School of Computer Science and Technology
(School of Cyberspace Security)

LLM for Machine Translation in Low-Resource Languages: From Text-Only to Multimodal Learning

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Outline

- LLM Everywhere
- Machine Translation with LLMs
- Challenges of LLM-based MT on LRLs
- Strategies for Text-only LLM-based MT
- Findings on Multi-modal LLM-based MT
- Conclusion

LLM Everywhere

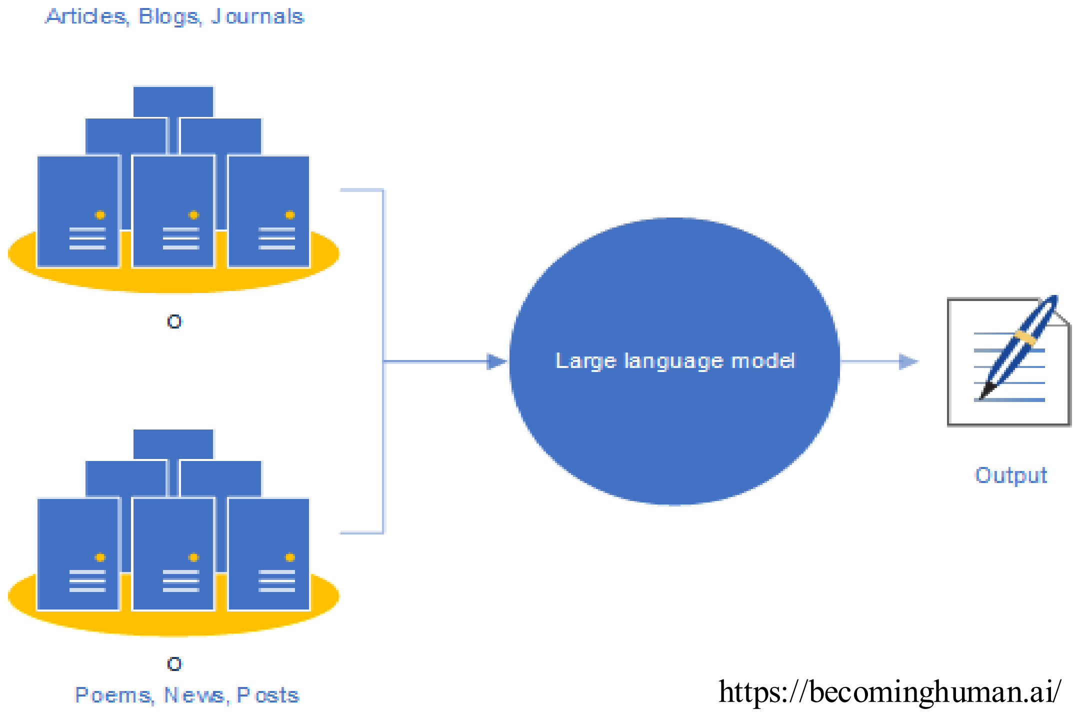
LLM

What Are Large Language Models?

Large Language Models (LLMs) are Transformer-based architectures trained on massive unlabeled text via **self-supervised** and **semi-supervised learning**, enabling them to generate natural, context-aware text across diverse formats and styles.

LLM

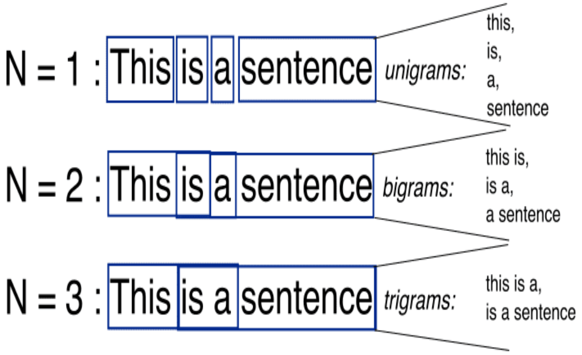
Large-scale Pre-trained Language Model



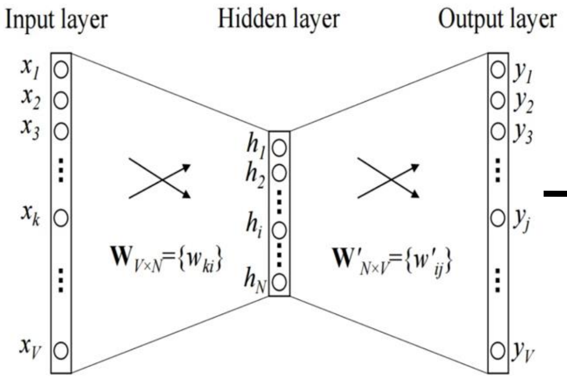
https://becominghuman.ai/

LLM

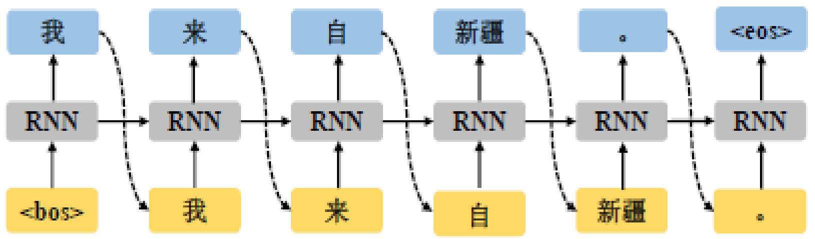
Language Models



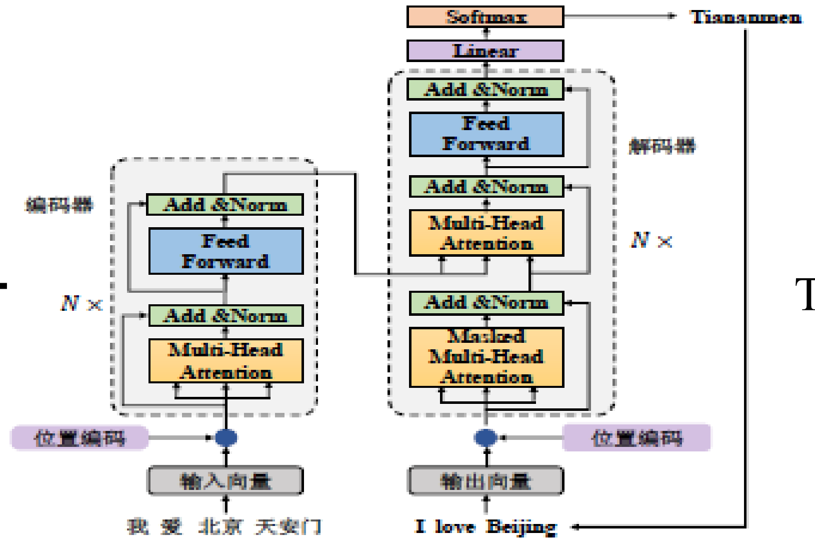
N-gram LM



Word2Vec



RNNLM



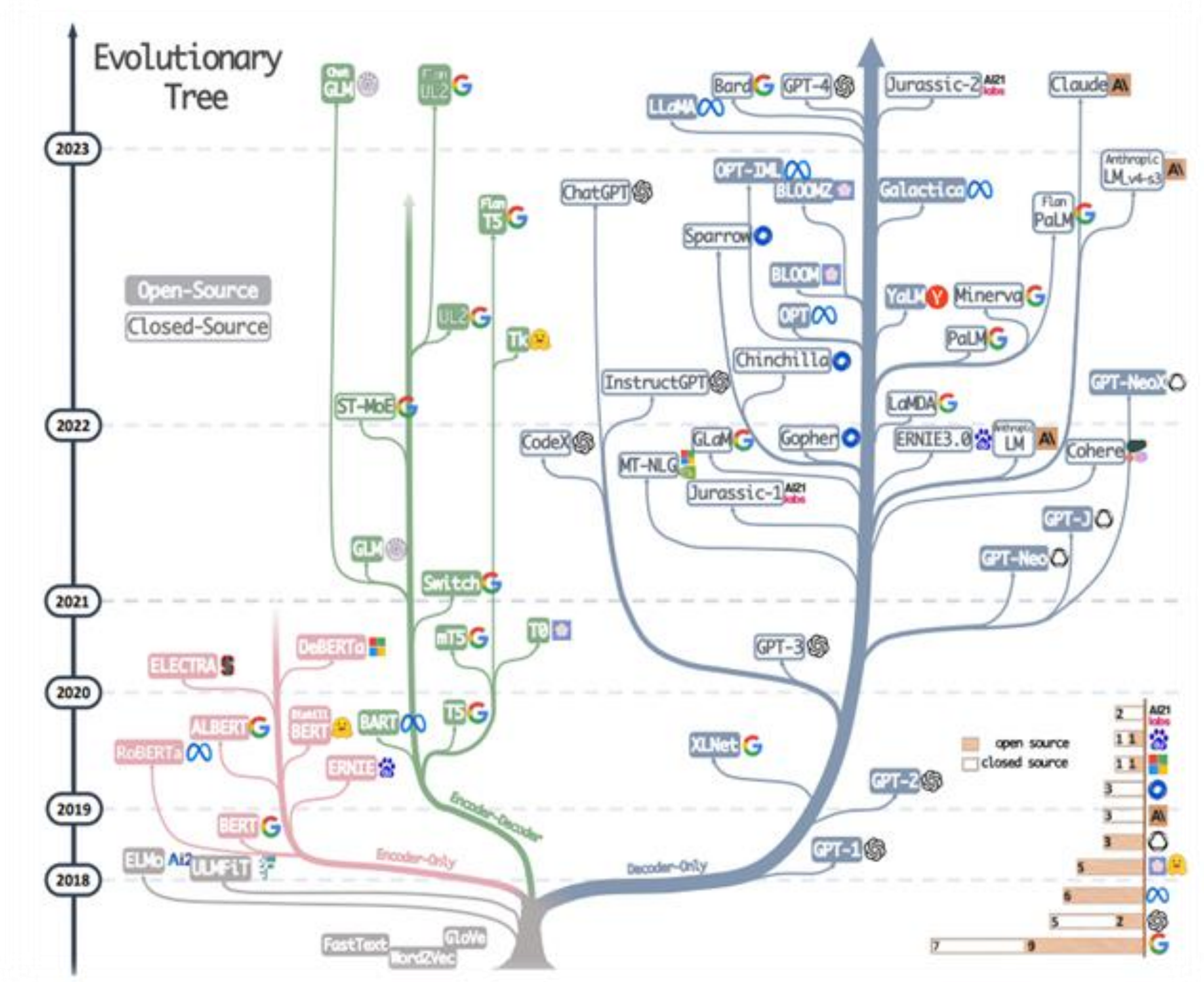
Transformer

PLM

LLM

LLM

The Evolutionary of LLM



(Yang et al., 2023)

- **GPT**Improving Language Understanding by Generative Pre-Training. 2018
- **GPT-2**Language Models are Unsupervised Multitask Learners. 2018.
- **GPT-3**"Language Models are Few-Shot Learners". NeurIPS 2020.
- **OPT**"OPT: Open Pre-trained Transformer Language Models". 2022.
- **PaLM**"PaLM: Scaling Language Modeling with Pathways". Aakanksha Chowdhery et al arXiv 2022.
- **BLOOM**"BLOOM: A 176B-Parameter Open-Access Multilingual Language Model".2022.
- **MT-NLG**"Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, A Large-Scale GenerativeLanguage Model". 2021.
- **Gopher**"Scaling Language Models: Methods, Analysis & Insights from Training Gopher", 2021.
- **chinchilla** "Training Compute-Optimal Large Language Models". 2022.
- **LaMDA**"LaMDA: Language Models for Dialog Applications".2021.
- **LLaMA**"LLaMA: Open and Efficient Foundation Language Models". 2023.
- **GPT-4** "GPT-4 Technical Report".2023.
- **BloombergGPT**BloombergGPT: A Large Language Model for Finance, 2023,
- **GPT-NeoX-20B**: "GPT-NeoX-20B: An Open-Source Autoregressive Language Model".2022.

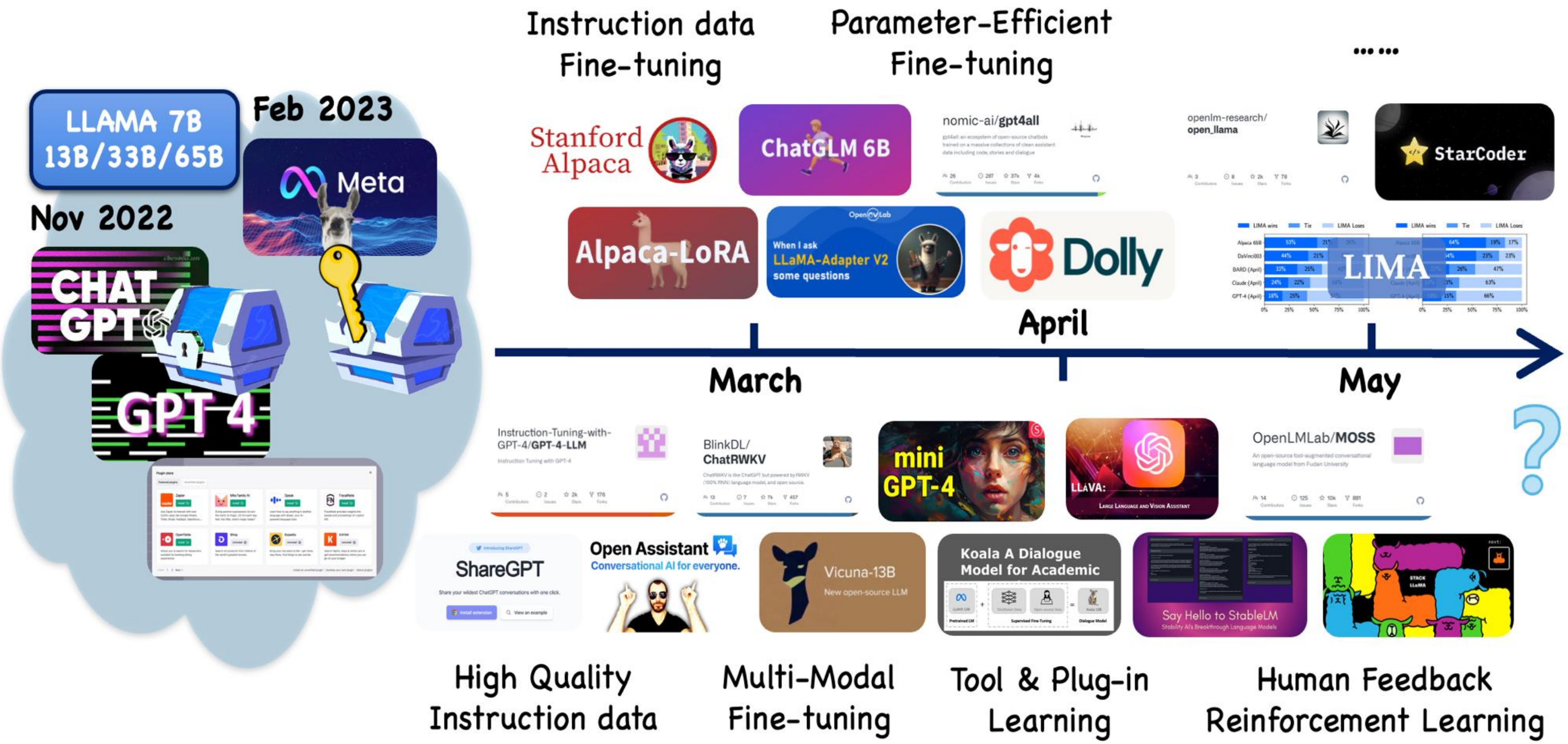
……

2026

LLM

Basic Fact - foundational models is rapidly evolving

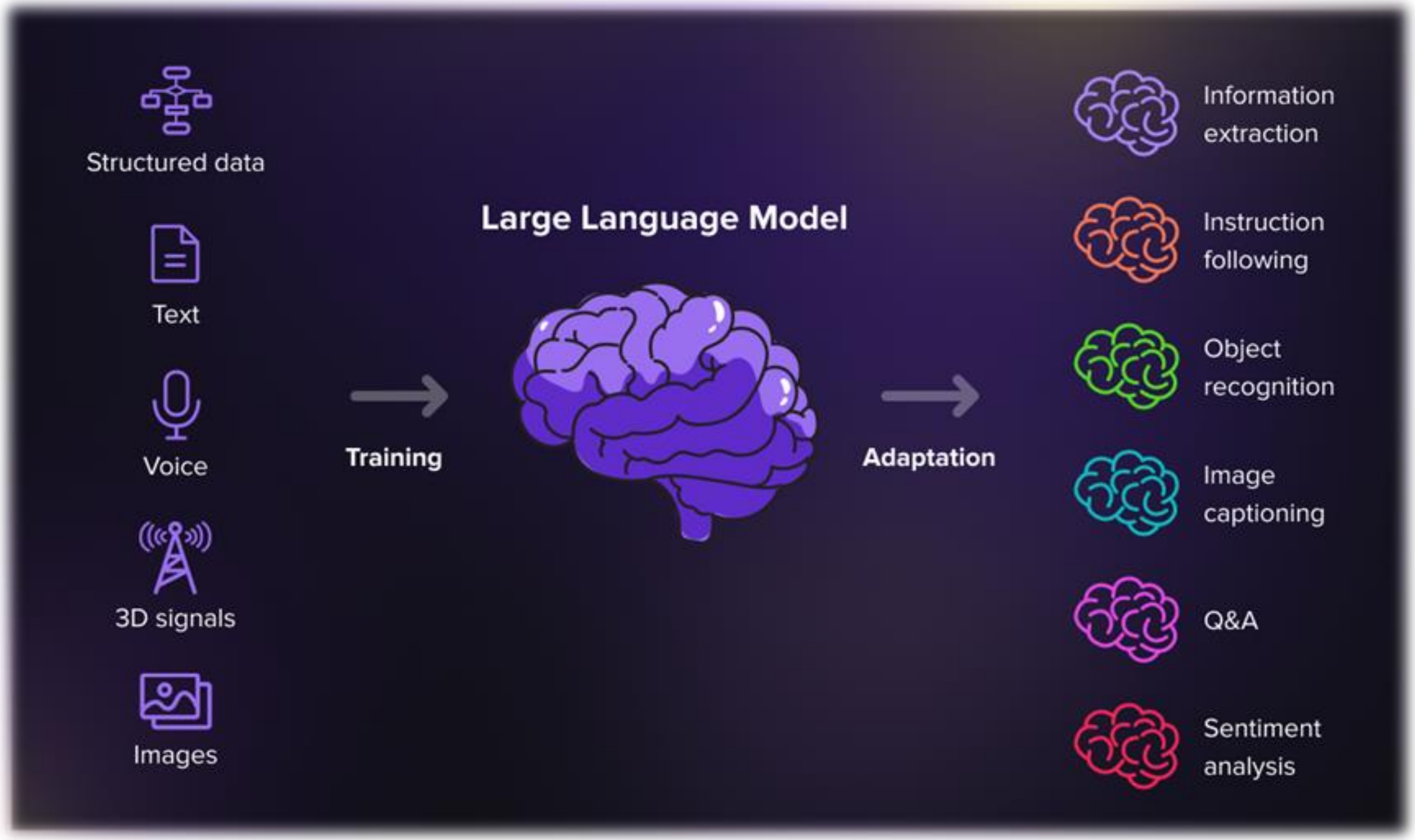
A growing number of instruction-tuned models have emerged


Instruction data Fine-tuning
Parameter-Efficient Fine-tuning
……
LLAMA 7B 13B/33B/65B
Feb 2023
Meta
Nov 2022
CHAT GPT
GPT 4
Stanford Alpaca
ChatGLM 6B
nomic-ai/gpt4all
openlm-research/open_llama
StarCoder
Alpaca-LoRA
When I ask LLaMA-Adapter V2 some questions
Dolly
LIMA
April
March
May
Instruction-Tuning-with-GPT-4/GPT-4-LLM
BlinkDL/ChatRWKV
mini GPT-4
LLaVA: Large Language and Vision Assistant
OpenLMLab/MOSS
?
ShareGPT
Open Assistant
Conversational AI for everyone.
Vicuna-13B
New open-source LLM
Koala A Dialogue Model for Academic
Say Hello to StableLM
High Quality Instruction data
Multi-Modal Fine-tuning
Tool & Plug-in Learning
Human Feedback Reinforcement Learning

(Ding et al., CCL2023)

