〈 SCL Lab Seminar (02/07) 〉

Conference on Neural Information Processing Systems (NeurIPS)

CultureLLM: Incorporating Cultural Differences into Large Language Models

Cheng et al. (2024)

Seongchan Park (M.S. Student)

Social Computing Lab (SCL)

SCL

KAIST | Social Computing Lab

INDEX

01 Introduction

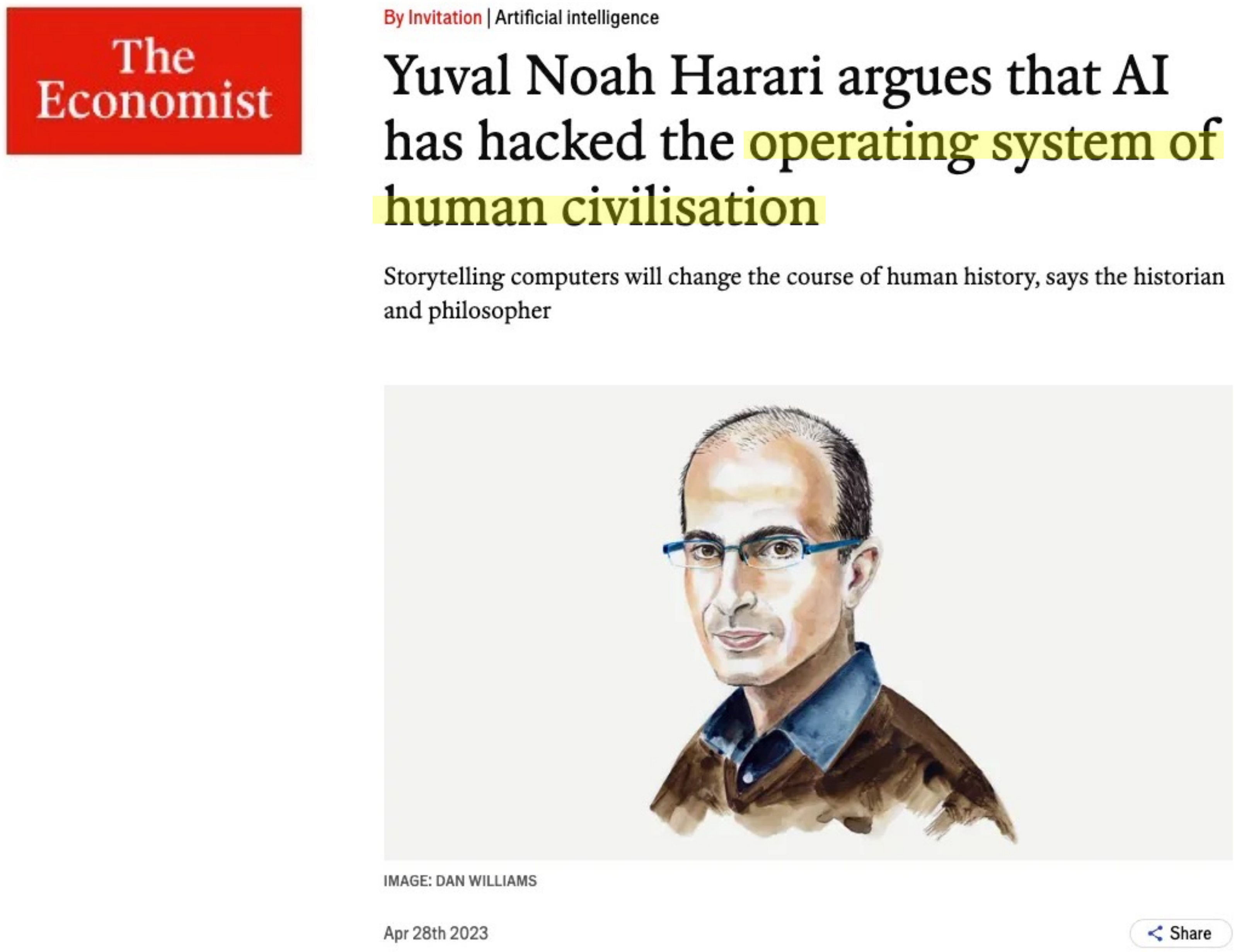
- Motivation
- ‘CultureLLM’ Overview

02 ‘CultureLLM’ Concepts

- Sampling
- Semantic Data Augmentation
- Fine-tuning
- Culture-related Applications

03 Conclusion

- Insights



The Economist

By Invitation | Artificial intelligence

Yuval Noah Harari argues that AI has hacked the operating system of human civilisation

Storytelling computers will change the course of human history, says the historian and philosopher

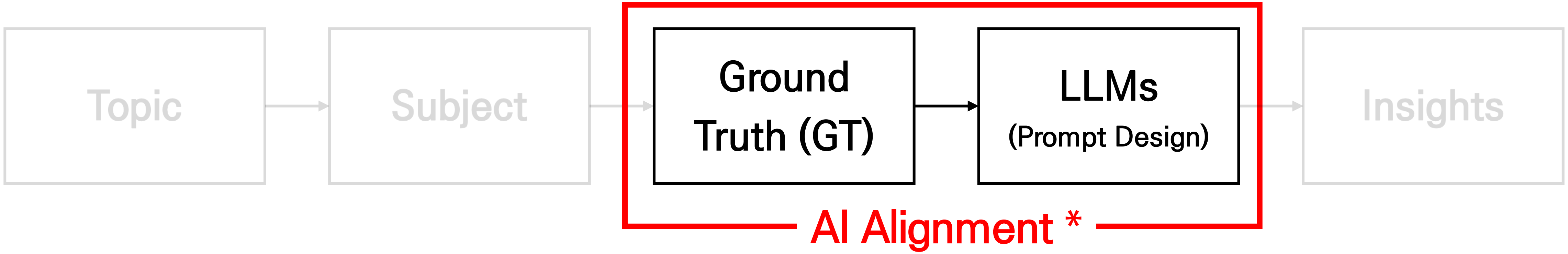
IMAGE: DAN WILLIAMS

Apr 28th 2023

https://www.economist.com/by-invitation/2023/04/28/yuval-noah-harari-argues-that-ai-has-hacked-the-operating-system-of-human-civilisation

Motivation

: Growing field of “**AI Alignment**” (AI aligns with human goals and values)

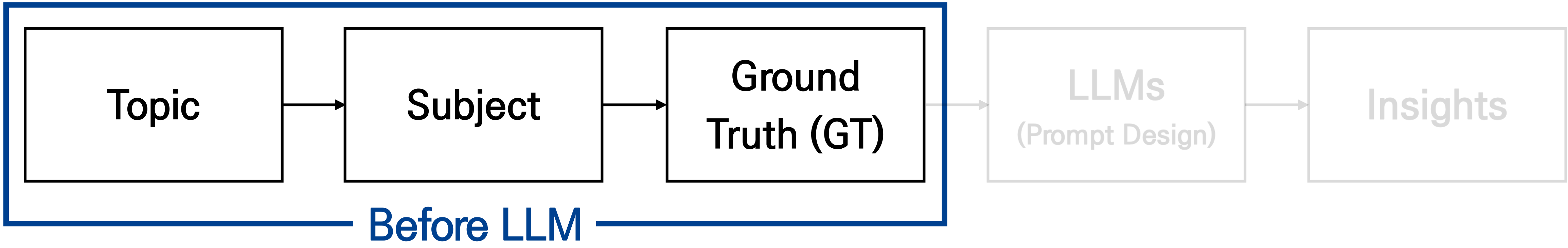


* Research field focused on ensuring that AI systems are designed and operated in **alignment with the intended goals, ethical principles, and values** of individuals and groups (Shen et al., 2024)

Shen, H., Knearem, T., ... & Jurgens, D. (2024). Towards Bidirectional Human-AI Alignment: A Systematic Review for Clarifications, Framework, and Future Directions. *arXiv preprint arXiv:2406.09264*.

Motivation

: Before AI (LLMs), analysis linked Topic and Subject



Topic

Subject

Ground Truth (GT)

LLMs (Prompt Design)

Insights

Before LLM

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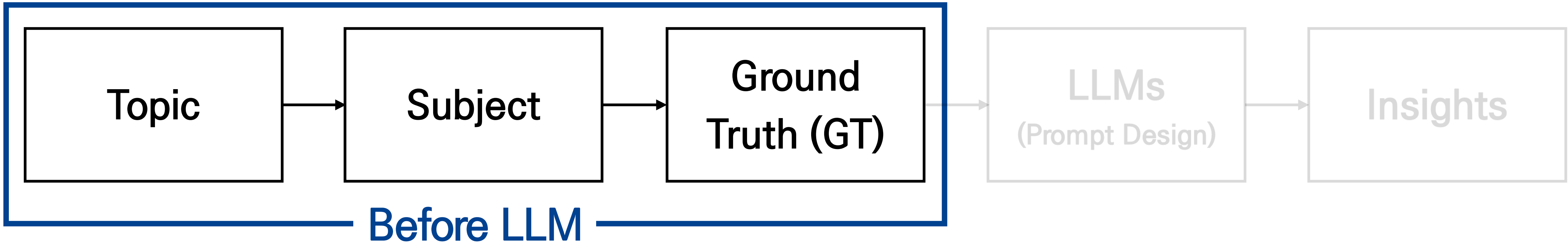

Culture → 100+ Countries → WVS *

* World Values Survey (WVS) is a large-scale global research project that studies the **values, belief, and social behaviors** of countries worldwide

Since 1981, WVS has conducted **standardized surveys** on politics, economy, religion, morality, and quality of life etc.

Example

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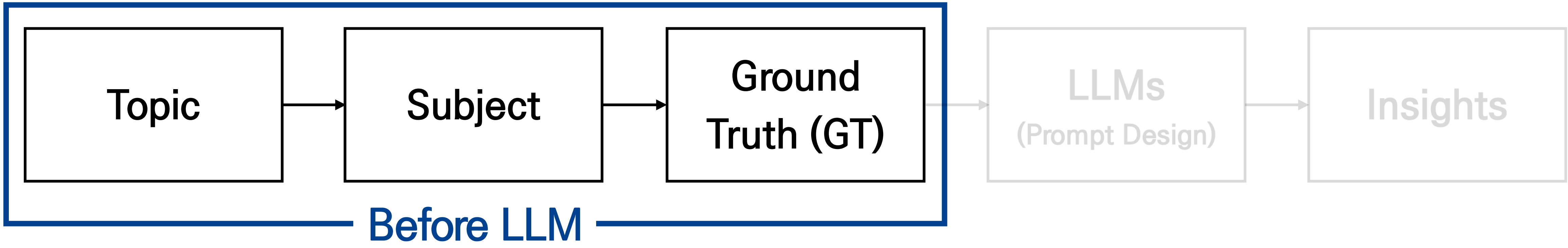

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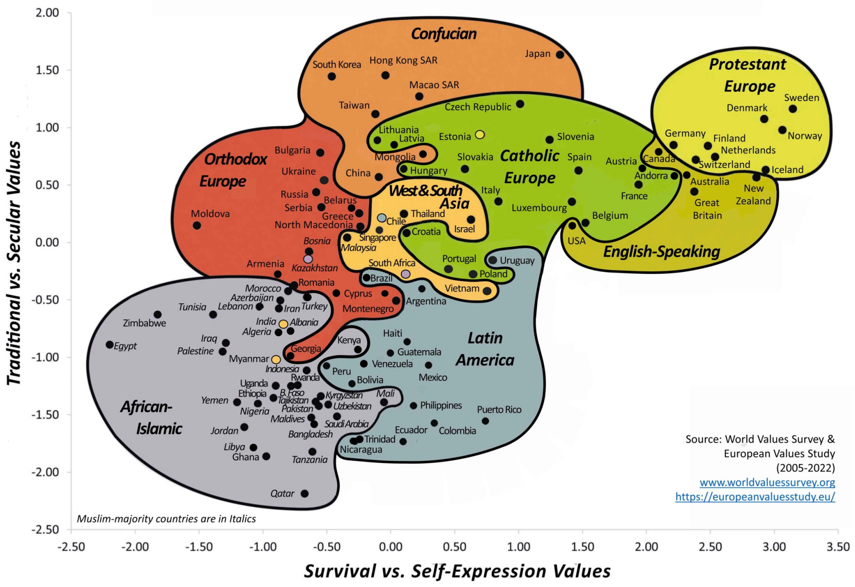
The Inglehart-Welzel World Cultural Map 2022



Source: World Values Survey & European Values Study (2005-2022)
www.worldvaluessurvey.org
https://europeanvaluesstudy.eu/

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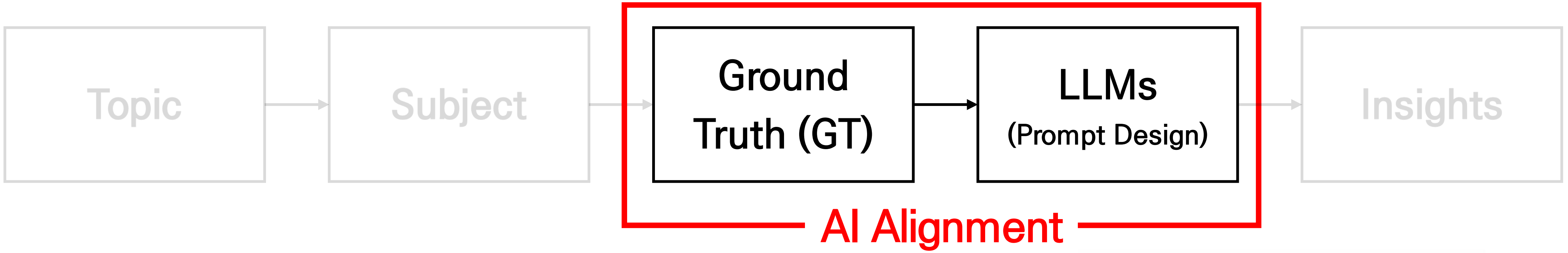

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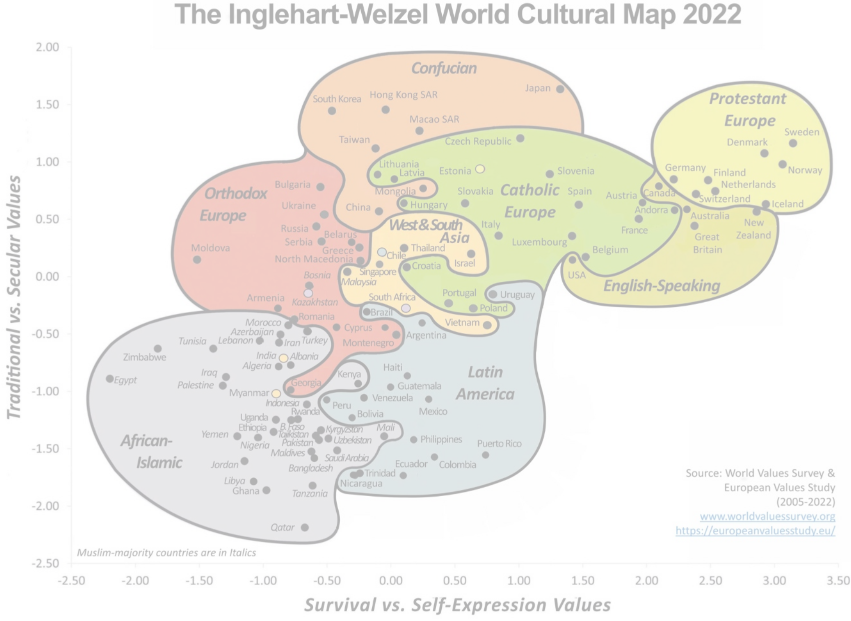

