Improving Multilingual Capabilities and Error Detection in Large Language Models

Wei Xu (associate professor)
College of Computing
Georgia Institute of Technology
Twitter/X @cocoweixu

Georgia Tech

Bloomberg CTO Speaker Series / Oct 29, 2024

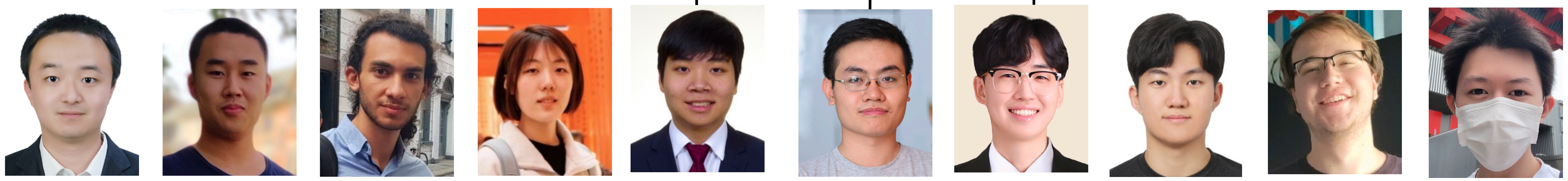
NLP X Research Lab

Generative AI
- evaluation of LLM-generated text
- reading/writing/voice assistant
- human-AI interactive system
- stylistics, personalization

Language Models
- multi-/cross-lingual capability
- decoding algorithms
- cultural alignment
- privacy, safety
- reasoning

NLP+X Interdisciplinary Research
- HCI, human-centered NLP
- Education, Healthcare, Law, Accessibility …

(co-advised with Alan Ritter)



Chao Jiang	Yao Dou	Tarek Naous	Geyang Guo	Jonathan Zheng	Duong Minh Le	Junmo Kang	Jeongrok Yu	Anton Lavrouk	Xiaofeng Wu
PhD student	PhD student	PhD student	PhD student	PhD student	PhD student	PhD student	MS student	MS student	MS student

Oleksandr Lavreniuk	Rachel Choi	Vishnesh Ramanathan	Govind Ramesh	Ian Ligon	Joseph Thomas	Julius Broomfield	Nour Allah El Senary	Siwan Yang	Suraj Mehrotra
Undergrad	Undergrad	Undergrad	Undergrad	Undergrad	Undergrad	Undergrad	Undergrad	Undergrad	Undergrad

Yao Dou[*1] Philippe Laban[*2] Claire Gardent[3] Wei Xu[1]

[1]Georgia Institute of Technology, [2]Salesforce AI, [3]CNRS/LORIA

[*]Equal Contribution

https://acl2024-text-generation-tutorial.github.io/

Tutorial Schedule

The tutorial will be held on Aug 11th (time are based on UTC+7 = Bangkok local time):

Time	Section	Presenter
9:00 - 9:15	Introduction [Slides]	Philippe
9:15 - 10:00	Section 1: Evaluation of LLM-generated Text [Slides]	Yao
10:00 - 10:45	Section 2: Models - (Text Simplification and Text Rewriting) [Slides]	Claire
10:45 - 11:00	Break	-
11:00 - 11:45	Section 3: Modeling Perspectives - (decoding, distillation, and diffusion LM) [Slides]	Wei
11:45 - 12:30	Section 4: from method to usable system: Human-Centered NLP [Slides]	Philippe

Today's Talk —

1 - Multilingual LLMs & Decoding

CODEC

(Le et al., ICLR 2024)

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

2 - Evaluation of LLMs

CAMEL & Thresh

(Naous et al., EMNLP 2024 & Heineman et al., EMNLP 2023)

Evaluate what LLMs are good and bad at, for things that may or may not be very obvious.

Today's Talk —

1 - Multilingual LLMs & Decoding

CODEC

(Le et al., ICLR 2024)

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

2 - Evaluation of LLMs

CAMEL & Thresh

(Naous et al., EMNLP 2024 & Heineman et al., EMNLP 2023)

Evaluate what LLMs are good and bad at, for things that may or may not be very obvious.

GPT-4 is surprisingly “good” at low resource languages

Masakhane NER 2.0

Lang.	GPT-4†	FT_{En}
Bambara	46.8	37.1
Ewe	75.5	75.3
Fon	19.4	49.6
Hausa	70.7	71.7
Igbo	51.7	59.3
Kinyarwanda	59.1	66.4
Luganda	73.7	75.3
Luo	**55.2**	35.8
Mossi	44.2	45.0
Chichewa	75.8	**79.5**
chiShona	66.8	35.2
Kiswahili	82.6	**87.7**
Setswana	62.0	64.8
Akan/Twi	52.9	50.1
Wolof	62.6	44.2
isiXhosa	69.5	24.0
Yoruba	**58.2**	36.0
isiZulu	60.2	43.9
AVG	60.4	54.5

GPT-4 is surprisingly “good” at low resource languages

Masakhane NER 2.0

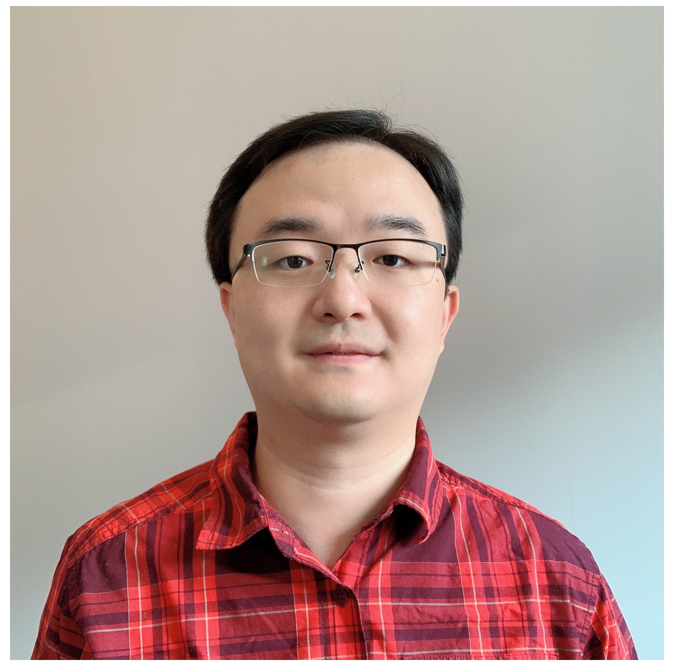
Lang.	GPT-4†	FT_{En}	Translate-train			Translate-test	
			Awes-align	EasyProject	CODEC (Δ_{FT})	Awes-align	CODEC (Δ_{FT})
Bambara	46.8	37.1	45.0	45.8	45.8 (+8.7)	50.0	**55.6** (+18.5)
Ewe	75.5	75.3	78.3	78.5	**79.1** (+3.8)	72.5	**79.1** (+3.8)
Fon	19.4	49.6	59.3	61.4	**65.5** (+15.9)	62.8	61.4 (+11.8)
Hausa	70.7	71.7	72.7	72.2	72.4 (+0.7)	70.0	**73.7** (+2.0)
Igbo	51.7	59.3	63.5	65.6	70.9 (+11.6)	**77.2**	72.8 (+13.5)
Kinyarwanda	59.1	66.4	63.2	71.0	71.2 (+4.8)	64.9	**78.0** (+11.6)
Luganda	73.7	75.3	77.7	76.7	77.2 (+1.9)	**82.4**	82.3 (+7.0)
Luo	**55.2**	35.8	46.5	50.2	49.6 (+13.8)	52.6	52.9 (+17.1)
Mossi	44.2	45.0	52.2	53.1	**55.6** (+10.6)	48.4	50.4 (+5.4)
Chichewa	75.8	**79.5**	75.1	75.3	76.8 (-2.7)	78.0	76.8 (-2.7)
chiShona	66.8	35.2	69.5	55.9	72.4 (+37.2)	67.0	**78.4** (+43.2)
Kiswahili	82.6	**87.7**	82.4	83.6	83.1 (-4.6)	80.2	81.5 (-6.2)
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)

Label Projection methods

[1] **CODEC**: “Constrained Decoding for Cross-lingual Label Projection” Duong Minh Le, Yang Chen, Alan Ritter, Wei Xu (ICLR 2024)
[2] **EasyProject:** “Frustratingly Easy Label Projection for Cross-lingual Transfer” Yang Chen, Chao Jiang, Alan Ritter, Wei Xu (ACL 2023 Findings)

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


Yang Chen


Chao Jiang

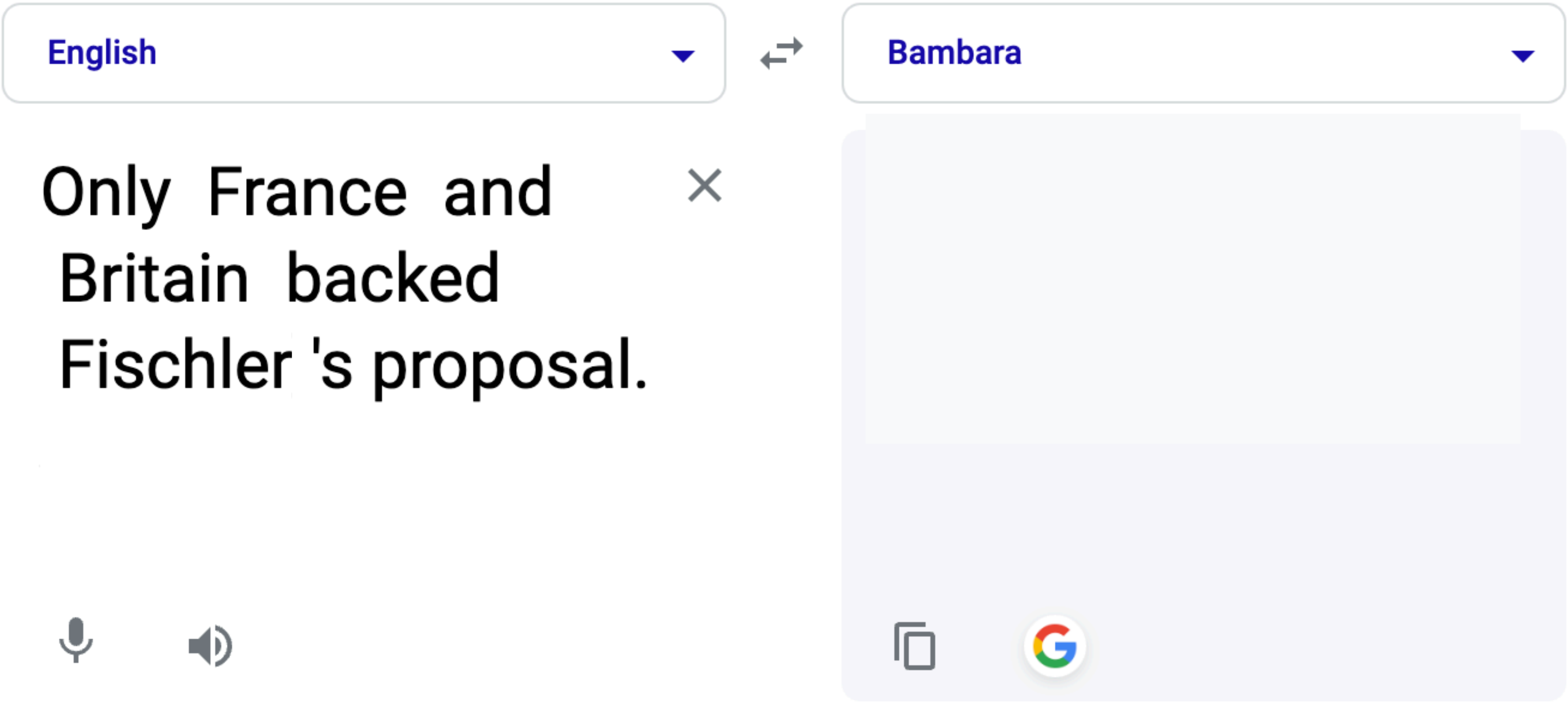

Alan Ritter


Wei Xu

A systematic study of marker-based approach for label projection

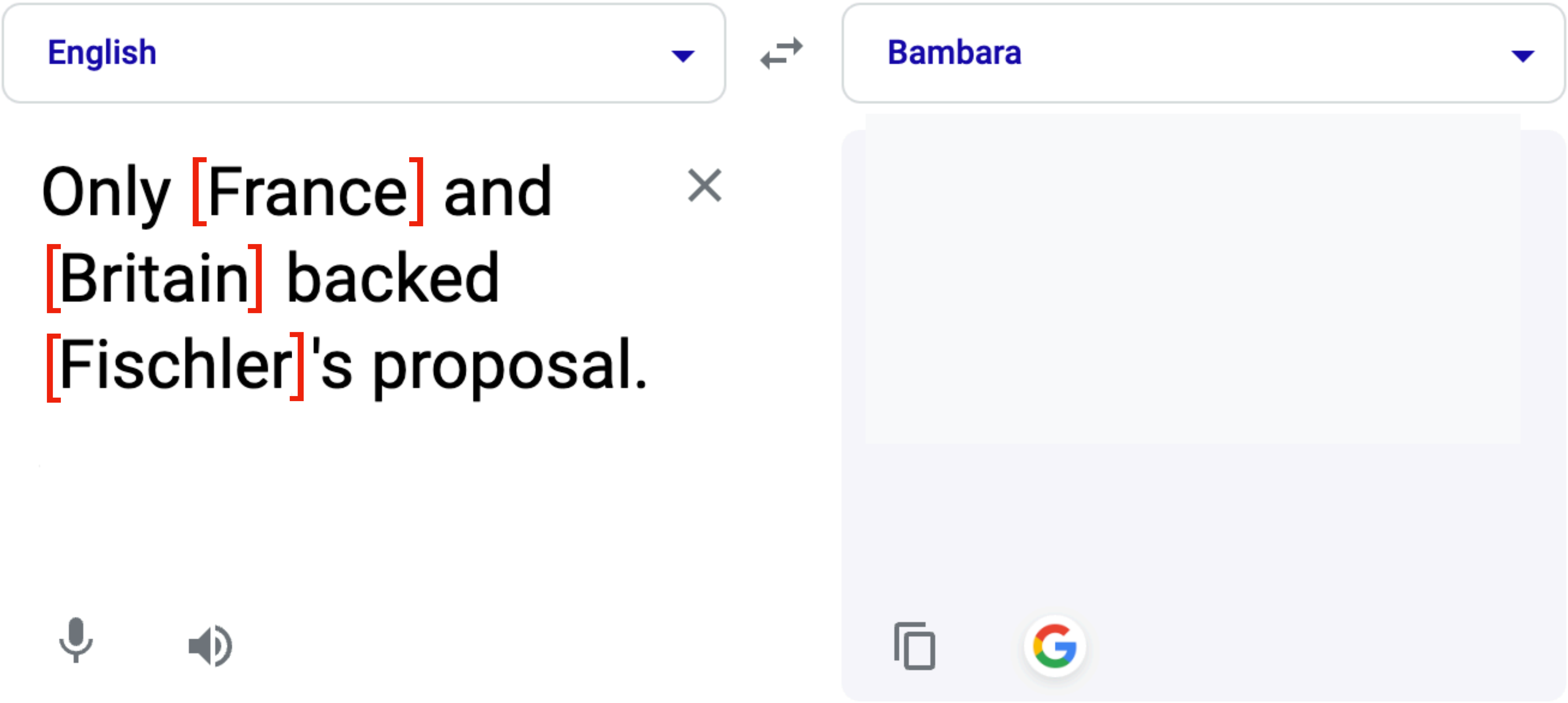
Marker-based Approach

Translating annotated training data from one language to the other



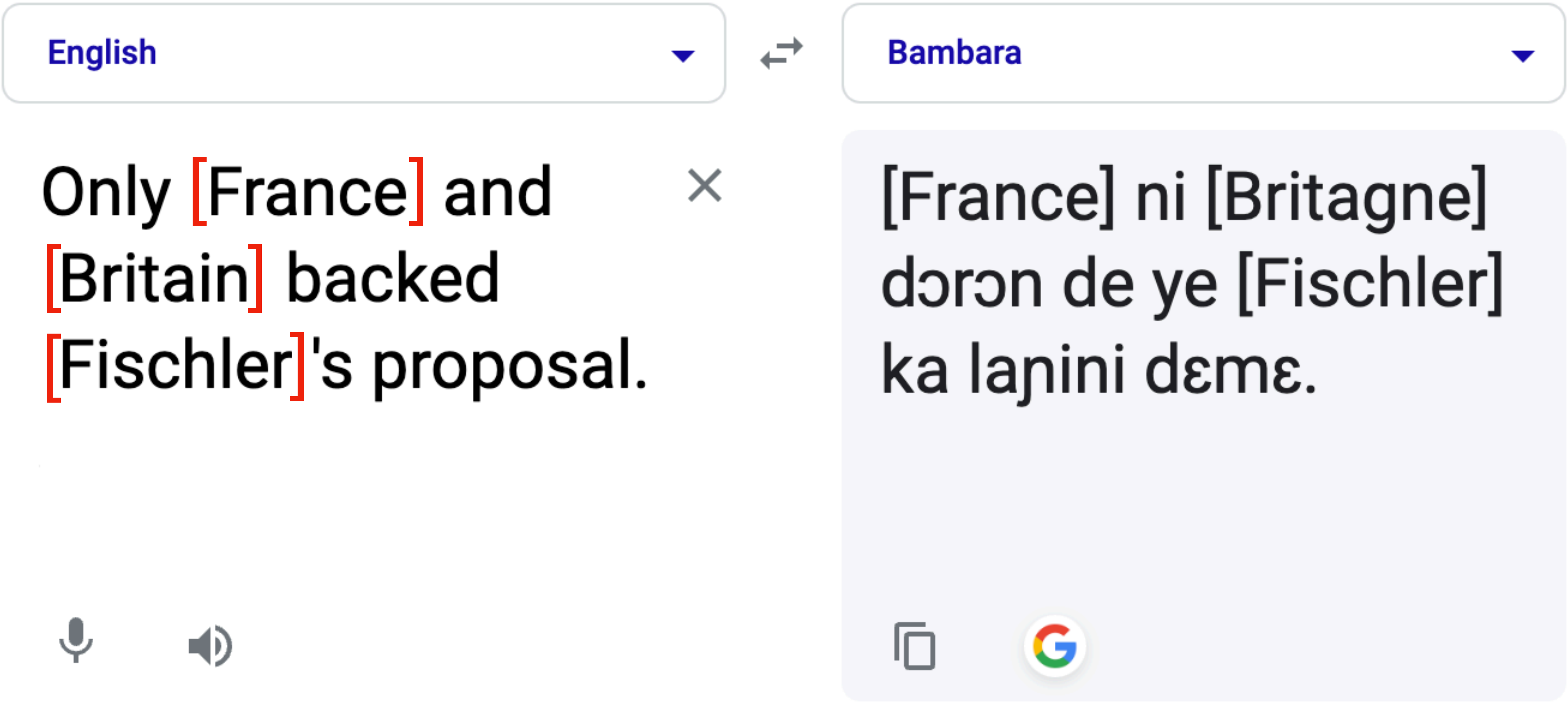
Marker-based Approach

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



Marker-based Approach

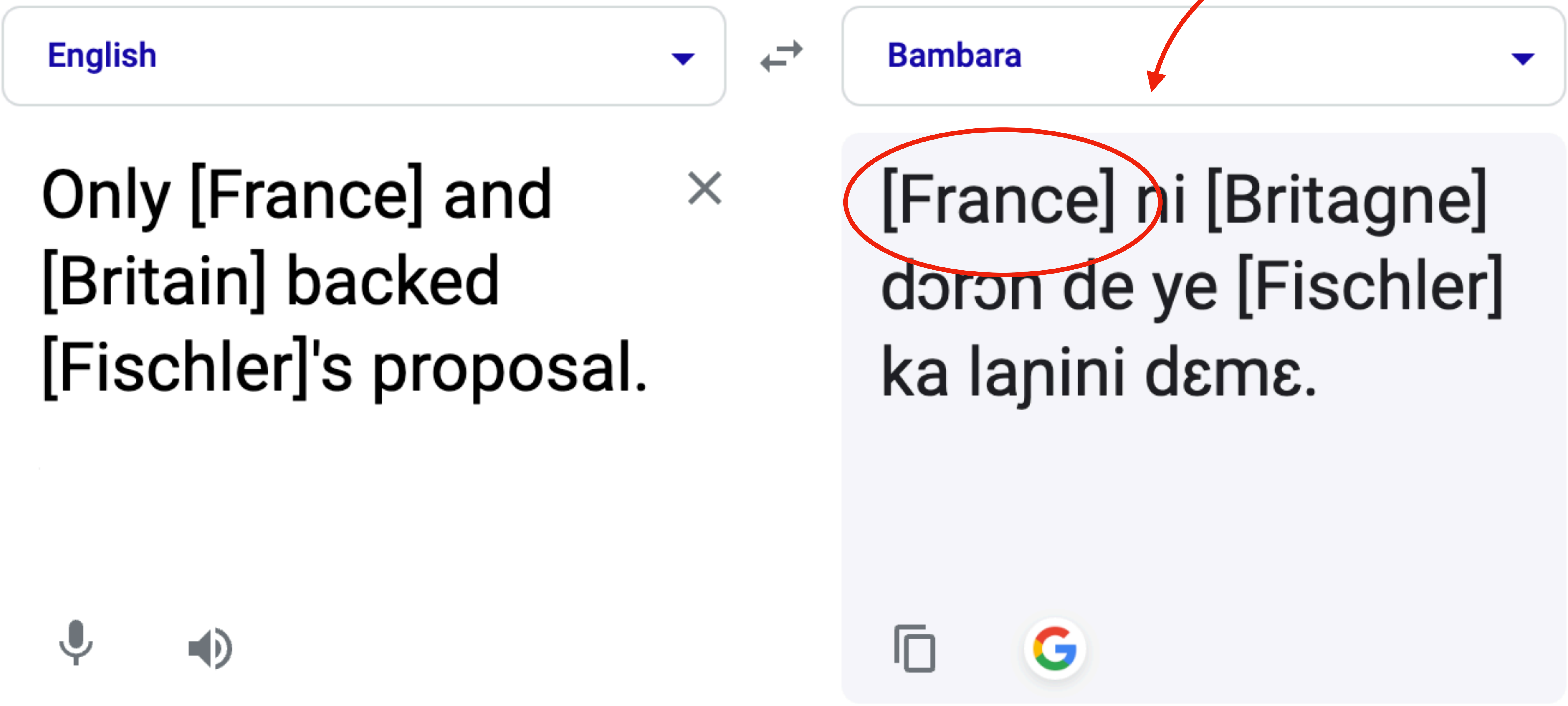
Translating annotated training data from one language to the other by injecting some markers [ ] around the text spans, then sending it directly to a Machine Translation system.



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.

though not without caveat
(will talk more later)



EasyProject - Easy Marker-based Projection

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

works the best

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

EasyProject - Easy Marker-based Projection

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

works the best

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

EasyProject - Easy Marker-based Projection

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

works the best

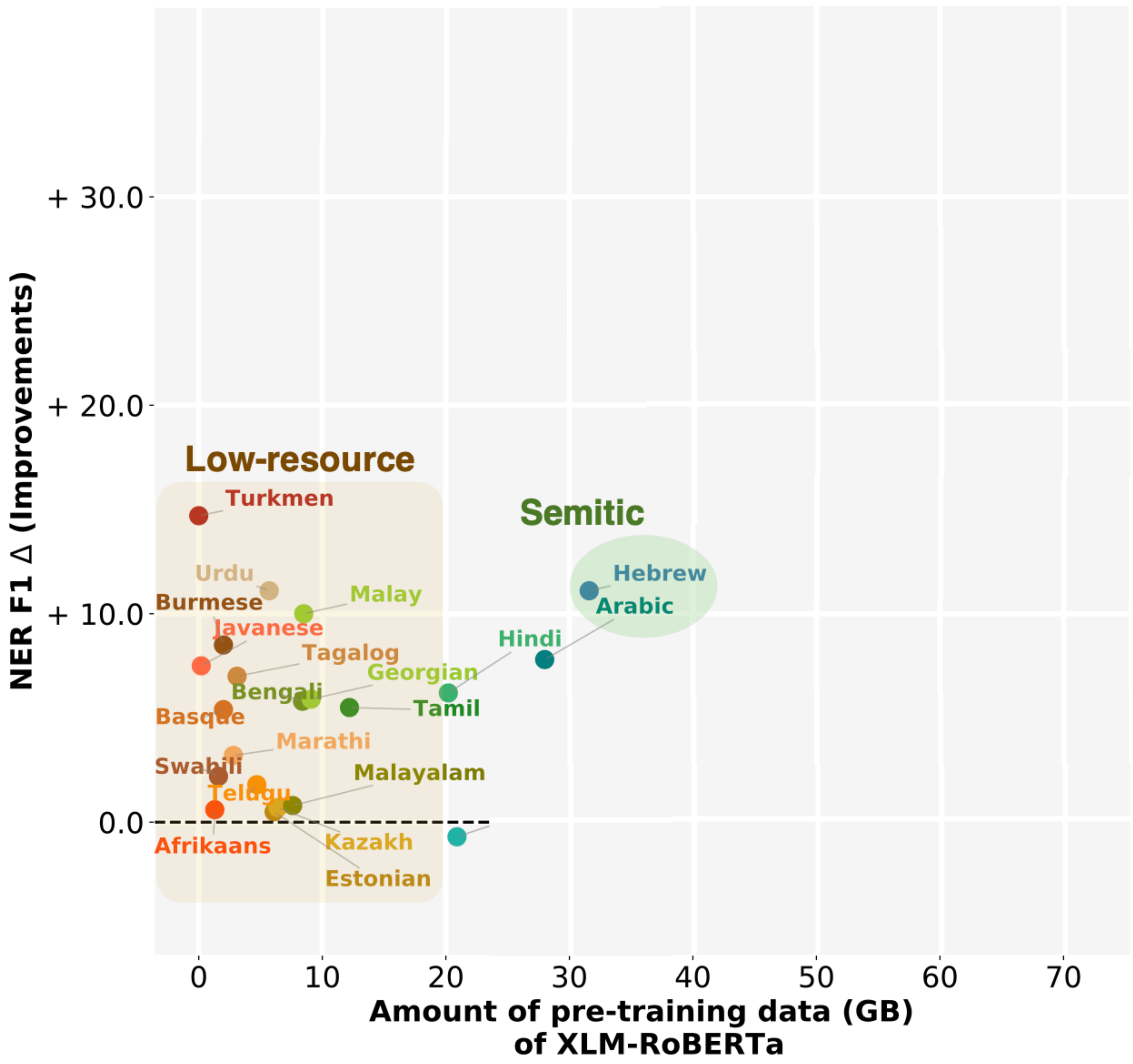
XML tags (e.g., <loc> </loc>) or [ ] “ ” ( ) < > { }

