



(Image Source: Garfield)

Enhancing Multilingual Capabilities in Large Language Models

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Today's Talk —

1 - Cross-lingual Transfer Learning

CODEC

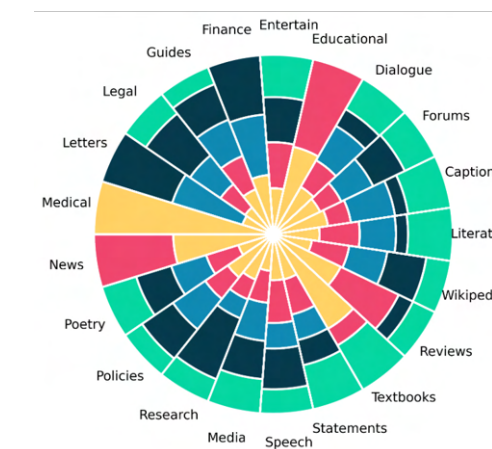


(Le et al., ICLR 2024)

Design decoding algorithms to improve performance on non-English languages.

2 - Multilingual Multi-domain Datasets

ReadMe++ & MedReadMe



(Naous et al., EMNLP 2024 & Chao et al., EMNLP 2024)

Support not only more languages but also more text domains/genres.

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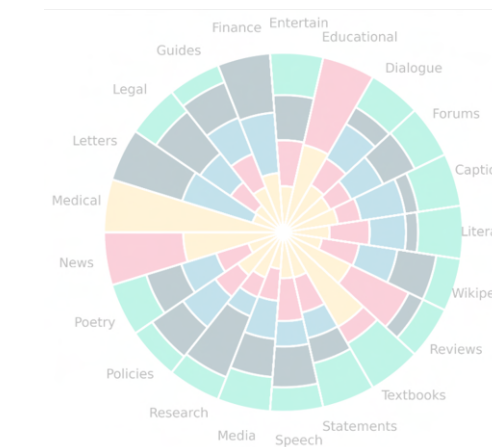


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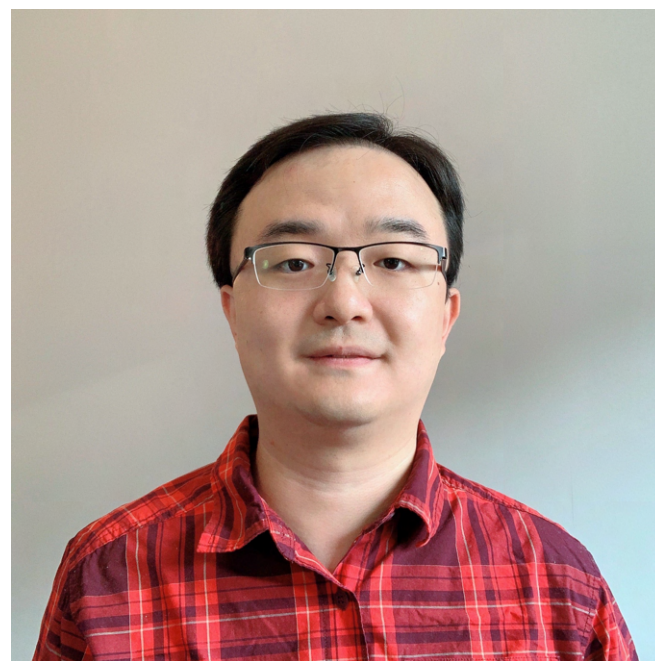
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Support not only more languages but also more text domains/genres.

Frustratingly Easy Label Projection for Cross-lingual Transfer (EasyProject)



Yang Chen



Chao Jiang



Alan Ritter



Wei Xu

A systematic study of marker-based
approach for label projection

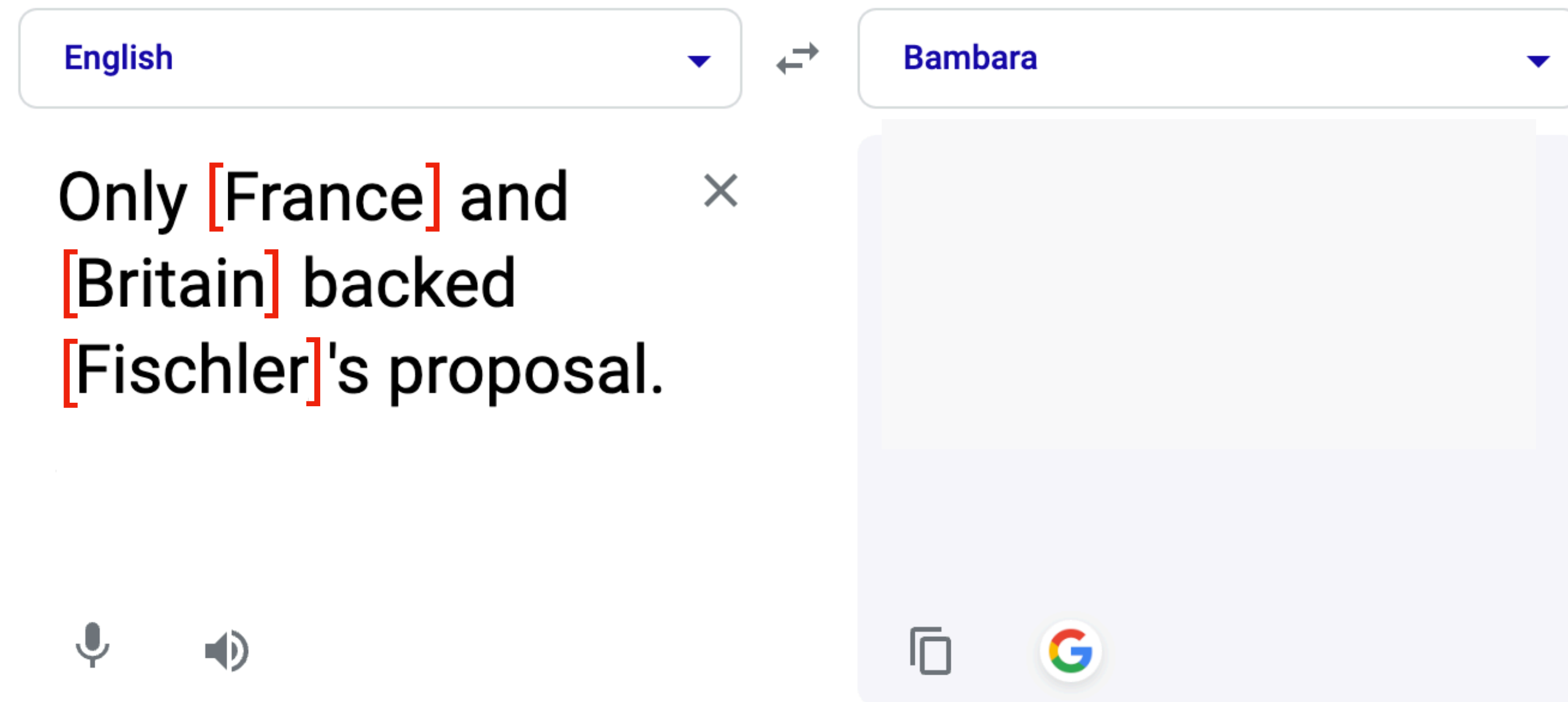
Marker-based Approach

Translating annotated training data from one language to the other

The image shows a Google Translate interface. On the left, a dropdown menu is set to "English". Below it, the text "Only France and Britain backed Fischler 's proposal." is entered. At the bottom left of this section are icons for a microphone and a speaker. In the center, a double-headed arrow indicates the translation direction. On the right, a dropdown menu is set to "Bambara". Below it, the translated text is displayed in a light blue box. At the bottom right of this section are icons for a document and the Google logo.

Marker-based Approach

Translating annotated training data from one language to the other by injecting some markers [] around the text spans



Marker-based Approach

Translating annotated training data from one language to the other by injecting some markers [] around the text spans, then sending it directly to a Machine Translation system.

The screenshot shows a Google Translate interface. On the left, the source language is set to "English". The input text is "Only [France] and [Britain] backed [Fischler]'s proposal.", where the words "France", "Britain", and "Fischler" are enclosed in red square brackets. A close button (X) is visible to the right of the text. Below the text are icons for a microphone and a speaker. On the right, the target language is set to "Bambara". The translated text is "[France] ni [Britagne] dɔrɔn de ye [Fischler] ka laɲini dɛmɛ." Below the translated text are icons for a document and the Google logo.

Marker-based Approach

Translating annotated training data from one language to the other by injecting some markers [] around the text spans, then sending it directly to a Machine Translation system.

The screenshot shows a machine translation interface with two language dropdown menus: "English" on the left and "Bambara" on the right. A double-headed arrow connects the two menus. Below the "English" menu, the text "Only [France] and [Britain] backed [Fischler]'s proposal." is displayed with a close button (X). Below the "Bambara" menu, the translated text "[France] ni [Britagne] dɔrɔn de ye [Fischler] ka laɲini dɛmɛ." is shown. A red oval highlights the word "[France]" in the Bambara text. A red arrow points from the text "though not without caveat (will talk more later)" to the "Bambara" dropdown menu. At the bottom of the Bambara text area, there are icons for a clipboard and the Google logo.

English

Bambara

though not without caveat
(will talk more later)

Only [France] and [Britain] backed [Fischler]'s proposal.


[France] ni [Britagne]
dɔrɔn de ye [Fischler]
ka laɲini dɛmɛ.

Marker-based Approach

- used by researchers “informally” as a hack
 - one of the earliest such accounts is by Lee et al. (2018)
 - then, used in MLQA (Lewis et al., 2020), XTREME (Hu et al., 2020) ...
-
- But, only described briefly in each paper
 - How well does it work? For different languages, tasks? Better or worse than word alignment?

EasyProject - Easy Marker-based Projection

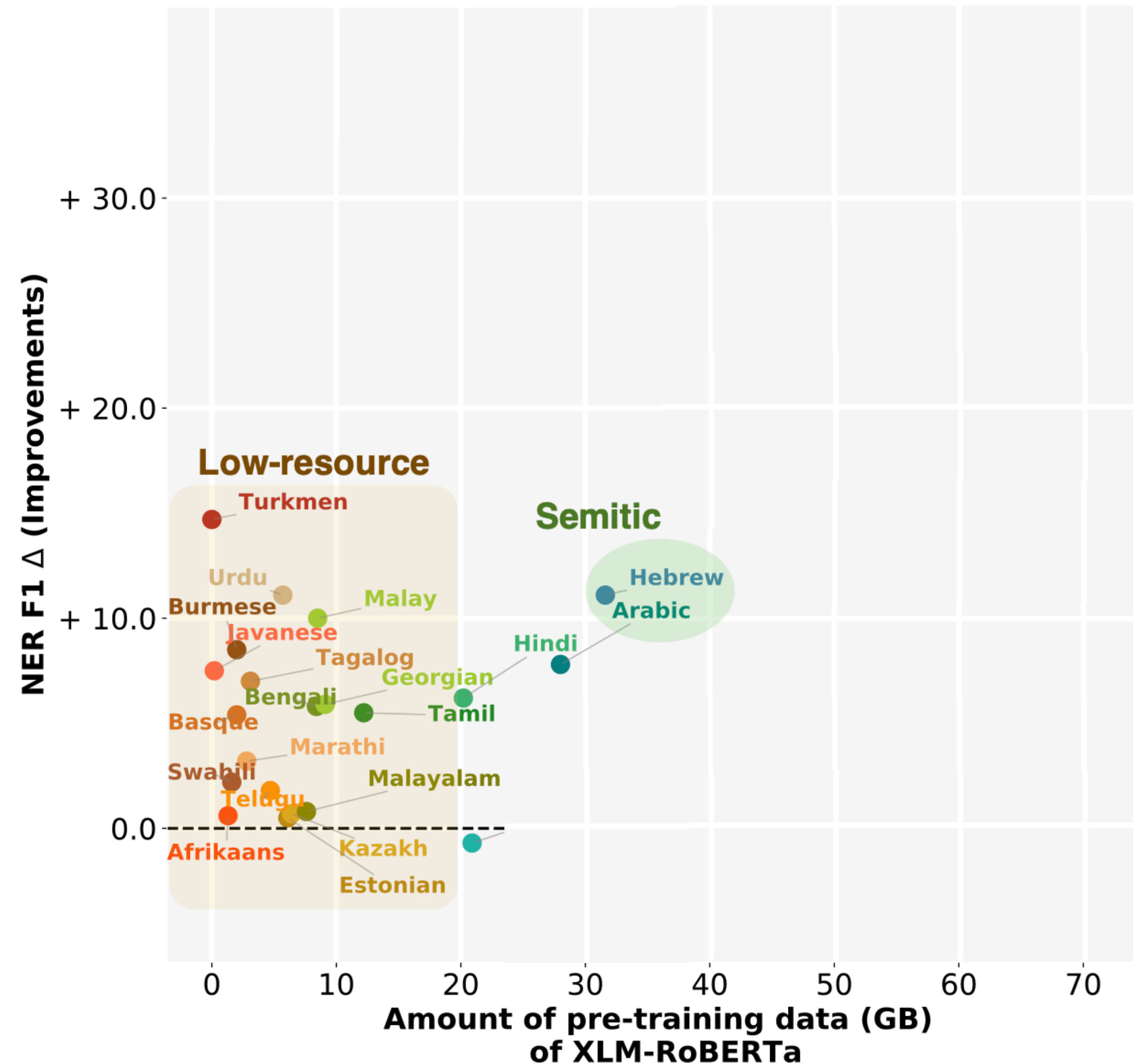
- Different markers all work to some extents, but vary for languages:

XML tags (e.g., <loc> </loc>) or  **[]** “ ” () < > { }

- If >1 spans to be projected in one sentence, do need to map the tags by fuzzy string matching
- Further fine-tuning MT system on synthetic data to make it more robust with punctuations

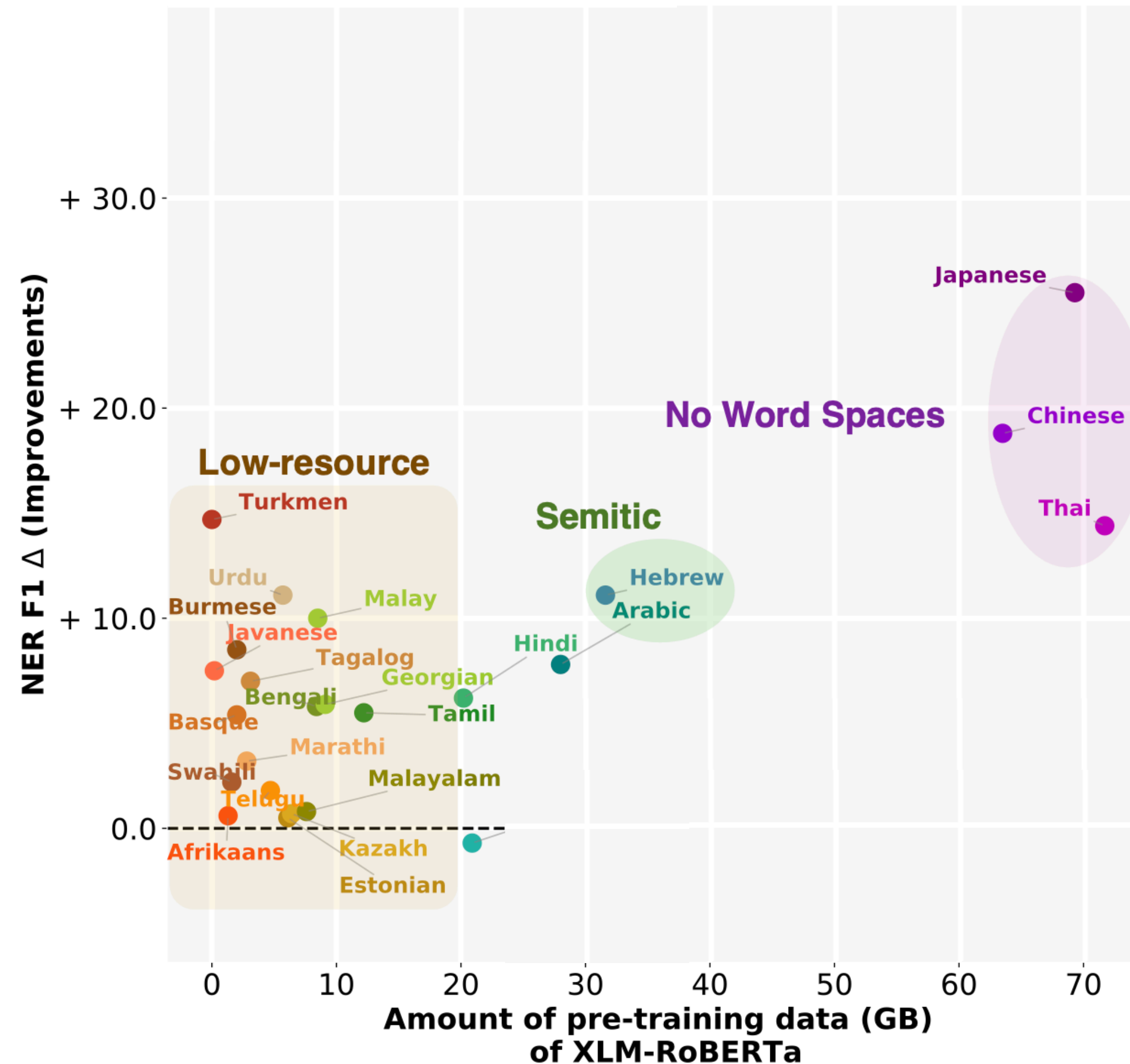
EasyProject - Easy Marker-based Projection

Especially promising for low-resource languages & languages that are written in non-Latin scripts