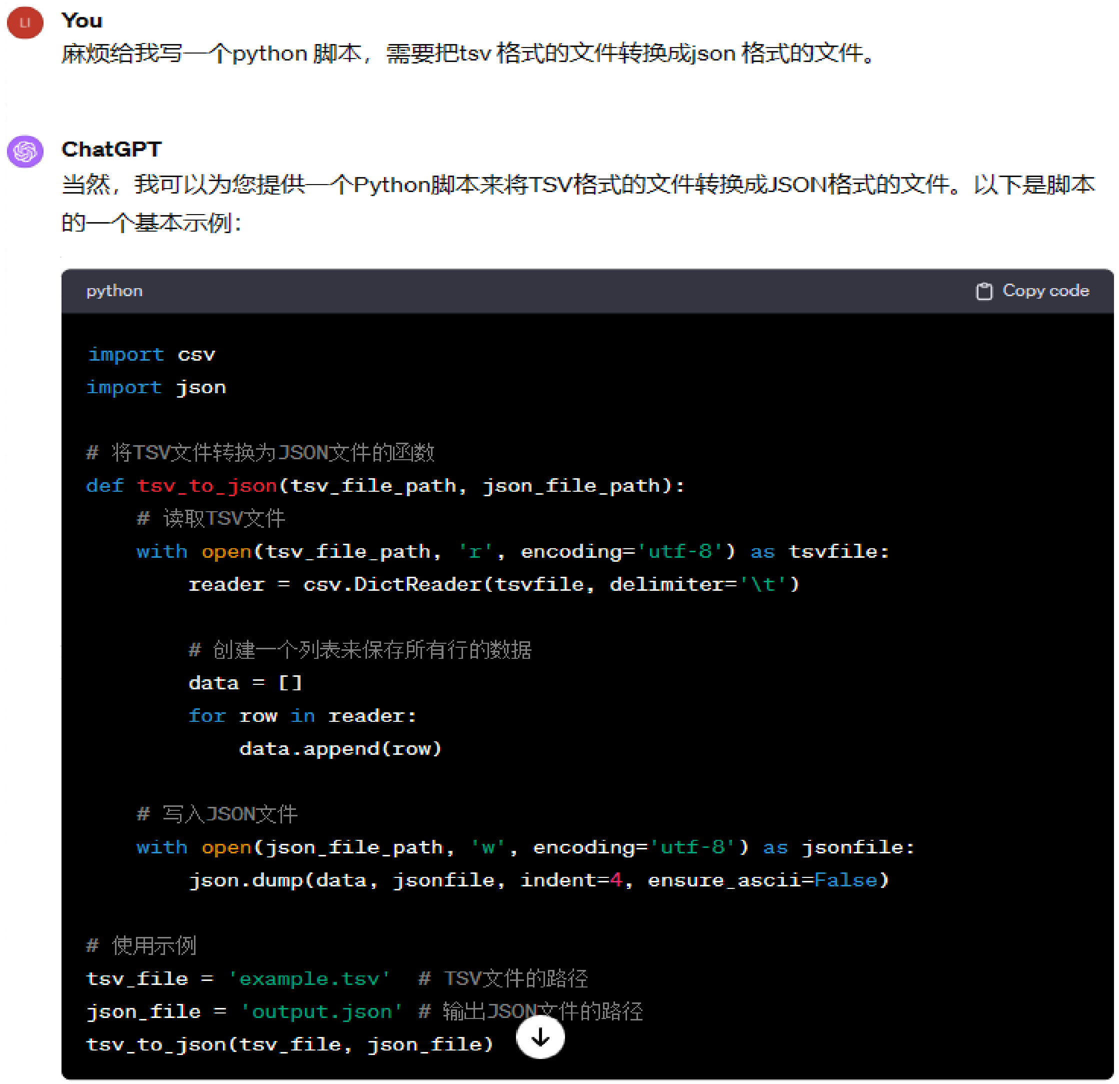
LLM

LLM performance on NLP down-stream tasks



https://blog.gopenai.com/

LLM Everywhere --- Conversation, QA, Outline, Recommend, MT, Coding



You

麻烦给我写一个python 脚本，需要把tsv 格式的文件转换成json 格式的文件。

ChatGPT

当然，我可以为您提供一个Python脚本来将TSV格式的文件转换成JSON格式的文件。以下是脚本的一个基本示例：

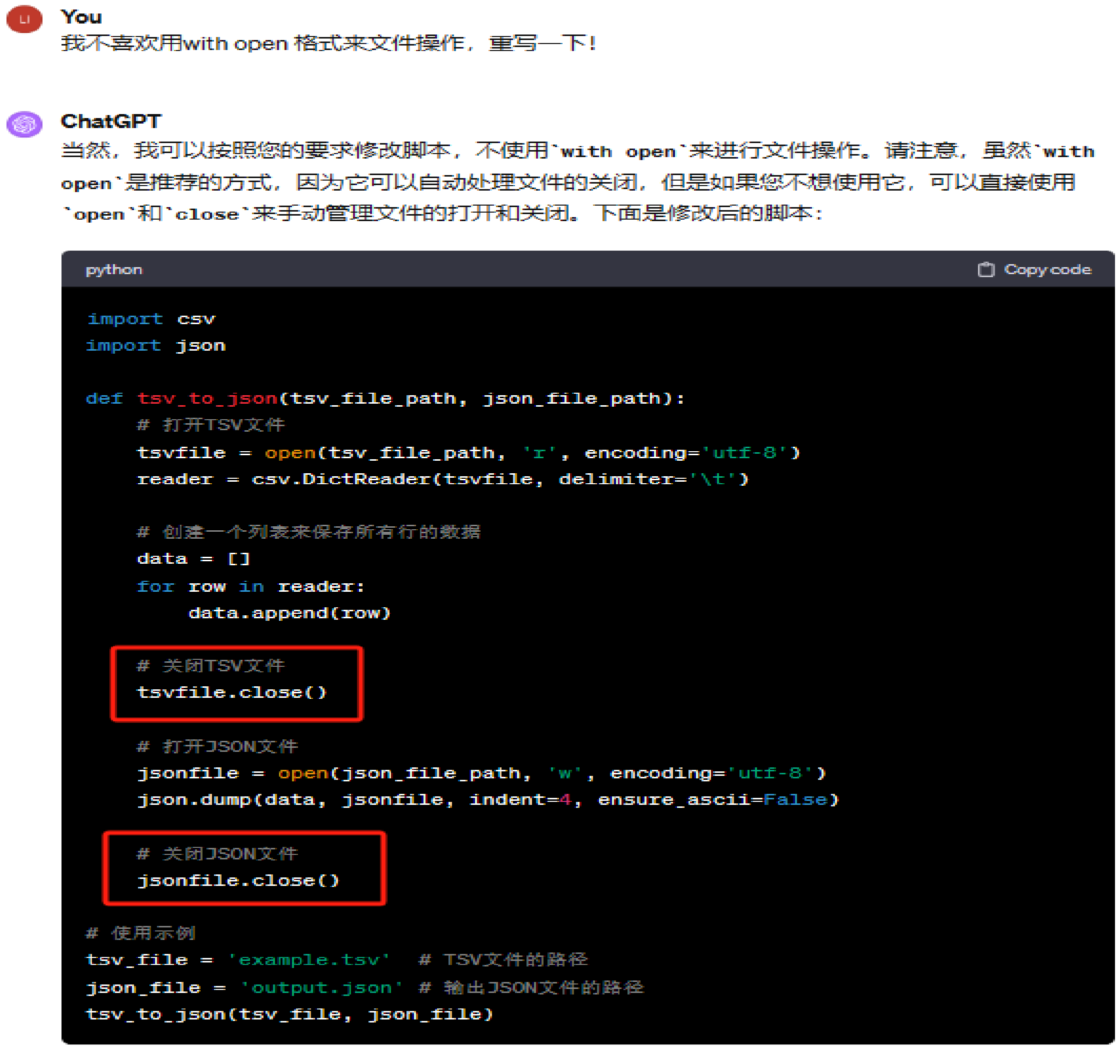
```python
import csv
import json

# 将TSV文件转换为JSON文件的函数
def tsv_to_json(tsv_file_path, json_file_path):
    # 读取TSV文件
    with open(tsv_file_path, 'r', encoding='utf-8') as tsvfile:
        reader = csv.DictReader(tsvfile, delimiter='\t')

        # 创建一个列表来保存所有行的数据
        data = []
        for row in reader:
            data.append(row)

    # 写入JSON文件
    with open(json_file_path, 'w', encoding='utf-8') as jsonfile:
        json.dump(data, jsonfile, indent=4, ensure_ascii=False)

# 使用示例
tsv_file = 'example.tsv'  # TSV文件的路径
json_file = 'output.json' # 输出JSON文件的路径
tsv_to_json(tsv_file, json_file)
```



You

我不喜欢用with open 格式来文件操作，重写一下！

ChatGPT

当然，我可以按照您的要求修改脚本，不使用`with open`来进行文件操作。请注意，虽然`with open`是推荐的方式，因为它可以自动处理文件的关闭，但是如果您不想使用它，可以直接使用`open`和`close`来手动管理文件的打开和关闭。下面是修改后的脚本：

```python
import csv
import json

def tsv_to_json(tsv_file_path, json_file_path):
    # 打开TSV文件
    tsvfile = open(tsv_file_path, 'r', encoding='utf-8')
    reader = csv.DictReader(tsvfile, delimiter='\t')

    # 创建一个列表来保存所有行的数据
    data = []
    for row in reader:
        data.append(row)

    # 关闭TSV文件
    tsvfile.close()

    # 打开JSON文件
    jsonfile = open(json_file_path, 'w', encoding='utf-8')
    json.dump(data, jsonfile, indent=4, ensure_ascii=False)

    # 关闭JSON文件
    jsonfile.close()

# 使用示例
tsv_file = 'example.tsv'  # TSV文件的路径
json_file = 'output.json' # 输出JSON文件的路径
tsv_to_json(tsv_file, json_file)
```

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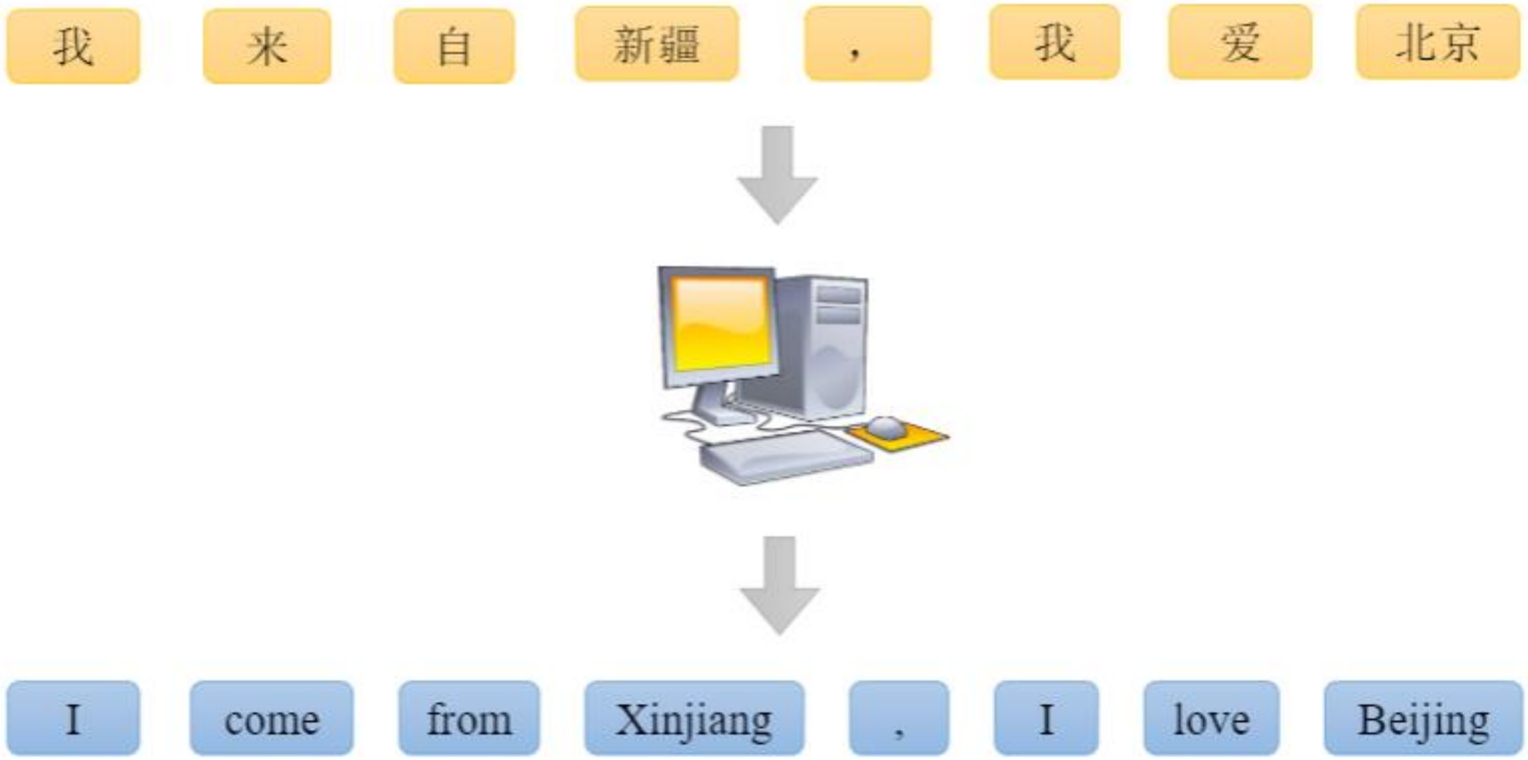
Machine Translation with LLMs

MT

Machine Translation

- Use computers to transform one sequence into another.

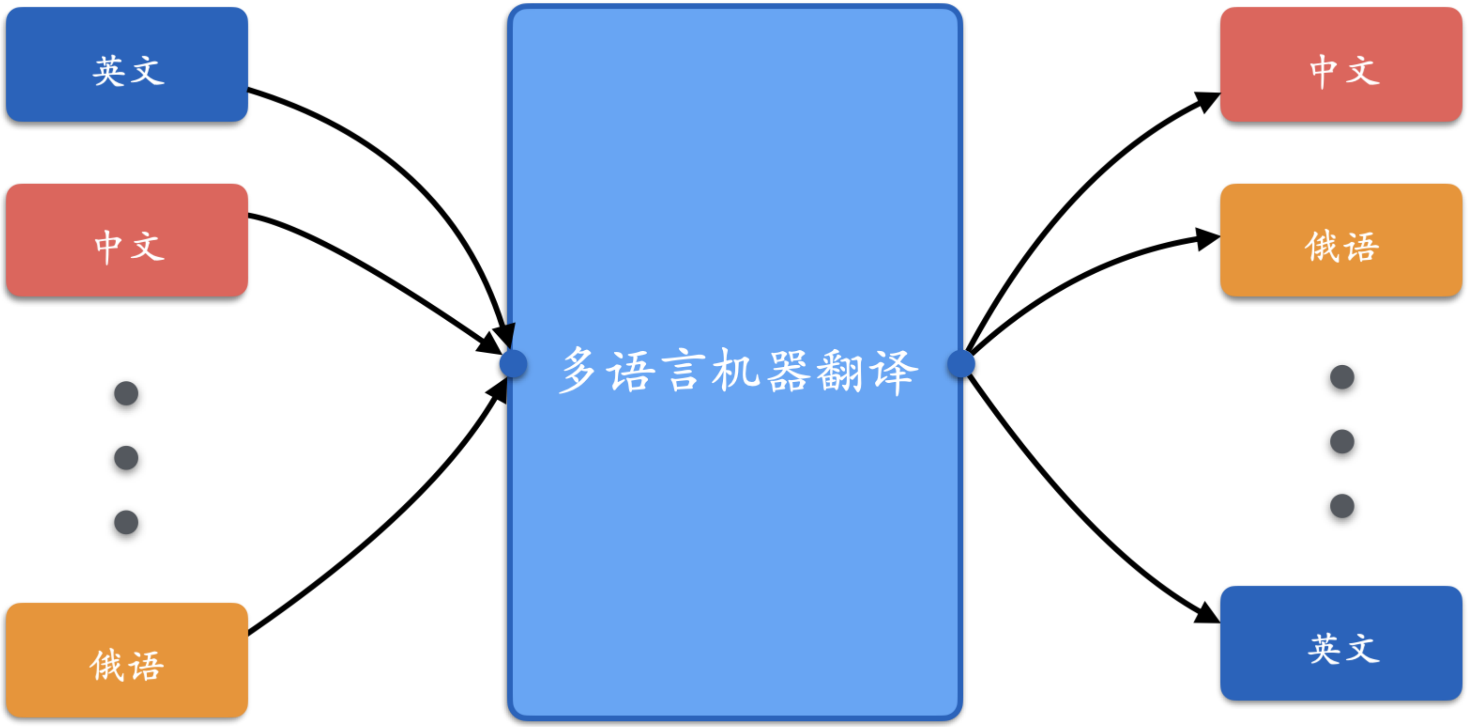


我 来 自 新疆 ， 我 爱 北京

I come from Xinjiang , I love Beijing

Multi-lingual MT

- Multilingual machine translation aims to enable translation between multiple languages using a single unified model, thereby significantly improving translation performance for low-resource languages while greatly reducing deployment costs.



英文

中文

俄语

多语言机器翻译

中文

俄语

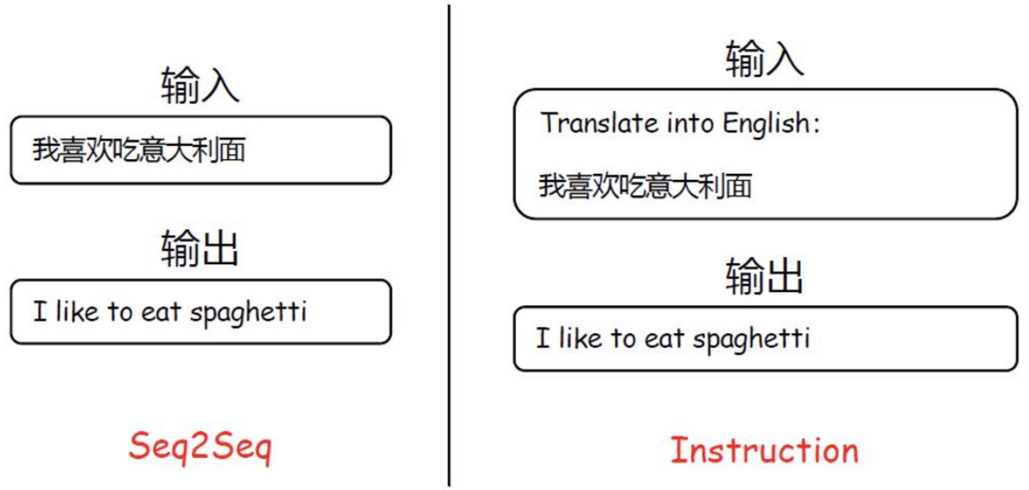
英文

Huang, CCMT2023

MT with LLM

Machine Translation with LLM

- General Model v.s. Specific Task（Translation)
  - Specifying model behavior through instruction.
  - In-context Learning (ICL)



输入

我喜欢吃意大利面

输出

I like to eat spaghetti

Seq2Seq

输入

Translate into English:

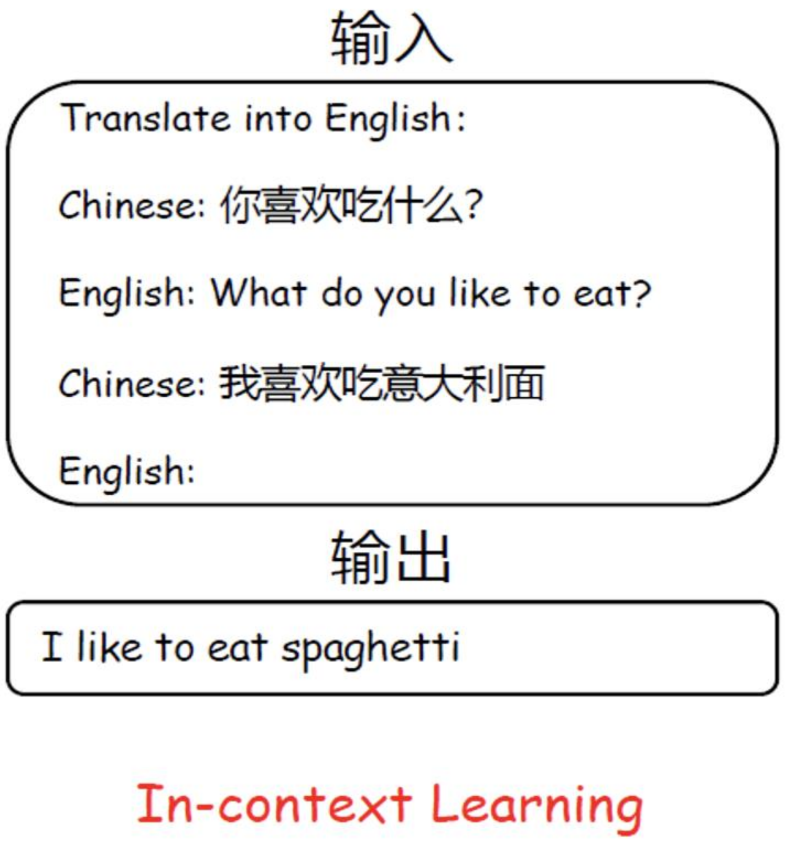
我喜欢吃意大利面

输出

I like to eat spaghetti

Instruction

Acquiring the ability to directly **follow instructions** through instruction learning.



输入

Translate into English:

Chinese: 你喜欢吃什么?

English: What do you like to eat?

Chinese: 我喜欢吃意大利面

English:

输出

I like to eat spaghetti

In-context Learning

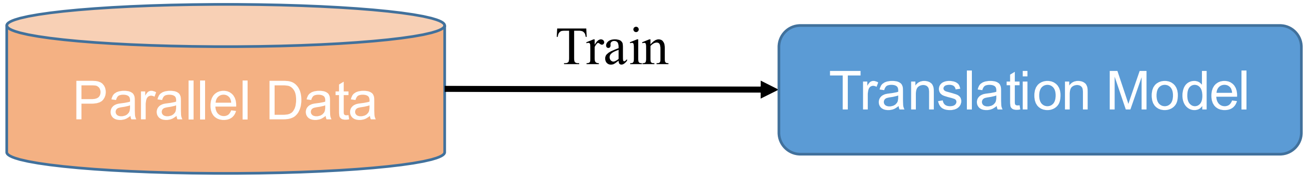
A **small number of examples** obtained during **pre-training**.

Prof. Huang CCL 2023

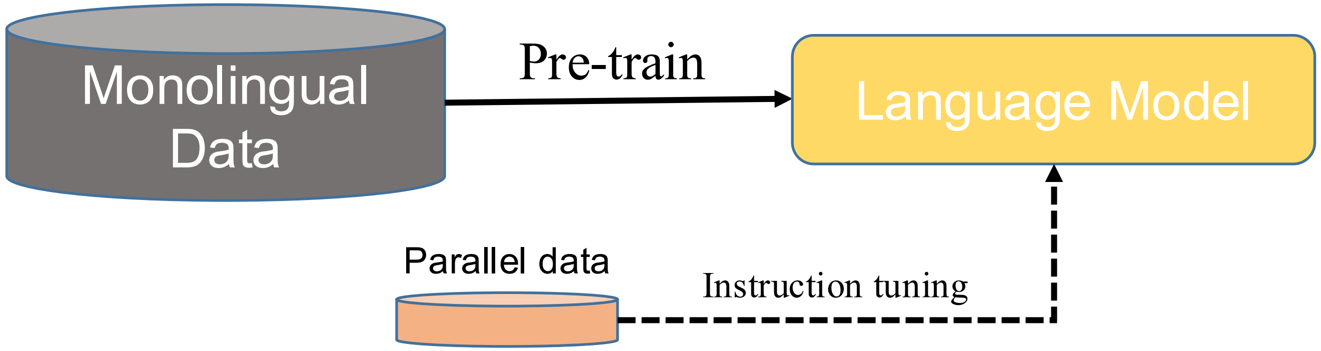
MT with LLM

The paradigm of learning is shifting

- **NMT:** Translation knowledge is primarily learned from parallel data.



- **LLM:** General knowledge (including translation knowledge) is primarily learned from monolingual data.