- 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

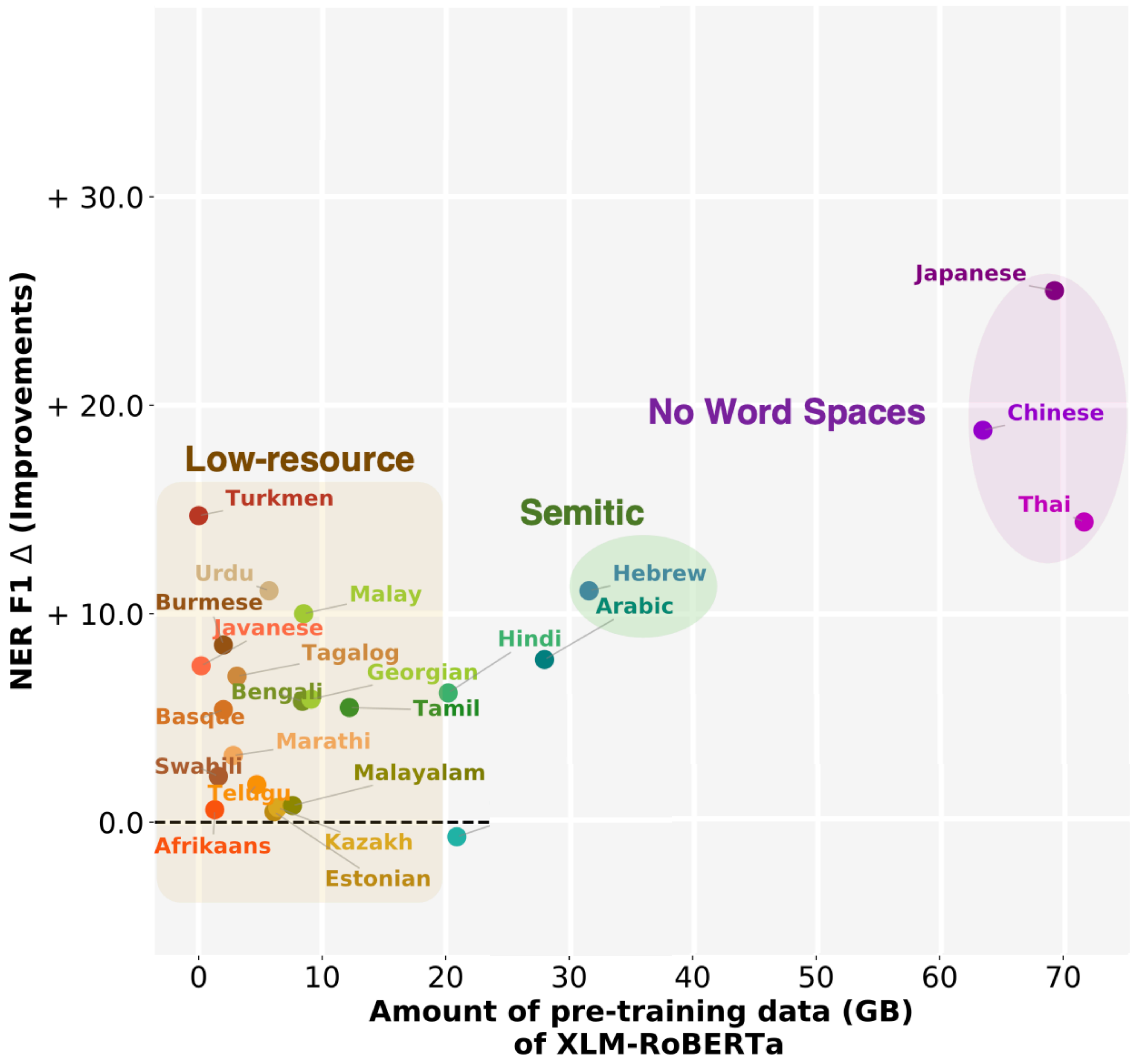
EasyProject - Easy Marker-based Projection

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



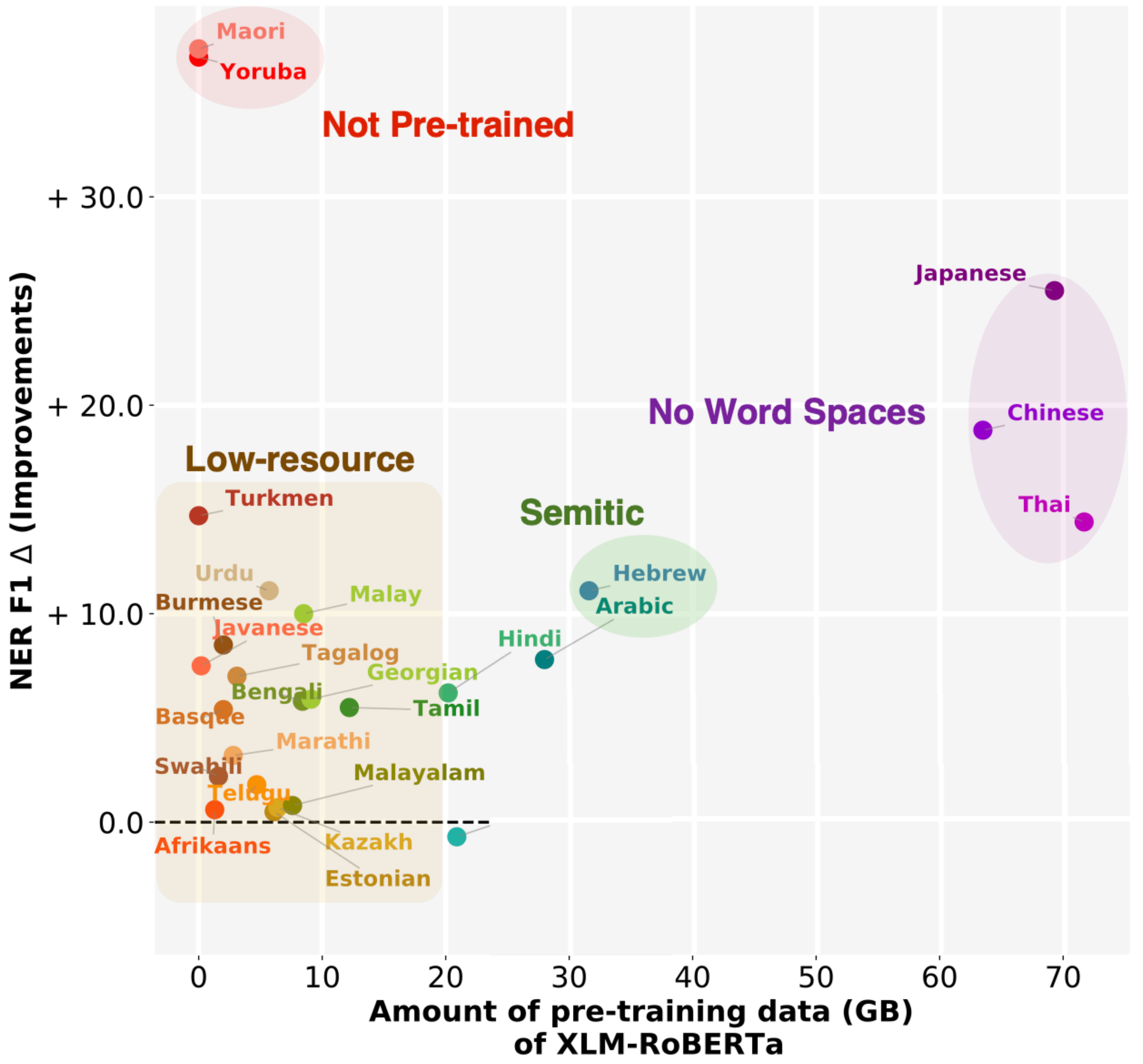
EasyProject - Easy Marker-based Projection

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



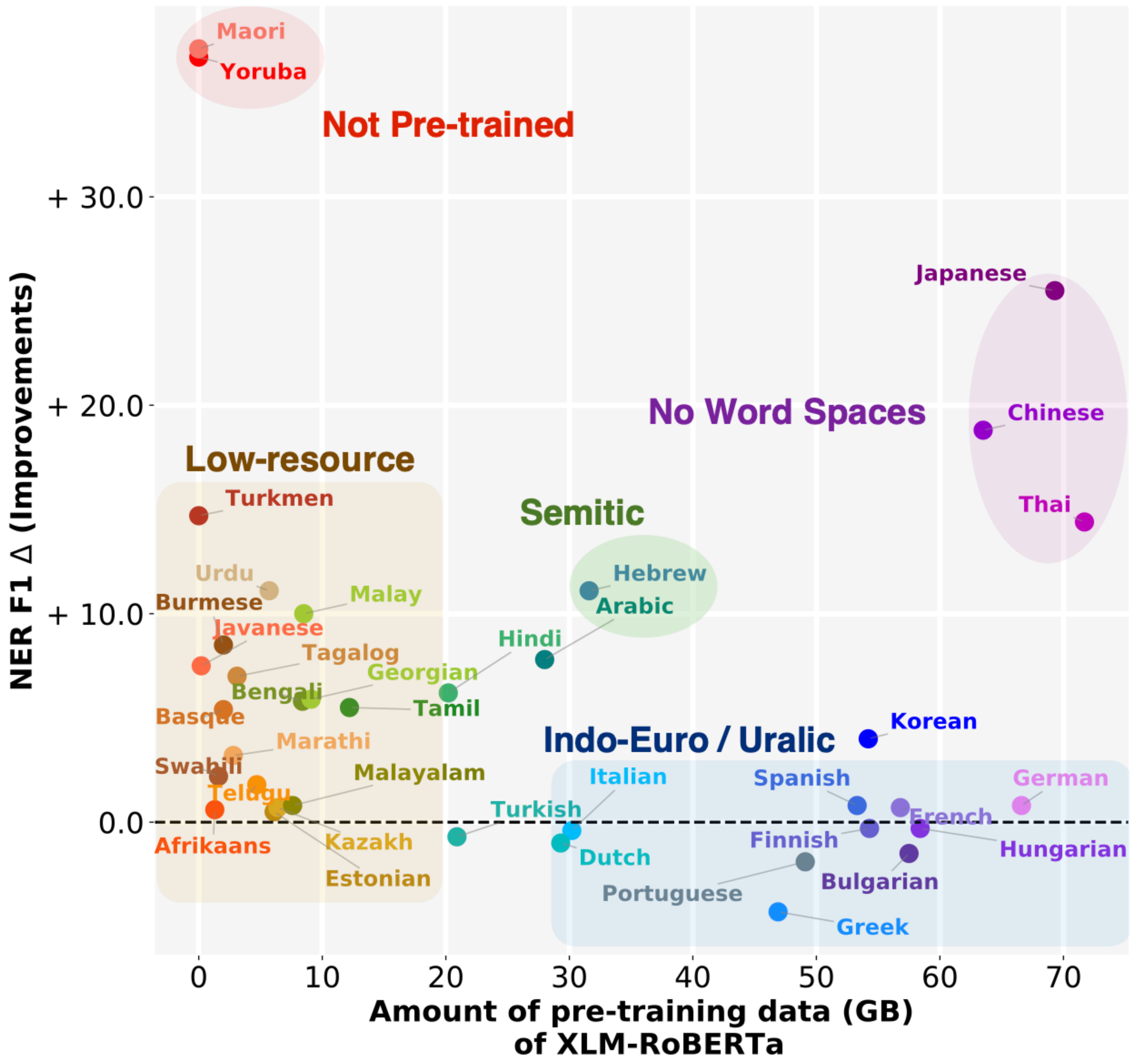
EasyProject - Easy Marker-based Projection

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



EasyProject - Easy Marker-based Projection

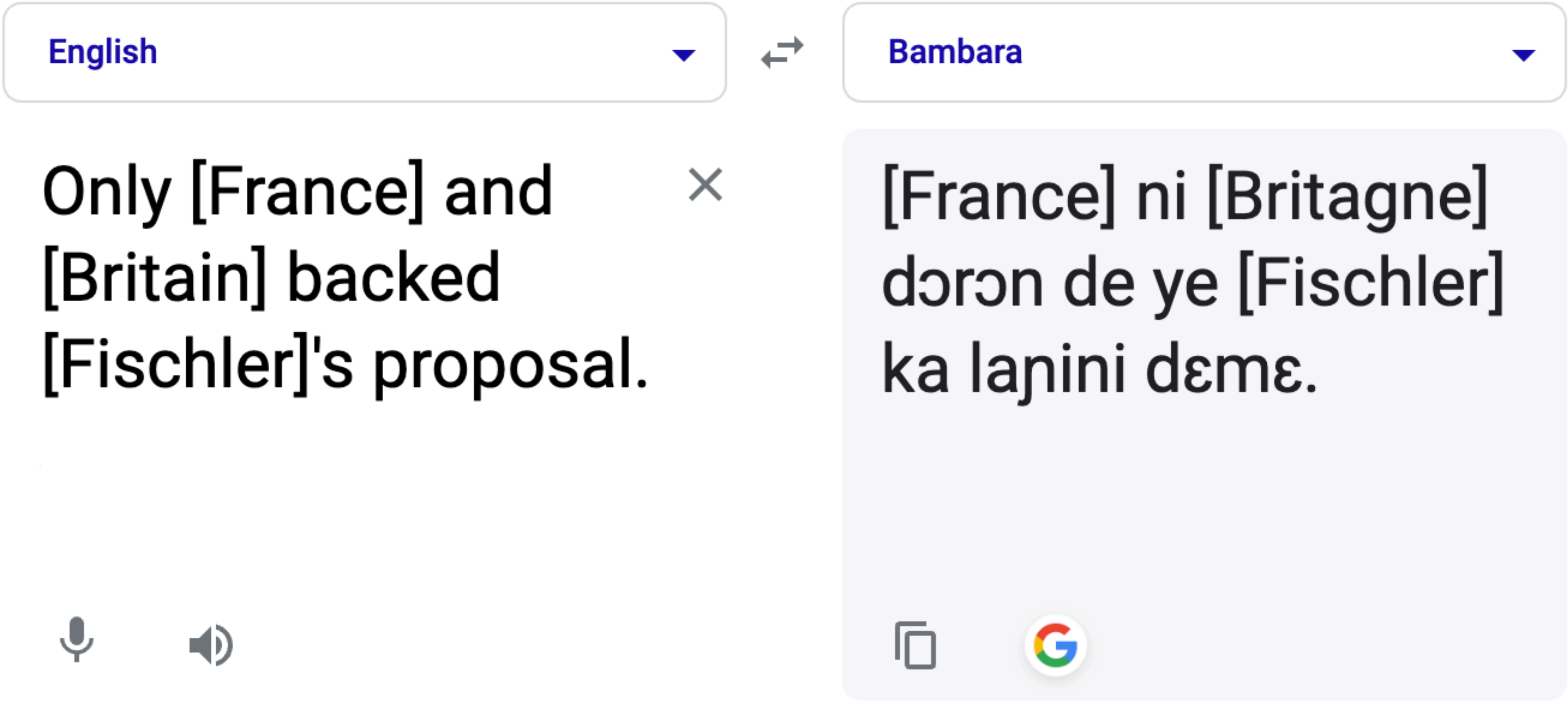
Especially promising for low-resource languages & languages that are written in non-Latin scripts



Zero-shot Cross-lingual Label Projection

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

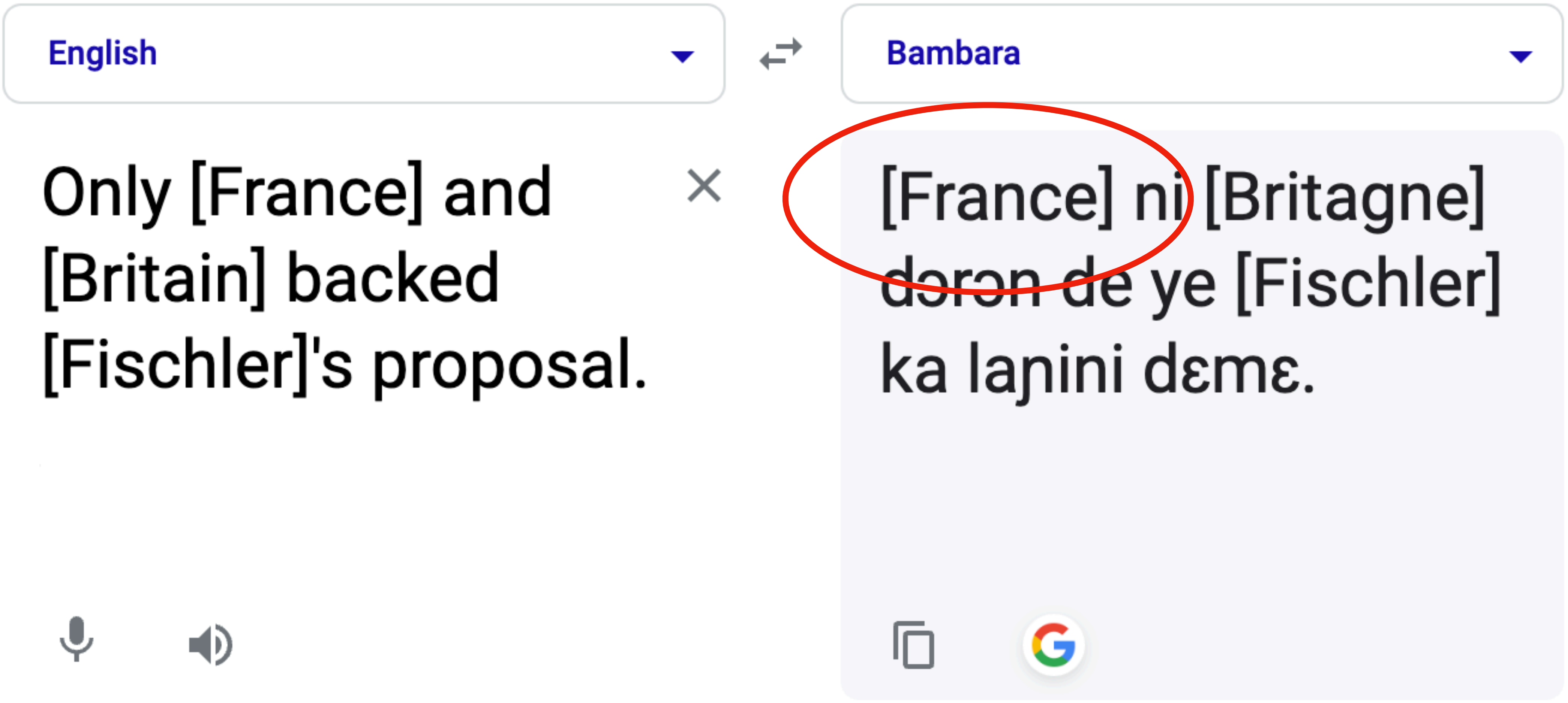
marker-based approach



Zero-shot Cross-lingual Label Projection

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

marker-based approach



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.

Only need a MT system & work surprisingly well !

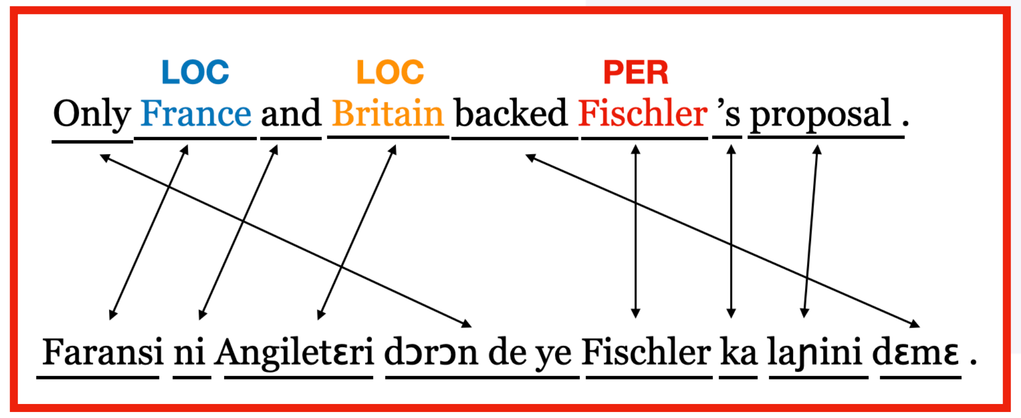
But, degraded MT quality due to injected markers

word alignment-based approach

English | Bambara

Only France and Britain backed Fischler 's proposal .

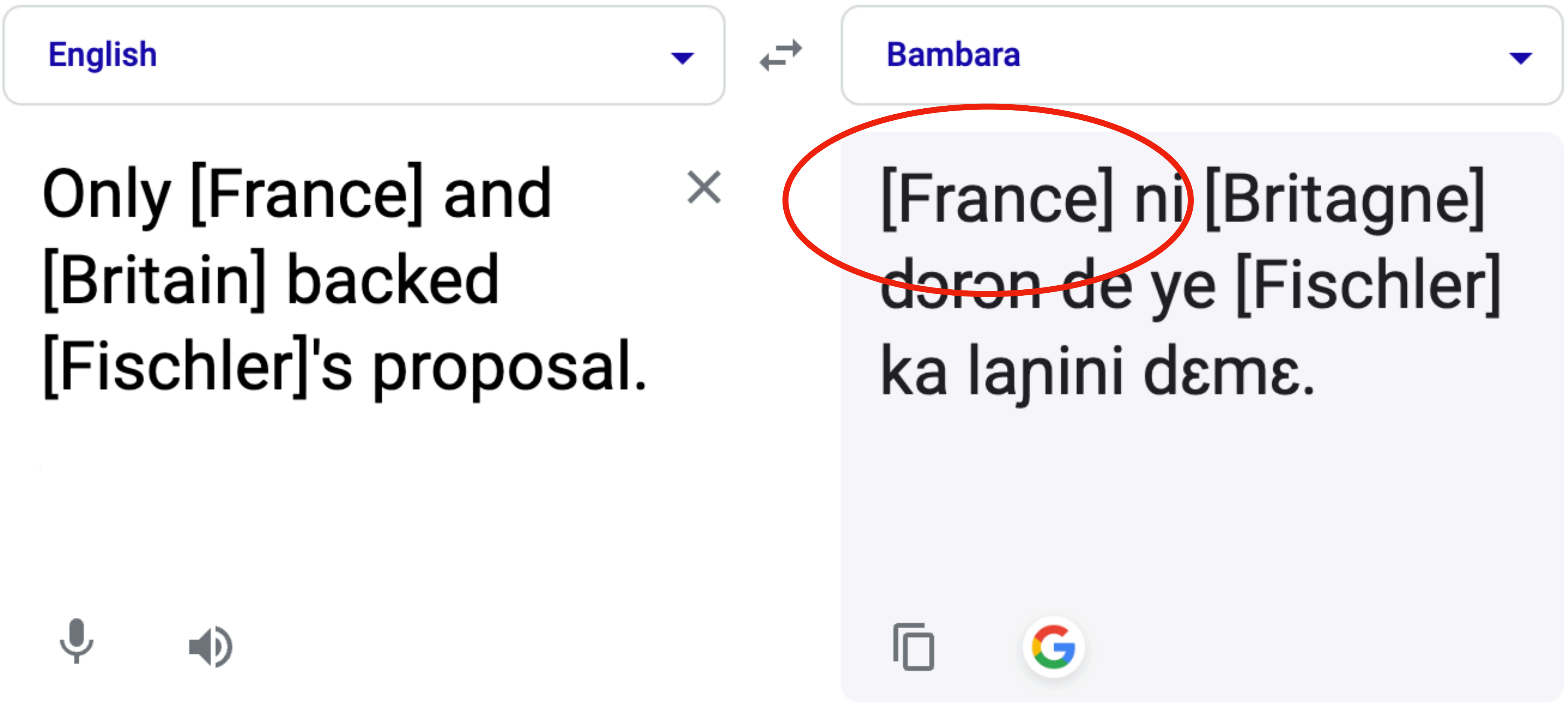
Faransi ni Angletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ .



Zero-shot Cross-lingual Label Projection

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

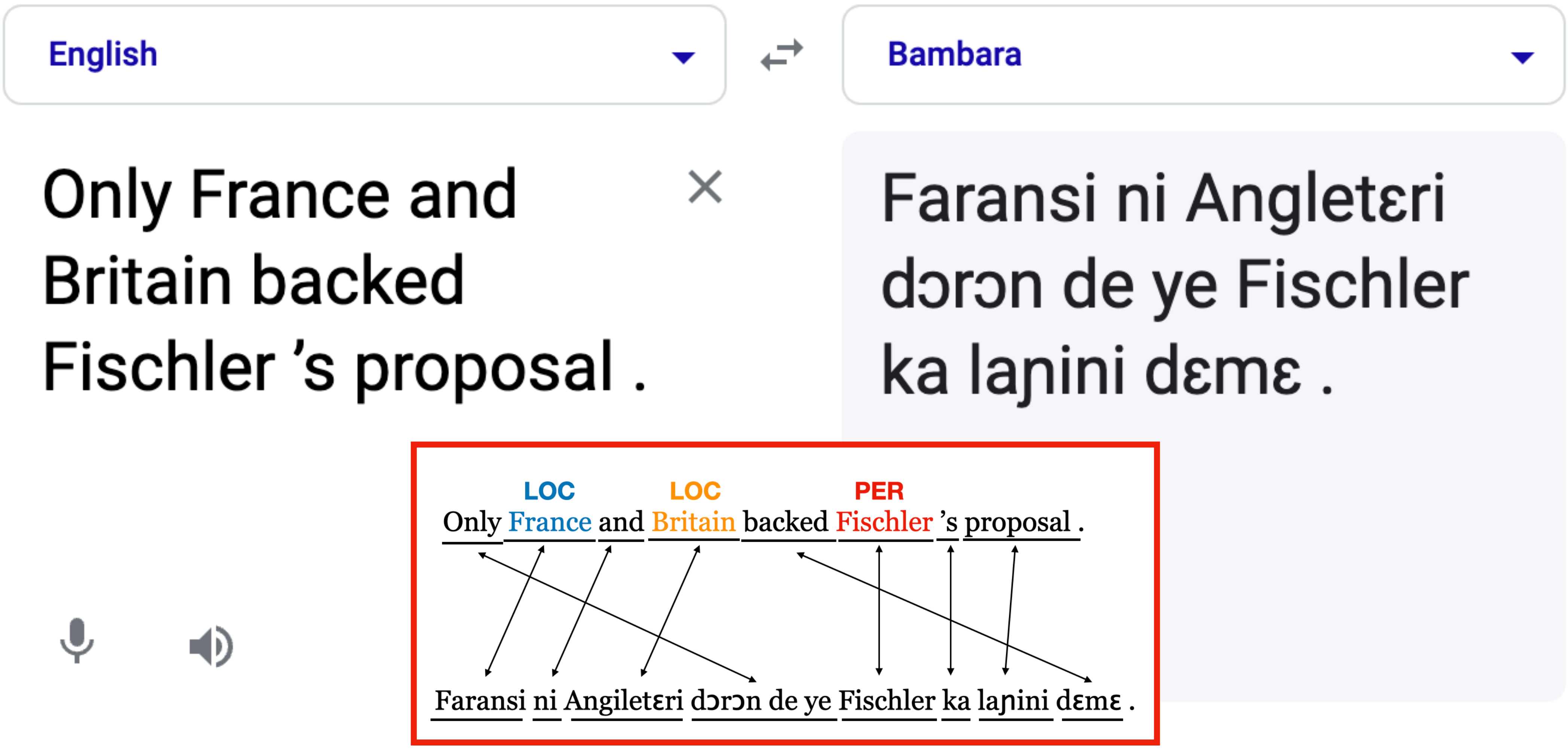
marker-based approach



Only need a MT system & work surprisingly well !