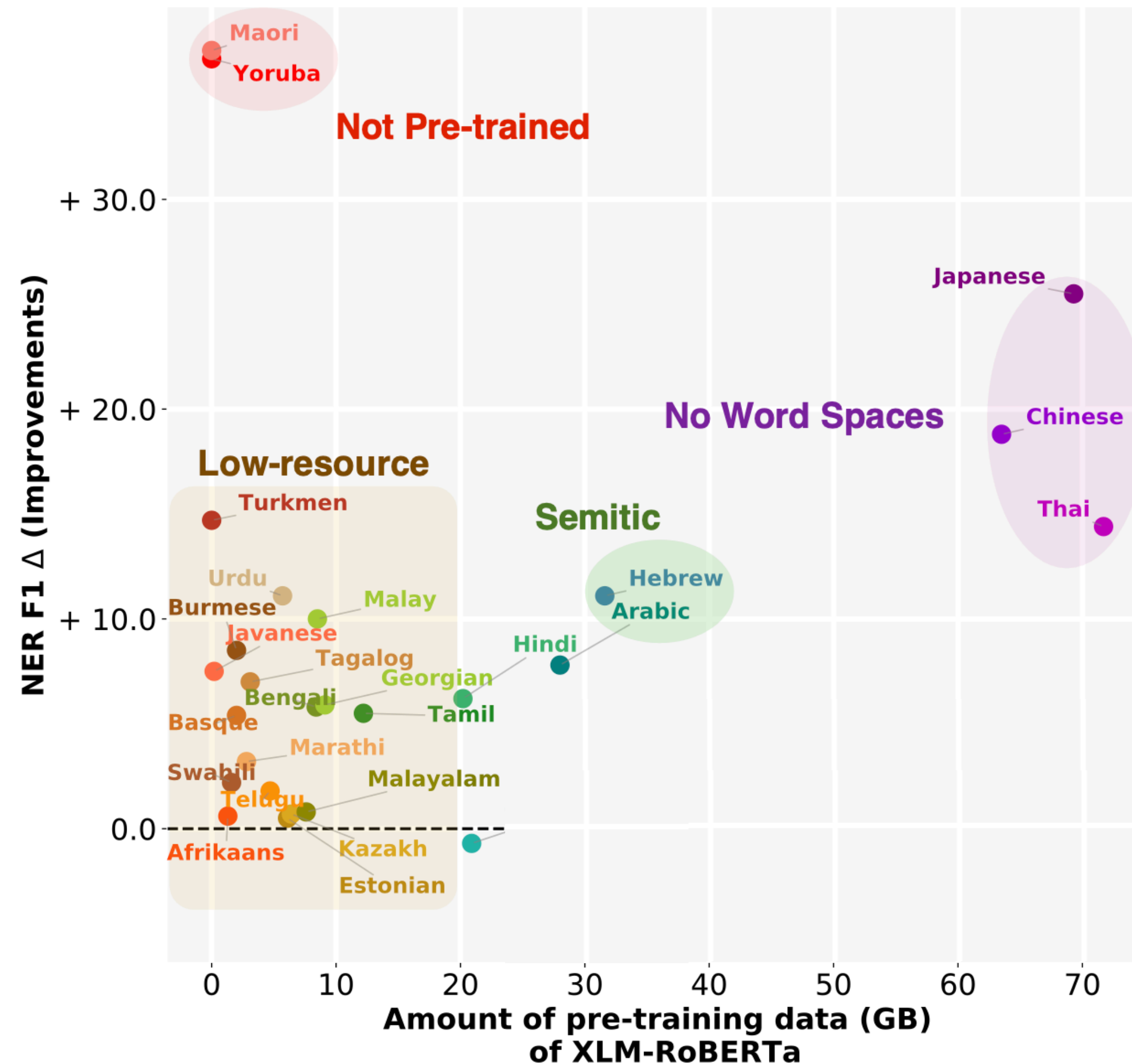
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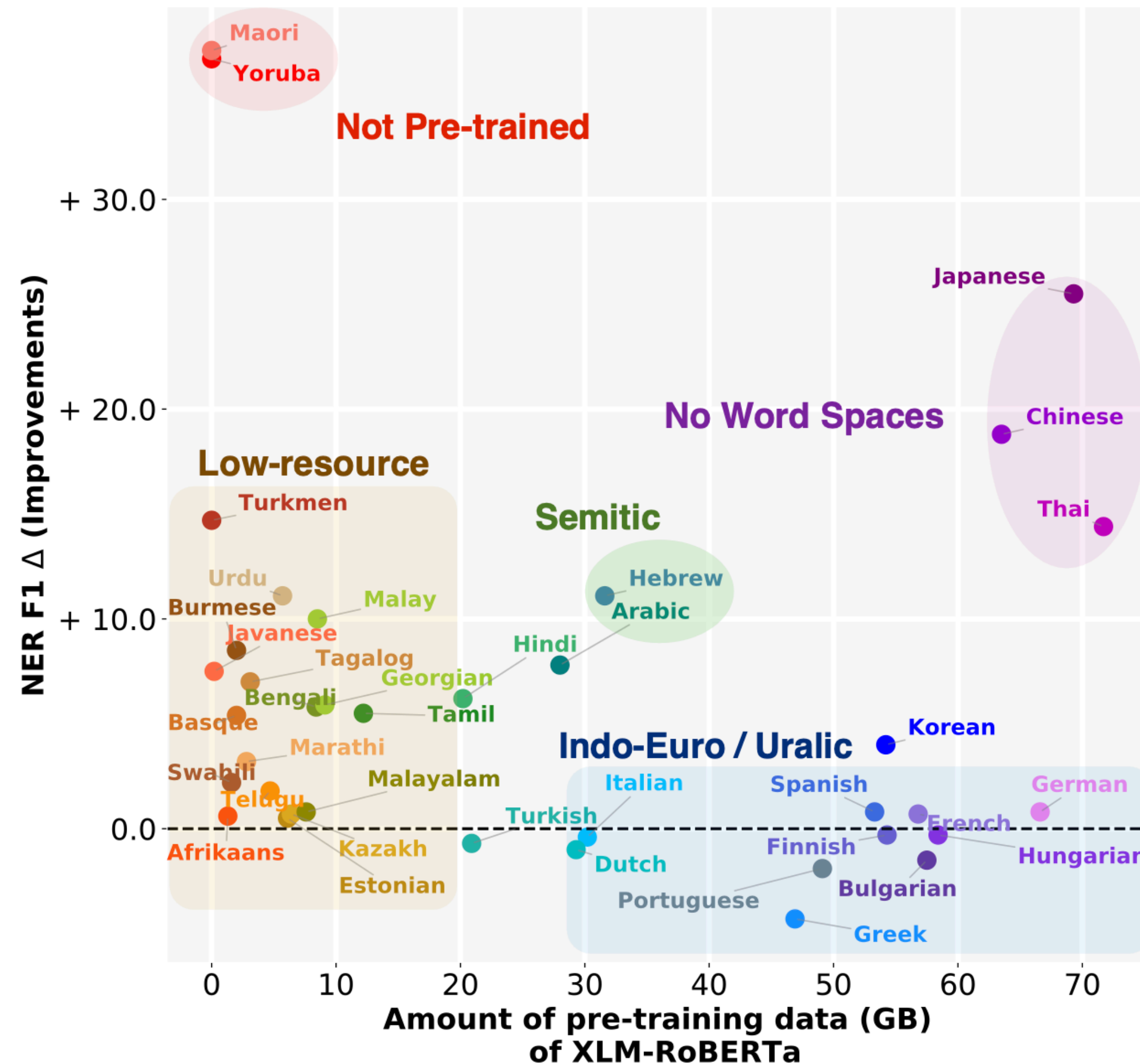
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Zero-shot Cross-lingual Label Projection

Two families of approaches, but each has **pros** and **cons**.

marker-based approach

The screenshot shows a Google Translate interface. On the left, the source language is set to 'English' and the text is 'Only [France] and [Britain] backed [Fischler]'s proposal.' On the right, the target language is set to 'Bambara' and the translated text is '[France] ni [Britagne] daron de ye [Fischler] ka lajini demε.' A red circle highlights the words '[France] ni [Britagne]' in the Bambara translation. At the bottom of the interface, there are icons for voice input, voice output, copy, and the Google logo.

Only need a MT system
&
work surprisingly well !

But, degraded
MT quality
due to injected markers

Zero-shot Cross-lingual Label Projection

Two families of approaches, but each has **pros** and **cons**.

marker-based approach

English ↔ Bambara

Only [France] and [Britain] backed [Fischler]'s proposal. × [France] ni [Britagne] dɔrɔn de ye [Fischler] ka laɲini dɛmɛ.

word alignment-based approach

English ↔ Bambara

Only France and Britain backed Fischler 's proposal . × Faransi ni Angletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ .

Only need a MT system & work surprisingly well !

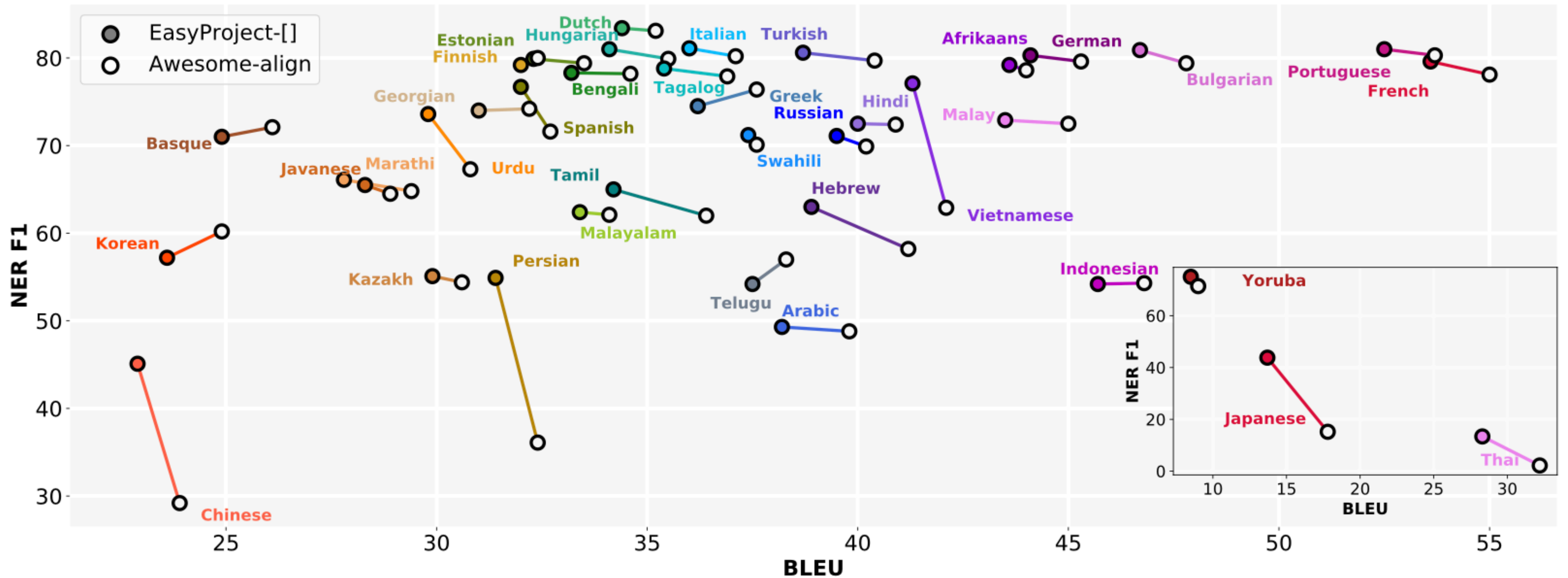
But, degraded MT quality due to injected markers

normally better MT quality

Require not only neural MT, but also a separate word alignment model

EasyProject - Easy Marker-based Projection

Despite degraded MT quality, marker-based approach still works surprisingly well for the end task!



Can we do marker-based approach without scarifying the translation quality?

Constrained Decoding for Cross-lingual Label Projection (CODEC)



Duong Minh Le



Yang Chen



Alan Ritter

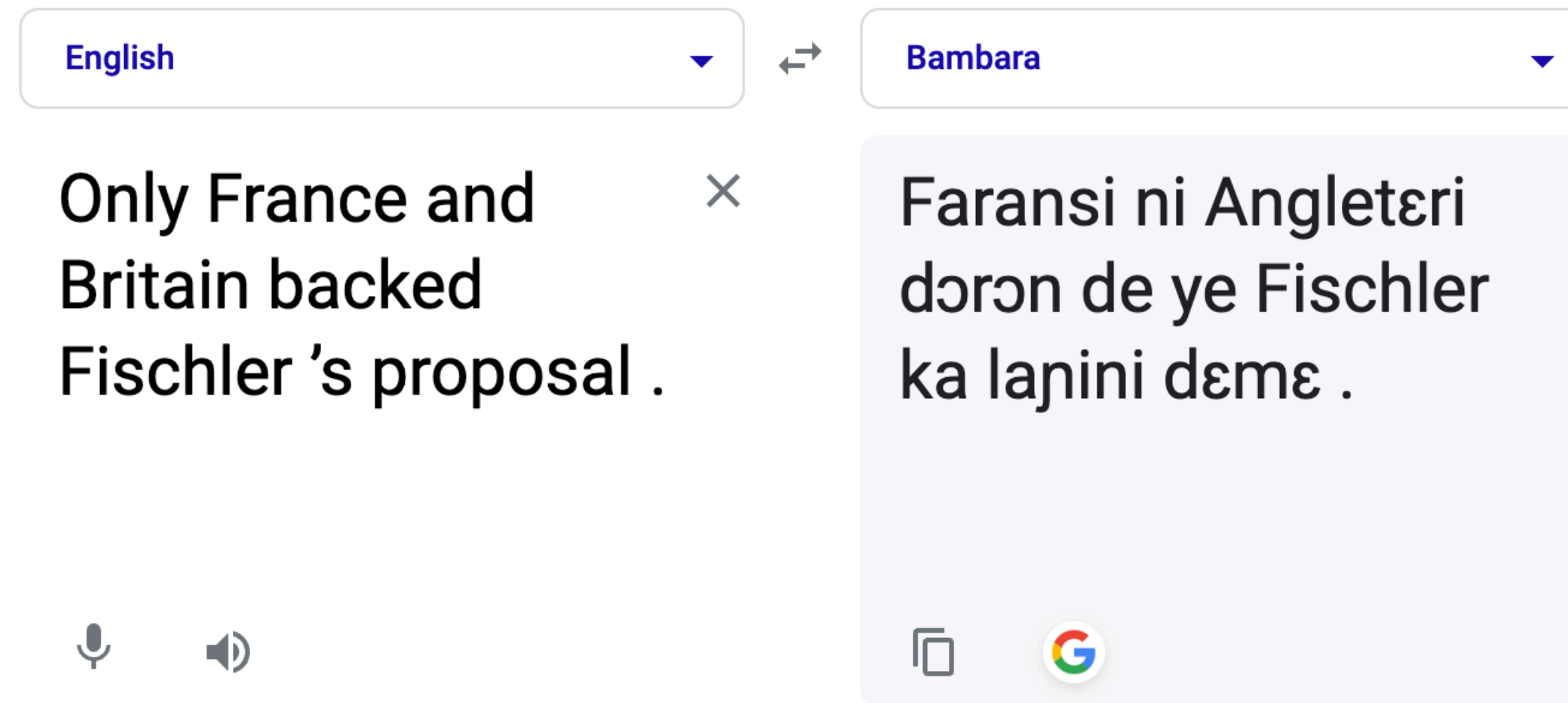


Wei Xu

A better technical solution for
marker-based label projection

Key Idea

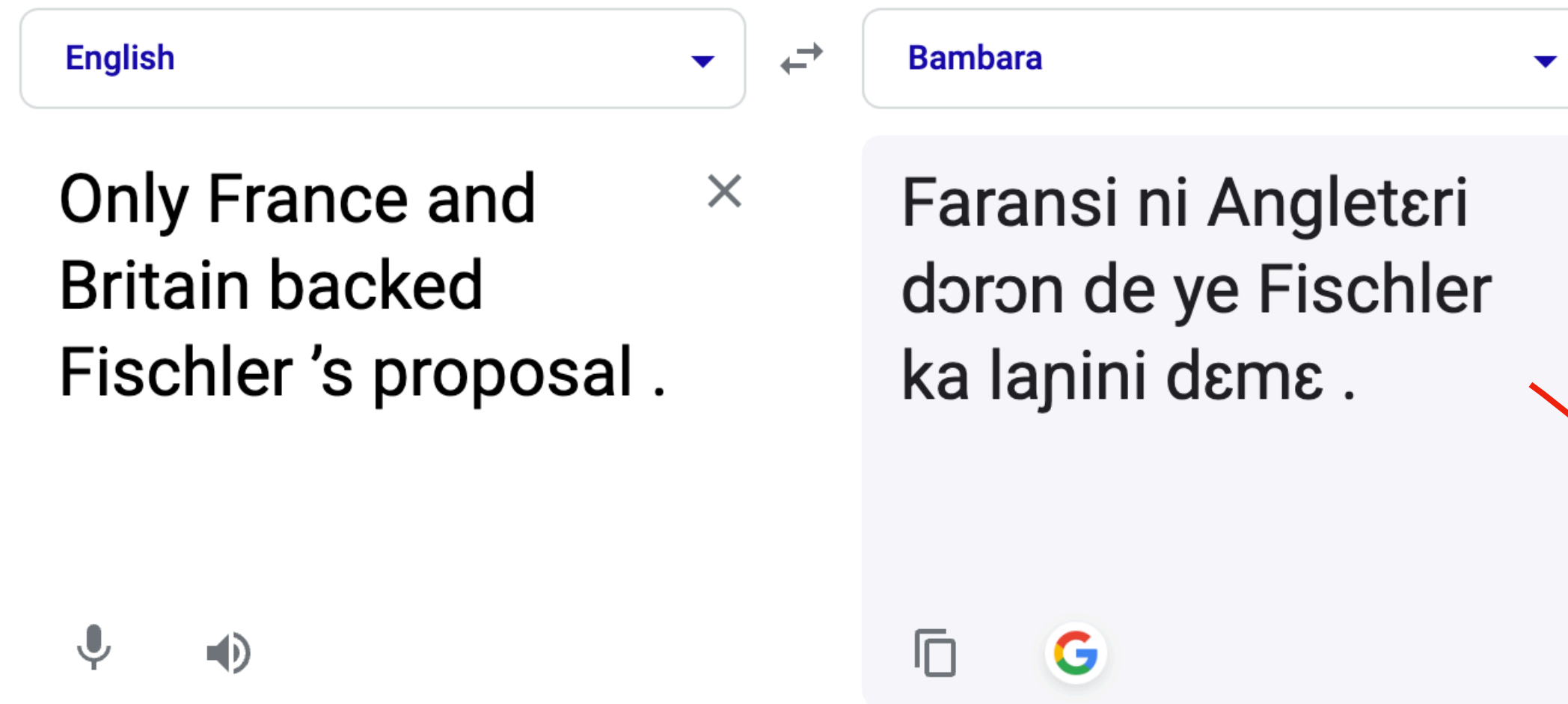
Step 1. Translate the original sentence as usual without markers.



Step 2. Run translation model for a 2nd time to insert markers as a constrained decoding problem.

Key Idea

Step 1. Translate the original sentence as usual without markers.

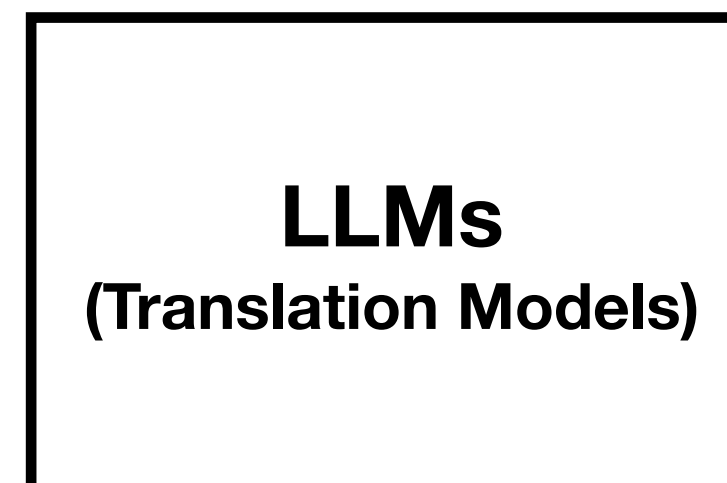


Impose two constraints:
(1) keeping the same translation
(2) having the correct number of [] s

Step 2. Run translation model for a 2nd time to insert markers as a constrained decoding problem.

Input sentence:

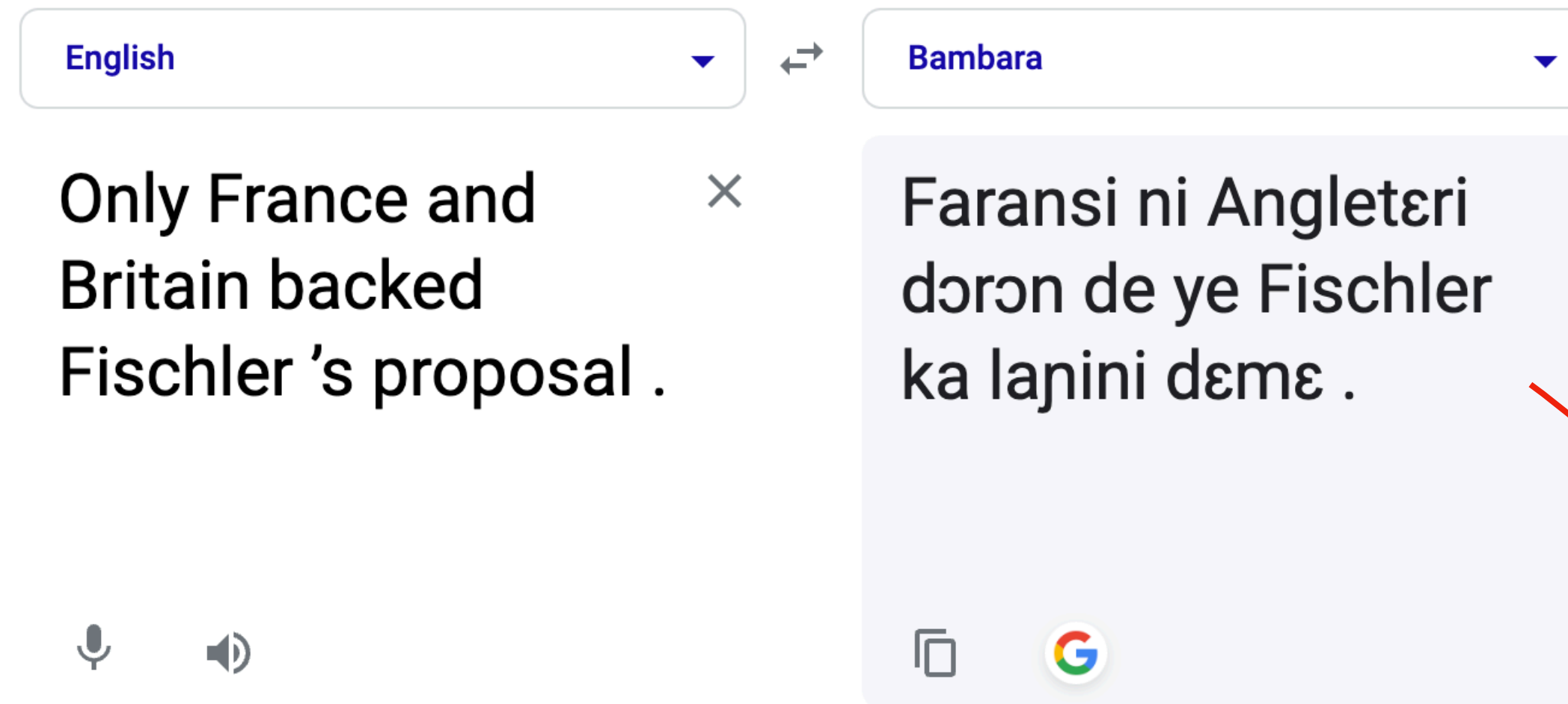
Only [France] and [Britain] backed [Fischler]'s proposal.



Translated Output:

Key Idea

Step 1. Translate the original sentence as usual without markers.



Impose two constraints:
(1) keeping the same translation
(2) having the correct number of [] s

Step 2. Run translation model for a 2nd time to insert markers as a constrained decoding problem.