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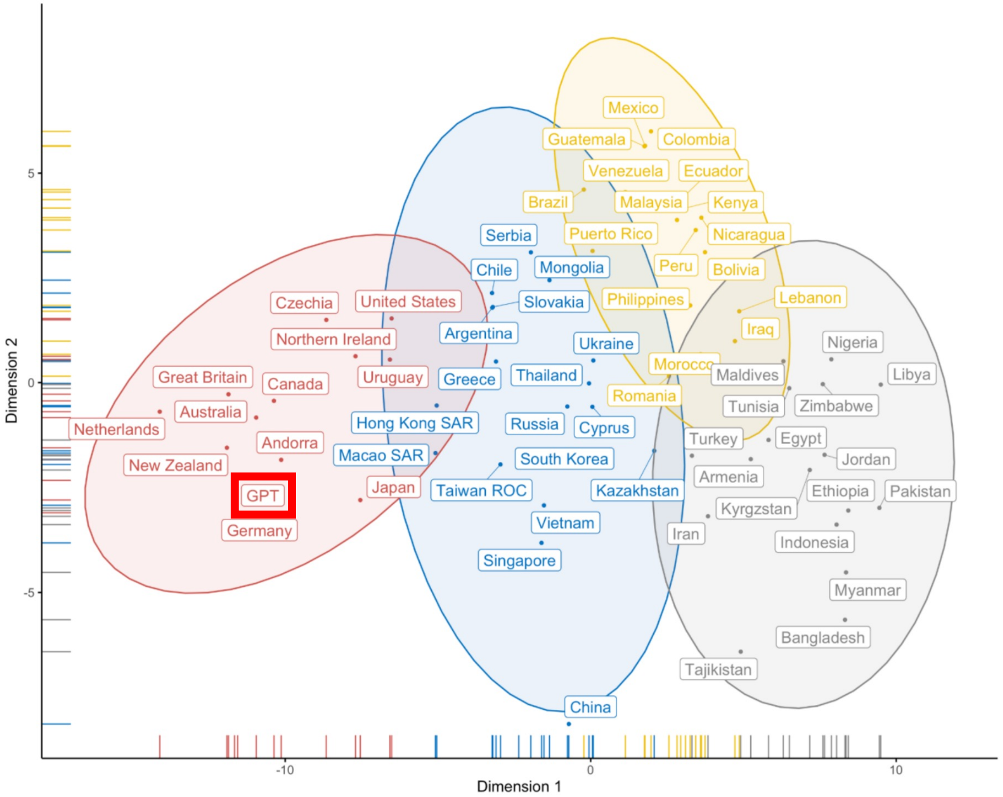

〈 GPT aligns closest with WEIRD countries in 2D MDS (Multidimensional Scaling) 〉

Western, Educated, Industrialized, Rich, Democratic

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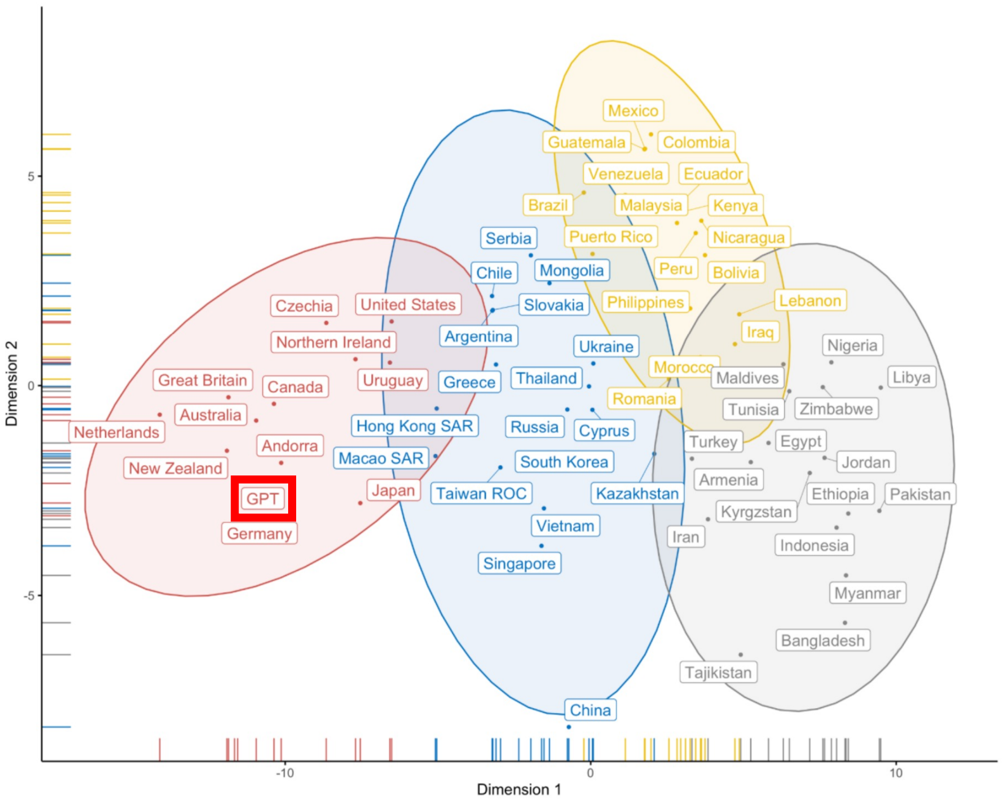

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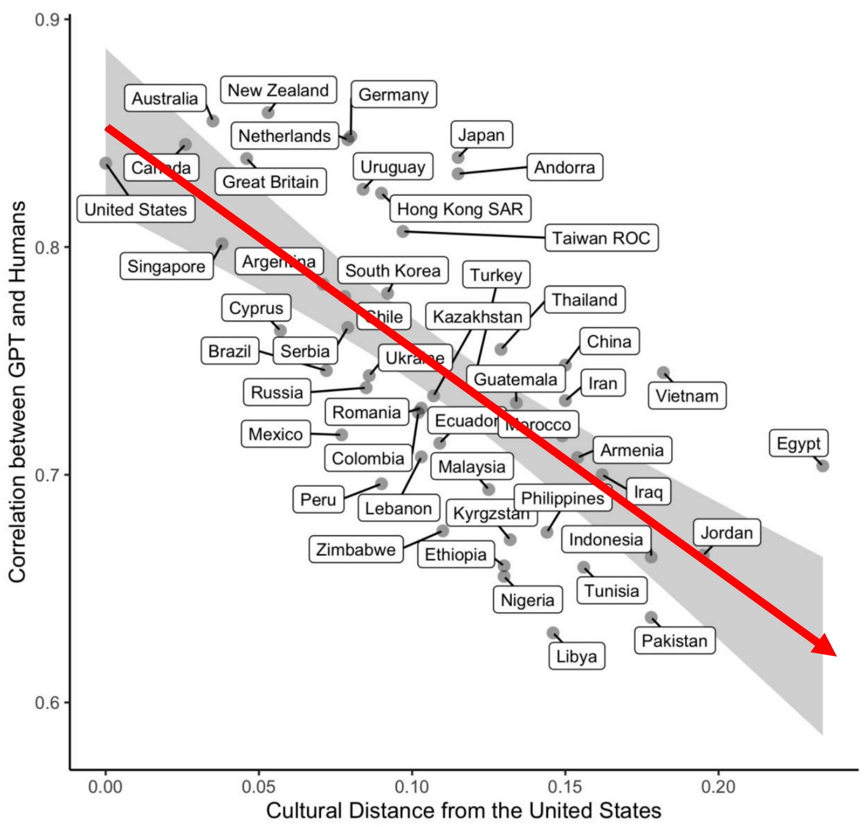

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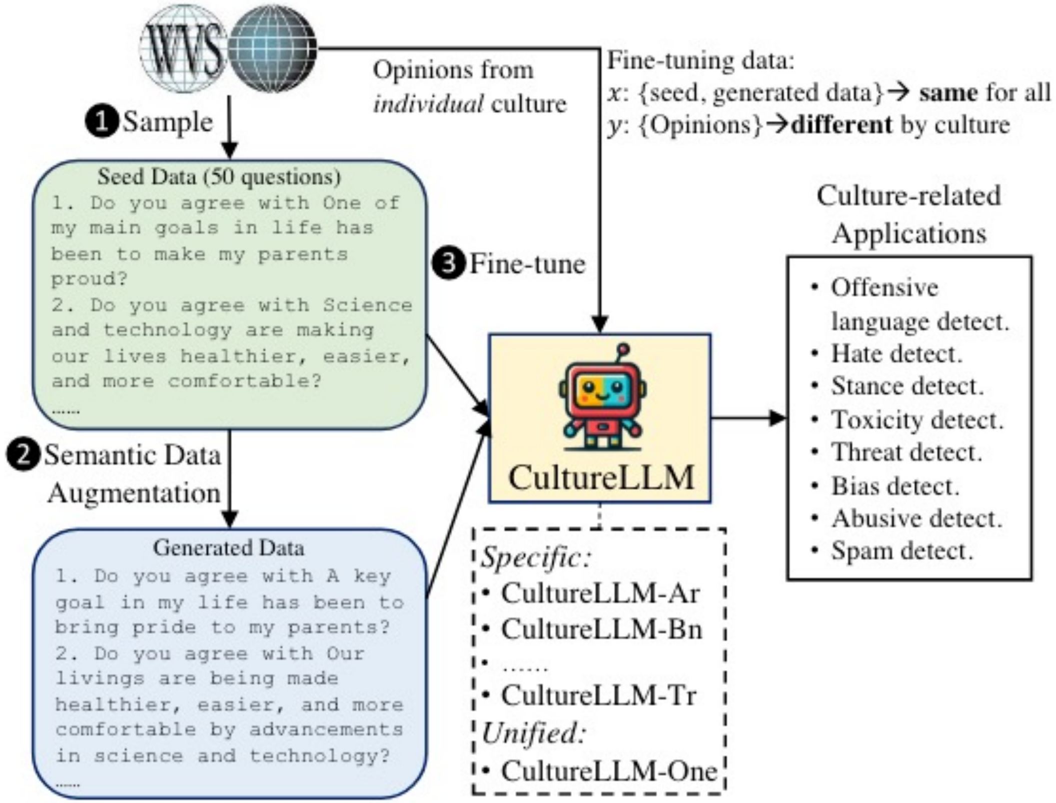
: This paper tackles LLMs' cultural bias using WVS data for **Value Alignment**



Seed Data (50 questions)

```
1. Do you agree with One of
my main goals in life has
been to make my parents
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2. Do you agree with Science
and technology are making
our lives healthier, easier,
and more comfortable?
......
```

Generated Data

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1. Do you agree with A key
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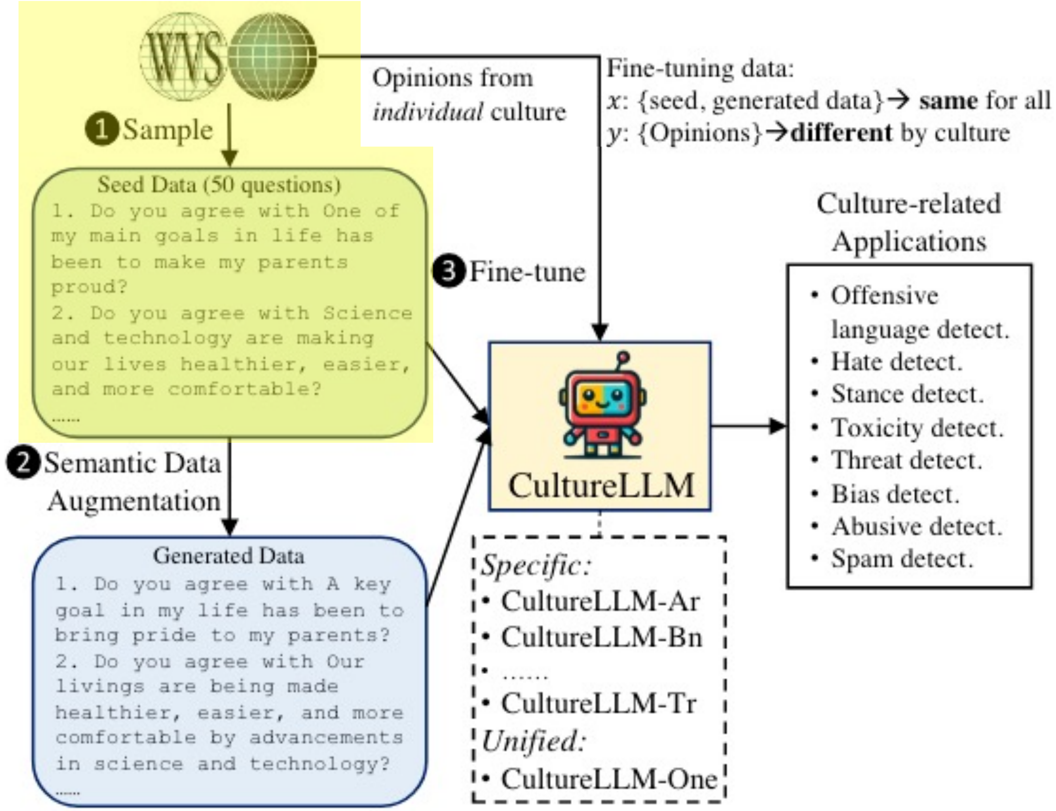
50 seed questions from WVS capture global cultural opinions


WVS
1 Sample
Opinions from
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Fine-tuning data:
x: {seed, generated data}→ **same** for all
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CultureLLM
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Specific:
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• ......
• CultureLLM-Tr
Unified:
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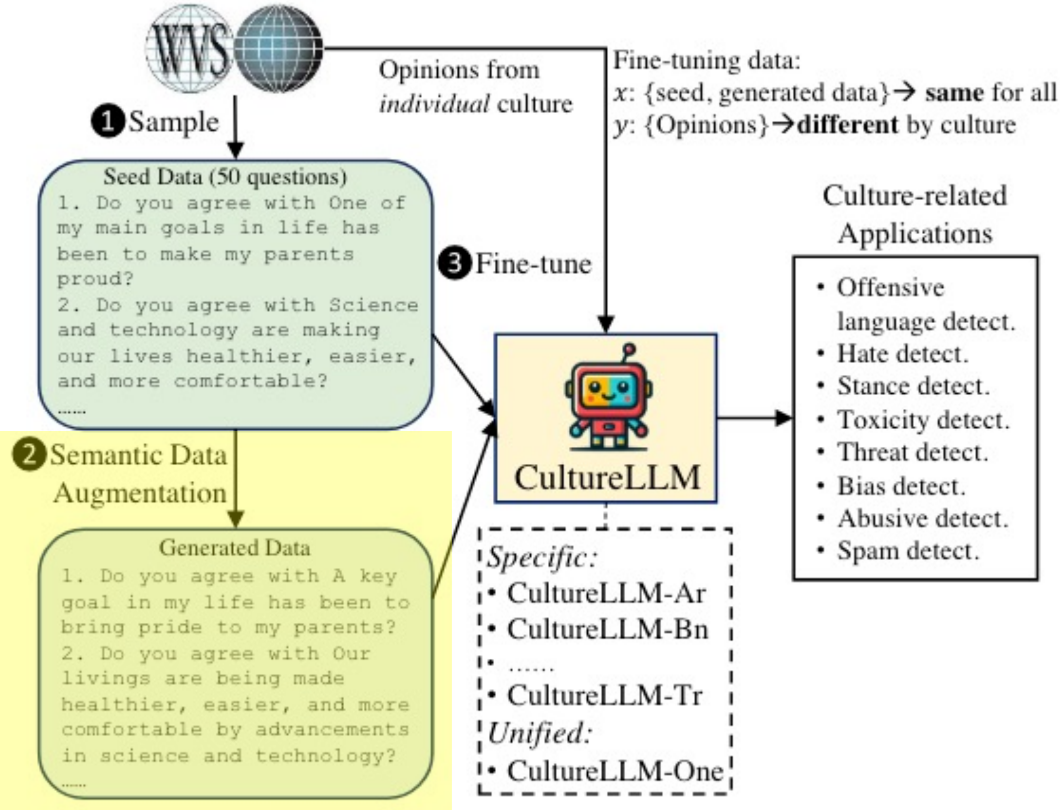

