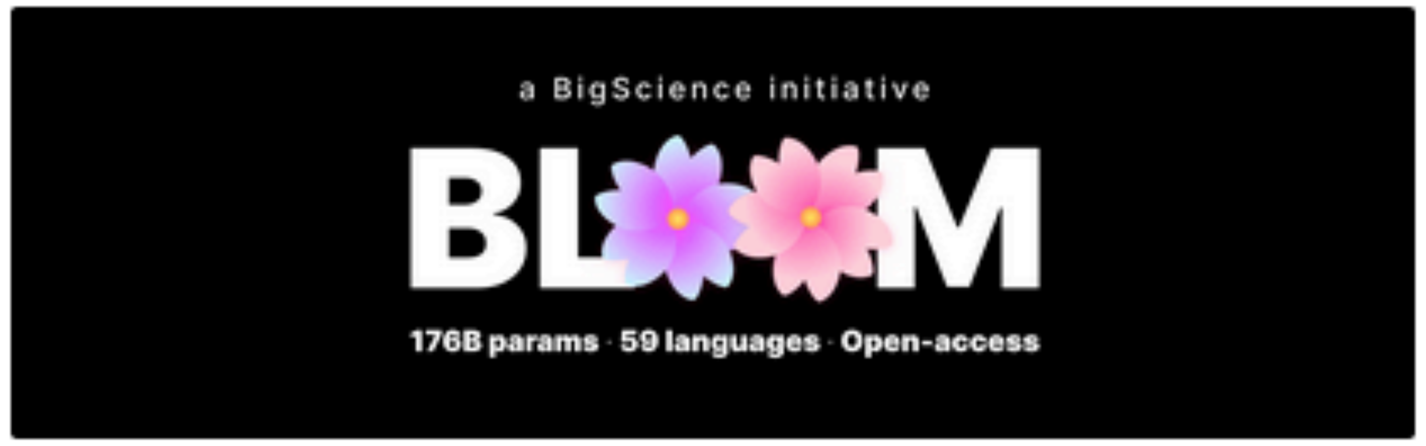
mLMMs: m = ?

Examining Model Cards

Exa… …ards

Model card | Files | Metrics | Community 276 | Settings

Edit model card



BigScience Large Open-science Open-access Multilingual Language Model
Version 1.3 / 6 July 2022

Current Checkpoint: **Training Iteration 95000**

Link to paper: here

Total seen tokens: **366B**

Model Details

BLOOM is an autoregressive Large Language Model (LLM), trained to continue text from a prompt on vast amounts of text data using industrial-scale computational resources. As such, it is able to output coherent text **in 46 languages** and 13 programming languages that is hardly distinguishable from text written by humans. BLOOM can also be instructed to perform text tasks it hasn't been explicitly trained for, by casting them as text generation tasks.

Multilingualism in LMMs

$m = 1$: monolingual LLMs

- ara: AraBERT, JASMINE, …
- eng: BERT, ELMO, GPT-2,T5, …
- fra: CamemBERT, BARThez, GPT-FR

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$m = 1 + \epsilon$: **‘almost’ monolingual LLMs**

- eng: OPT, Jurassic, Gopher, Chinchilla, Turing-NLG, Megatron-LM, Falcon, OLMO, Phi-2, …

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$m = 1 + 1$: **bilingual LLMs**

- eng+rus: YaLM
- eng+zho: GLM-130, PanGu, Baichuan
- eng+fra: CroissantLLM
- eng+ara: JAIS

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$m \in [5 : 25]$ **: 'familial' LLMs**

- Indic: IndicBERT (12), MuRIL (17)
- African: AfriBERTA (11), AfroXLM (17)
- Nordic: GPT-SW3 (5+1)
- European: Occiglot-v0 (5), Occiglot-v1 (24)

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$m \in [5:50]$ **: 'opportunistic' LMMs**

- Unicoder (15), VECO (50)
- PolyLM (20)
- mBART-25 (25)
- LLaMA, TowerLM (10), LLaMA-2 (20)
- BLOOM (46)
- Command+R (23)

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$m > [50]$ **: 'Massively Multilingual' LLMs**

- mBERT (104), remBERT (104), XLM-R (100), VECO-2.0 (109)
- GPT-3 (94), XGLM (114)
- PALM (100+)
- mT5 (100)
- *Aya* (101)

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- African: AfriBERTA (11), AfroXLM (17)
- Nordic: GPT-SW3 (5+1)
- European: Occiglot-v0 (5), Occiglot-v1 (24)

$m \gg 100$: **'Extremely Multilingual' LMMs**

- Serengeti (517)
- MadLad-400 (419)
- Glot500-m (511)
- MALA500 (534)

Multingualism in LMMs

$m \in [5:50]$: **'opportunistic' LMMs**
- Unicoder (15), VECO (50)
- PolyLM (20)
- mBART-25 (25)
- LLaMA, TowerLM (10), LLaMA-2 (20)
- BLOOM (46)
- Command+R (23)

$m > [50]$: **'Massively Multilingual' LLMs**
- mBERT (104), remBERT (104), XLM-R (100), VECO-2.0 (109)
- GPT-3 (94), XGLM (114)
- PALM (100+)
- mT5 (100)
- *Aya* (101)

$m > 0$: **'Vaguely documented' LMMs**
- Mistral
- ChatGPT
- Claude
- … and many more

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- Glot500-m (511)
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Going Beyond Language counts

Language distributions in mLLMs

Comparing published statistics is *hard*

- variability in language / variety names (and scripts)
- errors in LID
- units of measures (tokens vs. bytes vs. #docs)
- corpus building details (genre matters)
- language sampling details

When the information is even given…

Only correct solution: go back to data (if possible)… and count

[A Survey on Multilingual Large Language Models: Corpora, Alignment, and Bias (Xu et al, 2024)]

Glot500: design choices

1. Select reliable sources

- curated multilingual corpora
- new data crawls
- multiple domains: web, news, science, religion, etc
- excludes toxicity by design

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- normal / special char ratios
- insufficient number of words
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4. Final selection = Glot500-c

- > 30k sentences
- from 2000+ to 511 language / 34 scripts
- 610Gb of text 1.5b sentences
- head vs. tail languages
- 1000 dev+test sentences / language

Glot500-c: m = 511 languages

100 “head”
411 ‘’tail”

Language-Script	|Sent|	Family	Head	Language-Script	|Sent|	Family	Head	Language-Script	|Sent|	Family	Head
hbs_Latn	63411156	indo1319		vec_Latn	514240	indo1319		swh_Latn	95776	atla1278	yes
mal_Mlym	48098273	drav1251	yes	jpn_Jpan	510722	japo1237	yes	alt_Cyrl	95148	turk1311	
aze_Latn	46300705		yes	lus_Latn	509250	sino1245		rmn_Grek	94533	indo1319	
guj_Gujr	45738685	indo1319	yes	crs_Latn	508755	indo1319		miq_Latn	94343	misu1242	
ben_Beng	43514870	indo1319	yes	kqn_Latn	507913	atla1278		kaa_Cyrl	88815	turk1311	
kan_Knda	41836495	drav1251	yes	ndo_Latn	496613	atla1278		kos_Latn	88603	aust1307	
tel_Telu	41580525	drav1251	yes	snd_Arab	488730	indo1319	yes	grn_Latn	87568		
mlt_Latn	40654838	afro1255		yue_Hani	484700	sino1245		lhu_Latn	87255	sino1245	
fra_Latn	39197581	indo1319	yes	tiv_Latn	483064	atla1278		lzh_Hani	86035	sino1245	
spa_Latn	37286756	indo1319	yes	kua_Latn	473535	atla1278		ajp_Arab	83297	afro1255	
eng_Latn	36122761	indo1319	yes	kwy_Latn	473274	atla1278		cmn_Hani	80745	sino1245	yes
fil_Latn	33493255	aust1307	yes	hin_Latn	466175	indo1319		gcf_Latn	80737	indo1319	
nob_Latn	32869205	indo1319		iku_Cans	465011			rmn_Cyrl	79925	indo1319	
rus_Cyrl	31787973	indo1319	yes	kal_Latn	462430	eski1264		kjh_Cyrl	79262	turk1311	
deu_Latn	31015993	indo1319	yes	tdt_Latn	459818	aust1307		rng_Latn	78177	atla1278	
tur_Latn	29184662	turk1311	yes	gsw_Latn	449240	indo1319		mgh_Latn	78117	atla1278	
pan_Guru	29052537	indo1319	yes	mfe_Latn	447435	indo1319		xmv_Latn	77896	aust1307	
mar_Deva	28748897	indo1319	yes	swc_Latn	446378	atla1278		ige_Latn	77114	atla1278	
por_Latn	27824391	indo1319	yes	mon_Latn	437950	mong1349		rmy_Latn	76991	indo1319	
nld_Latn	25061426	indo1319	yes	mos_Latn	437666	atla1278		srm_Latn	76884	indo1319	
ara_Arab	24524122		yes	kik_Latn	437228	atla1278		bak_Latn	76809	turk1311	
zho_Hani	24143786		yes	cnh_Latn	436667	sino1245		gur_Latn	76151	atla1278	
ita_Latn	23539857	indo1319	yes	gil_Latn	434529	aust1307		idu_Latn	75106	atla1278	
ind_Latn	23018106	aust1307	yes	pon_Latn	434522	aust1307		yom_Latn	74818	atla1278	
ell_Grek	22033282	indo1319	yes	umb_Latn	431589	atla1278		tdx_Latn	74430	aust1307	
bul_Cyrl	21823004	indo1319	yes	lvs_Latn	422952	indo1319		mzn_Arab	73719	indo1319	
swe_Latn	20725883	indo1319	yes	sco_Latn	411591	indo1319		cfm_Latn	70227	sino1245	
ces_Latn	20376340	indo1319	yes	ori_Orya	410827		yes	zpa_Latn	69237	otom1299	
isl_Latn	19547941	indo1319	yes	arg_Latn	410683	indo1319		kbd_Cyrl	67914	abkh1242	
pol_Latn	19339945	indo1319	yes	kur_Latn	407169	indo1319	yes	lao_Laoo	66966	taik1256	yes
ron_Latn	19190217	indo1319	yes	dhv_Latn	405711	aust1307		nap_Latn	65826	indo1319	
dan_Latn	19174573	indo1319	yes	luo_Latn	398974	nilo1247		qub_Latn	64973	quec1387	

Usual suspects
Minority script
Minority variety
Minority language

Glot500-c: m = 511 languages

100 “head”
411 ‘’tail”

Language-Script	|Sent|	Family	Head	Language-Script	|Sent|	Family	Head	Language-Script	|Sent|	Family	Head
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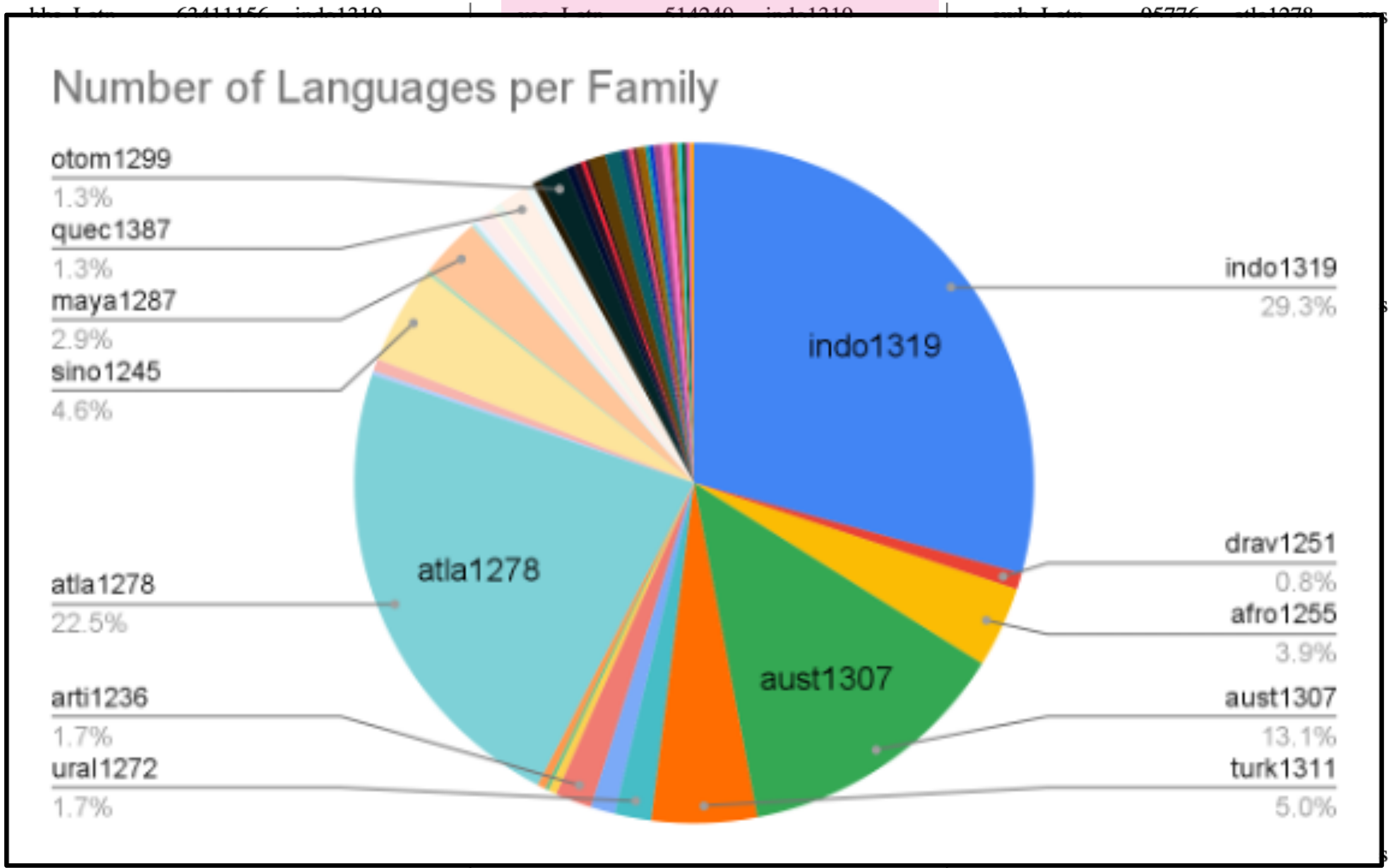

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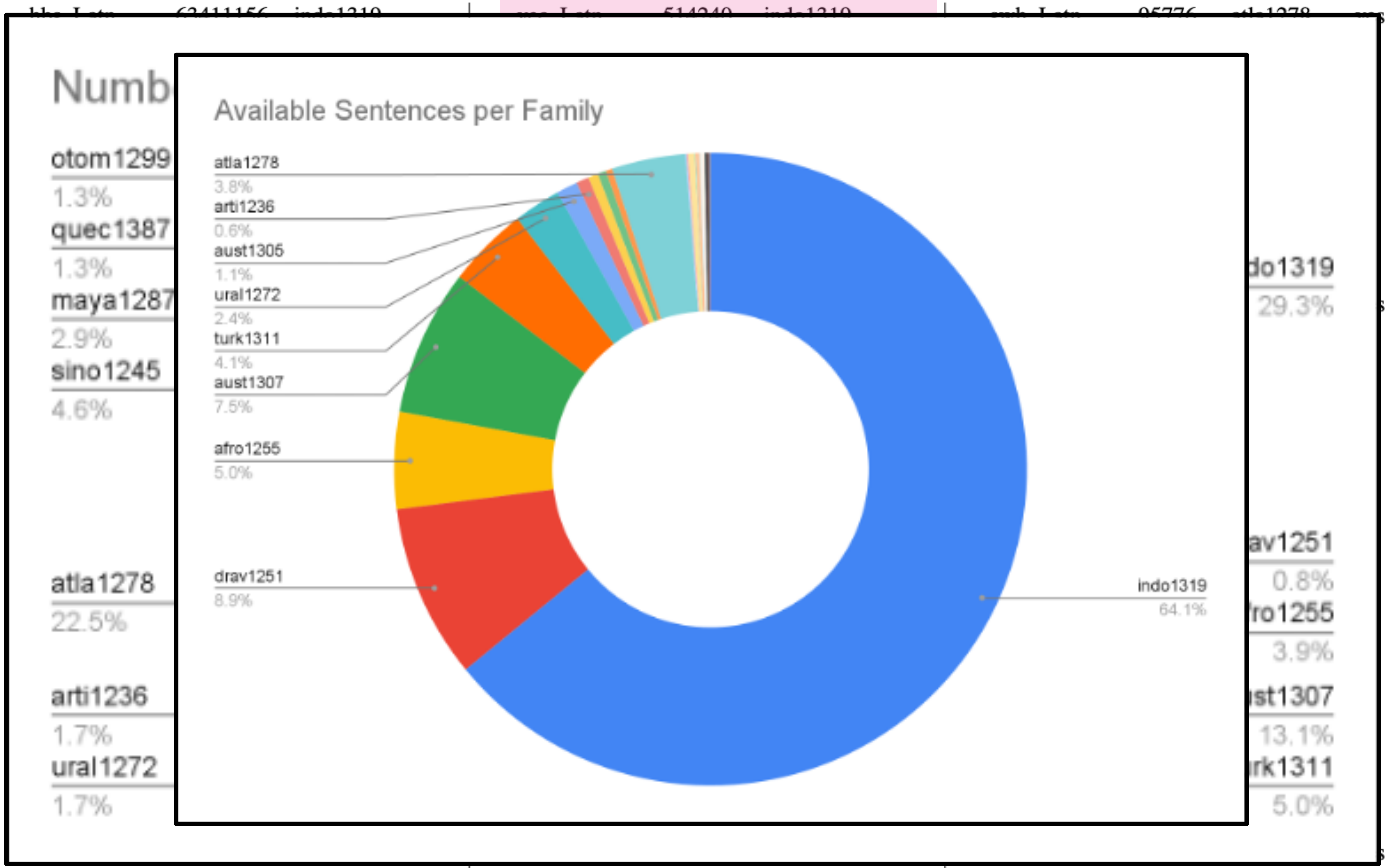

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Language ID is key

2. Language Identification

- per sentence LID
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Is this reliable ? Will it scale ?
Also domains ? genres ?