In-context Learning

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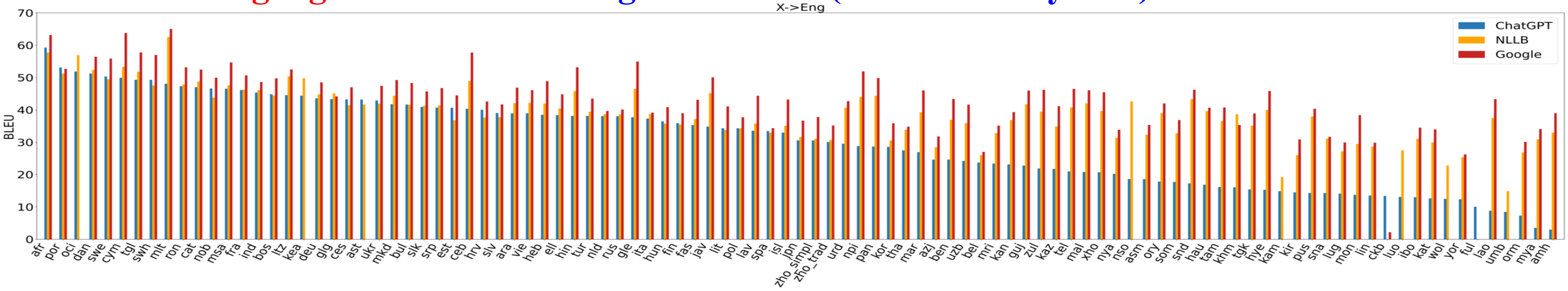
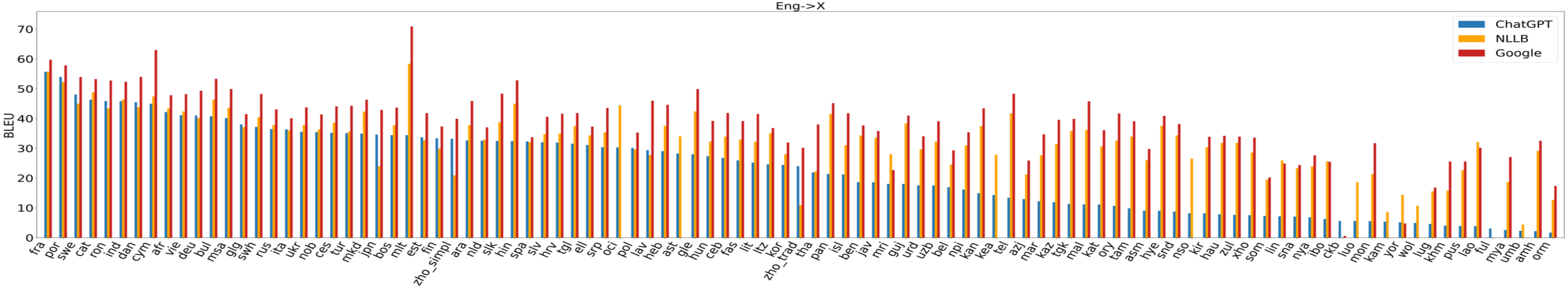
LLM-based MT v.s. NMT

- **LLMs still lag behind strong supervised baselines：** ChatGPT (16.67%) v.s. NLLB (83.33%)
- **Low-resource languages: far behind Google Translate (commercial system)**


X->Eng
ChatGPT
NLLB
Google
BLEU
0
10
20
30
40
50
60
70
afr por oci dan swe cym tgl swh mlt ron cat nob msa fra ind bos ltz kea deu glg ces ast ukr mkd bul slk srp est ceb hrv slv ara vie heb ell hin tur nld rus gle ita hun fin fas jav lit pol lav spa isl jpn zho_simpl zho_trad urd npi pan kor tha mar azj ben uzb bel mri kan guj zul kaz tel mal xho nya nso asm ory som snd hau tam khm tgk hye kam kir pus sna lug mon lin ckb luo ibo kat wol yor ful lao umb orm mya amh



Zhu W, et al. Multilingual Machine Translation with Large Language Models: Empirical Results and Analysis, arXiv:2304.04675

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Pros of LLM-based MT

1. Context Understanding
→ Accuracy & fluency

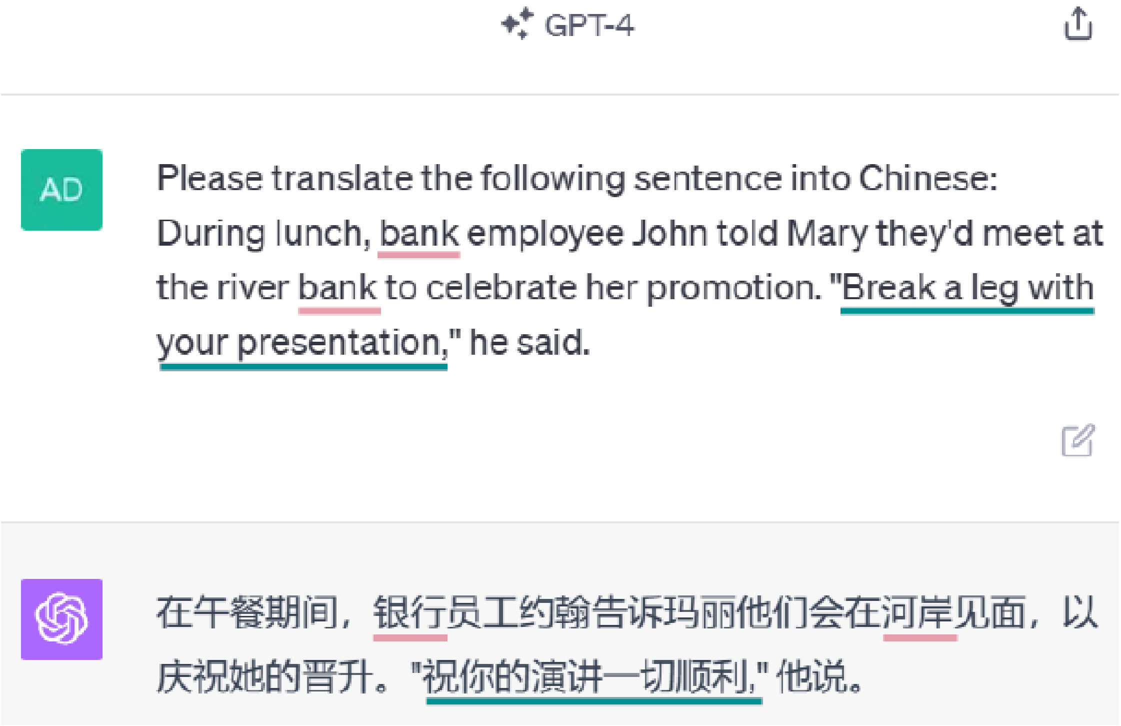
2. Interactive Translation
→ Real-time user feedback / guidance

3. Versatile Text Processing
→ Formal, spoken, slang

4. Document-Level Translation
→ Consistency & context in long/complex texts

5. Multilingual Capability
→ Simultaneous multi-language translation

Context



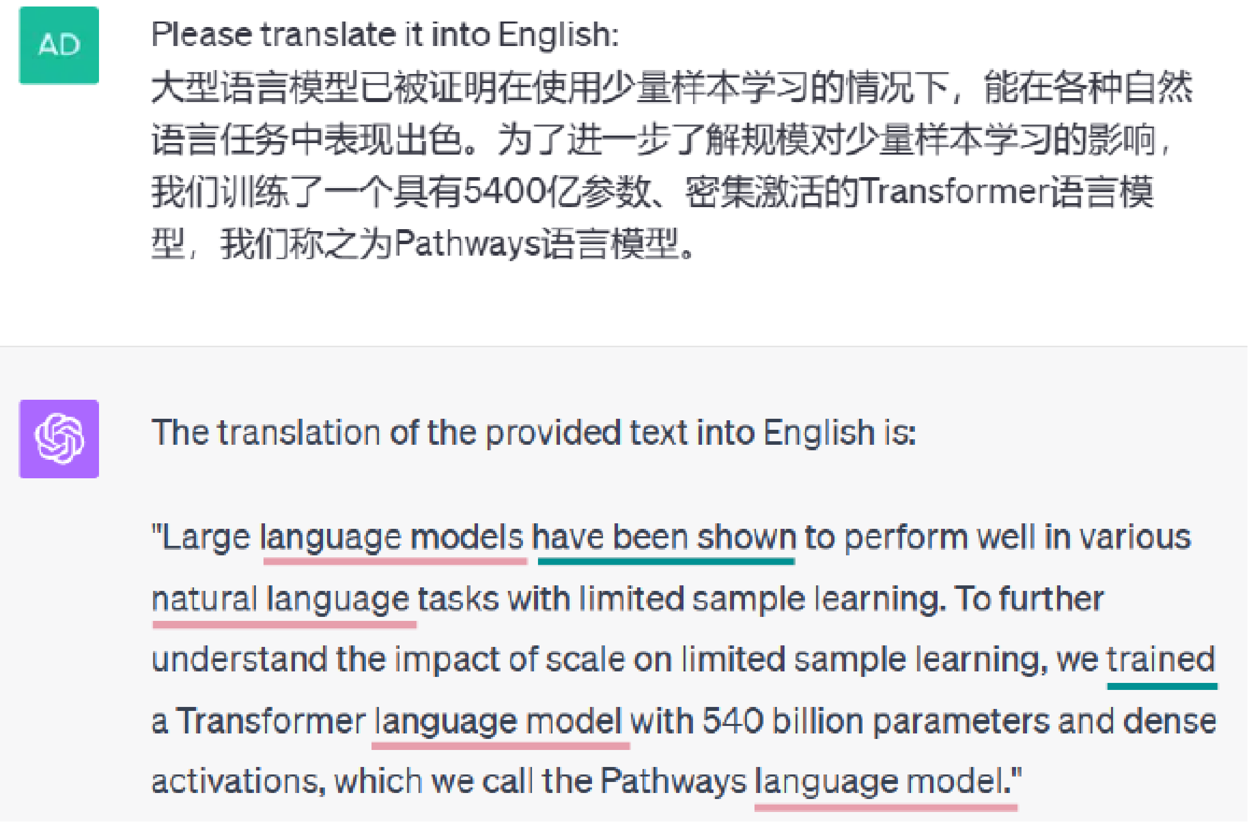
Please translate the following sentence into Chinese: During lunch, bank employee John told Mary they'd meet at the river bank to celebrate her promotion. "Break a leg with your presentation," he said.

在午餐期间，银行员工约翰告诉玛丽他们会在河岸见面，以庆祝她的晋升。"祝你的演讲一切顺利," 他说。

Prof. Liu CCMT 2023

Pros of LLM-based MT

Interactive Translation

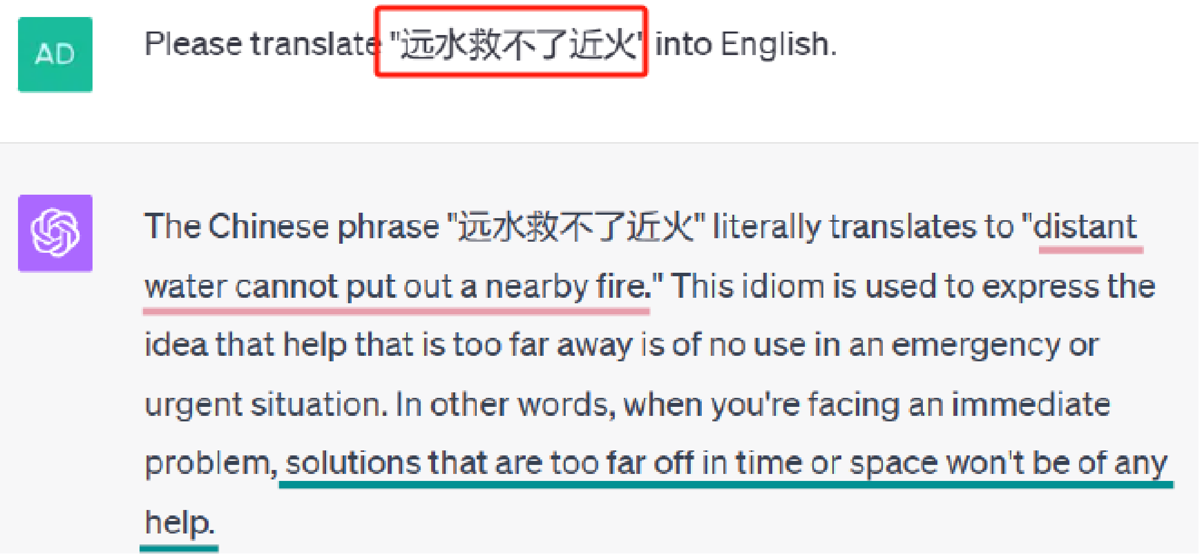


Please translate it into English:
大型语言模型已被证明在使用少量样本学习的情况下，能在各种自然语言任务中表现出色。为了进一步了解规模对少量样本学习的影响，我们训练了一个具有5400亿参数、密集激活的Transformer语言模型，我们称之为Pathways语言模型。

The translation of the provided text into English is:

"Large language models have been shown to perform well in various natural language tasks with limited sample learning. To further understand the impact of scale on limited sample learning, we trained a Transformer language model with 540 billion parameters and dense activations, which we call the Pathways language model."

Versatile Text Processing



Please translate "远水救不了近火" into English.

The Chinese phrase "远水救不了近火" literally translates to "distant water cannot put out a nearby fire." This idiom is used to express the idea that help that is too far away is of no use in an emergency or urgent situation. In other words, when you're facing an immediate problem, solutions that are too far off in time or space won't be of any help.

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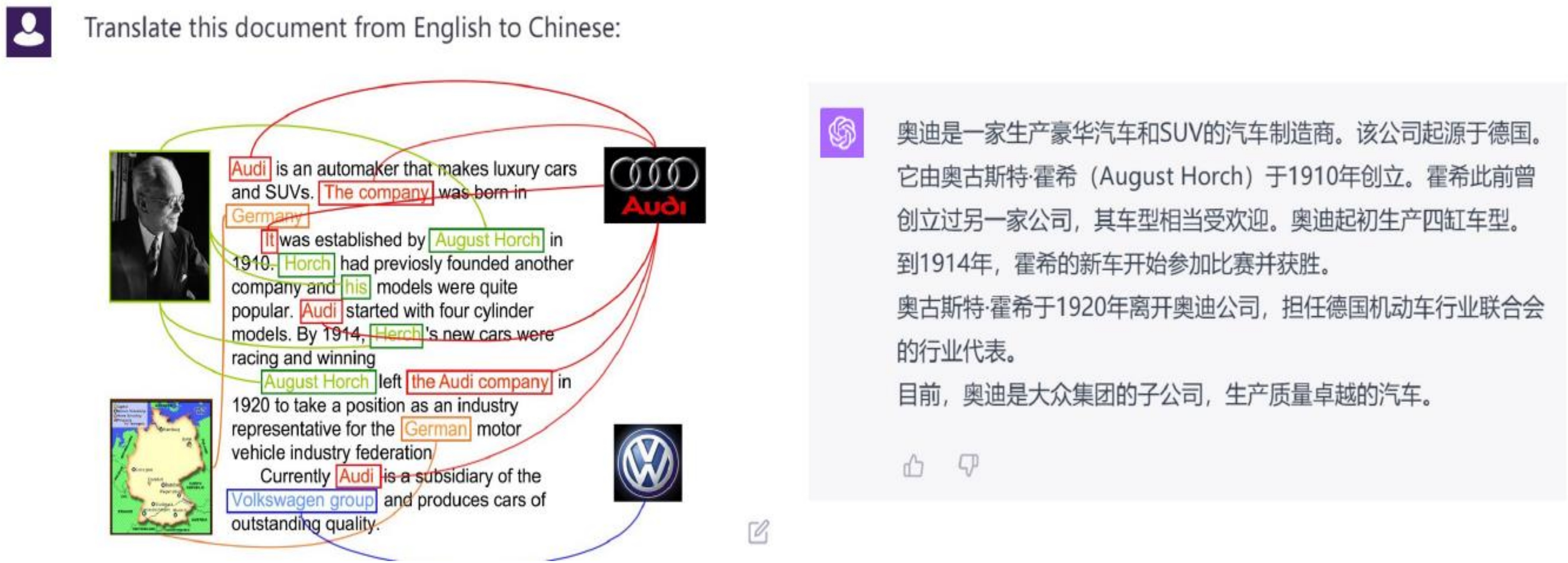
Pros of LLM-based MT

Document-Level Translation



Translate this document from English to Chinese:

Audi is an automaker that makes luxury cars and SUVs. The company was born in Germany

It was established by August Horch in 1910. Horch had previosly founded another company and his models were quite popular. Audi started with four cylinder models. By 1914, Horch's new cars were racing and winning

August Horch left the Audi company in 1920 to take a position as an industry representative for the German motor vehicle industry federation

Currently Audi is a subsidiary of the Volkswagen group and produces cars of outstanding quality.

奥迪是一家生产豪华汽车和SUV的汽车制造商。该公司起源于德国。它由奥古斯特·霍希（August Horch）于1910年创立。霍希此前曾创立过另一家公司，其车型相当受欢迎。奥迪起初生产四缸车型。到1914年，霍希的新车开始参加比赛并获胜。

奥古斯特·霍希于1920年离开奥迪公司，担任德国机动车行业联合会的行业代表。

目前，奥迪是大众集团的子公司，生产质量卓越的汽车。

Wang et al. Document-Level Machine Translation with Large Language Models. EMNLP 2023.

Prof. Liu CCMT 2023

Cons of LLM-based MT

1. Domain Expertise & Knowledge Transfer
    - Limited domain-specific terminology capture
    - Catastrophic forgetting during adaptation

2. Low-Resource Languages
    - Rare language pairs: room for improvement

3. Evaluation Bottlenecks
    - Traditional metrics fall short for high-quality translations

4. Computational Overhead
    - High cost for fine-tuning & adaptation

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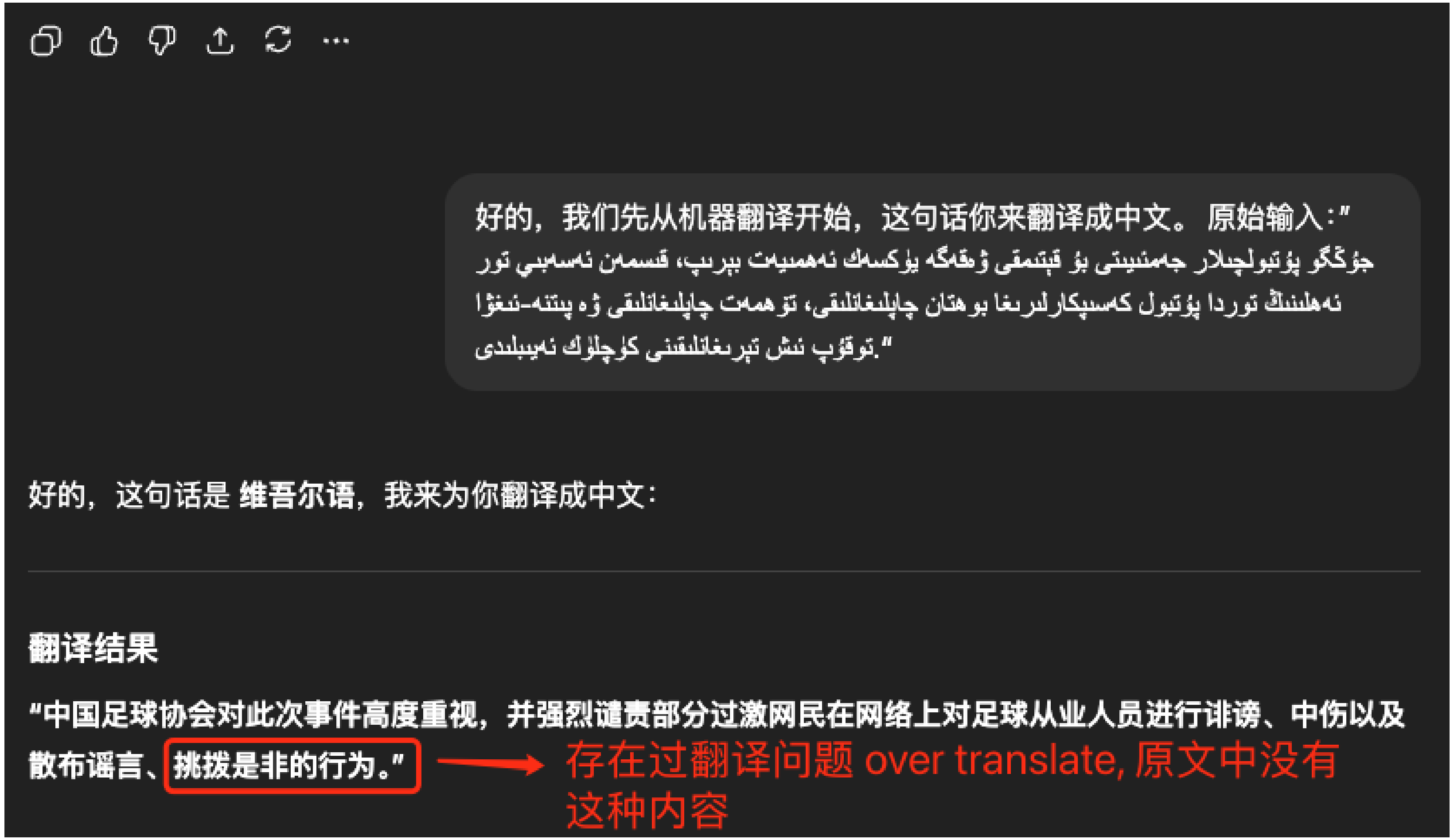
Challenges of LLM-based MT on LRLs

Closed model (GPT): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



好的，我们先从机器翻译开始，这句话你来翻译成中文。 原始输入：" جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى."