But, degraded MT quality due to injected markers

word alignment-based approach

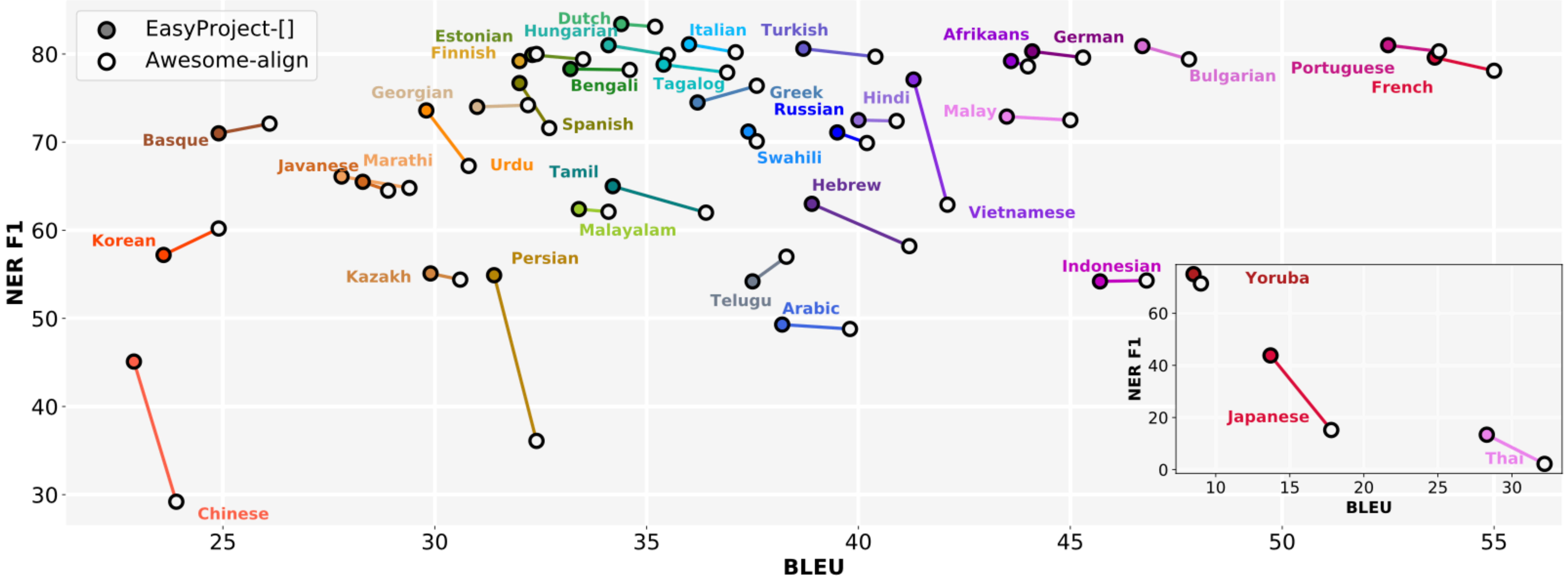


normally better MT quality

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!



Yang Chen, Chao Jiang, Alan Ritter, Wei Xu. “Frustratingly Easy Label Projection for Cross-lingual Transfer” (ACL 2023 Findings)

Can we do marker-based approach <u>without</u> scarifying the translation quality?

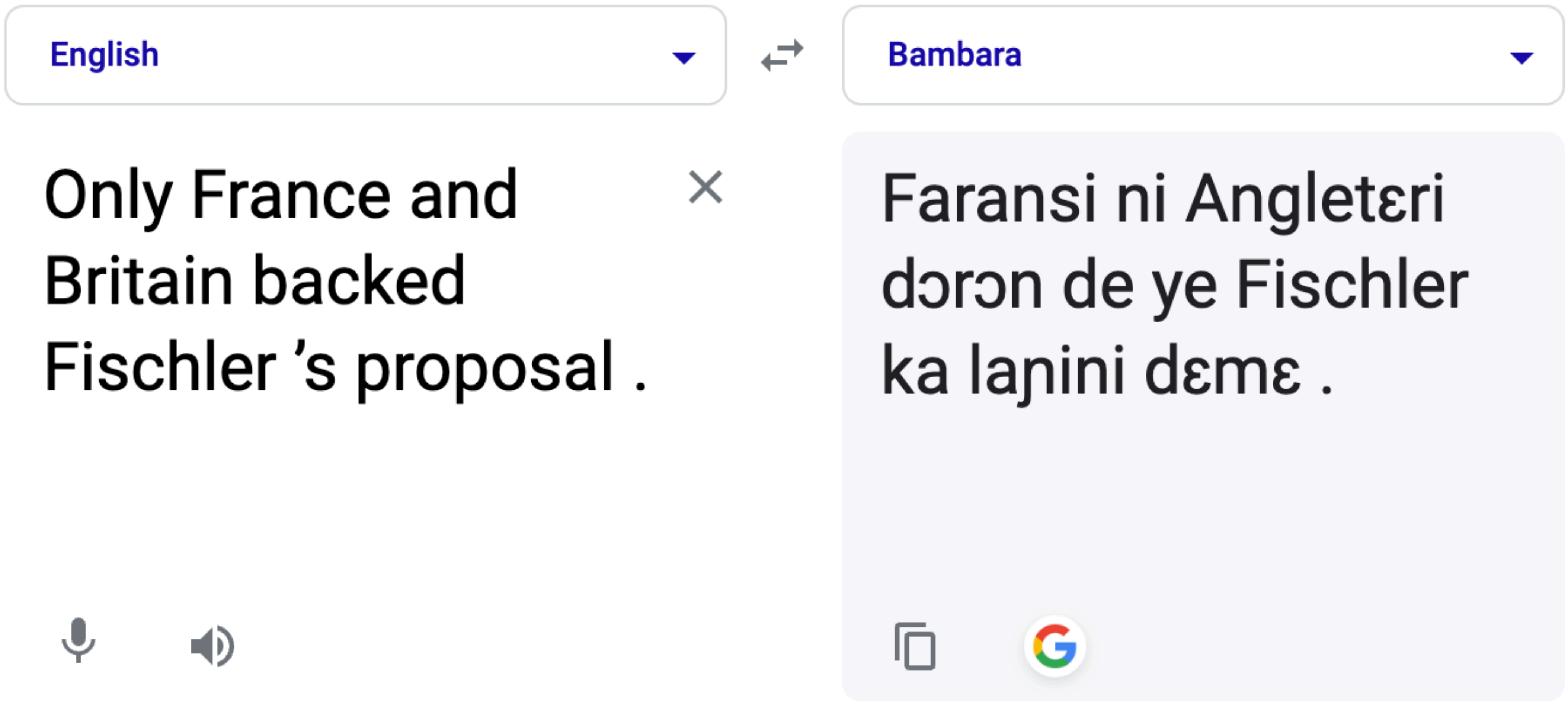
Constrained Decoding for Cross-lingual Label Projection (CODEC)

Duong Minh Le Yang Chen Alan Ritter Wei Xu

A better technical solution for marker-based label projection

Key Idea

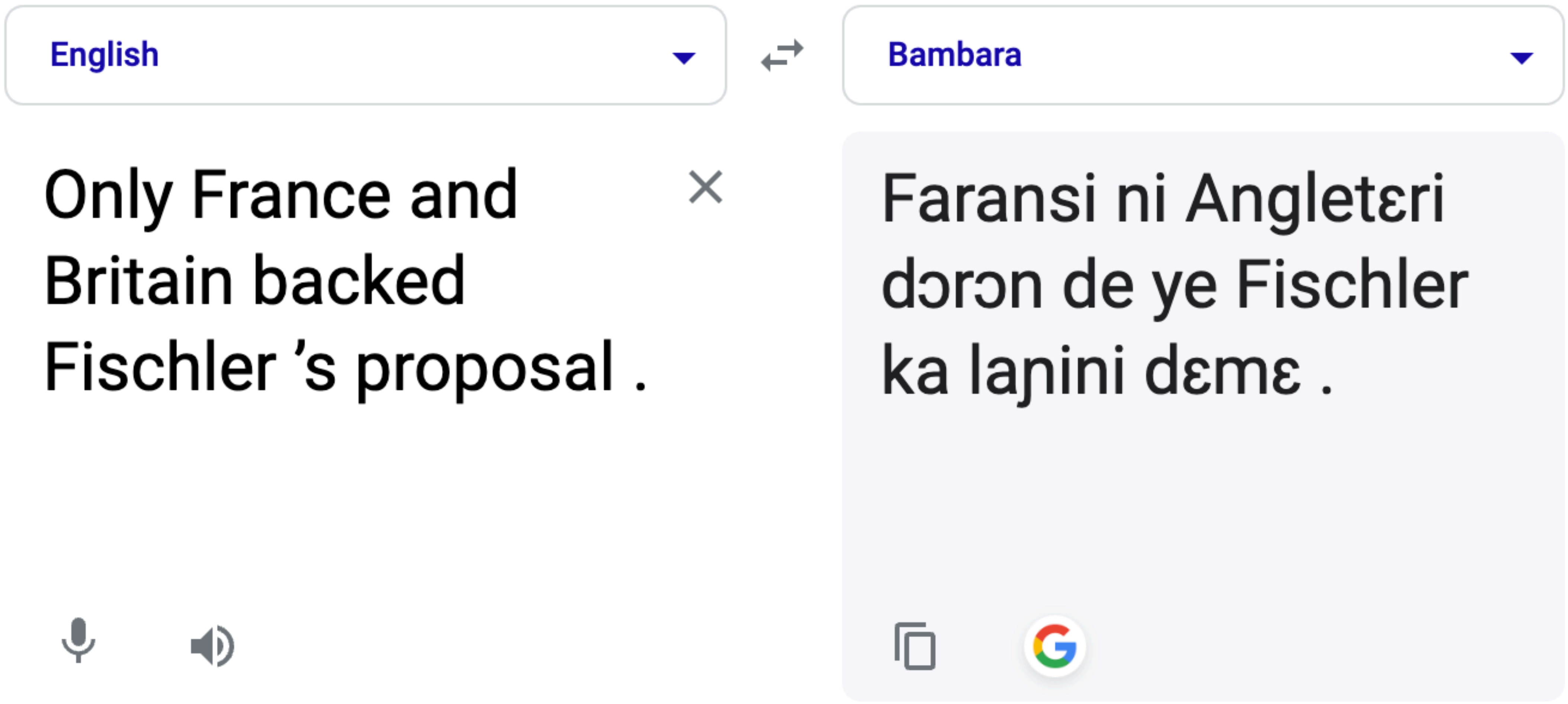
Step 1. Translate the original sentence as usual without markers.



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.



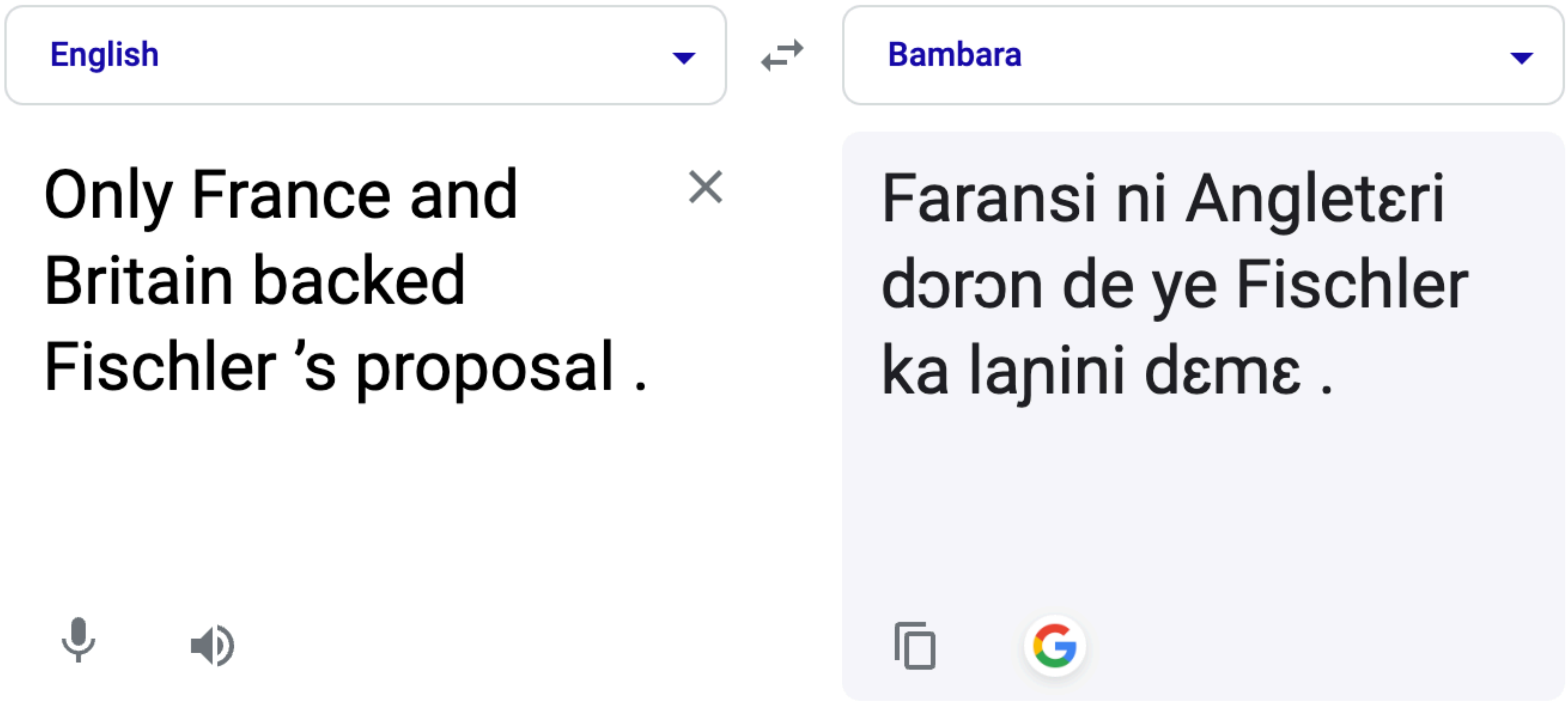
Step 2. Run translation model for a 2nd time to insert markers as a constrained decoding problem.

Input sentece:

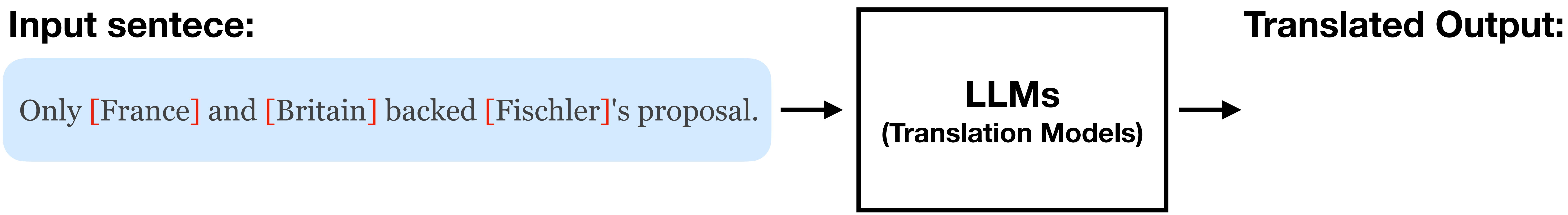
Only [France] and [Britain] backed [Fischler]'s proposal.

Key Idea

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

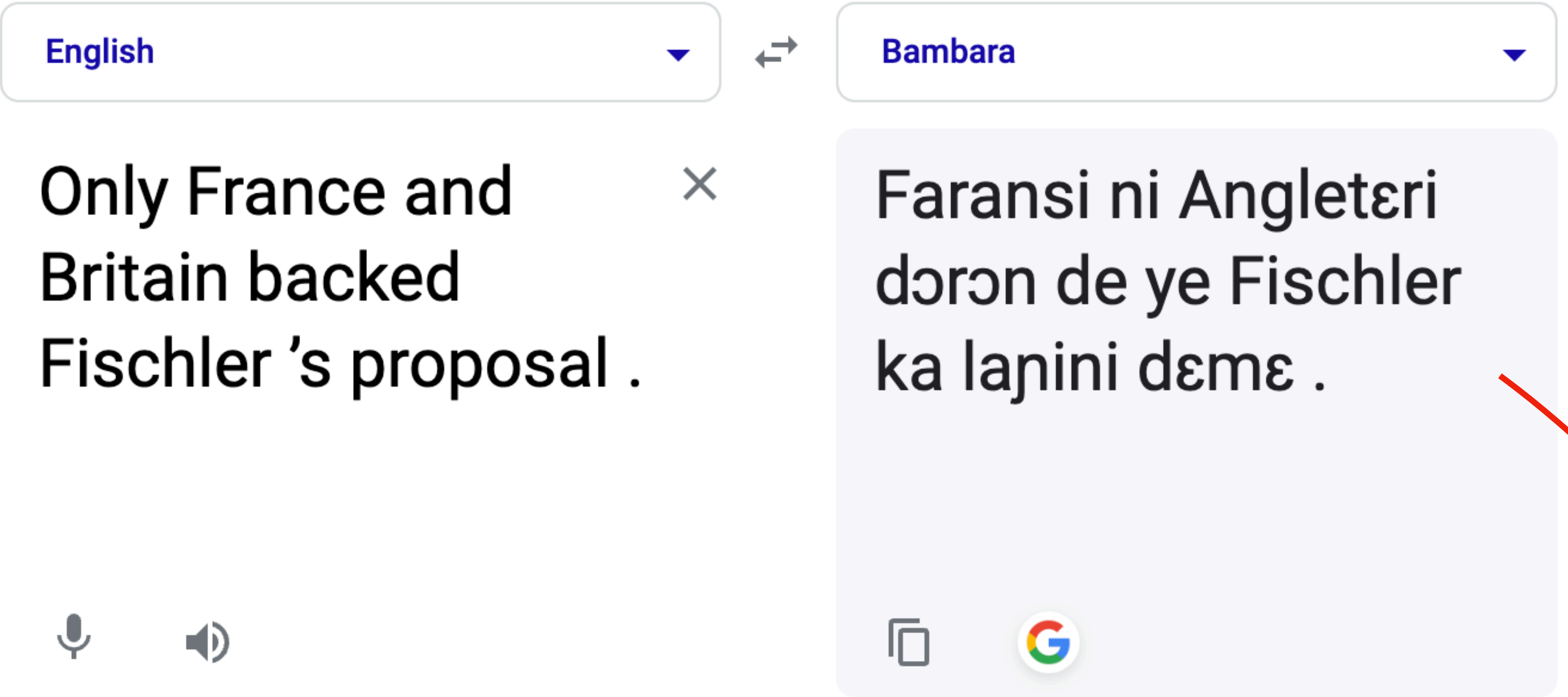


Step 2. Run translation model for a 2nd time to insert markers as a constrained decoding problem.



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 sentece:

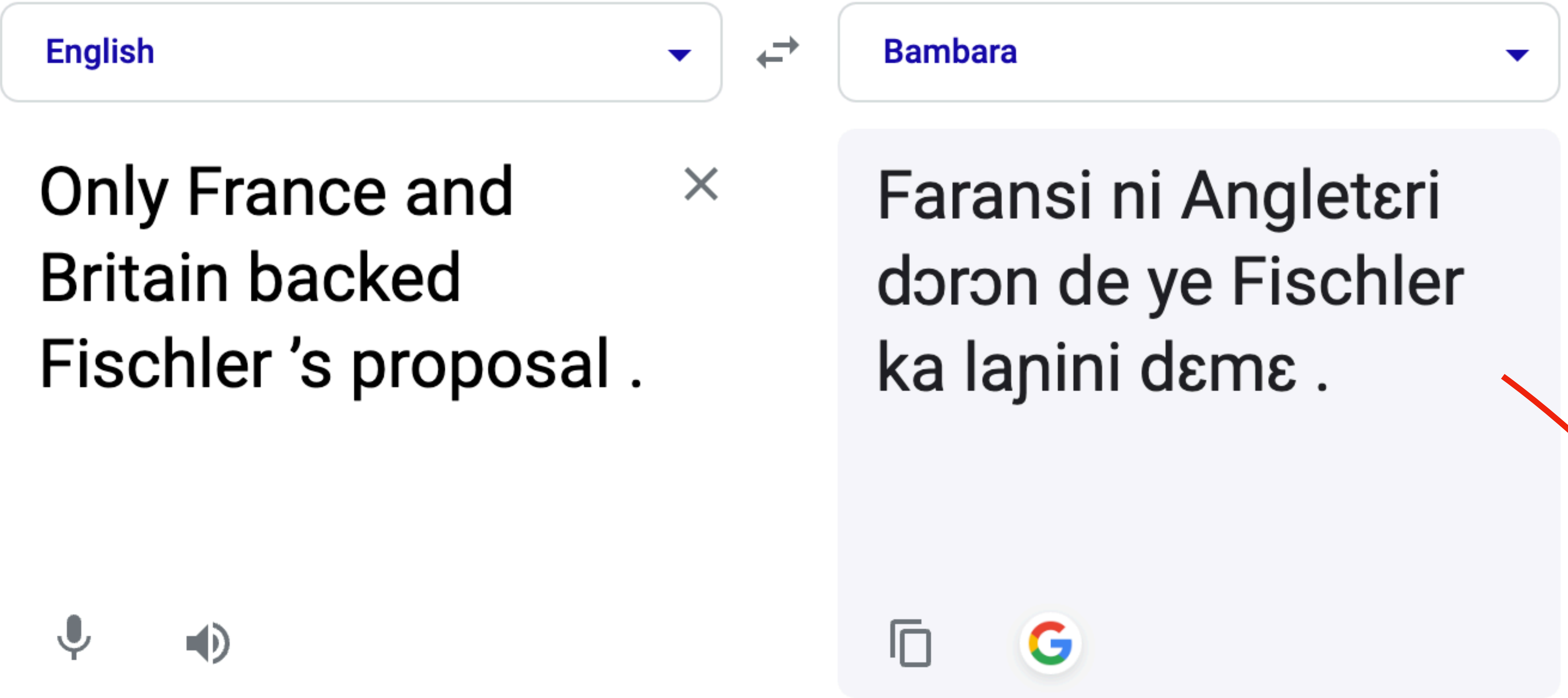
Only [France] and [Britain] backed [Fischler]'s proposal.

→ **LLMs** **(Translation Models)** →

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 sentece:

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

→ **LLMs (Translation Models)** →

Translated Output:

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

Key Idea — more formally

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

$$y^{tmpl} = \arg\max_{y} \log P_{\tau}(y|x)$$

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

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

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

An Efficient Constrained Decoding Algorithm

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

An Efficient Constrained Decoding Algorithm

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

Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angiletɛri dɔrɔn de ye Fischler ka laŋini dɛmɛ ."

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

$$\epsilon \xrightarrow{-0.65} \text{Faransi} \xrightarrow{-0.37} \text{ni} \xrightarrow{-0.56} \text{Ang} \xrightarrow{-0.34} \text{ile} \longrightarrow \cdots$$

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

$$\epsilon \xrightarrow{-0.64} \text{Faransi} \xrightarrow{-0.68} \text{ni} \xrightarrow{-6.26} \text{Ang} \xrightarrow{-0.38} \text{ile} \longrightarrow \cdots$$

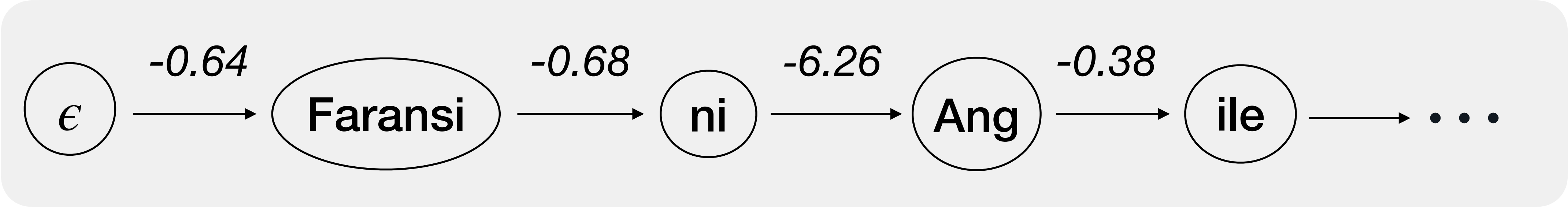
An Efficient Constrained Decoding Algorithm

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

Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angiletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ ."

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

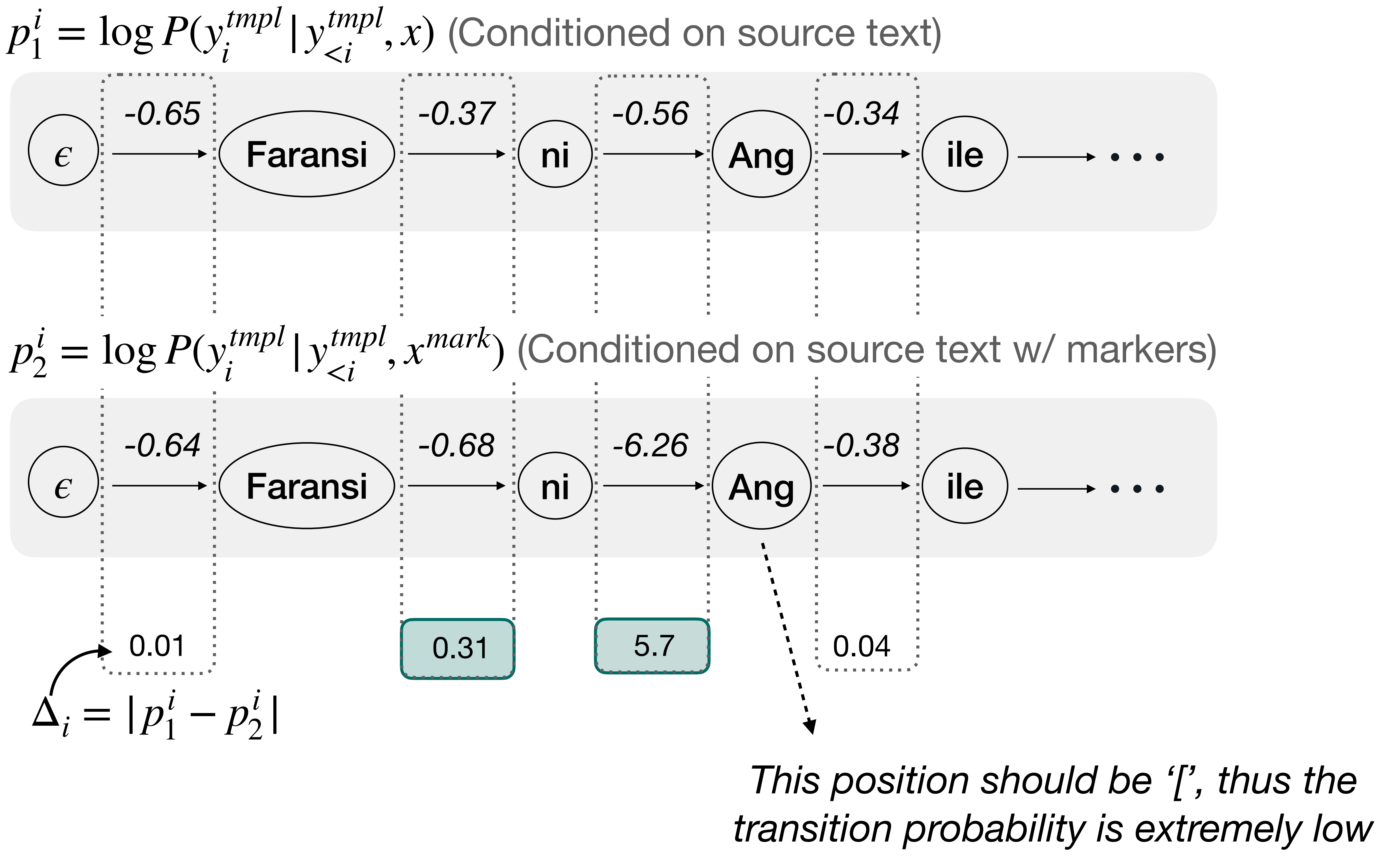
$p_2^i = \log P(y_i^{tmpl} | y_{<i}^{tmpl}, x^{mark})$ (Conditioned on source text w/ markers)



An Efficient Constrained Decoding Algorithm

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

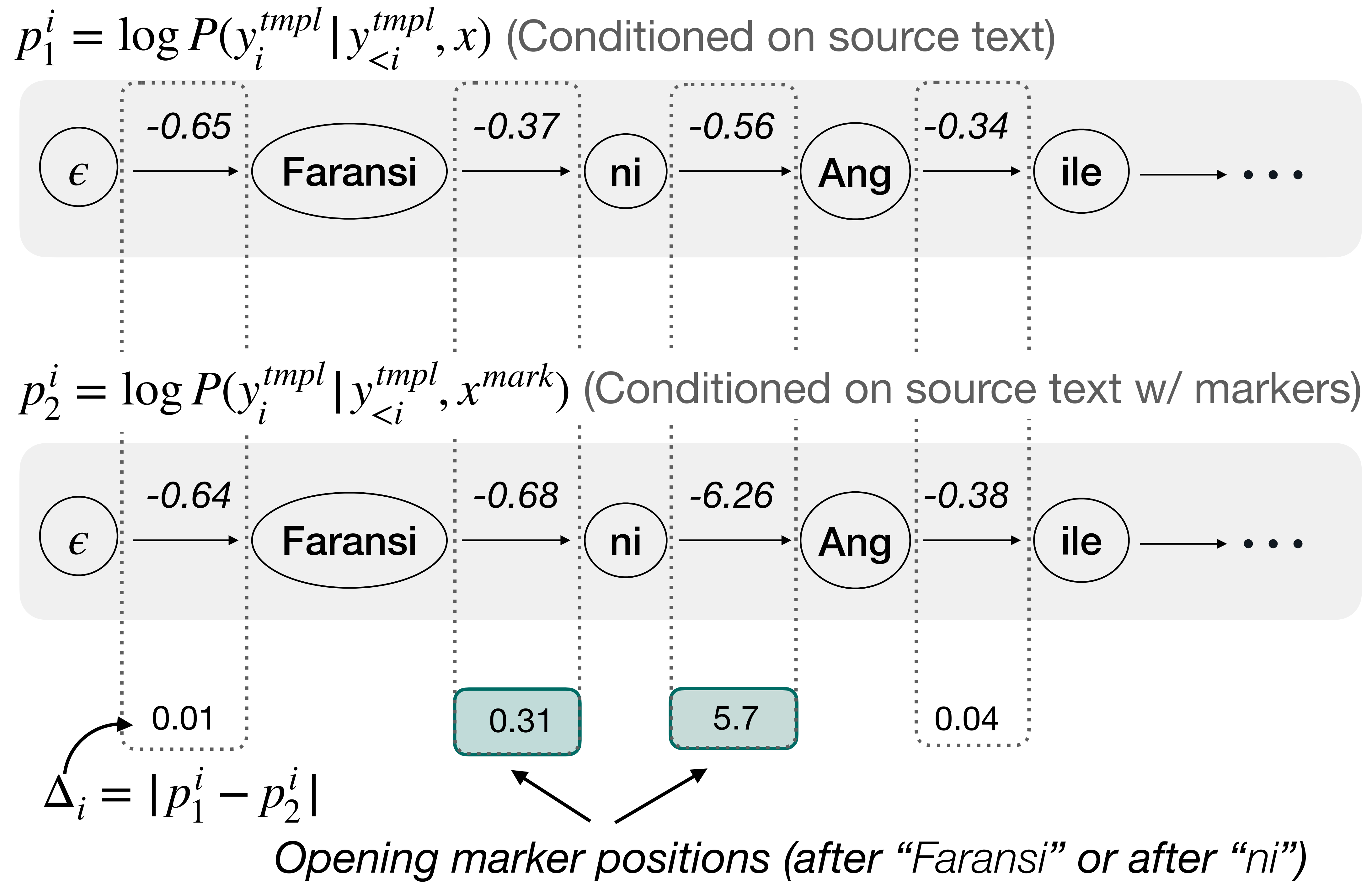
Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angiletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ ."