Auditing data with GlotScript

		Corpus Code: ISO 639-3	Scripts	ACC↑	ACC70↑	ACC50↑
Highest ACC	mC4	st:sot (S Sotho)	Latn:1000	**1.000**	**1.000**	**1.000**
		fil:fil (Filipino)	Latn:998, Cyrl:1, Hani:1	0.998	0.999	**1.000**
		ro:ron (Romanian)	Latn:996, Zyyy:4, Cyrl:1	0.995	0.997	**1.000**
		id:ind (Indonesian)	Latn:995, Zyyy:3, Hani:1, Hebr:1	0.995	**1.000**	**1.000**
		sw:swa (Swahili)	Latn:995, Zyyy:5	0.995	**1.000**	**1.000**
Lowest ACC		ne:nep (Nepali)	Deva:609, Hani:219, Latn:88, Hang:44, Thai:12, Laoo:8, Zyyy:8, Orya:7, Other:5	0.609	0.730	**0.797**
		mn:mon (Mongolian)	Cyrl:502, Hebr:348, Latn:135, Zyyy:14, Hani:1	0.502	0.557	**0.570**
		cy:cym (Welsh)	Grek:603, Latn:367, Zyyy:11, Hebr:9, Cyrl:5, Zzzz:4, Arab:1	**0.367**	0.338	0.295
		sd:snd (Sindhi)	Latn:654, Arab:329, Zyyy:12, Zzzz:2, Cyrl:1, Hang:1, Telu:1	**0.329**	0.271	0.222
		mr:mar (Marathi)	Hani:454, Thai:252, Latn:119, Deva:116, Zyyy:34, Guru:10, Beng:4, Khmr:3, Other: 8	0.116	0.136	**0.141**
Highest ACC	OSCAR	id:ind (Indonesian)	Latn:998, Zyyy:2	0.998	**1.000**	**1.000**
		war:war (Waray)	Latn:997, Zyyy:3	**0.997**	**0.997**	0.996
		als:gsw (Swiss G)	Latn:996, Zyyy:3, Cyrl:1	0.996	0.996	**1.000**
		vo:vol (Volapük)	Latn:994, Arab:4, Cyrl:1	0.994	**1.000**	**1.000**
		nds:nds (Low G)	Latn:994, Zyyy:2, Cyrl:2, Hang:1, Thaa:1	0.994	**1.000**	**1.000**
Lowest ACC		am:amh (Amharic)	Ethi:822, Latn:164, Zyyy:12, Hani:1, Arab:1	0.822	0.883	**0.940**
		gu:guj (Gujarati)	Gujr:802, Latn:180, Zyyy:12, Deva:6	0.802	0.863	**0.883**
		si:sin (Sinhala)	Sinh:801, Latn:188, Zyyy:11	0.801	0.905	**0.948**
		th:tha (Thai)	Thai:800, Latn:181, Zyyy:18, Hani:1	0.800	0.883	**0.917**
		te:tel (Telugu)	Telu:799, Latn:188, Zyyy:9, Deva:3, Cyrl:1	0.799	0.880	**0.908**

Script-languages mismatches detection finds many errors

Language Identification at scale

Existing tools are limited

Fastext LID	176
Compact Langage Detector	107
whatlang	69
OpenLID	200
franc-s	82
franc-m	187
franc-l	417

Quality at a Glance: An Audit of Web-Crawled Multilingual Datasets (Kreutzer et al, 2022),

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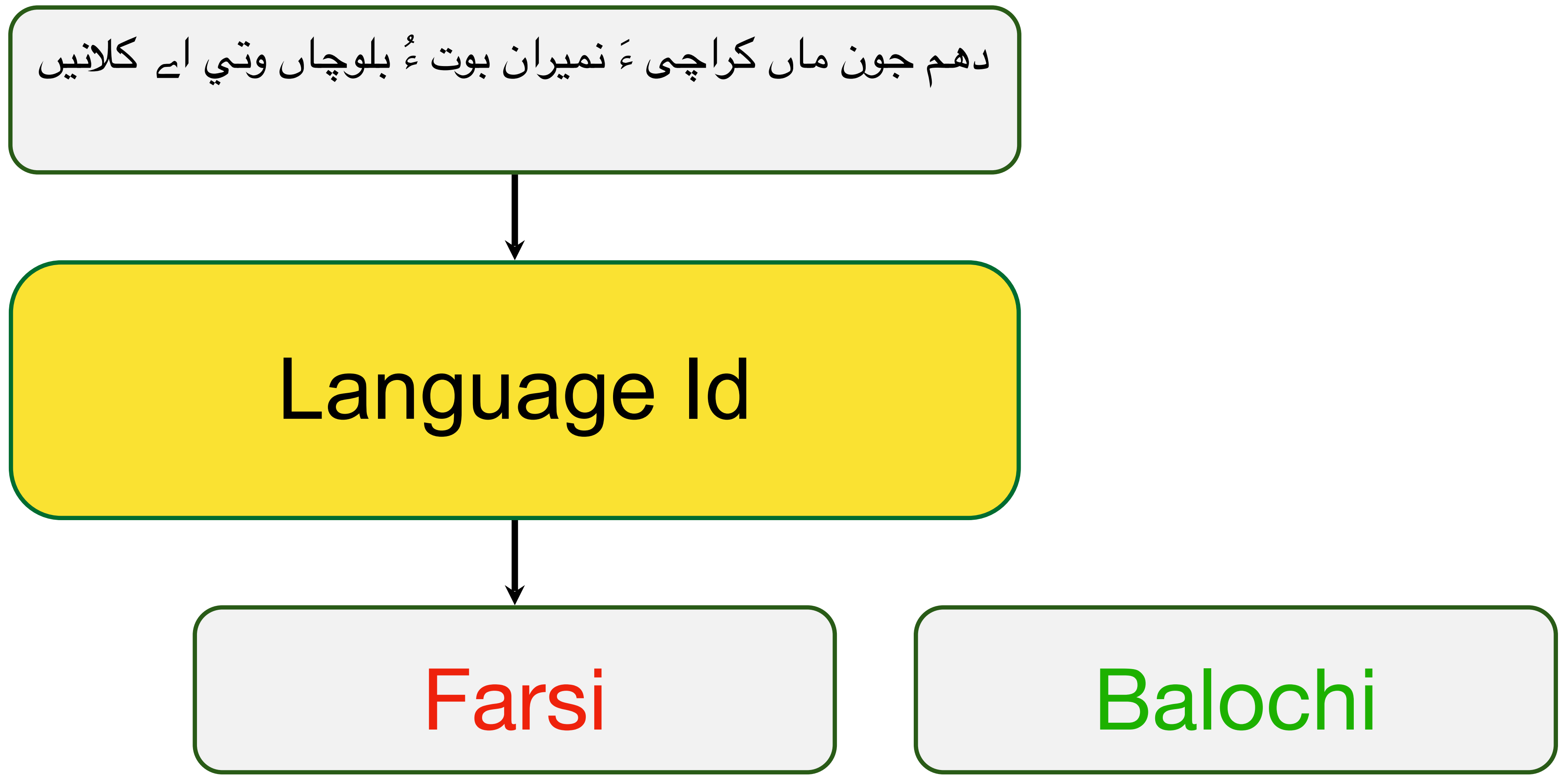

« out-of-model cousin error »

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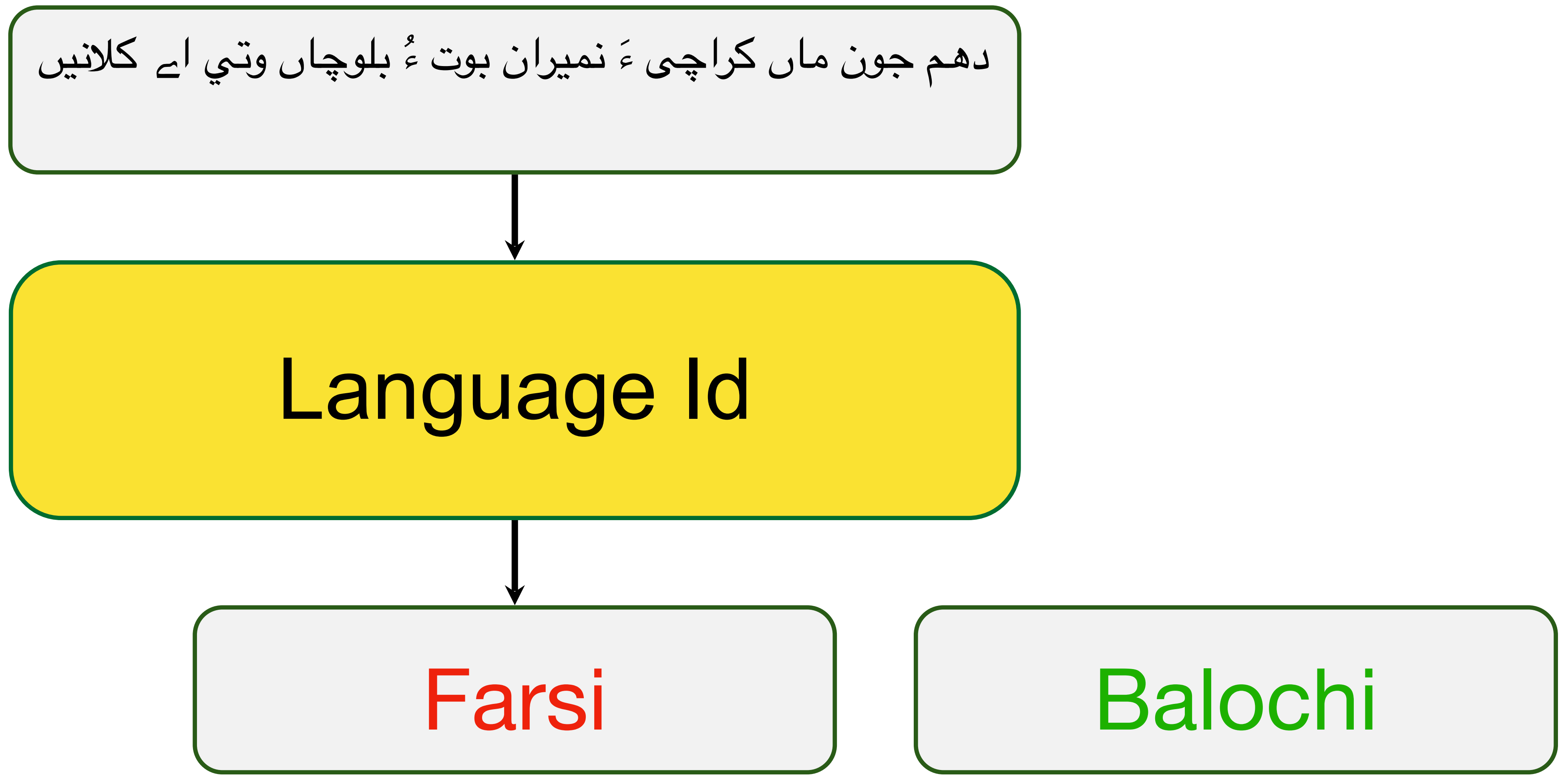
Other issues

- speed
- implementation / deployment
- lack of openness
- lack of documentation
- lack confidence estimation
- lack of rejection model
- **errors**



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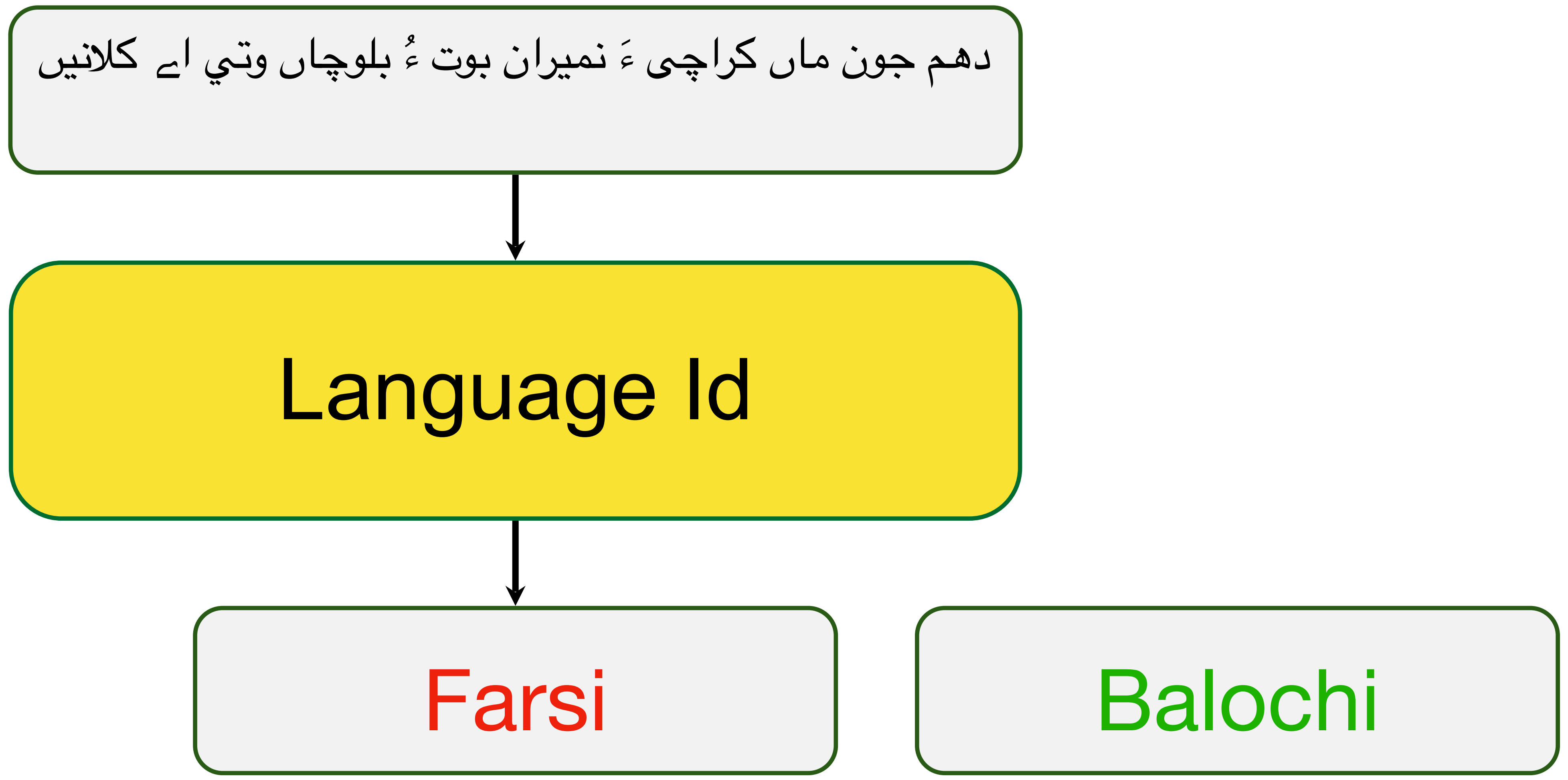


« out-of-model cousin error »

Quality at a Glance: An Audit of Web-Crawled Multilingual Datasets (Kreutzer et al, 2022),

Designing your own

- selecting / naming languages
- curating corpora
- the language mix, again

Training and testing GlotLID

Train corpus (V1.0)

- >1800+ languages scripts
- multiple reliable sources
- mixture of domains:
  - Wikipedia
  - religious texts
  - collaborative translations
  - academia
  - storybooks
  - news sites

Implementation: FastText

- linear classifier
- char & word n-gram features
- highly optimized for speed (training and inference)
- use with a pinch of salt

Bag of Tricks for Efficient Text Classification (Joulin et al., EACL 2017)

Test data

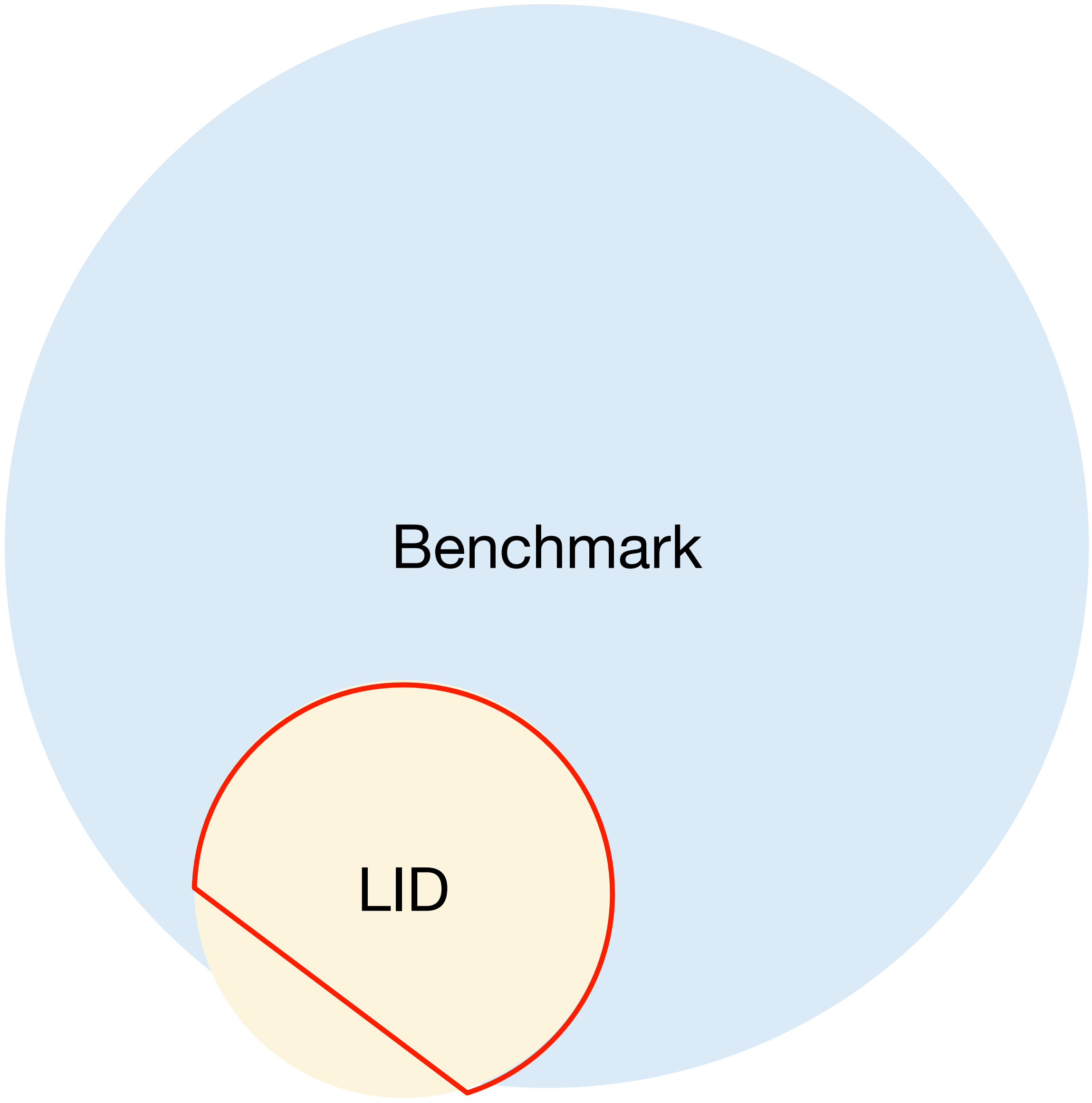
- GlotLID-c (testset) (1800+)
- Universal Declaration of Human Rights (UDHR) (204)
- Flores 200

Language verification

Closed set assumption

- set of possible languages known (differs for each baseline)