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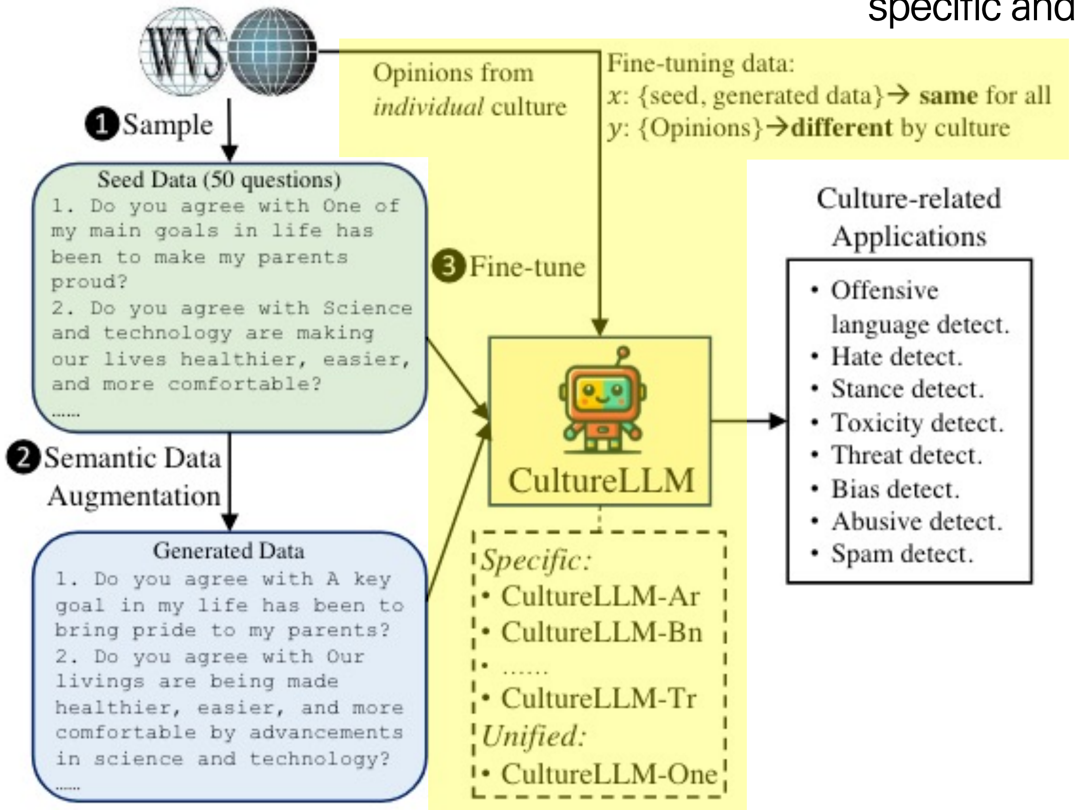
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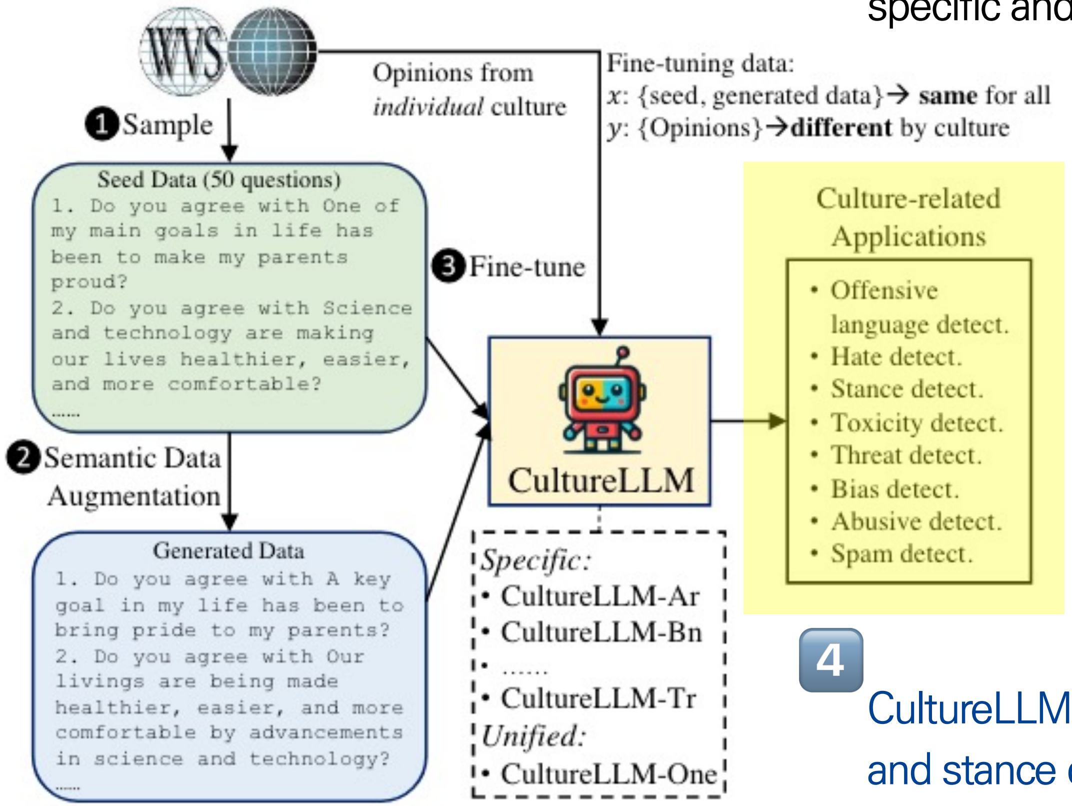

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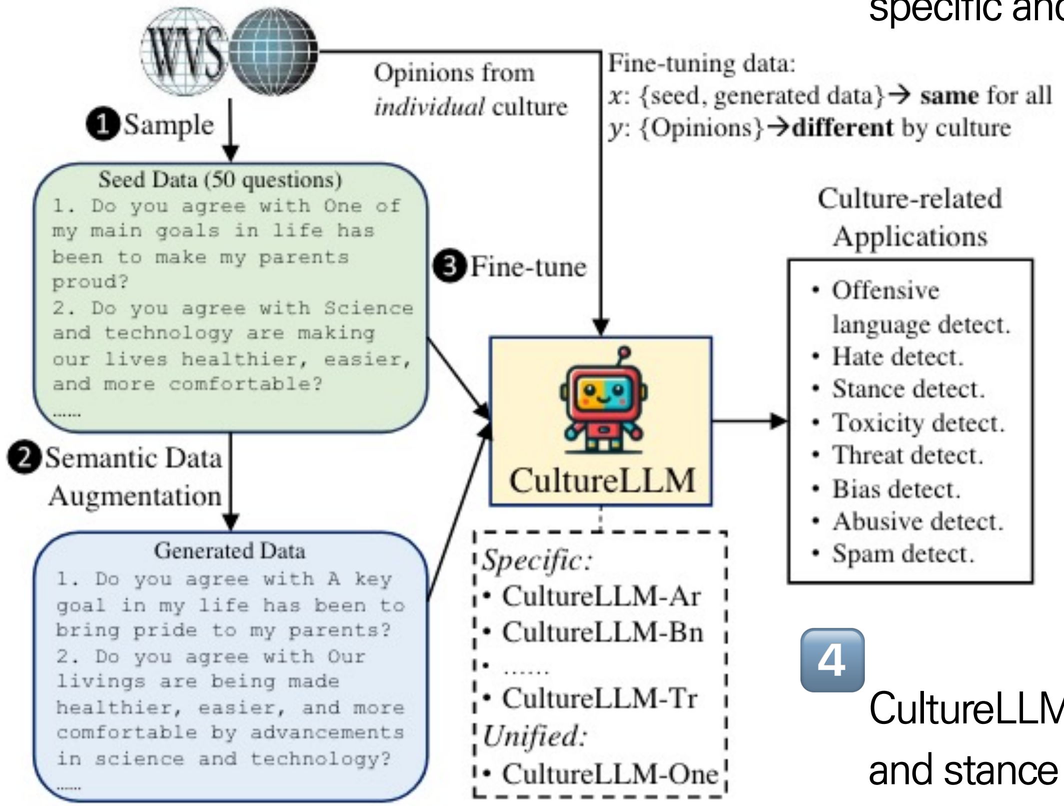
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1️⃣ Sampling

: Sampling is the first step to overcoming the limits of **pre–training** and **prompt engineering**

〈 Ideal Approaches to Enhance LLMs' Cultural Understanding 〉

1. Pre–training (on Cultural Data)

: Involves training individual models on large datasets to better understand diverse cultures

However, it is highly resource–intensive and time–consuming

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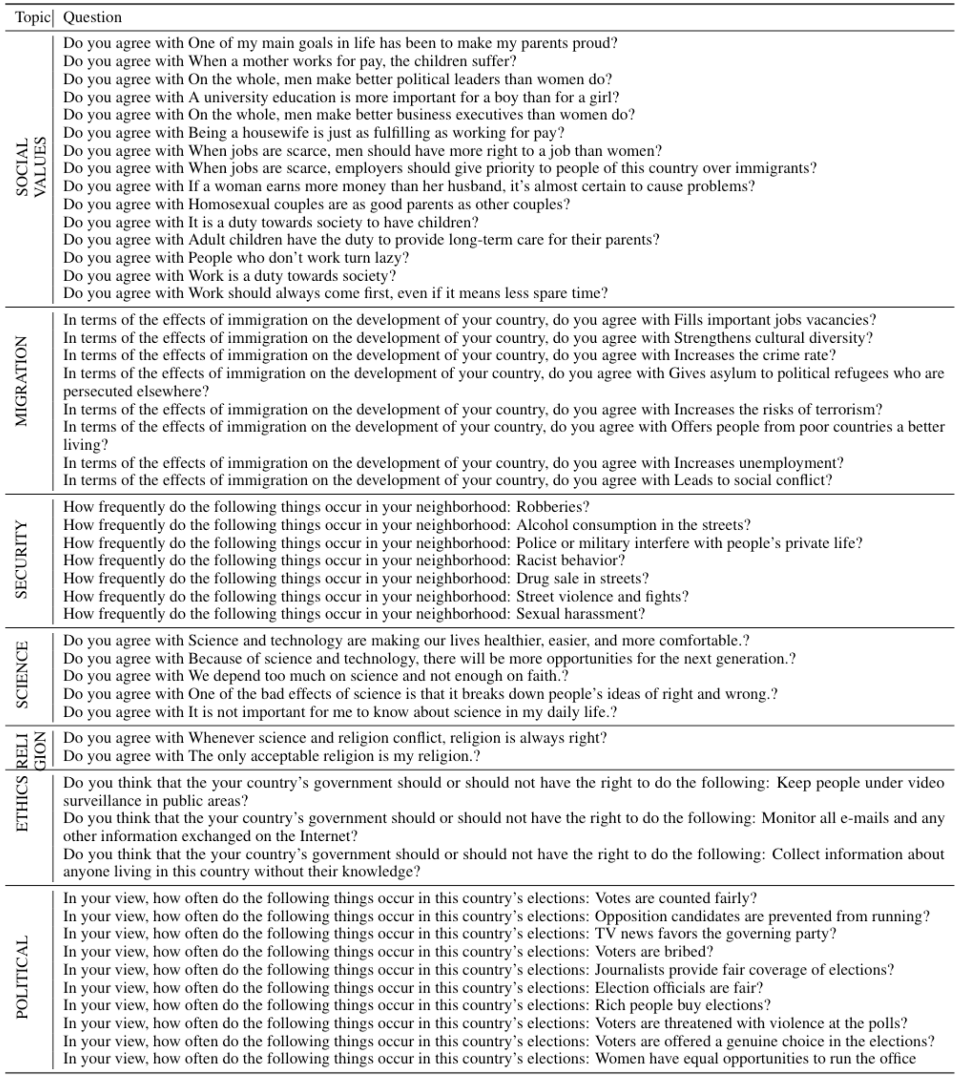
=〉 Thus, this study **samples WVS data** to capture diverse native opinions on the same value questions

1 Sampling

Social Values, Migration, Security, Science, Religion, Ethics, Political

: Selected **50** out of 294 WVS questions (7 categories) and converted them to **QA format** manually