An Efficient Constrained Decoding Algorithm

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

Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angiletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ ."



An Efficient Constrained Decoding Algorithm

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

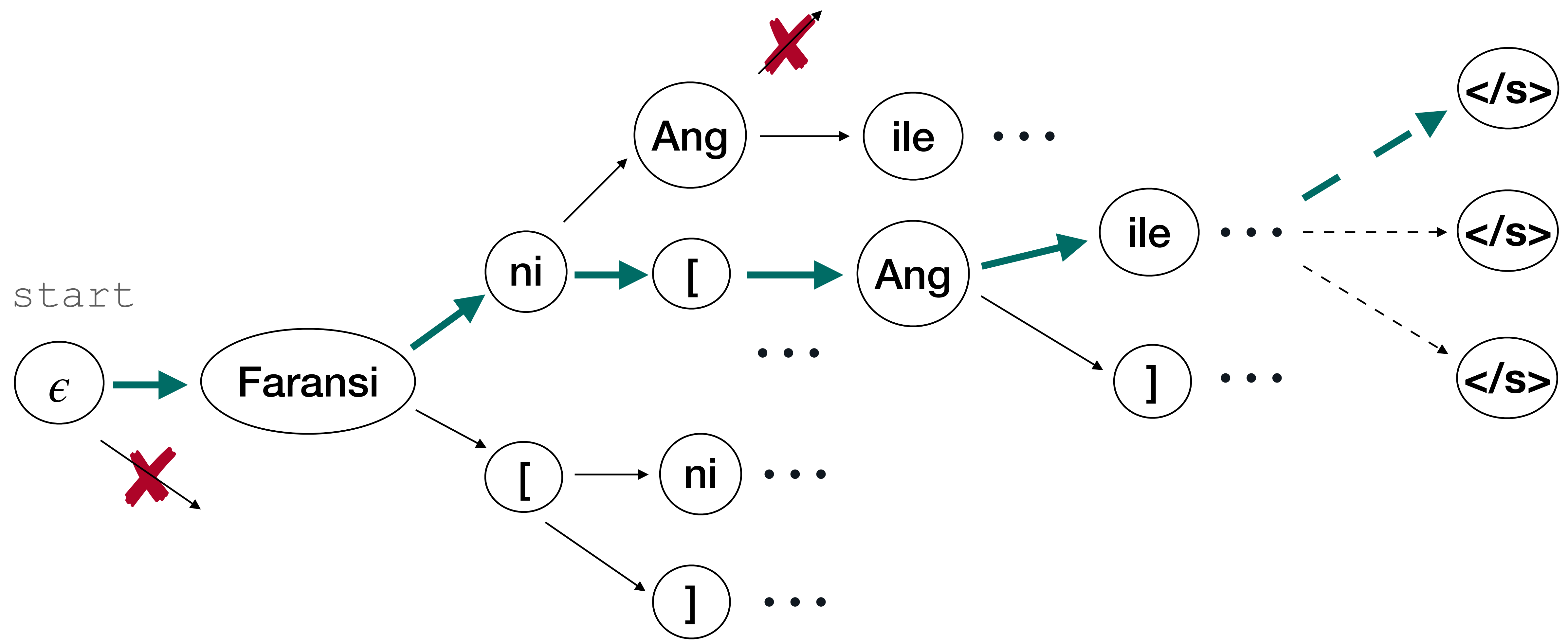
$$d = \min\left(\max\left(j + \delta, q\right), |y^k|\right)$$

An Efficient Constrained Decoding Algorithm

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

$$d = \min\left(\max\left(j + \delta, q\right), |y^k|\right)$$

Input:	$x =$ “Only France and Britain backed Fischler 's proposal .”	$x^{mark} =$ ”Only France and [Britain] backed Fischler 's proposal .”	$y^{tmpl} =$ ”Faransi ni Angilətɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ .”



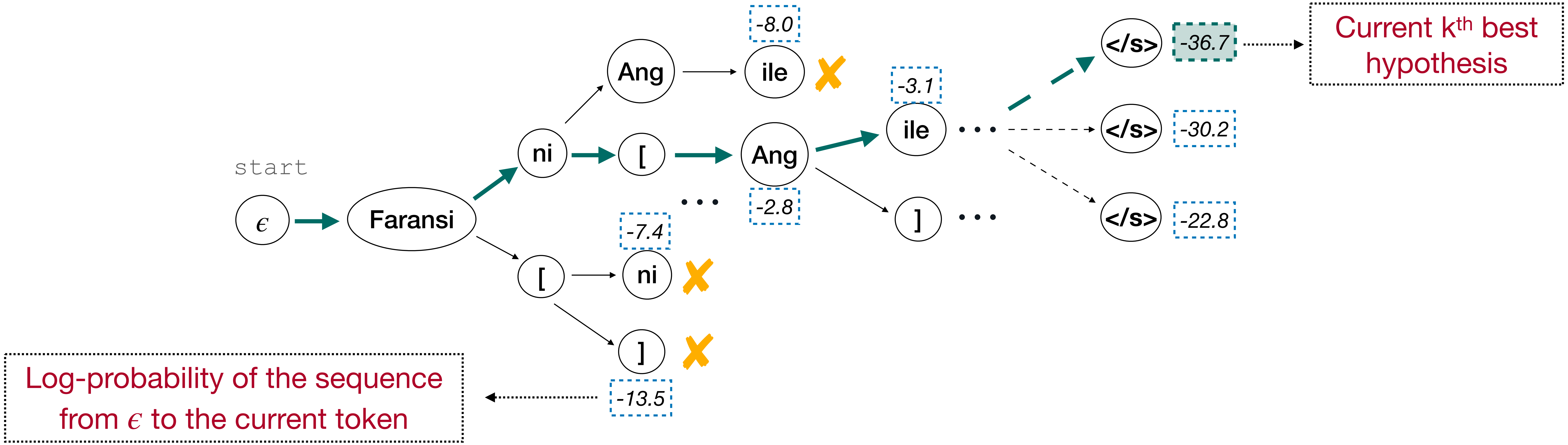
✘ *Prune opening-marker positions*

An Efficient Constrained Decoding Algorithm

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

$$d = \min\left(\max\left(j + \delta, q\right), |y^k|\right)$$

Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angilətɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ ."

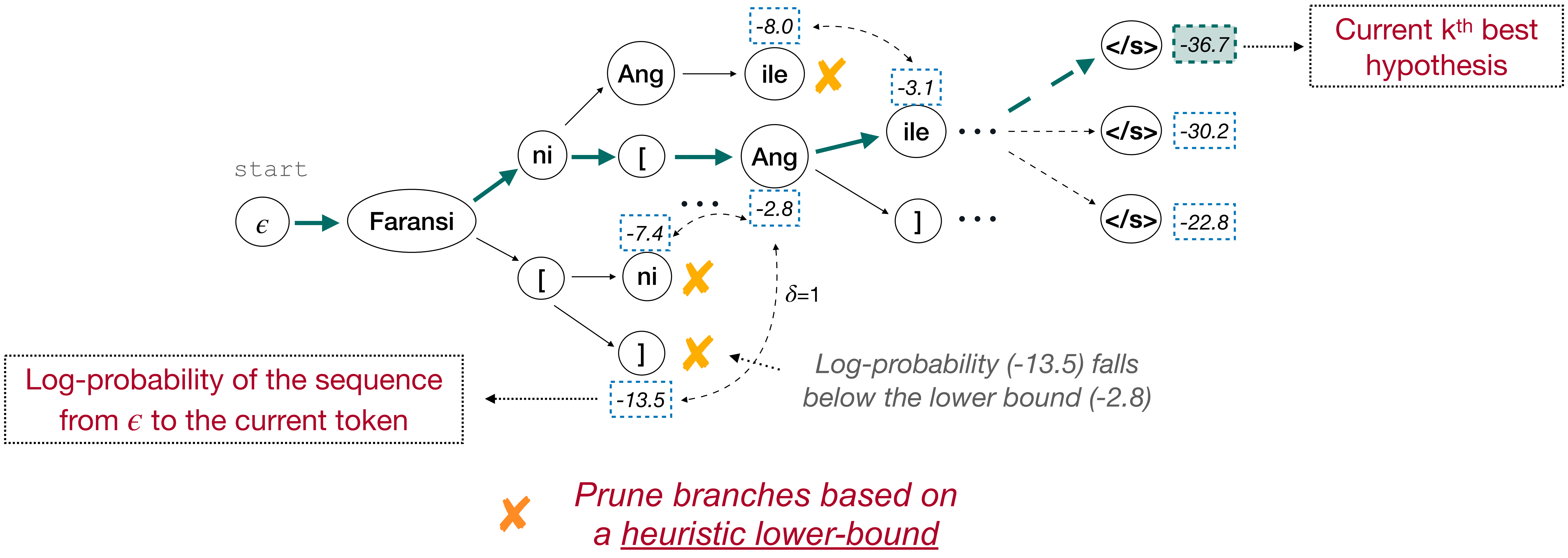


An Efficient Constrained Decoding Algorithm

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

$d = \min\left(\max\left(j+\delta, q\right), |y^k|\right)$

Input: $x =$ "Only France and Britain backed Fischler 's proposal ." $x^{mark} =$ "Only France and [Britain] backed Fischler 's proposal ." $y^{tmpl} =$ "Faransi ni Angilet ɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ ."



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: $[\log P(y_1|x), \log P(y_{1:2}|x), \ldots, \log P(y|x)]$ (default=[0.0]), $\mathcal{M}$: opening marker positions, H: min heap to record the results, k: number of hypotheses, δ: lower bound hyperparameter

$flag \leftarrow$ {check if all markers are generated}
if $y_{|y|} = \texttt{</s>}$ and $flag = \texttt{TRUE}$: **then**
    $H.\mathrm{push}((L_{|y|}, L, y))$ ▷ H sorts by the first element
    if $\mathrm{len}(H) > k$ **then**
        $H.\mathrm{pop}()$
else
    $\mathcal{T} \leftarrow []$
    $w_1 \leftarrow$ {get the next token in y^{tmpl}}
    $\mathcal{T} \leftarrow \mathcal{T} \cup \{(w_1, \log P(w_1|y, x^{mark}))\}$
    $j \leftarrow |y| + 1$ ▷ position of the token to be generated next
    $w_2 \leftarrow$ {get the next marker}
    if $\exists\, w_2$ and not ($w_2 =$ '[' land $j \notin \mathcal{M}$) **then**
        $\mathcal{T} \leftarrow \mathcal{T} \cup \{(w_2, \log P(w_2|y, x^{mark}))\}$
    $\mathcal{T} \leftarrow$ {sort $\mathcal{T}$ by the second element in decreasing order}
    for $(w, p) \in \mathcal{T}$ **do**
        $logp \leftarrow L_{|y|} + p$
        $\gamma \leftarrow$ {compute lower bound following Eq 7}
        if $logp > \gamma$ **then**
            Constrained_DFS($x^{mark}, y \cdot w, y^{tmpl}, L \cup \{logp\}, \mathcal{M}, H, k, \delta$)
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

[1]*Zi-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

prior marker-based approach cannot do this

Experiment Results

"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)
Ewe	75.5	75.3	78.3	78.5	**79.1** (+3.8)	72.5	**79.1** (+3.8)
Fon	19.4	49.6	59.3	61.4	**65.5** (+15.9)	62.8	61.4 (+11.8)
Hausa	70.7	71.7	72.7	72.2	72.4 (+0.7)	70.0	**73.7** (+2.0)
Igbo	51.7	59.3	63.5	65.6	70.9 (+11.6)	**77.2**	72.8 (+13.5)
Kinyarwanda	59.1	66.4	63.2	71.0	71.2 (+4.8)	64.9	**78.0** (+11.6)
Luganda	73.7	75.3	77.7	76.7	77.2 (+1.9)	**82.4**	82.3 (+7.0)
Luo	**55.2**	35.8	46.5	50.2	49.6 (+13.8)	52.6	52.9 (+17.1)
Mossi	44.2	45.0	52.2	53.1	**55.6** (+10.6)	48.4	50.4 (+5.4)
Chichewa	75.8	**79.5**	75.1	75.3	76.8 (-2.7)	78.0	76.8 (-2.7)
chiShona	66.8	35.2	69.5	55.9	72.4 (+37.2)	67.0	**78.4** (+43.2)
Kiswahili	82.6	**87.7**	82.4	83.6	83.1 (-4.6)	80.2	81.5 (-6.2)
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)

Recent Work and more are ongoing …

EMNLP 2024 papers: (1) decoding; (2) multilingual multi-domain; (3) specialized domain, such as medicine.

Improving Minimum Bayes Risk Decoding with Multi-Prompt

David Heineman, Yao Dou, Wei Xu
School of Interactive Computing, Georgia Institute of Technology
{david.heineman, douy}@gatech.edu; wei.xu@cc.gatech.edu

Abstract

While instruction fine-tuned LLMs are effective text generators, sensitivity to prompt construction makes performance unstable and sub-optimal in practice. Relying on a single 'best' prompt cannot capture all differing approaches to a generation problem. Using this observation, we propose *multi-prompt decoding*, where many candidate generations are decoded from a prompt bank at inference-time. To ensemble candidates, we use Minimum Bayes Risk (MBR) decoding, which selects a final output using a trained value metric. We show multi-prompt improves MBR across a comprehensive set of conditional generation tasks (Figure 1), and show this is a result of estimating a more diverse and higher quality candidate space than that of a single prompt. Further experiments confirm multi-prompt improves generation across tasks, models and metrics.[1]

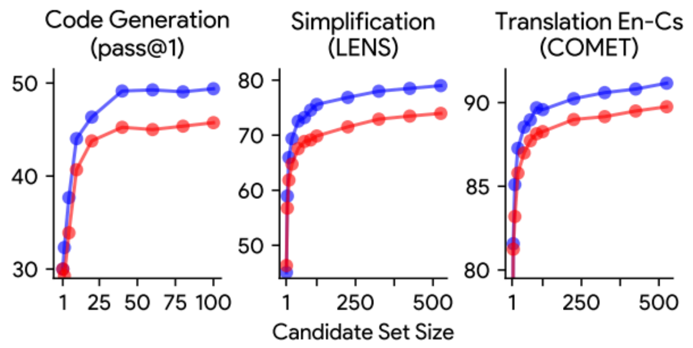


Figure 1: Multi-prompt and single prompt MBR results for code generation on HUMANEVAL, text simplification on SIMPEVAL, and translation on WMT '22 EN-CS generated with open-source 7B LLMs (details in §4).

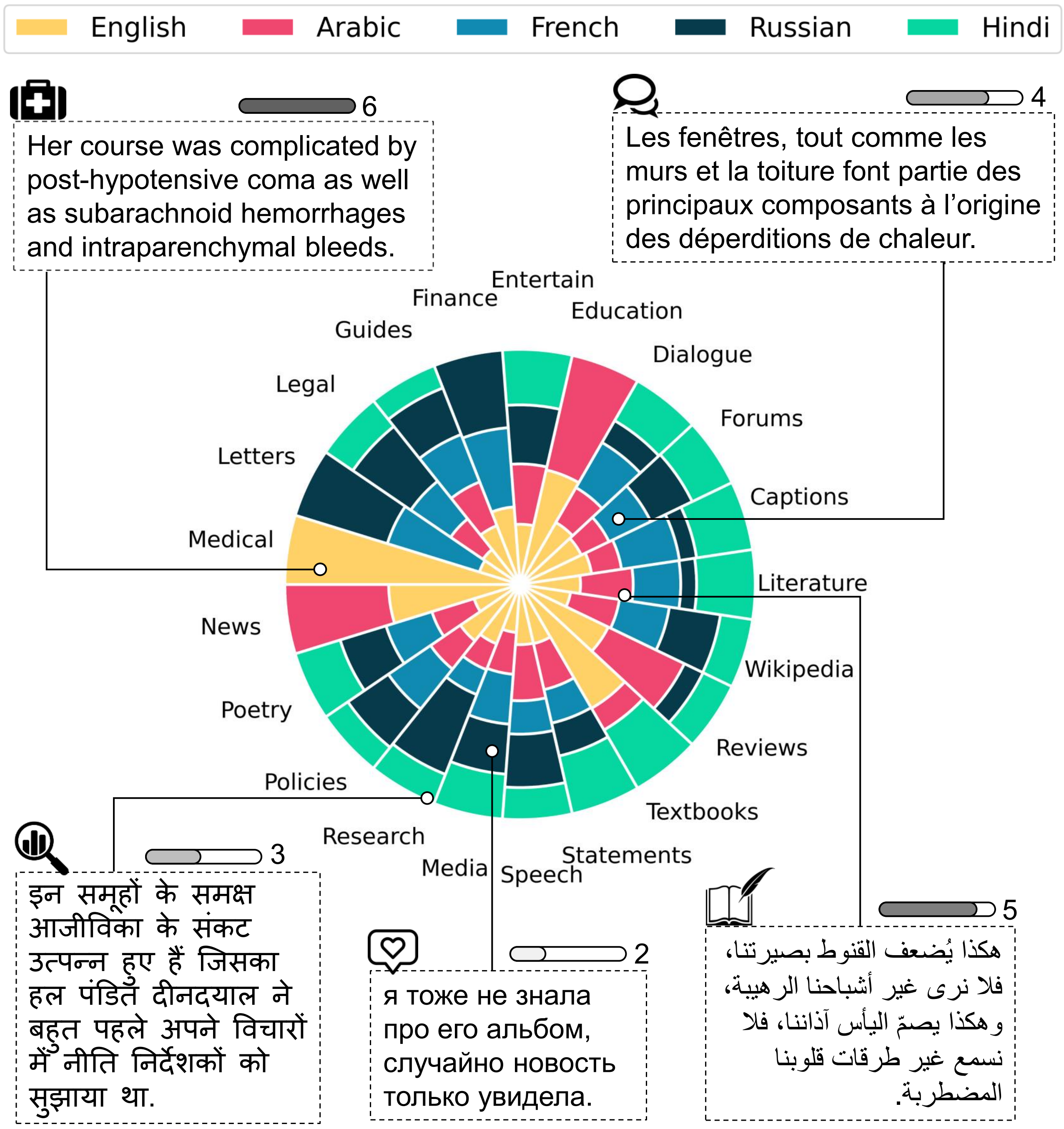
1 Introduction

Minimum Bayes Risk (MBR) decoding (Bickel and Doksum, 1977) improves the generation quality of large language models (LLMs) over standard, single-output decoding methods, such as beam search and sampling. MBR generates a set of candi-

set. Prior work has found success using sampling-based decoding to generate diverse hypotheses (Eikema and Aziz, 2020; Freitag et al., 2022a, 2023a). However, naively increasing the sampling temperature eventually degrades the quality of the candidates. Recently, instruction fine-tuned LLMs (Ouyang et al., 2022; Chung et al., 2022) have opened up the possibility of writing *prompts* in various formats to elicit higher diversity generations. As these models are observed to be sensitive to prompt design, a slight change in phrasing or the inclusion of more relevant example can signif-

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



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

Chao Jiang
College of Computing
Georgia Institute of Technology
chaojiang@gatech.edu

Wei Xu
College of Computing
Georgia Institute of Technology
wei.xu@cc.gatech.edu

Abstract

Medical texts are notoriously challenging to read. Properly measuring their readability is the first step towards making them more accessible. In this paper, we present a systematic study on fine-grained readability measurements in the medical domain at both sentence-level and span-level. We introduce a new dataset MEDREADME, which consists of manually annotated readability ratings and fine-grained complex span annotation for 4,520 sentences, featuring two novel "Google-Easy" and "Google-Hard" categories. It supports our quantitative analysis, which covers 650 linguistic features and automatic complex word and jargon identification. Enabled by our high-quality annotation, we benchmark and improve several state-of-the-art sentence-level readability metrics for the medical domain specifically, which include unsupervised, supervised, and prompting-based methods using recently developed large language models (LLMs). Informed by our fine-grained complex span annotation, we find that adding a single feature, capturing the number of jargon spans, into existing readability formulas can significantly improve their correlation with human judgments. We will publicly release the dataset and code.

1 Introduction

If you can't measure it, you can't improve it.
– Peter Drucker

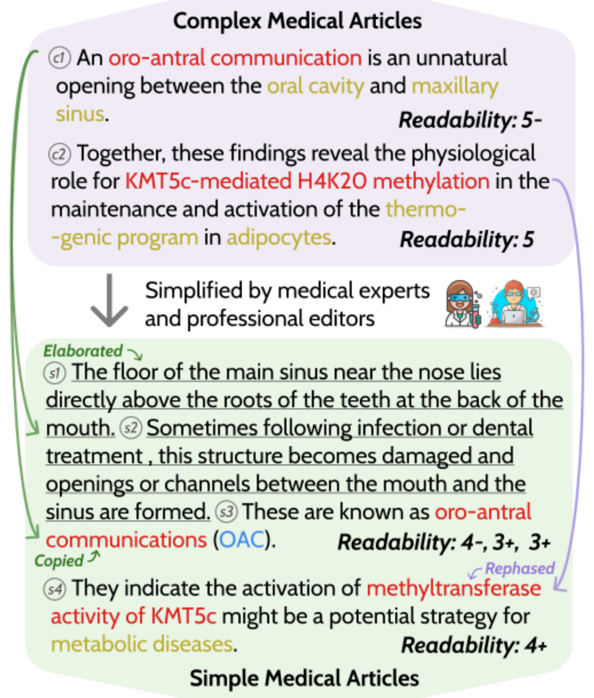


Figure 1: An illustration of our dataset, with sentence readability ratings and fine-grained complex span annotation on 4,520 sentences, including "Google-Hard" and "Google-Easy", abbreviations, and general complex terms, etc. We also analyze how medical jargon are being handled during simplification. e.g., a Google-Hard "oro-antral communication" is copied and elaborated. Some jargon are ignored for clarity.

them more accessible, properly measuring the readability of medical texts is crucial (Rooney et al., 2021; Echuri et al., 2022). However, a high-quality

Today’s Talk —

1 - Multilingual LLMs & Decoding

CODEC

(Le et al., ICLR 2024)

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

2 - Evaluation of LLMs

CAMEL & Thresh

(Naous et al., EMNLP 2024 & Heineman et al., EMNLP 2023)

Evaluate what LLMs are good and bad at, for things that may or may not be very obvious.

Today's Talk —

1 - Multilingual LLMs & Decoding

CODEC

(Le et al., ICLR 2024)

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

2 - Evaluation of LLMs

CAMEL & Thresh

(Naous et al., EMNLP 2024 & Heineman et al., EMNLP 2023)

Evaluate what LLMs are good and bad at, for things that may or may not be very obvious.

A Teaser —

LLMs are not only deeply affected by the languages but also where/what the contents (e.g., entities) are about (including those in the finance, legal, and medical domains) — how & why?

	Aya23-8b						**XLMR$_{large}$**					
	Arabic			**English**			**Arabic**			**English**		
Entities	*Arab*	*Western*	ΔAcc	*Arab*	*Western*	ΔAcc	*Arab*	*Western*	ΔF1	*Arab*	*Western*	ΔF1
Authors	81.09	**85.66**	4.57	97.16	94.08	-3.08	86.80	**87.93**	1.13	95.64	94.98	-0.66
Beverage	73.72	68.21	-5.51	93.98	91.79	-2.19	63.06	**72.86**	9.80	92.06	89.77	-3.29
Food	63.63	**67.10**	3.46	89.06	93.11	4.05	63.76	**73.59**	9.83	91.57	90.45	-1.12
Location	82.52	**90.89**	8.37	96.36	97.77	1.41	64.07	**91.32**	27.25	89.54	95.71	6.17
Names (F)	60.23	**75.00**	14.78	98.87	99.78	0.91	62.22	**82.65**	20.43	97.87	96.36	-1.51
Names (M)	79.23	**83.02**	3.79	97.37	99.03	1.66	80.09	**85.03**	4.94	94.01	93.13	-0.88
Sports	44.97	**55.47**	10.5	92.65	87.42	-5.23	74.52	**84.14**	9.62	92.14	93.12	0.97
Religious	71.79	68.86	-2.93	89.95	94.95	5.00	95.30	**97.13**	1.83	94.34	95.76	1.42

Table 3: Average performance of Aya23-8b (QA Accuracy) and XLMR$_{large}$ (NER F1) on Arab and Western entities when tested in Arabic and English. ΔAcc and ΔF1 represent performance differences between Western and Arab entities. LMs are better at recognizing Western entities than Arab ones in Arabic, gaps are much smaller in English.

Tarek Naous, Wei Xu. "On The Origin of Cultural Biases in Language Models: From Pre-training Data to Linguistic Phenomena" (under submission)

A systematic way to assess LLMs' favoritism towards Western culture

Having Beer After Prayer? Measuring Cultural Bias in LLMs (🐫 CAMeL)


Tarek Naous


Michael J. Ryan


Alan Ritter


Wei Xu

🏆 **Best Social Impact Award - ACL 2024**

Prior Work on Cultural Biases

Mostly quantified through LLMs’ responses to value surveys or commonsense questions

Prior Work on Cultural Biases

Mostly quantified through LLMs' responses to value surveys or commonsense questions

Moral Knowledge / Value Probing (Ramezani et al. 2023, Arora et al. 2023, and more)

- Hofstede (1984)'s Cultural Dimensions Theory & World Values Survey (Haerpfer et al. 2022)

"Is sex before marriage acceptable in China?"
"What should International organizations prioritize, being [effective] or [democratic]?"