好的，这句话是 **维吾尔语**，我来为你翻译成中文：

翻译结果

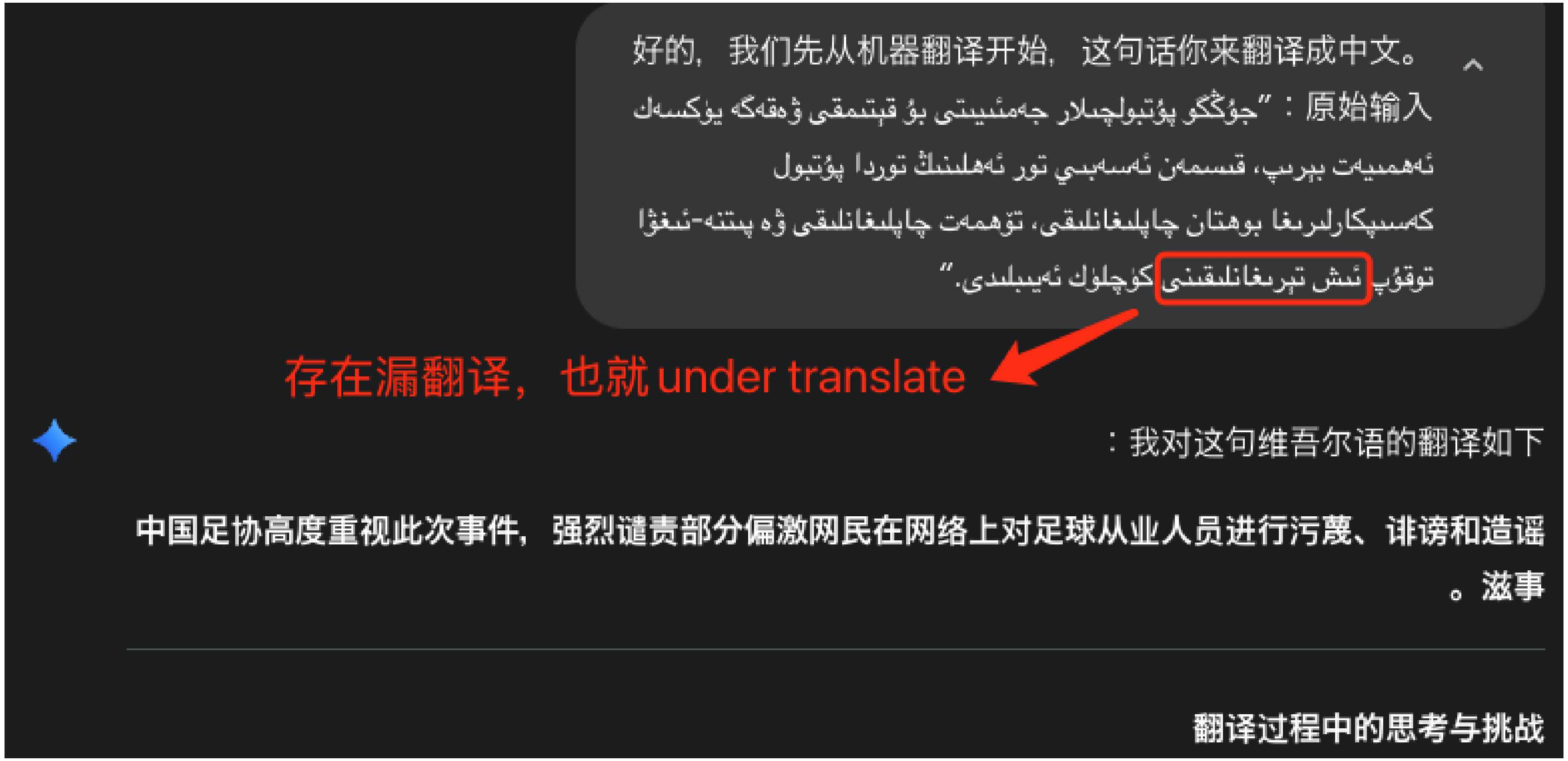
"中国足球协会对此次事件高度重视，并强烈谴责部分过激网民在网络上对足球从业人员进行诽谤、中伤以及散布谣言、挑拨是非的行为。"

→ 存在过翻译问题 over translate, 原文中没有这种内容

Ug→Zh translation sample

Closed model (Gemini): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



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原始输入：“جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”

存在漏翻译，也就 under translate

我对这句维吾尔语的翻译如下：

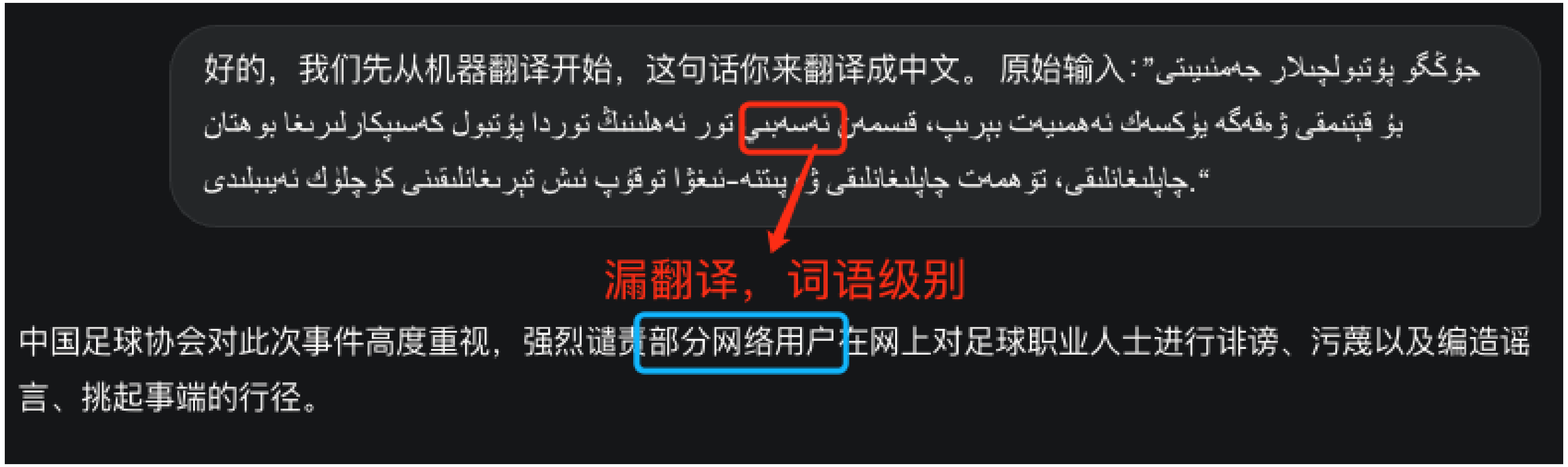
中国足协高度重视此次事件，强烈谴责部分偏激网民在网络上对足球从业人员进行污蔑、诽谤和造谣滋事。

翻译过程中的思考与挑战

Ug→Zh translation sample

Closed model (Grok): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



好的，我们先从机器翻译开始，这句话你来翻译成中文。原始输入：”جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.“

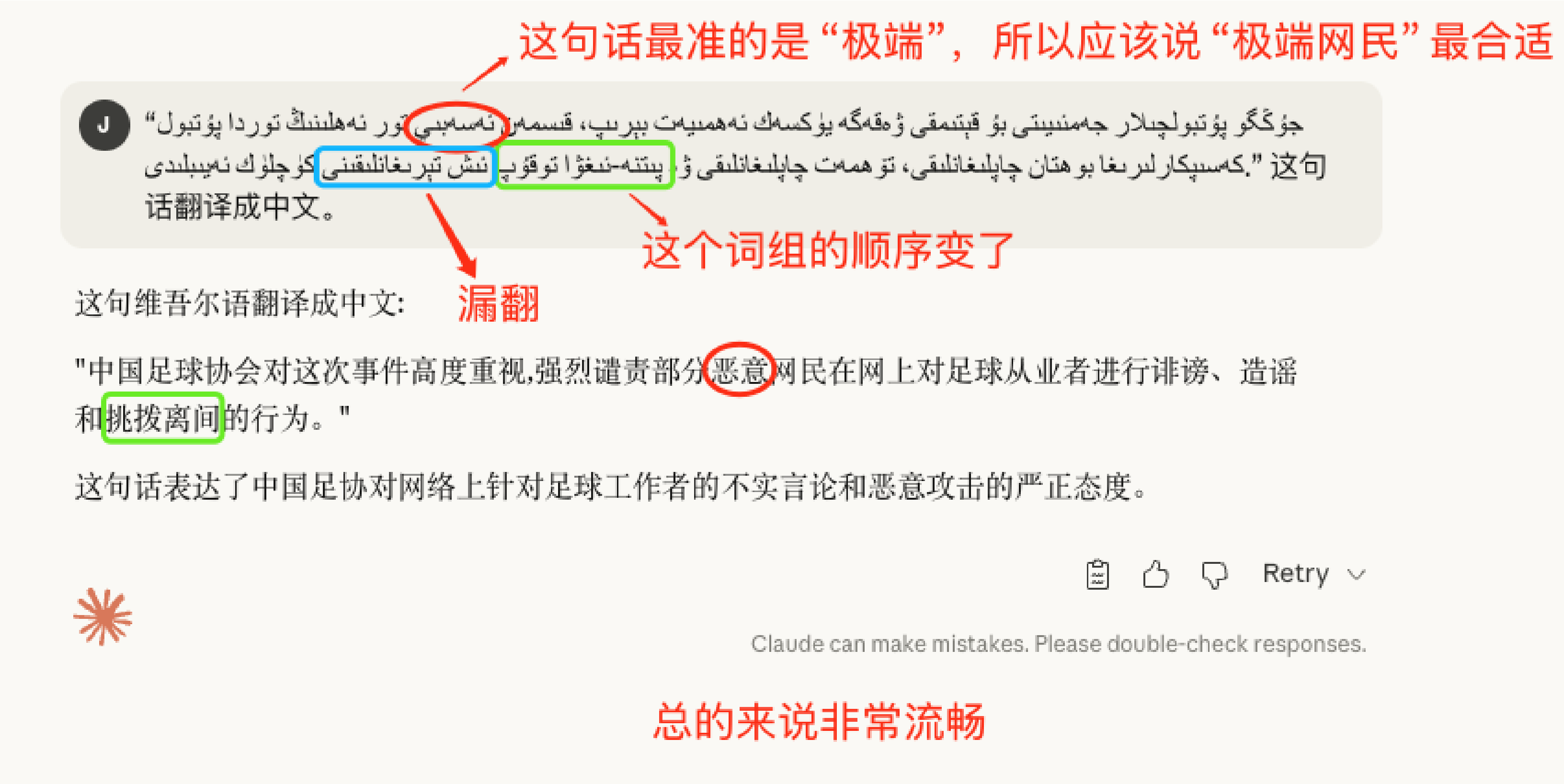
漏翻译，词语级别

中国足球协会对此次事件高度重视，强烈谴责部分网络用户在网上对足球职业人士进行诽谤、污蔑以及编造谣言、挑起事端的行径。

Ug→Zh translation sample

Closed model (Claude): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



这句话最准的是“极端”，所以应该说“极端网民”最合适

J “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.” 这句话翻译成中文。

这个词组的顺序变了

漏翻

这句维吾尔语翻译成中文:

"中国足球协会对这次事件高度重视,强烈谴责部分恶意网民在网上对足球从业者进行诽谤、造谣和挑拨离间的行为。"

这句话表达了中国足协对网络上针对足球工作者的不实言论和恶意攻击的严正态度。

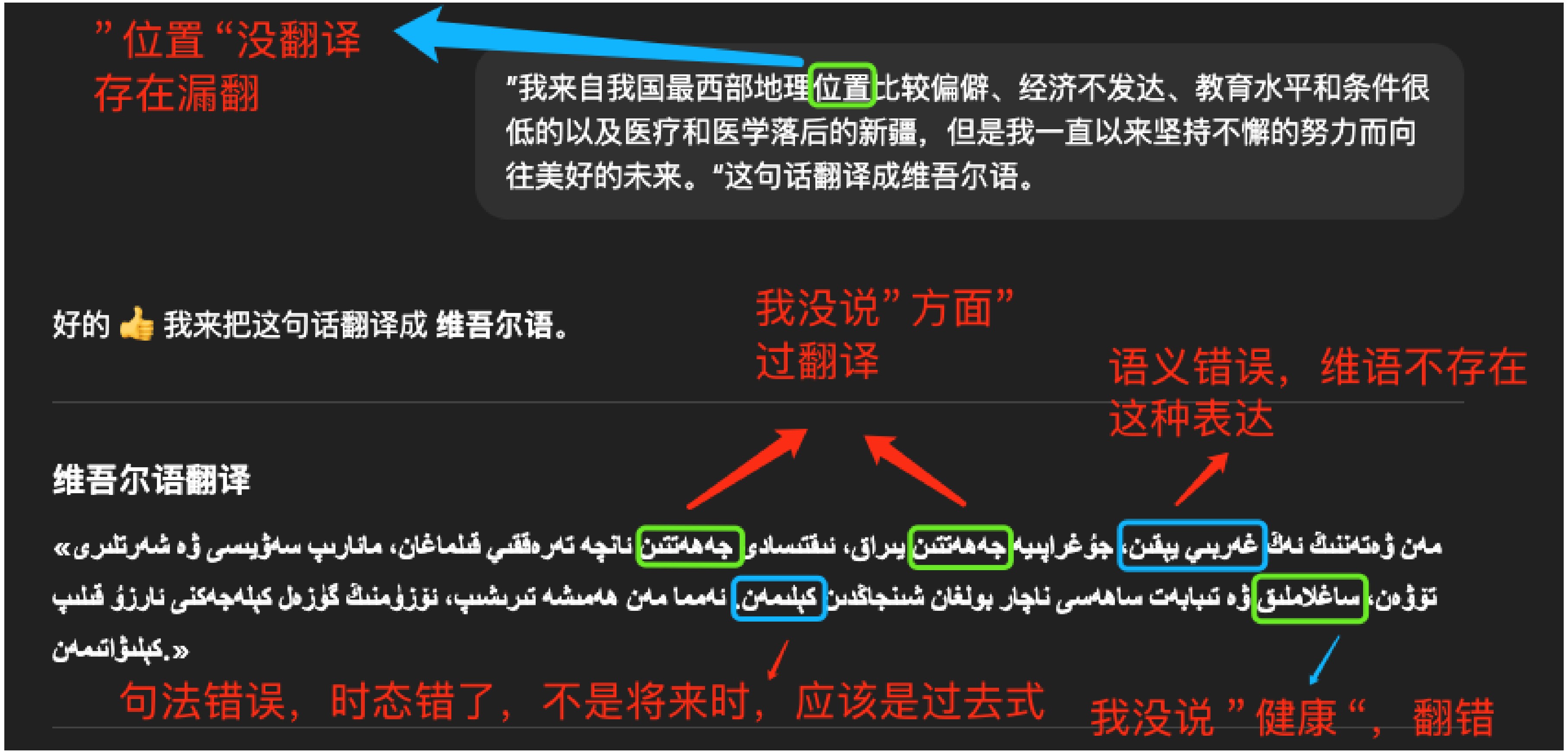
Claude can make mistakes. Please double-check responses.

总的来说非常流畅

Ug→Zh translation sample

Closed model (GPT): MT

Original Input：“我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



”位置“没翻译
存在漏翻

"我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。"这句话翻译成维吾尔语。

好的 👍 我来把这句话翻译成 **维吾尔语**。

我没说”方面”
过翻译

语义错误，维语不存在
这种表达

维吾尔语翻译

«مەن ۋەتەننىڭ ئەڭ غەربىي يېقىن، جۇغراپىيە جەھەتتىن يىراق، ئىقتىسادى جەھەتتىن ئانچە تەرەققىي قىلماغان، مائارىپ سەۋىيىسى ۋە شەرتلىرى
تۆۋەن، ساغلاملىق ۋە تىبابەت ساھەسى ناچار بولغان شىنجاڭدىن كېلىمەن. ئەمما مەن ھەمىشە تىرىشىپ، ئۆزۈمنىڭ گۈزەل كېلەچەكنى ئارزۇ قىلىپ
كېلىۋاتىمەن.»

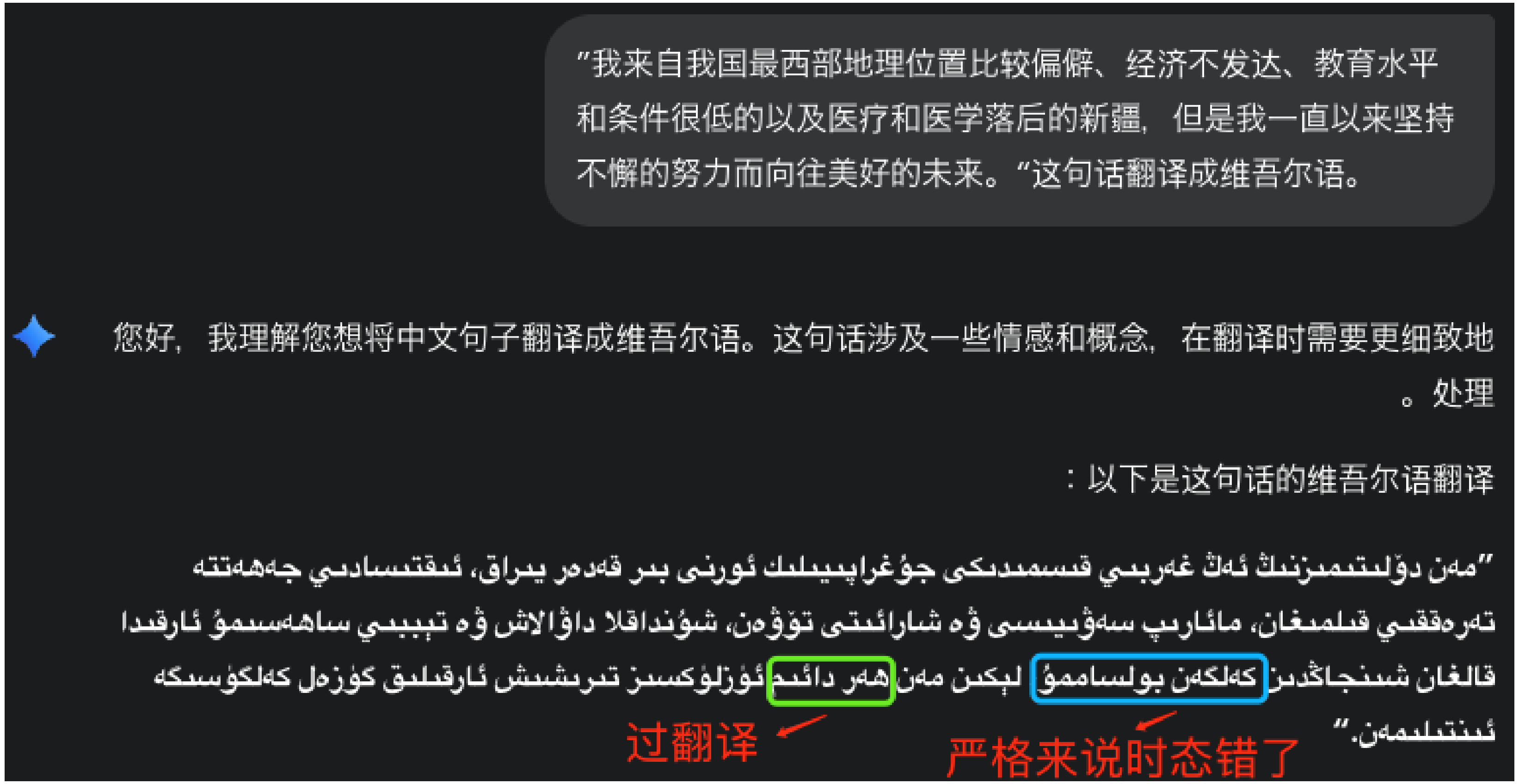
句法错误，时态错了，不是将来时，应该是过去式

我没说”健康“，翻错

Zh →Ug translation sample

Closed model (Gemini): MT

Original Input：“我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



"我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。"这句话翻译成维吾尔语。

您好，我理解您想将中文句子翻译成维吾尔语。这句话涉及一些情感和概念，在翻译时需要更细致地处理。

以下是这句话的维吾尔语翻译：

”مەن دۆلىتىمىزنىڭ ئەڭ غەربىي قىسمىدىكى جۇغراپىيىلىك ئورنى بىر قەدەر يىراق، ئىقتىسادىي جەھەتتە
تەرەققىي قىلمىغان، مائارىپ سەۋىيىسى ۋە شارائىتى تۆۋەن، شۇنداقلا داۋالاش ۋە تىببىي ساھەسىمۇ ئارقىدا
قالغان شىنجاڭدىن كەلگەن بولساممۇ لېكىن مەن ھەر دائىم ئۆزلۈكسىز تىرىشىش ئارقىلىق گۈزەل كەلگۈسىگە
ئىنتىلىمەن.“