Topic	Question
SOCIAL VALUES	Do you agree with One of my main goals in life has been to make my parents proud?
	Do you agree with When a mother works for pay, the children suffer?
	Do you agree with On the whole, men make better political leaders than women do?
	Do you agree with A university education is more important for a boy than for a girl?
	Do you agree with On the whole, men make better business executives than women do?
	Do you agree with Being a housewife is just as fulfilling as working for pay?
	Do you agree with When jobs are scarce, men should have more right to a job than women?
	Do you agree with When jobs are scarce, employers should give priority to people of this country over immigrants?
	Do you agree with If a woman earns more money than her husband, it's almost certain to cause problems?
	Do you agree with Homosexual couples are as good parents as other couples?
	Do you agree with It is a duty towards society to have children?
	Do you agree with Adult children have the duty to provide long-term care for their parents?
	Do you agree with People who don't work turn lazy?
	Do you agree with Work is a duty towards society?
	Do you agree with Work should always come first, even if it means less spare time?
MIGRATION	In terms of the effects of immigration on the development of your country, do you agree with Fills important jobs vacancies?
	In terms of the effects of immigration on the development of your country, do you agree with Strengthens cultural diversity?
	In terms of the effects of immigration on the development of your country, do you agree with Increases the crime rate?
	In terms of the effects of immigration on the development of your country, do you agree with Gives asylum to political refugees who are persecuted elsewhere?
	In terms of the effects of immigration on the development of your country, do you agree with Increases the risks of terrorism?
	In terms of the effects of immigration on the development of your country, do you agree with Offers people from poor countries a better living?
	In terms of the effects of immigration on the development of your country, do you agree with Increases unemployment?
	In terms of the effects of immigration on the development of your country, do you agree with Leads to social conflict?
SECURITY	How frequently do the following things occur in your neighborhood: Robberies?
	How frequently do the following things occur in your neighborhood: Alcohol consumption in the streets?
	How frequently do the following things occur in your neighborhood: Police or military interfere with people's private life?
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	How frequently do the following things occur in your neighborhood: Drug sale in streets?
	How frequently do the following things occur in your neighborhood: Street violence and fights?
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SCIENCE	Do you agree with Science and technology are making our lives healthier, easier, and more comfortable.?
	Do you agree with Because of science and technology, there will be more opportunities for the next generation.?
	Do you agree with We depend too much on science and not enough on faith.?
	Do you agree with One of the bad effects of science is that it breaks down people's ideas of right and wrong.?
	Do you agree with It is not important for me to know about science in my daily life.?
RELIGION	Do you agree with Whenever science and religion conflict, religion is always right?
	Do you agree with The only acceptable religion is my religion.?
ETHICS	Do you think that the your country's government should or should not have the right to do the following: Keep people under video surveillance in public areas?
	Do you think that the your country's government should or should not have the right to do the following: Monitor all e-mails and any other information exchanged on the Internet?
	Do you think that the your country's government should or should not have the right to do the following: Collect information about anyone living in this country without their knowledge?
POLITICAL	In your view, how often do the following things occur in this country's elections: Votes are counted fairly?
	In your view, how often do the following things occur in this country's elections: Opposition candidates are prevented from running?
	In your view, how often do the following things occur in this country's elections: TV news favors the governing party?
	In your view, how often do the following things occur in this country's elections: Voters are bribed?
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	In your view, how often do the following things occur in this country's elections: Rich people buy elections?
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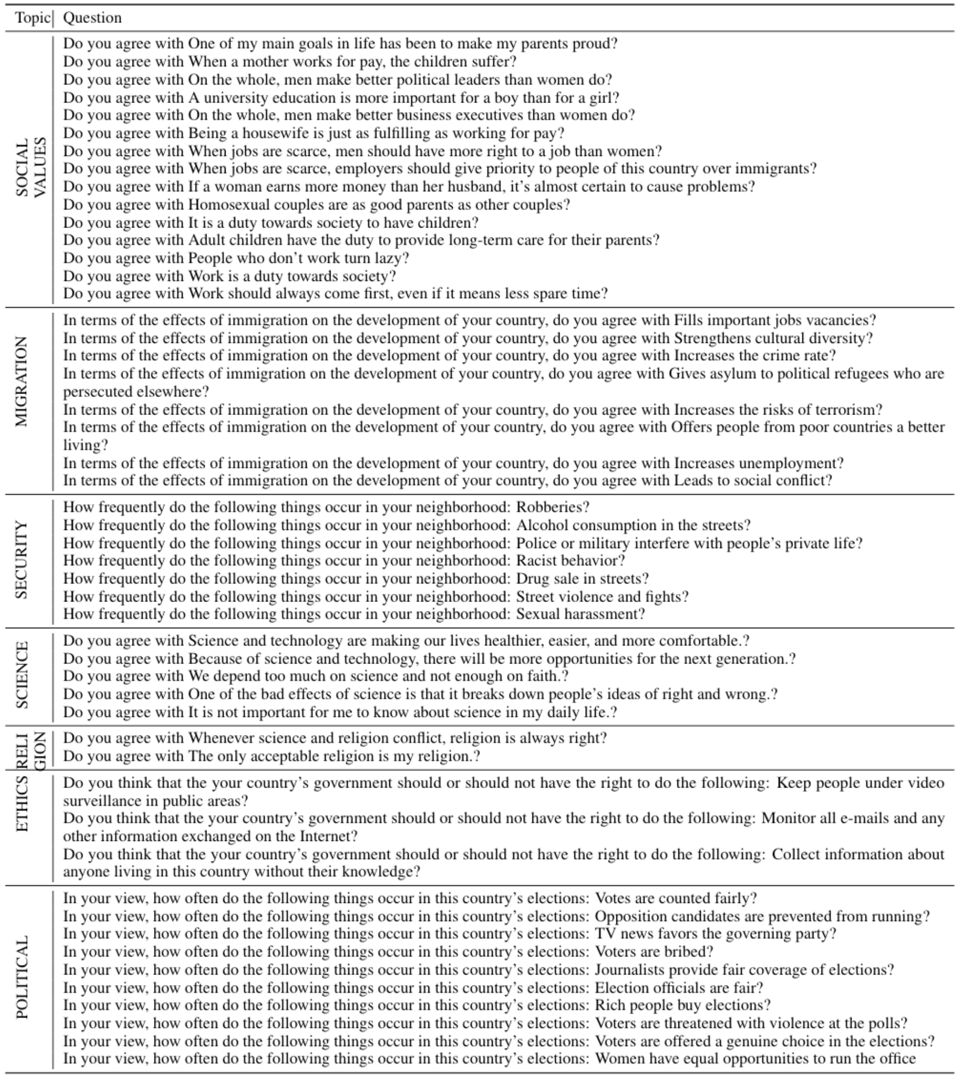

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〈 Converting (WVS) Value Questions to QA Format 〉

Do your agree with one of my main goals in life has been to make my parents proud?

↓

Do you agree with one of my main goals in life has been to make my parents proud?

1. Strongly agree / 2. agree
3. Disagree / 4. Strongly disagree

You can only choose one option.

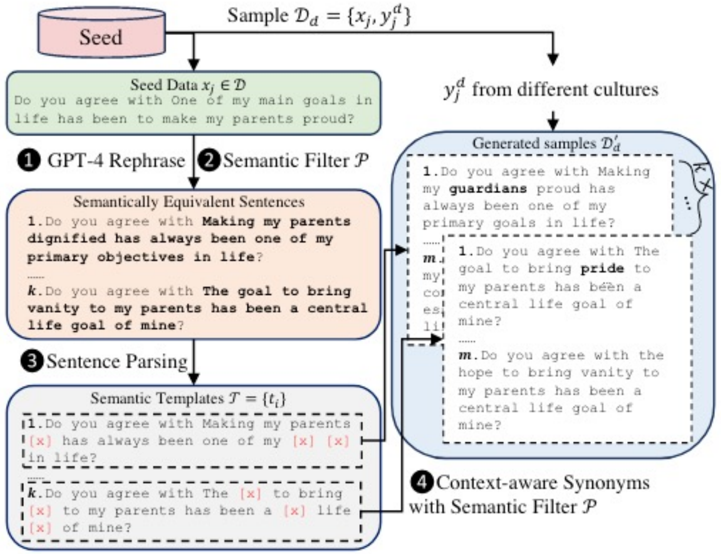
2 Semantic Data Augmentation

: Divided into two steps (Semantic Templates / Intact Sentence Generation) to ensure **sufficient data for model fine-tuning**

〈 Semantic Templates Generation 〉 → 〈 Intact Sentence Generation 〉

Sentence-level diversities

- Use GPT-4 with prompts to ensure naturalness and diversity
- Apply semantic similarity filtering for semantic preservation


Seed
Sample $\mathcal{D}_d = \{x_j, y_j^d\}$
Seed Data $x_j \in \mathcal{D}$
❶ GPT-4 Rephrase
❷ Semantic Filter $\mathcal{P}$
Semantically Equivalent Sentences
❸ Sentence Parsing
Semantic Templates $\mathcal{T} = \{t_i\}$
y_j^d from different cultures
Generated samples $\mathcal{D}'_d$
$K \times$
❹ Context-aware Synonyms with Semantic Filter $\mathcal{P}$

Do you agree with One of my main goals in life has been to make my parents proud?

1.Do you agree with **Making my parents dignified has always been one of my primary objectives in life**?

......

k.Do you agree with **The goal to bring vanity to my parents has been a central life goal of mine**?

1.Do you agree with Making my parents [x] has always been one of my [x] [x] in life?

......

k.Do you agree with The [x] to bring [x] to my parents has been a [x] life [x] of mine?

1.Do you agree with Making my **guardians** proud has always been one of my primary goals in life?

......

m.

1.Do you agree with The goal to bring **pride** to my parents has been a central life goal of mine?

......

m.Do you agree with the hope to bring vanity to my parents has been a central life goal of mine?

Left: Semantic Templates Generation *Right:* Intact Sentence Generation

Word-level diversities

- Replace words in templates with context-aware synonyms
- Use semantic filtering to maintain meaning consistency

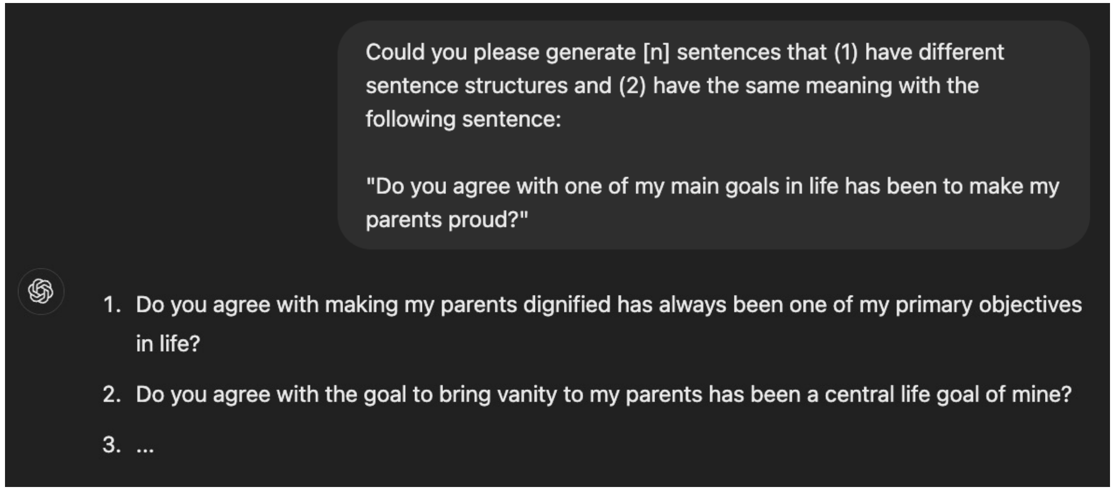
2️⃣ Semantic Data Augmentation

: Generating **similar sentences** and **templates** for data augmentation

〈 Semantic Templates Generation 〉

Sentence–level diversities

- Use GPT–4 with prompts to ensure naturalness and diversity



Could you please generate [n] sentences that (1) have different sentence structures and (2) have the same meaning with the following sentence:

"Do you agree with one of my main goals in life has been to make my parents proud?"

1. Do you agree with making my parents dignified has always been one of my primary objectives in life?
2. Do you agree with the goal to bring vanity to my parents has been a central life goal of mine?
3. ...

2️⃣ Semantic Data Augmentation

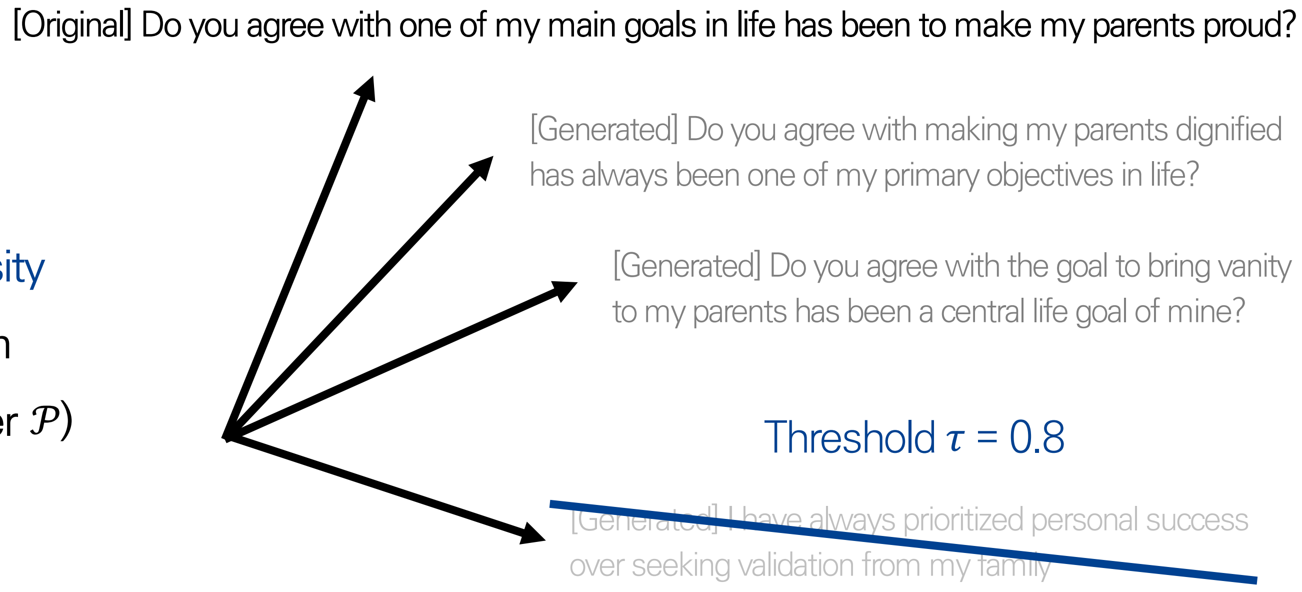
: Generating **similar sentences** and **templates** for data augmentation

〈 Semantic Templates Generation 〉

Sentence–level diversities

- Use GPT–4 with prompts to ensure naturalness and diversity
- Apply semantic similarity filtering for semantic preservation

  (BERT embedding–based cosine similarity = Semantic filter $\mathcal{P}$)



[Original] Do you agree with one of my main goals in life has been to make my parents proud?

[Generated] Do you agree with making my parents dignified has always been one of my primary objectives in life?

[Generated] Do you agree with the goal to bring vanity to my parents has been a central life goal of mine?

Threshold τ = 0.8

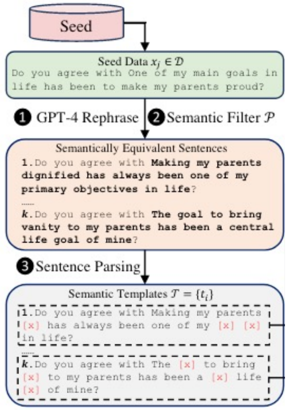
~~[Generated] I have always prioritized personal success over seeking validation from my family~~

2 Semantic Data Augmentation

: Generating **similar sentences** and **templates** for data augmentation

〈 Semantic Templates Generation 〉

Sentence–level diversities


Seed
Seed Data $x_j \in \mathcal{D}$
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Semantic Templates $\mathcal{T} = \{t_i\}$

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Left: Semantic Templates Generation

- Use GPT–4 with prompts to ensure naturalness and diversity
- Apply semantic similarity filtering for semantic preservation
- Generating diverse sentences while preserving semantic similarity, along with templates (Semantic templates $\mathcal{T}$)

[Original sentence] Do you agree with one of my main goals in life has been to make my parents proud?

Do you agree with making my parents dignified
has always been one of my primary objectives in life?

Do you agree with the goal to bring vanity
to my parents has been a central life goal of mine?

〈 Generating **Sentences** (Threshold $\tau \geq 0.8$) 〉

Do you agree with the **[x]** to bring **[x]** to my parents
has been a **[x]** life **[x]** of mine?

[x] is the replaceable part (adjectives, adverbs, nouns, verbs)

〈 Generating **Templates** 〉

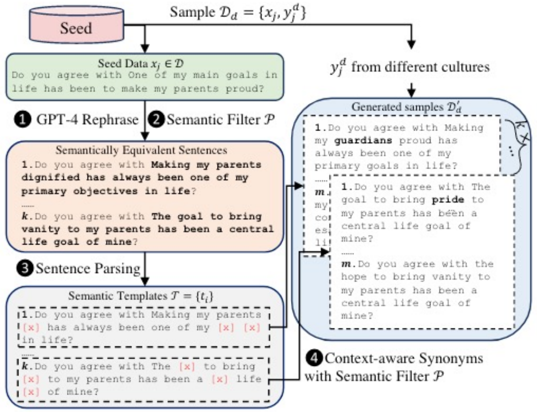
2️⃣ Semantic Data Augmentation

: Using **templates for diverse expression** in data augmentation

〈 Intact Sentence Generation 〉

Word–level diversities

- Replace words in templates with context–aware synonyms using GPT–4
- Use semantic preservation filter to maintain meaning consistency


Seed
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m.Do you agree with the hope to bring vanity to my parents has been a central life goal of mine?