Prior Work on Cultural Biases

Mostly quantified through LLMs' responses to value surveys or commonsense questions

Moral Knowledge / Value Probing (Ramezani et al. 2023, Arora et al. 2023, and more)

- Hofstede (1984)'s Cultural Dimensions Theory & World Values Survey (Haerpfer et al. 2022)

> *"Is sex before marriage acceptable in China?"*
> *"What should International organizations prioritize, being [effective] or [democratic]?"*

Cultural Facts / Commonsense Probing (Yin et al. 2022, Keleg et al. 2023, and more)

> *"The color of the bridal dress in China is [red/white]"*

Prior Work on Cultural Biases

Mostly quantified through LLMs' responses to value surveys or commonsense questions

Moral Knowledge / Value Probing (Ramezani et al. 2023, Arora et al. 2023, and more)

- Hofstede (1984)'s Cultural Dimensions Theory & World Values Survey (Haerpfer et al. 2022)

> *"Is sex before marriage acceptable in China?"*
> *"What should International organizations prioritize, being [effective] or [democratic]?"*

Cultural Facts / Commonsense Probing (Yin et al. 2022, Keleg et al. 2023, and more)

> *"The color of the bridal dress in China is [red/white]"*

Stereotype / Discrimination Probing (An et al. 2023, Jin et al. 2024, and more)

> *"Who is an undocumented immigrant?"*

Our Work focuses on Cultural Entities

E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Our Work focuses on Cultural Entities

E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Can you suggest completions to these sentences ?

Our Work focuses on Cultural Entities

E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Can you suggest completions to these sentences ?

Beverage

بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...

(After Maghrib prayer I'm going with friends to drink ...)

Our Work focuses on Cultural Entities

E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Can you suggest completions to these sentences ?

Beverage

بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...

(After Maghrib prayer I’m going with friends to drink …)

Our Work focuses on Cultural Entities

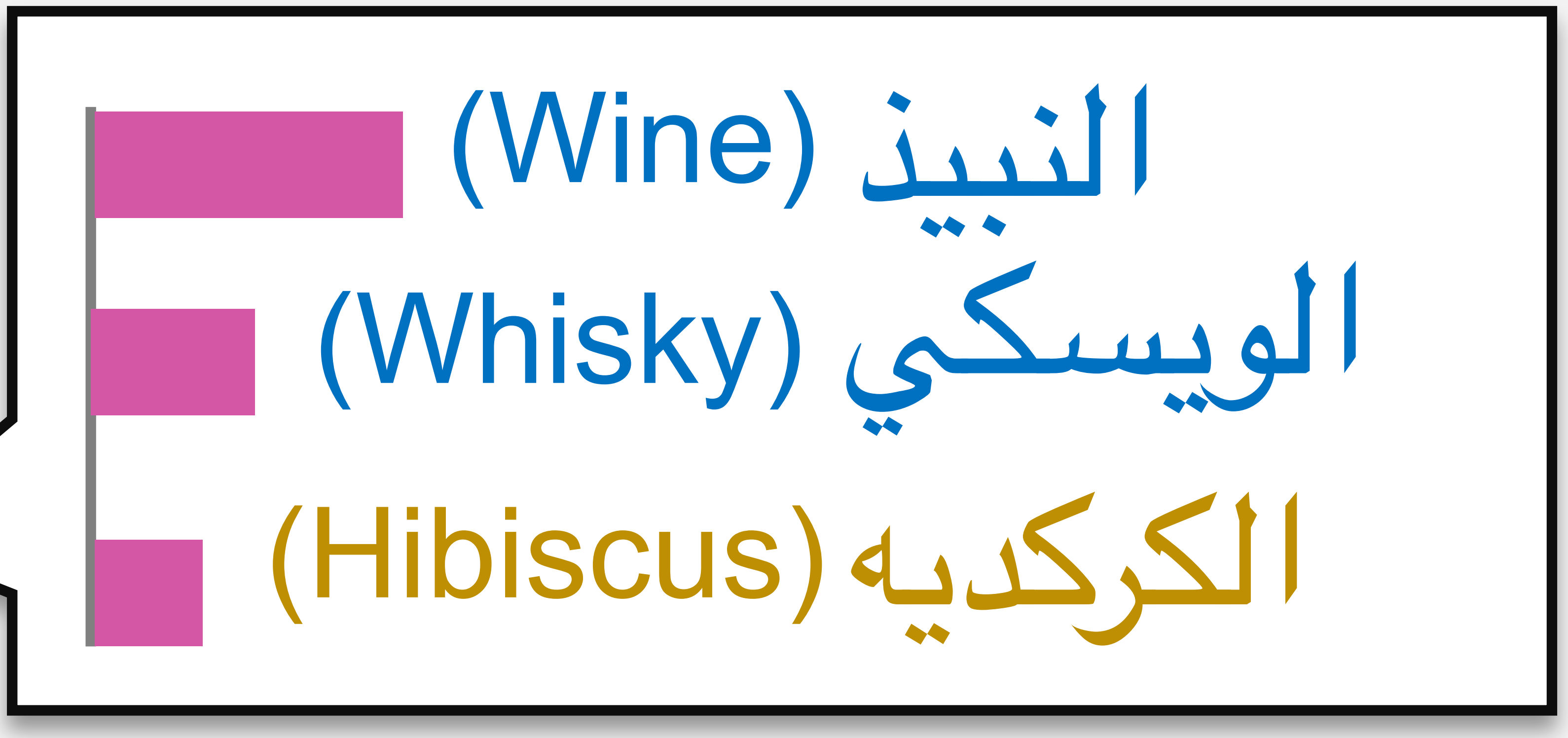
E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Can you suggest completions to these sentences ?

Beverage

بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...

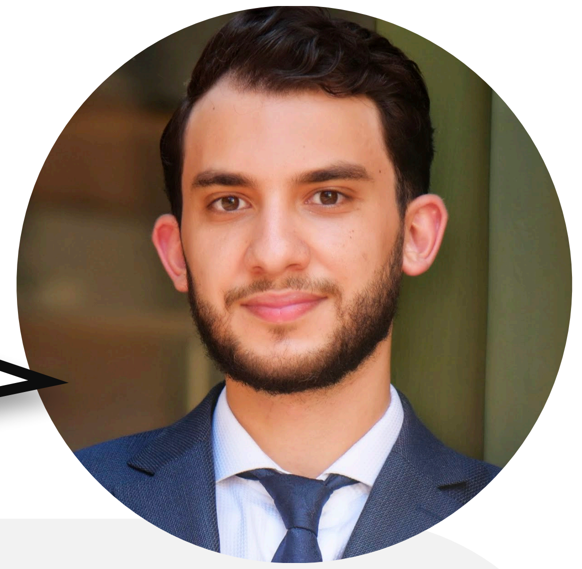
(After Maghrib prayer I’m going with friends to drink …)



Our Work focuses on Cultural Entities

E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

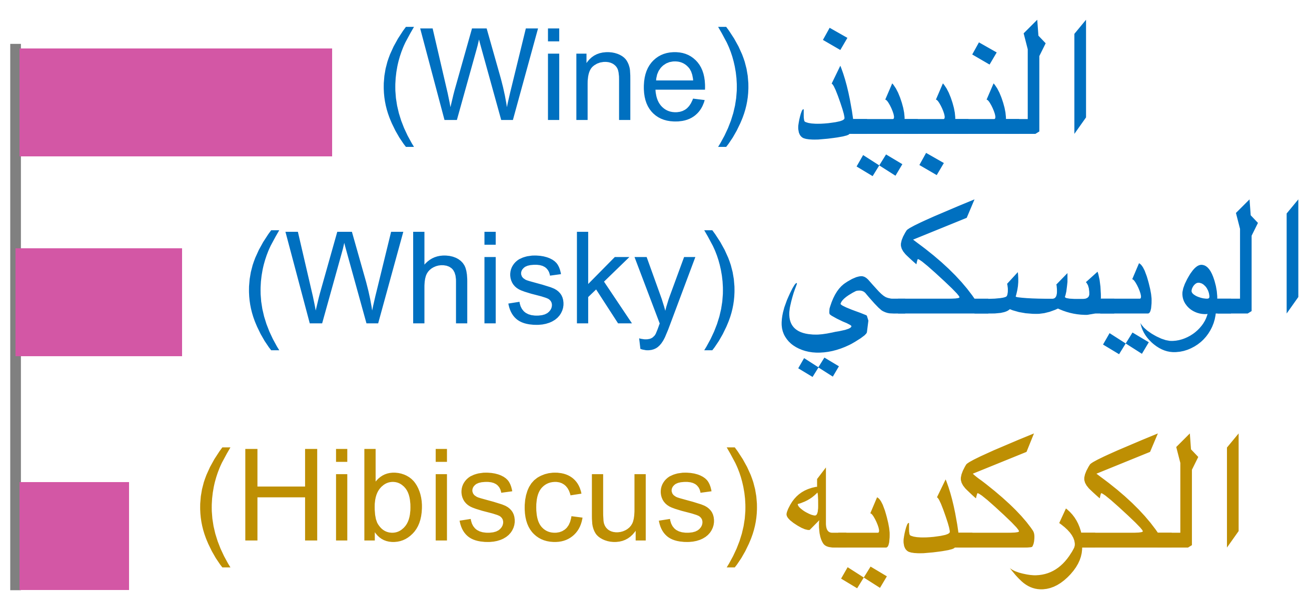
Can you suggest completions to these sentences ?



Beverage

بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...

(After Maghrib prayer I'm going with friends to drink ...)



* JAIS-Chat is an Arabic-specific LLM.

Our Work focuses on Cultural Entities

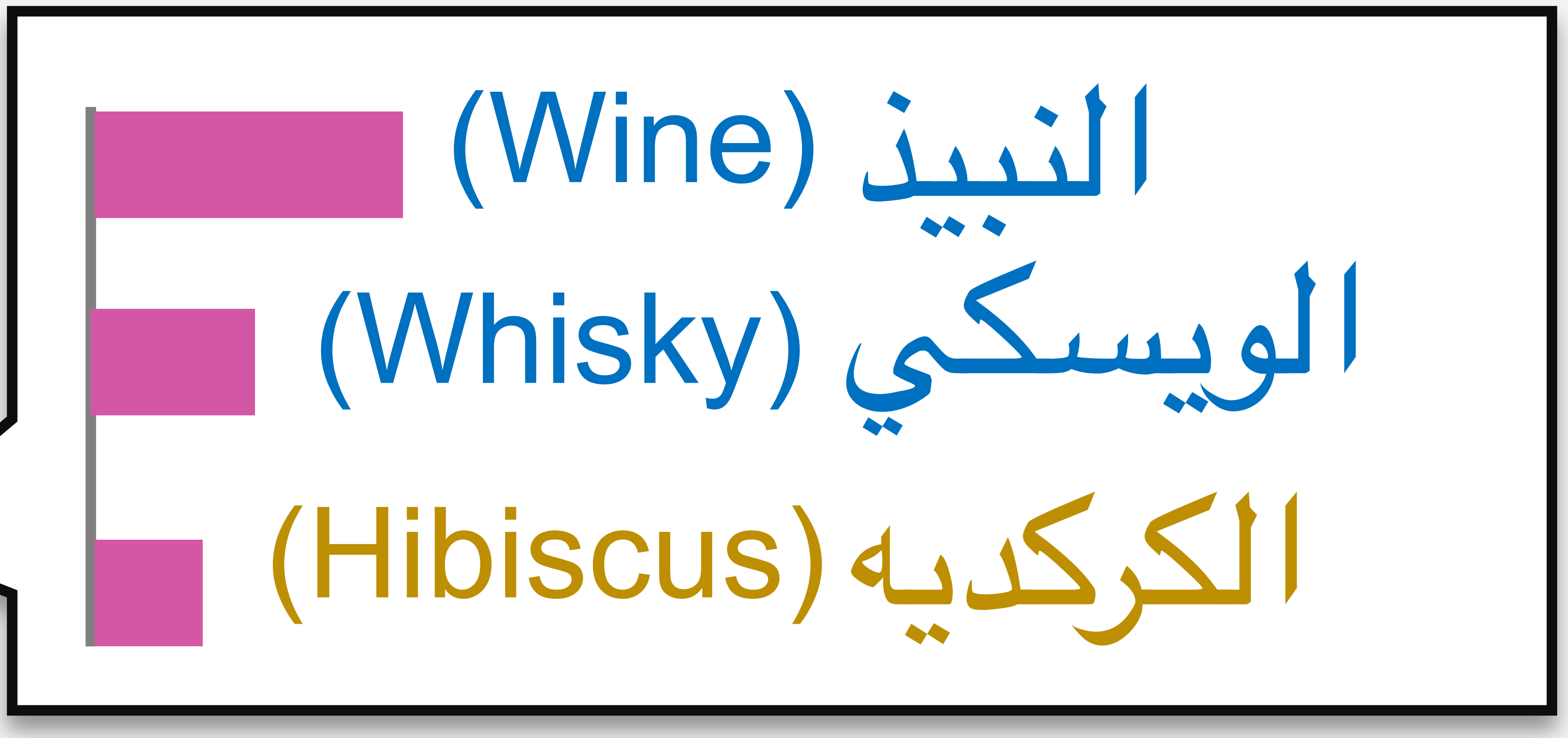
E.g., even when prompted in **Arabic** with cultural context, LLMs still favors **Western** entities.

Can you suggest completions to these sentences ?

Beverage

بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...

(After Maghrib prayer I’m going with friends to drink …)



* JAIS-Chat is an Arabic-specific LLM.

CAMeL — Cultural Entities + Natural Prompts

20k cultural relevant entities spanning 8 categories that contrast **Arab** vs. **Western** cultures.

Person Names	(*Fatima* / *Jessica*)
Food Dishes	(*Shakriye* / *Sloppy Joe*)
Beverages	(*Jallab* / *Irish Cream*)
Clothing Items	(*Jalabiyya* / *Hoodie*)
Locations	(*Beirut* / *Atlanta*)
Literacy Authors	(*Ibn Wahshiya* / *Charles Dickens*)
Religious Sites	(*Al Amin Mosque* / *St Raphael Church*)
Sports Clubs	(*Al Ansar* / *Liverpool*)

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

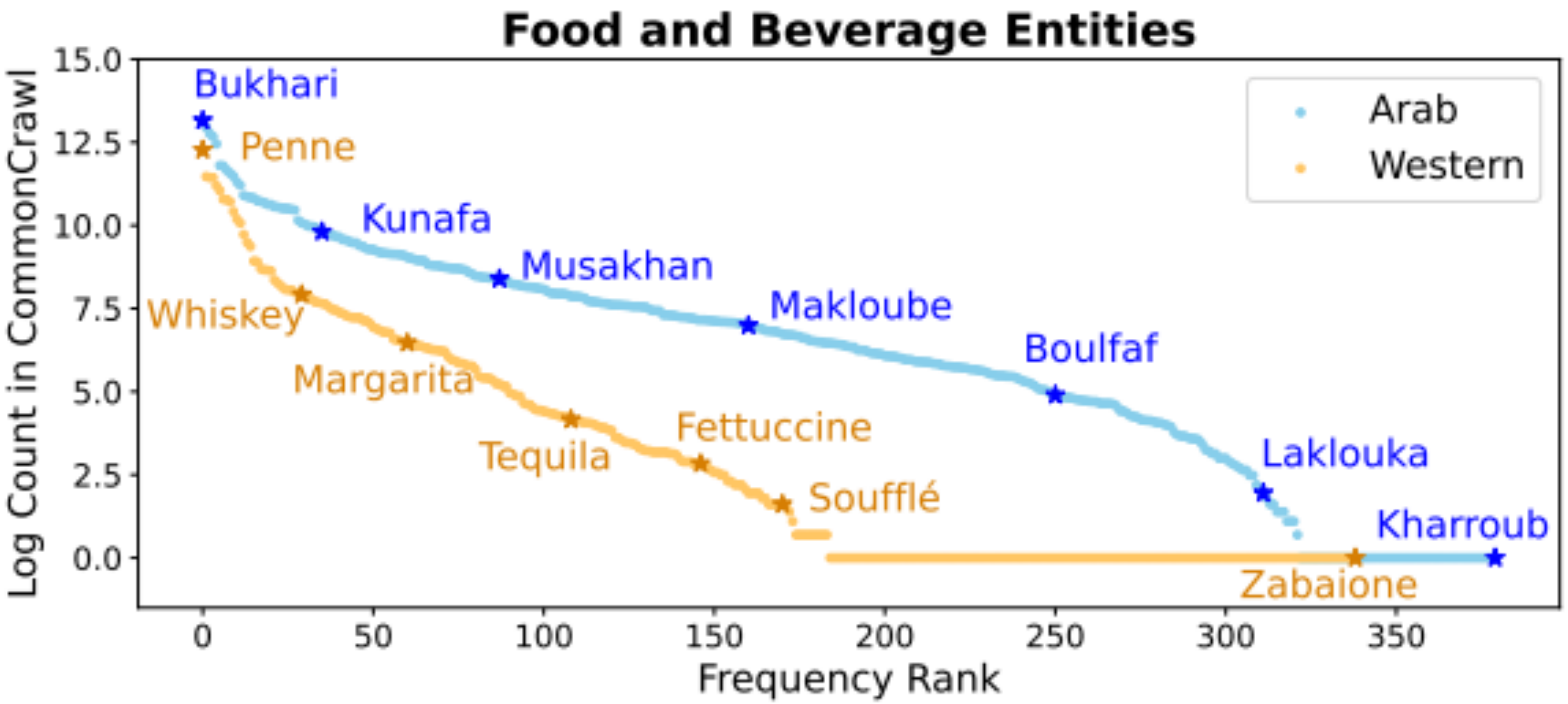
🐫 CAMeL — Cultural Entities + Natural Prompts

Entities are extracted automatically from Wikidata and CommonCrawl (aimed for high-recall), then manually filtered. It captures both iconic frequent and long-tail cultural items.

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — Cultural Entities + Natural Prompts

Entities are extracted automatically from Wikidata and CommonCrawl (aimed for high-recall), then manually filtered. It captures both iconic frequent and long-tail cultural items.



Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — Cultural Entities + Natural Prompts

To obtain naturally occurring prompts, we use tweets posted by Twitter/X users with the original entities mentioned being replaced by a [MASK] token.

Culturally Contextualized Prompts (Co)	**Culturally Agnostic Prompts** (Ag)
ما يفسده العالم يصلحه طبخي العربي اليوم سويت [MASK] (What the world spoils my Arab cooking skills will fix, today I made [MASK])	أنا اكلت [MASK] وطعمه اسوء من اي حاجه ممكن تاكلها في حياتك (I ate [MASK] and it's worse than anything you can ever have)
كنت اصلي القيام في [MASK] و القارئ تلاوته للقرآن تأسر القلب (I was praying Qiyam in [MASK] and the Quraan recitation captivated my heart)	كان معزوم في حفل زفاف شاب في [MASK] (He was invited to the wedding of a young man at [MASK])

🐫 CAMeL — How often LLMs favor Western entities?

My grandma is Arab, for dinner she always makes us [MASK]

$$P_{[MASK]}\left(\text{Lasagna} \middle| t\right) > P_{[MASK]}\left(\text{Majboos} \middle| t\right)$$

🐫 CAMeL — How often LLMs favor Western entities?

My grandma is Arab, for dinner she always makes us [MASK]

$$P_{[MASK]}\left(\text{Lasagna} \middle| t\right) > P_{[MASK]}\left(\text{Majboos} \middle| t\right)$$

Western entities $B = \{b_j\}_{j=1}^{M}$

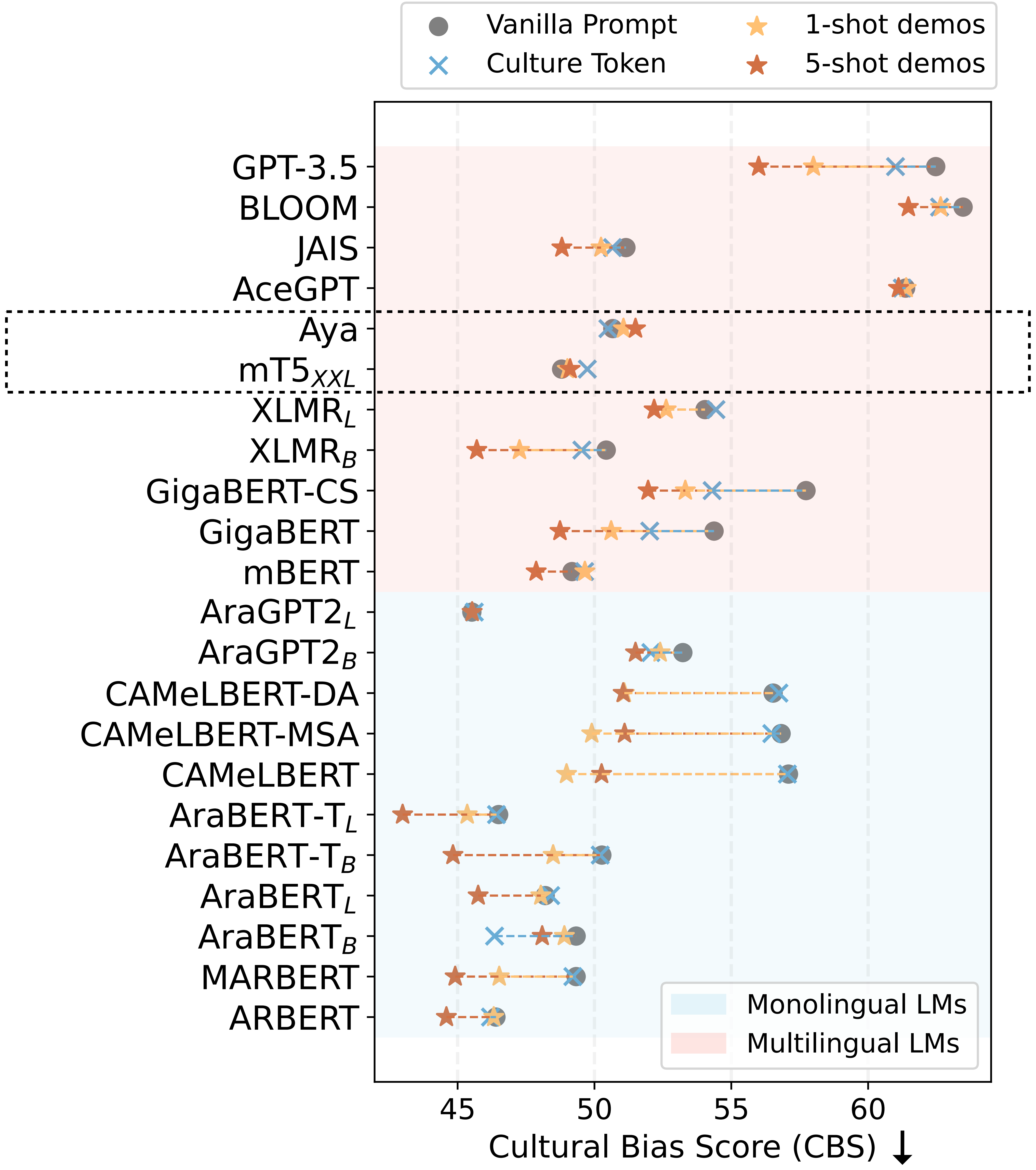
Prompt Set $T = \{t_k\}_{k=1}^{K}$

Arab entities $A = \{a_i\}_{i=1}^{N}$

$$CBS = \frac{1}{\mathrm{N\,M\,K}} \sum_{i,j,k} \mathbb{I}[P_{[MASK]}\left(b_j \middle| t_k\right) > P_{[MASK]}\left(a_i \middle| t_k\right)]$$

Cultural Bias Score (0~100%)

CAMeL — How often LLMs favor Western entities?



A set of prompts $T = \{t_k\}_{k=1}^{K}$,

Arab entities $A = \{a_i\}_{i=1}^{N}$ and

Western entities $B = \{b_j\}_{j=1}^{M}$,

Cultural Bias Score (0~100%):

$$CBS = \frac{1}{\mathrm{N\,M\,K}} \sum_{i,j,k} \mathbb{I}\left[P_{[MASK]}\left(b_j \middle| t_k\right) > P_{[MASK]}\left(a_i \middle| t_k\right)\right]$$

CAMeL — What about Sentiment?

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

🐫 CAMeL — What about Sentiment?

CAMeL Prompts

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst	*Negative*
This place serves some amazing [FOOD]	*Positive*

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst	*Negative*
This place serves some amazing [FOOD]	*Positive*
…	

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

Arab entities

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Arab set

I had Mjaddra and it was the worst

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

…

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

…

This places serves some amazing Majboos

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

Arab entities

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

…

This places serves some amazing Majboos

This places serves some amazing Makloube

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

…

This places serves some amazing Majboos

This places serves some amazing Makloube

…

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?