Input sentence:

Only [France] and [Britain] backed [Fischler]'s proposal.

LLMs
(Translation Models)

Translated Output:

[Faransi] ni [Angileteri] dɔrɔn de ye [Fischler] ka laɲini dɛmɛ .

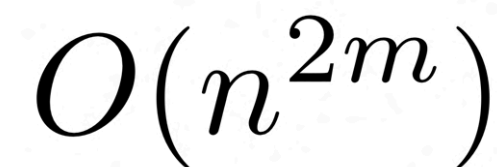
Key Idea — more formally

Step 1. Translate the original sentence as usual without markers.

$$y^{tmp} = \arg \max_y \log P_\tau(y|x)$$

Step 2. Run translation model another time to insert m marker pairs $[\]$ into y^{tmp} .

$$y^* = \arg \max_{y \in \mathcal{Y}} \log P_\tau(y|x^{mark}; y^{tmp})$$


$$O(n^{2m})$$

An Efficient Constrained Decoding Algorithm

(1) Prune opening marker positions based on the contrastive log-likelihood difference.

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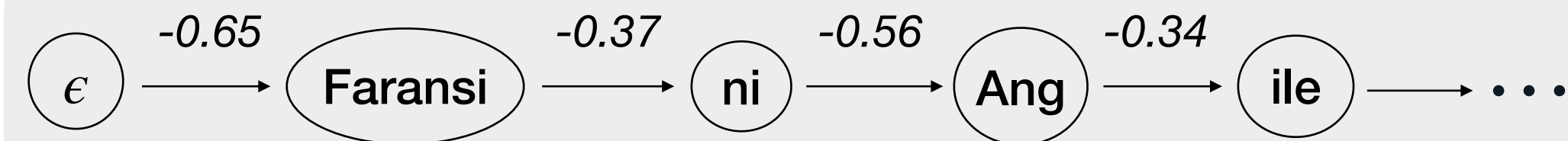
Input:

x = “Only France and Britain backed
Fischler 's proposal .”

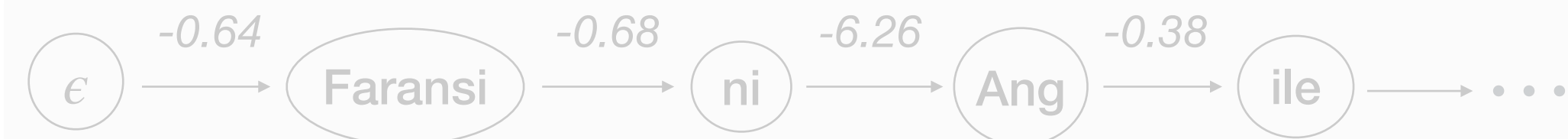
x^{mark} = “Only France and [Britain] backed
Fischler 's proposal .”

y^{tpl} = “Faransi ni Angileteri dōron de ye
Fischler ka laḡini dεme .”

$$p_1^i = \log P(y_i^{tpl} | y_{<i}^{tpl}, x) \text{ (Conditioned on source text)}$$



$$p_2^i = \log P(y_i^{tpl} | y_{<i}^{tpl}, x^{mark}) \text{ (Conditioned on source text w/ markers)}$$



An Efficient Constrained Decoding Algorithm

(1) Prune opening marker positions based on the contrastive log-likelihood difference.

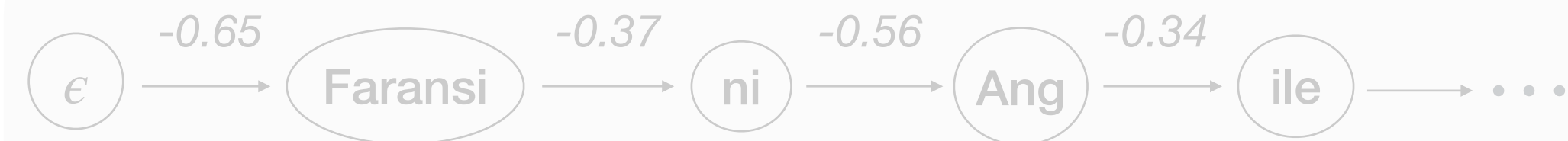
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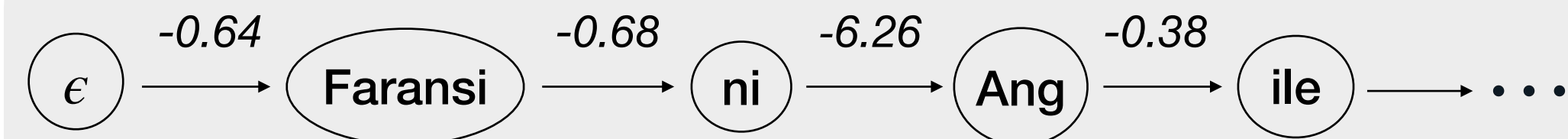
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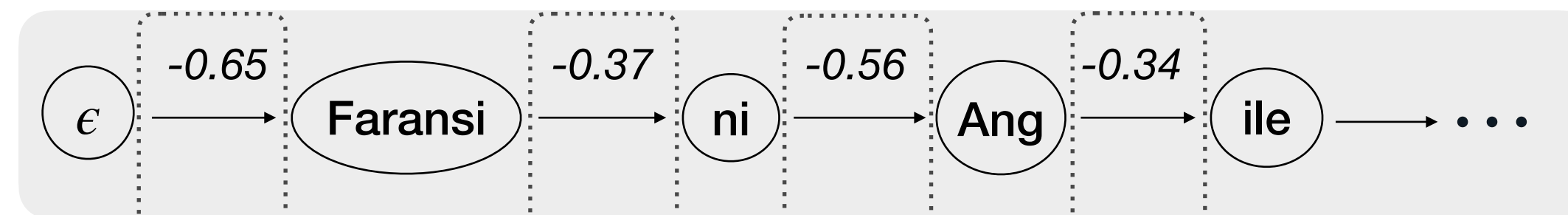
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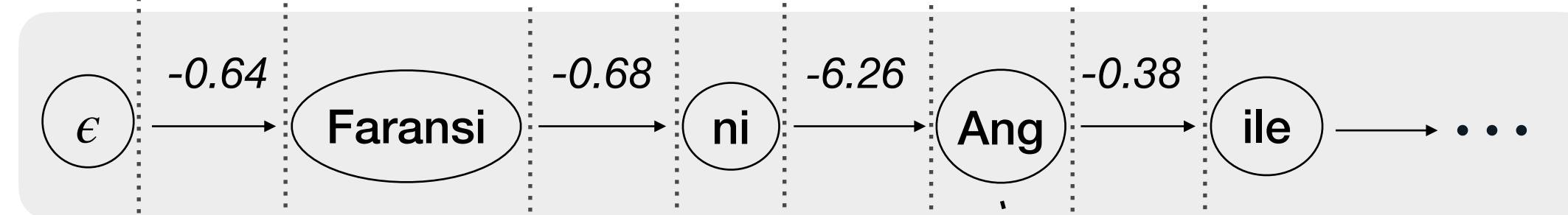
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$$\Delta_i = |p_1^i - p_2^i|$$

0.01

0.31

5.7

0.04

This position should be '[', thus the transition probability is extremely low

An Efficient Constrained Decoding Algorithm

(1) Prune opening marker positions based on the contrastive log-likelihood difference.

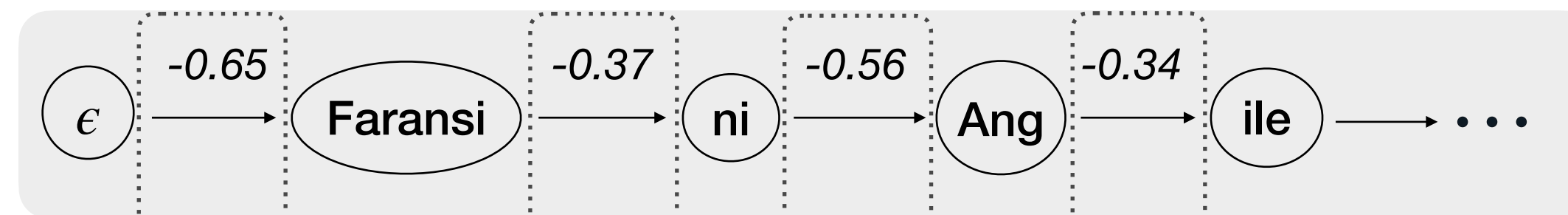
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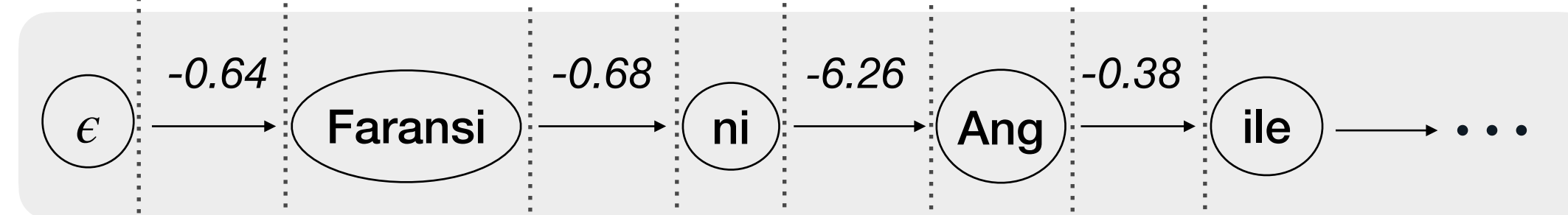
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$$\Delta_i = |p_1^i - p_2^i|$$

0.01 0.31 5.7 0.04

Opening marker positions (after “Faransi” or after “ni”)

An Efficient Constrained Decoding Algorithm

(2) A branch-and-bound search algorithm with a heuristic lower bound $L_d^k = \log P(y_{1:d}^k | x^{mark})$.
 $d = \min(\max(j + \delta, q), |y^k|)$

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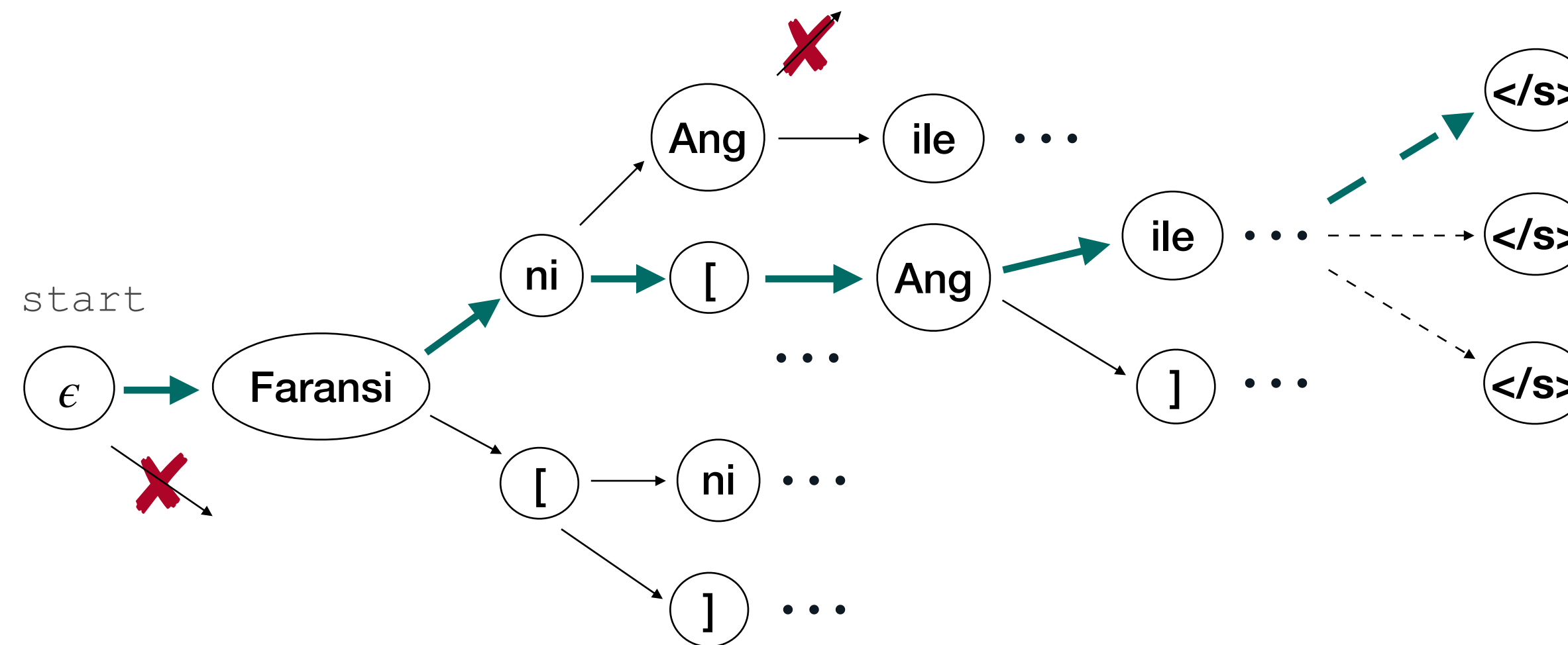
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X *Prune opening-marker positions*

An Efficient Constrained Decoding Algorithm

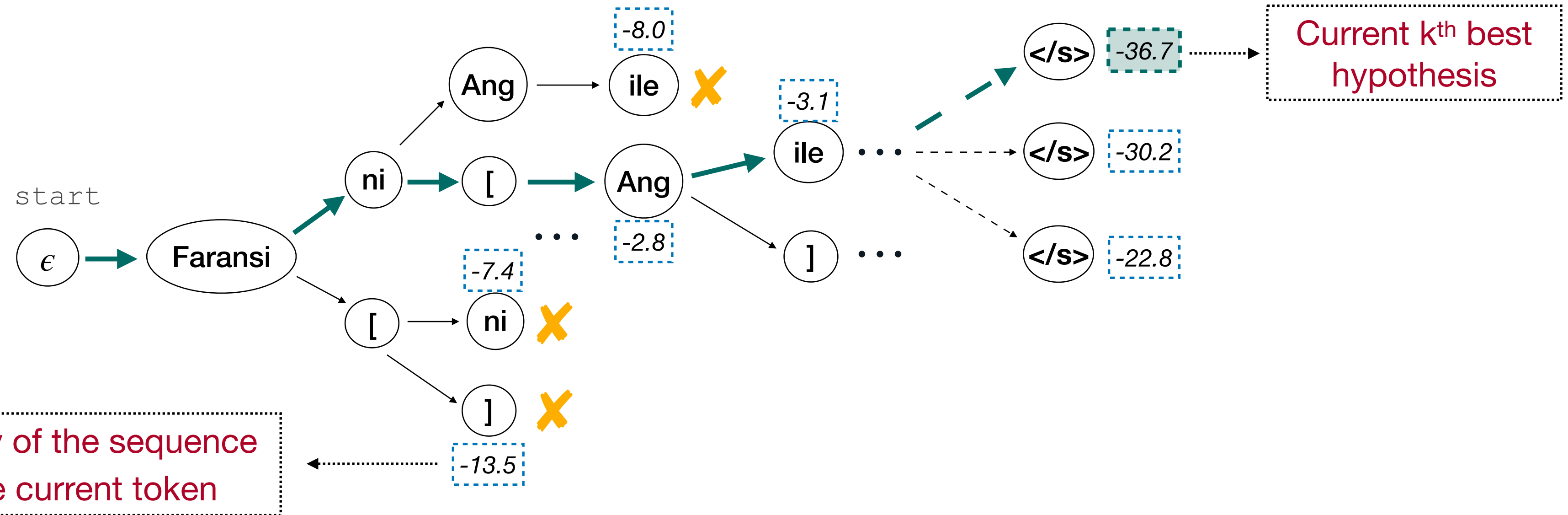
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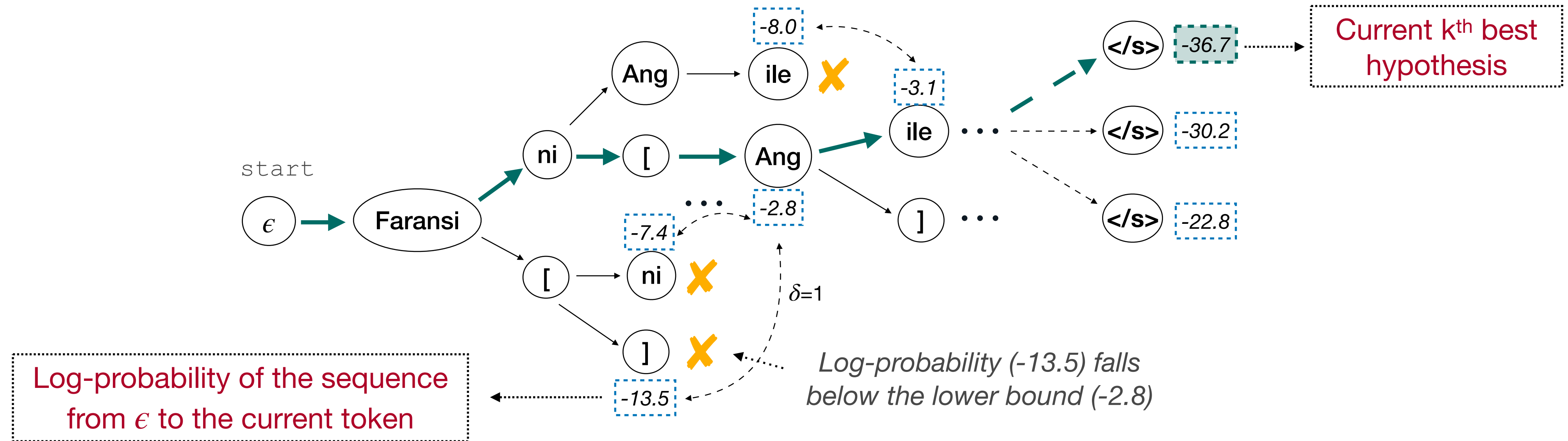
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Fischler ka lapini deme ."



Log-probability of the sequence from ϵ to the current token

X Prune branches based on a heuristic lower-bound

An Efficient Constrained Decoding Algorithm

Algorithm 1 Constrained_DFS: Searching for top-k best hypotheses

Input x^{mark} : Source sentence with marker, y : translation prefix (default: ϵ), y^{tmpl} : translation template,
 L : $[\log P(y_1|x), \log P(y_{1:2}|x), \dots, \log P(y|x)]$ (default= $[0.0]$), \mathcal{M} : opening marker positions
 H : min heap to record the results, k : number of hypotheses, δ : lower bound hyperparameter

```
1:  $flag \leftarrow \{\text{check if all markers are generated}\}$ 
2: if  $y_{|y|} = \langle /s \rangle$  and  $flag = \text{TRUE}$ : then
3:    $H.\text{push}((L_{|y|}, L, y))$  ▷  $H$  sorts by the first element
4:   if  $\text{len}(H) > k$  then
5:      $H.\text{pop}()$ 
6: else
7:    $\mathcal{T} \leftarrow []$ 
8:    $w_1 \leftarrow \{\text{get the next token in } y^{tmpl}\}$ 
9:    $\mathcal{T} \leftarrow \mathcal{T} \cup \{(w_1, \log P(w_1|y, x^{mark}))\}$ 
10:   $j \leftarrow |y| + 1$  ▷ position of the token to be generated next
11:   $w_2 \leftarrow \{\text{get the next marker}\}$ 
12:  if  $\exists w_2$  and not  $(w_2 = '[' \text{ and } j \notin \mathcal{M})$  then
13:     $\mathcal{T} \leftarrow \mathcal{T} \cup \{(w_2, \log P(w_2|y, x^{mark}))\}$ 
14:   $\mathcal{T} \leftarrow \{\text{sort } \mathcal{T} \text{ by the second element in decreasing order}\}$ 
15:  for  $(w, p) \in \mathcal{T}$  do
16:     $\text{log}p \leftarrow L_{|y|} + p$ 
17:     $\gamma \leftarrow \{\text{compute lower bound following Eq 7}\}$ 
18:    if  $\text{log}p > \gamma$  then
19:      Constrained_DFS( $x^{mark}, y \cdot w, y^{tmpl}, L \cup \{\text{log}p\}, \mathcal{M}, H, k, \delta$ )
20: return  $H$ 
```

Experiment Results

CODEC outperforms GPT-4, EasyProject and Awesome-align for NER and Event Extraction tasks.

- **Label Projection baselines:**

- Alignment-based (***Awes-align***): Utilize a word-alignment system (*Awesome-align*¹) to perform label projection
- Marker-based (***EasyProject***): insert markers into the source sentence then translate

- **Zero-shot Cross-lingual transfer (FT_{En})**

The multilingual model is fine-tuned only on the English data

¹Zi-Yi Dou and Graham Neubig. *Word alignment by fine-tuning embeddings on parallel corpora*. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pp. 2112–2128, Online, April 2021

Experiment Results

More importantly, CODEC shines on low-resource languages, such as MasakhaNER 2.0 dataset.