		FLORES-200								UDHR							
		CLD3		FT176		OpenLID		NLLB		CLD3		FT176		OpenLID		NLLB	
		$\lvert L\rvert = 96$		$\lvert L\rvert = 108$		$\lvert L\rvert = 195$		$\lvert L\rvert = 188$		$\lvert L\rvert = 100$		$\lvert L\rvert = 124$		$\lvert L\rvert = 159$		$\lvert L\rvert = 172$	
LID Model	$\boldsymbol{\theta}$	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**
baselines	.0	.952	**.0104**	.881	**.0093**	**.923**	**.0051**	.950	**.0053**	.922	.0101	.739	**.0081**	.881	**.0063**	.854	**.0058**
GlotLID-M	.0	**.983**	**.0104**	**.991**	**.0093**	.922	**.0051**	**.954**	**.0053**	**.952**	**.0100**	**.927**	**.0081**	**.926**	.0064	**.925**	.0060



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		CLD3 $\lvert L\rvert = 96$		**FT176** $\lvert L\rvert = 108$		**OpenLID** $\lvert L\rvert = 195$		**NLLB** $\lvert L\rvert = 188$		**CLD3** $\lvert L\rvert = 100$		**FT176** $\lvert L\rvert = 124$		**OpenLID** $\lvert L\rvert = 159$		**NLLB** $\lvert L\rvert = 172$	
LID Model	$\boldsymbol{\theta}$	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**
baselines	.0	.952	**.0104**	.881	**.0093**	**.923**	**.0051**	.950	**.0053**	.922	.0101	.739	**.0081**	.881	**.0063**	.854	**.0058**
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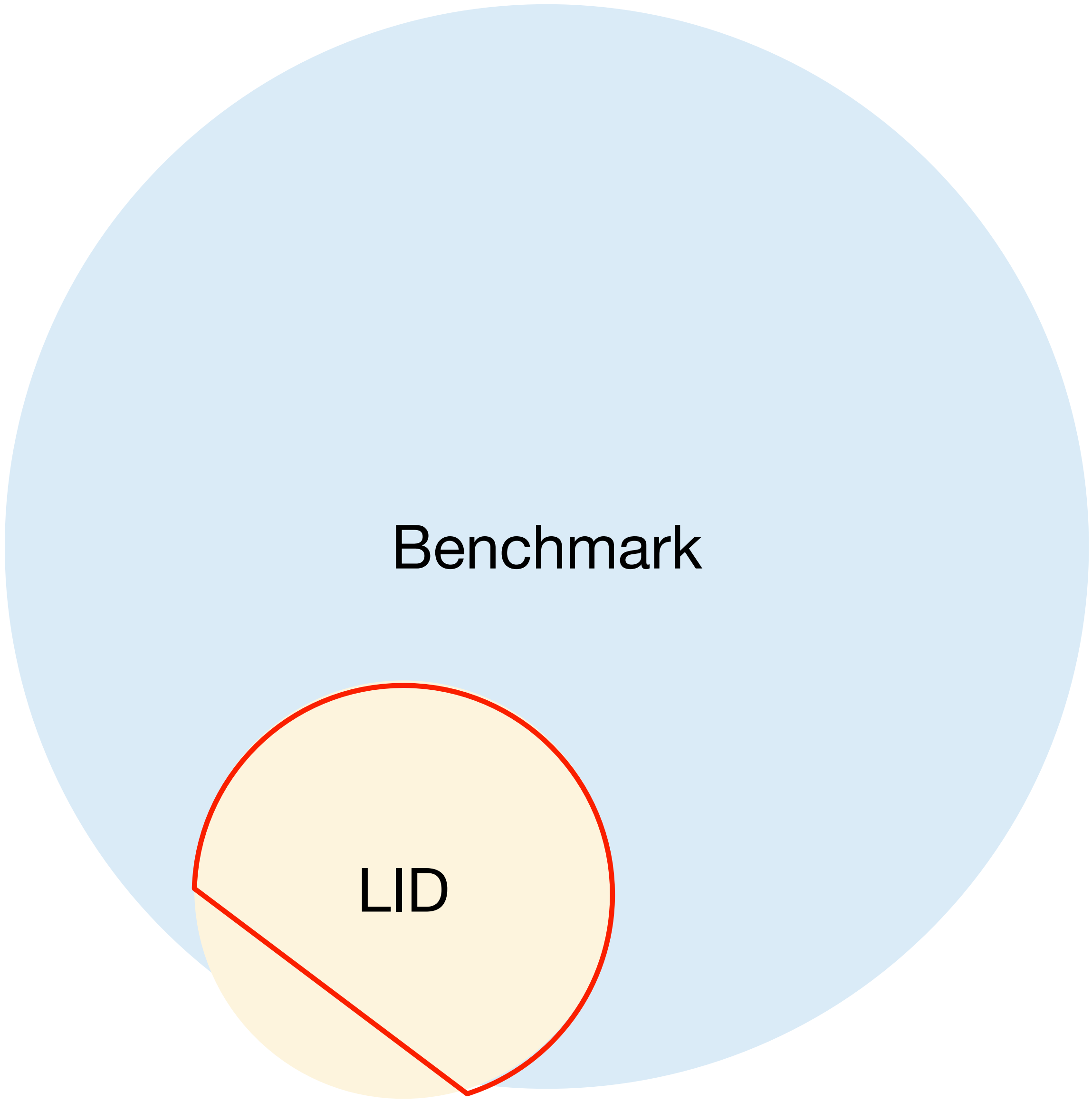


Corpus building for low-resource languages

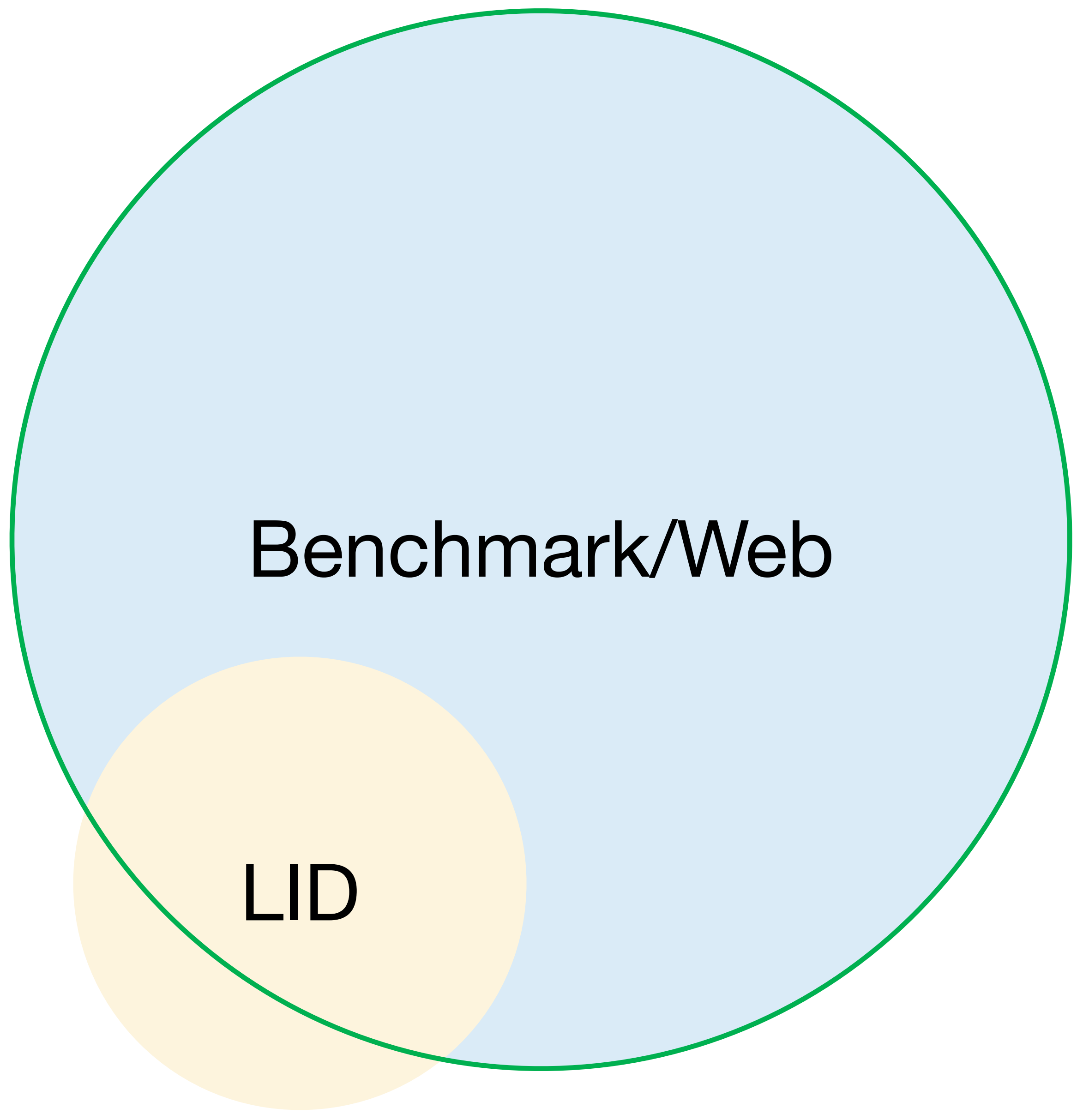
- Negatives >> Positives
- FPR matters
- F1 not important for HR

Evaluating GlotLID

Open set assumption : a realistic setting

- set of possible languages is unknown
- rejection matters

			- rejection		+ rejection	
			GlotLID-M, θ=.0		GlotLID-M, θ=.5	
Benchmark		$\|L\|$	**F1↑**	**FPR↓**	**F1↑**	**FPR↓**
GlotLID-C	all	1832	.940	.0005	.938	.0003
GlotLID-C	subset	1665	.977	.0003	.973	.0002
UDHR	all	374	.750	.0015	.734	.0007
UDHR	subset	342	.784	.0014	.770	.0006
FLORES-200	all	196	.917	.0042	.887	.0013
FLORES-200	subset	177	.957	.0029	.924	.0010



Language Identification unsolved

	FLORES-200						UDHR					
	language	FP	cl	top FP source	#FP	%	language	FP	cl	top FP source	#FP	%
most errors	arb:St Arabic	3787	.18	ars:Najdi Arabi	829	.22	cmn:Mandarin Ch	596	.38	chr:Cherokee	81	.14
	arz:Egyptian Ar	1726	.32	apc:Levantine A	440	.25	qub:Huallaga Hu	247	.00	qvh:Huamalíes-D	55	.22
	pes:Ir. Persian	1495	.40	prs:Dari	905	.61	fin:Finnish	224	.22	krl:Karelian	138	.62
	cmn:Mandarin Ch	1008	.00	yue:Yue Chinese	1008	.99	wuu:Wu Chinese	172	.24	hak:Hakka Chine	44	.26
	hin:Hindi	977	.51	awa:Awadhi	693	.71	rus:Russian	157	.28	niv:Gilyak	44	.28
most noisy	arb:St Arabic	3787	.18	ars:Najdi Arabi	829	.22	evn:Evenki	36	.23	oaa:Orok	19	.53
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	prs:Dari	338	.24	pbt:S Pashto	310	.92	hrv:Croatian	84	.42	bos:Bosnian	39	.46
	dyu:Dyula	255	.25	bam:Bambara	255	.99	tzm:C Atlas Tam	52	.02	zgh:St Moroccan	52	.99
	apc:Levantine A	161	.42	ajp:S Levantine	70	.43	uzn:N Uzbek	72	.46	cbu:Candoshi-Sh	16	.22

Kargaran et al 2023: https://arxiv.org/abs/2310.16248

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	pes:Ir. Persian	1495	.40	prs:Dari	905	.61	fin:Finnish	224	.22	krl:Karelian	138	.62
	cmn:Mandarin Ch	1008	.00	yue:Yue Chinese	1008	.99	wuu:Wu Chinese	172	.24	hak:Hakka Chine	44	.26
	hin:Hindi	977	.51	awa:Awadhi	693	.71	rus:Russian	157	.28	niv:Gilyak	44	.28
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	prs:Dari	338	.24	pbt:S Pashto	310	.92	hrv:Croatian	84	.42	bos:Bosnian	39	.46
	dyu:Dyula	255	.25	bam:Bambara	255	.99	tzm:C Atlas Tam	52	.02	zgh:St Moroccan	52	.99
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New issues

- more realistic data (register, domains, etc)
- code-mixed inputs
- improved calibration

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most errors	arb:St Arabic	3787	.18	ars:Najdi Arabi	829	.22	cmn:Mandarin Ch	596	.38	chr:Cherokee	81	.14
	arz:Egyptian Ar	1726	.32	apc:Levantine A	440	.25	qub:Huallaga Hu	247	.00	qvh:Huamalíes-D	55	.22
	pes:Ir. Persian	1495	.40	prs:Dari	905	.61	fin:Finnish	224	.22	krl:Karelian	138	.62
	cmn:Mandarin Ch	1008	.00	yue:Yue Chinese	1008	.99	wuu:Wu Chinese	172	.24	hak:Hakka Chine	44	.26
	hin:Hindi	977	.51	awa:Awadhi	693	.71	rus:Russian	157	.28	niv:Gilyak	44	.28
most noisy	arb:St Arabic	3787	.18	ars:Najdi Arabi	829	.22	evn:Evenki	36	.23	oaa:Orok	19	.53
	arz:Egyptian Ar	1726	.32	apc:Levantine A	440	.25	quz:Cusco Quech	82	.40	qxu:Arequipa-La	61	.74
	prs:Dari	338	.24	pbt:S Pashto	310	.92	hrv:Croatian	84	.42	bos:Bosnian	39	.46
	dyu:Dyula	255	.25	bam:Bambara	255	.99	tzm:C Atlas Tam	52	.02	zgh:St Moroccan	52	.99
	apc:Levantine A	161	.42	ajp:S Levantine	70	.43	uzn:N Uzbek	72	.46	cbu:Candoshi-Sh	16	.22

Kargaran et al 2023: https://arxiv.org/abs/2310.16248

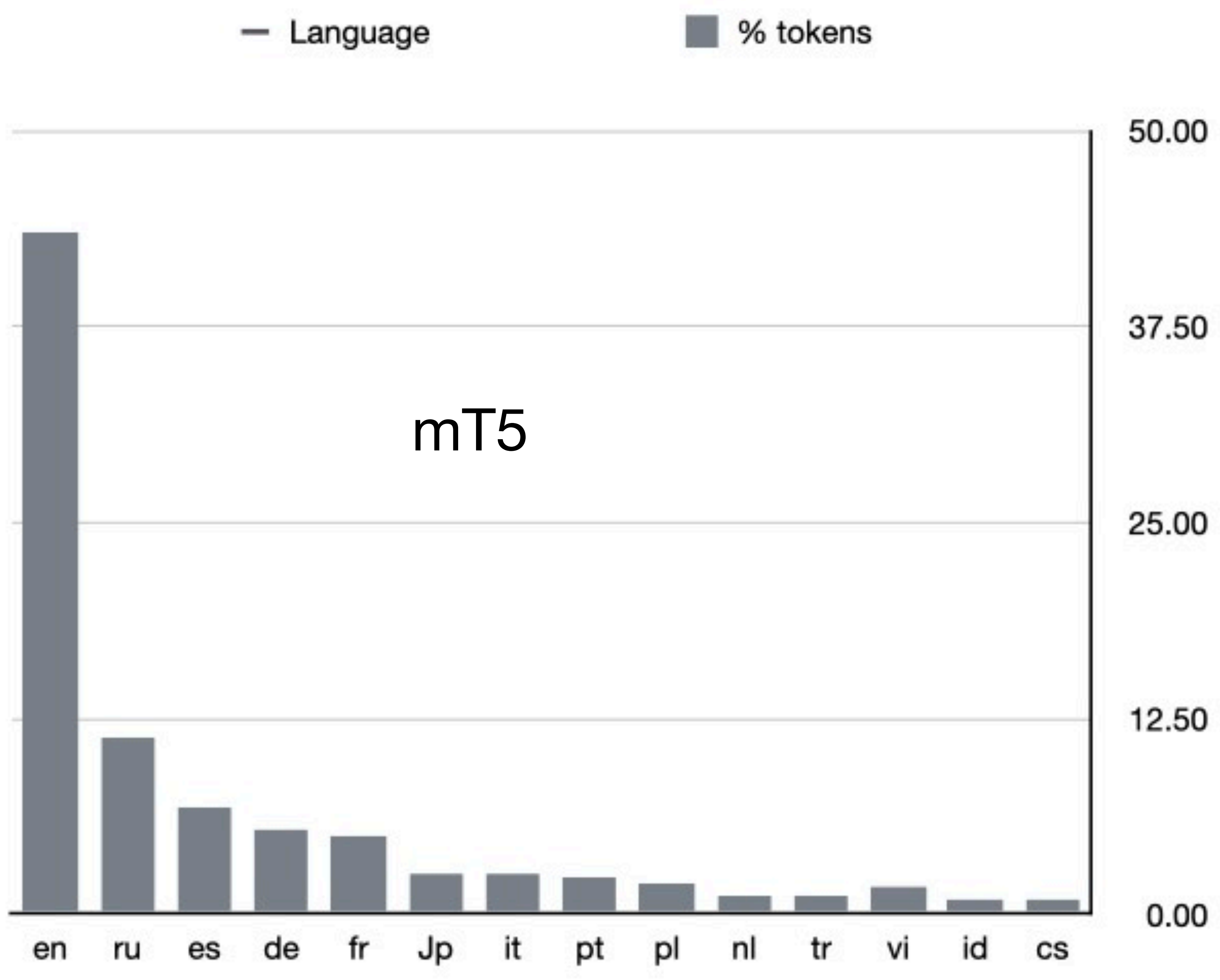
https://huggingface.co/spaces/cis-lmu/glotlid-space