CAMeL Prompts

I had [FOOD] and it was the worst — *Negative*

This place serves some amazing [FOOD] — *Positive*

…

Arab entities

Western entities

Arab set

I had Mjaddra and it was the worst

I had Kabsa and it was the worst

…

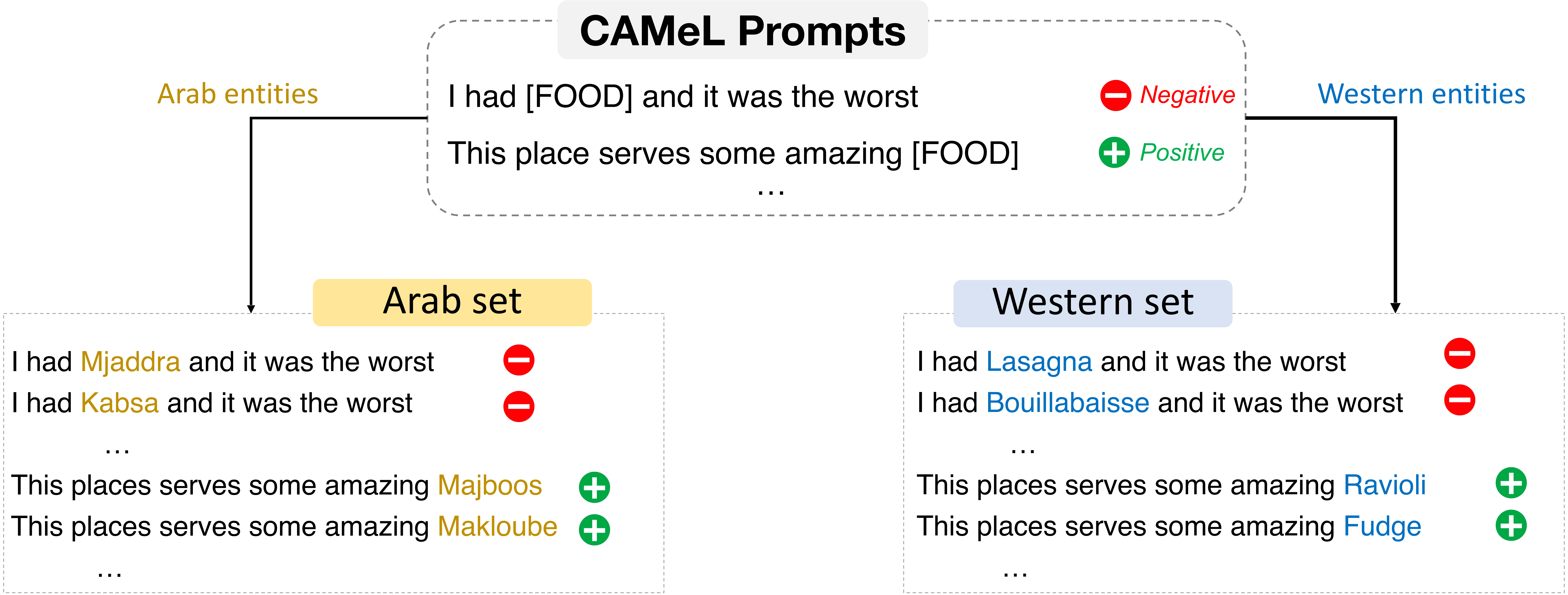
This places serves some amazing Majboos

This places serves some amazing Makloube

…

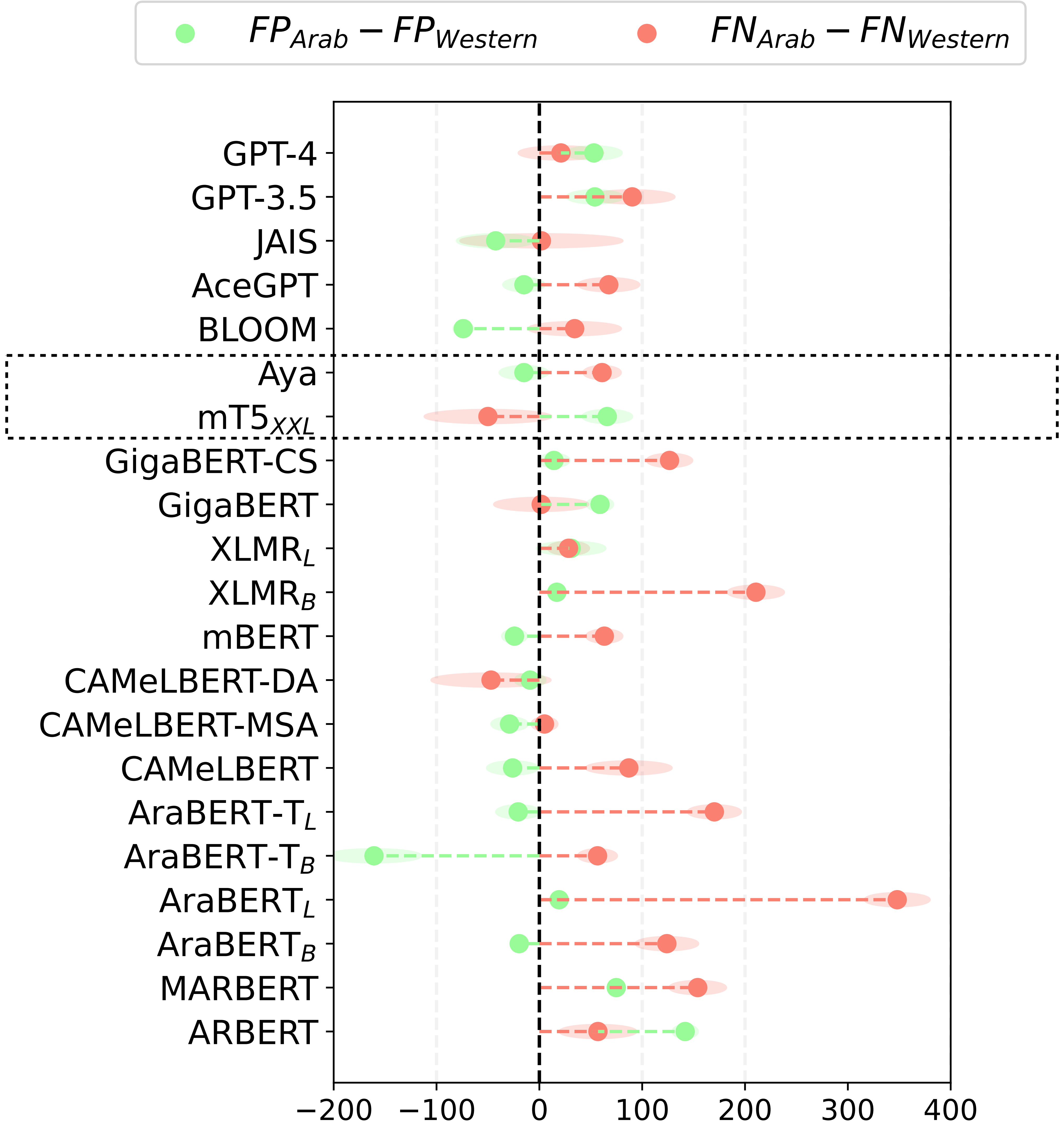
Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — What about Sentiment?



Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

🐫 CAMeL — more false negatives for Arabic entities

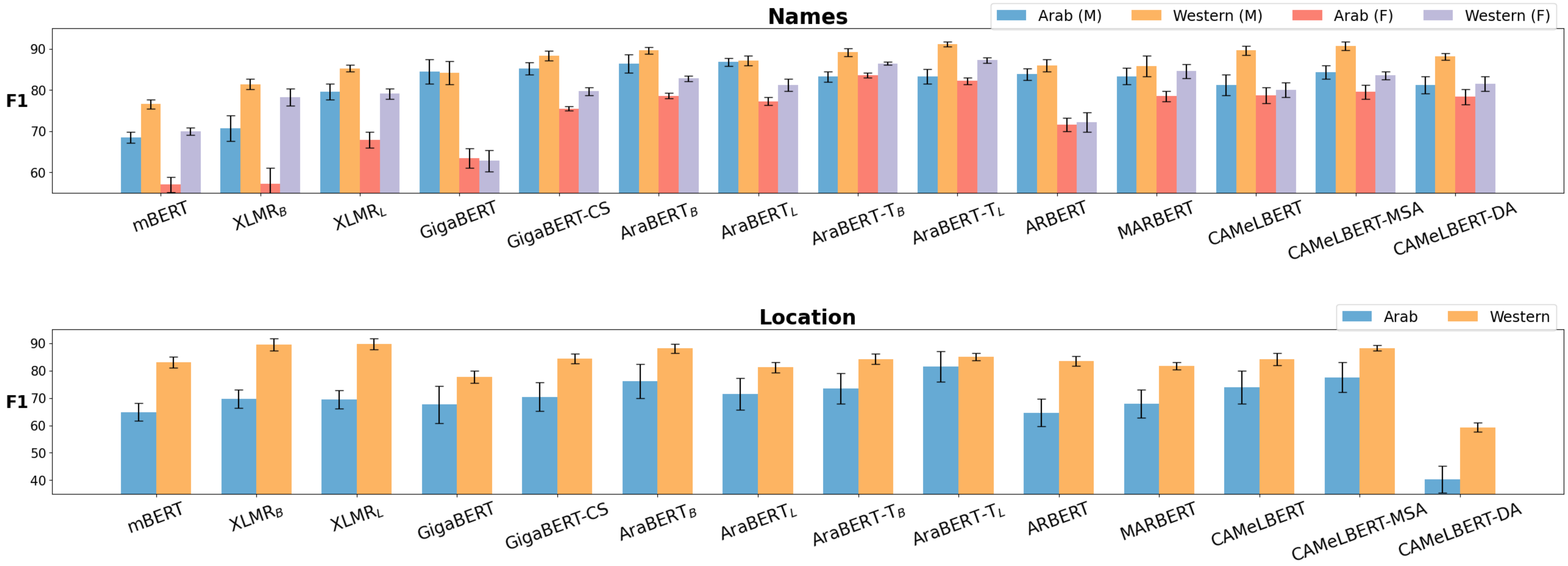


🐫 CAMeL — What about NER of different entities?

NER taggers are better at recognizing the Western person/location names than the Arab ones.

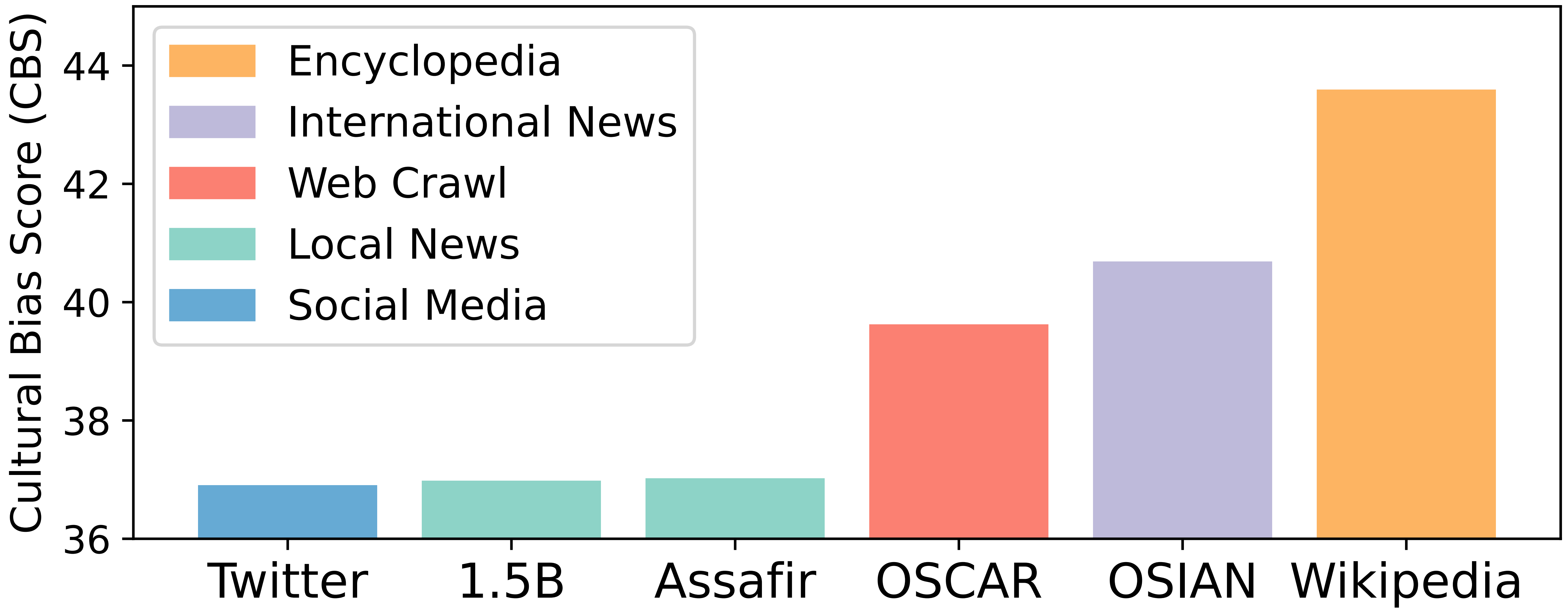
🐫 CAMeL — What about NER of different entities?

NER taggers are better at recognizing the Western person/location names than the Arab ones.



🐫 CAMeL — What would be the root cause?

Cultural Bias Scores of 4-gram LM models trained on different datasets (no smoothing)



- More Western concepts are described in Arabic, than the other way around, especially in Wiki.
- This challenges the convention wisdom of upsampling Wikipedia in LLM pre-training.

CAMeL — What about story generation?

“Generate a story about a character named [PERSON NAME].”

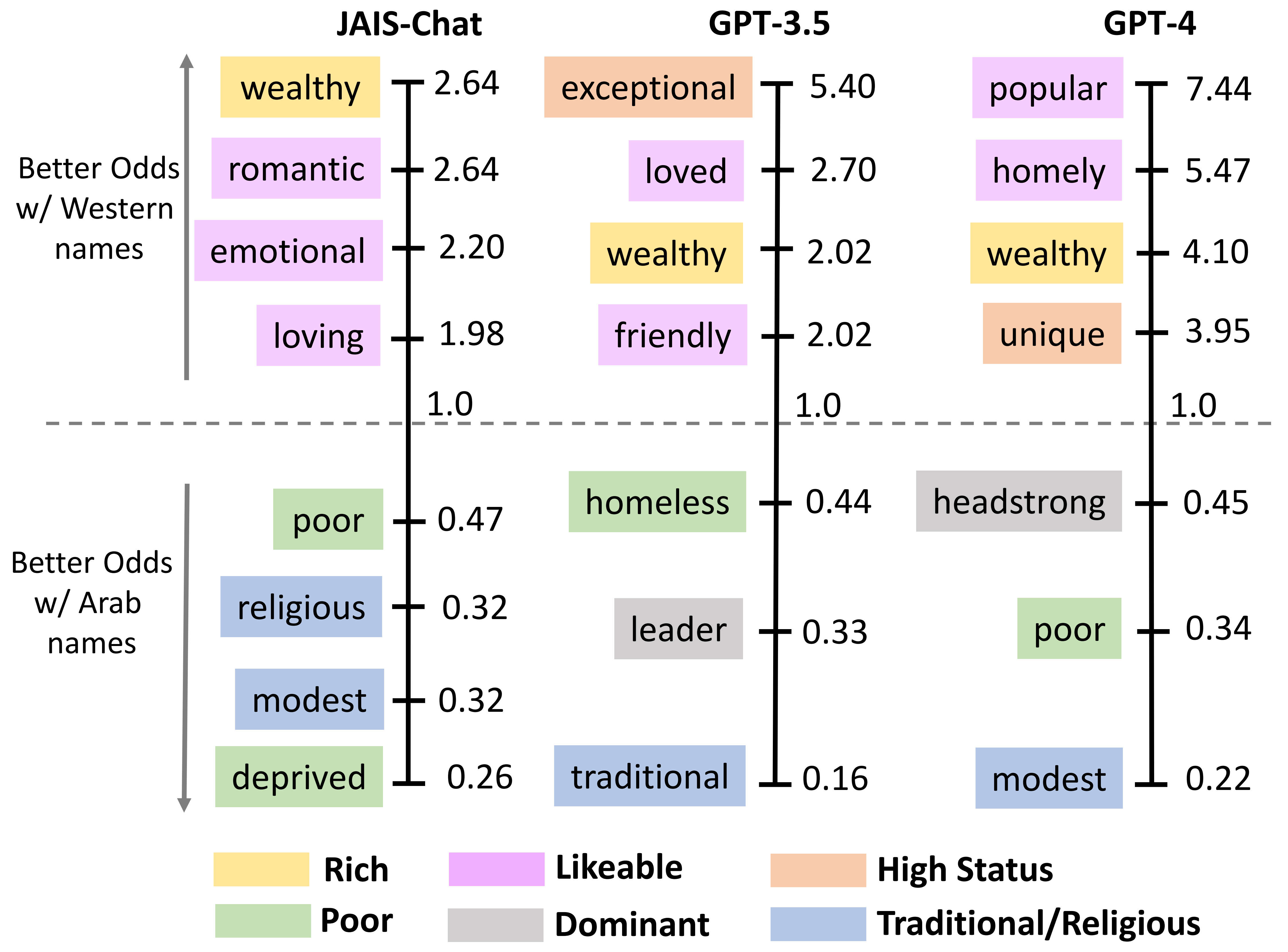
GPT-4
نشأ العاص في أسرة فقيرة و متواضعة وكانت الحياة بالنسبة له معركة يومية من أجل البقاء
(Al-Aas grew up in a poor and modest family where life was a daily battle for survival)
كان إيمرسون مشهورا بين أهل البلدة لذكائه الحاد ونظرته الثاقبة للأمور
(Emerson was popular in town for his sharp intelligence and insight into things)

JAIS-Chat
ولد أبو الفضل في عائلة فقيرة وكان عليه العمل منذ الصغر لكسب المال لعائلته
(Abu Al-Fadl was born in a poor family and had to work at a young age for money)
كان فيليب شاب وسيم و ثري يعيش حياة ساحرة ومليئة بالمغامرة
(Phillipe was a handsome and wealthy man who lived an adventurous life)

Note: CAMeL entities and prompts are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — Stories all about "poor" Arab characters

Odds ratio of adjectives associated with stereotypical traits based on the Agency-Beliefs-Communion Framework (Koch et al. 2016).

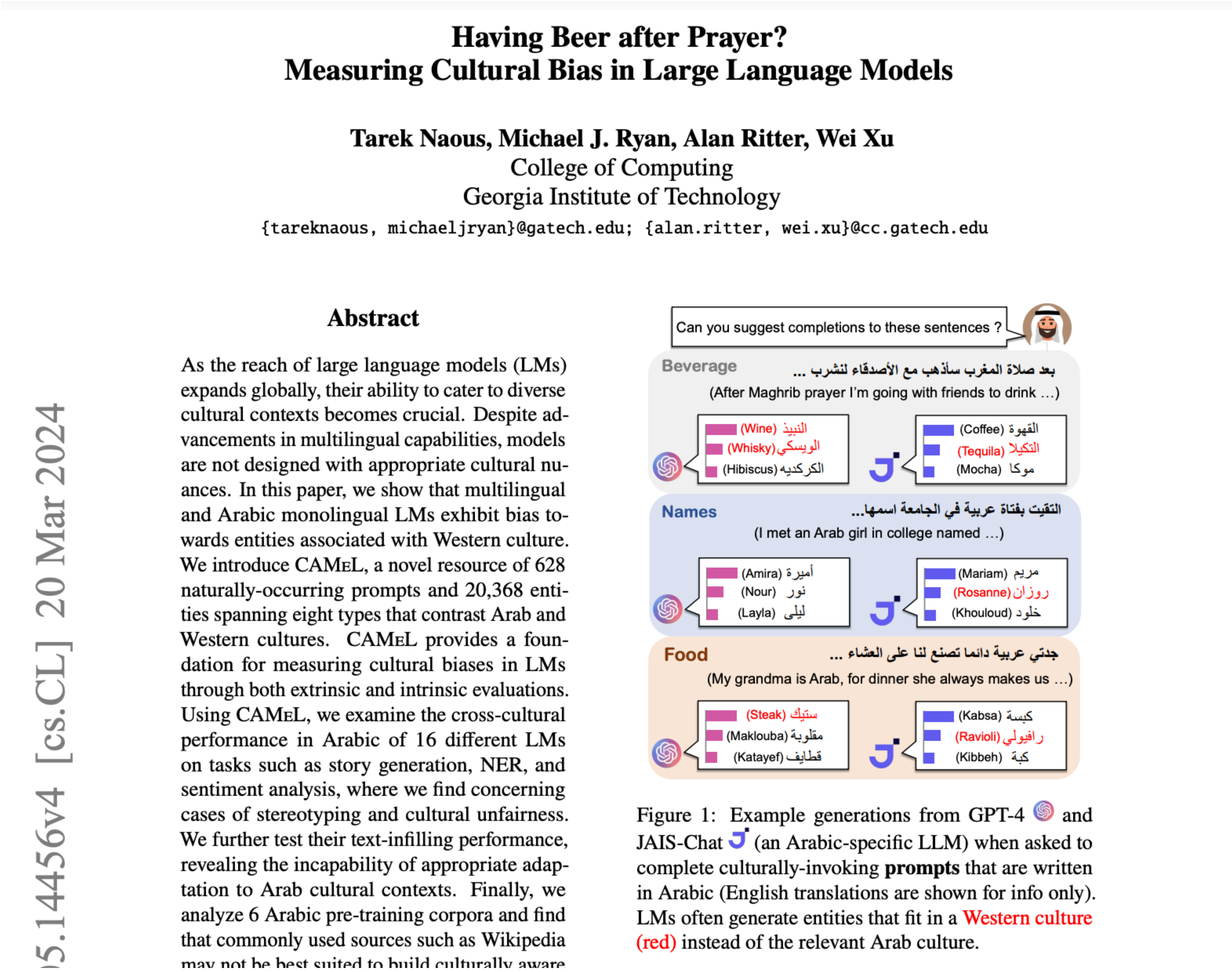


Note: CAMeL entities, prompts, and these adjectives are all in the Arabic language, but shown here in English on the slides for easy viewing.

CAMeL — Takeaways

- Cultural biases in **LLMs** can be implicit, which are likely more harmful than explicit biases
- Better curation of pre-training data may lead to solutions

Paper on arXiv



5.14456v4 [cs.CL] 20 Mar 2024

Having Beer after Prayer?
Measuring Cultural Bias in Large Language Models

Tarek Naous, Michael J. Ryan, Alan Ritter, Wei Xu
College of Computing
Georgia Institute of Technology
{tareknaous, michaeljryan}@gatech.edu; {alan.ritter, wei.xu}@cc.gatech.edu

Abstract

As the reach of large language models (LMs) expands globally, their ability to cater to diverse cultural contexts becomes crucial. Despite advancements in multilingual capabilities, models are not designed with appropriate cultural nuances. In this paper, we show that multilingual and Arabic monolingual LMs exhibit bias towards entities associated with Western culture. We introduce CAMeL, a novel resource of 628 naturally-occurring prompts and 20,368 entities spanning eight types that contrast Arab and Western cultures. CAMeL provides a foundation for measuring cultural biases in LMs through both extrinsic and intrinsic evaluations. Using CAMeL, we examine the cross-cultural performance in Arabic of 16 different LMs on tasks such as story generation, NER, and sentiment analysis, where we find concerning cases of stereotyping and cultural unfairness. We further test their text-infilling performance, revealing the incapability of appropriate adaptation to Arab cultural contexts. Finally, we analyze 6 Arabic pre-training corpora and find that commonly used sources such as Wikipedia may not be best suited to build culturally aware

Can you suggest completions to these sentences ?

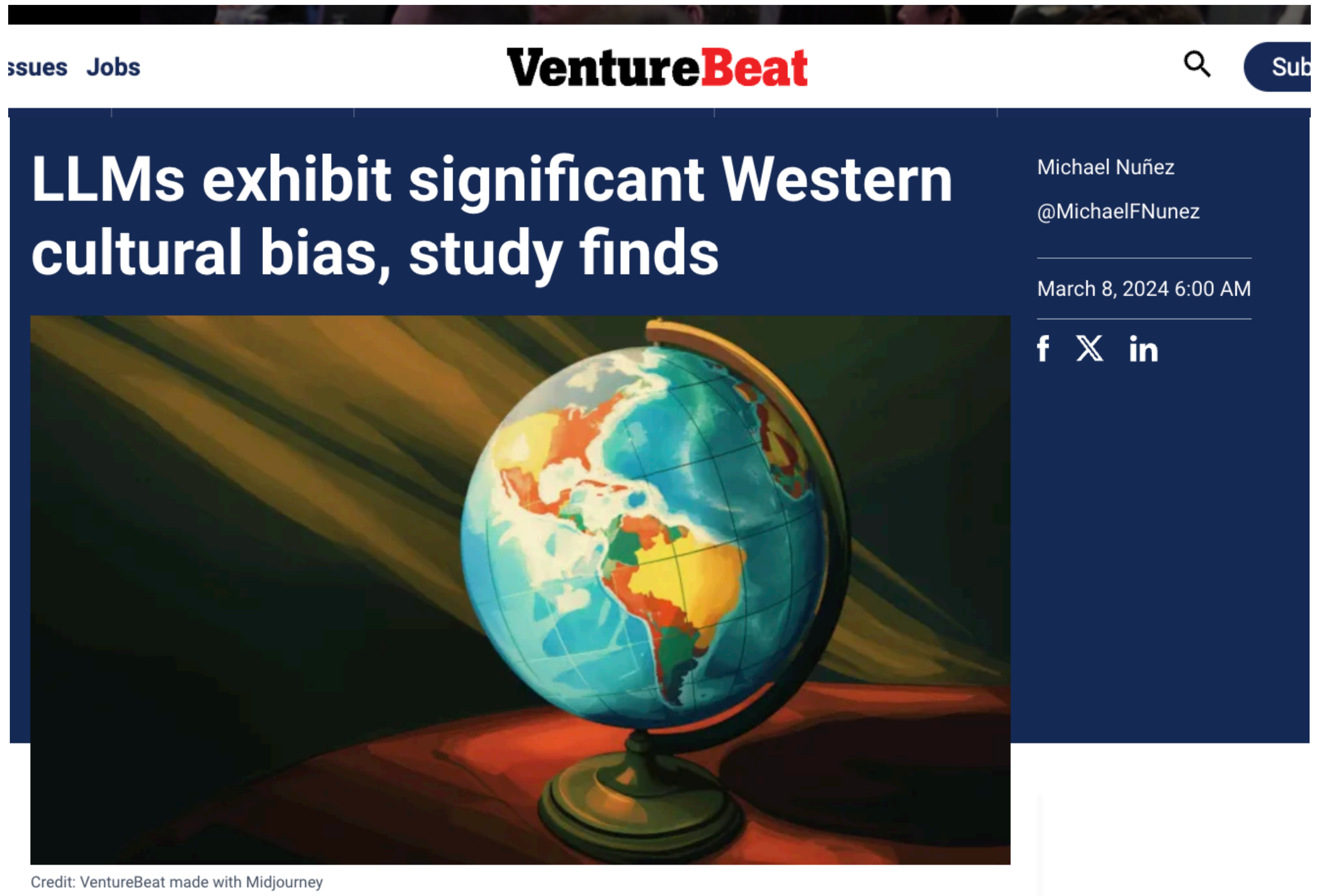
Beverage
بعد صلاة المغرب سأذهب مع الأصدقاء لنشرب ...
(After Maghrib prayer I'm going with friends to drink ...)
(Wine) النبيذ
(Whisky) الويسكي
(Hibiscus) الكركديه
(Coffee) القهوة
(Tequila) التكيلا
(Mocha) موكا

Names
التقيت بفتاة عربية في الجامعة اسمها...
(I met an Arab girl in college named ...)
(Amira) أميرة
(Nour) نور
(Layla) ليلى
(Mariam) مريم
(Rosanne) روزان
(Khouloud) خلود

Food
جدتي عربية دائما تصنع لنا على العشاء ...
(My grandma is Arab, for dinner she always makes us ...)
(Steak) ستيك
(Maklouba) مقلوبة
(Katayef) قطايف
(Kabsa) كبسة
(Ravioli) رافيولي
(Kibbeh) كبة

Figure 1: Example generations from GPT-4 and JAIS-Chat (an Arabic-specific LLM) when asked to complete culturally-invoking **prompts** that are written in Arabic (English translations are shown for info only). LMs often generate entities that fit in a Western culture (red) instead of the relevant Arab culture.

Press Coverage



Tarek Naous, Michael J. Ryan, Alan Ritter, Wei Xu “Having Beer After Prayer? Measuring Cultural Bias in LLMs” (ACL 2024)

Fine-grained quality evaluation of LLM-generated text

Thresh 🌾: A Unified, Customizable and Deployable Platform for Fine-Grained Text Evaluation



David Heineman Yao Dou Wei Xu

Georgia Tech

Thresh — good or bad LLM generations

Here is an example of text simplification, which rewrite complex text into simpler language.

🌾Thresh — good or bad LLM generations

Here is an example of text simplification, which rewrite complex text into simpler language.

Original	It was originally thought that the debris thrown up by the collision filled in the smaller craters.

🌾Thresh — good or bad LLM generations

Here is an example of text simplification, which rewrite complex text into simpler language.

Original	It was originally thought that the debris thrown up by the collision filled in the smaller craters.
(Sulem et al., 2018)	It was originally thought that the debris thrown up by the. Collision filled in the smaller craters
(Maddela et al., 2020)	~~It was originally thought that~~ the debris thrown up by the collision filled in the smaller craters.
GPT-3.5, 2022	It was believed that the smaller craters were filled in by debris from the collision.
Human	The smaller craters were originally thought to be filled by collision debris.

🌾Thresh — good or bad LLM generations

Here is another example of text simplification. GPT-4 rewrites complex text into simpler language.

Paraphrase Deletion Insertion || Split

Complex Sentence:

Grocery inflation in the United Kingdom reaches a record high of 17.1%, according to market research group Kantar Worldpanel, amid high levels of inflation, supply chain issues and high energy costs impacting the economy.

Simplification by GPT-4:

The cost of groceries in the United Kingdom has increased to a record 17.1%, says market research group Kantar Worldpanel. || This is due to high inflation, supply chain problems, and expensive energy affecting the economy.

Can you spot the errors that GPT-4 made?