Lang.	GPT-4 [†]	FT _{En}	Translate-train		
			Awes-align	EasyProject	CODEC (Δ_{FT})
Bambara	46.8	37.1	45.0	45.8	45.8 (+8.7)
Ewe	75.5	75.3	78.3	78.5	79.1 (+3.8)
Fon	19.4	49.6	59.3	61.4	65.5 (+15.9)
Hausa	70.7	71.7	72.7	72.2	72.4 (+0.7)
Igbo	51.7	59.3	63.5	65.6	70.9 (+11.6)
Kinyarwanda	59.1	66.4	63.2	71.0	71.2 (+4.8)
Luganda	73.7	75.3	77.7	76.7	77.2 (+1.9)
Luo	55.2	35.8	46.5	50.2	49.6 (+13.8)
Mossi	44.2	45.0	52.2	53.1	55.6 (+10.6)
Chichewa	75.8	79.5	75.1	75.3	76.8 (-2.7)
chiShona	66.8	35.2	69.5	55.9	72.4 (+37.2)
Kiswahili	82.6	87.7	82.4	83.6	83.1 (-4.6)
Setswana	62.0	64.8	73.8	74.0	74.7 (+9.9)
Akan/Twi	52.9	50.1	62.7	65.3	64.6 (+14.5)
Wolof	62.6	44.2	54.5	58.9	63.1 (+18.9)
isiXhosa	69.5	24.0	61.7	71.1	70.4 (+46.4)
Yoruba	58.2	36.0	38.1	36.8	41.4 (+5.4)
isiZulu	60.2	43.9	68.9	73.0	74.8 (+30.9)
AVG	60.4	54.5	63.6	64.9	67.1 (+12.7)

- NER: mDeBERTa-v3
- MT: NLLB

Experiment Results

prior marker-based approach
cannot do this

“Translate-test” - CODEC can also translate test data in source language into a high-resource language to run inference on, then project predicted span labels back to the test data.

Lang.	GPT-4 [†]	FT _{En}	Translate-train			Translate-test	
			Awes-align	EasyProject	CODEC (Δ_{FT})	Awes-align	CODEC (Δ_{FT})
Bambara	46.8	37.1	45.0	45.8	45.8 (+8.7)	50.0	55.6 (+18.5)
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Setswana	62.0	64.8	73.8	74.0	74.7 (+9.9)	81.4	80.3 (+15.5)
Akan/Twi	52.9	50.1	62.7	65.3	64.6 (+14.5)	72.6	73.5 (+23.4)
Wolof	62.6	44.2	54.5	58.9	63.1 (+18.9)	58.1	67.2 (+23.0)
isiXhosa	69.5	24.0	61.7	71.1	70.4 (+46.4)	52.7	69.2 (+45.2)
Yoruba	58.2	36.0	38.1	36.8	41.4 (+5.4)	49.1	58.0 (+22.0)
isiZulu	60.2	43.9	68.9	73.0	74.8 (+30.9)	64.1	76.9 (+33.0)
AVG	60.4	54.5	63.6	64.9	67.1 (+12.7)	65.8	70.4 (+16.0)

Error Analysis

Underline marks the projection errors.



only marks sub-words
as an entity

Augmented data in low-resource languages

English Data

EasyProject

Awesome-align

Codec

chiShona

India_{LOC} and Pakistan_{LOC} have fought ... region of Kashmir_{LOC} ...

India_{LOC} ne Pakistan_{LOC} ...
ye Kashmir_{LOC} chibviro ...

India_{LOC} nePakistan ...
zvinetso yeKashmir_{LOC} ...

India_{LOC} nePakistan_{LOC} ...
zvinetso yeKashmir_{LOC} ...

isiZulu

State media quoted China_{LOC}'s top negotiator with Taipei_{LOC}, Tang Shubei_{PER}, ... from Taiwan_{LOC} ...

Imithombo ... we China_{LOC} ne Taipei_{LOC}, uTang Shubei_{PER}, ... elivela eTaiwan_{LOC} ...

Imithombo_{LOC} ... waseChina neTaipei, uTang Shubei_{PER}, ... elivela eTaiwan ...

Imithombo ... waseChina_{LOC} neTaipei_{LOC}, uTang Shubei_{PER}, ... elivela eTaiwan_{LOC} ...

having difficulty
to project multiple spans

Today's Talk —

1 - Cross-lingual Transfer Learning

CODEC

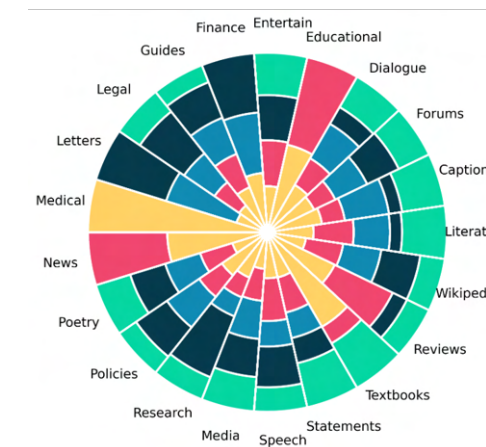


(Le et al., ICLR 2024)

Design decoding algorithms to improve performance on non-English languages.

2 - Multilingual Multi-domain Datasets

ReadMe++ & MedReadMe



(Naous et al., EMNLP 2024 & Chao et al., EMNLP 2024)

Support not only more languages but also more text domains/genres.

Today's Talk —

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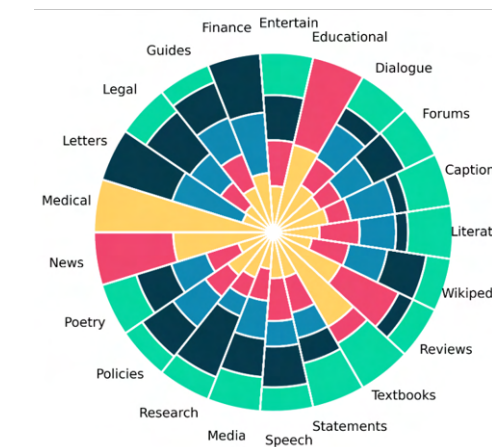


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Support not only more languages but also more text domains/genres.

Text Simplification

Rewrite complex text into simpler language while retain its original meaning.

Science

Preserved on ancient teeth, a fossilized microbial world

By Deborah Netburn, Los Angeles Times

Published: 03/05/2014 Word Count: 682



The layers of calcified plaque entomb the bacteria that also live in our mouths -- turning them into small fossils even when we are alive. And when we die, these dense, calcified micro-fossils remain intact, even as most of the rest of us decomposes.

Text Simplification

Rewrite complex text into simpler language while retain its original meaning.

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And when we die, these dense, calcified micro-fossils remain intact, even as most of the rest of us decomposes.

Text Simplification

Rewrite complex text into simpler language while retain its original meaning.

The **layers** of ~~calcified~~ plaque **entomb** the bacteria that also ~~live~~ in our mouths -- turning them into **small** fossils ~~even when we are alive.~~

split

The **buildup** of plaque **can trap** the bacteria that live in our mouths.

It turns them into **tiny** fossils.

~~And when we die,~~ these ~~dense, calcified~~ micro-fossils **remain intact,** ~~even as most of the rest of us decomposes.~~

paraphrase

Even after death, these micro-fossils **don't break down.**

Human Text Simplification

Professional editors rewrite news articles into 4 different readability levels for grade 3-12 students.

NEWSELA

WAR & PEACE SCIENCE KIDS MONEY HEALTH

SCIENCE 1738 SHARE

Archaeologist may have found remains of ancient Egyptian Queen Nefertiti

By Robert Gebelhoff, Washington Post. 08.17.15

The 3,330-year-old bust of Nefertiti sits in an exhibition in the Kulturforum in Berlin, Germany, March 1, 2005. Photo: AP/Herbert Knosowski

Nefertiti — she's an ancient Egyptian queen and the source of a fantastic mystery regarding the iconic remnants of long-lost royalty.

For decades, archaeologists have speculated on the location of the queen's remains, the last royal mummy missing from the dynasty of the famous King Tutankhamun, better known as King Tut. But now, an archaeologist claims that he has found her

MAX
1140L
960L
720L
420L
WRITE
QUIZ

NEWSELA

WAR & PEACE SCIENCE KIDS MONEY LAW HEALTH

SCIENCE 1738 SHARE

Mystery of ancient Egypt solved? Tomb of queen may be hidden near King Tut

By Washington Post, adapted by Newsela staff. 08.17.15

The 3,330-year-old bust of Nefertiti sits in an exhibition in the Kulturforum in Berlin, Germany, March 1, 2005. Photo: AP/Herbert Knosowski

The ancient Egyptian Queen Nefertiti has long been at the center of a mystery.

For years, archaeologists have wondered where her tomb might be hidden. Nefertiti belonged to the family line of the famous King Tutankhamun, better known as King Tut. Indeed, some believe she was Tut's mother. While the other royals in her line are

1140L
960L
720L
420L
WRITE
QUIZ

Wei Xu, Chris Callison-Burch, Courtney Napoles. "Problems in Current Text Simplification Research: New Data Can Help" (TACL 2015)

Yang Zhong, Chao Jiang, Wei Xu, Jessy Li. "Discourse Level Factors for Sentence Deletion in Text Simplification" (AAAI 2020)

Why Text Simplification?

It can help a lot of people!

- Children (Leonardo et al., 2018) ← research on education using Newsela data
 - Second language learners (Housel et al., 2020) ←
 - Deaf and hard-of-hearing students (Alonzo et al., 2020) ← using our EMNLP 2018 work on lexical simplification
 - People with dyslexia (Rello et al., 2013)
 - People with autism spectrum disorder (González-Navarro et al., 2014)
- and many others ... e.g., to read legal & medical documents (Trienes et al. 2024; Joseph et al. 2024), etc.



Other Text Generation Tasks

- **Multilingual split and rephrase** (Daniel Kim*, Mounica Maddela*, Reno Kriz, Wei Xu, Chris Callison-Burch — EMNLP 2021)

An additional advantage is that a shorter ramp can be used, thereby reducing weight and improving the rear view of the driver.

Another advantage is that a shorter ramp can be used. || This saves weight and improves the look of the rear of the vehicle.

- **Neutralizing biased languages** (Zhong Yang, Jingfeng Yang, Diyi Yang, Wei Xu — EMNLP 2021 Findings)

A Golden duck may refer to: A cricket 'golden' duck in which a **batsman** is out for nought on the first ball **he** faces.

A cricket 'golden' duck in which a **batter** is out for nought on the first ball **they** face.



- **Large-scale paraphrase identification and generation** (Yao You, Chao Jiang, Wei Xu - EMNLP 2022)

- **Style transfer** (Wei Xu, Alan Ritter, Bill Dolan, Ralph Grishman, Colin Cherry - COLING 2012)

If you will not be **turned**, you will be **destroyed!** — Star Wars

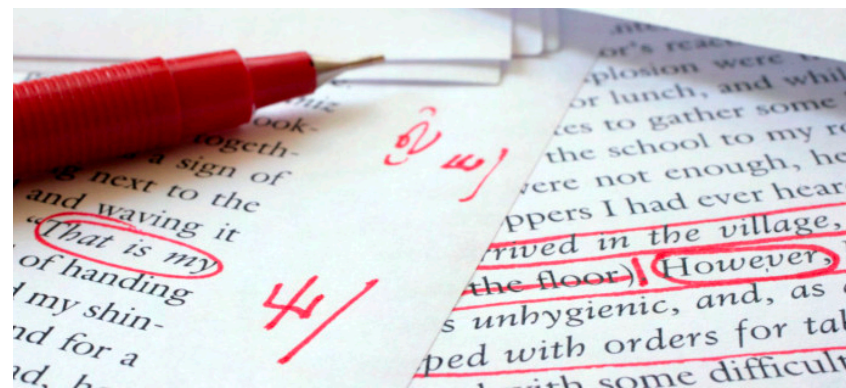
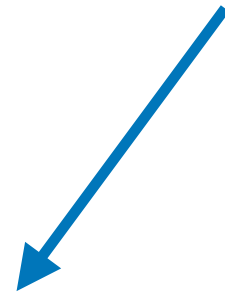
If you will not be **turn'd**, you will be **undone!**



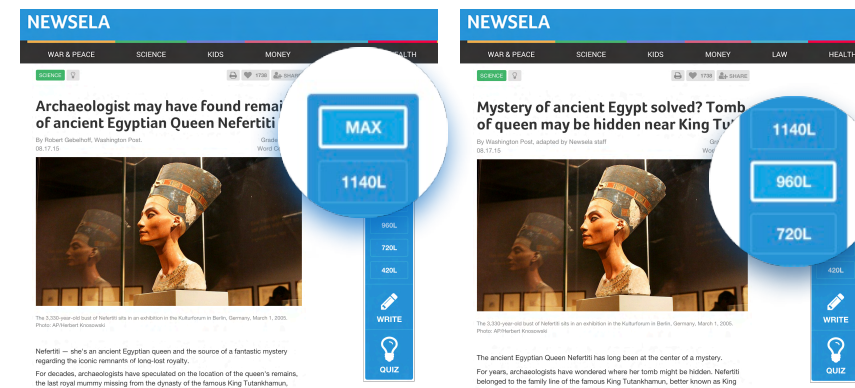
Automatic Text Simplification

It is a great benchmark for natural language generation (NLG) models.

Need both **diversity** and **controllability** from the model to meet users' varied reading needs.



complicated rewriting



good training data



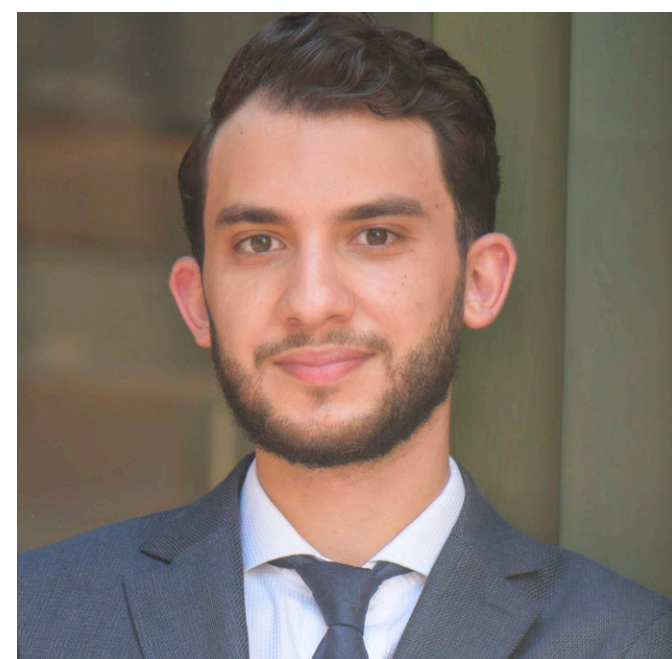
~reliable evaluation

(covers other text-to-text tasks: splitting, compression, paraphrase generation, style transfer, etc.)

Revisiting Non-English Text Simplification: a Unified Multilingual Benchmark



Michael J. Ryan



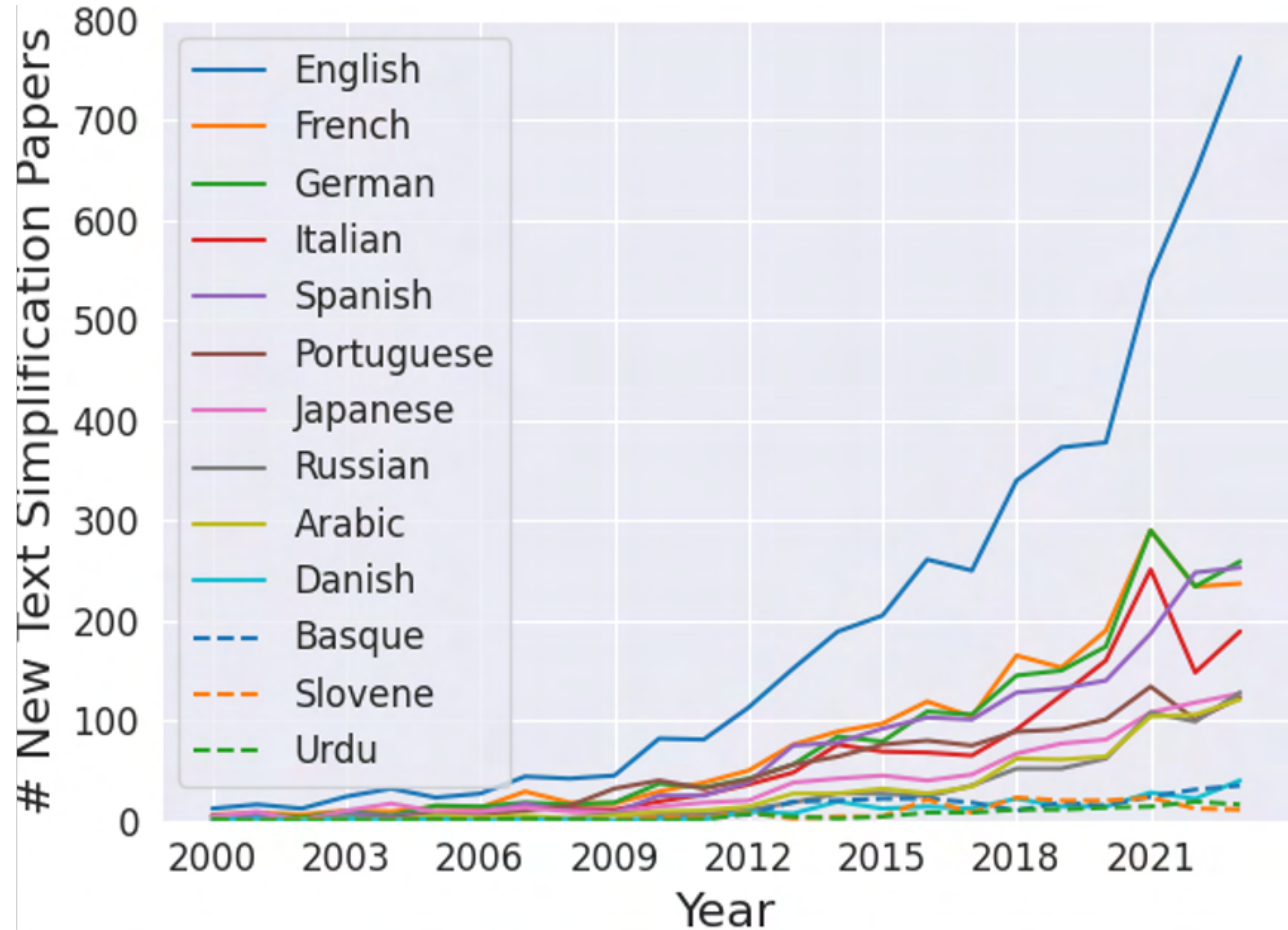
Tarek Naous.