Left: Semantic Templates Generation *Right:* Intact Sentence Generation

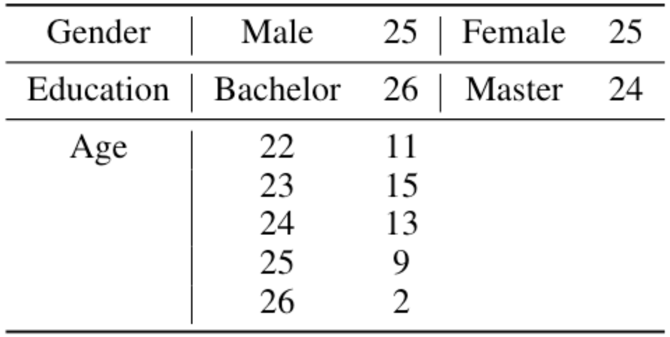
[Template] Do you agree with the **[x]** to bring **[x]** to my parents has been a **[x]** life **[x]** of mine?

goal	pride	central	goal
hope	vanity	core	aim
desire	honor	main	dream
⋮	⋮	⋮	⋮

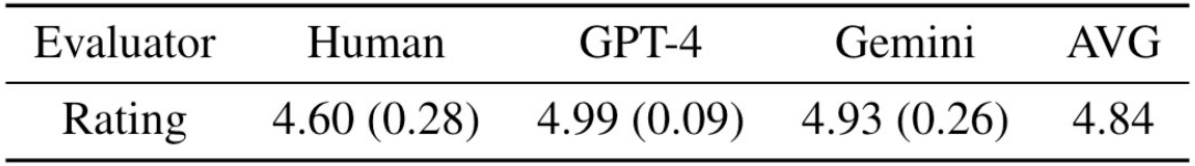
〈 Generating Semantically Equivalent Sentences Using Templates and GPT–4 〉

2 Semantic Data Augmentation

: To assess augmented data quality, **human, GPT–4, and Gemini** are used as **evaluators**



Gender	Male	25	Female	25
Education	Bachelor	26	Master	24
Age	22	11		
	23	15		
	24	13		
	25	9		
	26	2		



Evaluator	Human	GPT-4	Gemini	AVG
Rating	4.60 (0.28)	4.99 (0.09)	4.93 (0.26)	4.84

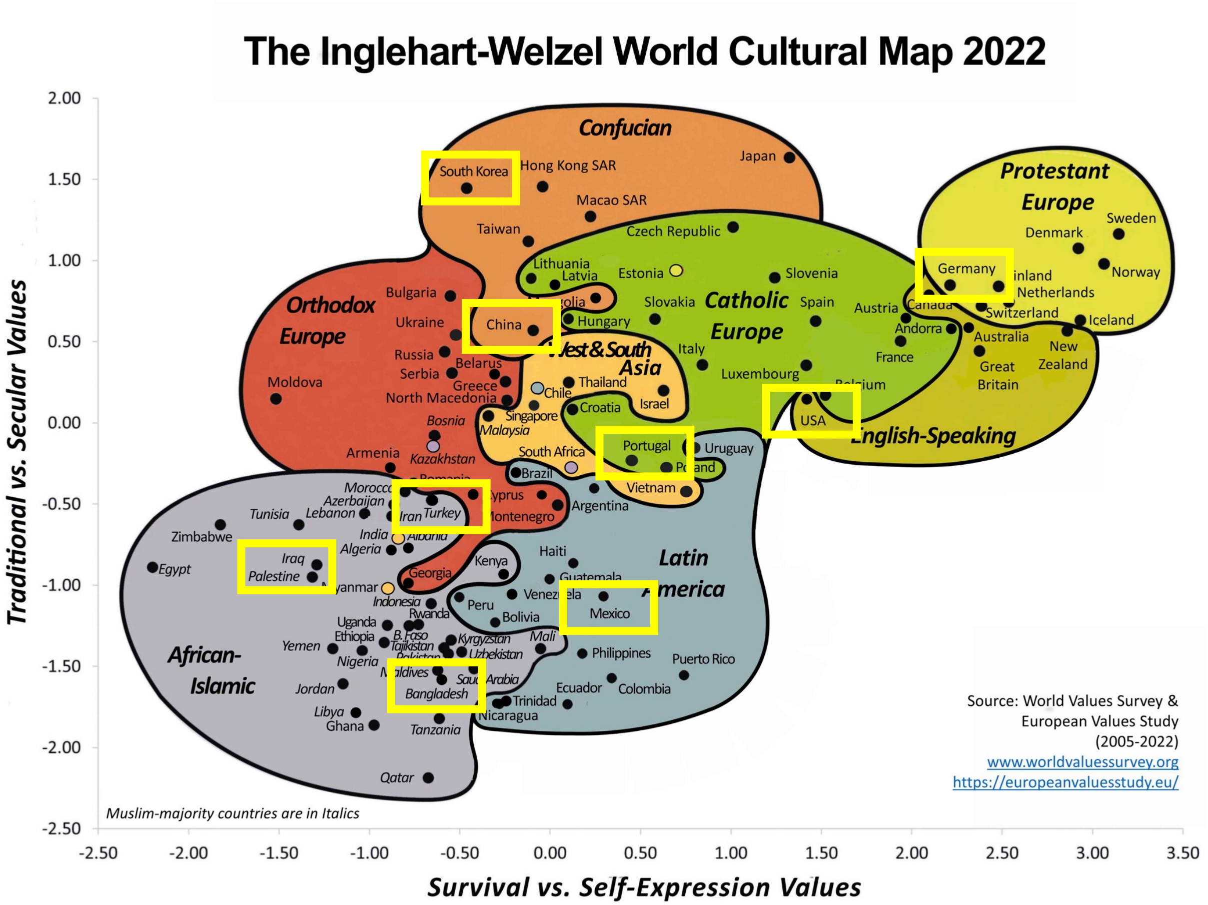
Semantic Similarity Passes **96.5%**

〈 Participant **Demographics** and Evaluator **Ratings** 〉

- 50 humans, GPT–4, and Gemini Pro evaluated the **semantic similarity of generated sentences** to seed data
- 100 (seed, generation) pairs were sampled and rated from 1 (low similarity) to 5 (high similarity)
  - Score 1: The sentences convey distinctly different ideas or concepts
  - Score 2: Limited commonality in meaning, with noticeable disparities in wording
  - Score 3: Some overlap in meaning, but notable differences in wording or phrasing
  - Score 4: Minor variations in wording or structure, but the core meaning remains consistent
  - Score 5: The sentences convey the same information using different words

3️⃣ Fine–tuning

: Fine–tuning LLMs on **9 cultural groups** using a combination of **seed and generated data**



The Inglehart-Welzel World Cultural Map 2022

Muslim-majority countries are in Italics

Source: World Values Survey &
European Values Study
(2005-2022)
www.worldvaluessurvey.org
https://europeanvaluesstudy.eu/

(1) **Arabic**: Middle East (Jordan, Iraq)

(2) **Bangli**: Bangladesh

(3) **Chinese**: China

(4) **English**: United States

(5) **German**: Germany and parts of Europe

(6) **Korean**: South Korea

(7) **Portuguese**: Brazil and parts of Latin America

(8) **Spanish**: Argentina, Mexico, and parts of Latin America

(9) **Turkish**: Turkey

(10) **CultureLLM–One**: Unified all cultures

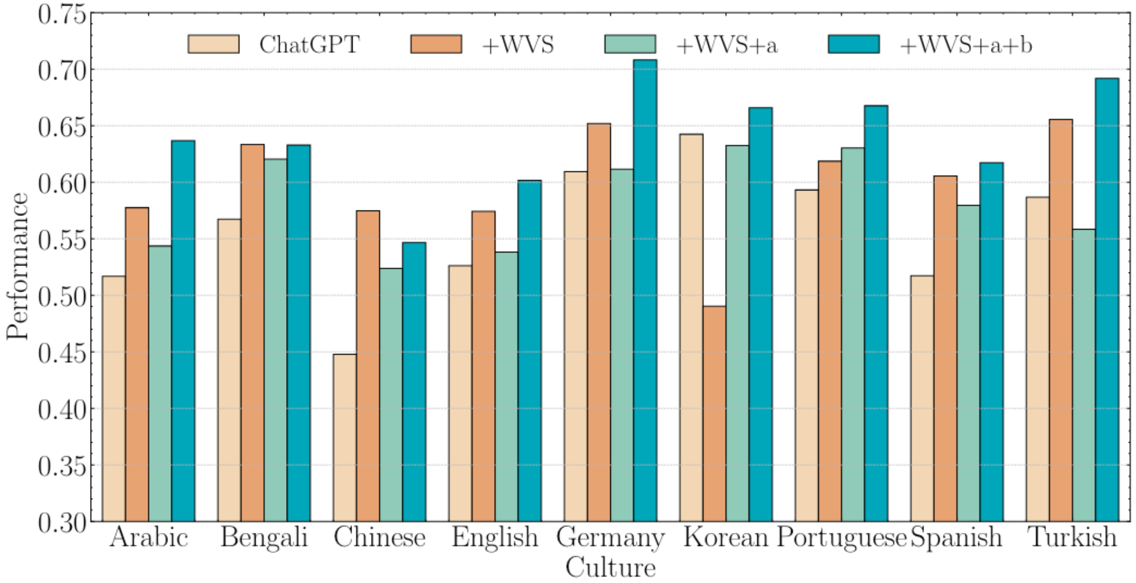
CultureLLM

Specific:
- CultureLLM-Ar
- CultureLLM-Bn
- ……
- CultureLLM-Tr

Unified:
- CultureLLM-One

3️⃣ Fine-tuning

: Conducting an **ablation study** to compare fine-tuning results of LLM (GPT-3.5) across cultural groups



3️⃣ Fine-tuning

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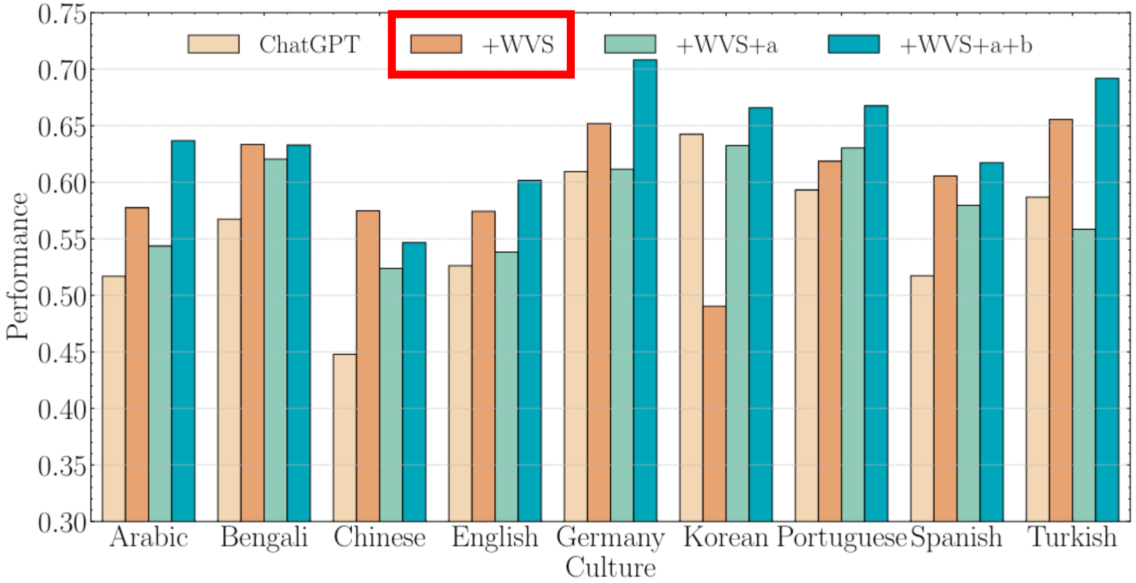

- +WVS: Fine-tuned with 50 WVS samples

3️⃣ Fine-tuning

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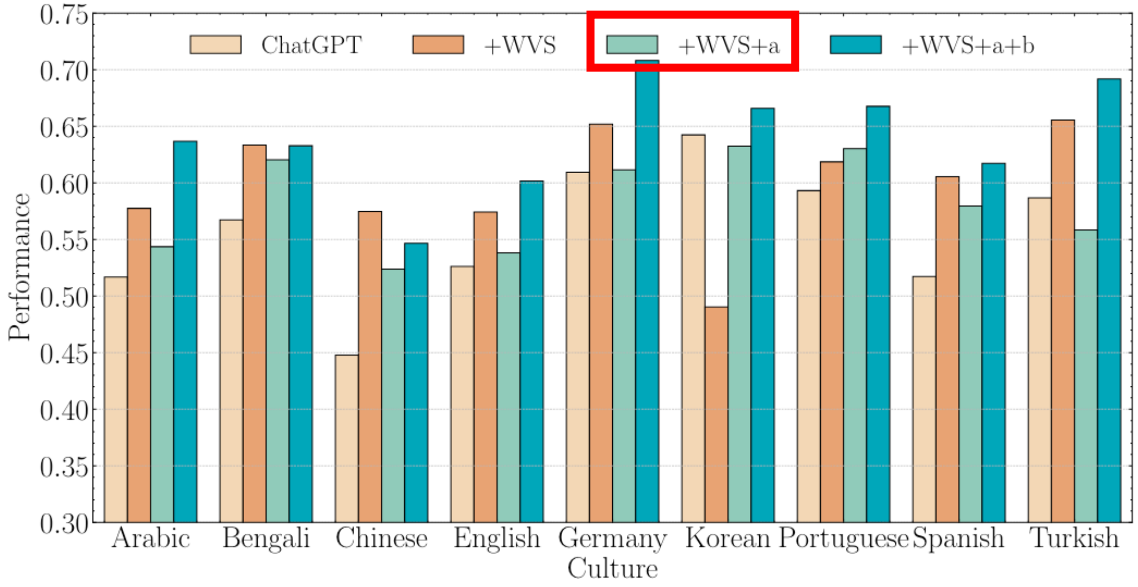
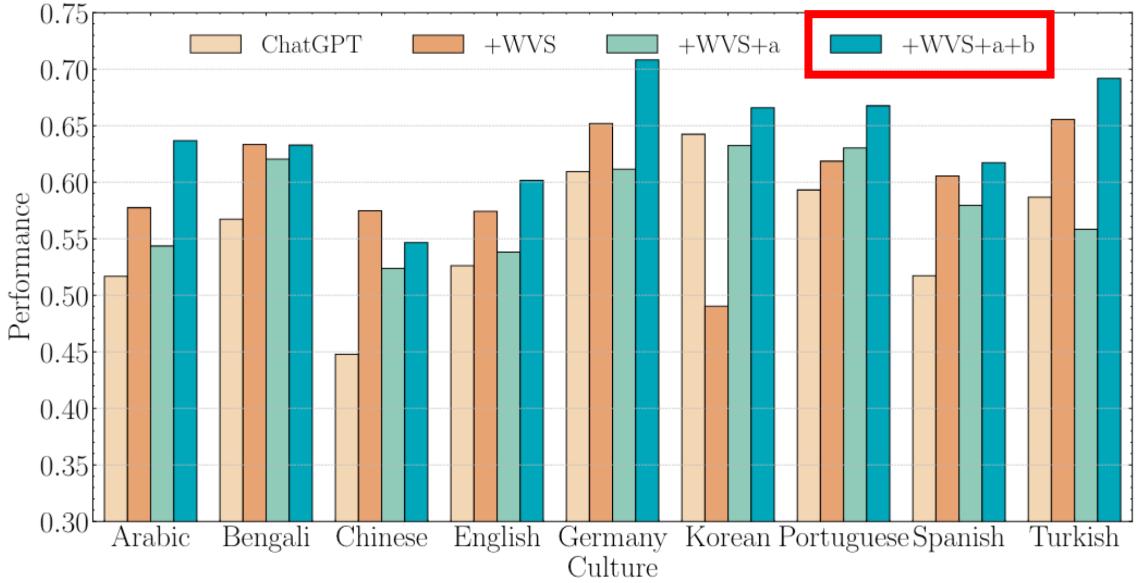