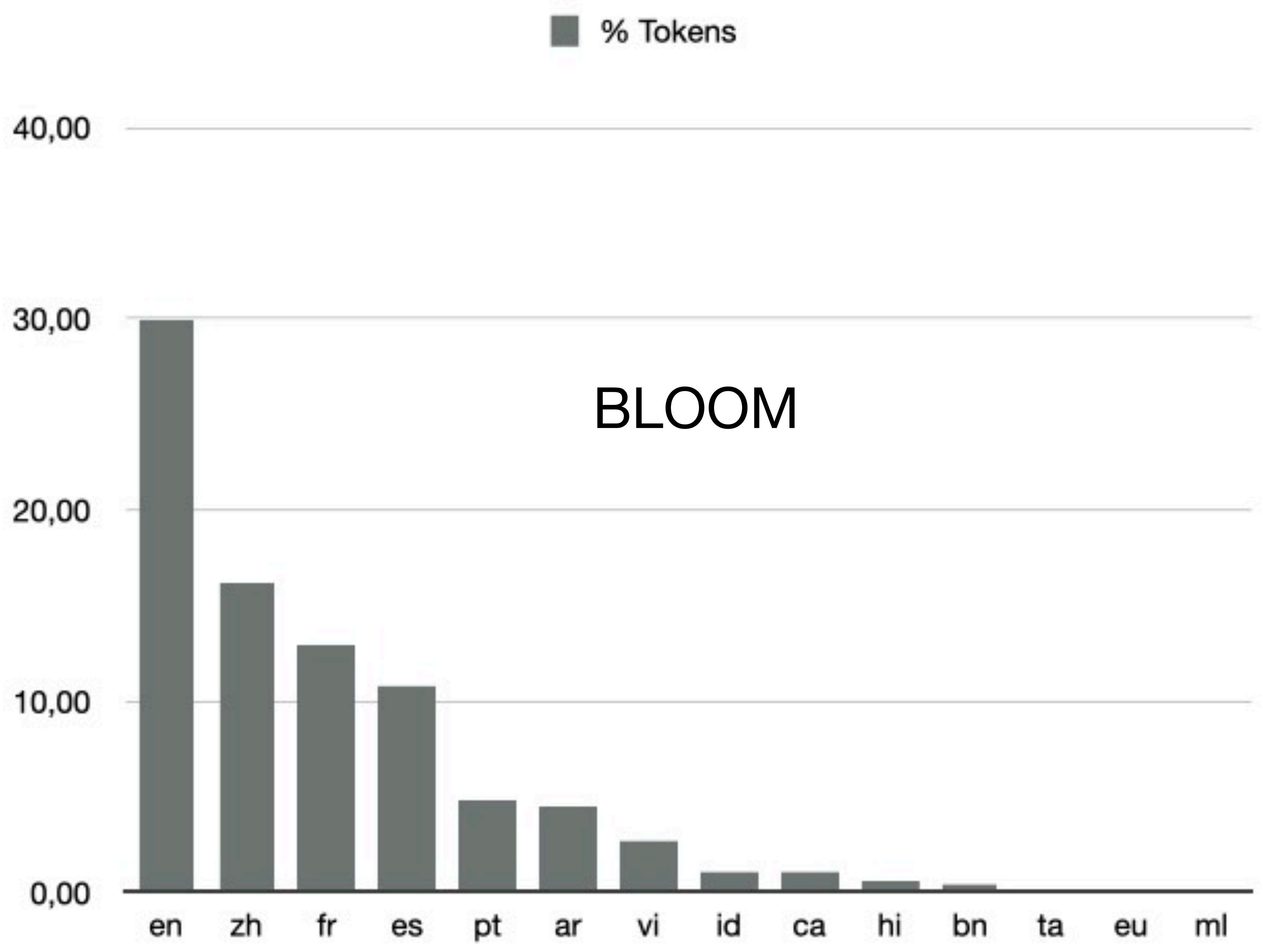
New issues

- more realistic data (register, domains, etc)
- code-mixed inputs
- improved calibration

Data unbalance in mLLMs

Data unbalance in mLLMs





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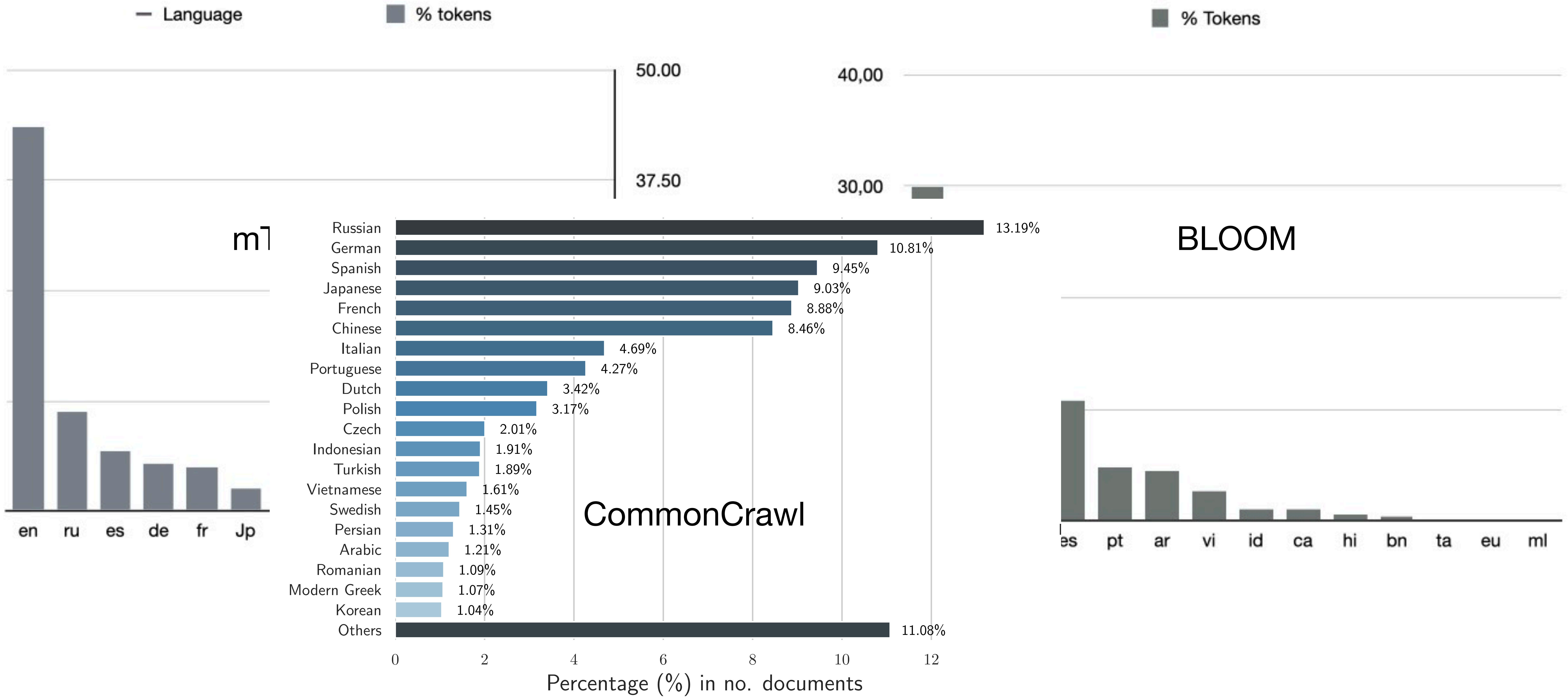
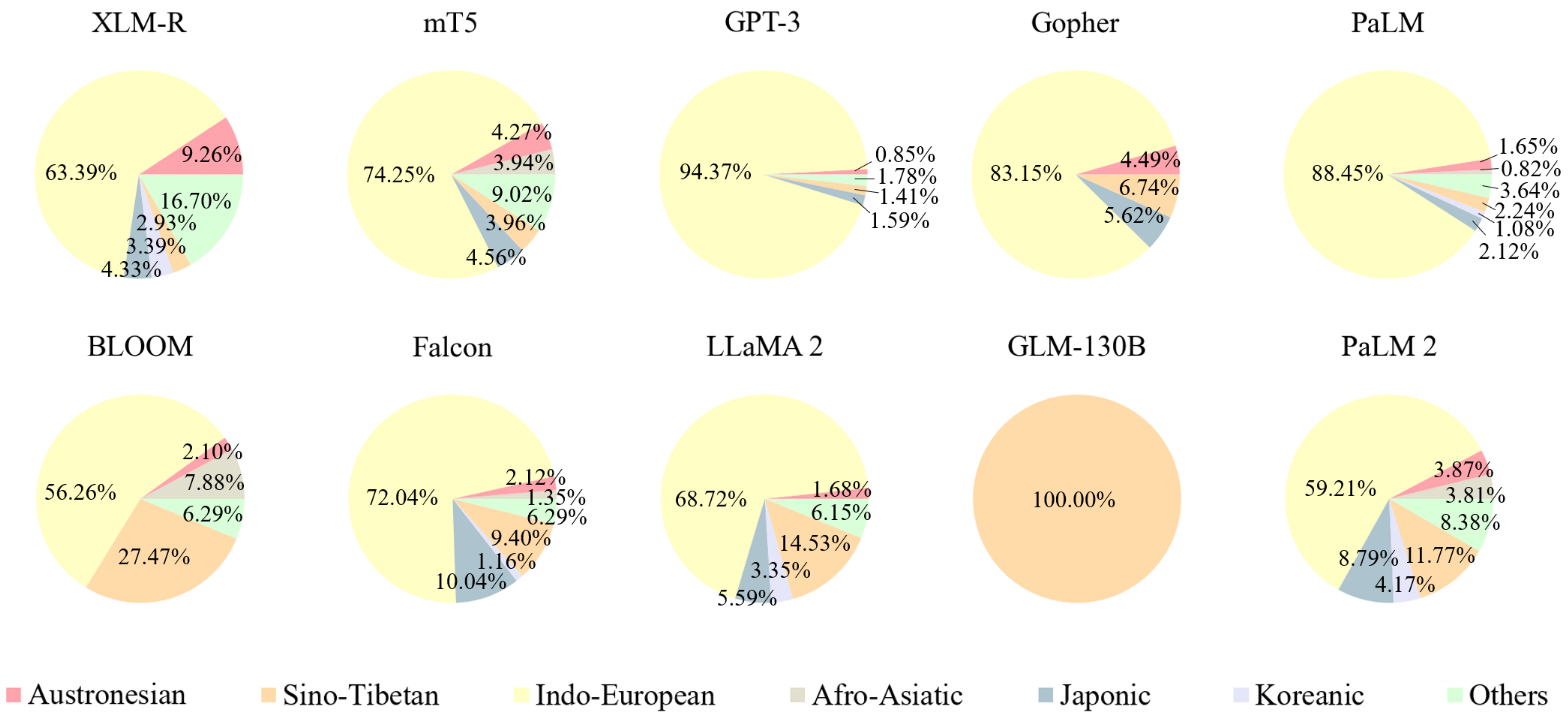


[RefinedWeb: The RefinedWeb Dataset for Falcon LLM (Penedo et al, 2023)]

Data unbalance in mLLMs



A Survey on Multilingual Large Language Models: Corpora, Alignment, and Bias (Xu et al., IEE TNNLS, 2024)

“there is no multilingualism, only proofs of multilingualism”

Training Glot500-m

Starting point: XLM-R-(B)

- 100 head languages
- « Pure encoder »
- Trained on CommonCrawl with MLM loss
- 250k vocab with *SentencePiece (SP)*
- base (270m) and large (550m) parameters

Unsupervised Cross-lingual Representation Learning at Scale (Conneau et al., ACL 2020)

An ‘’academic” configuration

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Extended subword vocabulary

- train SP model on Glot500-m (250k)
- temp = 0.3
- merge « old » and « new » types
- 401k vocabulary

An ‘’academic” configuration

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Unsupervised Cross-lingual Representation Learning at Scale (Conneau et al., ACL 2020)

Training regime

- random language mixtures (temp = 0.3)
- MLM loss
- no change in model size
- two weeks of computation

Extended subword vocabulary

- train SP model on Glot500-m (250k)
- temp = 0.3
- merge « old » and « new » types
- 401k vocabulary

An ‘’academic” configuration

Proofs of multiligualism

mLLMs as a set of monolingual models

mLLMs as representation learners

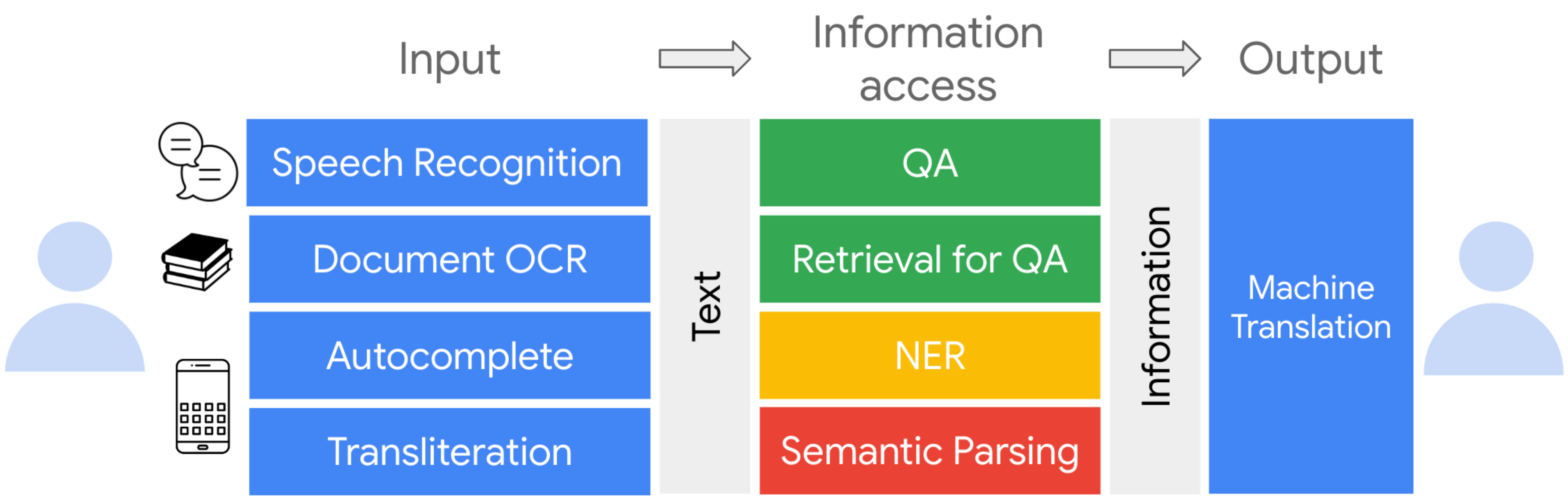
- recovering good bilingual associations
- yielding good (word, sentence) alignments
- encoding linguistic features
- effective cross-lingual performance

A wealth of multilingual benchmarks

- XTreme, XTreme-R, XTreme-Up
- X-GLUE
- Mega, MegaVerse
- BUFFET

mLLMs for text generation

- good models of multilingual texts
- good machine translation systems
- generating realistic mixed-language



[Xtremeup: A User-Centric Scarce-Data Benchmark for Under-Represented Languages (Ruder et al, 2023)]

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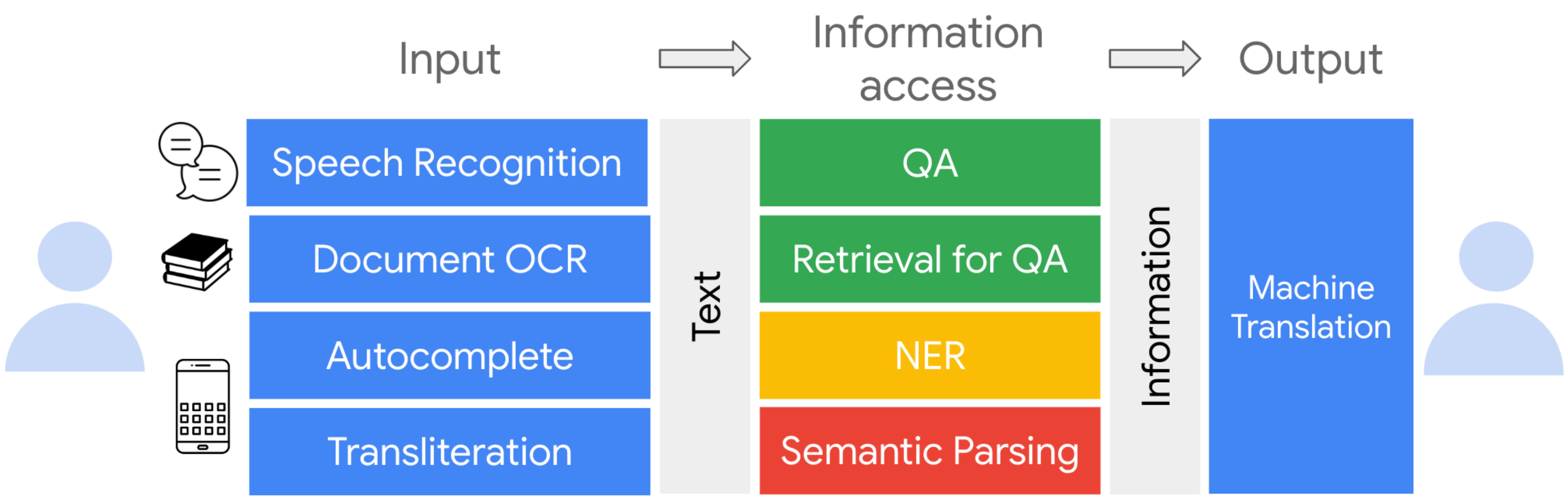

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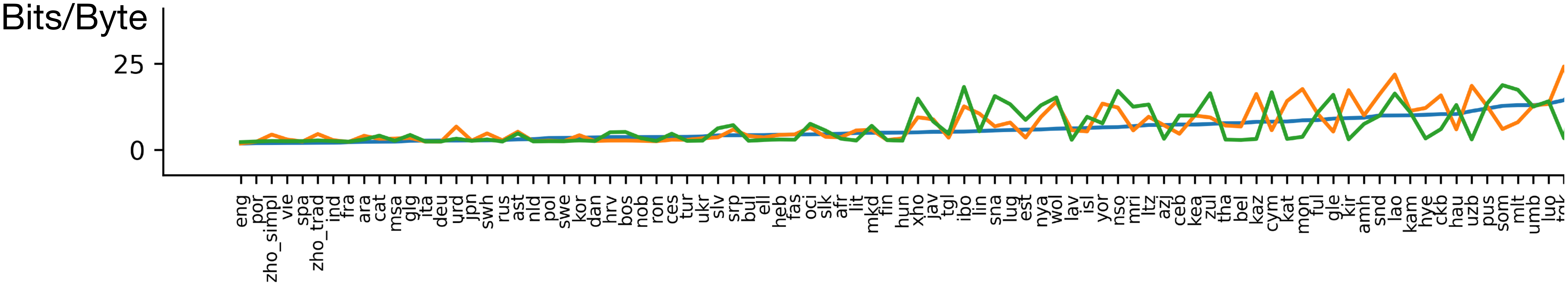
Require annotated benchmarks - possibly via MT

PPL is a weak signal



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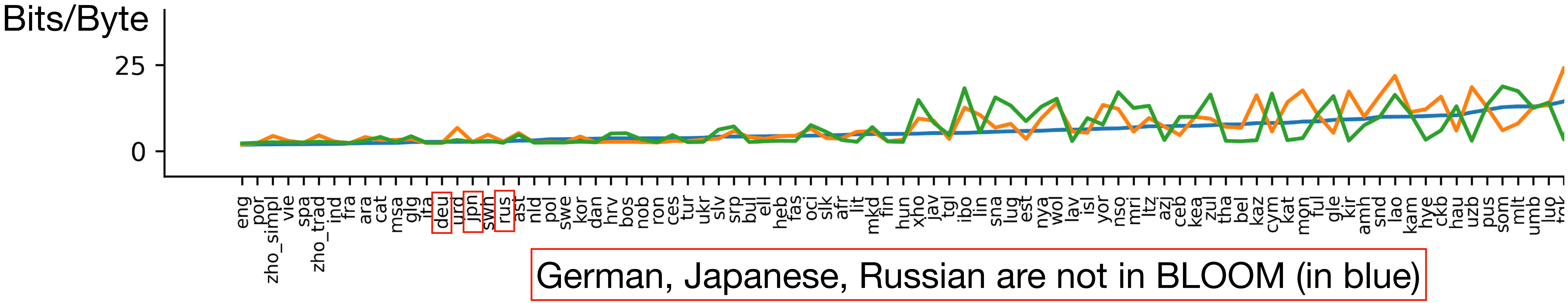