Wei Xu

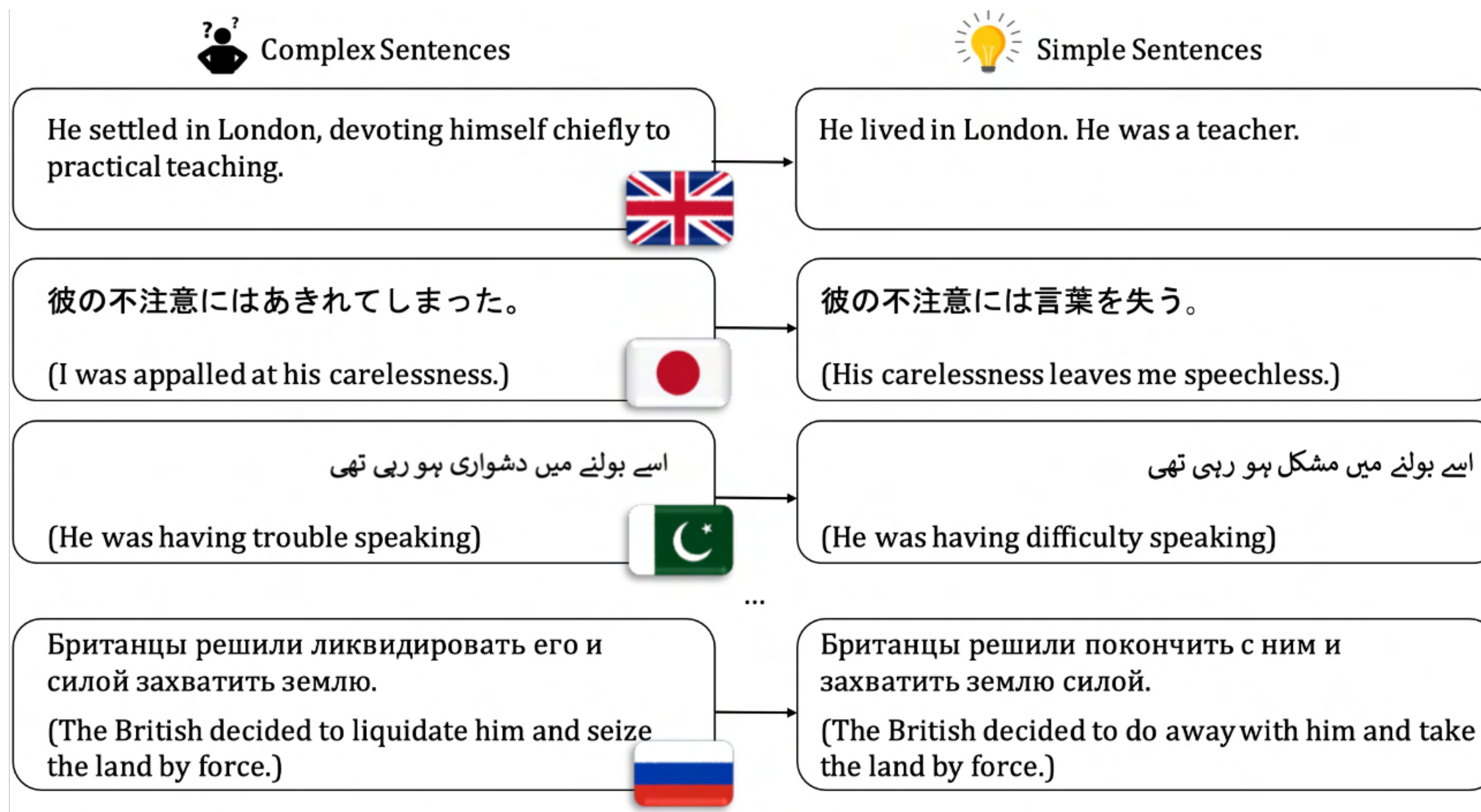
Growth of Text Simplification Research

- **In 2023 alone:**
 - 763 new papers on English text simplification
 - 237 new papers on French
 - <20 papers related to Urdu or Slovene simplification



(Count based on Google Scholar)

We introduce MultiSim of parallel texts



12 languages and growing (now 15)

Corpus	Source(s)	Simplification Author	Collection Strategy	Alignment Level	Sentence Aligned	Complex Sentences	Simple Sentences	Access
Arabic Corpora <i>Saaq al-Bambuu</i> (Khallaf and Sharoff, 2022)		writer	★	sentence	auto	2,980	2,980	private
Basque Corpora <i>CBST</i> (Gonzalez-Dios et al., 2018)		translator, teacher		document	manual	458	591	on request
Brazilian Portuguese Corpora <i>PorSimples</i> (Aluísio and Gasperin, 2010)		linguist		document	manual	7,902	10,174	on request
Danish Corpora <i>DSim</i> (Klerke and Sjøgaard, 2012)		journalists	★	sentence	auto	47,887	60,528	on request
English Corpora † <i>ASSET</i> (Alva-Manchego et al., 2020) <i>Newsela EN</i> (Xu et al., 2015) <i>Wiki-Auto</i> (Jiang et al., 2020)		crowdsourcing experts		sentence	manual	2,359	23,590	open source
		experts	★	document	auto	393,798	402,222	on request
		crowdsourcing	⚙️	document	auto	10,144,476	1,241,671	open source
French Corpora <i>Alector</i> (Gala et al., 2020) <i>CLEAR</i> (Grabar and Cardon, 2018) <i>WikiLarge FR</i> (Cardon and Grabar, 2020)		experts		document	NA	1,230	1,192	open source
		crowdsourcing, experts	⚙️	sentence	auto	4,596	4,596	open source
		crowdsourcing		sentence	auto	307,067	308,409	open source
German Corpora <i>GEOLinoTest</i> (Mallinson et al., 2020) <i>German News</i> (Säuberli et al., 2020) <i>Klexikon</i> (Aumiller and Gertz, 2022) <i>Simple Patho</i> (Trienes et al., 2023) <i>Simple German</i> (Battisti et al., 2020) <i>TextComplexityDE</i> (Naderi et al., 2019)		linguist		sentence	manual	1,198	1,198	open source
		news agency	★	document	auto	15,239	14,344	on request
		crowdsourcing	⚙️	document	NA	771,059	96,870	open source
		medical students		paragraph	manual	22,191	26,551	private
		government	★	document	auto	12,806	8,400	on request*
		native speaker		document	manual	250	250	open source
Italian Corpora <i>AdminIT</i> (Miliani et al., 2022) <i>SIMPITIKI Wiki</i> (Tonelli et al., 2016) <i>PaCCSS-IT</i> (Brunato et al., 2016) <i>Teacher</i> (Brunato et al., 2015) <i>Terence</i> (Brunato et al., 2015)		researchers		sentence	manual	777	763	open source
		crowdsourcing	⚙️	sentence	manual	575	575	open source
		crowdsourcing	⚙️	sentence	auto	63,006	63,006	open source
		teachers		document	manual	204	195	open source
		experts		document	manual	1,035	1,060	open source
Japanese Corpora <i>EasyJapanese</i> (Maruyama and Yamamoto, 2018) <i>EasyJapaneseExtended</i> (Katsuta and Yamamoto, 2018) <i>Japanese News</i> (Goto et al., 2015)		students		sentence	manual	50,000	50,000	open source
		crowdsourcing		sentence	manual	34,400	35,000	open source
		journalists, teachers	★	document	auto	13,356	13,356	private
Russian Corpora <i>RuAdapt Encyclopedia</i> (Dmitrieva et al., 2021) <i>RuAdapt Fairytale</i> (Dmitrieva et al., 2021) <i>RuAdapt Lit</i> (Dmitrieva and Tiedemann, 2021) <i>RSSE</i> (Sakhovskiy et al., 2021) <i>RuWikiLarge</i> (Sakhovskiy et al., 2021)		researchers		document	auto	9,729	10,230	open source
		researchers		document	auto	310	404	open source
		writers		document	auto	24,152	28,259	on request
		crowdsourcing		sentence	manual	2,000	6,804	open source
		crowdsourcing		sentence	auto	278,499	289,788	on request
Slovene Corpora <i>SloTS</i> (Gorenc and Robnik-Šikonja, 2022)		experts	★	sentence	manual	1,181	1,287	open source
Spanish Corpora <i>FIRST</i> (Orasan et al., 2013) <i>Newsela ES</i> (Xu et al., 2015) <i>Simplext</i> (Saggion et al., 2015)		experts		document	manual	320	332	private
		experts	★	document	auto	46,256	45,519	on request
		researchers		document	manual	1,108	1,742	on request
Urdu Corpora <i>SimplifyUREval</i> (Qasmi et al., 2020)		expert		sentence	manual	500	736	open source

Table 1: Important properties of text simplification parallel corpora. †Common English corpora included for comparison. Many other English corpora omitted. *Only scripts to replicate the corpus are available upon request. Simple German results differ from original paper because of changes to availability of online articles. *Sources*: Literature, Science Communications, News, Wikipedia, Websites, Medical Documents, Government, Encyclopedic. *Collection Strategies*: Automatic, Translation, Annotator, Target Audience Resource.

Open Source

MultiSim data and code (loaders) are available - <https://github.com/XenonMolecule/MultiSim>

Paper on arXiv

Revisiting non-English Text Simplification: A Unified Multilingual Benchmark

Michael J. Ryan, Tarek Naous, Wei Xu
School of Interactive Computing
Georgia Institute of Technology

{michaeljryan, tareknaous}@gatech.edu; wei.xu@cc.gatech.edu

Abstract

Recent advancements in high-quality, large-scale English resources have pushed the frontier of English Automatic Text Simplification (ATS) research. However, less work has been done on multilingual text simplification due to the lack of a diverse evaluation benchmark that covers complex-simple sentence pairs in many languages. This paper introduces the MULTI-SIM benchmark, a collection of 27 resources in 12 distinct languages containing over 1.7 million complex-simple sentence pairs. This benchmark will encourage research in developing more effective multilingual text simplification models and evaluation metrics. Our experiments using MULTI-SIM with pre-trained multilingual language models reveal exciting performance improvements from multilingual training in non-English settings. We observe strong performance from Russian in zero-shot cross-lingual transfer to low-resource languages. We further show that few-shot prompting with BLOOM-176b achieves comparable quality to reference simplifications outperforming fine-tuned models in most languages. We validate these findings through human evaluation.¹

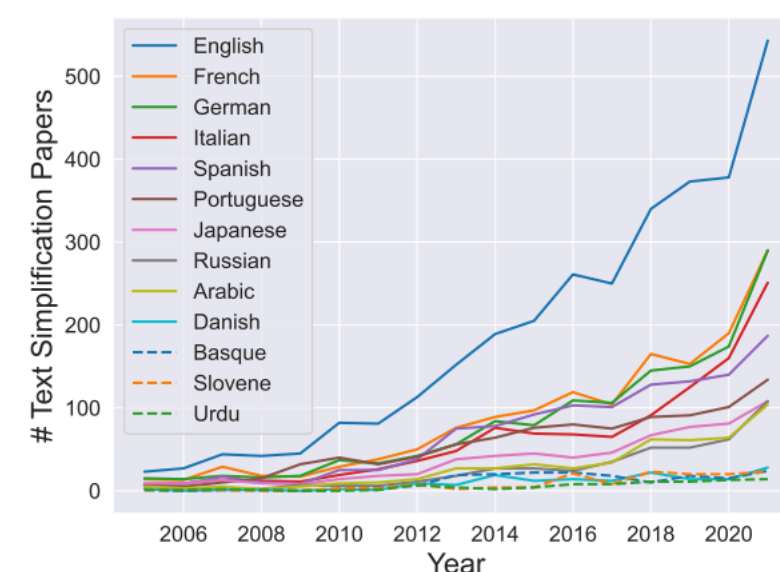


Figure 1: Papers published each year with content related to text simplification and a specific language according to Google Scholar. The quantity of English text simplification work vastly exceeds all other languages.

with the same content written using both complicated and simple sentences (Xu et al., 2015; Jiang et al., 2020; Alva-Manchego et al., 2020). These resources enable the training of large language models for ATS in English (Scarton and Specia, 2018; Martin et al., 2020; Omelianchuk et al., 2021). ATS research in other languages has received much less

Data on Huggingface



Datasets: MichaelR207 / **MultiSim** like 4

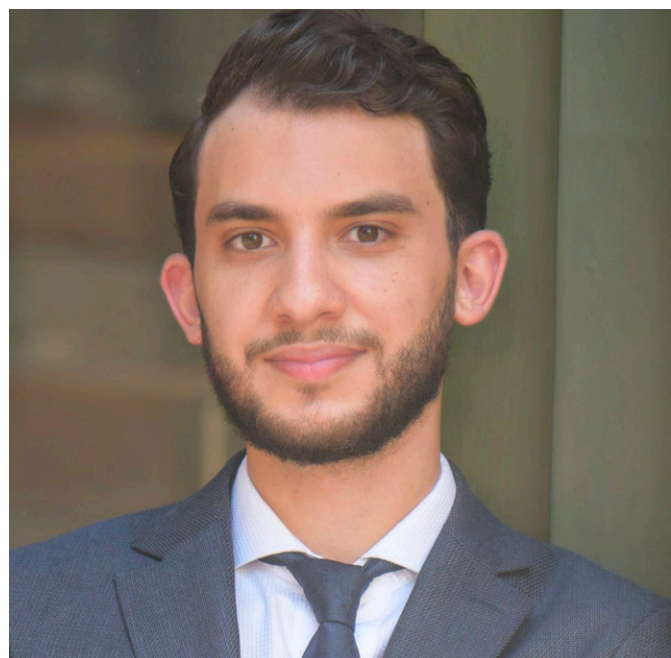
Total downloads

548 (all time)

105.15678v1 [cs.CL] 25 May 2023

1 Introduction

Benchmarking Multilingual LMs for Multi-domain Readability Assessment (ReadMe++)



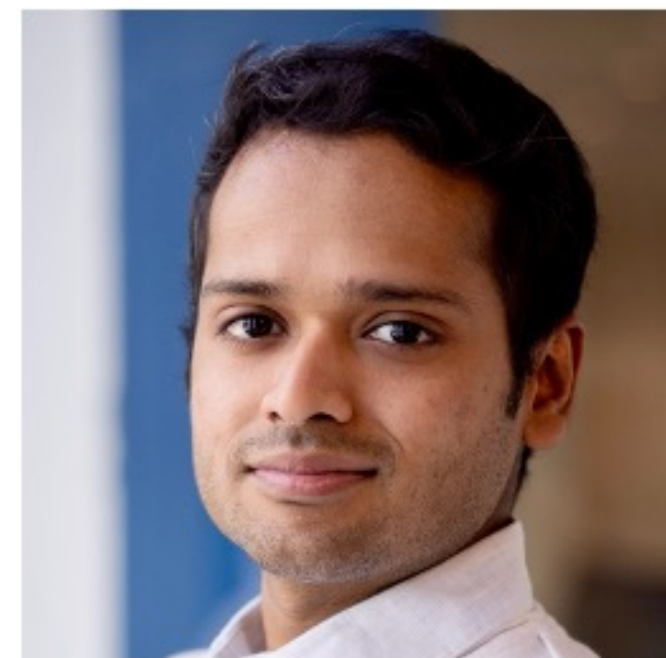
Tarek Naous



Michael J. Ryan



Anton Lavrouk

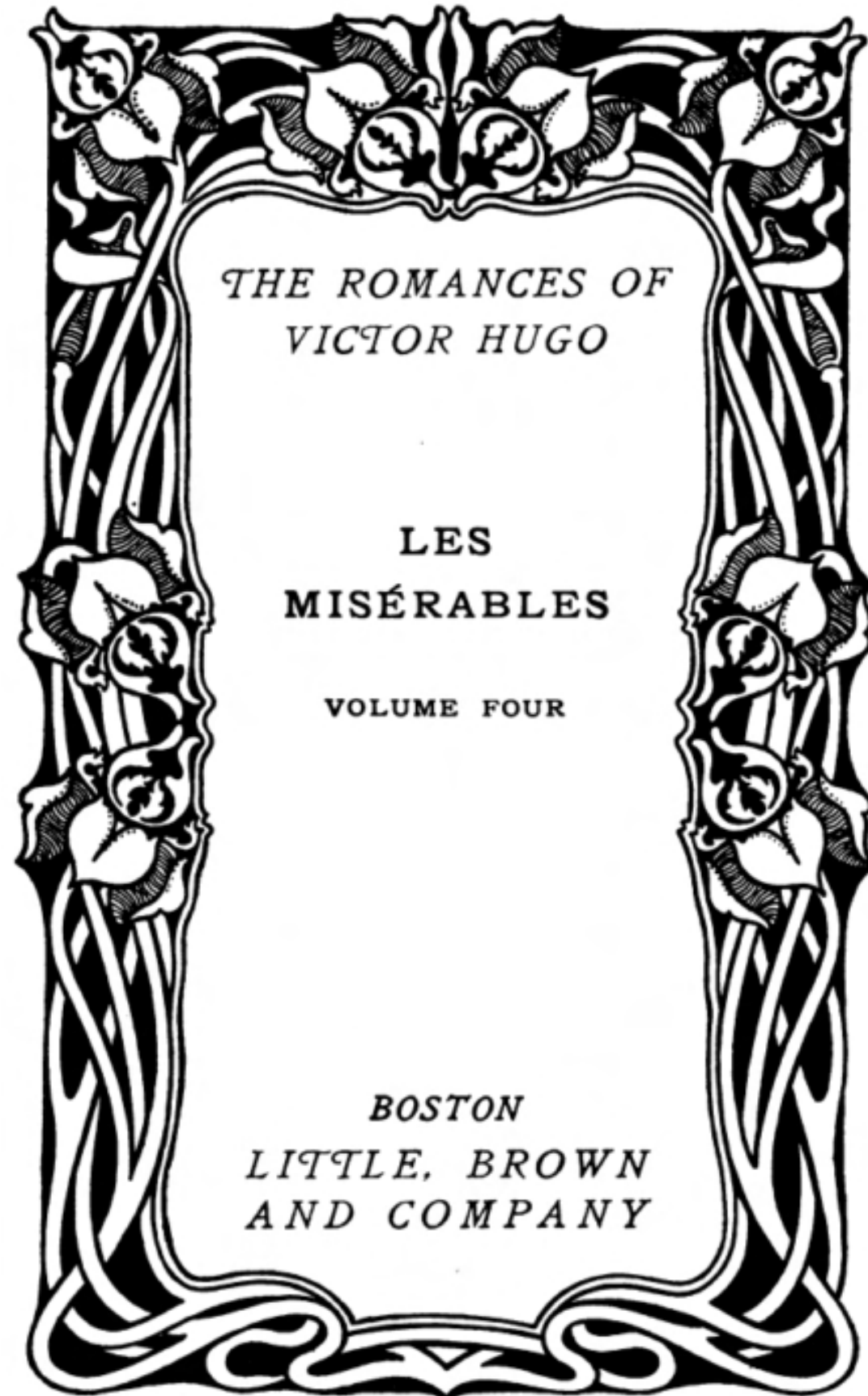


Mohit Chandra



Wei Xu

Different Readability Levels



“In the uncoerced slowness of its gait, suppleness and agility were discernible.”



“In its voluntary slow movement, its flexibility and agility were noticeable.”



“In its voluntary slow movement, you could still see how flexible and quick it is.”



Prior Work on Readability Measurements

Human-annotated Resources ([Arase et al. 2022](#), [Brunato et al. 2018](#), and more)

- CEFR: Common European Framework of Reference for Languages
- Mostly using either Wikipedia or news data

Level	Description	Rating
A1	Can understand very short, simple texts a single phrase at a time, picking up familiar names, words and basic phrases and rereading as required.	1
A2	Can understand short, simple texts on familiar matters of a concrete type.	2
B1	Can read straightforward factual texts on subjects related to his/her field and interest with a satisfactory level of comprehension.	3
B2	Can read with a large degree of independence, adapting style and speed of reading to different texts and purpose.	4
C1	Can understand in detail lengthy, complex texts, whether or not they relate to his/her own area of speciality, provided he/she can reread difficult sections.	5
C2	Can understand and interpret critically virtually all forms of the written language including abstract, structurally complex, or highly colloquial literary and non-literary writings.	6

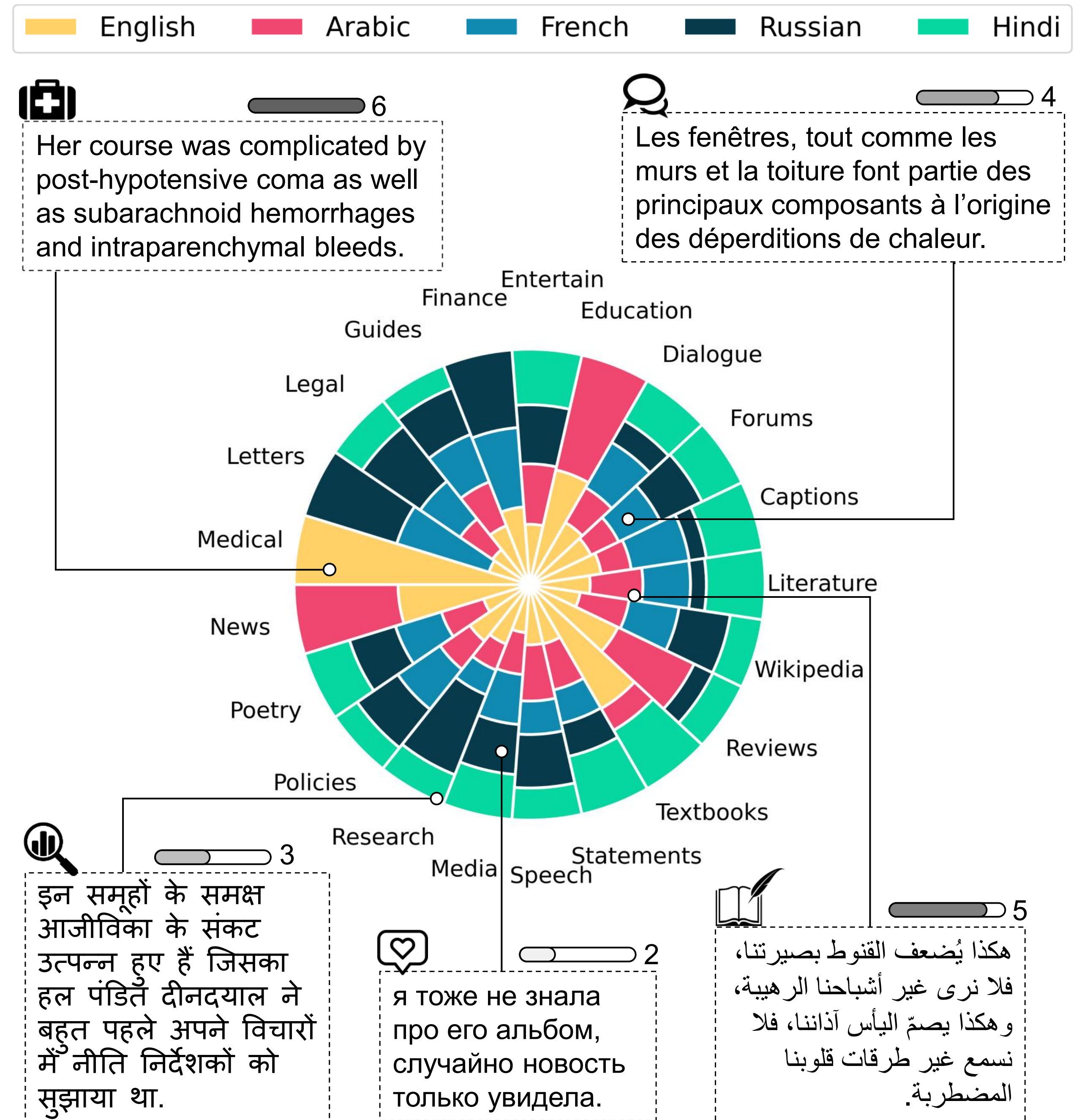
Our Work - Readme++

- **More diverse languages**

- 5 different languages
- written in 4 different scripts
- 9,465 human-annotated sentences