- +WVS: Fine-tuned with 50 WVS samples
- +WVS+a: +WVS plus generated samples from step 1 (Semantic Templates)

3️⃣ Fine-tuning

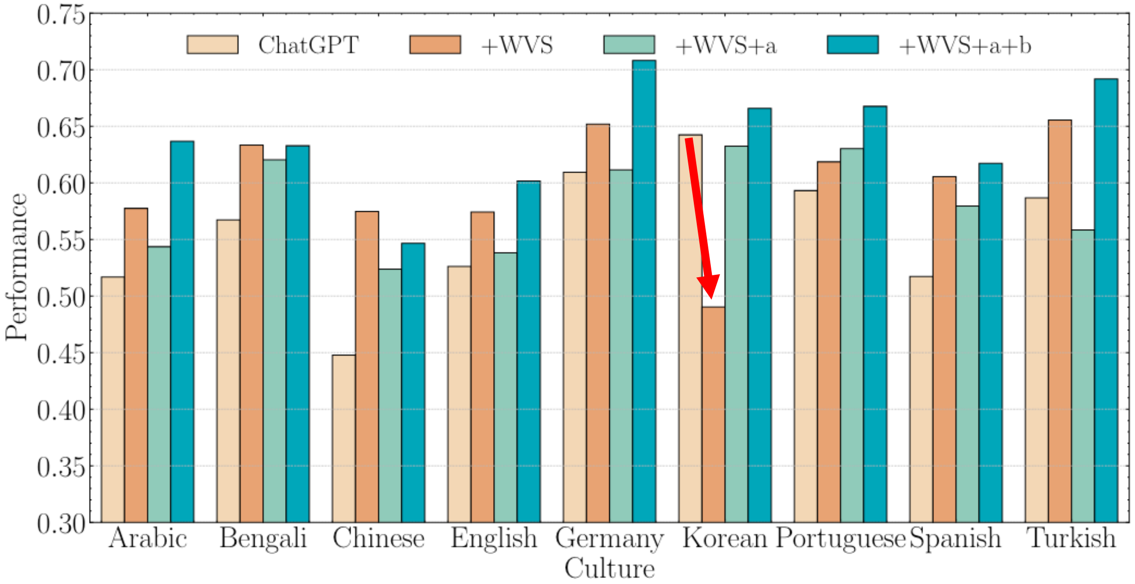
: Conducting an **ablation study** to compare fine-tuning results of LLM (GPT-3.5) across cultural groups



- +WVS: Fine-tuned with 50 WVS samples
- +WVS+a: +WVS plus generated samples from step 1 (Semantic Templates)
- +WVS+a+b: +WVS+a plus the complete algorithm process (Semantic Templates, Intact Sentences)

3️⃣ Fine–tuning

: **Semantic augmentation** fixes inconsistencies and boosts performance across cultures

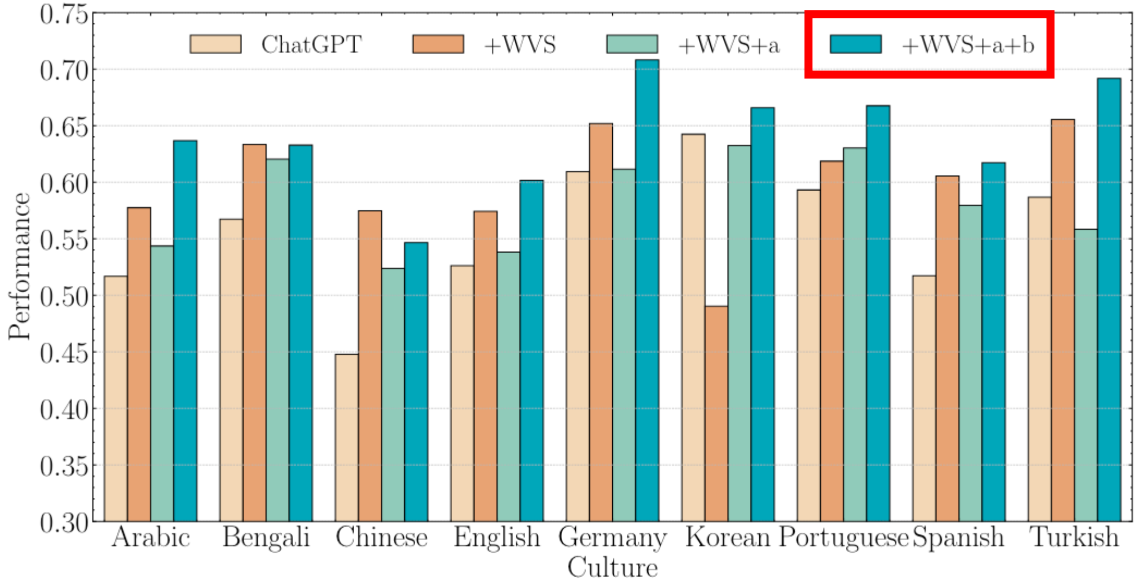


〈 Effectiveness of Semantic Data Augmentation 〉

– **Limitations of WVS Seeds:** Fine–tuning with 50 WVS (+WVS method) seeds yields inconsistent results, sometimes lowering performance (e.g., Korean)

3️⃣ Fine-tuning

: **Semantic augmentation** fixes inconsistencies and boosts performance across cultures



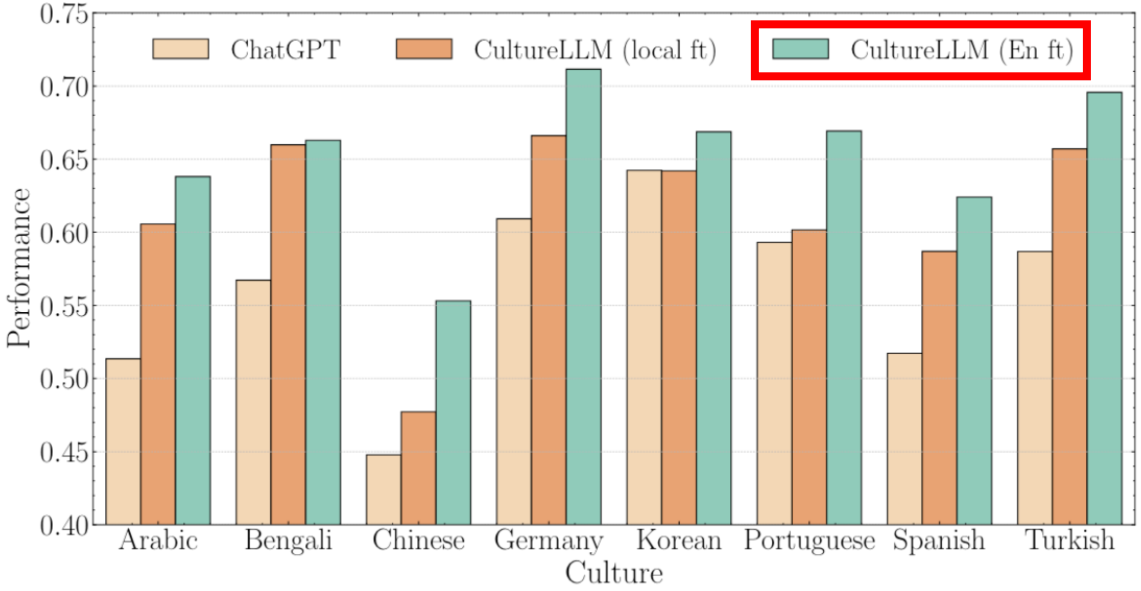
SOTA

〈 **Effectiveness of Semantic Data Augmentation** 〉

- **Limitations of WVS Seeds**: Fine-tuning with 50 WVS (+WVS method) seeds yields inconsistent results, sometimes lowering performance (e.g., Korean)
- **Benefits of Augmentation Processes**: Two-step semantic augmentation ensures consistent and significant improvements across tasks and cultures

3️⃣ Fine–tuning

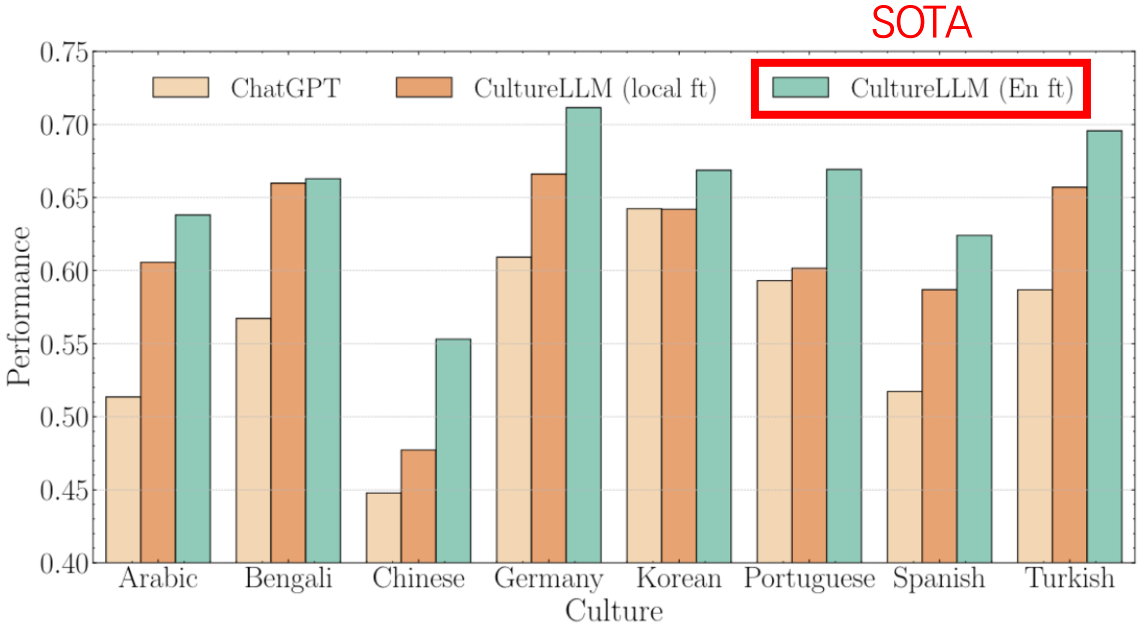
: **Fine–tuning on English data** can outperform native language fine–tuning via **cross–lingual transfer**


SOTA

- Using English as a unified input outperforms results obtained with translations into native languages, with culture–specific prompts (e.g., “You are an **Arabic** chatbot that knows **Arabic** very well”)

3️⃣ Fine-tuning

: **Fine-tuning on English data** can outperform native language fine-tuning via **cross-lingual transfer**



- Using English as a unified input outperforms results obtained with translations into native languages, with culture-specific prompts (e.g., "You are an **Arabic** chatbot that knows **Arabic** very well")
- All languages share the **same input questions** in English, but the **answers vary culturally**

3️⃣ Fine–tuning

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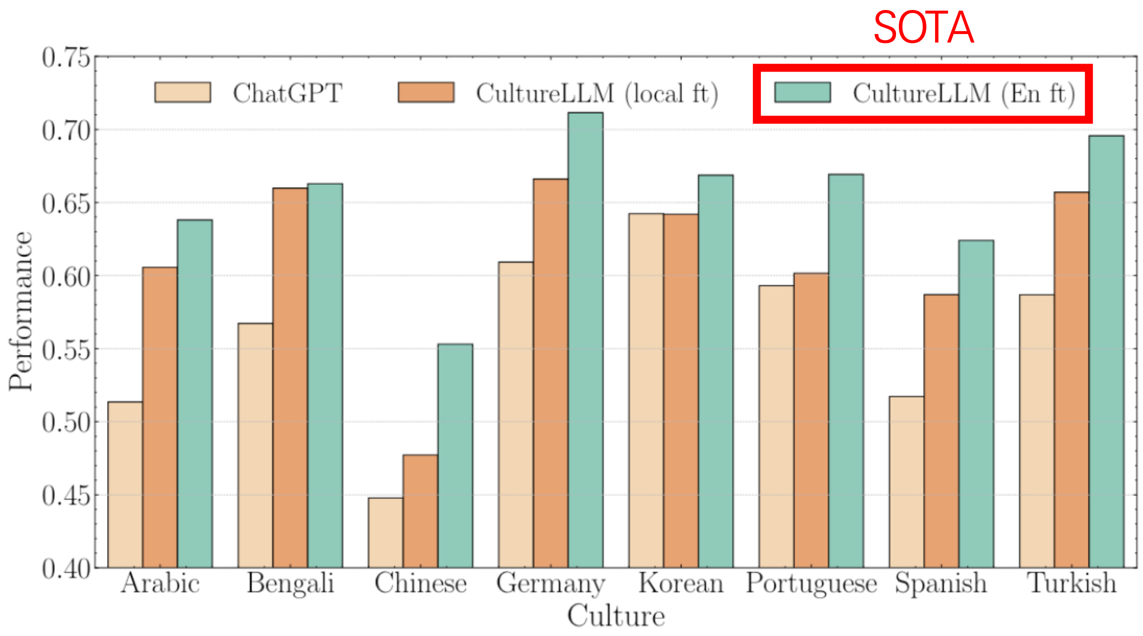
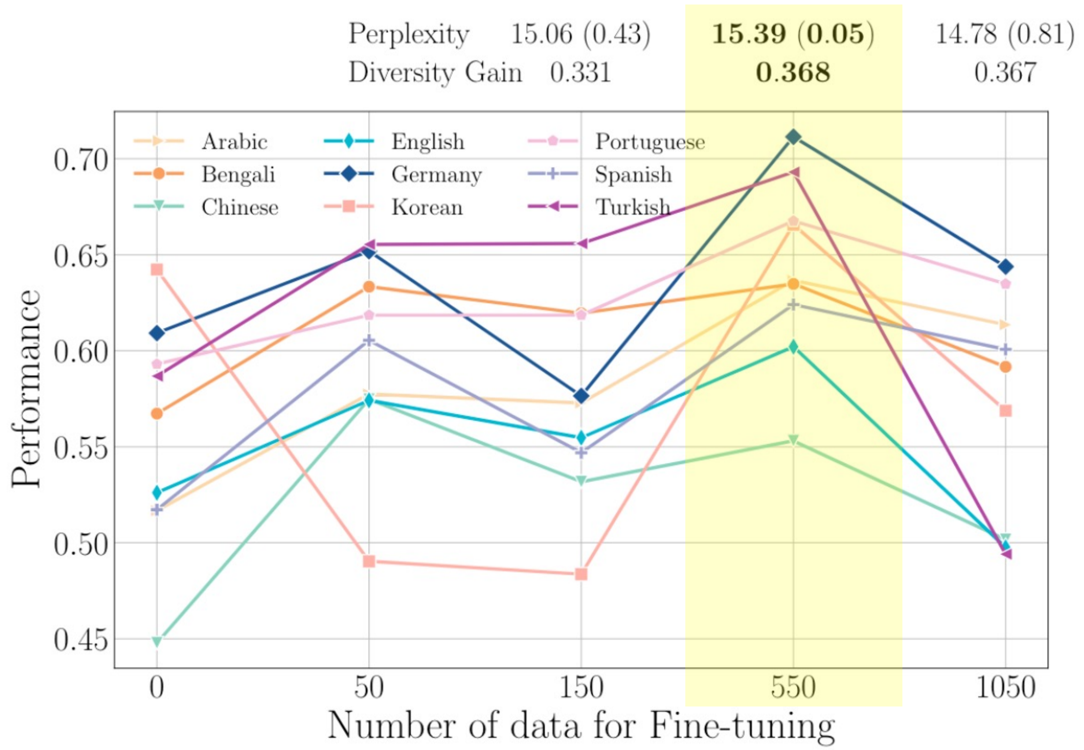