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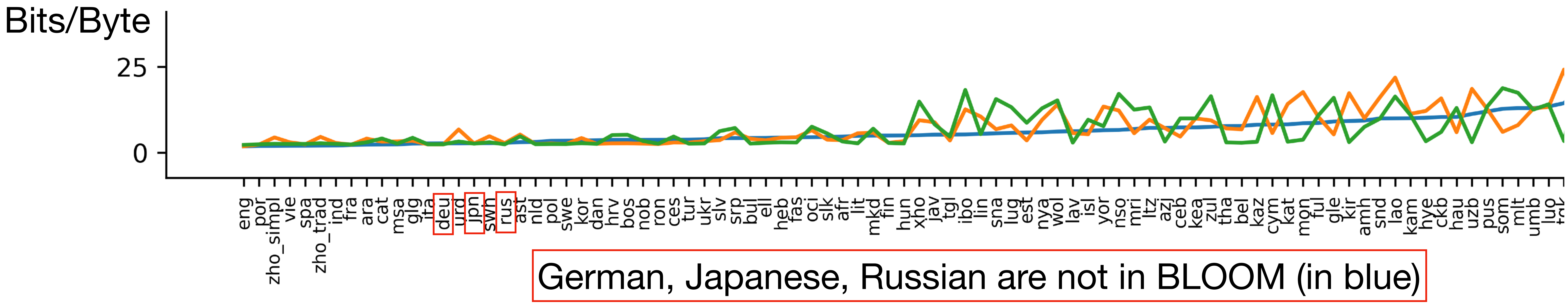
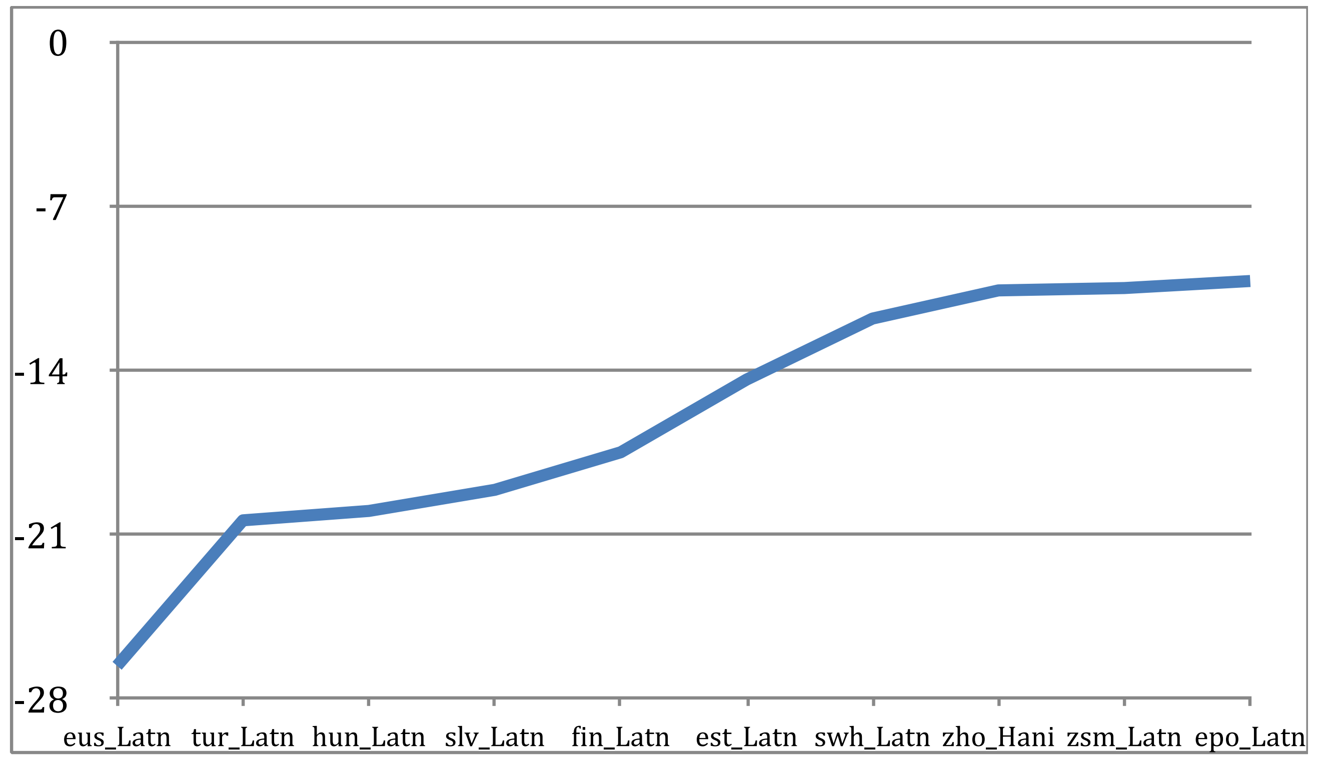
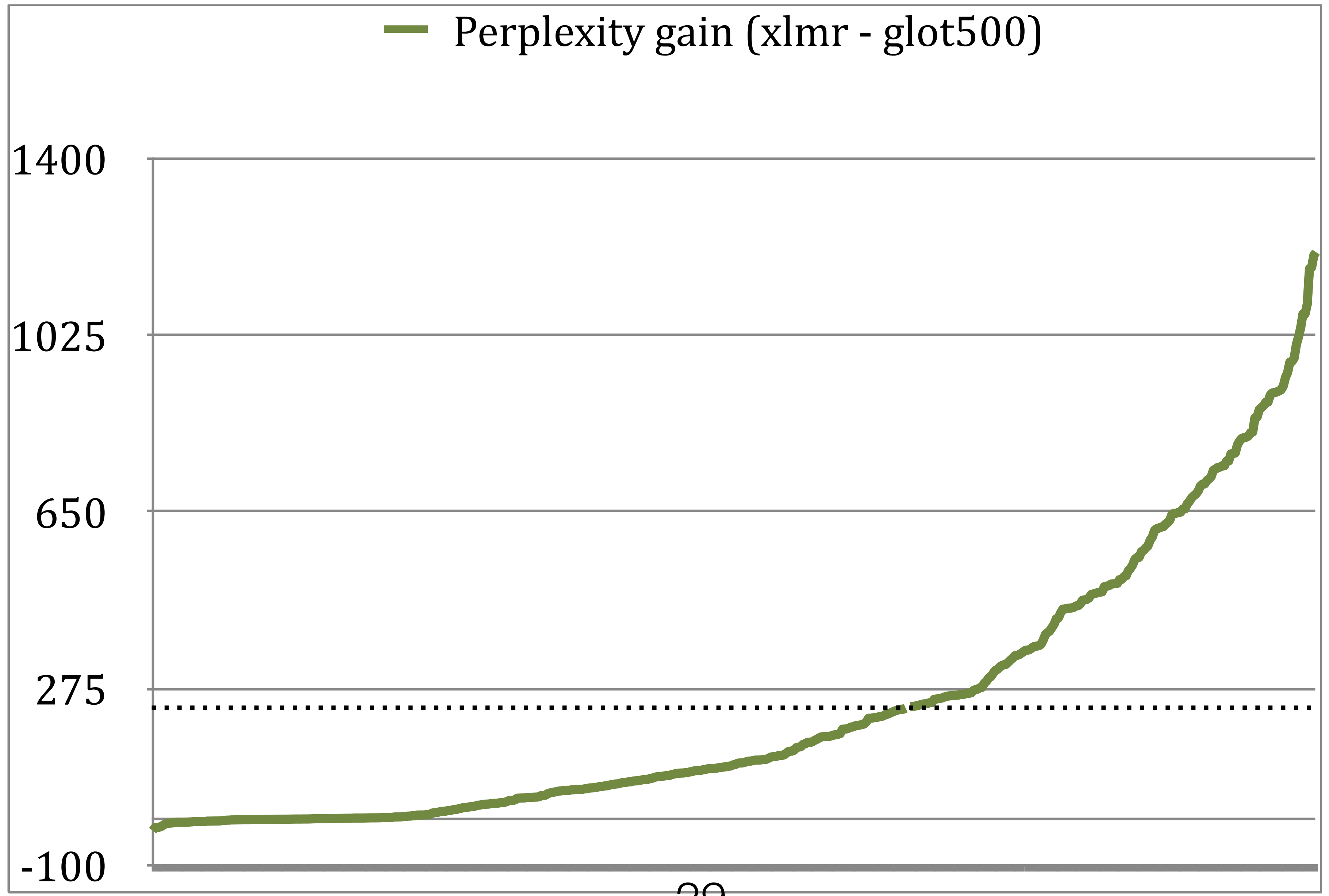
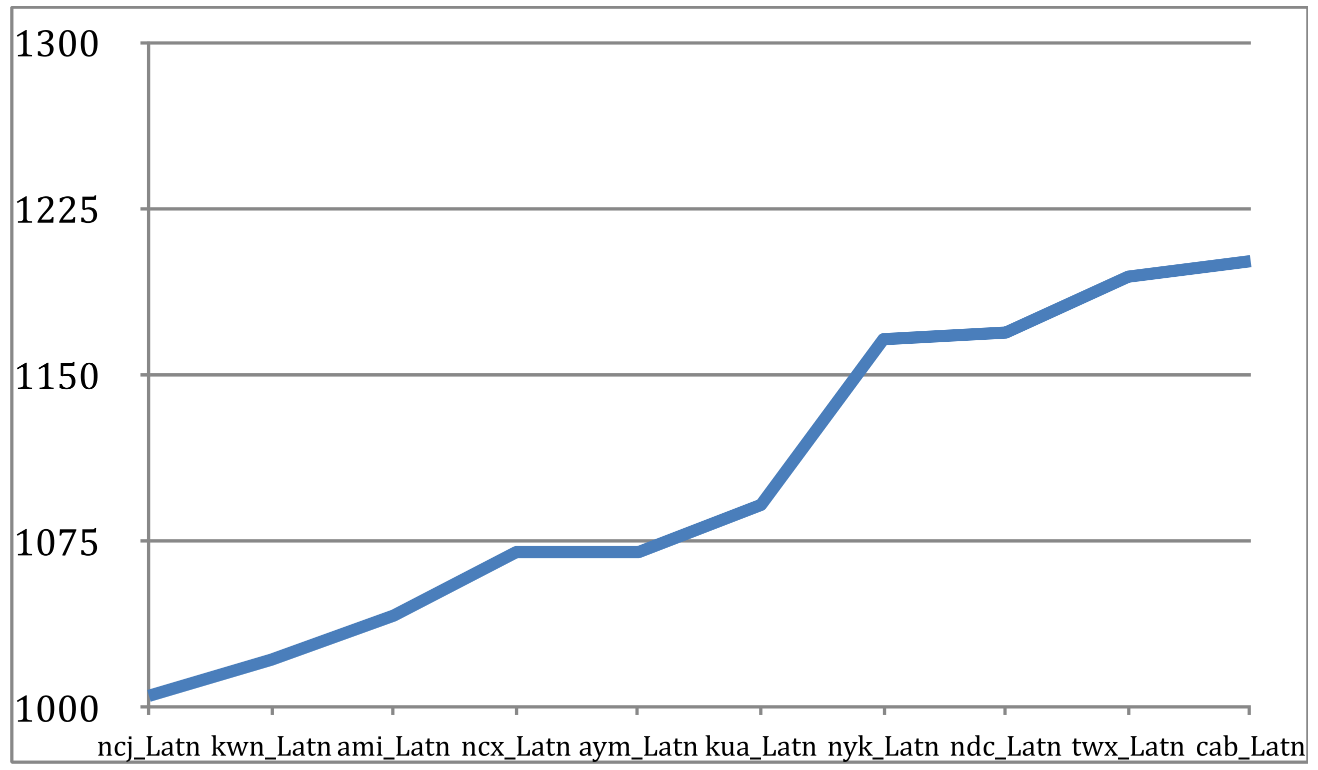


``losers” (87)

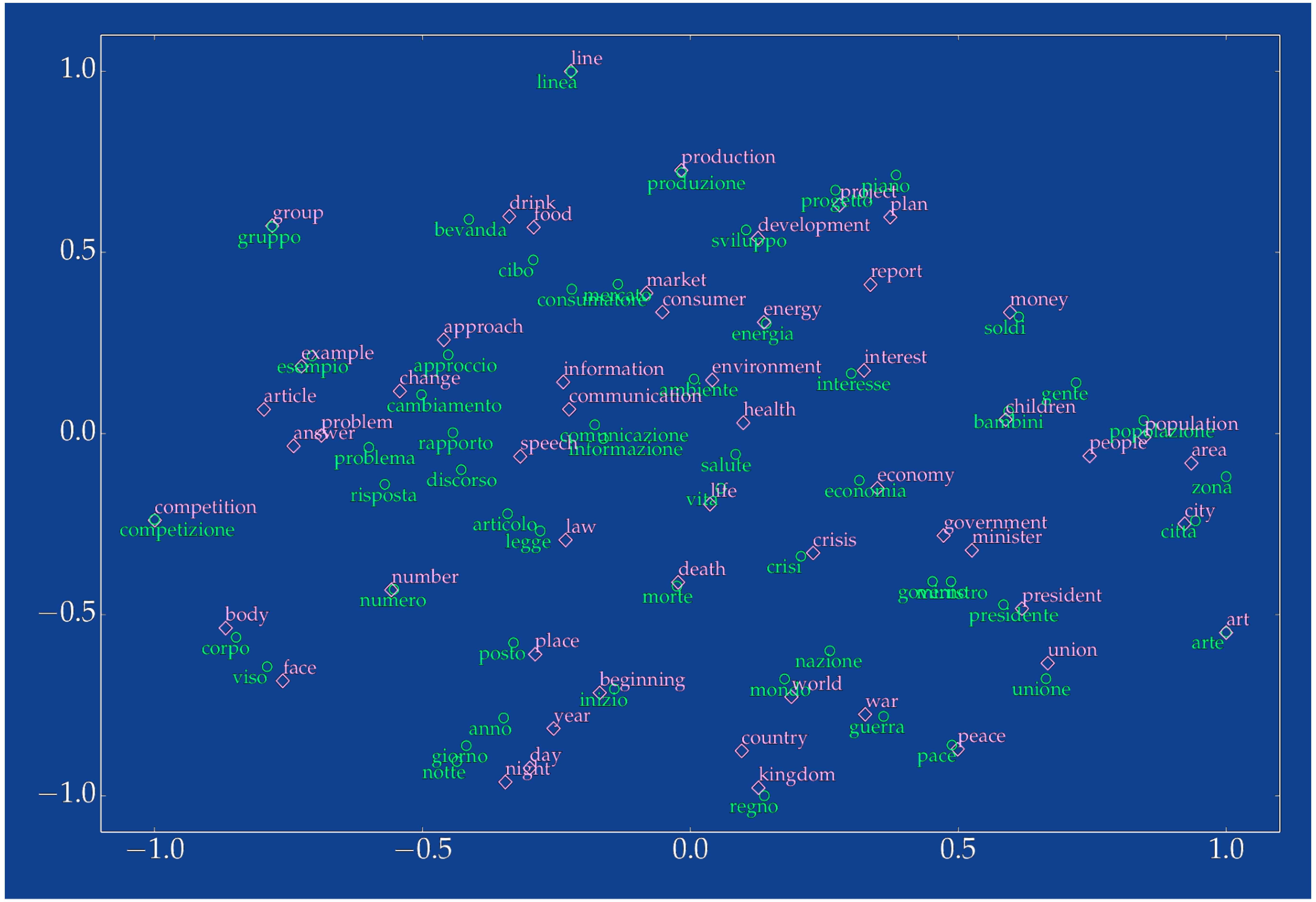






``winners” (424)

mReps yield good alignments



[Unsupervised Cross-Lingual Representation Learning](Ruder et al., ACL)

Bilingual Lexicon Induction with context independent models

mReps yield good alignments

Similarity ⇒ Alignment

+ monotonicity, low distortion
+ symmetry, low fertility, “pigeon hole” principle

mReps yield good alignments

Sentence level

In the gayest and happiest spirits she set forward with her father;	Elle partit avec son père, le visage souriant;
not always listening, but always agreeing to what he said;	elle n' écoutait pas toujours, mais elle acquiesçait de confiance.
They arrived .	Ils arrivèrent .
It is Frank and Miss Fairfax, said Mrs. Weston .	– C'est Frank et Mlle Fairfax, dit aussitôt Mme Weston .
I was just going to tell you of our agreeable surprize in seeing him arrive this morning.	– J'allai justement vous faire part de l'agréable surprise que nous avons eue en le voyant arriver.
He stays till tomorrow, and Miss Fairfax has been persuaded to spend the day with us .	Il reste jusqu'à demain et Mlle Fairfax a bien voulu, sur notre demande , venir passer la journée.