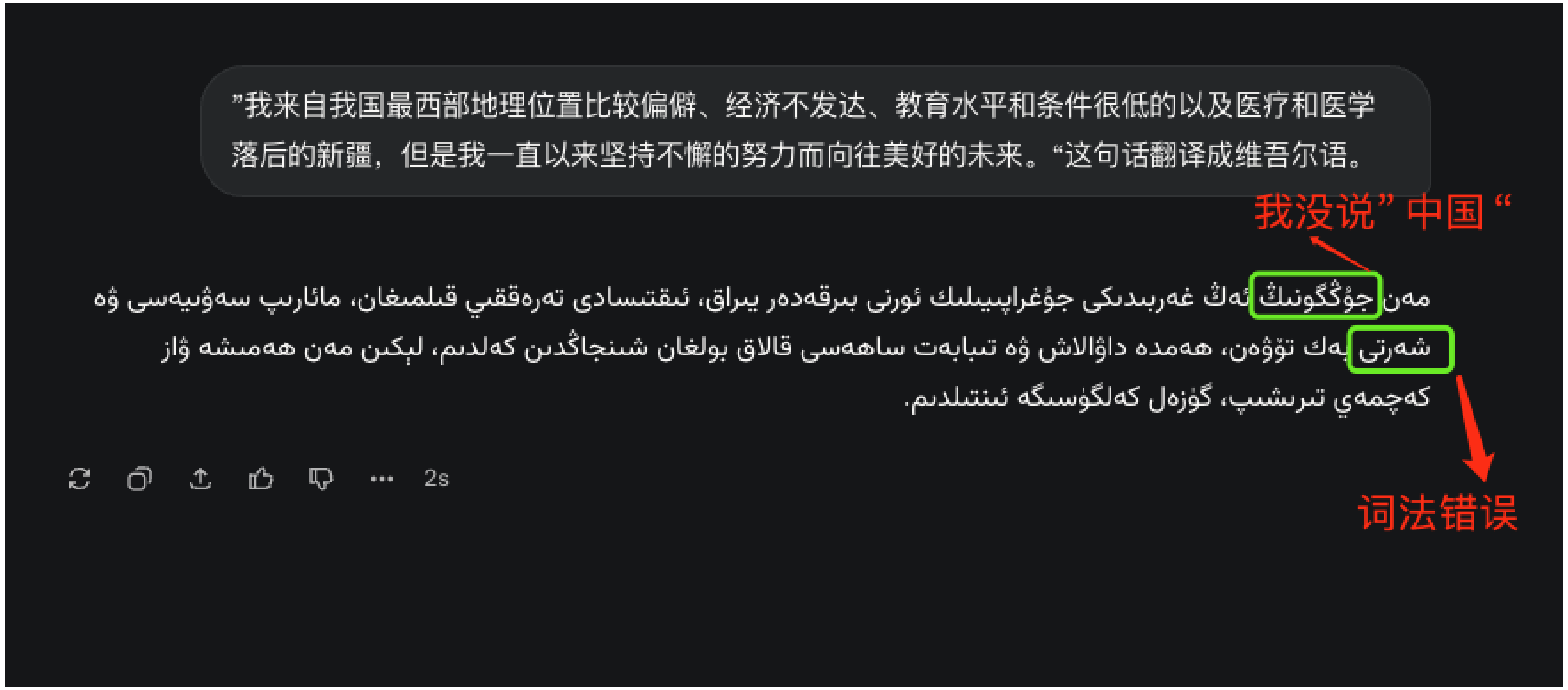
过翻译

严格来说时态错了

Zh →Ug translation sample

Closed model (Grok): MT

Original Input： “我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



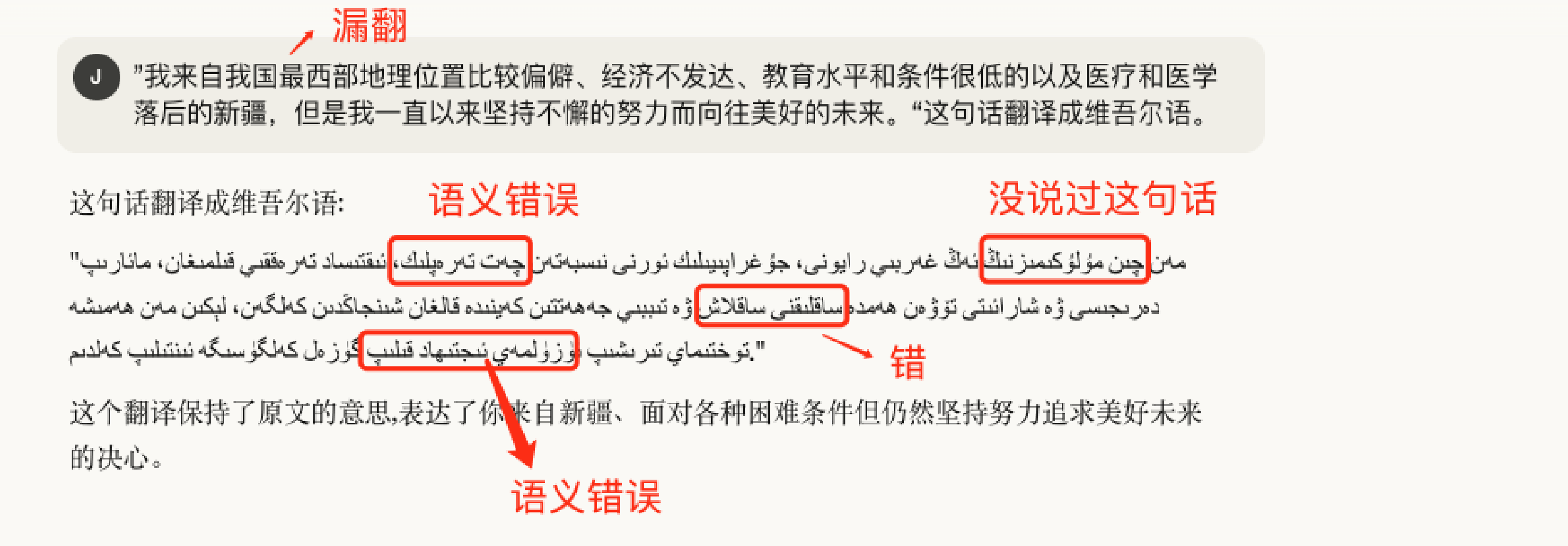
”我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。“这句话翻译成维吾尔语。

مەن جۇڭگونىڭ ئەڭ غەربىدىكى جۇغراپىيىلىك ئورنى بىرقەدەر يىراق، ئىقتىسادى تەرەققىي قىلمىغان، مائارىپ سەۋىيەسى ۋە
شەرتى بەك تۆۋەن، ھەمدە داۋالاش ۋە تېبابەت ساھەسى قالاق بولغان شىنجاڭدىن كەلدىم، لېكىن مەن ھەمىشە ۋاز
كەچمەي تىرىشىپ، گۈزەل كەلگۈسىگە ئىنتىلدىم.

Zh →Ug translation sample

Closed model (Claude): MT

Original Input：“我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



J ”我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。“这句话翻译成维吾尔语。

这句话翻译成维吾尔语:

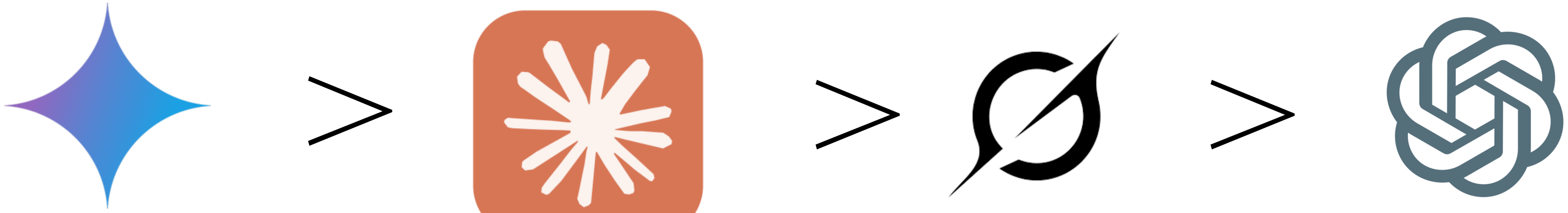
"مەن چىن مۇلۇكىمىزنىڭ ئەڭ غەربىي رايونى، جۇغراپىيىلىك ئورنى نىسبەتەن چەت تەرەپلىك، ئىقتىساد تەرەققىي قىلمىغان، مائارىپ دەرىجىسى ۋە شارائىتى تۆۋەن ھەمدە ساقلىقنى ساقلاش ۋە تىببىي جەھەتتىن كەينىدە قالغان شىنجاڭدىن كەلگەن، لېكىن مەن ھەمىشە توختىماي تىرىشىپ ئۈزۈلمەي ئىجتىھاد قىلىپ گۈزەل كەلگۈسىگە ئىنتىلىپ كەلدىم."

这个翻译保持了原文的意思,表达了你来自新疆、面对各种困难条件但仍然坚持努力追求美好未来的决心。

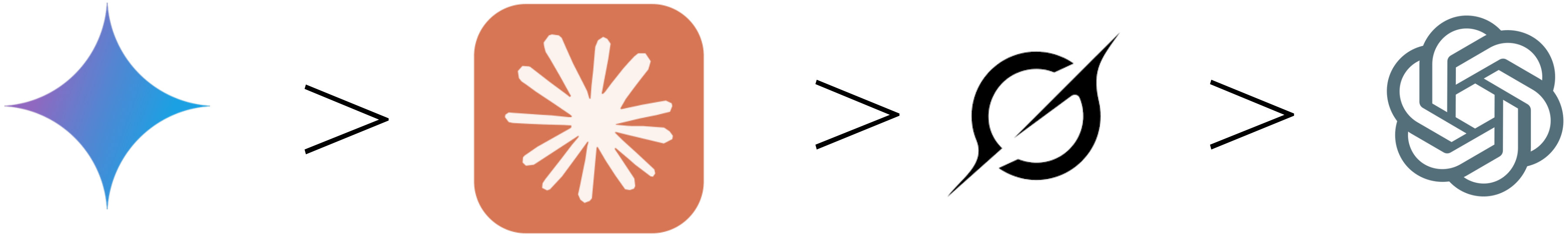
Zh →Ug translation sample

MT Performance Comparison

Zh →Ug translation sample

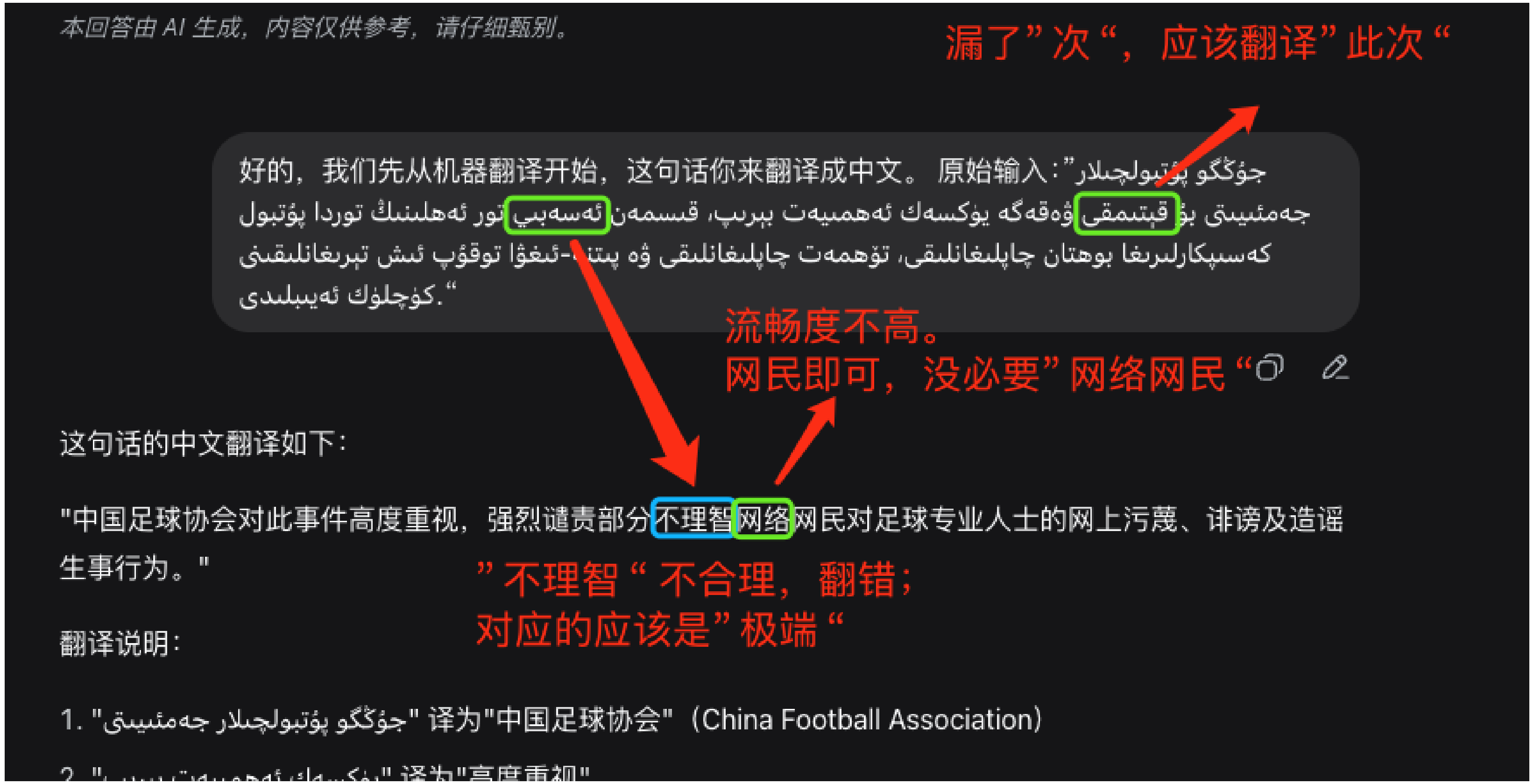


Ug→Zh translation sample



Open model (DeepSeek): MT

Original Input: ”جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۇكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان“



本回答由 AI 生成，内容仅供参考，请仔细甄别。

好的，我们先从机器翻译开始，这句话你来翻译成中文。原始输入：”جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۇكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.“

这句话的中文翻译如下：

"中国足球协会对此事件高度重视，强烈谴责部分不理智网络网民对足球专业人士的网上污蔑、诽谤及造谣生事行为。"

翻译说明：

1. "جۇڭگو پۇتبولچىلار جەمئىيىتى" 译为"中国足球协会"（China Football Association）

2. "يۇكسەك ئەھمىيەت بېرىپ" 译为"高度重视"

漏了”次“，应该翻译”此次“

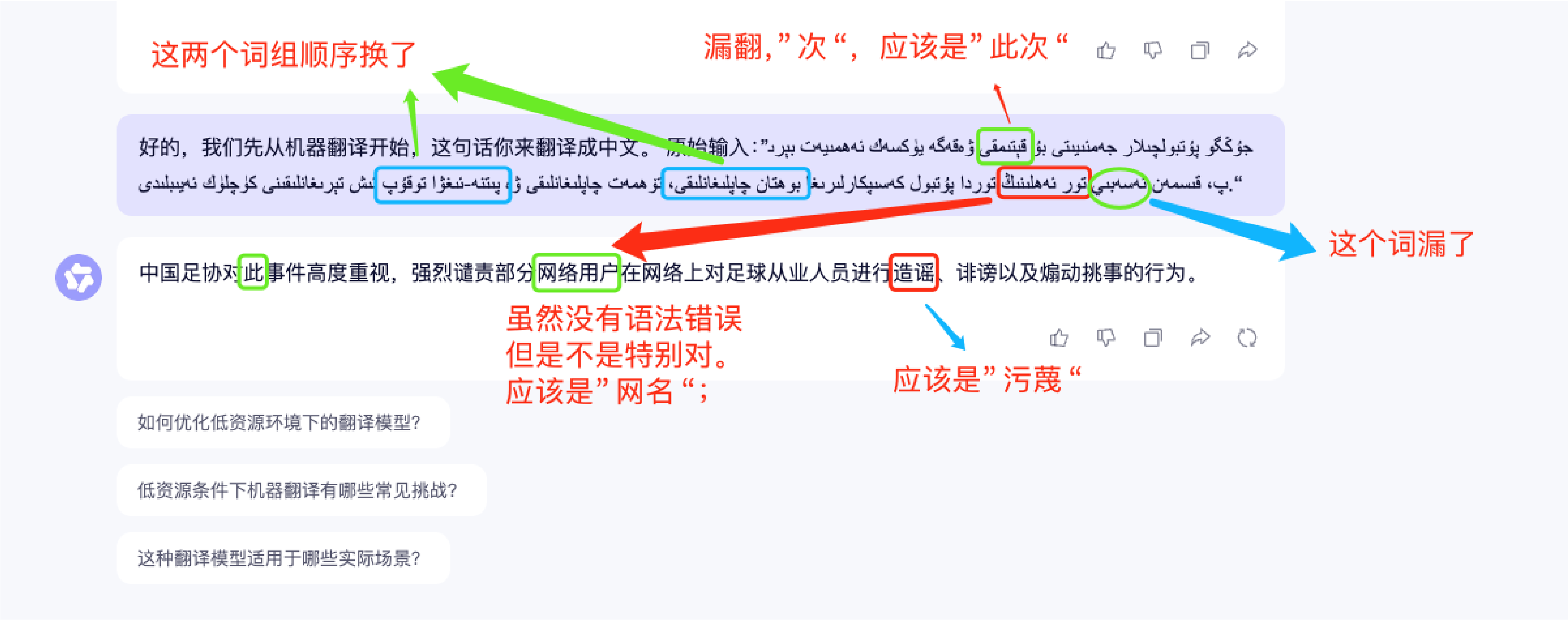
流畅度不高。
网民即可，没必要”网络网民“

”不理智“不合理，翻错；
对应的应该是”极端“

Ug→Zh translation sample

Open model (Qwen): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



好的，我们先从机器翻译开始，这句话你来翻译成中文。原始输入："جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى."

中国足协对此事件高度重视，强烈谴责部分网络用户在网络上对足球从业人员进行造谣、诽谤以及煽动挑事的行为。

这两个词组顺序换了

漏翻，”次“，应该是”此次“

这个词漏了

虽然没有语法错误
但是不是特别对。
应该是”网名“；

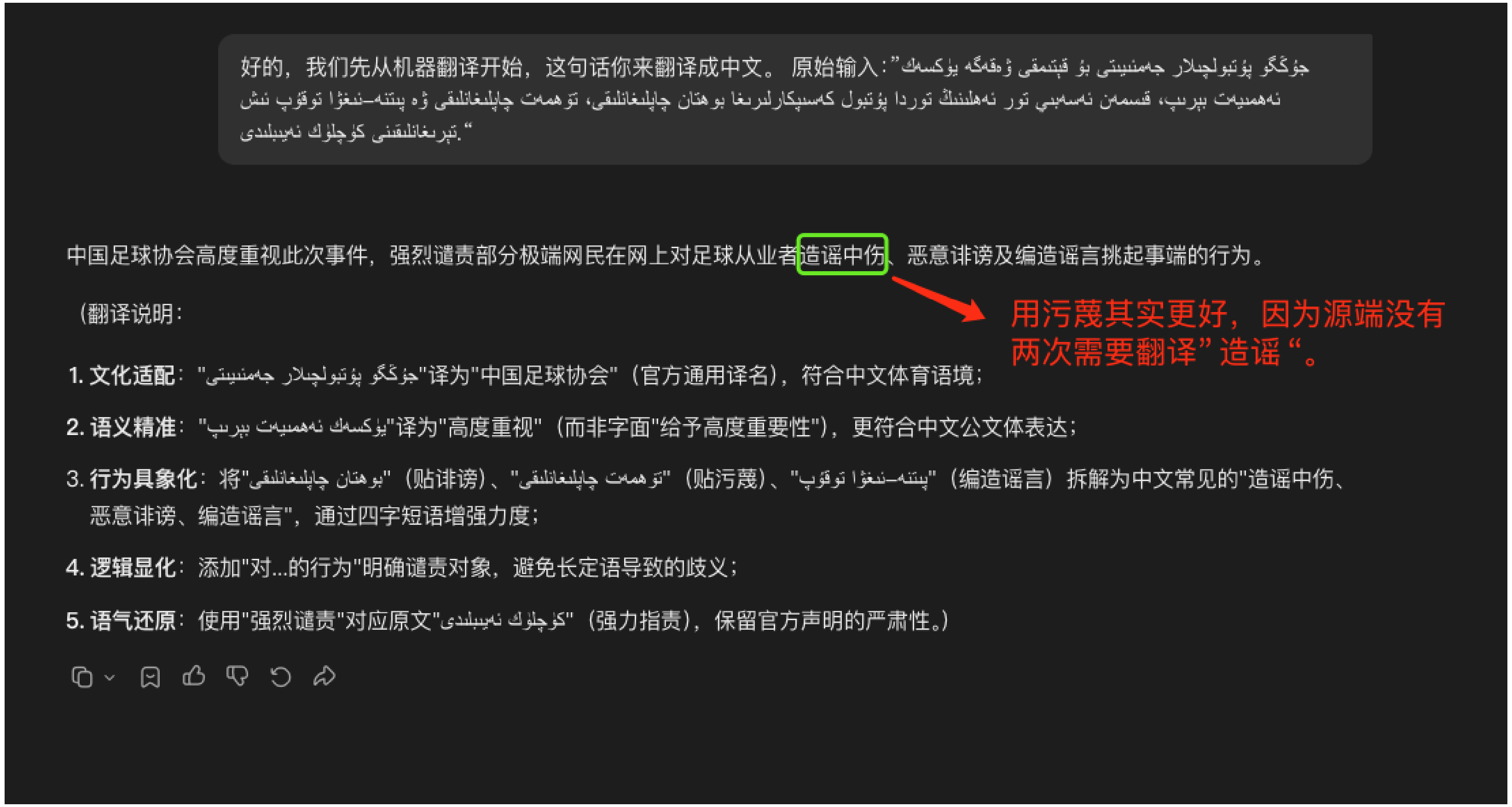
应该是”污蔑“

如何优化低资源环境下的翻译模型?
低资源条件下机器翻译有哪些常见挑战?
这种翻译模型适用于哪些实际场景?

Ug→Zh translation sample

Open model (Yuanbao): MT

Original Input: “جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە-ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.”