- Using English as a unified input outperforms results obtained with translations into native languages, with culture–specific prompts (e.g., “You are an **Arabic** chatbot that knows **Arabic** very well”)
- All languages share the **same input questions** in English, but the **answers vary culturally**
- Focuses on **cultural differences in opinions** regardless of native language, relying on **cross–lingual transfer**

3️⃣ Fine–tuning

: Conducting an **effectiveness analysis** by empirically testing the size of fine–tuning data



Perplexity	15.06 (0.43)	**15.39 (0.05)**	14.78 (0.81)
Diversity Gain	0.331	**0.368**	0.367

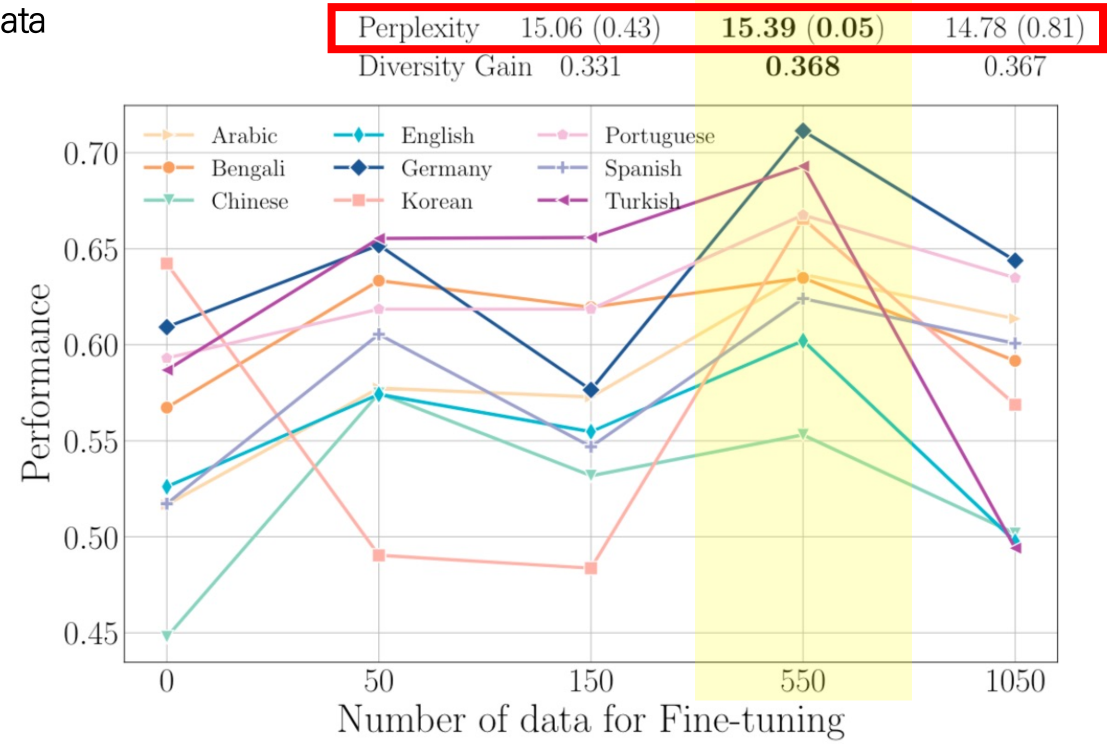
The model generates only specific modes of the data distribution while ignoring others

- Dataset **diversity and quality** are crucial in LLM training (risk of ‘mode collapse’)
- Performance improves with more data but **declines beyond 500 samples**

3️⃣ Fine–tuning

: Conducting an **effectiveness analysis** by empirically testing the size of fine–tuning data

- Perplexity: Measures how well a model predicts the probability distribution of data
  - **Lower perplexity** indicates the model predicts test data more accurately, reflecting better performance
  - **Higher perplexity** suggests the training data is more diverse and informative, enhancing the model's learning potential



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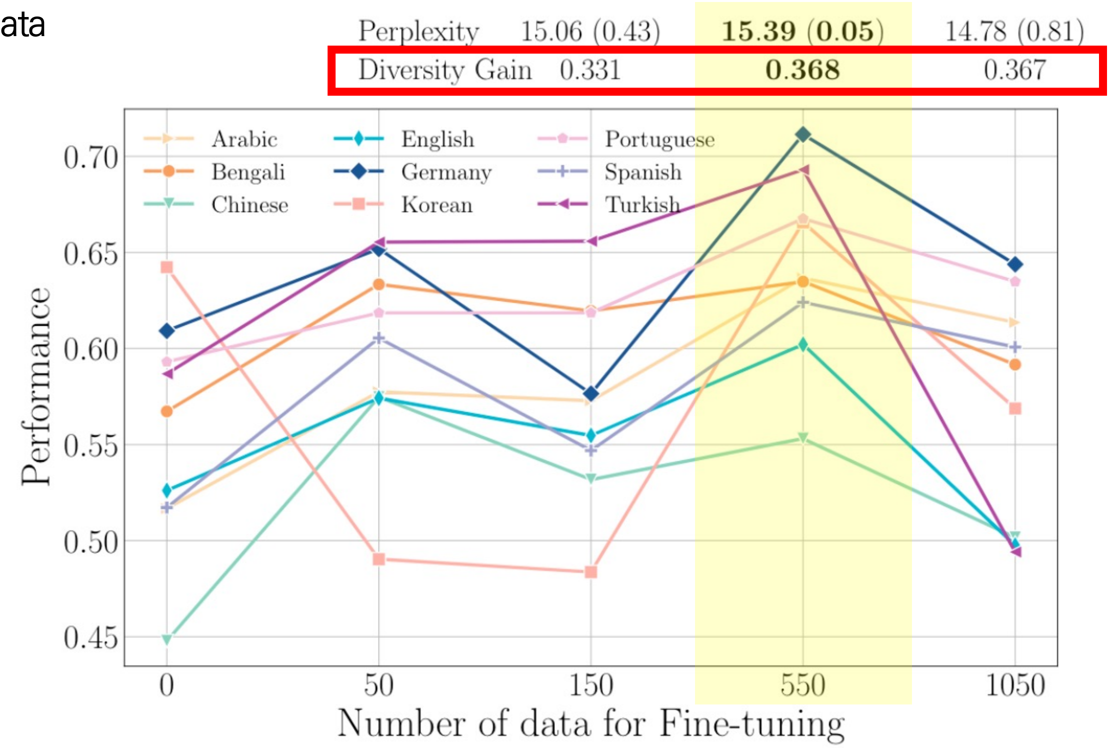
- Diversity Gain: Measures the variety and uniqueness of the generated text in terms of word choice and sentence structure
  - **Lower diversity gain** highlights a lack of variety, often resulting in repetitive or predictable text the model predicts
  - **Higher diversity gain** reflects greater variety in the generated text, minimizing repetitive patterns



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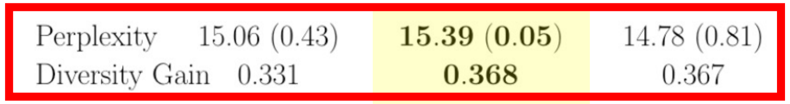

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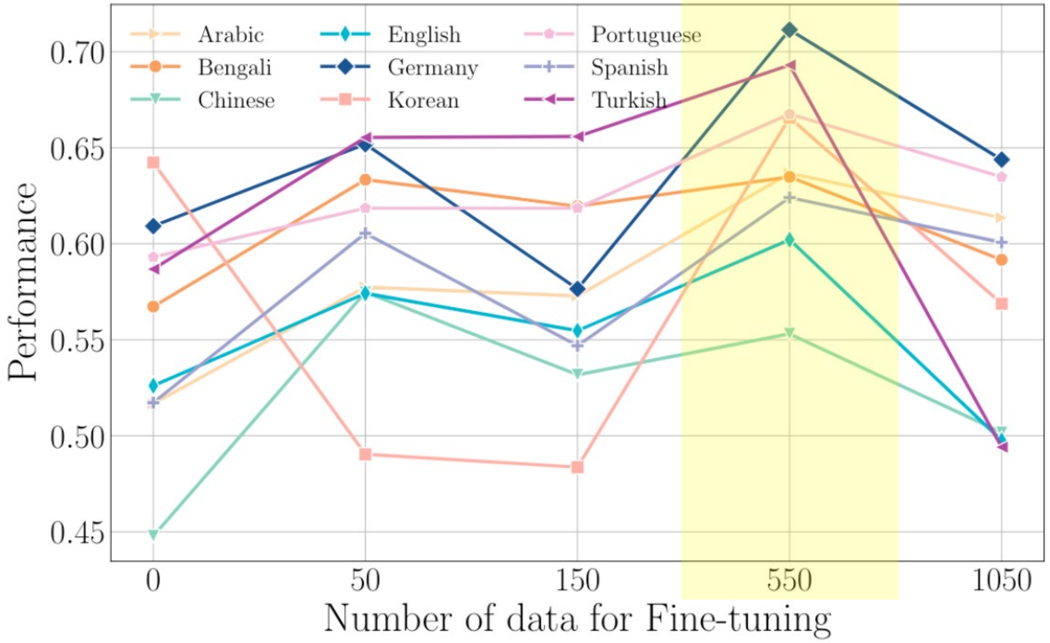


- Perplexity and diversity gain analysis show the **best results at 500 samples**

  => Despite using data augmentation with varied sentence and word styles, **dataset diversity still increased**

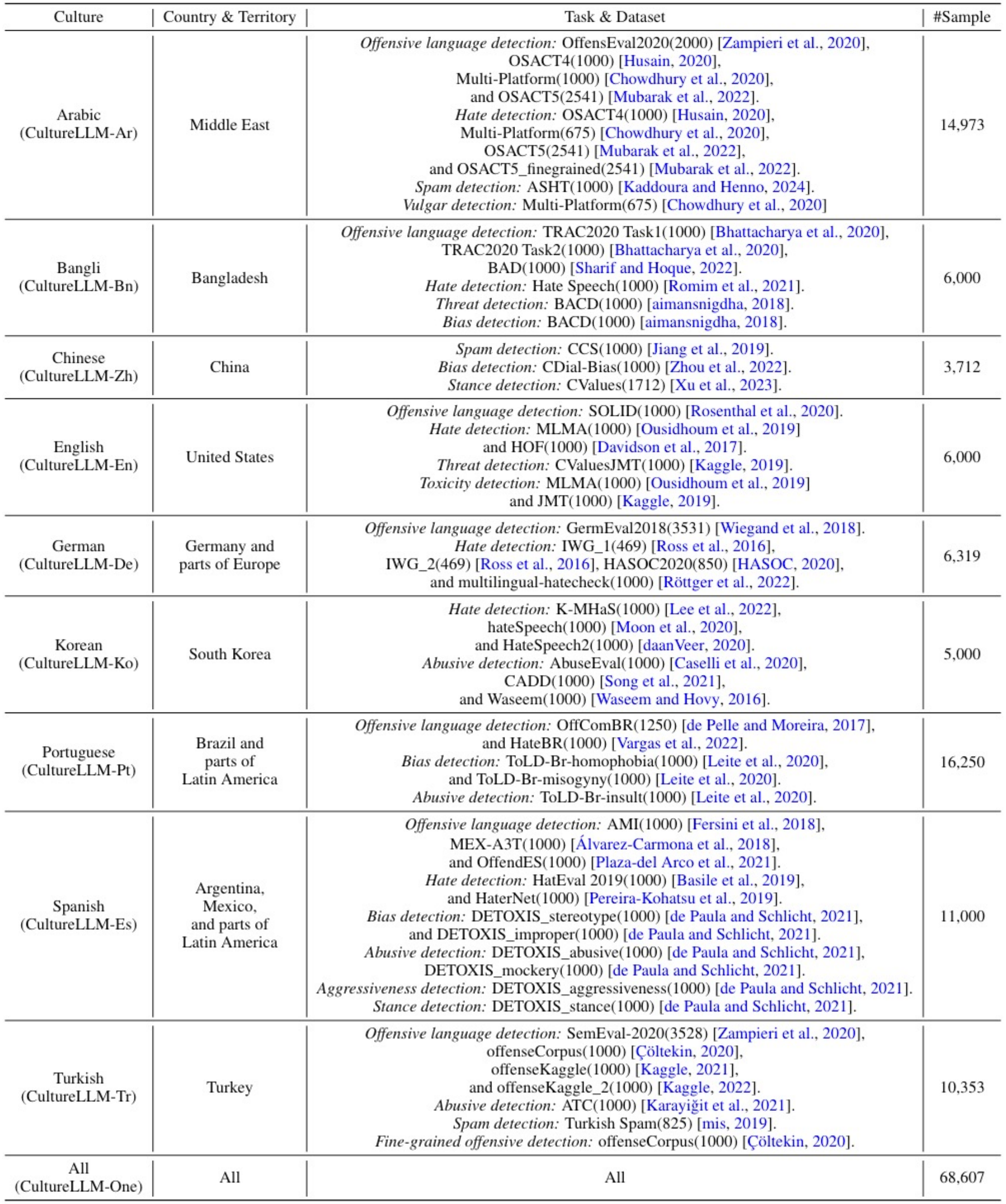
4 Culture-related Applications

- 8 evaluation tasks

  : Offensive language, Hate speech, Stance, Toxicity, Threat, Bias, Abusive, and Spam Detection

- 59 datasets
- Covering 9 languages
- Containing 68,607 test samples

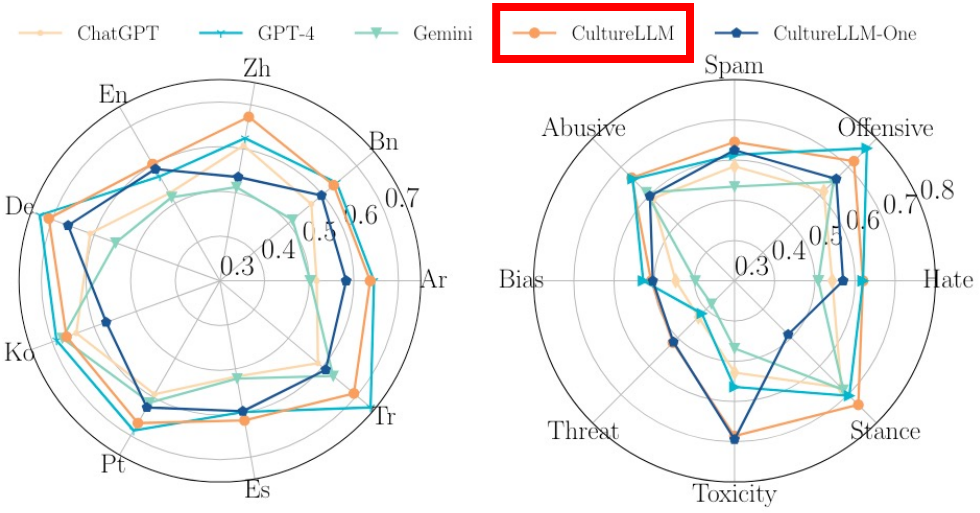
Applying various **CultureLLM** models to tasks across languages