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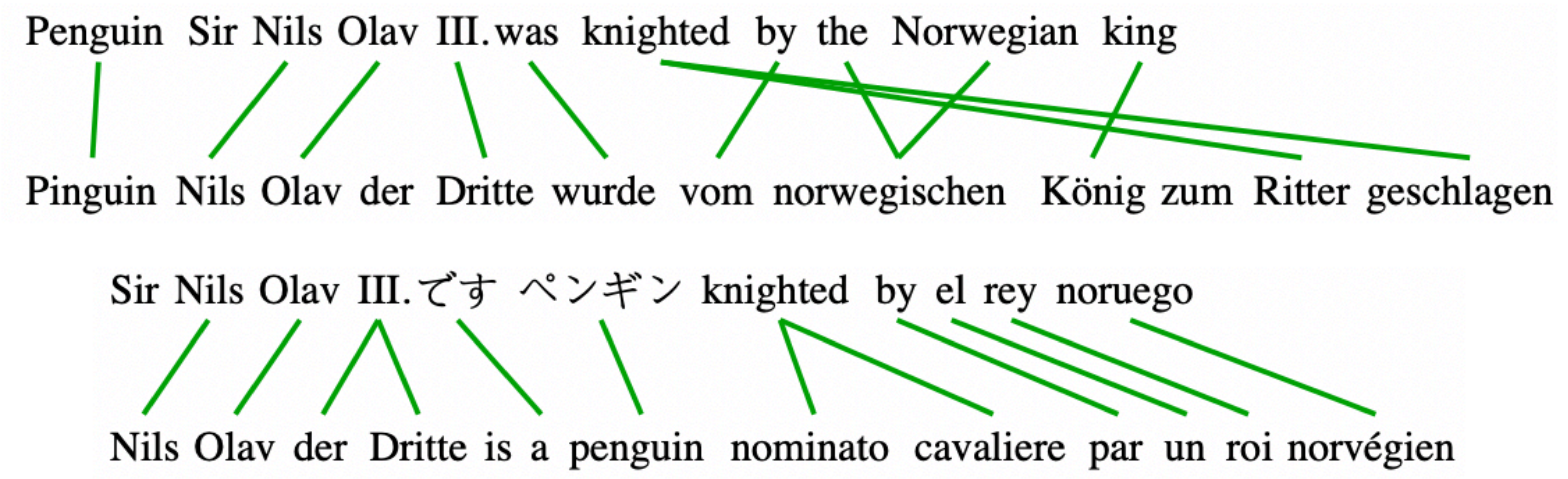
Word level



SimAlign: High Quality Word Alignments Without Parallel Training Data Using Static and Contextualized Embeddings (Jalili Sabet et al., Findings 2020)

Assessing alignment

Sentence Retrieval

- Tatoeba (68 head, 28 tail), acc@10
- Bible (94 head, 276 tail), acc@10

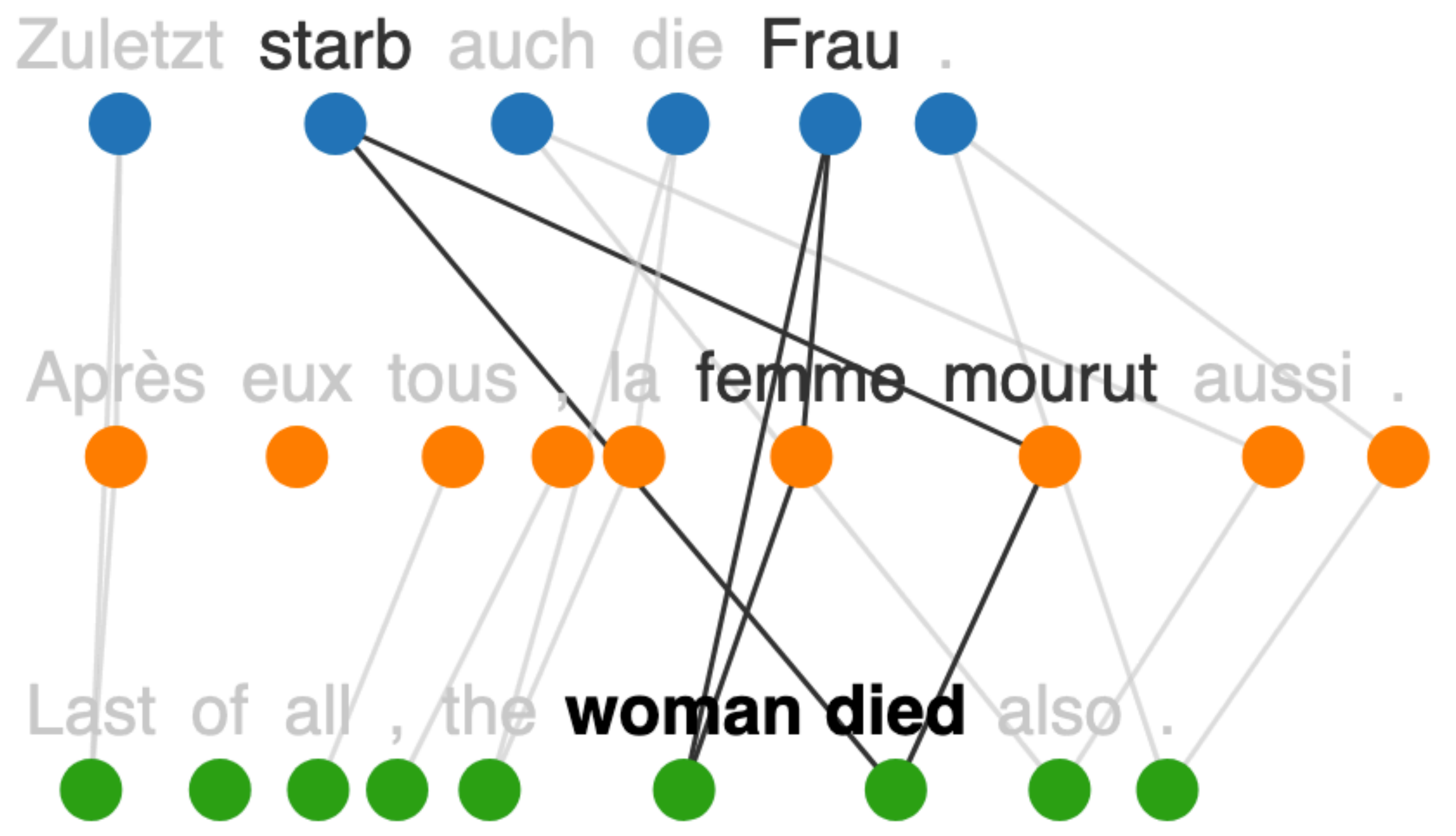
Find nearest foreign neighbor in multilingual space for 1000 (resp. 500) English sentences
Requires parallel data

Unsupervised multilingual evaluation

Round trip Alignment

- Bible (95 head, 288 tail), acc@10

Word *SimAlign* $L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_1$
Report exact matches, averaged over 5 runs
Requires parallel data



Assessing alignment

	all			head			tail		
	XLM-R-B	XLM-R-L	Glot500-m	XLM-R-B	XLM-R-L	Glot500-m	XLM-R-B	XLM-R-L	Glot500-m
[redacted]									
SR [Tatoeba]	56.6	60.4	**70.7**	66.2	71.1	**75.0**	32.6	33.6	**59.8**
SR [Bible]	19.3	20.1	**47.3**	54.2	58.3	**59.0**	7.4	7.1	**43.2**
RTA	2.8	3.3	**4.7**	3.4	4.1	**5.5**	2.6	3.1	**4.5**

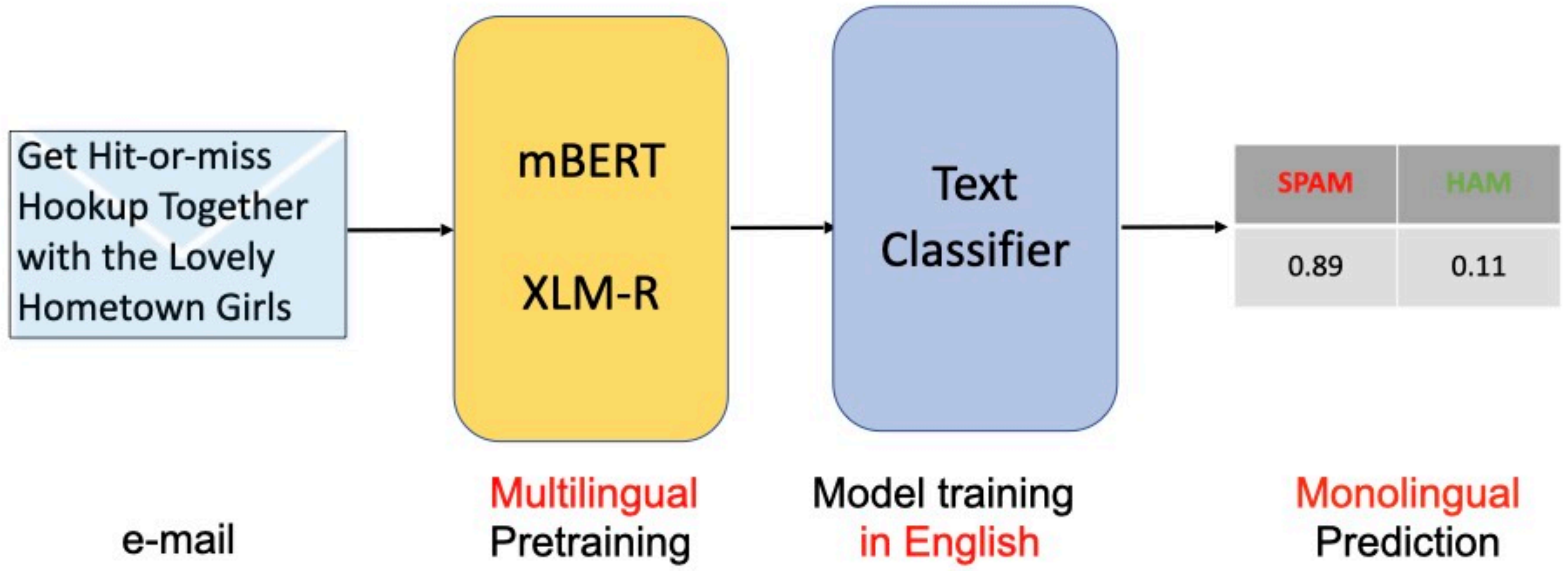
Glot500-m vs XLM-R

- outperforms all models on average
- better than XLM-R-B for head languages
- much better than XLM-R-* for tail languages

Caveats

- Only ~ 100 Tatoeba languages
- Tatoeba & Bible are very peculiar
- RTT is very hard

Zero-shot X-lingual transfer



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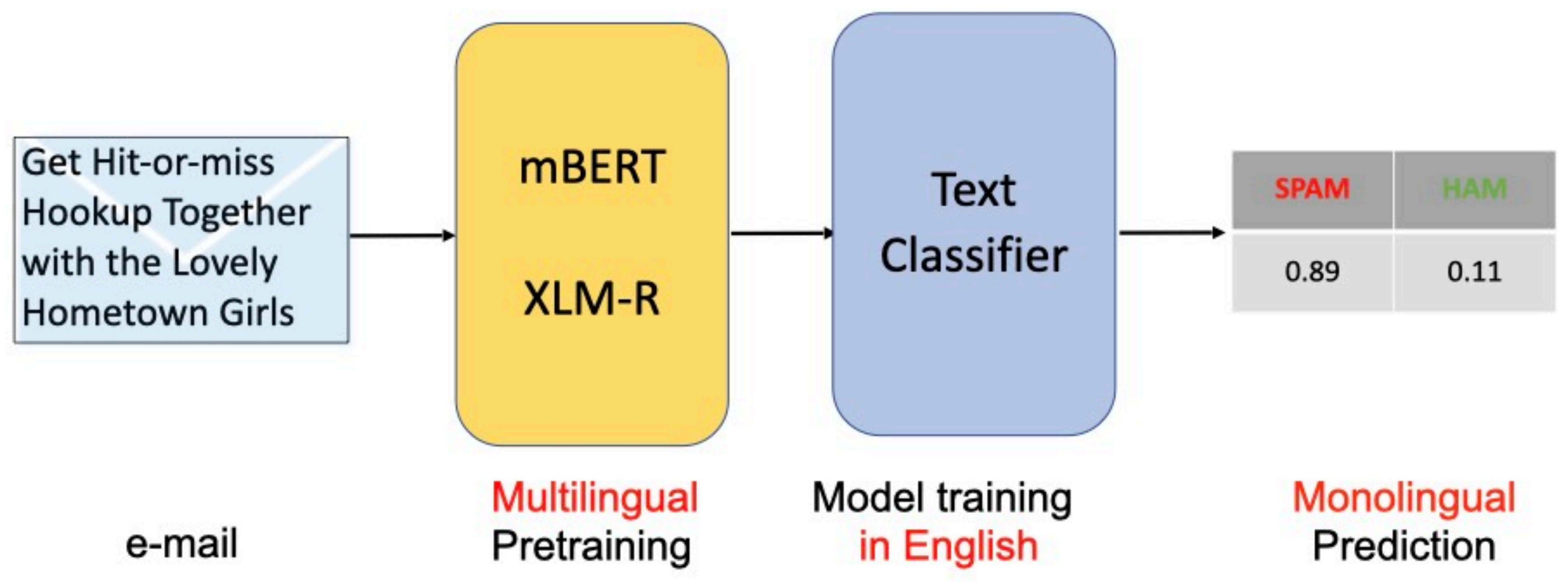

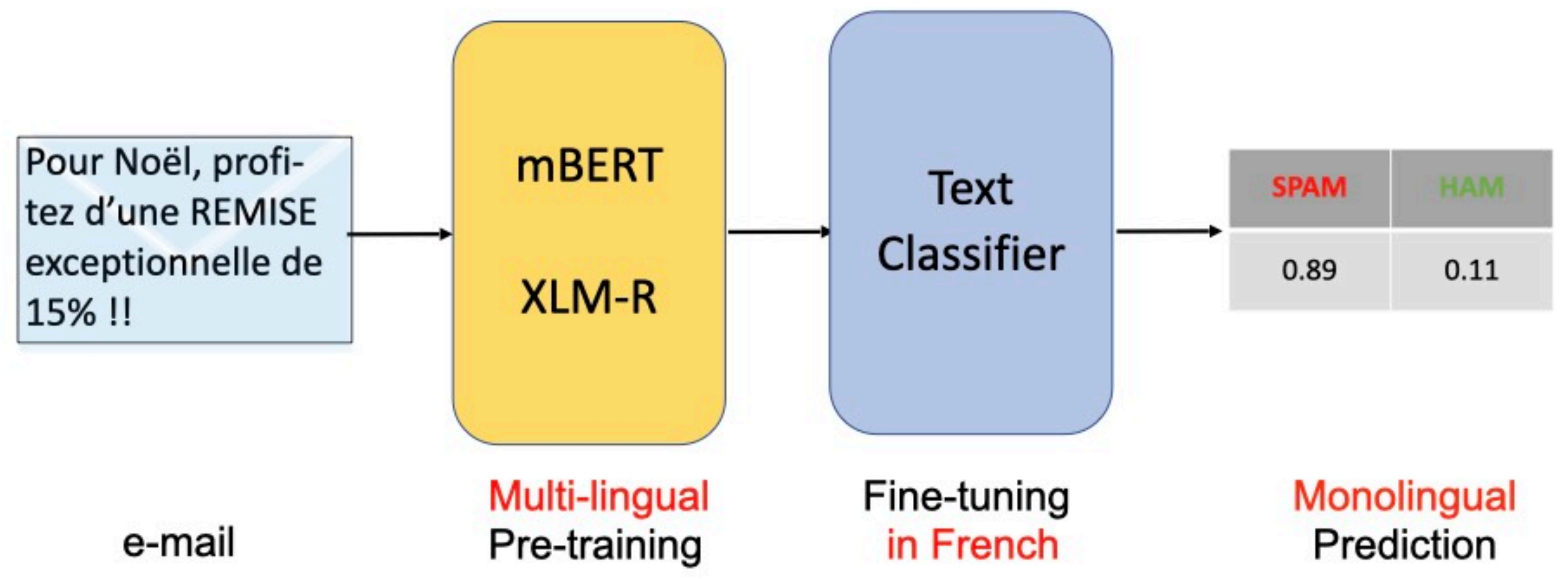

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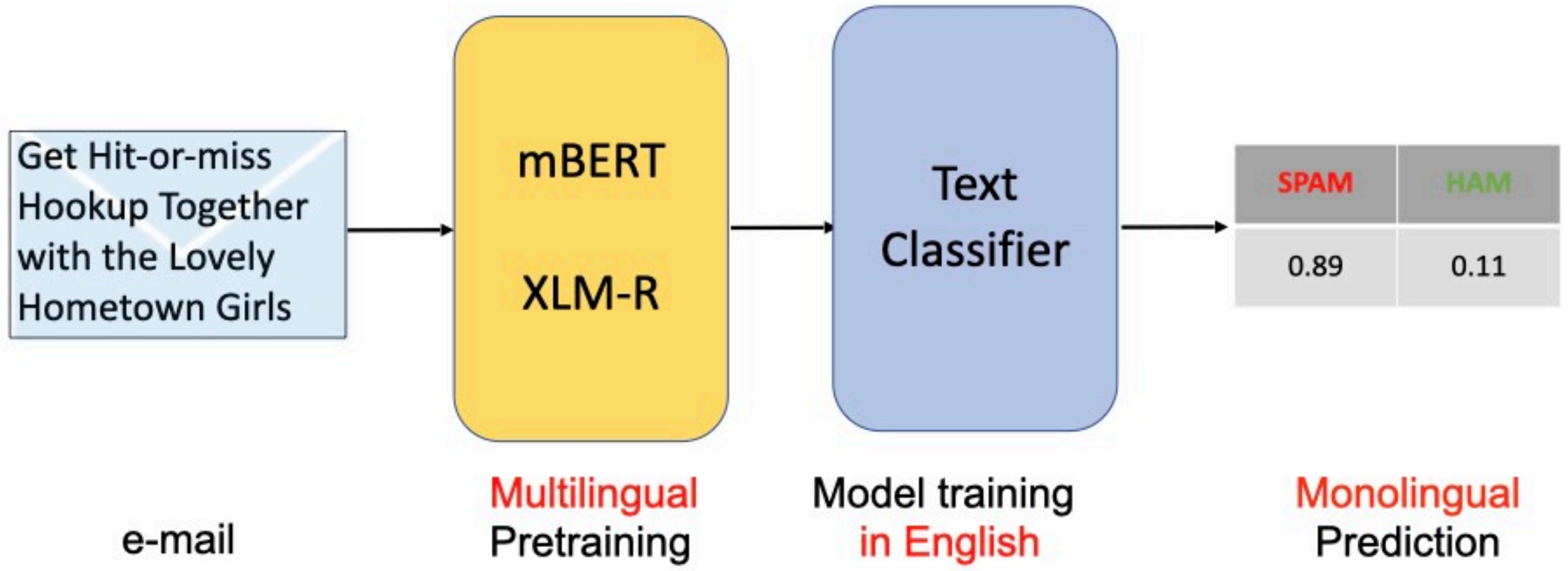
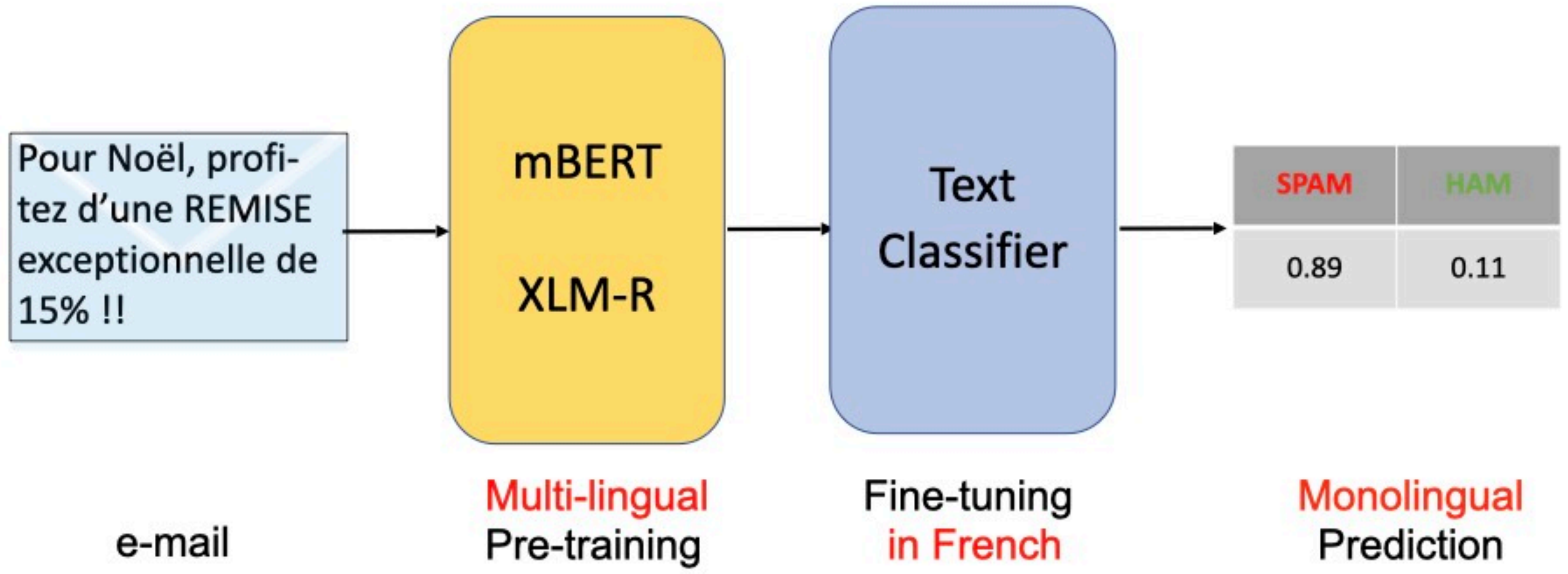
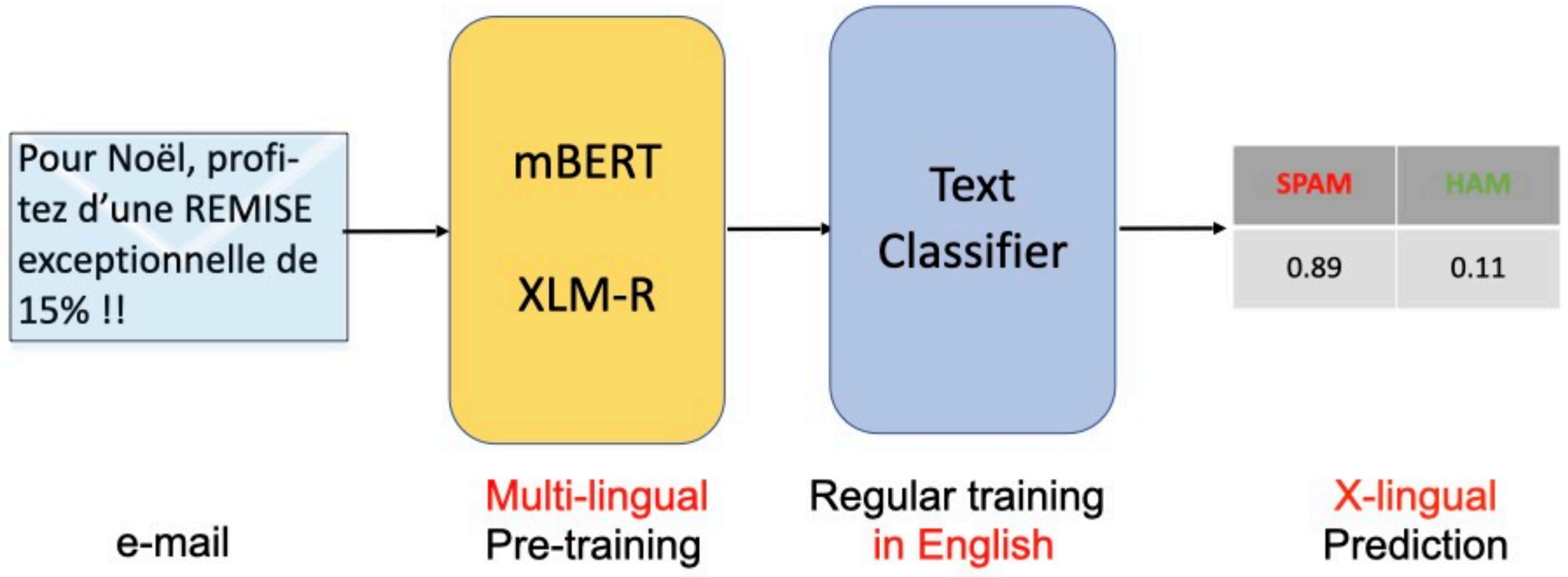