- **And, more diverse domains**

- 21 top-level domains
- 112 data sources
- all with open license



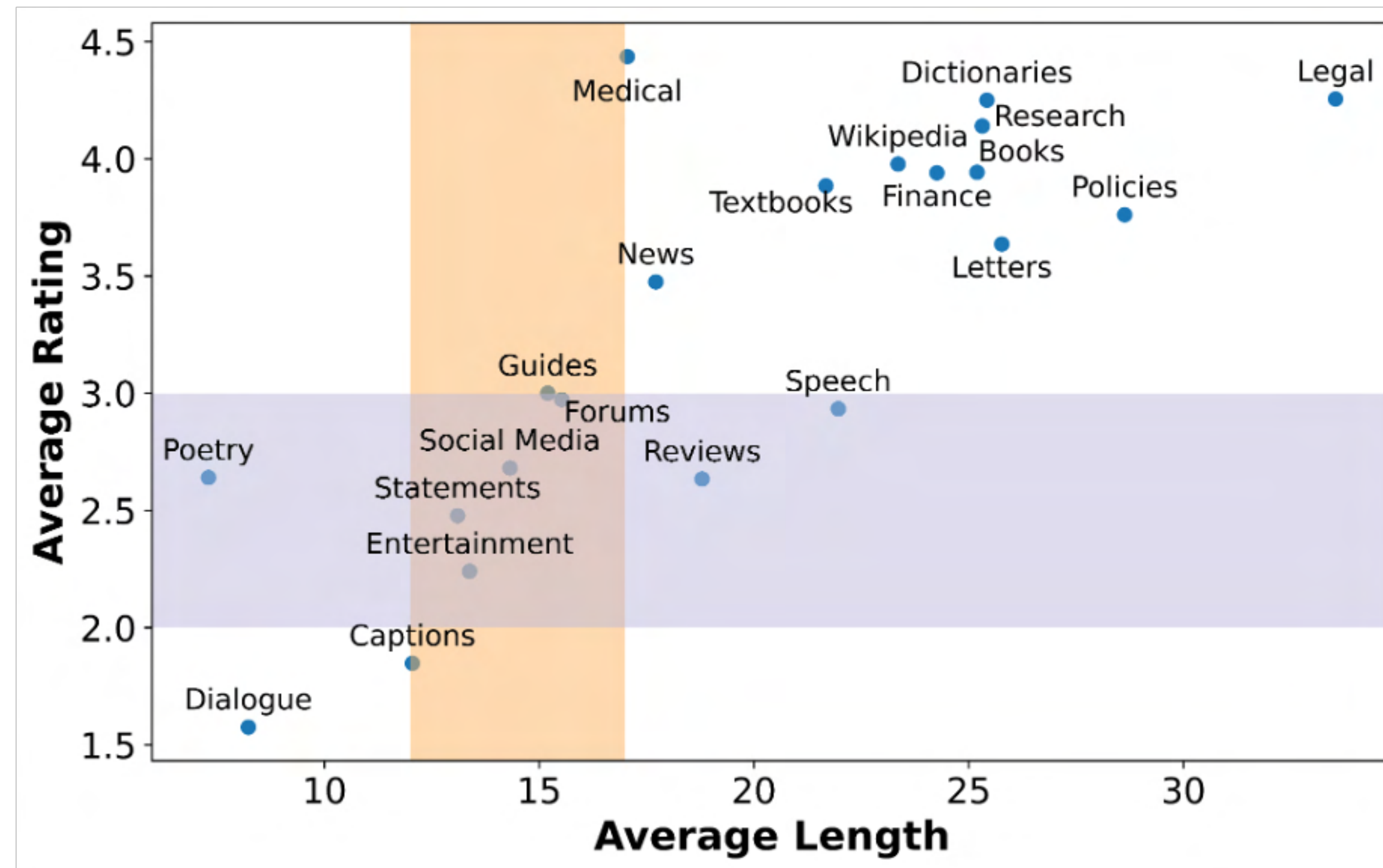
Our Work - Readme++

- A (partial) list of representative sources we sampled data from:

Domain (Abrv)	#	Examples of Data Sources — Full list for all languages in Appendix A		
		Arabic (ar)	English (en)	Hindi (hi)
CAPTIONS (Cap)	9	Images (ElJundi et al., 2020)	Videos (Wang et al., 2019)	Movies (Lison and Tiedemann, 2016)
DIALOGUE (Dia)	7	Open-domain (Naous et al., 2020)	Negotiation (He et al., 2018)	Task-oriented (Malviya et al., 2021)
DICTIONARIES (Dic)	2	Dictionaries (almaany.com)	Dictionaries (dictionary.com)	—
ENTERTAINMENT (Ent)	4	Jokes (almrsal.com)	Jokes (Weller and Seppi, 2019)	Jokes (123hindijokes.com)
FINANCE (Fin)	3	—	Finance (Malo et al., 2014)	—
FORUMS (For)	7	QA Websites (hi.quora.com)	StackOverflow (Tabassum et al., 2020)	Reddit (reddit.com)
GUIDES (Gui)	6	Online Tutorials (ar.wikihow.com)	Code Documentation (mathworks.com)	Cooking Recipes (narendramodi.in)
LEGAL (Leg)	9	UN Parliament (Ziemski et al., 2016)	Constitutions (constitutioncenter.org)	Judicial Rulings (Kapoor et al., 2022)
LETTERS (Let)	3	—	Letters (oflosttime.com)	—
LITERATURE (Lit)	3	Novels (hindawi.org/books/)	History (gutenberg.org)	Biographies (Public Domain Books)
MEDICAL TEXT (Med)	1	—	Clinical Reports (Uzuner et al., 2011)	—
NEWS ARTICLES (New)	2	Sports (Alfonse and Gawich, 2022)	Economy (Misra, 2022)	—
POETRY (Poe)	5	Poetry (aldiwan.net)	Poetry (poetryfoundation.org)	Poetry (hindionlinejankari.com)
POLICIES (Pol)	7	Olympic Rules (specialolympics.org)	Contracts (honeybook.com)	Code of Conduct (lonza.com)
RESEARCH (Res)	15	Politics (jcopolicy.uobaghdad.edu.iq)	Science & Engineering (arxiv.org)	Economics (journal.ijarms.org)
SOCIAL MEDIA (Soc)	3	Twitter (Zheng et al., 2022)	Twitter (Zheng et al., 2022)	Twitter (Zheng et al., 2022)
SPEECH (Spe)	4	Public Speech (state.gov/translations)	Public Speech (whitehouse.gov)	Ted Talks (ted.com/talks)
STATEMENTS (Sta)	6	Quotes (arabic-quotes.com)	Rumours (Zheng et al., 2022)	Quotes (wahh.in)
TEXTBOOKS (Tex)	3	Business (hindawi.org/books/)	Agriculture (open.umn.edu)	Psychology (ncert.nic.in)
USER REVIEWS (Rev)	12	Products (ElSahar and El-Beltagy, 2015)	Books (goodreads.com)	Movies (hindi.webdunia.com)
WIKIPEDIA (Wik)	1	Wikipedia (wikipedia.com)	Wikipedia (wikipedia.com)	Wikipedia (wikipedia.com)
Total	112			

What difference does this make?

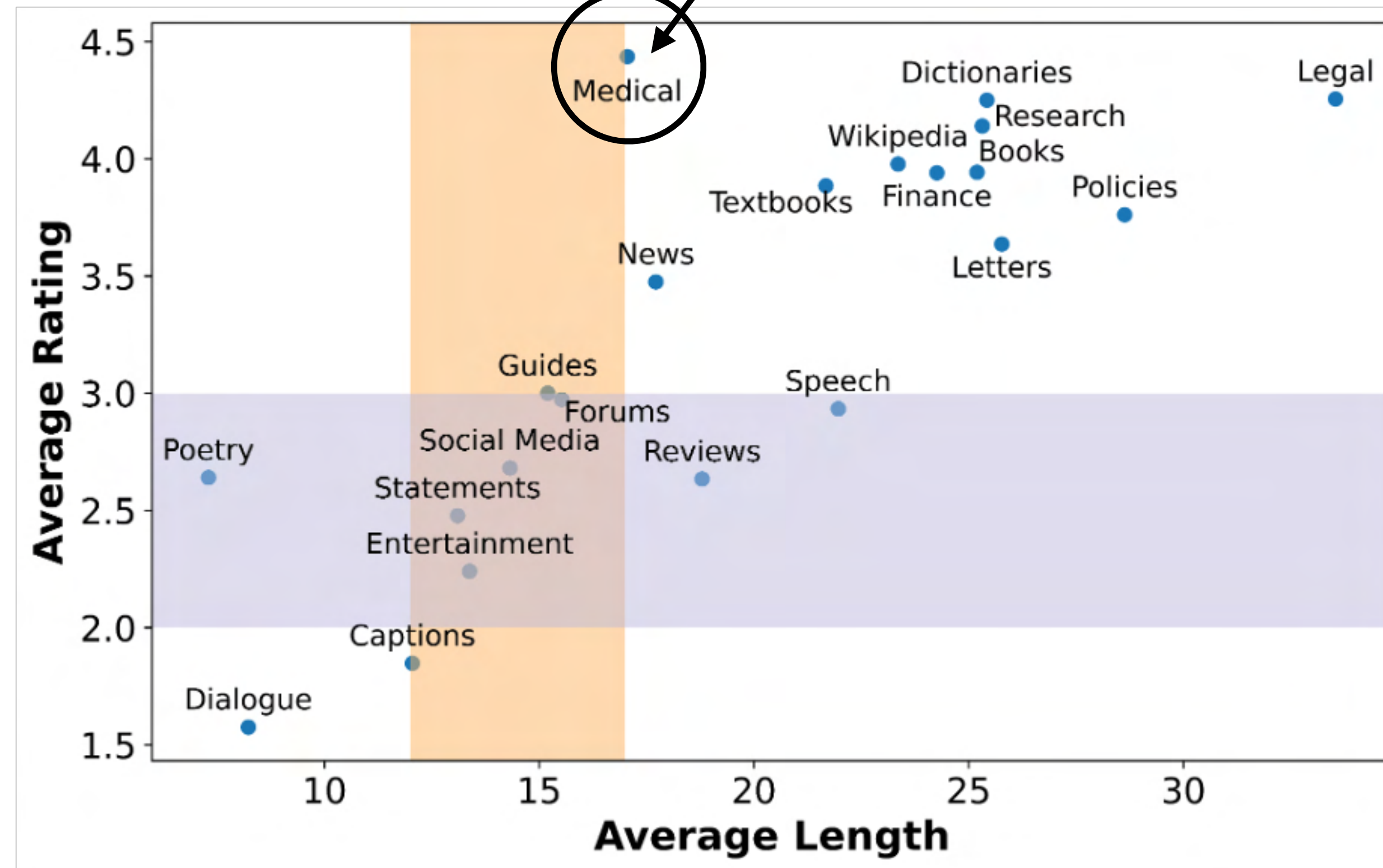
A wider range of topics and lengths of sentences that impact the readability are accounted for.



What difference does this make?

A wider range of topics and lengths of sentences that impact the readability are accounted for.

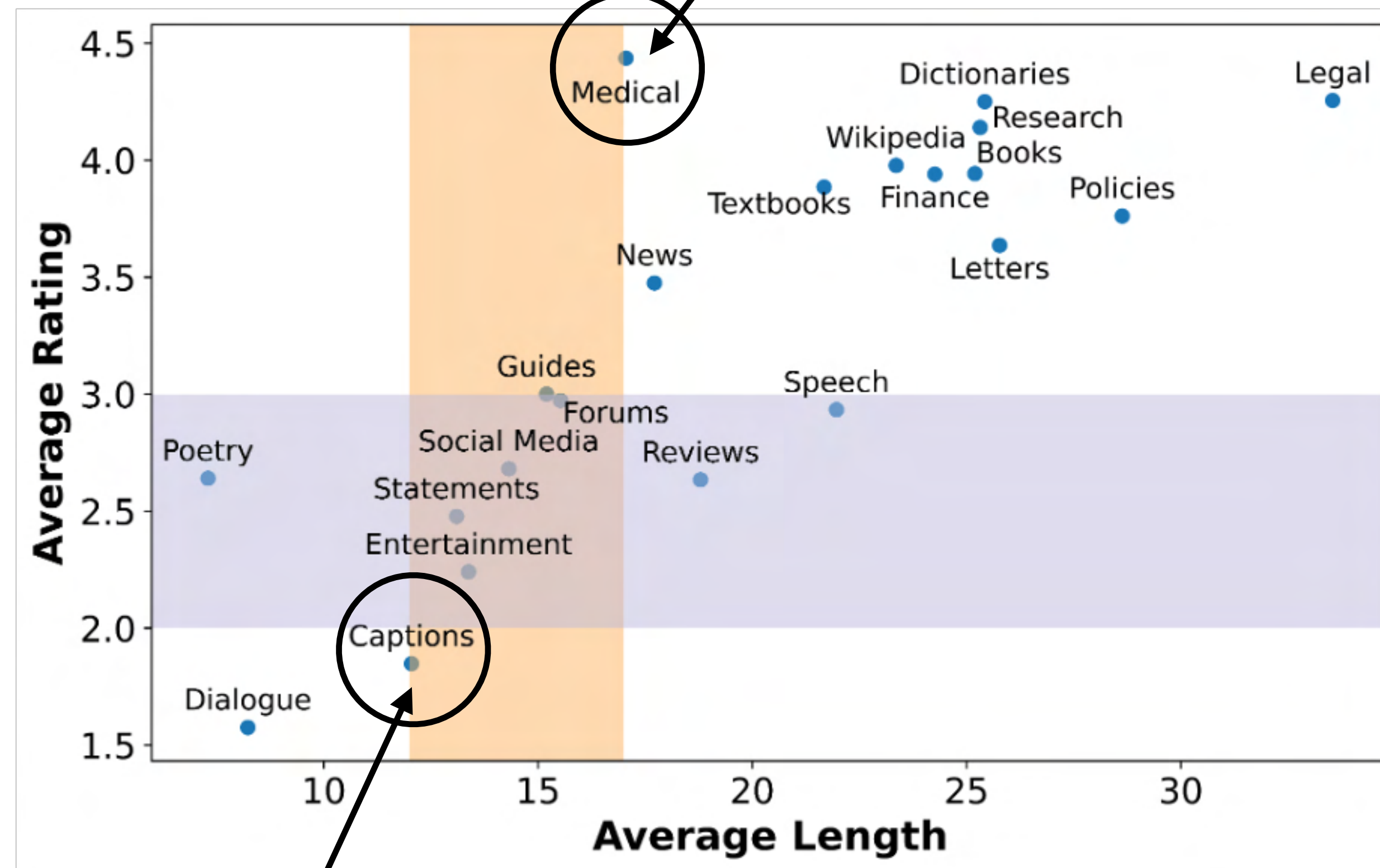
“With history, will go for cardiac catheterization evaluation.”



What difference does this make?

A wider range of topics and lengths of sentences that impact the readability are accounted for.

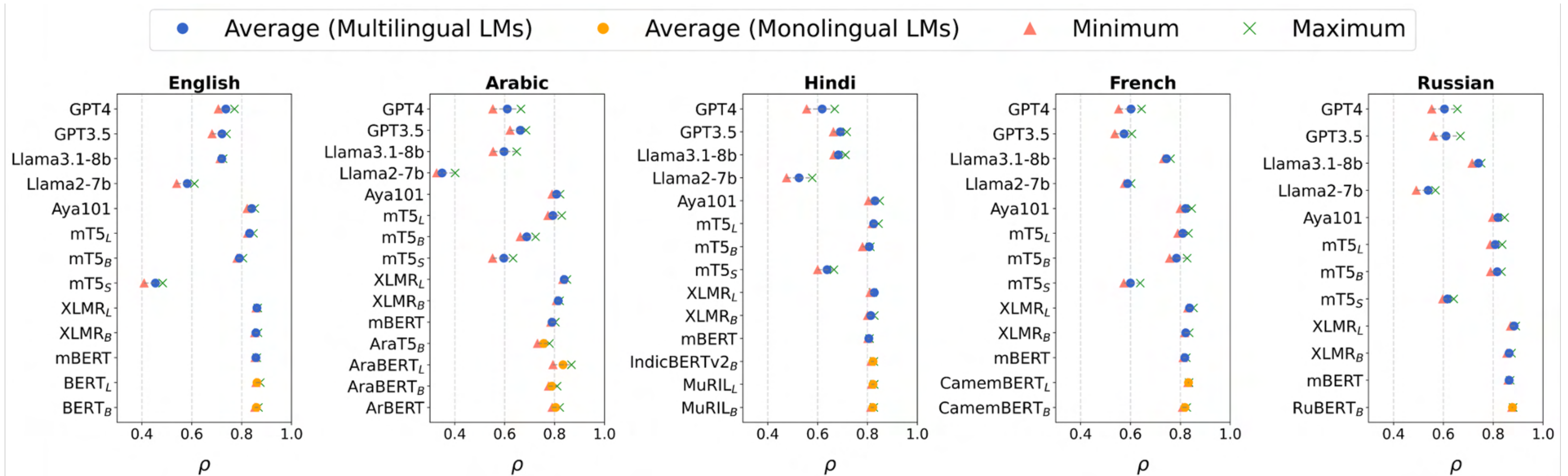
“With history, will go for cardiac catheterization evaluation.”



“A young boy is indoors showing his family his dance moves.”

Benchmarking multilingual LLMs

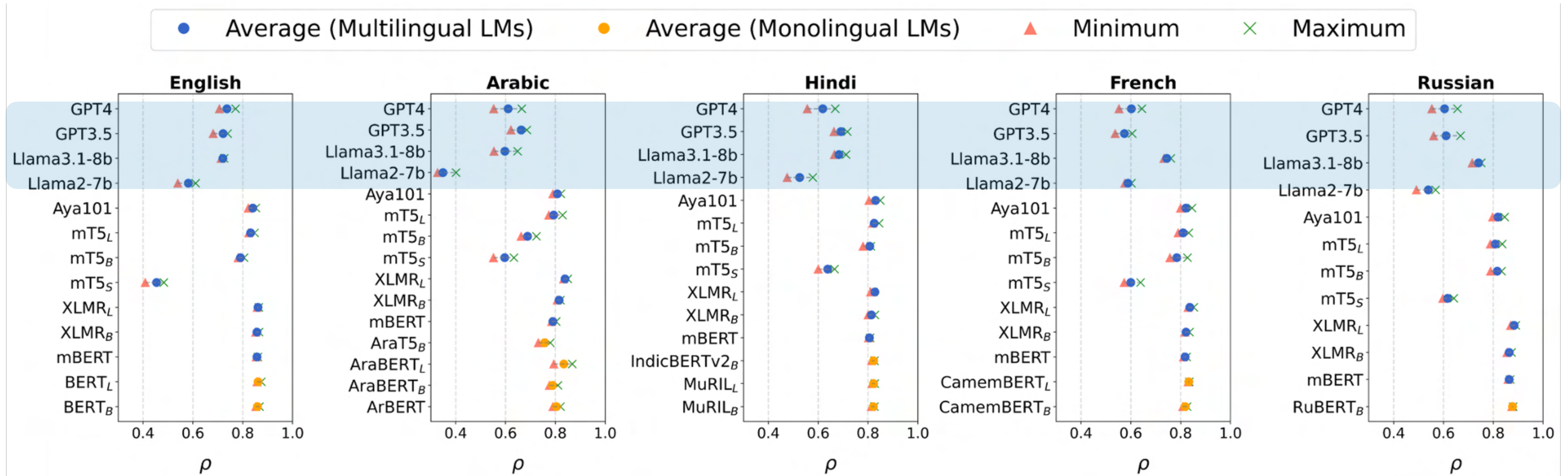
Fine-tuning LLMs perform better than 5-shot **prompting** of GPT-4 / Llama-3.1 (6-way classification)



i.e., human annotated data is very useful, not only for evaluation but also for fine-tuning.