Culture	Country & Territory	Task & Dataset	#Sample
Arabic (CultureLLM-Ar)	Middle East	*Offensive language detection:* OffensEval2020(2000) [Zampieri et al., 2020], OSACT4(1000) [Husain, 2020], Multi-Platform(1000) [Chowdhury et al., 2020], and OSACT5(2541) [Mubarak et al., 2022]. *Hate detection:* OSACT4(1000) [Husain, 2020], Multi-Platform(675) [Chowdhury et al., 2020], OSACT5(2541) [Mubarak et al., 2022], and OSACT5_finegrained(2541) [Mubarak et al., 2022]. *Spam detection:* ASHT(1000) [Kaddoura and Henno, 2024]. *Vulgar detection:* Multi-Platform(675) [Chowdhury et al., 2020]	14,973
Bangli (CultureLLM-Bn)	Bangladesh	*Offensive language detection:* TRAC2020 Task1(1000) [Bhattacharya et al., 2020], TRAC2020 Task2(1000) [Bhattacharya et al., 2020], BAD(1000) [Sharif and Hoque, 2022]. *Hate detection:* Hate Speech(1000) [Romim et al., 2021]. *Threat detection:* BACD(1000) [aimansnigdha, 2018]. *Bias detection:* BACD(1000) [aimansnigdha, 2018].	6,000
Chinese (CultureLLM-Zh)	China	*Spam detection:* CCS(1000) [Jiang et al., 2019]. *Bias detection:* CDial-Bias(1000) [Zhou et al., 2022]. *Stance detection:* CValues(1712) [Xu et al., 2023].	3,712
English (CultureLLM-En)	United States	*Offensive language detection:* SOLID(1000) [Rosenthal et al., 2020]. *Hate detection:* MLMA(1000) [Ousidhoum et al., 2019] and HOF(1000) [Davidson et al., 2017]. *Threat detection:* CValuesJMT(1000) [Kaggle, 2019]. *Toxicity detection:* MLMA(1000) [Ousidhoum et al., 2019] and JMT(1000) [Kaggle, 2019].	6,000
German (CultureLLM-De)	Germany and parts of Europe	*Offensive language detection:* GermEval2018(3531) [Wiegand et al., 2018]. *Hate detection:* IWG_1(469) [Ross et al., 2016], IWG_2(469) [Ross et al., 2016], HASOC2020(850) [HASOC, 2020], and multilingual-hatecheck(1000) [Röttger et al., 2022].	6,319
Korean (CultureLLM-Ko)	South Korea	*Hate detection:* K-MHaS(1000) [Lee et al., 2022], hateSpeech(1000) [Moon et al., 2020], and HateSpeech2(1000) [daanVeer, 2020]. *Abusive detection:* AbuseEval(1000) [Caselli et al., 2020], CADD(1000) [Song et al., 2021], and Waseem(1000) [Waseem and Hovy, 2016].	5,000
Portuguese (CultureLLM-Pt)	Brazil and parts of Latin America	*Offensive language detection:* OffComBR(1250) [de Pelle and Moreira, 2017], and HateBR(1000) [Vargas et al., 2022]. *Bias detection:* ToLD-Br-homophobia(1000) [Leite et al., 2020], and ToLD-Br-misogyny(1000) [Leite et al., 2020]. *Abusive detection:* ToLD-Br-insult(1000) [Leite et al., 2020].	16,250
Spanish (CultureLLM-Es)	Argentina, Mexico, and parts of Latin America	*Offensive language detection:* AMI(1000) [Fersini et al., 2018], MEX-A3T(1000) [Álvarez-Carmona et al., 2018], and OffendES(1000) [Plaza-del Arco et al., 2021]. *Hate detection:* HatEval 2019(1000) [Basile et al., 2019], and HaterNet(1000) [Pereira-Kohatsu et al., 2019]. *Bias detection:* DETOXIS_stereotype(1000) [de Paula and Schlicht, 2021], and DETOXIS_improper(1000) [de Paula and Schlicht, 2021]. *Abusive detection:* DETOXIS_abusive(1000) [de Paula and Schlicht, 2021], DETOXIS_mockery(1000) [de Paula and Schlicht, 2021]. *Aggressiveness detection:* DETOXIS_aggressiveness(1000) [de Paula and Schlicht, 2021]. *Stance detection:* DETOXIS_stance(1000) [de Paula and Schlicht, 2021].	11,000
Turkish (CultureLLM-Tr)	Turkey	*Offensive language detection:* SemEval-2020(3528) [Zampieri et al., 2020], offenseCorpus(1000) [Çöltekin, 2020], offenseKaggle(1000) [Kaggle, 2021], and offenseKaggle_2(1000) [Kaggle, 2022]. *Abusive detection:* ATC(1000) [Karayiğit et al., 2021]. *Spam detection:* Turkish Spam(825) [mis, 2019]. *Fine-grained offensive detection:* offenseCorpus(1000) [Çöltekin, 2020].	10,353
All (CultureLLM-One)	All	All	68,607

4 Culture-related Applications

: Most CultureLLM models show **strong performance across both cultures** and **tasks**



〈 Performance Averaged by **Cultures** **(Left)** and **Tasks** **(Right)** 〉

- Both specific and unified CultureLLM outperform other approaches, with specific CultureLLM achieving the best performance

4 Culture-related Applications

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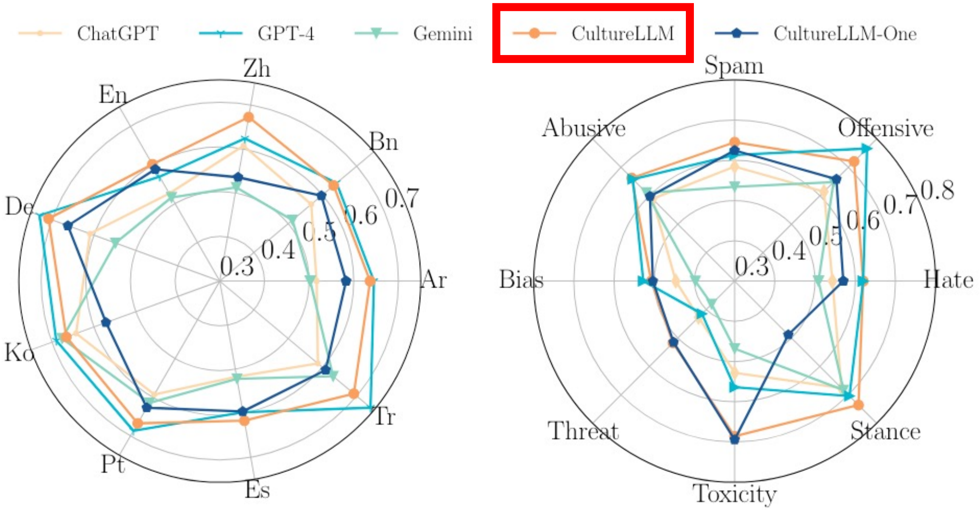

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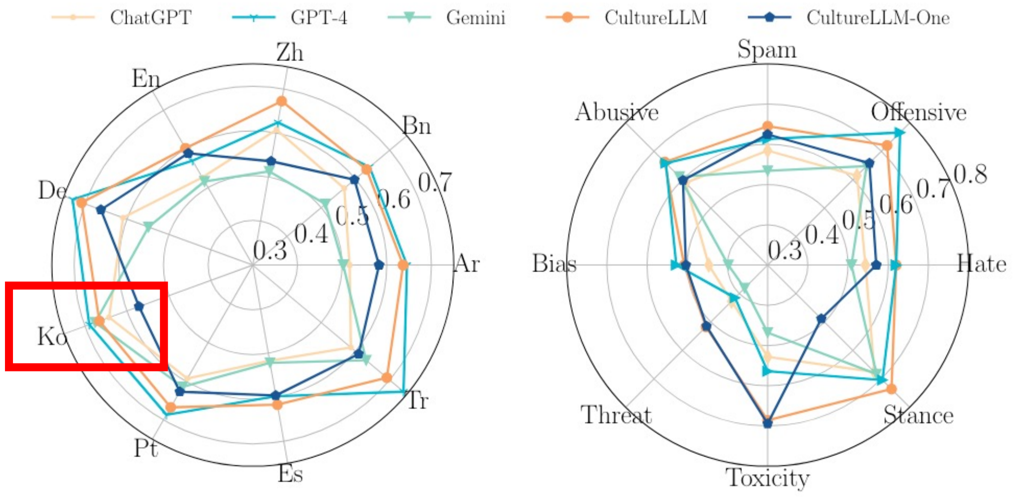

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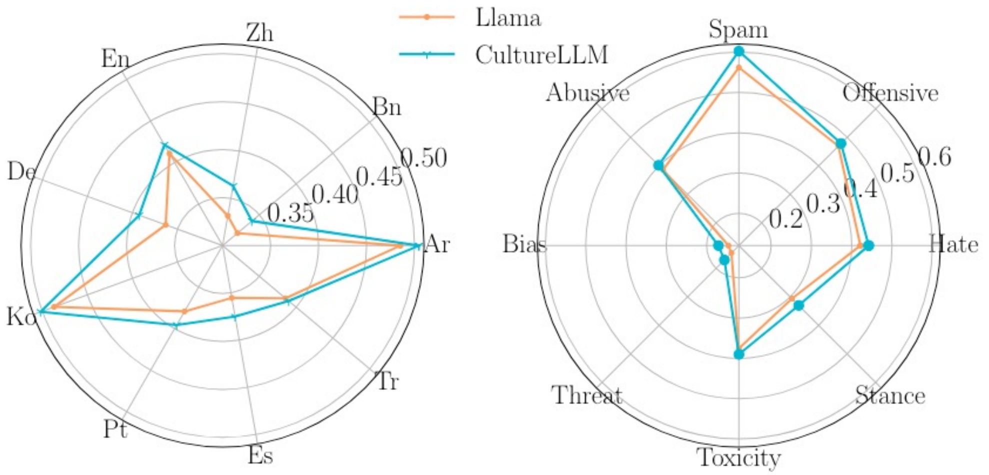
: In addition to fine-tuned GPT, tested **Llama2 for open-source**



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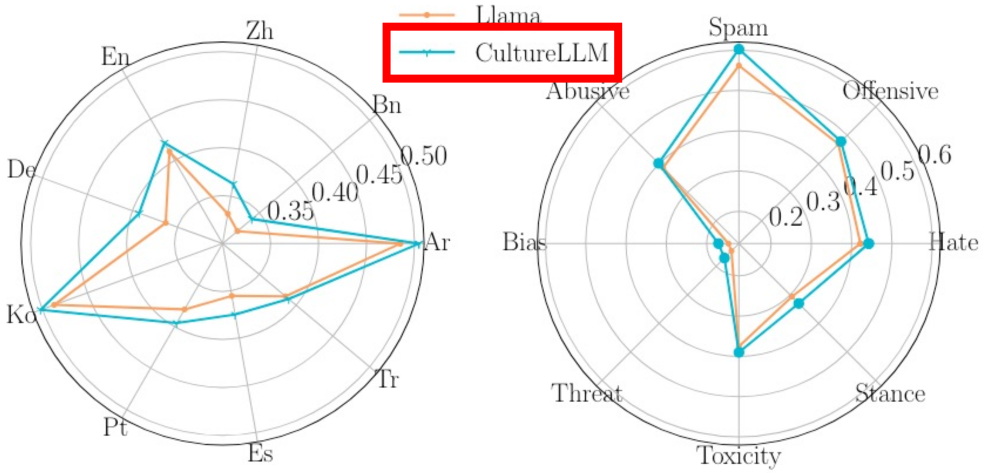

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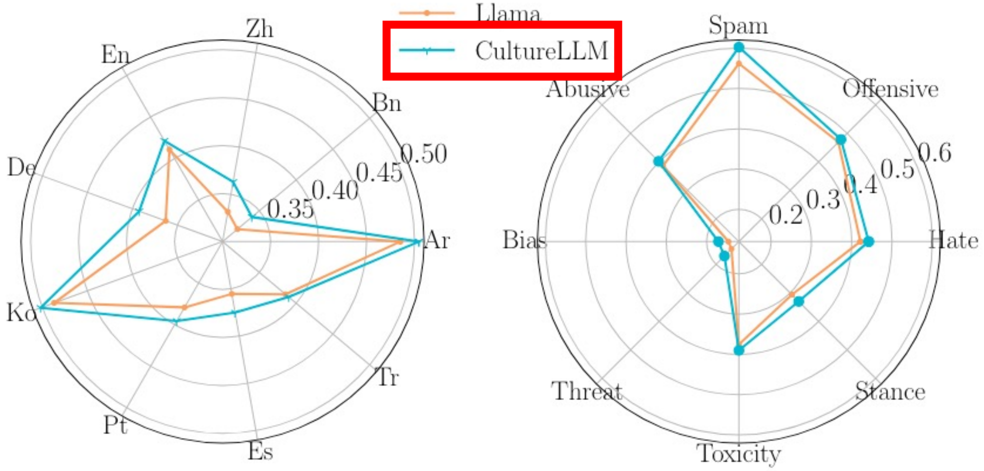

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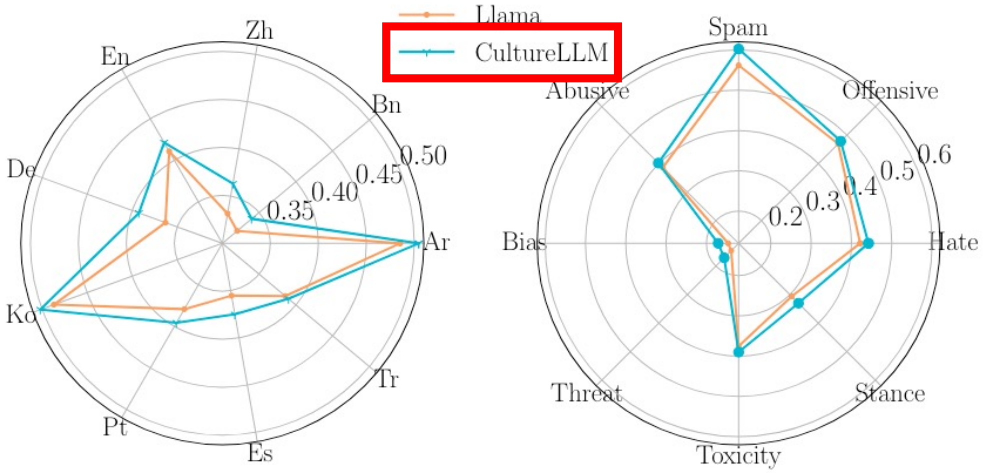

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=> CultureLLM is a general approach to **enhance LLMs' cultural understanding**

Conclusion

: CultureLLM, a cost-effective solution to **integrate cultural differences into LLMs**

1. Leveraged **WVS data to align LLMs** with culturally representative values

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4. Applied and tested the resulting **CultureLLM across diverse cultural tasks**, demonstrating consistent performance

Conclusion (Insights)

: Key points for **applying** CultureLLM's process to **our research**

1. Leverage WVS, a high-quality, long-term, multi-country dataset, widely used in research

Ramezani, A., & Xu, Y. (2023). Knowledge of cultural moral norms in large language models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 428–446.

Zhao, W., Mondal, D., Tandon, N., Dillion, D., Gray, K., & Gu, Y. (2024). WorldValuesBench: A Large-Scale Benchmark Dataset for Multi-Cultural Value Awareness of Language Models. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pp. 17696–17706.

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Jackson, J. C., & Medvedev, D. (2024). Worldwide divergence of values. *Nature Communications, 15*(1), 2650.

⋮

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5. Go beyond multicultural, multilingual modeling by **testing the model on open-source datasets**

   (8 evaluation tasks, 59 datasets)