好的，我们先从机器翻译开始，这句话你来翻译成中文。 原始输入：”جۇڭگو پۇتبولچىلار جەمئىيىتى بۇ قېتىمقى ۋەقەگە يۈكسەك ئەھمىيەت بېرىپ، قىسمەن ئەسەبىي تور ئەھلىنىڭ توردا پۇتبول كەسپكارلىرىغا بوھتان چاپلىغانلىقى، تۆھمەت چاپلىغانلىقى ۋە پىتنە–ئىغۋا توقۇپ ئىش تېرىغانلىقىنى كۈچلۈك ئەيىبلىدى.“

中国足球协会高度重视此次事件，强烈谴责部分极端网民在网上对足球从业者造谣中伤、恶意诽谤及编造谣言挑起事端的行为。

（翻译说明：

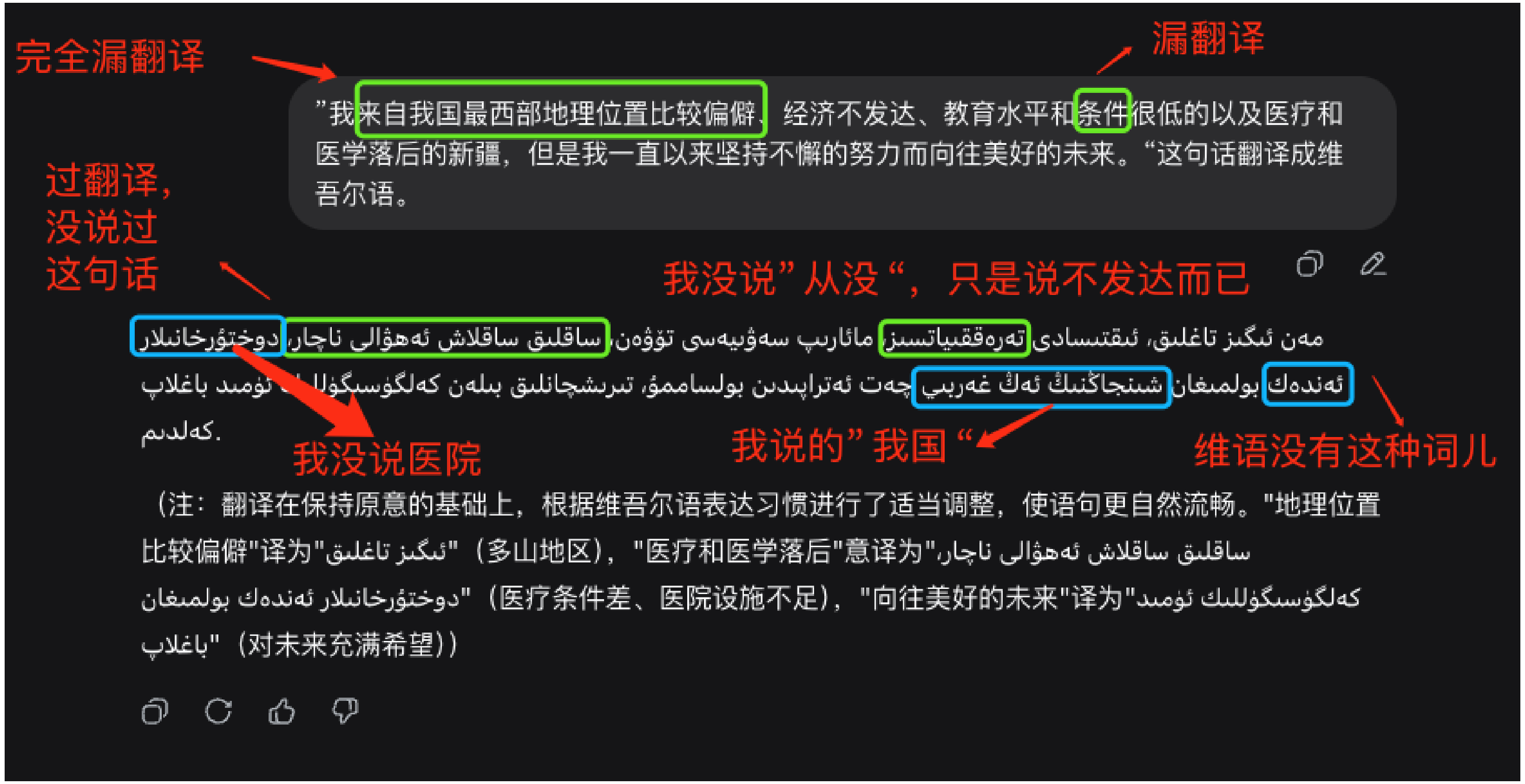
1. **文化适配**："جۇڭگو پۇتبولچىلار جەمئىيىتى"译为"中国足球协会"（官方通用译名），符合中文体育语境；
2. **语义精准**："يۈكسەك ئەھمىيەت بېرىپ"译为"高度重视"（而非字面"给予高度重要性"），更符合中文公文体表达；
3. **行为具象化**：将"بوھتان چاپلىغانلىقى"（贴诽谤）、"تۆھمەت چاپلىغانلىقى"（贴污蔑）、"پىتنە–ئىغۋا توقۇپ"（编造谣言）拆解为中文常见的"造谣中伤、恶意诽谤、编造谣言"，通过四字短语增强力度；
4. **逻辑显化**：添加"对...的行为"明确谴责对象，避免长定语导致的歧义；
5. **语气还原**：使用"强烈谴责"对应原文"كۈچلۈك ئەيىبلىدى"（强力指责），保留官方声明的严肃性。）

用污蔑其实更好，因为源端没有两次需要翻译”造谣“。

Ug→Zh translation sample

Open model (DeepSeek): MT

Original Input: “我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



”我来自我国最西部地理位置比较偏僻，经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。“这句话翻译成维吾尔语。

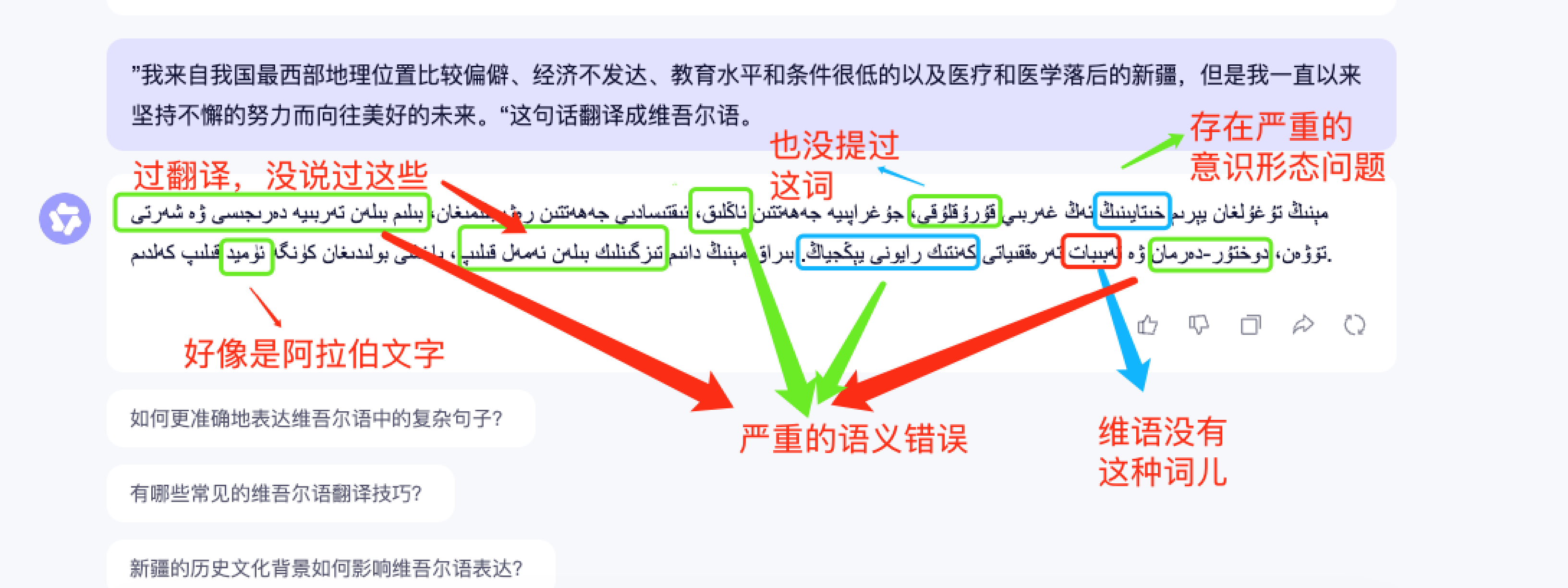
مەن ئىگىز تاغلىق، ئىقتىسادى تەرەققىياتسىز، مائارىپ سەۋىيەسى تۆۋەن، ساقلىق ساقلاش ئەھۋالى ناچار، دوختۇرخانىلار ئەندەك بولمىغان شىنجاڭنىڭ ئەڭ غەربىي چەت ئەتراپىدىن بولسامۇ، تىرىشچانلىق بىلەن كەلگۈسگۈللۈك ئۈمىد باغلاپ كەلدىم.

（注：翻译在保持原意的基础上，根据维吾尔语表达习惯进行了适当调整，使语句更自然流畅。"地理位置比较偏僻"译为"ئىگىز تاغلىق"（多山地区），"医疗和医学落后"意译为"ساقلىق ساقلاش ئەھۋالى ناچار، دوختۇرخانىلار ئەندەك بولمىغان"（医疗条件差、医院设施不足），"向往美好的未来"译为"كەلگۈسگۈللۈك ئۈمىد باغلاپ"（对未来充满希望））

Zh →Ug translation sample

Open model (Qwen): MT

Original Input：“我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



”我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。“这句话翻译成维吾尔语。

مېنىڭ تۇغۇلغان يېرىم خىتاينىڭ ئەڭ غەربىي قۇرۇقلۇقى، جۇغراپىيە جەھەتتىن ناگلىق، ئىقتىسادىي جەھەتتىن رەۋ[illegible]لەنمىغان، بىلىم بىلەن تەربىيە دەرىجىسى ۋە شەرتى

تۆۋەن، دوختۇر-دەرمان ۋە تىببات ئەرمەقىياتى كەنتتىك رايونى يېڭجىياڭ. بىراق مېنىڭ دائىم تىزگىنلىك بىلەن نەمەل قىلىپ، [illegible] بولىدىغان كۈنگە ئۈمىد قىلىپ كەلدىم

如何更准确地表达维吾尔语中的复杂句子?

有哪些常见的维吾尔语翻译技巧?

新疆的历史文化背景如何影响维吾尔语表达?

过翻译，没说过这些

也没提过这词

存在严重的意识形态问题

好像是阿拉伯文字

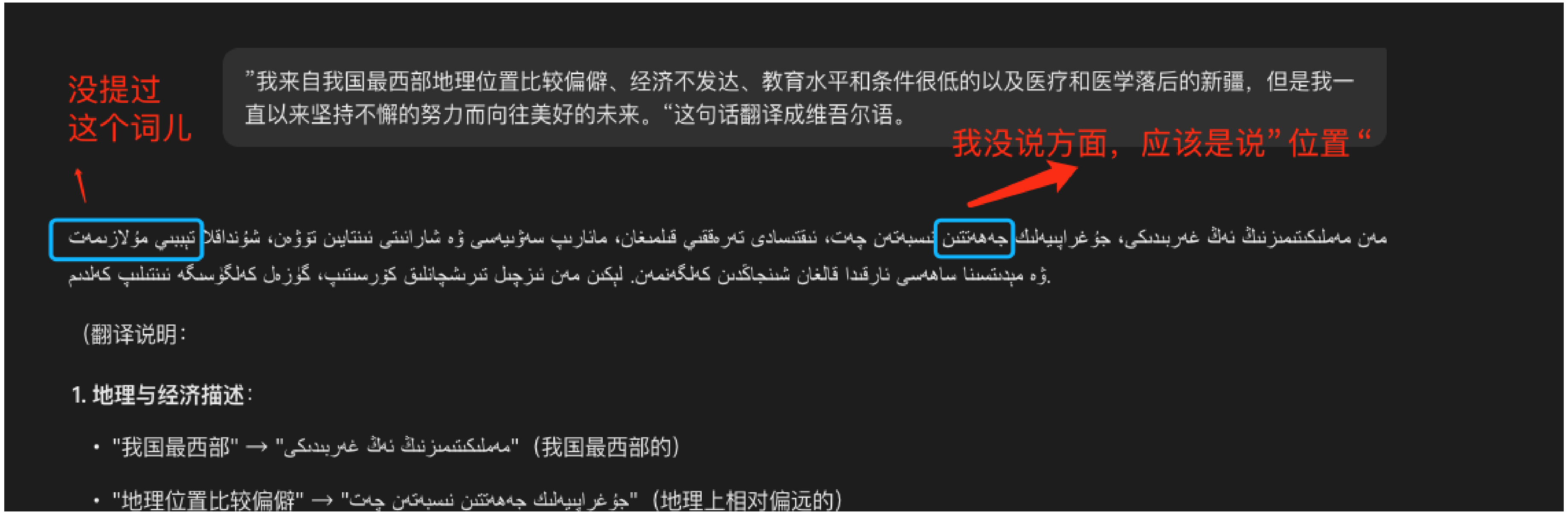
严重的语义错误

维语没有这种词儿

Zh →Ug translation sample

Open model (Yuanbao): MT

Original Input：“我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。”



”我来自我国最西部地理位置比较偏僻、经济不发达、教育水平和条件很低的以及医疗和医学落后的新疆，但是我一直以来坚持不懈的努力而向往美好的未来。“这句话翻译成维吾尔语。

مەن مەملىكىتىمىزنىڭ ئەڭ غەربىدىكى، جۇغراپىيەلىك جەھەتتىن نىسبەتەن چەت، ئىقتىسادى تەرەققىي قىلمىغان، مائارىپ سەۋىيەسى ۋە شارائىتى ئىنتايىن تۆۋەن، شۇنداقلا تېببىي مۇلازىمەت ۋە مېدىتسىنا ساھەسى ئارقىدا قالغان شىنجاڭدىن كەلگەنمەن. لېكىن مەن ئىزچىل تىرىشچانلىق كۆرسىتىپ، گۈزەل كەلگۈسىگە ئىنتىلىپ كەلدىم

（翻译说明：

1. 地理与经济描述：

- "我国最西部" → "مەملىكىتىمىزنىڭ ئەڭ غەربىدىكى"（我国最西部的）
- "地理位置比较偏僻" → "جۇغراپىيەلىك جەھەتتىن نىسبەتەن چەت"（地理上相对偏远的）

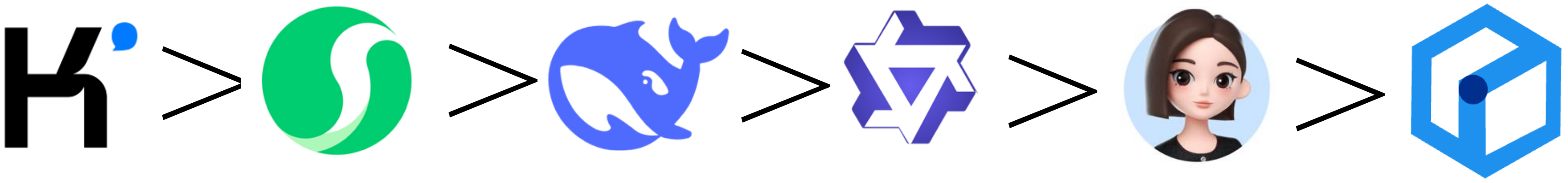
没提过
这个词儿

我没说方面，应该是说”位置“

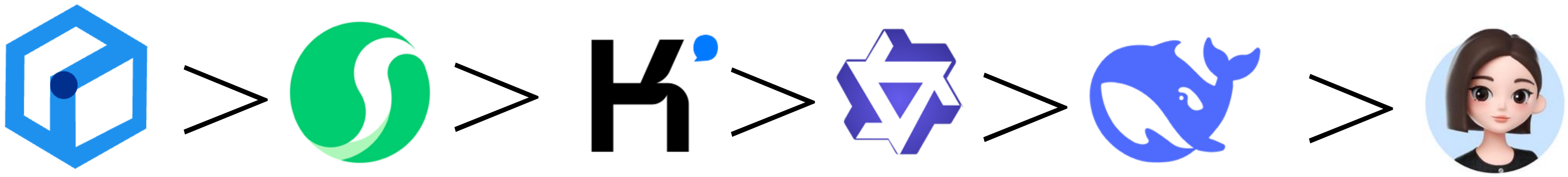
Zh →Ug translation sample

MT Performance Comparison

Ug→Zh translation sample



Zh →Ug translation sample



Main Challenges

- **Omission** – Missing content or phrases
- **Over-translation** – Unnecessary or redundant content
- **Semantic Errors** – Incorrect meaning or misinterpretation
- **Syntactic Errors** – Grammatical or structural issues
- **Word-level Errors** – Inaccurate lexical choices

Outline

- LLM Everywhere
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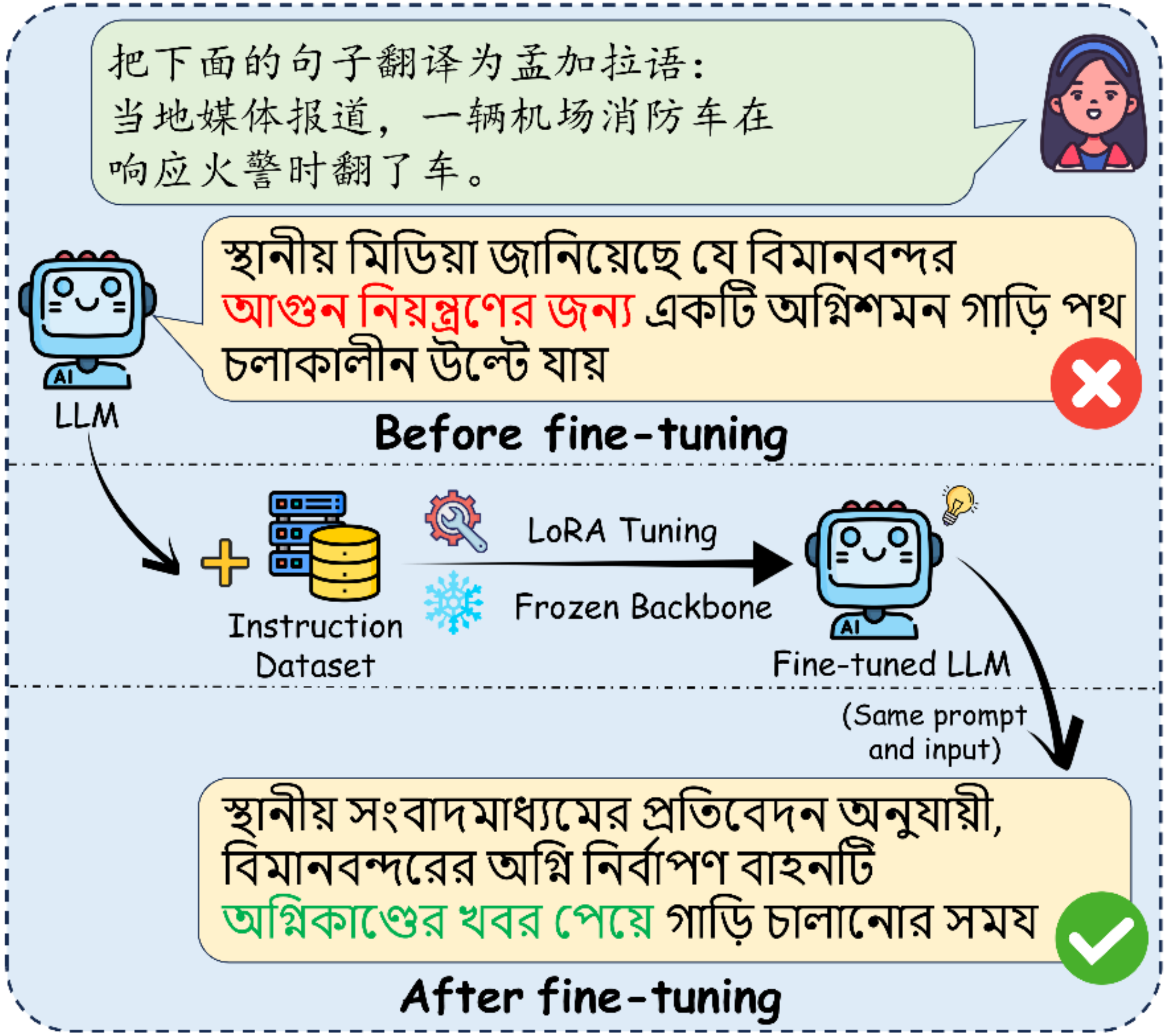
- Challenges of LLM-based MT on LRLs
- Strategies for Text-only LLM-based MT
- Findings on Multi-modal LLM-based MT
- Conclusion

Strategies for Text-only LLM-based MT

Constructing LRLs Instruction



把下面的句子翻译为孟加拉语：
当地媒体报道，一辆机场消防车在
响应火警时翻了车。

স্থানীয় মিডিয়া জানিয়েছে যে বিমানবন্দর
আগুন নিয়ন্ত্রণের জন্য একটি অগ্নিশমন গাড়ি পথ
চলাকালীন উল্টে যায়

স্থানীয় সংবাদমাধ্যমের প্রতিবেদন অনুযায়ী,
বিমানবন্দরের অগ্নি নির্বাপণ বাহনটি
অগ্নিকাণ্ডের খবর পেয়ে গাড়ি চালানোর সময়

Low-Resource Bottleneck: LLM performance constrained by scarce, low-quality instruction datasets

Proposed Solution: Refined Instruction Tuning — an automated pipeline for high-quality Chinese→X instruction corpora

Constructing LRLs Instruction

- Experiment
  - Dataset
    - Constructed high-quality instruction datasets for 8 low-resource Chinese → X directions (with approximately 5k instances per direction), covering Uyghur (ug), Tibetan (bo), Persian (fa), Hebrew (he), Urdu (ur), Bengali (bn), Vietnamese (vi), and Indonesian (id).

Region	Language	Size	AverageLength
China	zh→ug	5k	98.93
	zh→ur	5k	106.36
Middle East	zh→fa	5k	102.74
	zh→he	5k	99.09
South Asia	zh→ur	5k	104.03
	zh→bn	5k	97.08
Southeast Asia	zh→vi	5k	97.04
	zh→id	5k	97.27

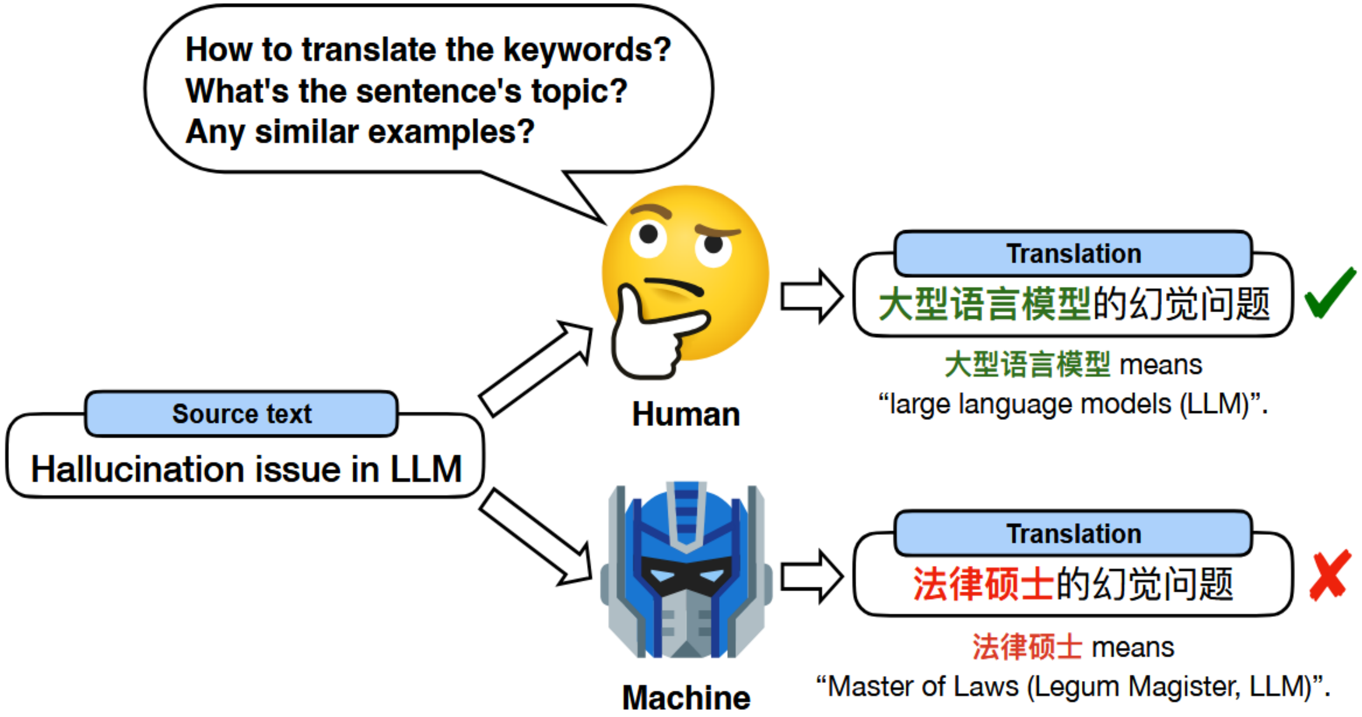
Constructing LRLs Instruction

- Experiment
  - Main experiment
    - Main experimental results on the FLOWERS+, IWSLT, and CCMatrix test sets, with scores being the average of four evaluation metrics: Chrf++, COMET, XCOMET-XL, and BLEURT.
    - FLORES+ (8 languages): Achieved a SOTA macro-average of 61.78 (+5.57 over Direct baseline) .