Benchmarking multilingual LLMs

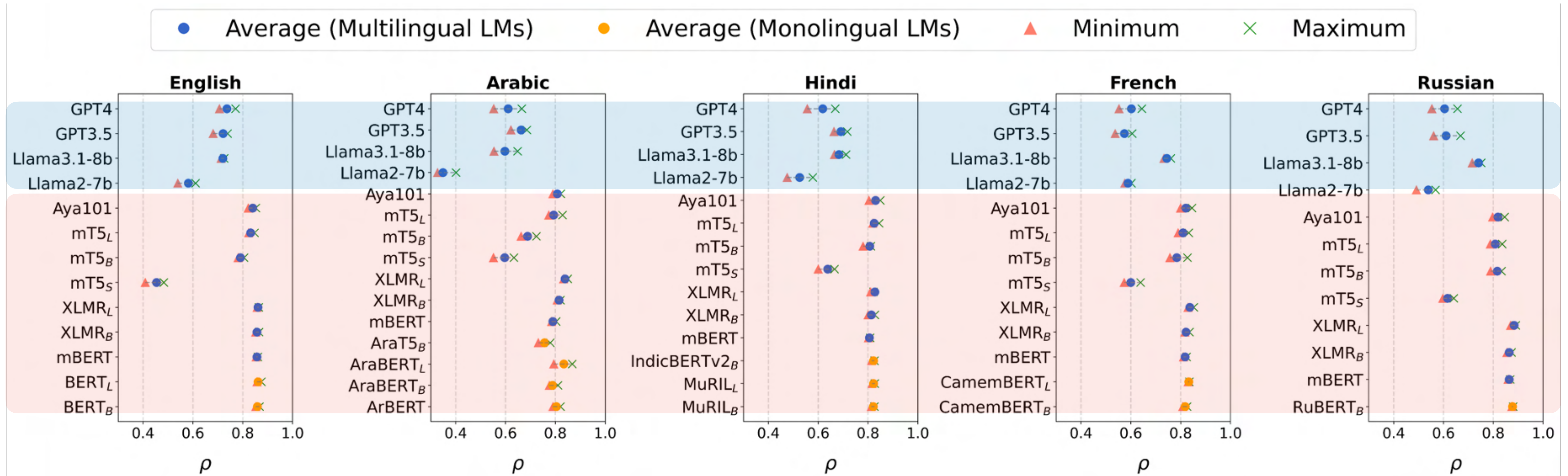
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Benchmarking multilingual LLMs

Fine-tuning LLMs perform better than 5-shot **prompting** of GPT-4 / Llama-3.1 (6-way classification)



i.e., human annotated data is very useful, not only for evaluation but also for fine-tuning.

Open Source

ReadMe++ data and models are available - <https://github.com/tareknaous/readme>

Paper on arXiv

README++: Benchmarking Multilingual Language Models for Multi-Domain Readability Assessment

Tarek Naous, Michael J. Ryan, Anton Lavrouk, Mohit Chandra, Wei Xu

College of Computing

Georgia Institute of Technology

{tareknaous, michaeljryan, antonlavrouk, mchandra9}@gatech.edu; wei.xu@cc.gatech.edu

Abstract

We present a comprehensive evaluation of large language models for multilingual readability assessment. Existing evaluation resources lack domain and language diversity, limiting the ability for cross-domain and cross-lingual analyses. This paper introduces README++, a multilingual multi-domain dataset with human annotations of 9757 sentences in Arabic, English, French, Hindi, and Russian, collected from 112 different data sources. This benchmark will encourage research on developing robust multilingual readability assessment methods. Using README++, we benchmark multilingual and monolingual language models in the supervised, unsupervised, and few-shot prompting settings. The domain and language diversity in README++ enable us to test more effective few-shot prompting, and identify shortcomings in state-of-the-art unsupervised methods. Our experiments also reveal exciting results of superior domain generalization and enhanced cross-lingual transfer capabilities by models trained on README++

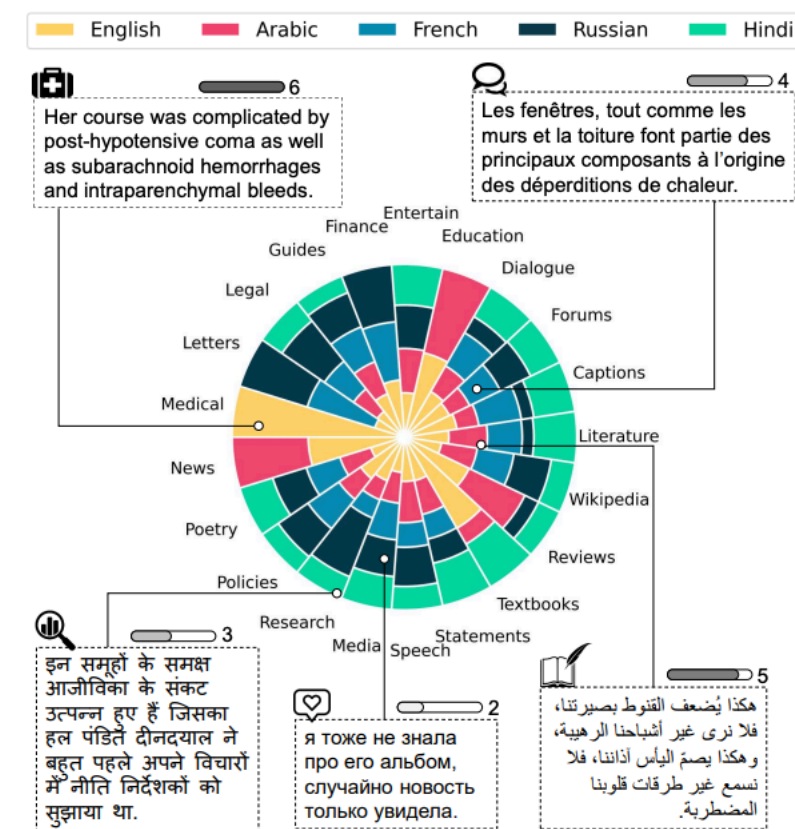


Figure 1: Language distribution per each domain in README++. Example sentences from each language are shown along with their human-annotated readability levels on a 6-point scale (1: easiest, 6: hardest).

Models on Huggingface

Installation

```
pip install readmepp
```



Usage

First import the class `ReadMe` and create a BERT predictor instance of it. The parameter `lang` is to specify language (we support "en", "ar", "fr", "ru", and "hi").

```
from readmepp import ReadMe  
  
predictor = ReadMe(lang='en')
```

To assess the readability of a sentence, use the `predict` function of the model:

```
sentence = 'Eukaryotes differ from prokaryotes in multiple ways, with unique biochemical pathway'  
  
prediction = predictor.predict(sentence)  
  
print(f"Predicted Readability Level: {prediction}")
```

English: <https://huggingface.co/tareknaous/readabert-en>

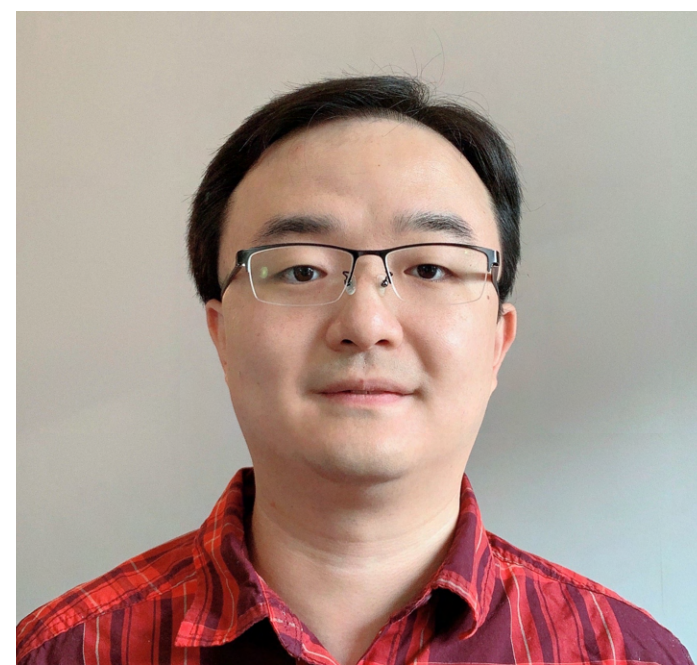
Arabic: <https://huggingface.co/tareknaous/readabert-ar>

Hindi: <https://huggingface.co/tareknaous/readabert-hi>

French: <https://huggingface.co/tareknaous/readabert-fr>

Russian: <https://huggingface.co/tareknaous/readabert-ru>

MedReadMe: A Systematic Study for Fine-grained Sentence Readability in Medical Domain



Chao Jiang



Wei Xu

“An oro-antral communication (OAC) is an unnatural opening between the oral cavity and maxillary sinus. When it fails to close spontaneously, it remains patent and is epithelialized to develop into an oro-antral fistula. These complications occur most commonly during extraction of upper molar and premolar teeth (48%).”

an snippet discussing oral and dental health from Cochrane

The screenshot shows the Cochrane Library interface. At the top left is the Cochrane Library logo with the tagline 'Trusted evidence. Informed decisions. Better health.' Below this is a navigation bar with links for 'Cochrane Reviews', 'Searching for trials', 'Clinical Answers', 'About', 'Help', and 'About Cochrane'. A search bar is located at the top right, with 'Review language: English' and 'Website language: English' selected. The main content area displays the title 'Interventions for treating oro-antral communications and fistulae due to dental procedures' by Salian Kiran Kumar Krishanappa, Prashanti Eachempati, Sumanth Kumbargere Nagraj, Naresh Yedthare Shetty, Soe Moe, Himanshi Aggarwal, and Rebecca J Mathew. It includes the publication date (16 August 2018) and a DOI link. On the right side, there are options to 'Download PDF', 'Cite this Review', 'Print', 'Comment', 'Share', and 'Follow'. Below these are 'AM score 31' and 'Cited in 1 guideline'. A 'Contents' sidebar on the right lists sections: Abstract, PICOs, Plain language summary, Authors' conclusions, Summary of findings, Background, Objectives, Methods, Results, Discussion, Figures and tables, and References. At the bottom left, there is an 'Abstract' section with a language selector and a 'Background' section with a paragraph of text.

Abstract

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Background

An oro-antral communication is an unnatural opening between the oral cavity and maxillary sinus. When it fails to close spontaneously, it remains patent and is epithelialized to develop into an oro-antral fistula. Various surgical and non-surgical techniques have been used for treating the condition. Surgical procedures include flaps, grafts and other techniques like re-implantation of third molars. Non-surgical techniques include allogenic materials and xenografts. This is an update of a review first published in May 2016.

“An *oro-antral communication (OAC)* is an unnatural opening between the *oral cavity* and *maxillary sinus*. When it fails to close *spontaneously*, it remains patent and is *epithelialized* to develop into an *oro-antral fistula*. These *complications* occur most commonly during extraction of *upper molar and premolar teeth (48%)*.”

Interventions for treating oro-antral communications and fistulae due to dental procedures

✉ Salian Kiran Kumar Krishanappa, Prashanti Eachempati, Sumanth Kumbargere Nagraj, Naresh Yedthare Shetty, Soe Moe, Himanshi Aggarwal, Rebecca J Mathew Authors' declarations of interest

Version published: 16 August 2018 Version history
<https://doi.org/10.1002/14651858.CD011784.pub3>

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“An *oro-antral communication (OAC)* is an unnatural opening between the *oral cavity* and *maxillary sinus*. When it fails to close *spontaneously*, it remains patent and is *epithelialized* to develop into an *oro-antral fistula*. These *complications* occur most commonly during extraction of *upper molar and premolar teeth (48%)*.”

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not all jargon and complex terms are equally difficult

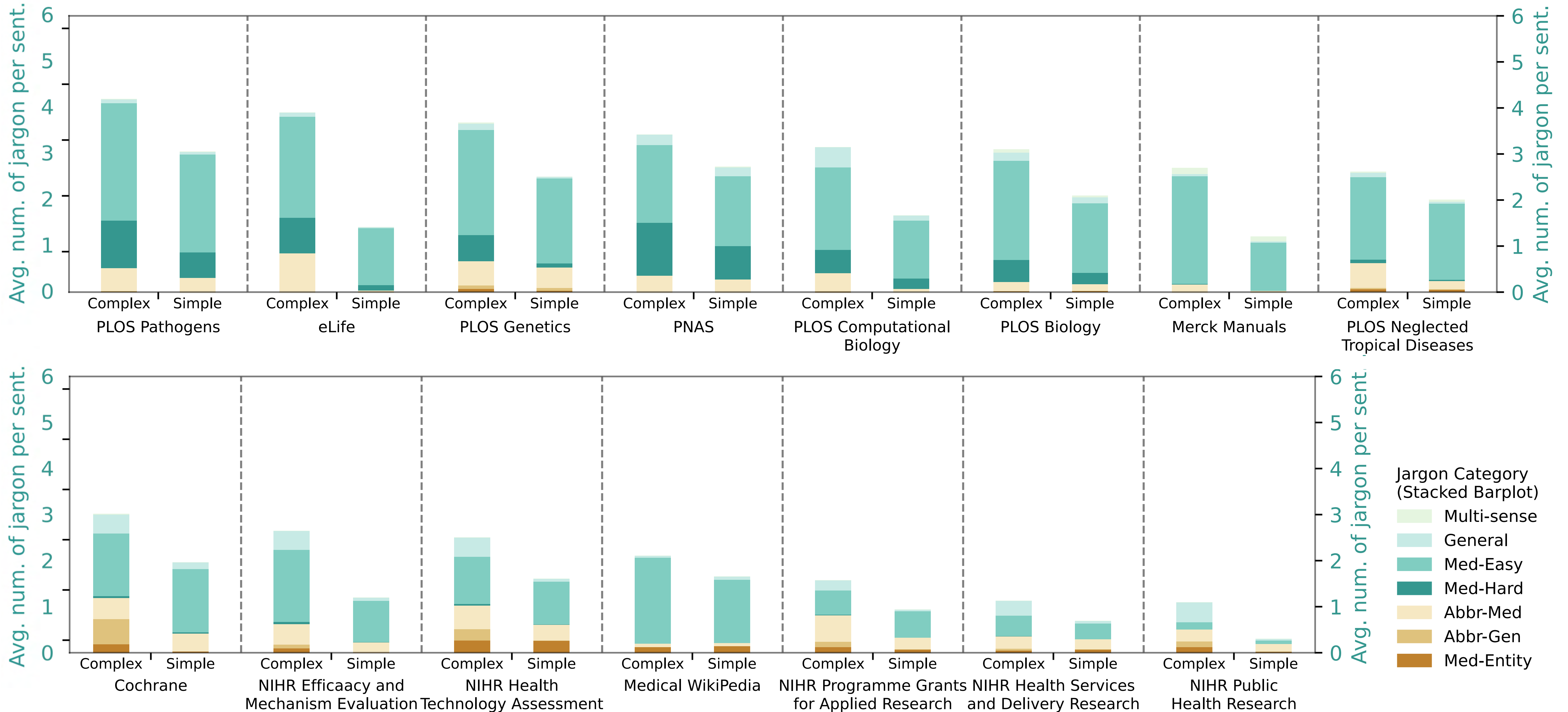
Medical - Google Hard

Abbreviations

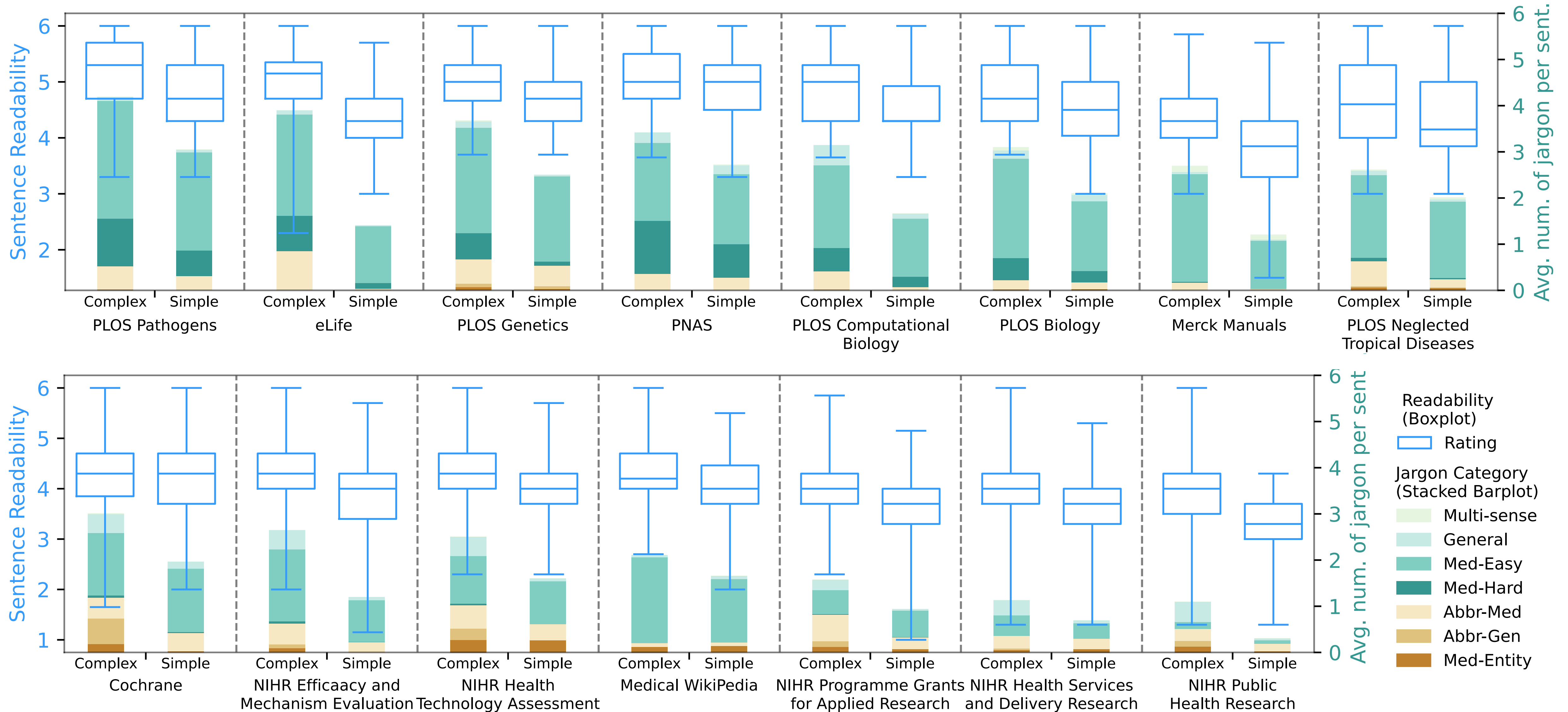
Medical - Google Easy

General Complex Words

Different Biomedical Data Sources also Vary




Different Biomedical Data Sources also Vary



Rank-and-Rate Annotation Framework

Rank and Rate Sentences on Readability

Signed in as 

[Sign out](#)

Batch ID: 

Submit and Continue

3

Jean Valjean remained silent, motionless, with his back towards the door, seated on the chair from which he had not stirred, and holding his breath in the dark.

3

3-

3+

These bead-like structures are called nucleosomes, and interactions between histones in different nucleosomes can link one nucleosome to another, to package the DNA into a very condensed form.

In a sketch or outline drawing, lines drawn often follow the contour of the subject, creating depth by looking like shadows cast from a light in the artist's position.

+ Context

The long-term functional outcomes of early administration of RDI of amino acids and the use of SMOFlipid, including neurodevelopment, body composition and metabolic health, should be evaluated.