Similar representations

$\Downarrow$

Identical labels

Evaluating zero-shot transfer

Text classification

- Sentence Classification (90 head, 284 tail) F1 using Taxi1500

Zero-shot transfer from English
6-way classification for test data (Bible)

Taxi1500: A Multilingual Dataset for Text Classification in 1500 Languages
C Ma et al (2023) arXiv preprint arXiv:2305.08487,

Sentence labeling

- NER (89 head, 75 tail), F1 using wikiAnn
- POS (63 head, 28 tail), F1 using UD

Zero-shot transfer from English
Requires gold labels

Standard benchmarks with fine-grained annotations
Mostly head languages

Improving tail languages

	all			head			tail		
	XLM-R-B	XLM-R-L	Glot500-m	XLM-R-B	XLM-R-L	Glot500-m	XLM-R-B	XLM-R-L	Glot500-m
TextClass	23.3	25.8	**48.7**	51.3	**60.5**	54.7	13.7	13.9	**46.6**
NER	55.3	59.5	**62.4**	61.8	**66.0**	63.9	47.5	51.8	**60.7**
POS	65.8	67.7	**71.8**	76.4	**78.4**	76.0	41.7	43.5	**62.3**

Glot500-m vs XLM-R

- outperforms all models on average
- better than XLM-R-B for head languages
- much better than XLM-R-* for tail languages

Also

- are averages that informative ?
- tail language scores remain poor

Where Glot500-m helps (or doesn't)

		language-script	XLMR	Glot500	gain		language-script	XLMR	Glot500	gain
high end	SentRetr Tatoeba	tat C Tatar	10.3	70.3	60.0	SentRetr Bible	uzn C Northern Uzbek	5.4	87.0	81.6
		nds L Low German	28.8	77.1	48.3		crs L Seselwa Creole	7.4	80.6	73.2
		tuk L Turkmen	16.3	63.5	47.3		srn L Sranan Tongo	6.8	79.8	73.0
		ile L Interlingue	34.6	75.6	41.0		uzb C Uzbek	6.2	78.8	72.6
		uzb C Uzbek	25.2	64.5	39.3		bcl L Central Bikol	10.2	79.8	69.6
low end		dtp L Kadazan Dusun	5.6	21.1	15.5		xav L Xavánte	2.2	5.0	2.8
		kab L Kabyle	3.7	16.4	12.7		mau L Huautla Mazatec	2.4	3.6	1.2
		pam L Pampanga	4.8	11.0	6.2		ahk L Akha	3.0	3.2	0.2
		lvs L Standard Latvian	73.4	76.9	3.5		aln L Gheg Albanian	67.8	67.6	-0.2
		nob L Bokmål	93.5	95.7	2.2		nob L Bokmål	82.8	79.2	-3.6
high end	NER	div T Dhivehi	0.0	50.9	50.9	POS	mlt L Maltese	21.3	80.3	59.0
		che C Chechen	15.3	61.2	45.9		sah C Yakut	21.9	76.9	55.0
		mri L Maori	16.0	58.9	42.9		sme L Northern Sami	29.6	73.6	44.1
		nan L Min Nan	42.3	84.9	42.6		yor L Yoruba	22.8	64.2	41.4
		tgk C Tajik	26.3	66.4	40.0		quc L K'iche'	28.5	64.1	35.6
low end		zea L Zeeuws	68.1	67.3	-0.8		lzh H Literary Chinese	11.7	18.4	6.7
		vol L Volapük	60.0	59.0	-1.0		nap L Neapolitan	47.1	50.0	2.9
		min L Minangkabau	42.3	40.4	-1.8		hyw A Western Armenian	79.1	81.1	2.0
		wuu H Wu Chinese	28.9	23.9	-5.0		kmr L Northern Kurdish	73.5	75.2	1.7
		lzh H Literary Chinese	15.7	10.3	-5.4		aln L Gheg Albanian	54.7	51.2	-3.5

"Winners":
- Languages not in XLM-R + large training data
- Scripts not in XLM-R
- "Cluster" effects

"Losers":
- Neighbors or superclass in XLM-R
- Small training data

Glot500-m: complementary results

Sentence Retrieval Bible

family	$\lvert L_G \rvert$	$\lvert L_X \rvert$	XLM-R-B	Glot500-m	gain
indo1319	91	50	41.5	61.4	19.9
atla1278	69	2	5.5	45.2	39.6
aust1307	53	6	13.7	47.0	33.2
turk1311	22	7	20.1	62.9	42.8
sino1245	22	2	7.6	38.9	31.3
maya1287	15	0	3.8	20.3	16.4
afro1255	12	5	13.0	34.3	21.4

Analysis per language family

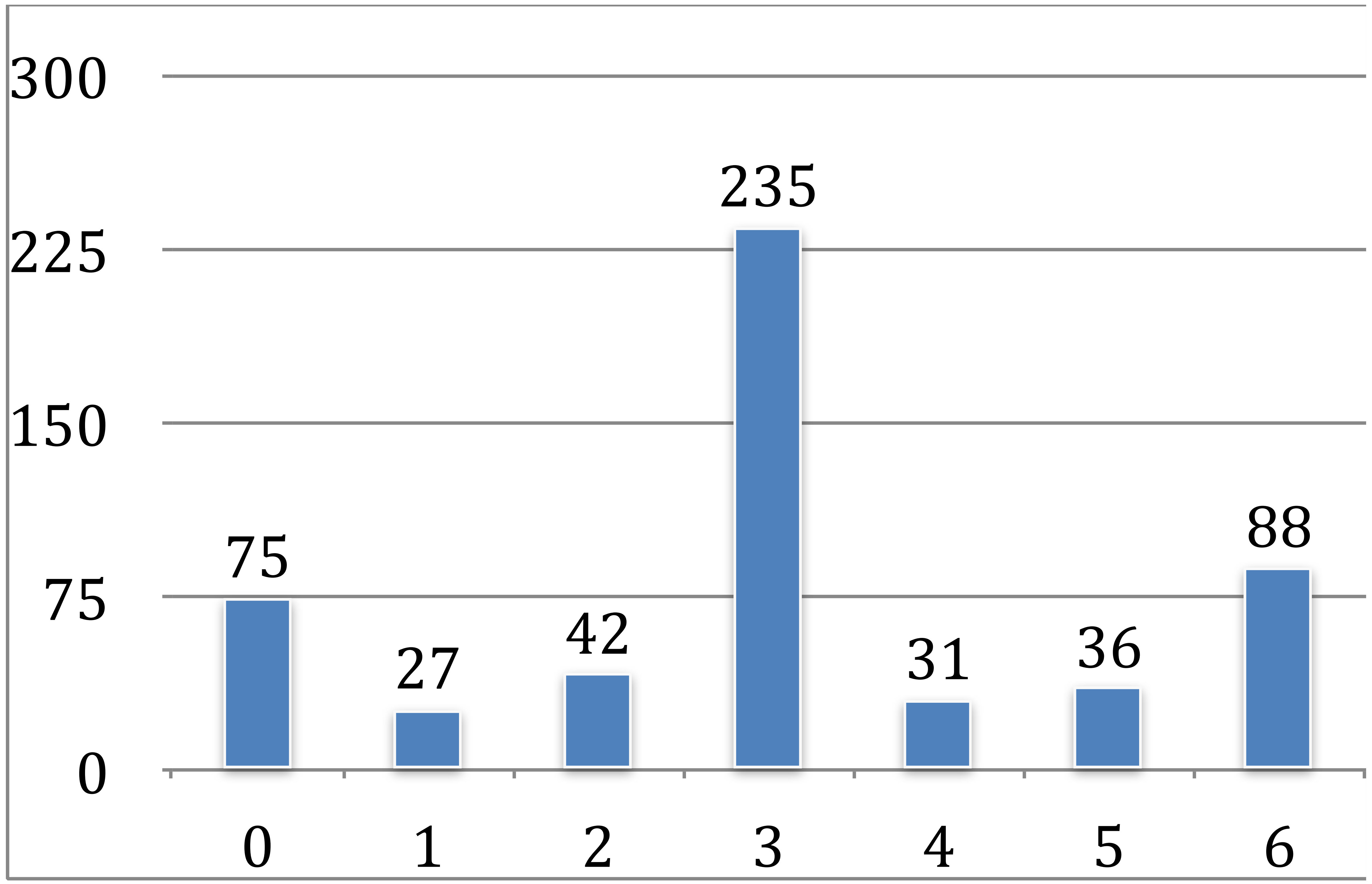
lang-script		XLM-R-B	Glot500	gain
uig_Arab	head	0.458	0.562	0.104
uig_Latn	tail	0.098	0.628	0.530
hin_Deva	head	0.670	0.766	0.096
hin_Latn	tail	0.136	0.432	0.296
uzb_Latn	head	0.548	0.676	0.128
uzb_Cyrl	tail	0.062	0.788	0.726
kaa_Cyrl	tail	0.176	0.738	0.562
kaa_Latn	tail	0.092	0.434	0.342
kmr_Cyrl	tail	0.040	0.424	0.384
kmr_Latn	tail	0.358	0.630	0.272
tuk_Cyrl	tail	0.136	0.650	0.514
tuk_Latn	tail	0.096	0.662	0.566

One language, two scripts

Also: the "curse of multilinguality"

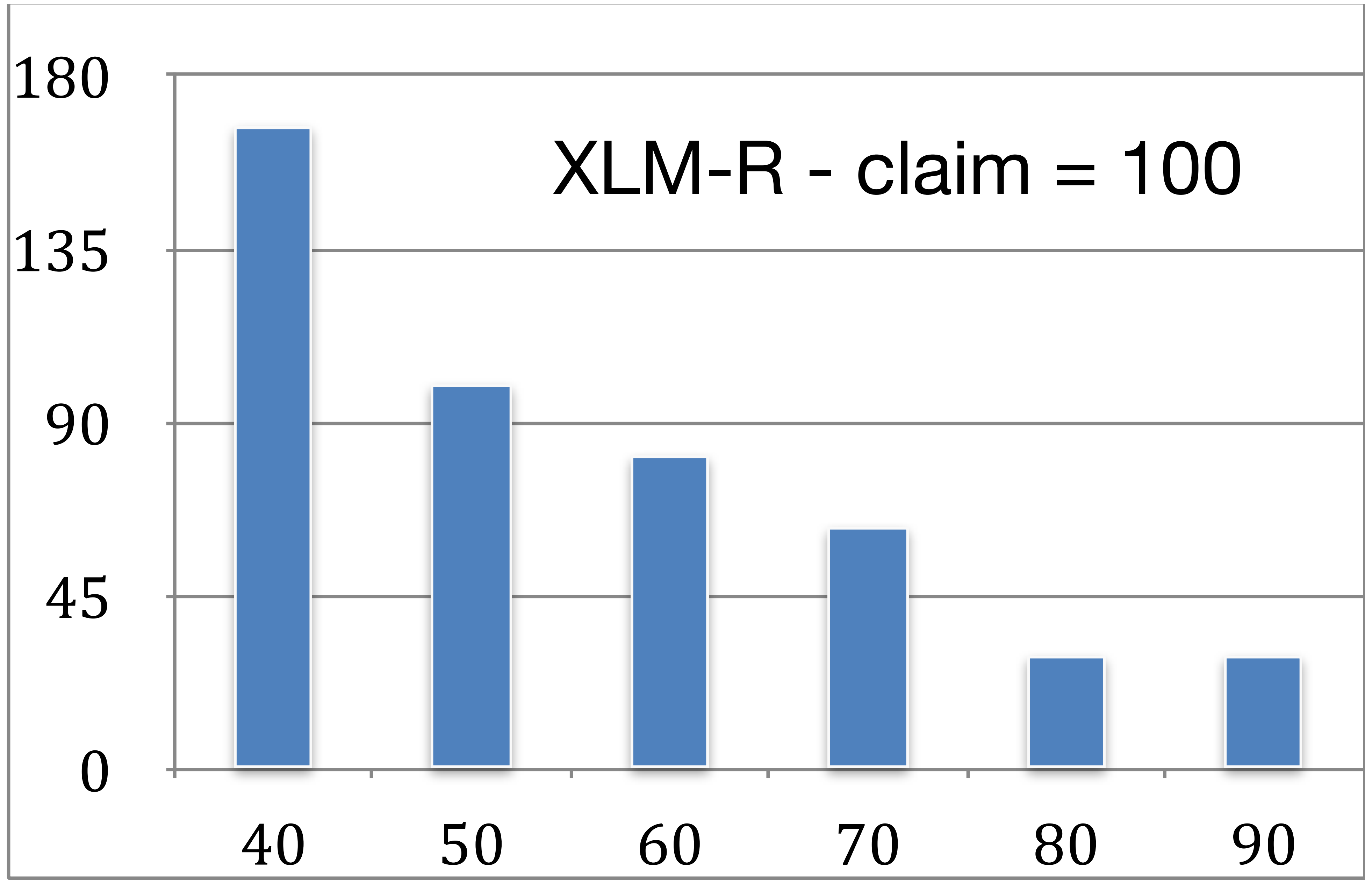
Check paper for complete results / language

Glot500-m: what coverage?