Method	**FLORES+** (zh→xx)							
	ug	bo	ur	bn	fa	he	vi	id
Madlad	42.99	40.64	54.10	56.85	60.31	61.74	70.58	75.08
Direct	35.52	40.73	52.94	55.53	64.25	54.29	74.30	72.11
COD	38.03	**49.35**	53.48	60.75	60.70	60.76	72.62	77.10
MAPS	37.15	48.22	55.28	**63.21**	66.15	**63.06**	74.95	78.44
CompTrans	34.37	46.58	52.10	53.10	62.92	58.51	73.59	77.17
Ours	**49.66**	45.84	**58.11**	57.45	**66.24**	62.29	**75.57**	**79.07**

Prior Knowledge and COT

- Motivation



How to translate the keywords?
What's the sentence's topic?
Any similar examples?

Source text
Hallucination issue in LLM

Human

Translation
大型语言模型的幻觉问题 ✓

大型语言模型 means
“large language models (LLM)”.

Machine

Translation
法律硕士的幻觉问题 ✗

法律硕士 means
“Master of Laws (Legum Magister, LLM)”.

Figure 1: The difference between machine and human translation in an English→Chinese example

- Inherent Limitations: LLMs struggle in low-resource translation via **Direct Prompting** due to a lack of explicit linguistic reasoning.

- Information Deficiency: Existing CoT methods suffer from coarse granularity, failing to systematically integrate the deep, **multi-source knowledge** required for precise translation.

Prior Knowledge and COT

- Dataset & Evaluation Metrics & Models
  - Dataset
    - The experiments utilize the official FLORES-200 benchmark alongside custom-curated test sets from IWSLT and CCMatrix, which were manually cleaned and filtered to ensure high-quality evaluation across diverse low-resource contexts.

Dataset	Language Pairs	Size (per pair)
FLORES-200	En ↔ {Fa, Ur, Lo, Uz}	1,012
IWSLT	Zh → {Fa, He, Id, Vi}	1,000
CCMatrix	Zh → {Fa, He, Id, Bn, Vi}	1,000

Table 1: Statistics of Evaluation Datasets

Prior Knowledge and COT

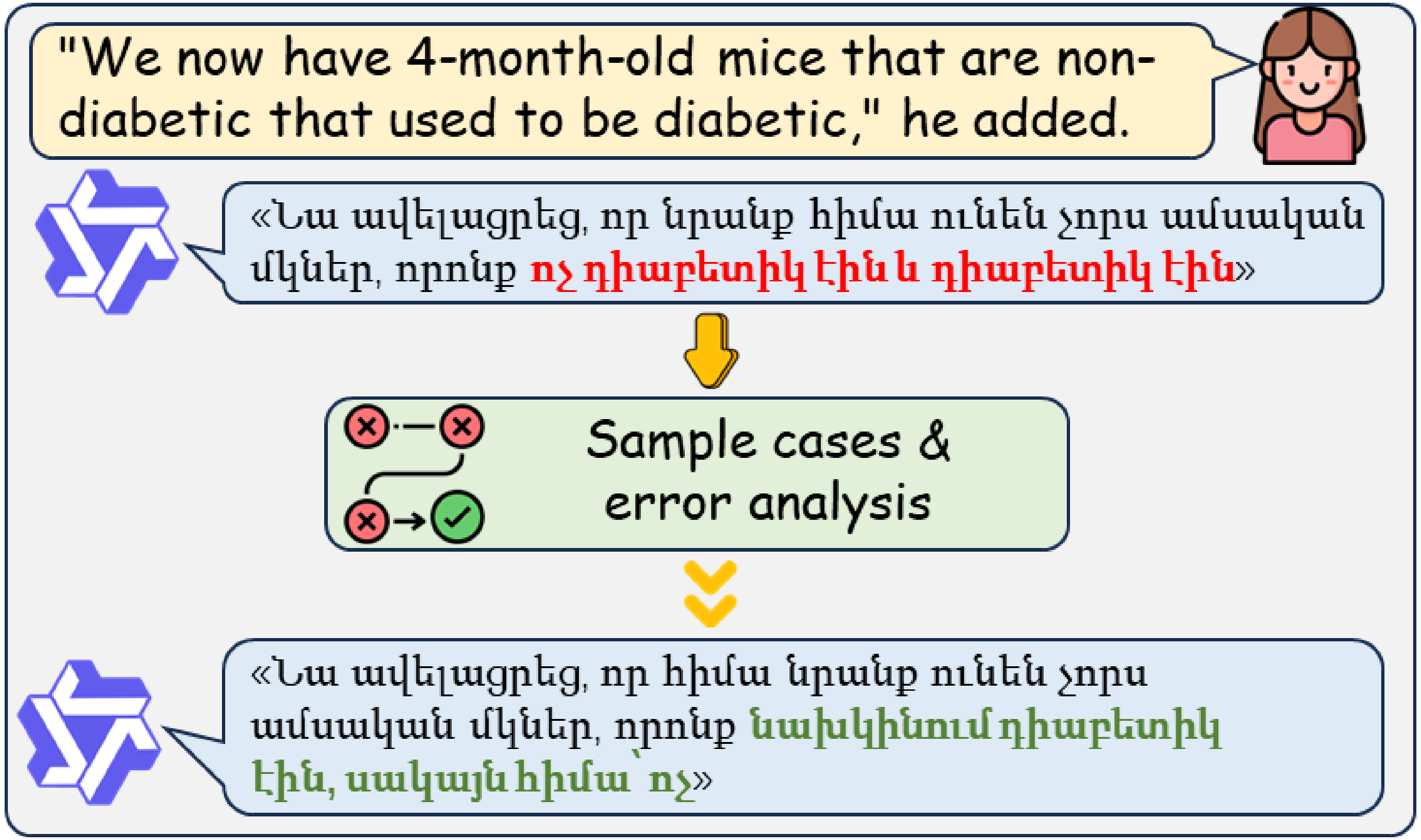
- Experiment
  - Main experiment
    - Achieved superior performance in most directions, notably reaching 88.10 on en-fa and 88.24 on en-uz. The model consistently outperforms 0-shot, MAPS and CompTra baselines across diverse language pairs.
    - Demonstrated substantial improvements in challenging low-resource directions, such as en-lo and en-uz. These results highlight strong cross-lingual transfer and generalization capabilities.

Method	Middle East		South Asia		Southeast Asia		Middle Asia	
	en-fa	fa-en	en-ur	ur-en	en-lo	lo-en	en-uz	uz-en
Madlad	85.31	87.78	79.15	87.05	**83.59**	**87.80**	N/A	N/A
0-shot	86.43	87.82	80.97	86.98	78.15	85.83	84.55	86.10
MAPS	87.59	**88.38**	82.24	87.61	79.86	80.54	87.25	**87.11**
COD	85.63	87.69	80.93	86.96	78.01	85.67	85.20	85.88
CompTra	84.77	87.26	78.79	86.30	72.75	84.61	84.00	85.59
Ours	**88.10**	88.27	**82.91**	**87.62**	82.14	86.57	**88.24**	86.96

Table 2: Main results across multiple low-resource language pairs on FLORES-200 using Qwen3-30B-A3B-Instruct-2507, evaluated with COMET.

RAG and Refined COT

- Motivation



"We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.

«Նա ավելացրեց, որ նրանք հիմա ունեն չորս ամսական մկներ, որոնք ոչ դիաբետիկ էին և դիաբետիկ էին»

«Նա ավելացրեց, որ հիմա նրանք ունեն չորս ամսական մկներ, որոնք նախկինում դիաբետիկ էին, սակայն հիմա՝ ոչ»

- Although LLMs demonstrate promising translation and self-refinement capabilities , their performance remains severely constrained in low-resource scenarios.
- Leveraging external knowledge via RAG assists LLM translation , but relying solely on contextual parallel examples and single-round generation is insufficient to resolve diverse errors.

RAG and Refined COT

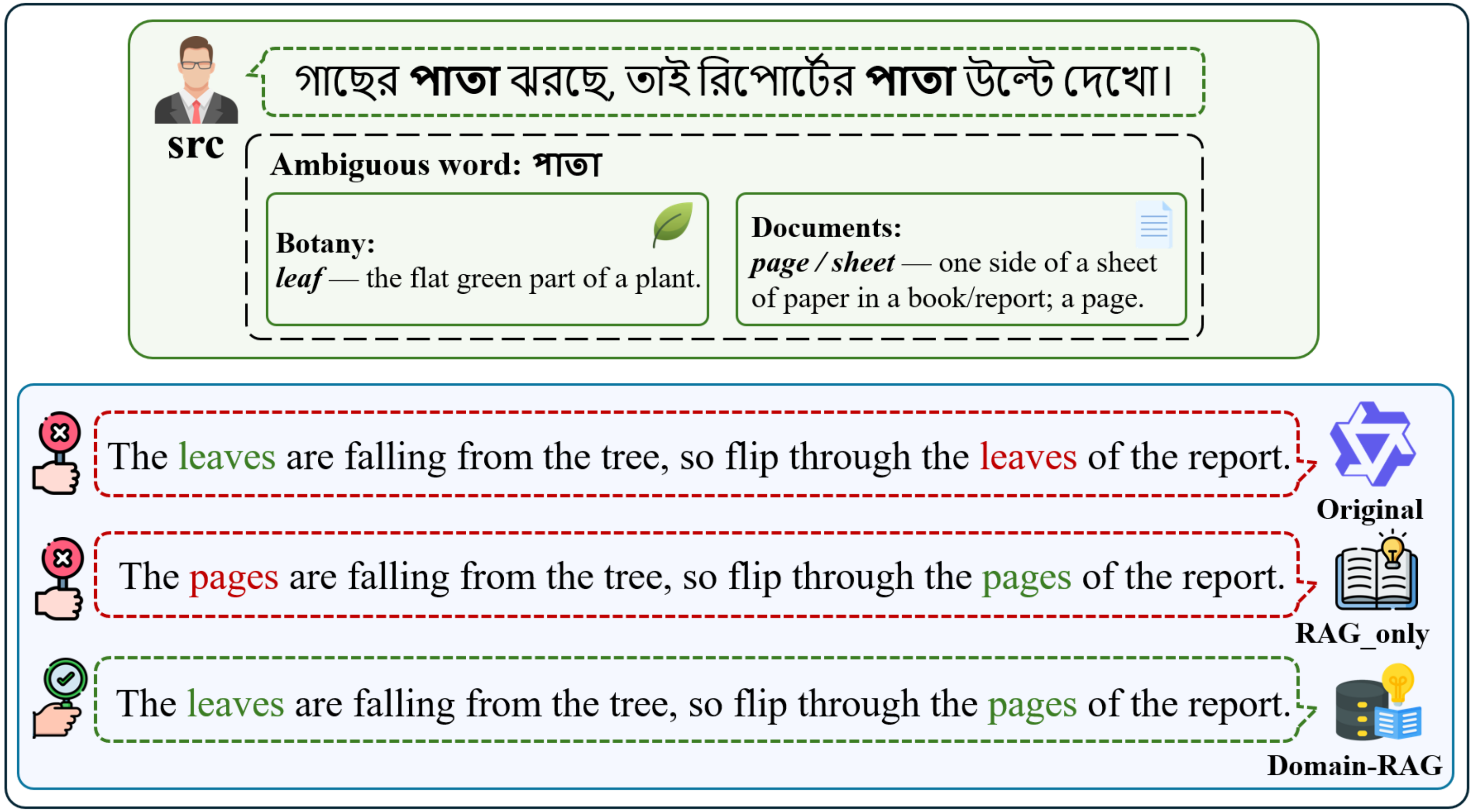
- Experiment
  - Main experiment
    - Main experimental results on the FLORES-200, NTREX-128, and TICO-19 with XCOMET-XL and BLEURT-20 metrics.
    - The method consistently achieves the strongest or highly competitive performance on the multi-domain dataset FLORES-200.

Method	Armenian		Azerbaijani		Hebrew		Lao	
	XCOMET	BLEURT	XCOMET	BLEURT	XCOMET	BLEURT	XCOMET	BLEURT
0-shot	59.85	67.48	58.09	60.55	62.30	59.99	46.02	57.33
Vanilla RAG	64.25	70.19	61.49	62.06	65.71	62.17	52.86	65.23
COD	64.14	68.43	60.67	61.60	64.47	61.36	48.56	57.96
MAPS	67.88	72.08	64.41	64.53	69.03	64.45	52.92	**63.77**
TEaR	63.32	69.27	60.86	61.36	66.00	62.28	48.35	59.88
CompTra	55.37	58.29	59.86	61.29	65.26	62.01	48.95	52.27
OURS	**68.32**	**71.80**	**65.44**	**64.68**	**71.45**	**65.83**	**54.01**	64.44

Method	Khmer		Tamil		Urdu		Bengali	
	XCOMET	BLEURT	XCOMET	BLEURT	XCOMET	BLEURT	XCOMET	BLEURT
0-shot	49.51	52.69	49.78	70.25	62.37	55.22	63.01	69.48
Vanilla RAG	55.40	58.19	51.94	72.32	64.22	55.88	66.08	71.43
COD	50.39	52.01	48.26	67.96	58.44	54.01	62.63	69.46
MAPS	55.59	57.39	**53.43**	72.87	67.03	**56.80**	68.19	72.30
TEaR	51.50	53.59	51.25	71.53	63.93	55.27	65.72	70.63
CompTra	48.47	43.73	43.05	55.45	59.87	54.61	52.95	58.87
OURS	**56.99**	**58.14**	53.74	**73.76**	**67.75**	56.95	**68.36**	**72.39**

Word Disambiguation

- Motivation



src

গাছের **পাতা** ঝরছে, তাই রিপোর্টের **পাতা** উল্টে দেখো।

Ambiguous word: পাতা

Botany:
leaf — the flat green part of a plant.

Documents:
page / sheet — one side of a sheet of paper in a book/report; a page.

✗ The leaves are falling from the tree, so flip through the leaves of the report.

Original

✗ The pages are falling from the tree, so flip through the pages of the report.

RAG_only

✓ The leaves are falling from the tree, so flip through the pages of the report.

Domain-RAG

- Low-resource languages lack sufficient high-quality bilingual data, making traditional RAG hard to apply.
- LLMs are vulnerable to lexical ambiguity in cross-domain translation, which may cause semantic hallucinations.
- Existing RAG systems rely on coarse sentence- or document-level retrieval and cannot precisely disambiguate high-risk ambiguous words.

Word Disambiguation

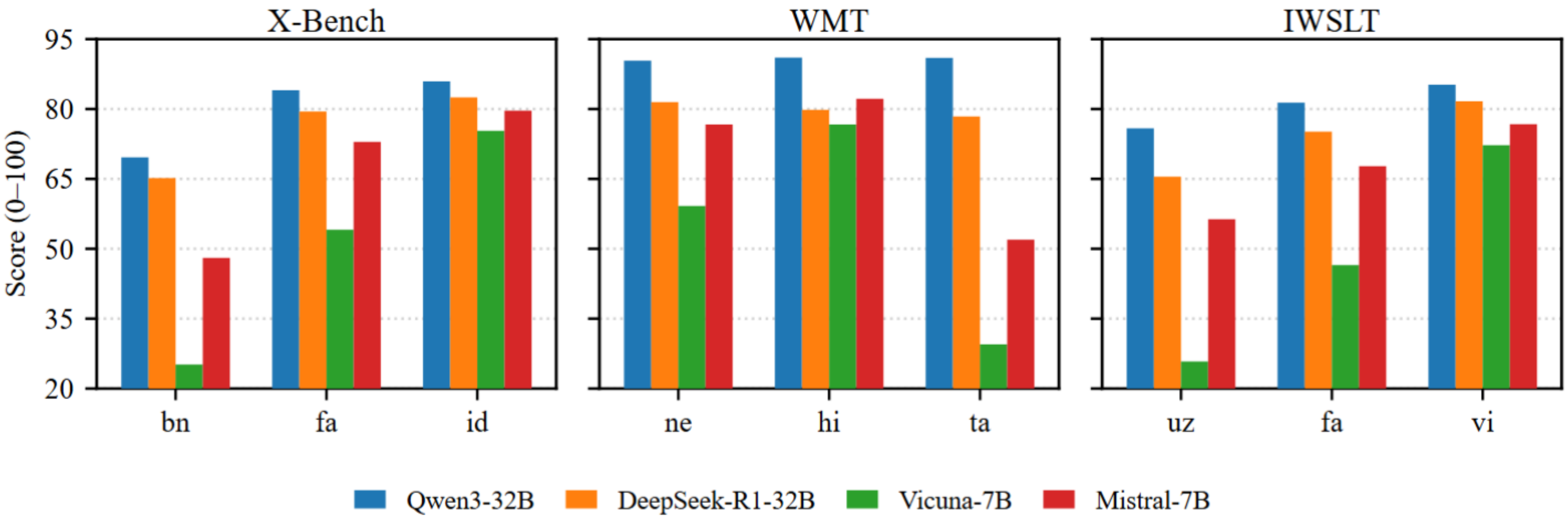
- Dataset

  - We evaluate Domain-aware RAG on three benchmarks: X-Bench , WMT , and IWSLT. As shown in Table, the X-Bench is a multi-domain benchmark that includes six Languages, such as Bengali (bn), Hungarian (hu), Urdu (ur), Persian (fa), Malay (ms), Indonesian (id), and seven domains. For each Language, we sample from public OPUS corpora.

Lan.	**OpenSubtitles**	**TED 2020**	**QED**	**Tanzil**	**wikimedia**	**WikiMatrix**	**Europarl**	**WMT-News**	**TEP**	**Size**
hu	✓	✓	✓			✓	✓	✓		**1.2K**
ms	✓	✓	✓	✓	✓					**1.1K**
ur	✓	✓	✓	✓	✓					**0.8K**
bn	✓	✓	✓	✓		✓				**0.9K**
fa		✓	✓	✓		✓			✓	**0.9K**
id	✓	✓	✓	✓		✓				**1.2K**

Word Disambiguation

- Ablation study
  - The Influence of Decision Agent.
    - We sample 500 instances per direction from X-Bench, WMT, and IWSLT and use ChatGPT-4o for scoring.Qwen3-32B is the most consistent top performer and is adopted as the default decision agent.



Outline

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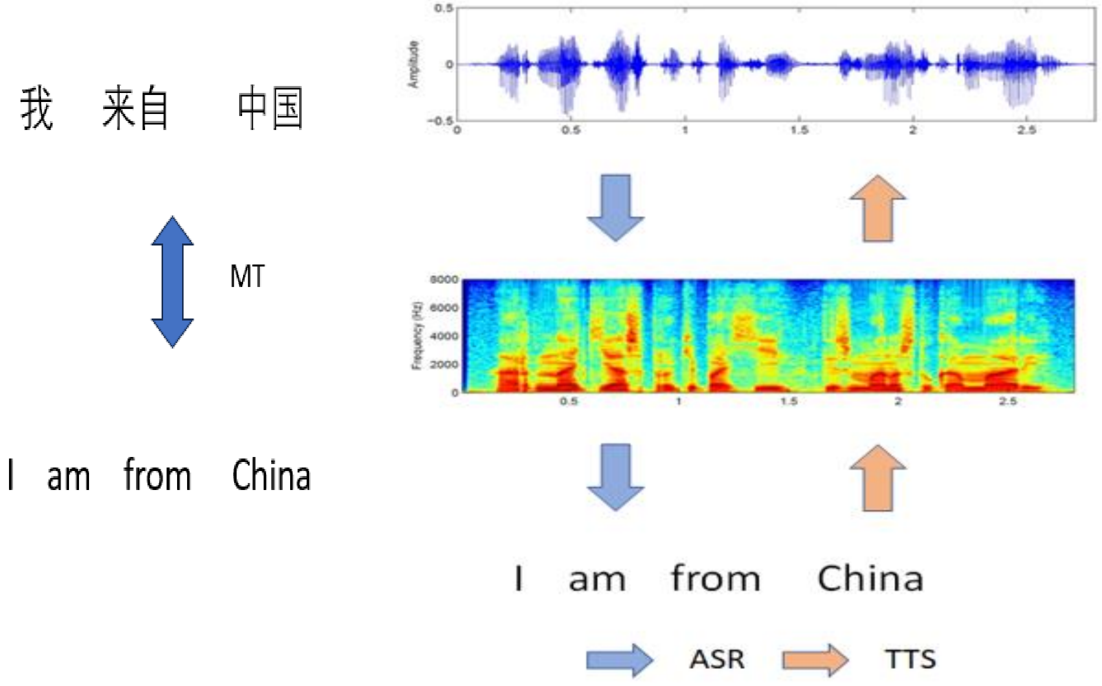
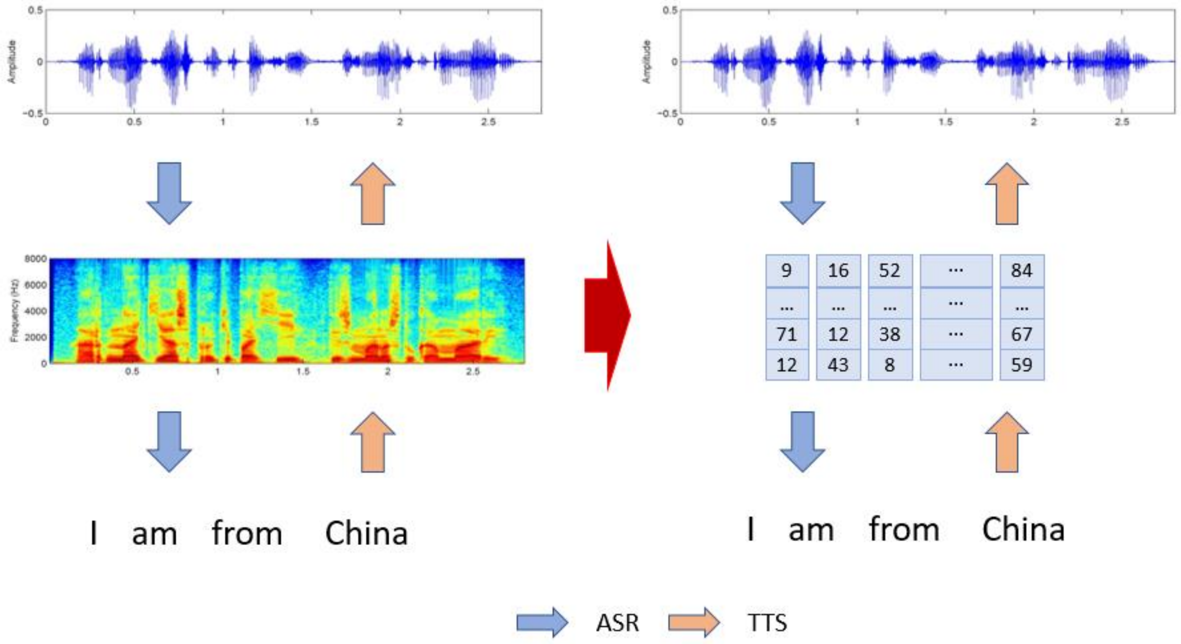
Findings on Multi-modal LLM-based MT