+ Context

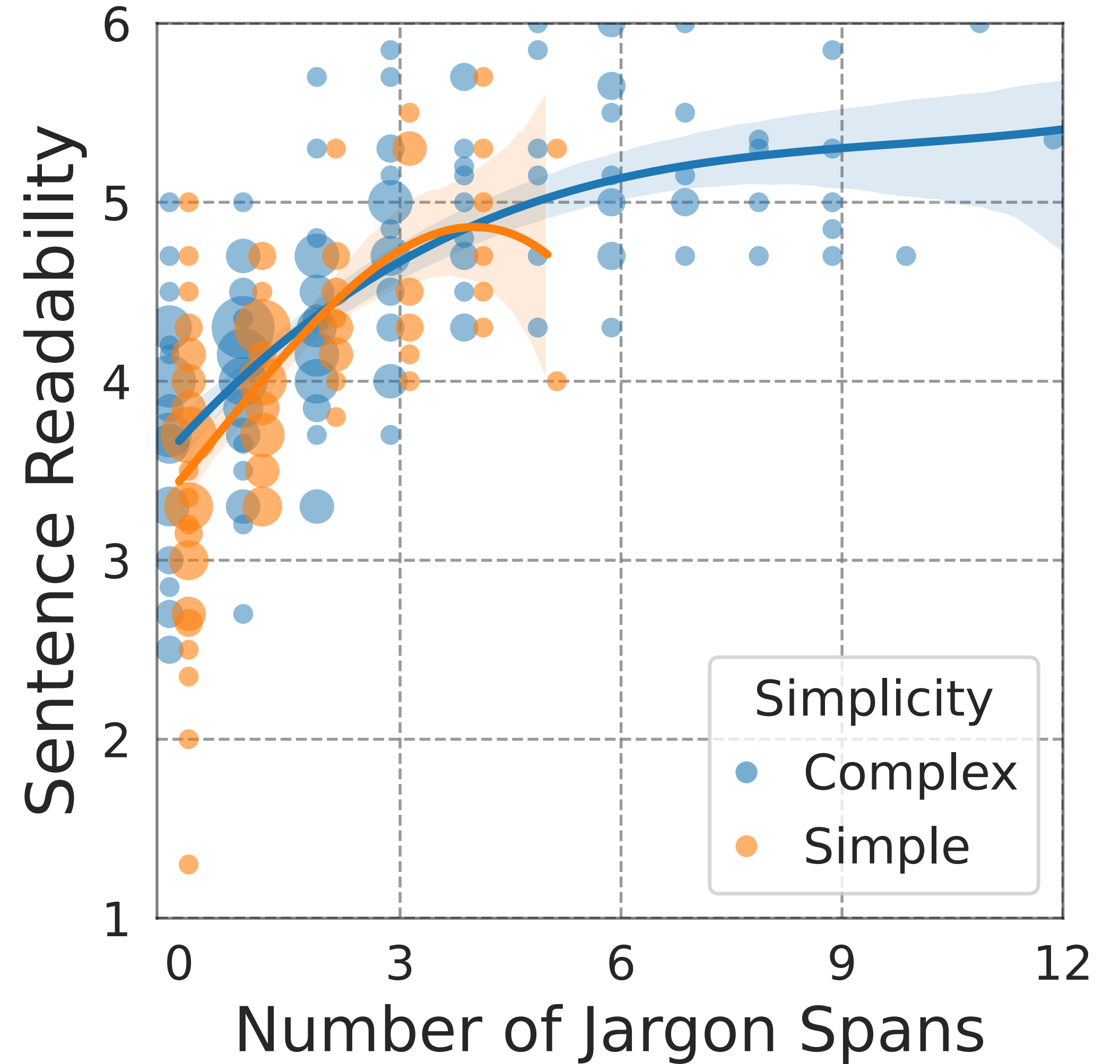
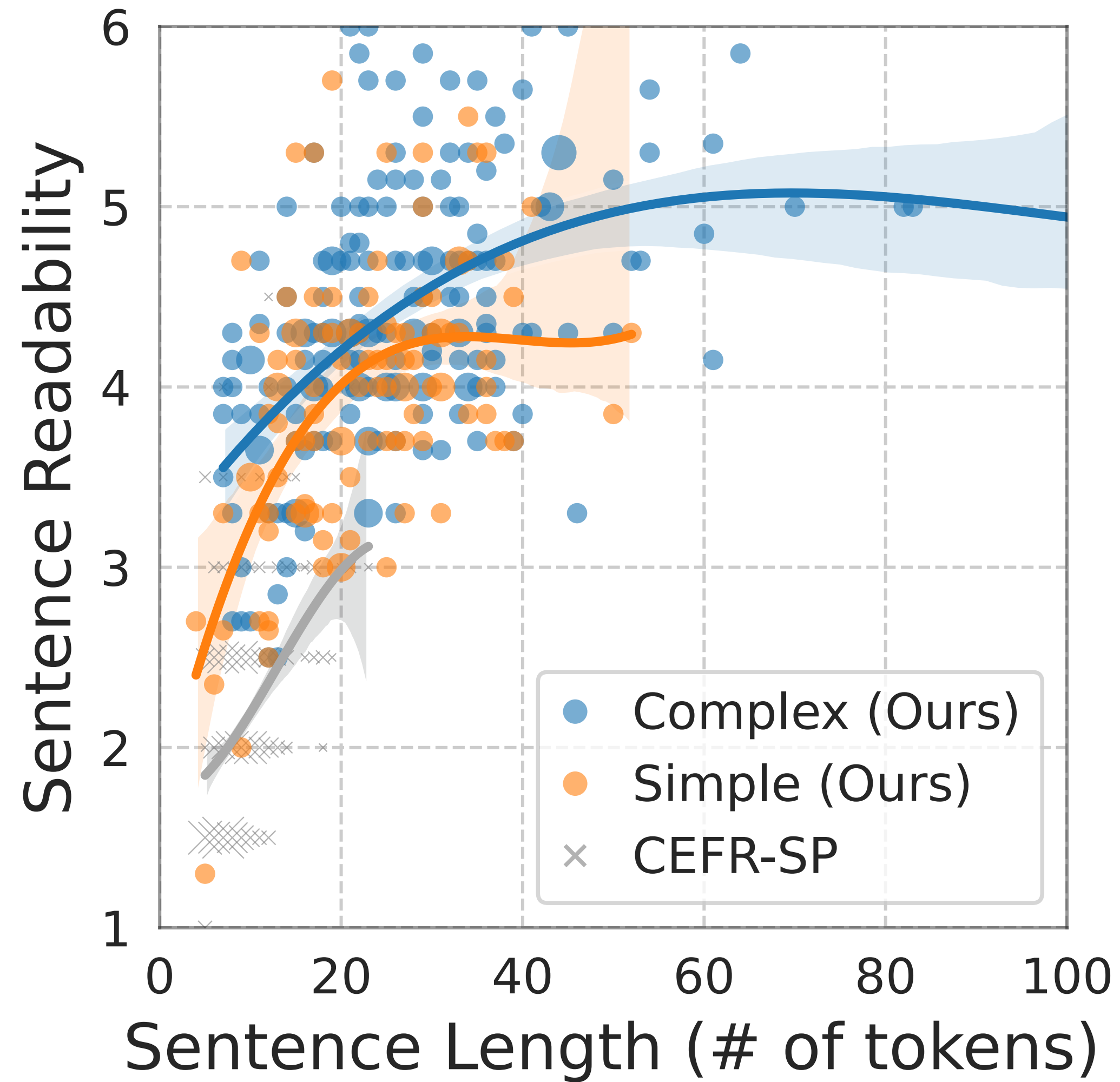
All these initiatives take hold as they do, from lead pipes being removed from schools and homes, to new factories being built in communities with a resurgence of American manufacturing.

+ Context

The illumination of the subject is also a key element in creating an artistic piece, and the interplay of light and shadow is a valuable method in the artist's toolbox.

+ Context

Jargon Greatly Affects Readability



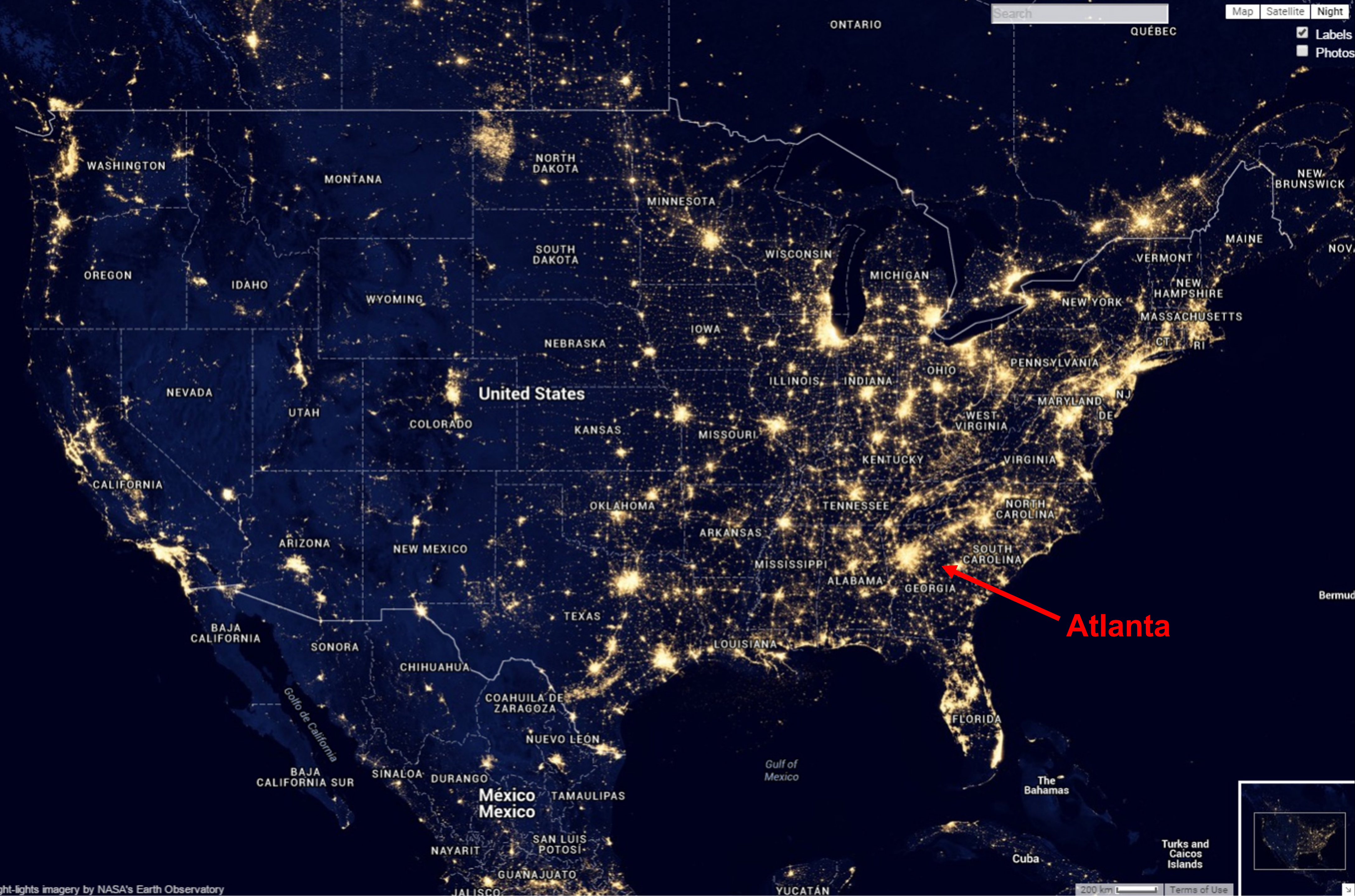
Medical Sentence Readability Measurements

$$\text{ReadMe++Jar} = \text{RoBERTa-large (fine-tuned on ReadMe++)} + \alpha \times \# \text{ Jargon}$$


Sources	5-shots		👤 Trained on Each Corpus				The Trained 👤 + an Jargon Term			
	GPT-4 (Achiam et al.)	Llama 2-7b (Touvron et al.)	ReadMe++ (Naous et al.)	CEFR-SP (Arase et al.)	CompDS (Brunato et al.)	MEDREADME (Ours)	ReadMe++ _{Jar} (Ours)	CEFR-SP _{Jar} (Ours)	CompDS _{Jar} (Ours)	MEDREADME _{Jar} (Ours)
Cochrane	0.908	0.549	0.858	0.899	0.870	0.947	0.842	0.850	0.785	0.882
PNAS	0.780	0.574	0.852	0.820	0.791	0.874	0.780	0.824	0.744	0.873
NIHR Series	0.713	0.580	0.824	0.753	0.706	0.885	0.697	0.687	0.634	0.700
eLife	0.538	0.127	0.594	0.715	0.608	0.712	0.812	0.802	0.777	0.861
PLOS Series	0.672	0.309	0.680	0.691	0.635	0.702	0.787	0.843	0.744	0.850
Wiki	0.670	0.429	0.824	0.709	0.607	0.843	0.712	0.619	0.673	0.709
MSD	0.766	0.328	0.784	0.778	0.757	0.867	0.918	0.880	0.863	0.937
Mean ± Std	0.721 ± 0.115	0.414 ± 0.17	0.774 ± 0.1	0.766 ± 0.073	0.711 ± 0.101	0.833 ± 0.092	0.793 ± 0.076	0.786 ± 0.096	0.746 ± 0.075	0.830 ± 0.090

Table 7: Pearson correlation (\uparrow) between human ground-truth readability and each **prompting** and **supervised** readability metric. All numbers are averaged over five runs, and all correlations are statistically significant. 👤 denotes RoBERTa-large models. “-Jar” means adding a “jargon” term (more details in §4.2). Prompt-based methods are competitive, while still outperformed by fine-tuned models in much smaller sizes.





Atlanta



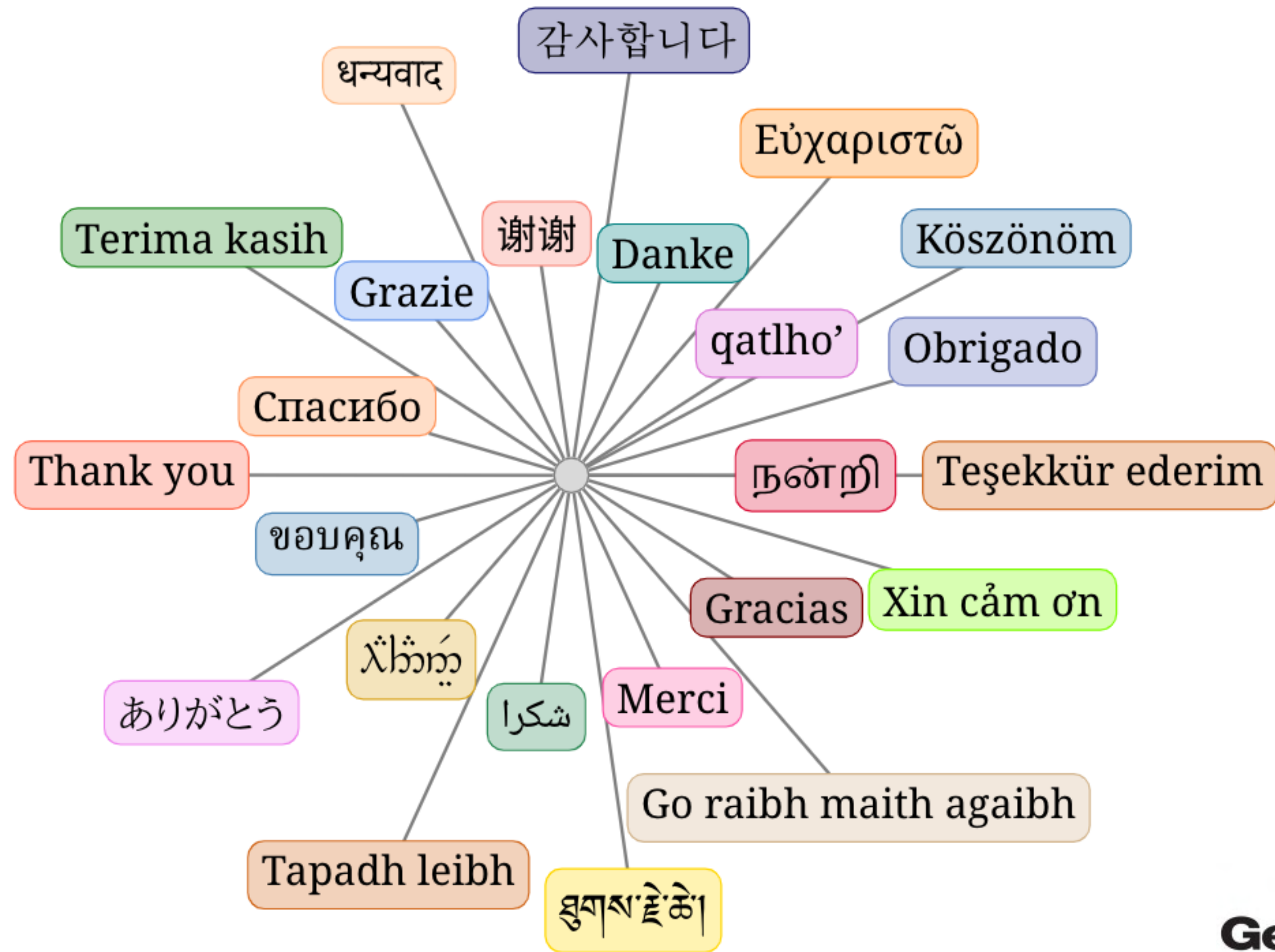


Georgia
Tech

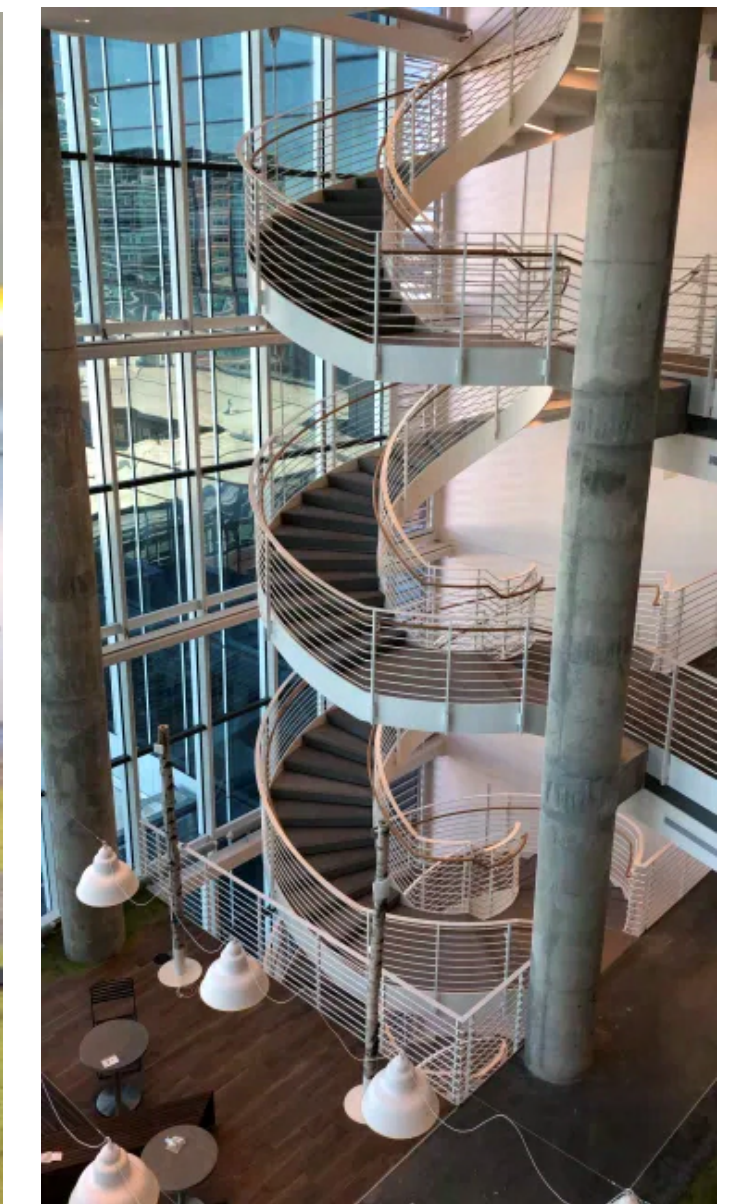
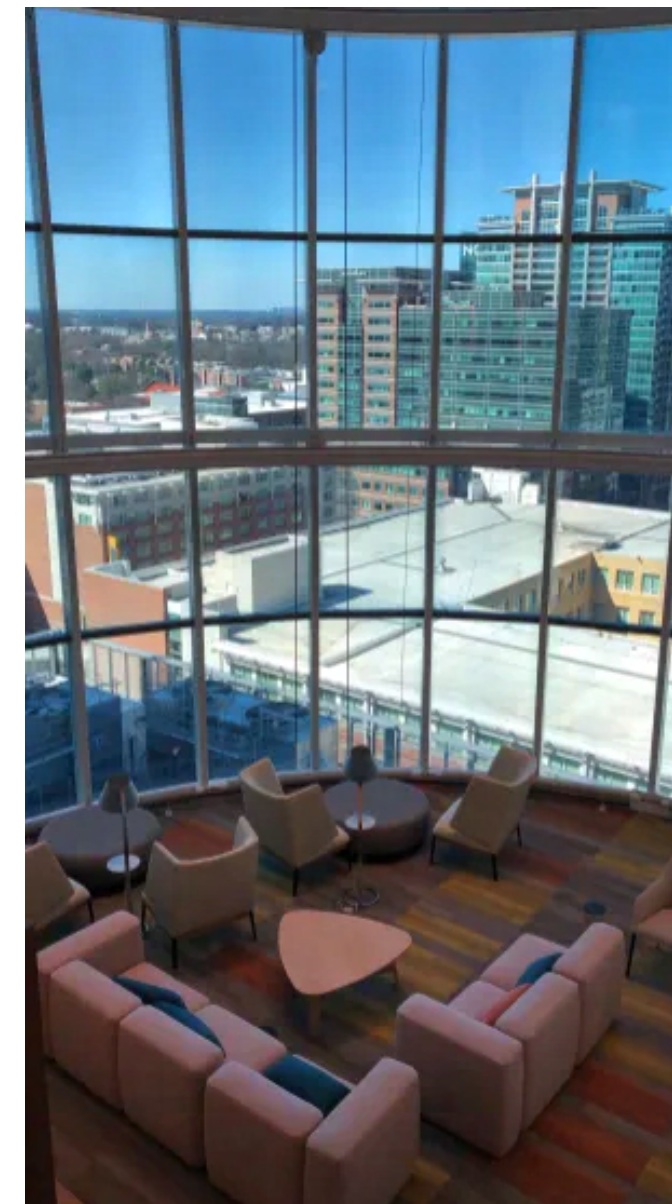
at&t

Thank you!

<https://cocoxu.github.io/>



(image credit: Overleaf)



(image credit: Georgia Tech)