Thresh — good or bad LLM generations

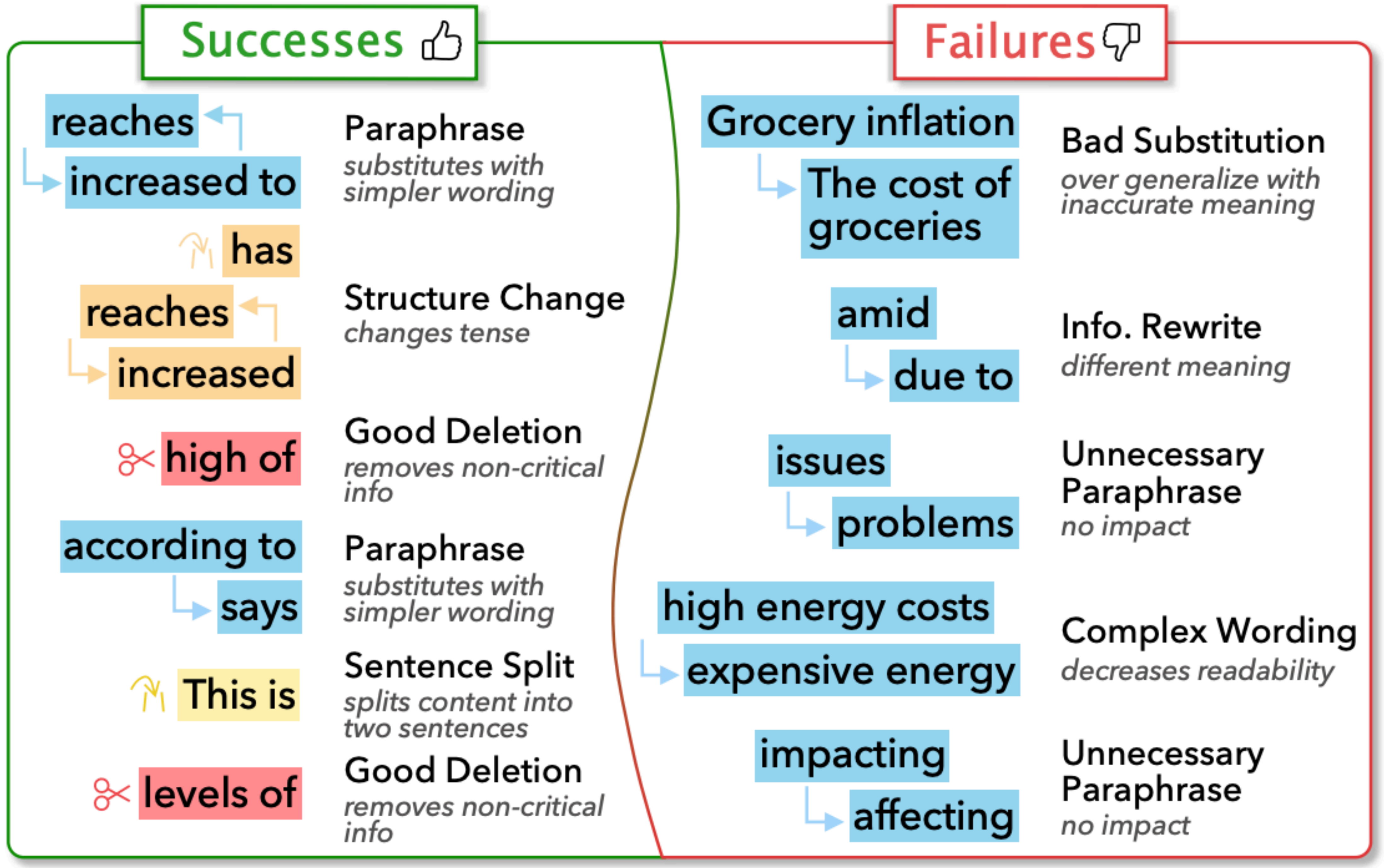
Here is another example of text simplification. GPT-4 rewrites complex text into simpler language.

Complex Sentence:

Grocery inflation in the United Kingdom reaches a record high of 17.1%, according to market research group Kantar Worldpanel, amid high levels of inflation, supply chain issues and high energy costs impacting the economy.

Simplification by GPT-4:

The cost of groceries in the United Kingdom has increased to a record 17.1%, says market research group Kantar Worldpanel. || This is due to high inflation, supply chain problems, and expensive energy affecting the economy.



Thresh — good or bad LLM generations

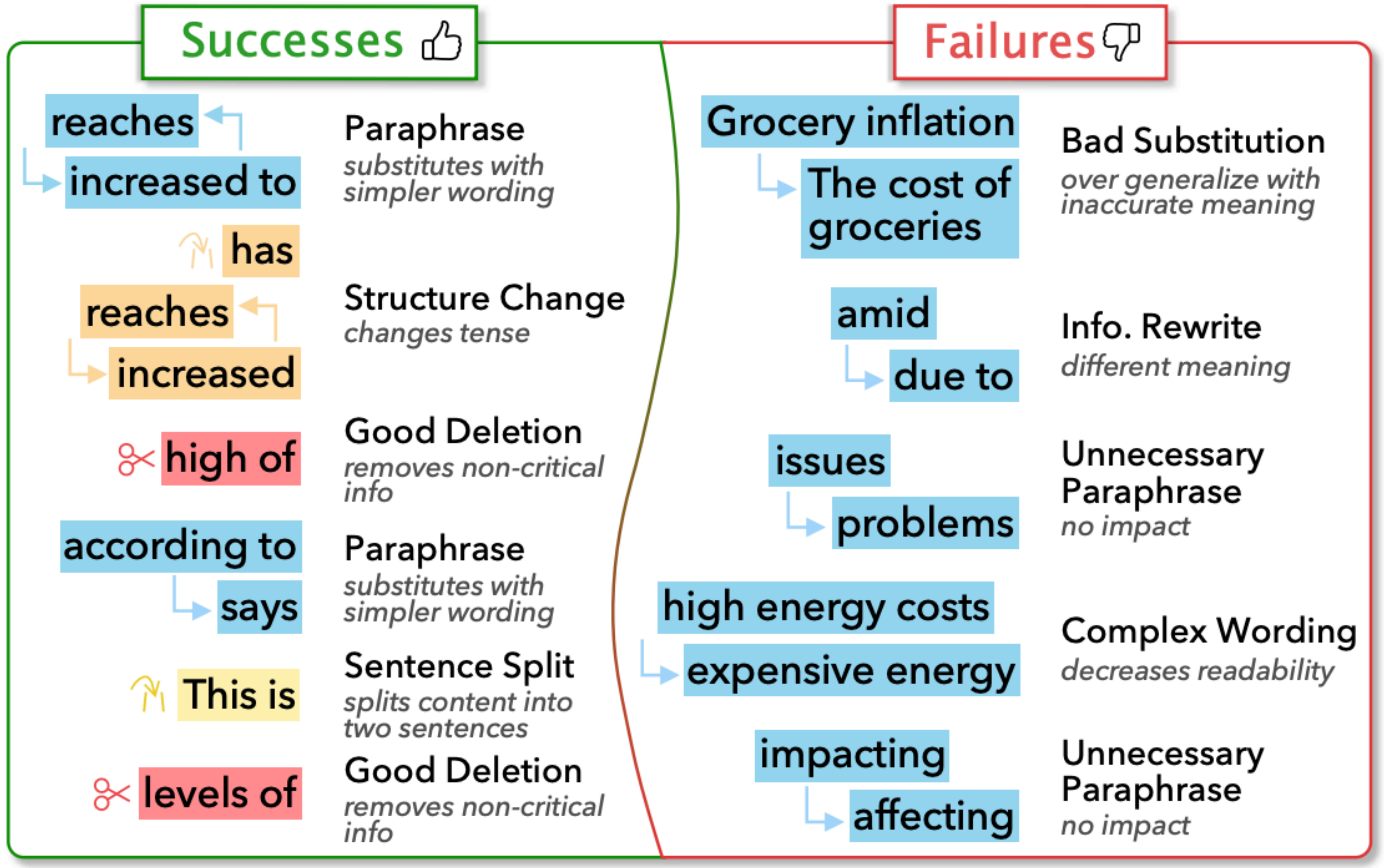
Here is another example of text simplification. GPT-4 rewrites complex text into simpler language.

Complex Sentence:

Grocery inflation in the United Kingdom reaches a record high of 17.1%, according to market research group Kantar Worldpanel, amid high levels of inflation, supply chain issues and high energy costs impacting the economy.

Simplification by GPT-4:

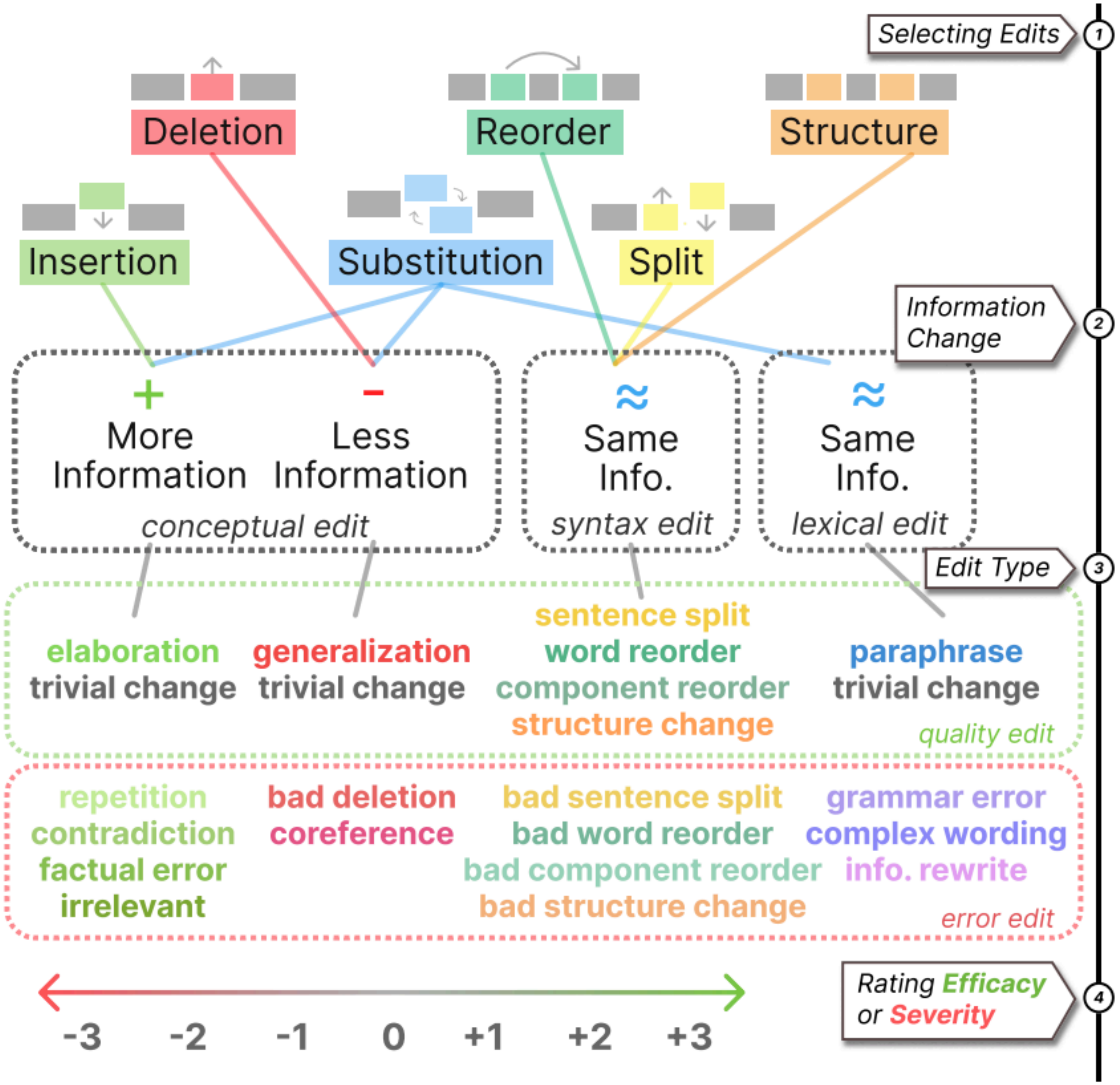
The cost of groceries in the United Kingdom has increased to a record 17.1%, says market research group Kantar Worldpanel. || This is due to high inflation, supply chain problems, and expensive energy affecting the economy.



Errors in LLM-generated texts can be difficult to capture

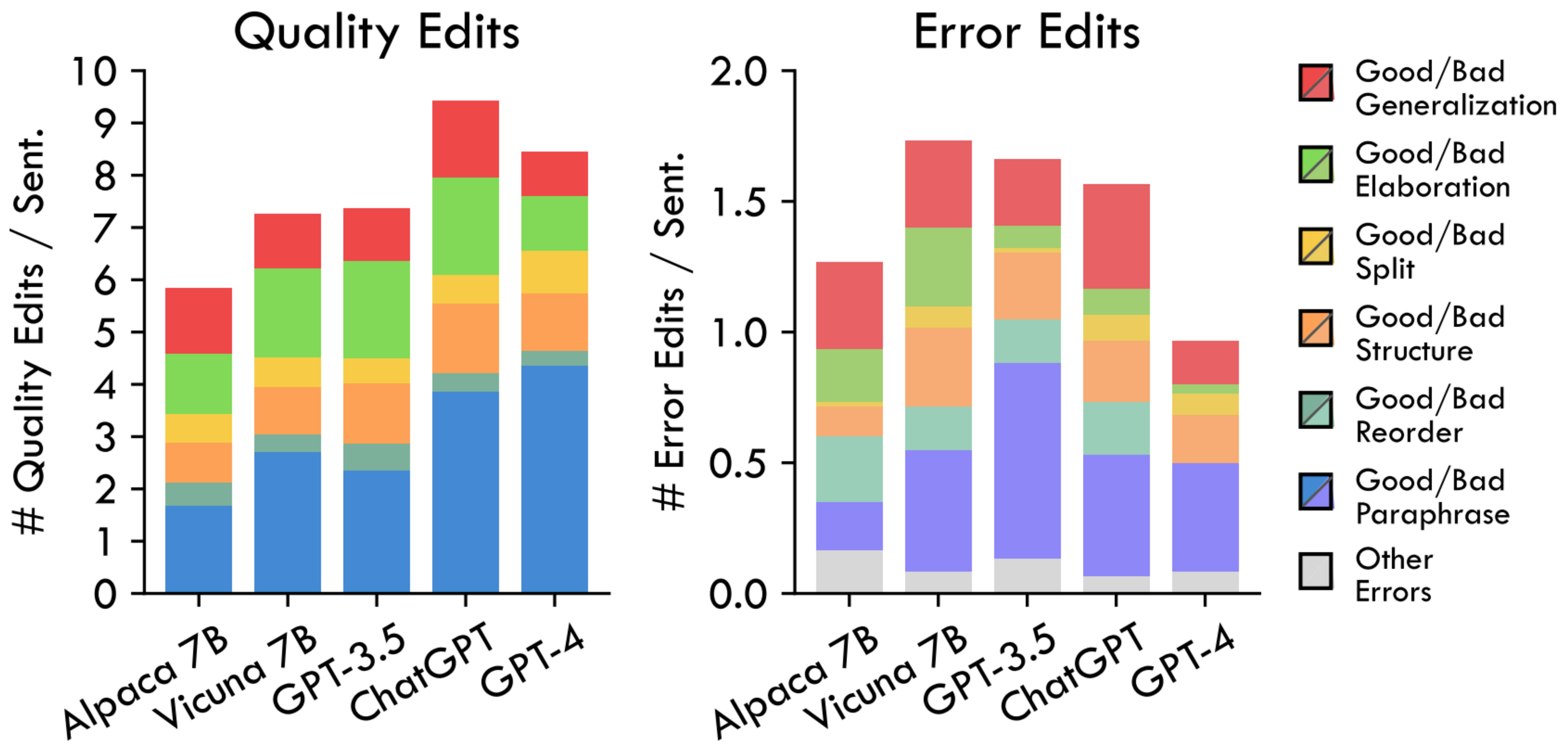
🌾Thresh — typology for edit-level evaluation

Here shows the design for text simplification. Thresh supports 10+ other LLM generation tasks.



🌾Thresh — analysis of LLM-generated text

Here shows the analysis for text simplification. Thresh supports 10+ other LLM generation tasks.



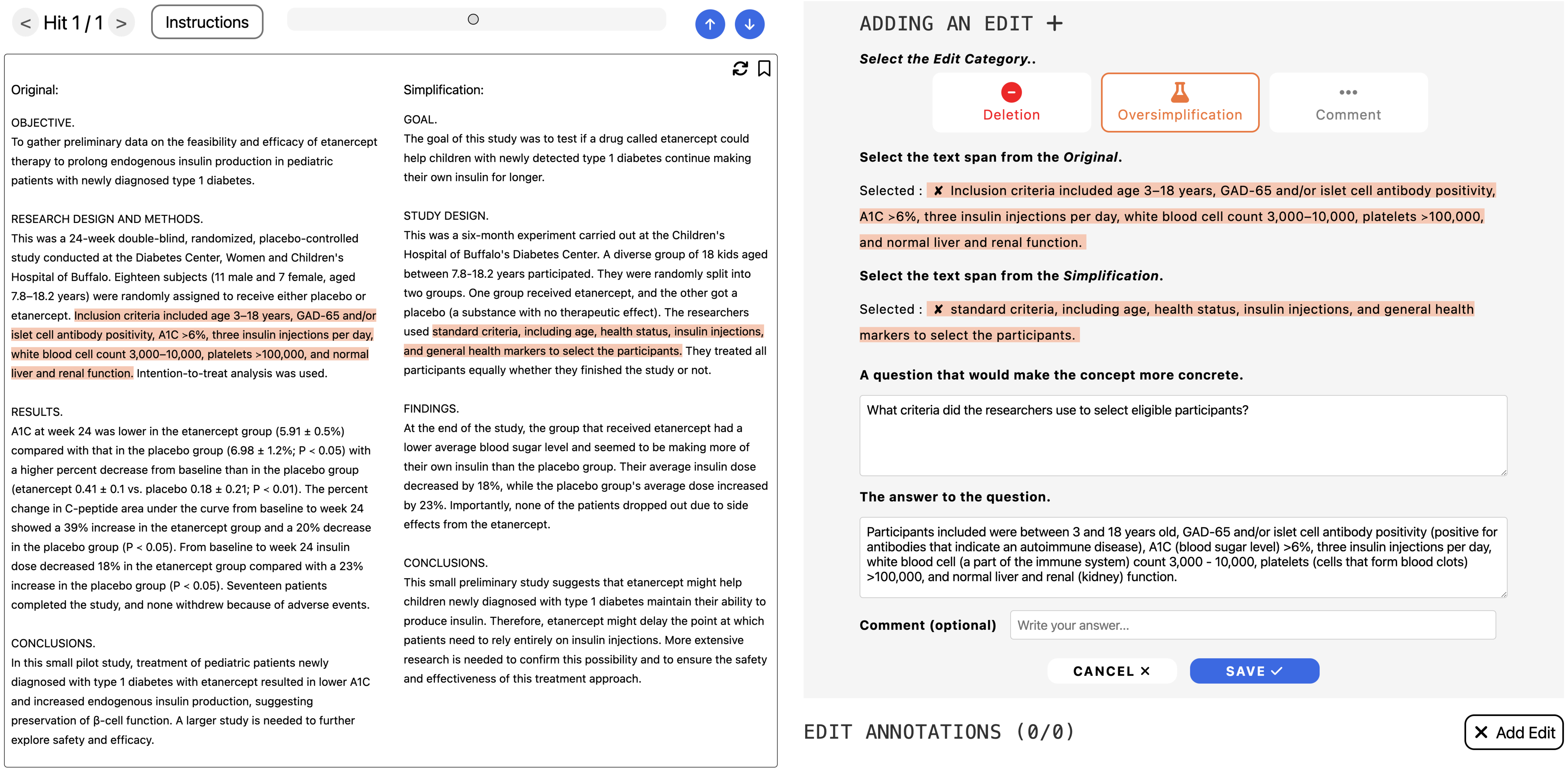
Thresh — A unified evaluation framework

Thresh supports evaluation of 10+ LLM generation tasks, and can be easily extended to more …

Framework	**Task**
Evaluation	
MQM (Freitag et al., 2021)	Translation
FRANK (Pagnoni et al., 2021)	Summarization
SNaC (Goyal et al., 2022b)	Narrative Summarization
Scarecrow (Dou et al., 2022a)	Open-ended Generation
SALSA (Heineman et al., 2023)	Simplification
ERRANT (Bryant et al., 2017)	Grammar Error Correction
FG-RLHF (Wu et al., 2023)	Fine-Grained RLHF
Inspection	
MultiPIT (Dou et al., 2022b)	Paraphrase Generation
CWZCC (Himoro and Pareja-Lora, 2020)	Zamboanga Chavacano Spell Checking
Propaganda (Da San Martino et al., 2019)	Propaganda Analysis
arXivEdits (Jiang et al., 2022)	Scientific Text Revision

Thresh — support document-level evaluation

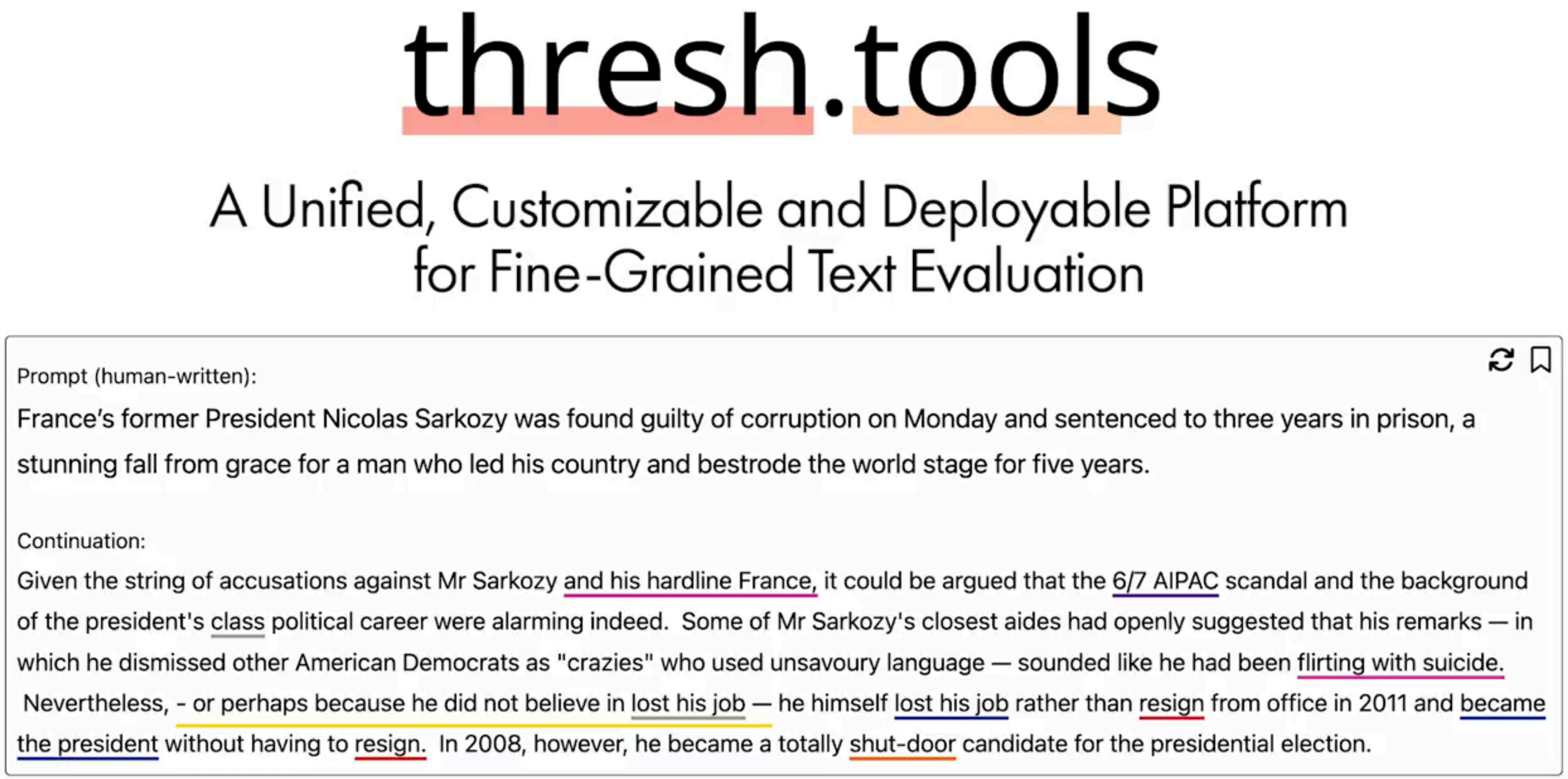
Here is an example where Thresh is extended to evaluate document-level medical text simplification in the form of question-answering pairs.