Multi-modal LLM-based MT --- Speech



Speech Processing vs NLP



9	16	52	…	84
…	…	…	…	…
71	12	38	…	67
12	43	8	…	59

From Continuous Signals to Discrete Tokens

Prof. Liu CCMT2023

Multi-modal LLM-based MT --- Image

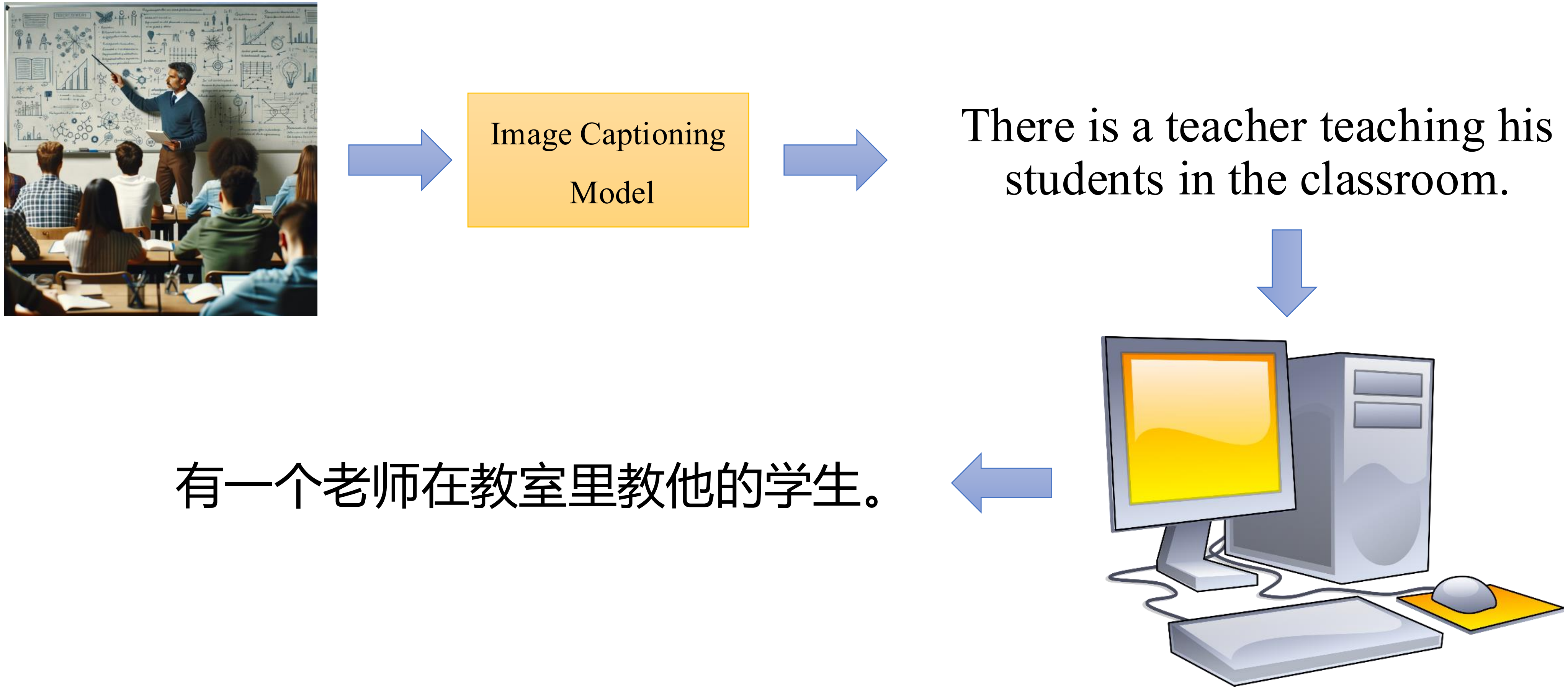
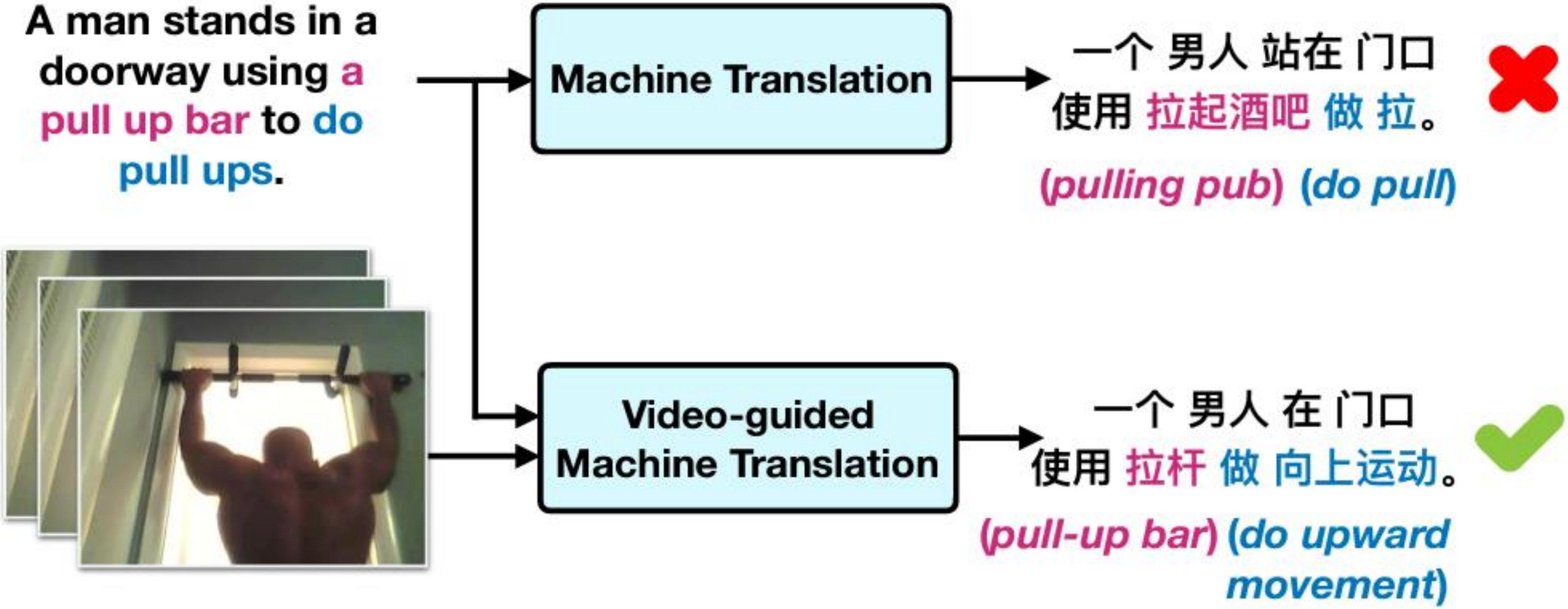


Image Captioning Model

There is a teacher teaching his students in the classroom.

有一个老师在教室里教他的学生。

Multi-modal LLM-based MT --- Video



A man stands in a doorway using a pull up bar to do pull ups.

Machine Translation

一个 男人 站在 门口 使用 拉起酒吧 做 拉。 ✗

(pulling pub) (do pull)

Video-guided Machine Translation

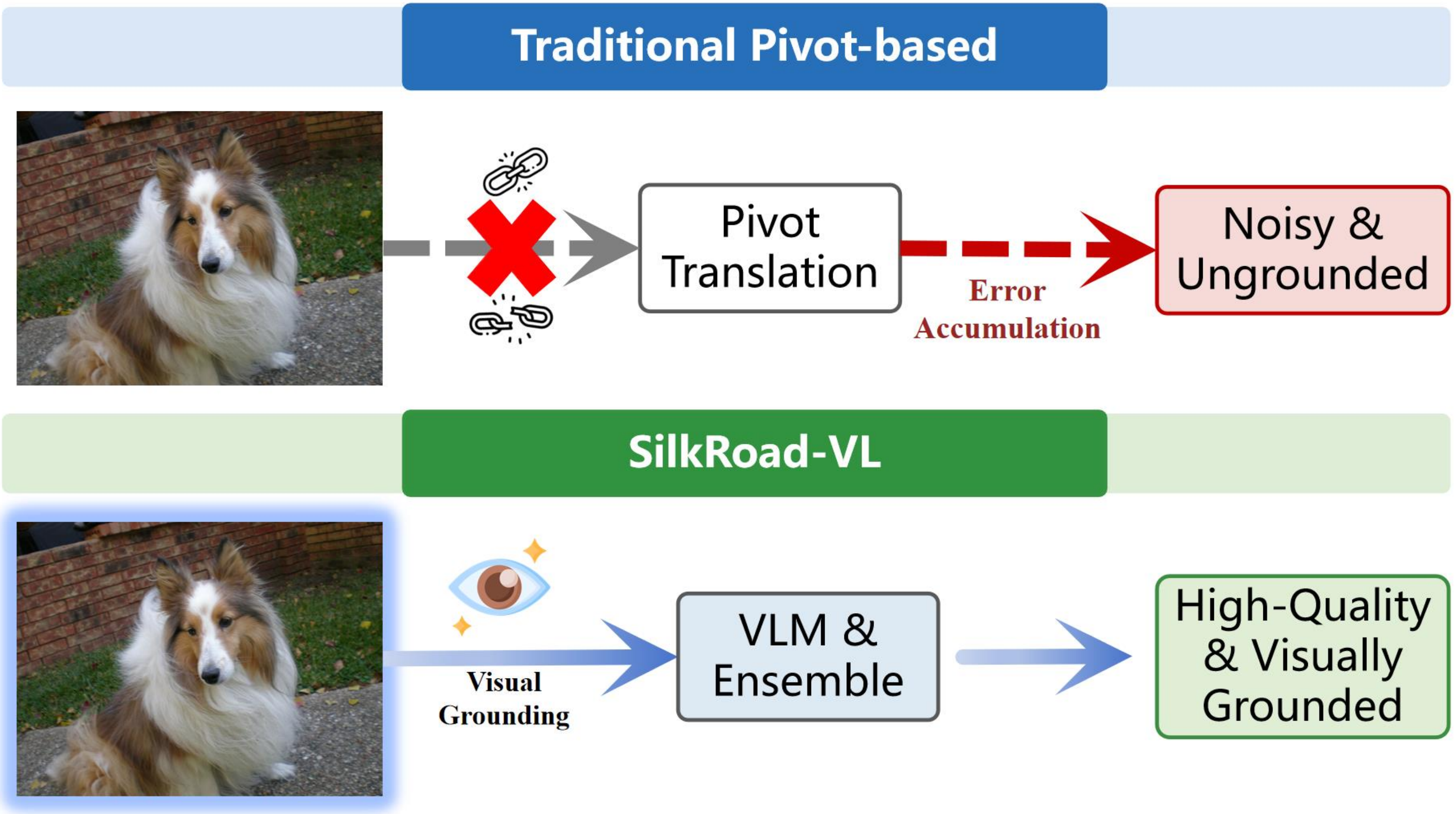
一个 男人 在 门口 使用 拉杆 做 向上运动。 ✓

(pull-up bar) (do upward movement)

Prof. Wang CCMT2023

Constructing Multi-modal Datasets

- Motivation



- Traditional pivot translation accumulates errors and lacks visual grounding, resulting in noisy and less accurate translations.
- We introduce visual information to directly support translation, improving translation quality and image-text consistency.

Constructing Multi-modal Datasets

- Experiment
  - Dataset statistics

Statistics of SilkRoad-VL Dataset

Language	Total	Short Count	Short Length	Long Count	Long Length
Uyghur(ug)	8.7k	3.7k	15.7	5.0k	34.7
Kazakh(kk)	26.1k	13.0k	14.8	13.2k	31.6
Kyrgyz(ky)	23.2k	12.8k	15.4	10.3k	33
Tajik(tg)	2.4k	1.8k	17	0.6k	40
Uzbek(uz)	14.9k	8.2k	15.2	6.7k	33
Urdu(ur)	9.6k	5.1k	23.3	4.5k	56.6
Total / Avg.	84.9k	44.6k	16.9	40.3k	38.2

Constructing Multi-modal Datasets

- Experiment
  - Main experiment

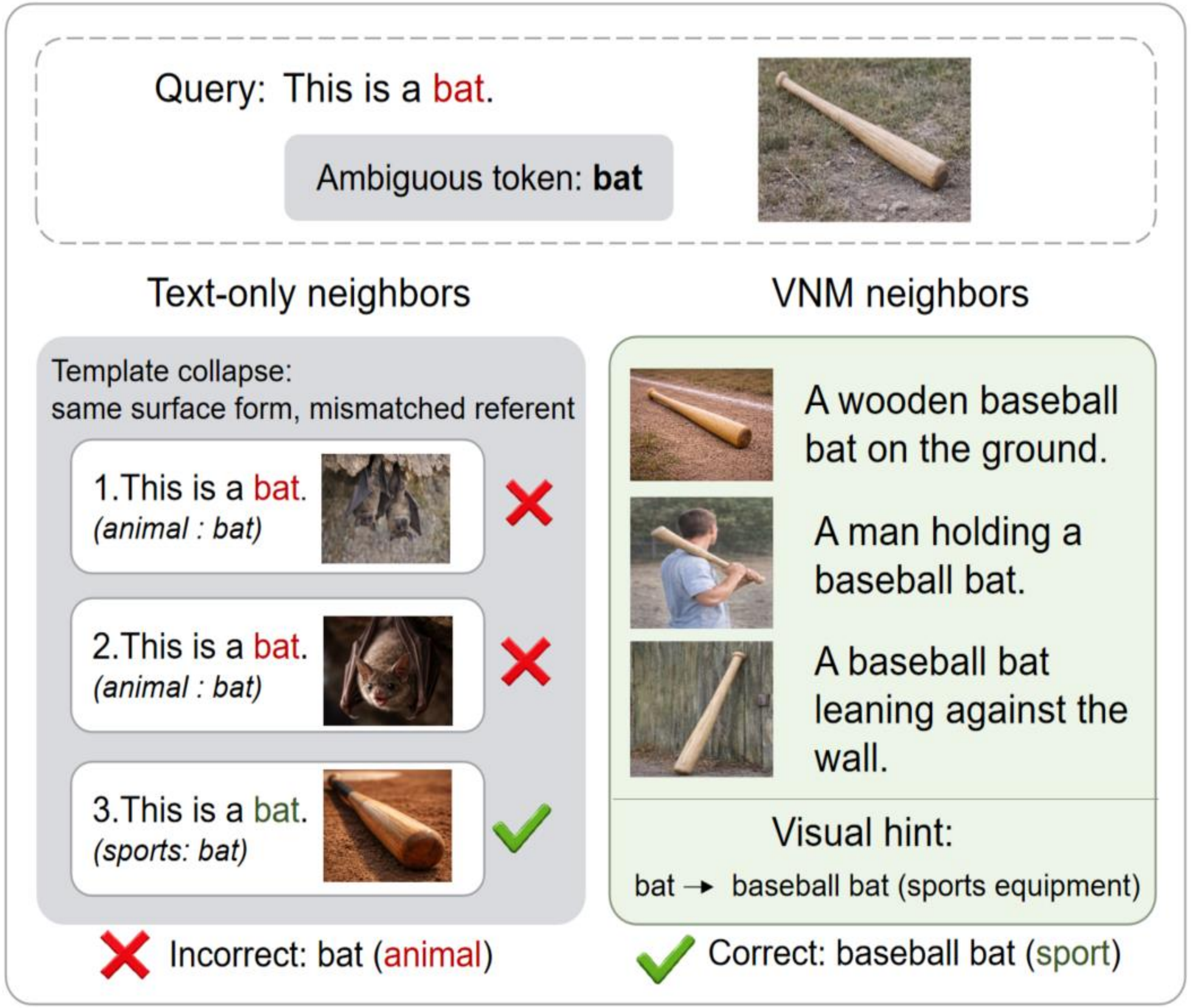
Comparison with strong baselines on the SilkRoad testset using the average of **COMET-Kiwi, BERTScore, and CLIP.**

Model	kk	ky	tg	ur	ug	uz
Qwen3-VL	52.69	49.93	46.61	55.11	47.14	54.53
Qwen2.5-VL	51.12	48.46	45.44	50.65	52.57	49.32
LLaVA-v1.6	41.12	42.55	41.75	41.4	41.28	44.91
LLaVA-1.5	49.93	48.18	44.82	43.49	42.38	47.06
InternVL3	46.21	44.59	44.94	46.6	44.62	45.85
Ours	**62.47**	**61.24**	**58.25**	**60.12**	**60.87**	**62.33**

Comparison with strong baselines on the Multi30k testset using the average of **COMET-Kiwi and CLIP.**

Model	kk	ky	tg	ur	ug	uz
Qwen3-VL	41.12	34.17	26.23	30.89	42.79	41.64
Qwen2.5-VL	34.07	30.15	24.78	36.43	34.77	33.55
LLaVA-v1.6	22.92	23.88	24.48	23.38	23.43	28.3
LLaVA-1.5	32.87	29.25	26.57	25.67	25.98	29.13
InternVL3	29.16	27.23	24.36	30.81	28.49	28.38
Ours	**50.36**	**49.35**	**40.2**	**48.41**	**48.98**	**49.06**

Vision Neighbor Memory


Query: This is a bat.
Ambiguous token: **bat**
Text-only neighbors
VNM neighbors
Template collapse:
same surface form, mismatched referent
1.This is a bat.
(animal : bat)
✗
2.This is a bat.
(animal : bat)
✗
3.This is a bat.
(sports: bat)
✓
A wooden baseball bat on the ground.
A man holding a baseball bat.
A baseball bat leaning against the wall.
Visual hint:
bat → baseball bat (sports equipment)
✗ Incorrect: bat (animal)
✓ Correct: baseball bat (sport)

- Motivation
  - Directly injecting visual information into multimodal translation is often unstable and may introduce noise.
  - In low-resource settings, text-only retrieval is weak at disambiguating short or templated sentences.
  - Therefore, we proposes using Visual Neighbor Memory as auxiliary evidence for disambiguation rather than letting vision dominate generation.

Vision Neighbor Memory

- Experiment
  - Main experiment
    - We conduct our main experiments on VG (zh→xx) with four low-resource target languages, where our method improves the average score from 51.02 to 57.81 (+6.79 over Direct). On Multi30K, our method further achieves the best overall average of 70.90, surpassing Direct by +1.34.

Method	**VG** (en→xx)				Multi30K(en→xx)		
	bn	hi	ha	ma	de	fr	cs
Direct	57.79	61.73	32.91	51.65	71.37	74.79	62.53
COD	58.85	62.27	34.91	55.20	**72.39**	75.05	64.51
MAPS	57.36	60.68	33.19	51.72	71.51	74.36	62.66
CompTrans	57.37	60.70	33.12	51.69	71.13	74.30	62.54
Ours	**63.36**	**63.81**	**44.32**	**59.75**	72.18	**75.93**	**64.60**

Outline

- LLM Everywhere
- Machine Translation with LLMs
- Challenges of LLM-based MT on LRLs
- Strategies for Text-only LLM-based MT
- Findings on Multi-modal LLM-based MT
- Conclusion

Conclusion

Text-only v.s. Multi-modal LLM-based MT

1. **Unified paradigm:** LLMs enable multilingual MT with reduced deployment cost.

2. **Text-only strategies:** Techniques such as CoT, RAG, and word sense disambiguation help compensate for limited parallel data.

3. **Multimodal MT:** Visual memory and cross-modal fusion provide additional support for low-resource translation.

4. **Data bottleneck:** High-quality instruction data remains critical; automated pipelines offer a scalable solution.

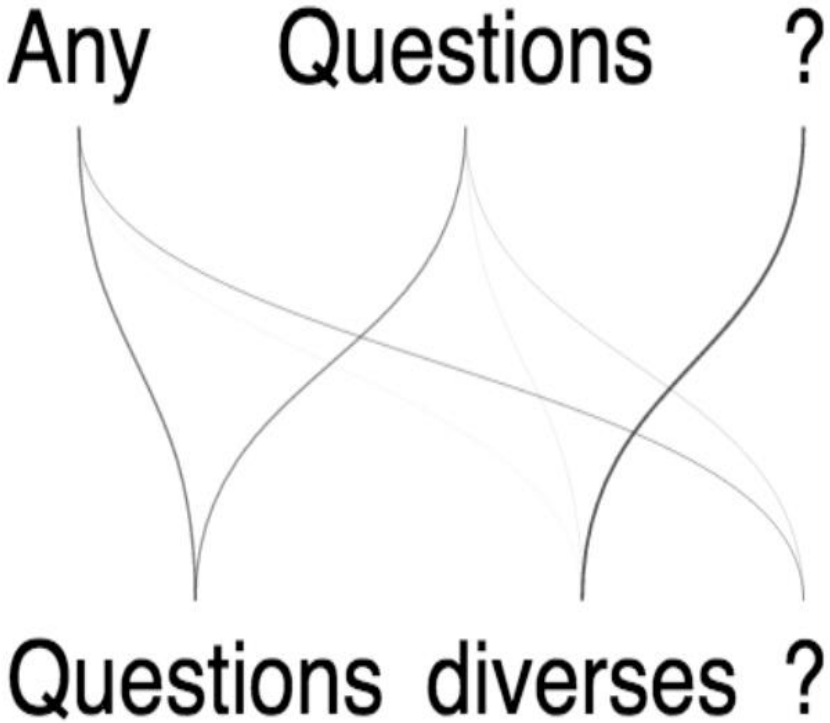
5. **Future directions:** Expand instruction corpora for more language pairs, integrate multimodal signals more effectively, and develop better evaluation metrics.

6. **Underlying cause:** The suboptimal performance of both **unimodal** and **multimodal** LLMs in **low-resource settings** ultimately stems from their **pre-trained foundation models**.

Contributors

Thank You!

Q & A



This inspiration comes from Dzmitry Bahdanau @ ICLR2014

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- I’m hiring **self-motivated** master's and PhD candidates to join my team as a research intern (RI).
- I am open to collaborations both **online** and **on-site**.
- Computational resources：
  - H100 80G 50
  - 5090 32G 10
  - 4090 24G 10
  - 3090 16G 8

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