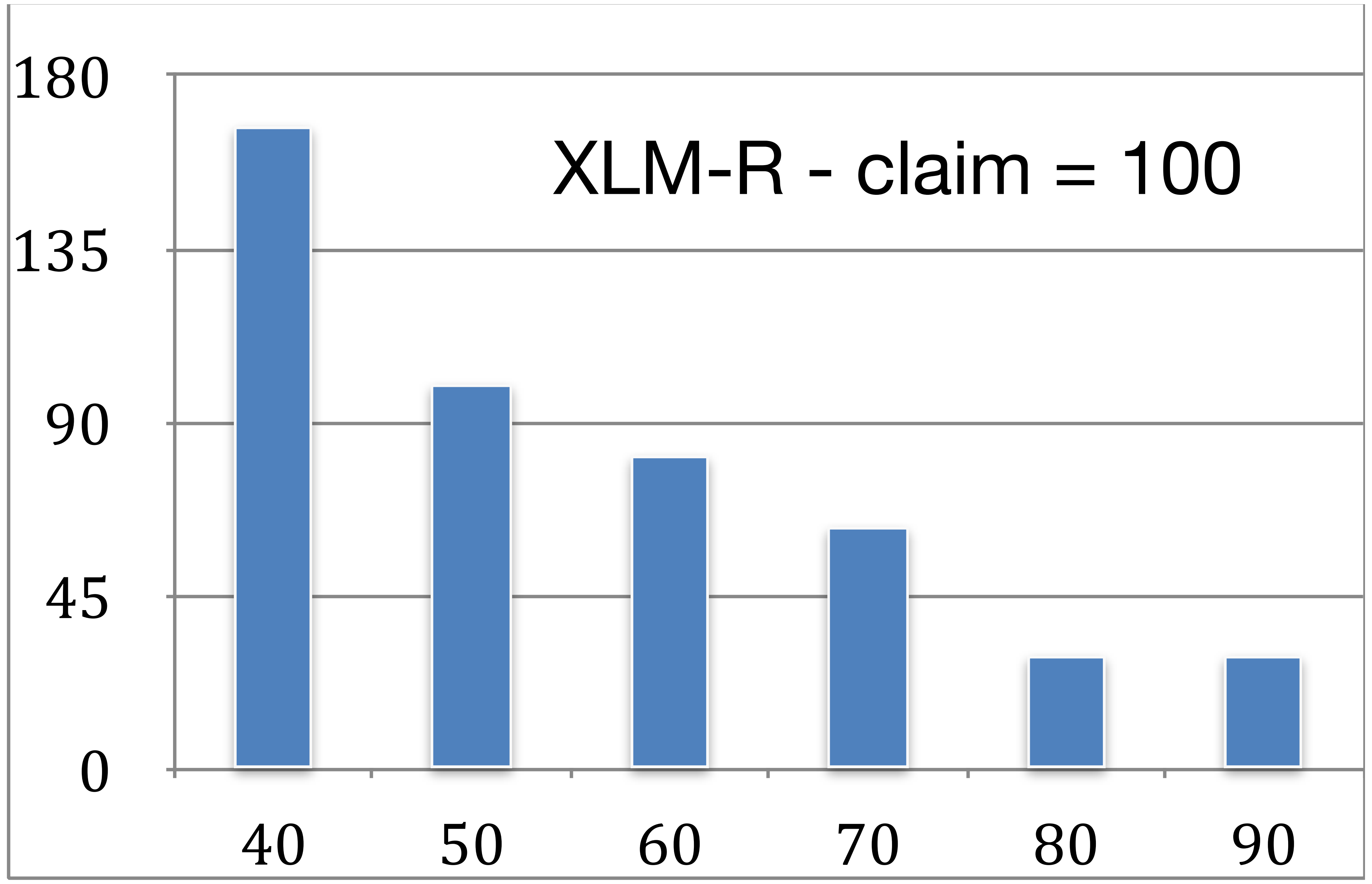
Number of tasks evaluated

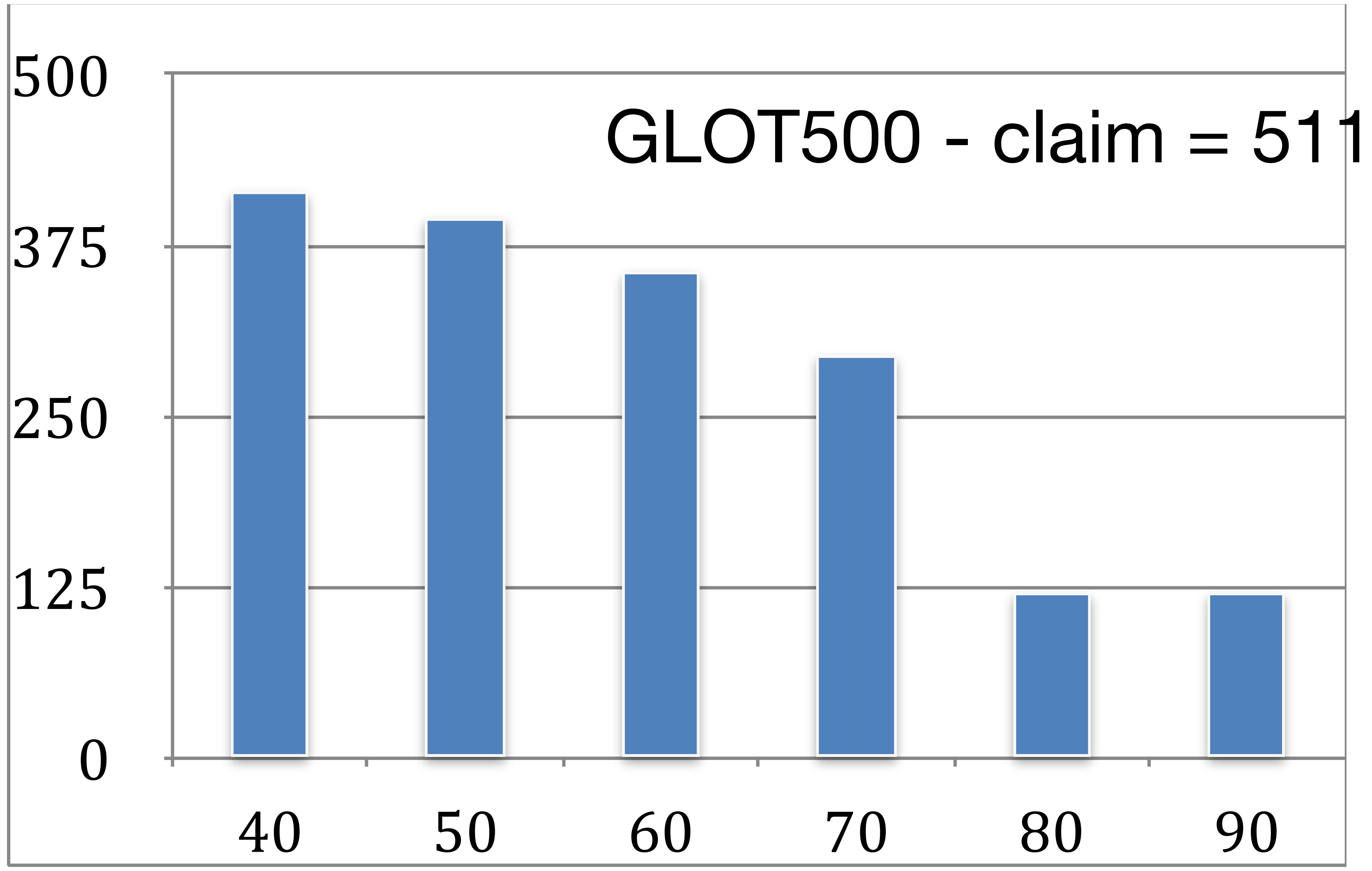
Glot500-m: what coverage?



Performance wrt French

Glot500-m: what coverage?





Performance wrt French

Glot500, some lessons learned

A useful artefact

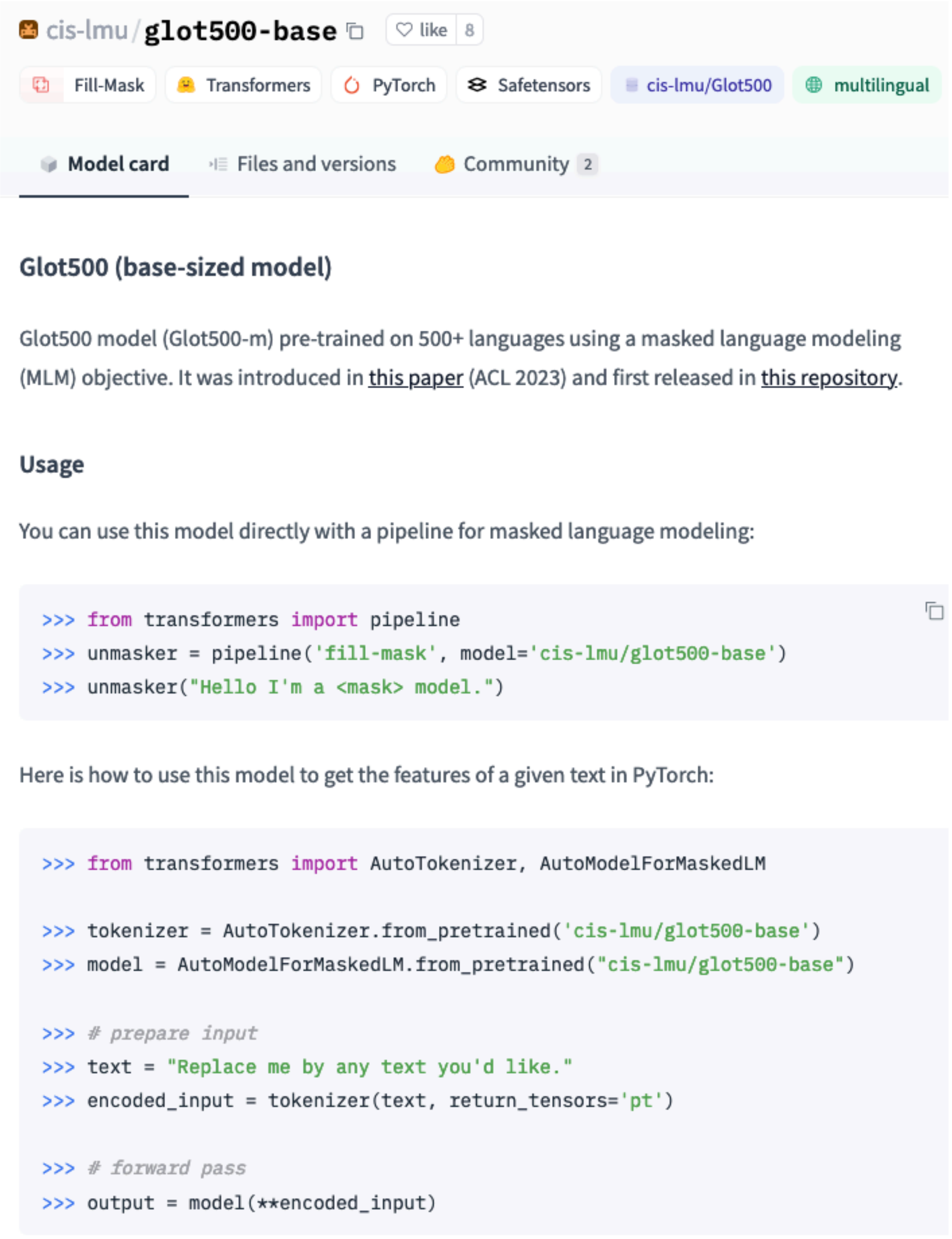
- extends the scope of ''modern" NLP for tail languages
- open-source, documented corpus collection

To be continued

- analysis of results
- analysis by langage families / scripts
- linguistic analysis of representations
- evaluation of text generation abilities

Limitations

- corpus selection and curation
- subword vocab size and training
- language choices
- filtering strategies



https://huggingface.co/cis-lmu/glot500-base

mLLMs are still a wonder

Open question and issues

mLLMs: more than a collection of monolingual models ?

- which linguistic properties help / break transfer?
- how critical is alignment? parallel data?
- how to measure positive / negative interference?
- how to measure language coverage?
- how to measure non-linguistic biases ?
  - racial, social, cultural, etc

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- impact of language distributions ?
- impact of model size?
- impact of vocabulary size?

- how to achieve fairness in mLLMs design?

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How about actual **multilingual tasks**?

- machine translation
- generating code-switched language
- summarization from multilingual texts

What happens with **multi-step training?**

- Effect of multilingual finetuning
- Effect of multilingual instruction tuning
- Effect of multilingual alignment

mLLMs are still a wonder ______________

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- impact of vocabulary size?

- how to achieve fairness in mLLMs design?

How about actual **multilingual tasks**?

- machine translation
- generating code-switched language
- summarization from multilingual texts

What happens with **multi-step training?**

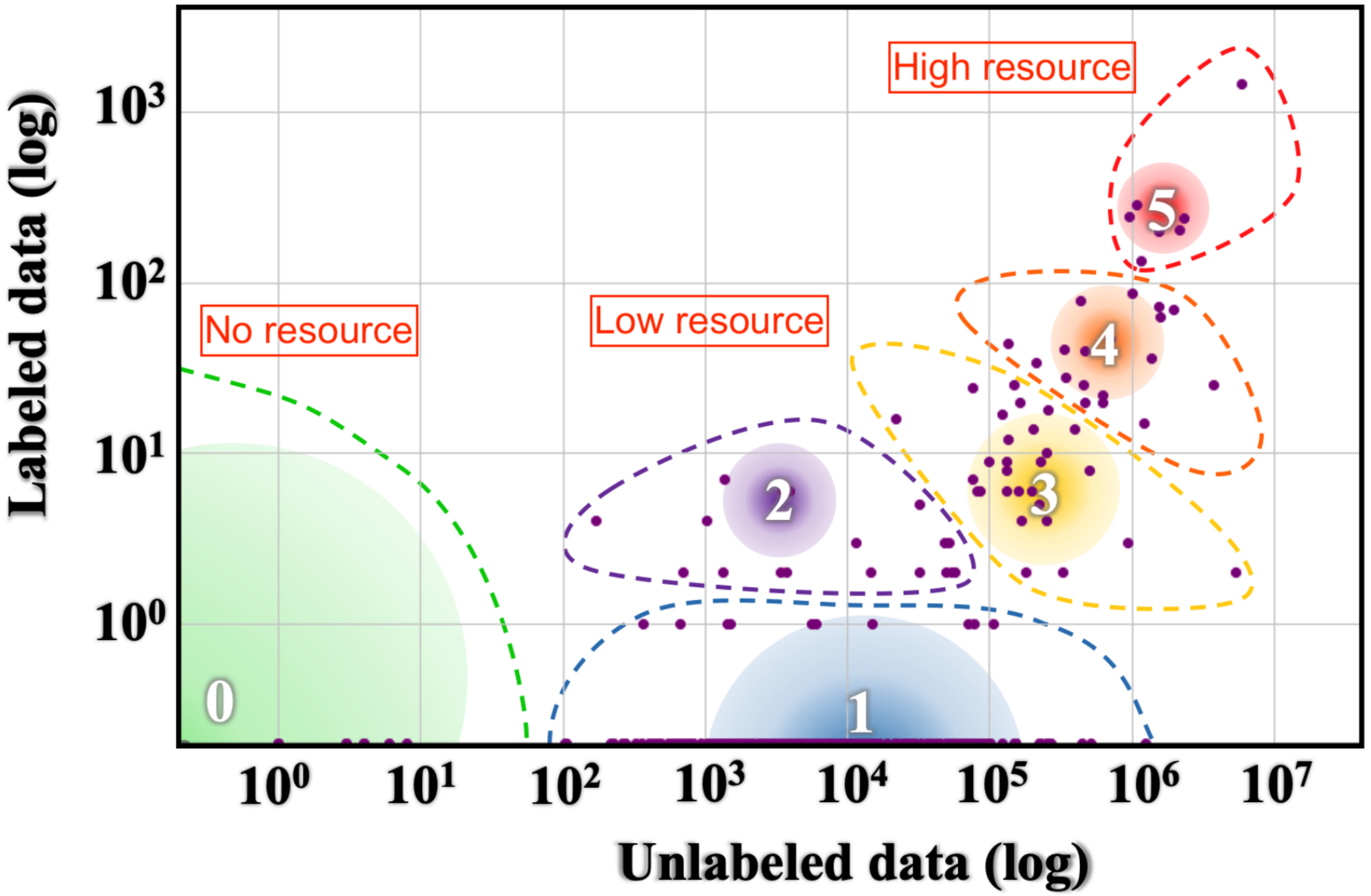
- Effect of multilingual finetuning
- Effect of multilingual instruction tuning
- Effect of multilingual alignment

What we need to do

- more tools (lid, cs id, variety id, etc)
- massively multilingual benchmarks
- better models of heterogeneous data
- more diverse samples of language use

- rethink data collection, evaluation and scores

A final word of caution



Towards "the next 1000 languages", really ?

Class	5 Example Languages	#Langs	#Speakers	% of Total Langs
0	Dahalo, Warlpiri, Popoloca, Wallisian, Bora	2191	1.2B	88.38%
1	Cherokee, Fijian, Greenlandic, Bhojpuri, Navajo	222	30M	5.49%
2	Zulu, Konkani, Lao, Maltese, Irish	19	5.7M	0.36%
3	Indonesian, Ukranian, Cebuano, Afrikaans, Hebrew	28	1.8B	4.42%
4	Russian, Hungarian, Vietnamese, Dutch, Korean	18	2.2B	1.07%
5	English, Spanish, German, Japanese, French	7	2.5B	0.28%

The State and Fate of Linguistic Diversity and Inclusion in the NLP World (Joshi et al., ACL 2020)

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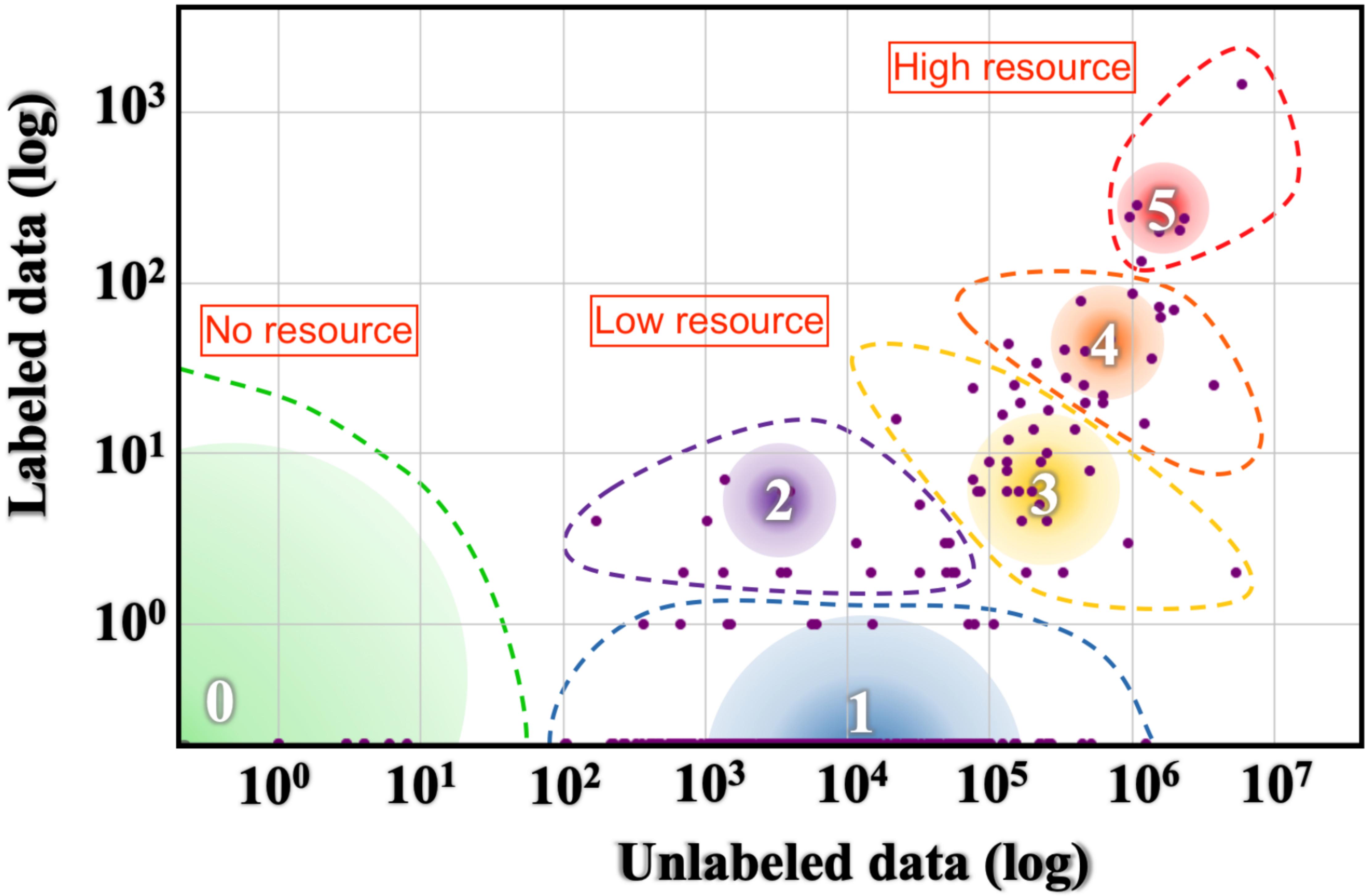

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Local Languages, third spaces, and other high-resource scenario (Bird, 2022)

The State and Fate of Linguistic Diversity and Inclusion in the NLP World (Joshi et al., ACL 2020)

Conclusions & Take aways

mLLMs can boost LTs for ``tail” languages
multilingual abilities remain poorly understood

Special thanks to the LMU/CIS team

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