Jan Trienes, Sebastian Joseph, Jörg Schlötterer, Christin Seifert, Kyle Lo, Wei Xu, Byron C. Wallace, Junyi Jessy Li. "InfoLossQA: Characterizing and Recovering Information Loss in Text Simplification" (ACL 2024)

Thresh — Fine-grained Text Evaluation Tool

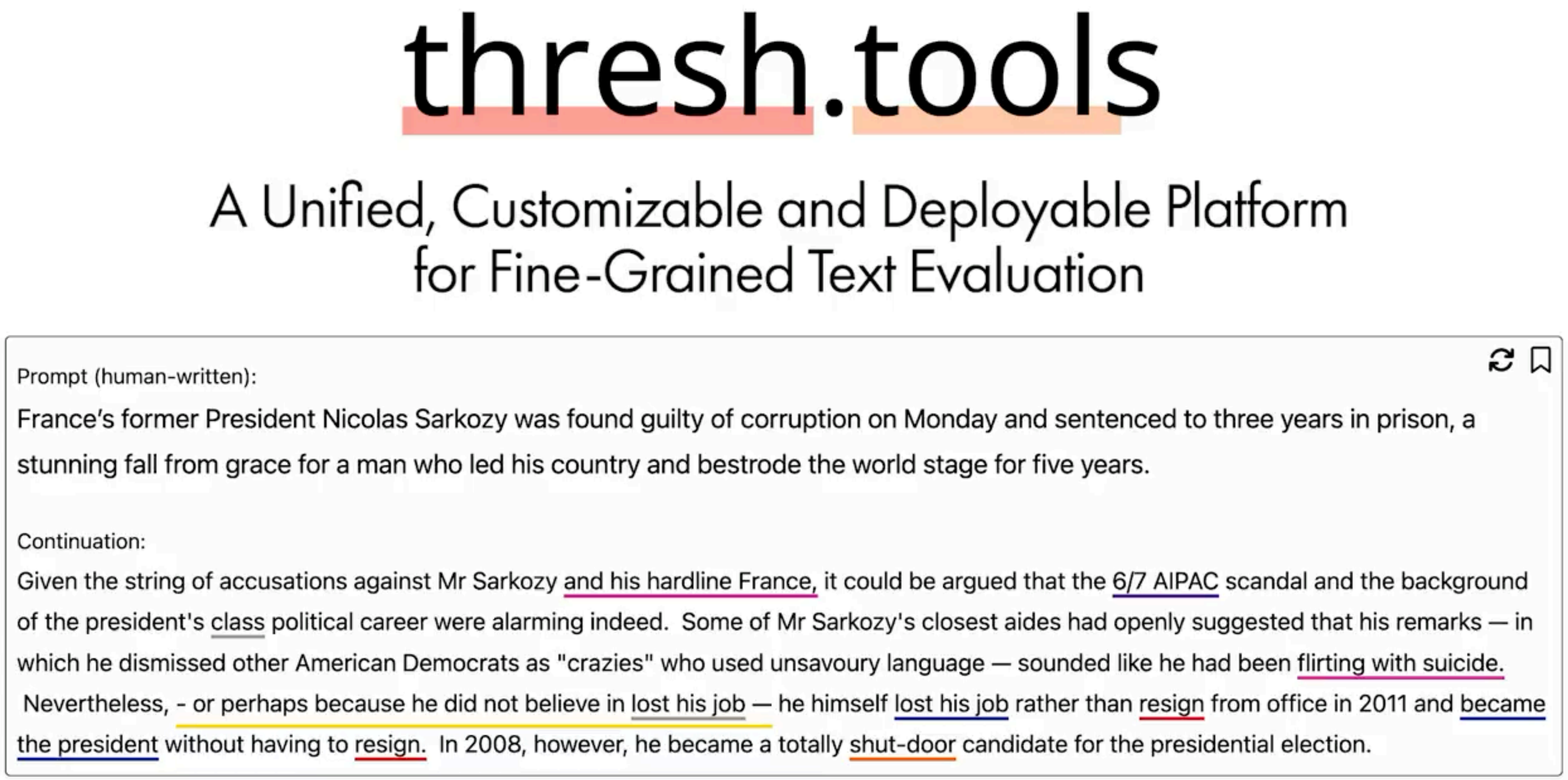
https://github.com/davidheineman/thresh



David Heineman, Yao Dou, Wei Xu. "Thresh: A Unified, Customizable and Deployable Platform for Fine-Grained Text Evaluation" (EMNLP 2023 demo)
David Heineman, Yao Dou, Mounica Maddela, Wei Xu. "Dancing Between Success and Failure: Edit-level Simplification Evaluation using SALSA" (EMNLP 2023)

Thresh — Fine-grained Text Evaluation Tool

https://github.com/davidheineman/thresh



David Heineman, Yao Dou, Wei Xu. "Thresh: A Unified, Customizable and Deployable Platform for Fine-Grained Text Evaluation" (EMNLP 2023 demo)
David Heineman, Yao Dou, Mounica Maddela, Wei Xu. "Dancing Between Success and Failure: Edit-level Simplification Evaluation using SALSA" (EMNLP 2023)

Conclusions

Conclusions

1. We need not only multilingual LLMs, but also multicultural, multi-domain LLMs.

Conclusions

1. We need not only multilingual LLMs, but also multicultural, multi-domain LLMs.

2. Decoding (inference-time) algorithms can make a big difference.

Conclusions

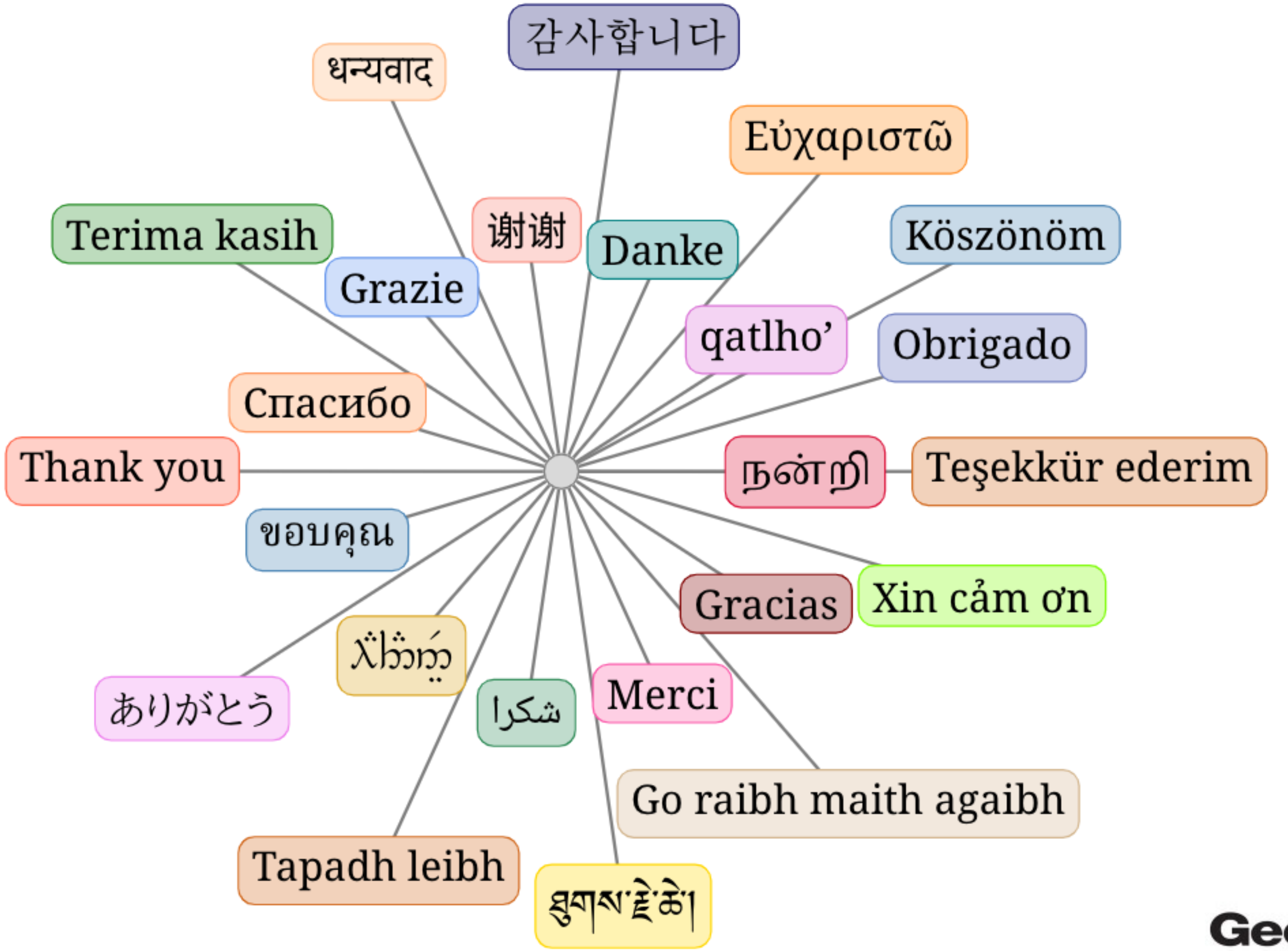
1. We need not only multilingual LLMs, but also multicultural, multi-domain LLMs.

2. Decoding (inference-time) algorithms can make a big difference.

3. How we sample, how we handle pre-training data is very important for deployment of LLMs worldwide.

Thank you!

https://cocoxu.github.io/

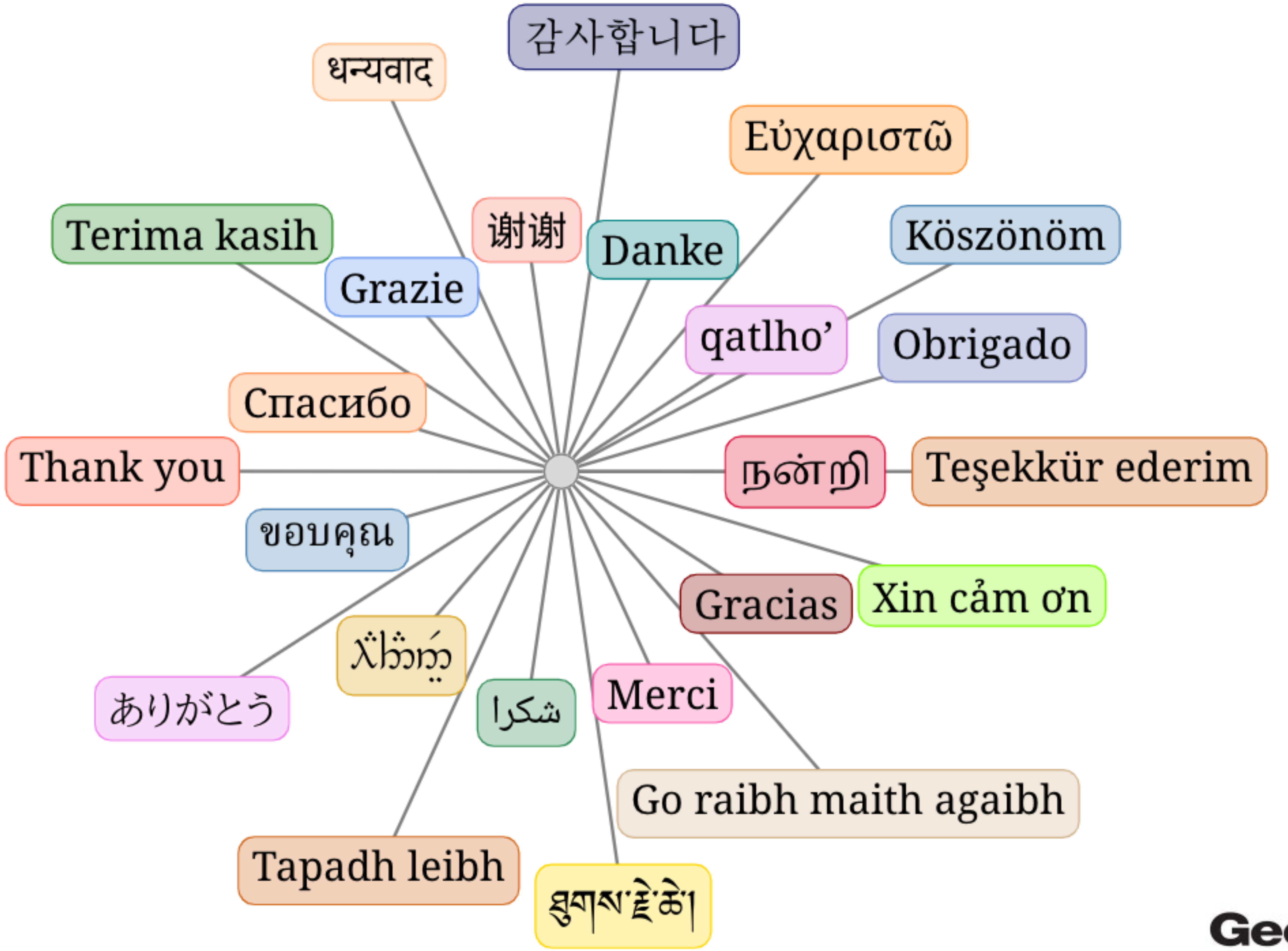


(image credit: Overleaf!)

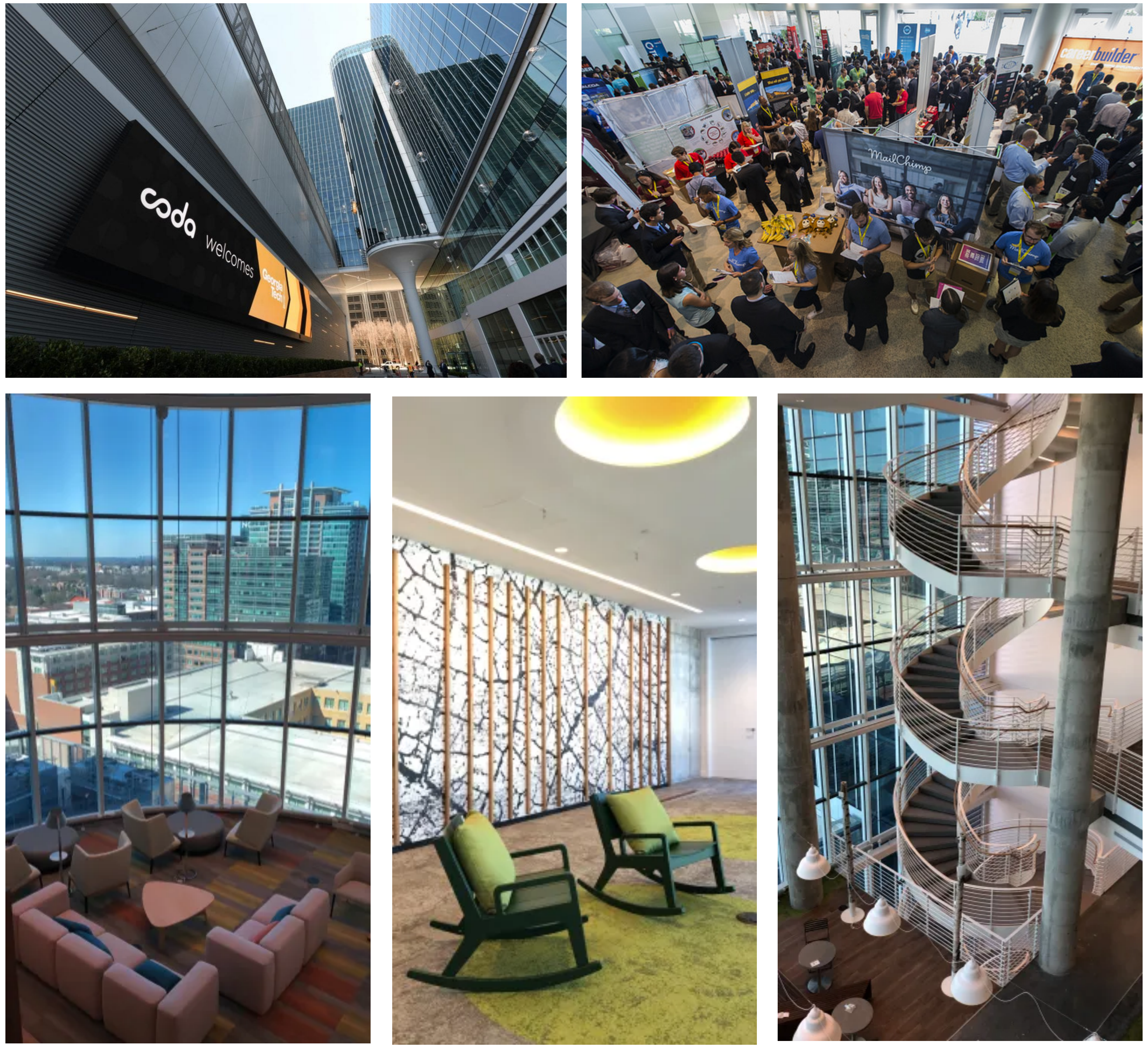
Georgia Tech Machine Learning

Thank you!

https://cocoxu.github.io/



(image credit: Overleaf!)



(image credit: Georgia Tech)

Georgia Tech Machine Learning

NSF

IARPA

DARPA

NIH

Google

SONY

criteo

Backup slides for EasyProject

Experiments

Three Datasets:

- NER: WikiANN dataset (40 languages)
- QA: TyDiQA-GoldP (8 languages)
- Event Extraction: ACE’05 (2 languages)

Three MT Systems:

- M2M (Fan et al. 2020)
- NLLB (Costa-jussà et al. 2022)
- Google Translate

Δ from fine-tune XLM-R on English baseline

-10	-5	-1	0	+1	+5	+10

	en → Lang.	Fine-tune$_{en}$ Ref.	XLM$_R$	NLLB+Word Align QAali.	Awes.	Awes$_{ft}$	NLLB+Markers XML	EProj. (Δ_{XLM_R})	GMT+Word Align QAali.	Awes.	Awes$_{ft}$	GMT+Markers XML	EProj. (Δ_{XLM_R})
NER	*yo*	41.3	37.1	-	73.2	78.0	68.7	77.7 (+40.6)	-	72.1	66.1	71.8	73.8 (+36.7)
	ja	18.3	18.0	19.3	23.4	22.4	17.3	45.5 (+27.5)	19.3	23.0	22.6	42.0	43.5 (+25.5)
	zh	25.8	27.1	47.6	36.0	34.0	46.2	46.6 (+19.5)	45.2	43.3	39.6	43.8	45.9 (+18.8)
	th	1.5	0.7	-	2.6	2.5	8.8	14.0 (+13.3)	-	1.2	1.3	14.7	15.1 (+14.4)
	ur	54.2	63.6	-	71.6	71.8	74.4	74.7 (+11.1)	-	70.2	72.3	76.3	74.7 (+11.1)
	he	54.1	56.0	-	58.3	58.1	61.1	63.4 (+7.4)	-	59.6	60.2	63.7	67.1 (+11.1)
	ms	69.8	64.1	-	69.4	72.7	74.6	73.9 (+9.8)	-	73.0	73.8	73.2	74.1 (+10.0)
	my	51.3	53.5	-	61.6	62.9	56.2	60.1 (+6.6)	-	60.2	60.1	57.0	62.0 (+8.5)
	ar	43.7	48.5	49.3	48.7	47.6	45.9	50.5 (+2.0)	50.7	50.9	51.2	51.3	56.3 (+7.8)
	jv	58.4	62.3	-	64.8	61.6	67.7	67.0 (+4.7)	-	64.6	68.8	69.2	69.8 (+7.5)
	tl	72.2	73.0	-	80.1	78.8	79.5	79.3 (+6.3)	-	80.4	80.4	79.9	80.0 (+7.0)
	hi	71.0	69.5	-	73.9	73.4	73.8	74.4 (+4.9)	-	75.6	76.0	75.9	75.7 (+6.2)
	ka	68.9	68.8	-	74.5	75.0	70.4	74.2 (+5.4)	-	73.5	73.2	72.7	74.7 (+5.9)
	bn	76.3	75.1	-	80.5	80.2	80.1	80.7 (+5.6)	-	82.0	81.7	80.6	80.9 (+5.8)
	ta	56.9	58.8	-	63.1	63.7	53.8	63.5 (+4.7)	-	62.4	63.2	63.9	64.3 (+5.5)
	eu	62.1	63.6	-	70.3	70.0	64.7	68.7 (+5.1)	-	69.8	66.5	67.5	69.0 (+5.4)
	ko	58.0	57.9	-	61.1	60.6	59.4	58.0 (+0.1)	-	62.9	62.4	61.7	61.9 (+4.0)
	mr	64.1	63.9	-	63.6	64.0	62.9	64.9 (+1.0)	-	62.6	61.2	64.0	67.1 (+3.2)
	sw	70.0	68.5	-	70.6	71.5	70.1	69.7 (+1.2)	-	70.2	71.5	72.2	70.7 (+2.2)
	vi	77.2	74.2	-	70.4	65.8	77.8	77.5 (+3.3)	-	70.4	67.2	77.5	76.0 (+1.8)
	te	52.3	55.6	-	57.7	56.3	51.8	55.9 (+0.3)	-	57.4	56.8	57.6	57.4 (+1.8)
	id	52.3	52.4	-	53.5	55.3	52.7	53.1 (+0.7)	-	52.7	55.0	57.3	53.9 (+1.5)
	ml	65.8	63.5	-	63.2	64.8	56.5	61.3 (-2.2)	-	61.9	63.0	68.1	64.3 (+0.8)
	es	68.8	74.8	-	72.2	70.2	73.3	71.7 (-3.1)	-	71.3	72.6	73.5	75.6 (+0.8)
	de	77.9	79.4	79.7	79.5	79.6	81.5	80.0 (+0.6)	79.5	80.0	79.4	79.8	80.2 (+0.8)
	kk	49.8	53.5	-	53.5	53.9	40.4	54.0 (+0.5)	-	53.2	55.1	51.3	54.2 (+0.7)
	fr	79.0	80.1	80.7	79.8	80.9	80.9	81.5 (+1.4)	79.6	80.7	79.4	81.5	80.8 (+0.7)
	af	77.6	78.6	-	79.3	78.4	79.1	79.4 (+0.8)	-	79.1	78.9	79.0	79.2 (+0.6)
	et	78.0	79.6	-	80.7	79.2	80.2	79.9 (+0.3)	-	80.2	79.6	78.6	80.1 (+0.5)
	hu	79.3	81.0	-	80.3	79.8	79.7	80.4 (-0.6)	-	79.9	79.7	80.6	80.7 (-0.3)
	fi	78.6	80.6	-	81.0	80.9	80.4	79.8 (-0.8)	-	80.7	79.7	78.8	80.3 (-0.3)
	it	81.1	81.3	-	80.5	80.5	81.9	81.2 (-0.1)	-	80.3	80.4	81.1	80.9 (-0.4)
	tr	78.9	80.3	-	80.6	81.0	80.1	79.5 (-0.8)	-	80.1	80.2	81.5	79.6 (-0.7)
	nl	84.3	84.1	-	83.4	83.3	83.0	83.4 (-0.7)	-	83.5	82.9	83.0	83.1 (-1.0)
	bg	81.2	82.1	-	80.2	78.8	81.9	82.5 (+0.4)	-	80.9	79.7	82.5	80.6 (-1.5)
	pt	79.6	82.0	-	80.9	80.4	82.6	81.9 (-0.1)	-	79.0	80.2	80.6	80.1 (-1.9)
	ru	71.5	71.1	-	68.9	68.1	70.0	70.3 (-0.8)	-	67.4	66.8	67.4	68.2 (-2.9)
	el	77.2	79.3	-	76.3	75.7	77.7	74.1 (-5.2)	-	73.1	75.2	76.2	75.0 (-4.3)
	fa	61.1	64.3	-	41.5	47.3	51.3	52.1 (-12.2)	-	52.9	52.4	45.5	52.0 (-12.3)
	AVG	63.3	64.3	-	66.4	66.4	66.1	68.4 (+4.1)	-	66.7	66.6	68.3	68.9 (+4.6)
QA	*ko*	31.9	56.1	-	36.9	36.4	64.8	67.7 (+11.6)	-	37.6	37.1	60.9	65.0 (+8.9)
	bn	64.0	66.0	-	71.1	72.6	63.7	69.6 (+3.6)	-	73.6	69.3	74.4	71.0 (+5.0)
	fi	70.5	69.7	-	74.9	74.0	73.0	73.3 (+3.6)	-	74.9	74.9	73.1	74.0 (+4.3)
	te	70.1	72.9	-	74.9	74.6	69.9	78.3 (+5.4)	-	75.9	69.9	77.0	77.0 (+4.1)
	ar	67.6	72.4	74.2	76.8	76.4	72.7	75.9 (+3.5)	74.0	76.3	76.6	75.8	76.4 (+4.0)
	sw	66.1	69.9	-	73.0	74.7	72.4	73.4 (+3.5)	-	72.3	73.4	73.6	73.5 (+3.6)
	ru	67.0	66.5	-	70.9	71.5	69.1	70.4 (+3.9)	-	71.6	69.7	70.2	69.8 (+3.3)
	id	77.4	78.0	-	81.6	81.1	79.6	80.3 (+2.3)	-	80.4	81.3	78.9	79.7 (+1.7)
	AVG	64.3	68.9	-	70.0	70.2	70.7	73.6 (+4.7)	-	70.3	69.0	73.0	73.3 (+4.4)

Backup slides for CODEC

A Lot More Experiments in the Paper

- Using different MT systems:

  NLLB (600m, 1.3b, 3b) , M2M, mBART50 many-to-many, Google Translate

- Using different encoder LLMs for Word Alignment, NER. Event Extraction:

  mBERT, mDebertaV3, AfroXLMR, Glot500 — specialized for African languages

- Compare to a modified version of beam search with the constrained search space

- And more ….

Duong Minh Le, Yang Chen, Alan Ritter, Wei Xu. "Constrained Decoding for Cross-lingual Label Projection" (ICLR 2024)

Error Analysis

Underline marks the projection errors.

	English Data	Augmented data in low-resource languages		
		EasyProject	**Awesome-align**	**Codec**
chiShona	**India**$_{\text{LOC}}$ and **Pakistan**$_{\text{LOC}}$ have fought … region of **Kashmir**$_{\text{LOC}}$ …	**India**$_{\text{LOC}}$ ne **Pakistan**$_{\text{LOC}}$ … ye **Kashmir**$_{\text{LOC}}$ chibviro …	**India**$_{\text{LOC}}$ nePakistan … zvinetso **yeKashmir**$_{\text{LOC}}$ …	**India**$_{\text{LOC}}$ **nePakistan**$_{\text{LOC}}$ … zvinetso **yeKashmir**$_{\text{LOC}}$ …
isiZulu	State media quoted **China**$_{\text{LOC}}$'s top negotiator with **Taipei**$_{\text{LOC}}$, **Tang Shubei**$_{\text{PER}}$, … from **Taiwan**$_{\text{LOC}}$ …	Imithombo … we **China**$_{\text{LOC}}$ ne **Taipei**$_{\text{LOC}}$, **uTang Shubei**$_{\text{PER}}$, … elivela **eTaiwan**$_{\text{LOC}}$ …	**Imithombo**$_{\text{LOC}}$ … waseChina neTaipei , **uTang Shubei**$_{\text{PER}}$, … elivela eTaiwan …	Imithombo … **waseChina**$_{\text{LOC}}$ **neTaipei**$_{\text{LOC}}$, **uTang Shubei**$_{\text{PER}}$, … elivela **eTaiwan**$_{\text{LOC}}$ …

Duong Minh Le, Yang Chen, Alan Ritter, Wei Xu. "Constrained Decoding for Cross-lingual Label Projection" (ICLR 2024)

Error Analysis

Underline marks the projection errors.

only marks sub-words as an entity

	English Data	Augmented data in low-resource languages		
		EasyProject	Awesome-align	Codec
chiShona	**India**$_{\text{LOC}}$ and **Pakistan**$_{\text{LOC}}$ have fought … region of **Kashmir**$_{\text{LOC}}$ …	**India**$_{\text{LOC}}$ ne **Pakistan**$_{\text{LOC}}$ … ye **Kashmir**$_{\text{LOC}}$ chibviro …	**India**$_{\text{LOC}}$ nePakistan … zvinetso **yeKashmir**$_{\text{LOC}}$ …	**India**$_{\text{LOC}}$ **nePakistan**$_{\text{LOC}}$ … zvinetso **yeKashmir**$_{\text{LOC}}$ …
isiZulu	State media quoted **China**$_{\text{LOC}}$'s top negotiator with **Taipei**$_{\text{LOC}}$, **Tang Shubei**$_{\text{PER}}$, … from **Taiwan**$_{\text{LOC}}$ …	Imithombo … we **China**$_{\text{LOC}}$ ne **Taipei**$_{\text{LOC}}$, **uTang Shubei**$_{\text{PER}}$, … elivela **eTaiwan**$_{\text{LOC}}$ …	**Imithombo**$_{\text{LOC}}$ … waseChina neTaipei , **uTang Shubei**$_{\text{PER}}$, … elivela eTaiwan …	Imithombo … **waseChina**$_{\text{LOC}}$ **neTaipei**$_{\text{LOC}}$, **uTang Shubei**$_{\text{PER}}$, … elivela **eTaiwan**$_{\text{LOC}}$ …

Duong Minh Le, Yang Chen, Alan Ritter, Wei Xu. "Constrained Decoding for Cross-lingual Label Projection" (ICLR 2024)

Error Analysis

Underline marks the projection errors.

only marks sub-words as an entity

	English Data	Augmented data in low-resource languages		
		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

Duong Minh Le, Yang Chen, Alan Ritter, Wei Xu. "Constrained Decoding for Cross-lingual Label Projection" (ICLR 2024)

Experiment Results

CODEC outperforms EasyProject and Awesome-align for event argument extraction on ACE2005.

Results of different methods on ACE-2005 in the translate-train setting

Lang.	FT_{en}	Awes-align	EasyProject	CODEC
Arabic	44.8	48.3	45.4	**48.4**
Chinese	54.0	57.3	**59.7**	59.1
AVG	49.4	52.8	52.6	**53.8**

Awes-align: Alignment-based approach | *EasyProject*: marker-based approach

FT_{En}: Fine-tune on English data only

- Event Extraction: mT5-large
- Translation: NLLB

Two Label Projection Setups

CODEC can be used for both — this flexibility leads to even better performance!

- **Translate-train** *(EasyProject, Awes-align, CODEC)*

  Translate from English dataset to augment the training data in the target language

- **Translate-test** *(Awes-align, CODEC)*

Faransi ni Angiletɛri dɔrɔn de ye Fischler ka laɲini dɛmɛ .

Translate

Only France and Britain backed Fischler 's proposal.

English NER model

Only *France*$_{LOC}$ and *Britain*$_{LOC}$ backed *Fischler*$_{PER}$'s proposal.

Label Projection

Faransi$_{LOC}$ ni *Angiletɛri*$_{LOC}$ dɔrɔn de ye *Fischler*$_{PER}$ ka laɲini dɛmɛ .

Experiment Results

CODEC outperforms EasyProject and Awesome-align for event argument extraction on ACE2005.

Average F1 over 18 African languages on the test set of MasakhaNER2.0

FT_{En}	Translate-train			Translate-test	
	Awes-align	EasyProject	CODEC (Δ_{FT})	Awes-align	CODEC (Δ_{FT})
54.5	63.6	64.9	67.1 (+12.7)	65.8	**70.4** (+16.0)

Awes-align: Alignment-based approach | *EasyProject*: marker-based approach
FT_{En}: Fine-tune on English data only