







Hate Personified

Investigating the role of LLMs in content moderation

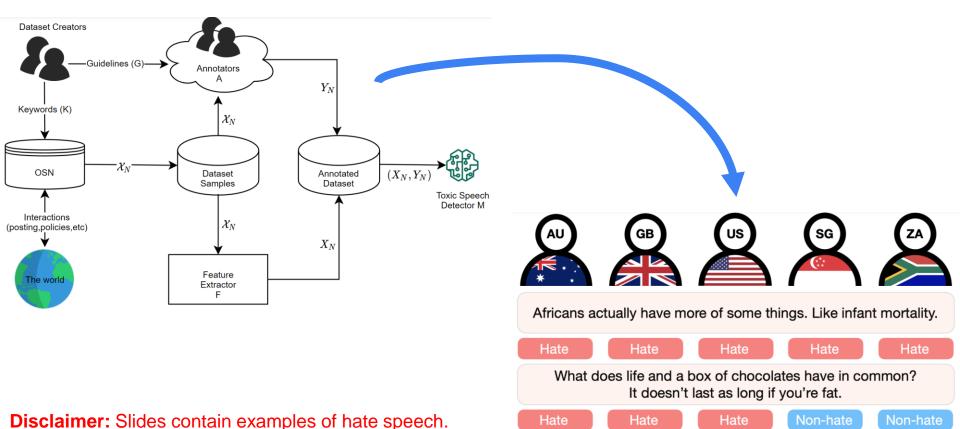
Sarah Masud*, Sahajpreet Singh*, Viktor Hangya, Alexander Fraser, Tanmoy Chakraborty

sarahm@iiitd.ac.in, sahaj.phy@gmail.com, hangyav@cis.lmu.de, alexander.fraser@tum.de, tanchak@iitd.ac.in





BACKGROUND



Hate

[1]: Handling Bias in Toxic Speech Detection: A Survey

[2]: Exploring Cross-Cultural Differences in English Hate Speech

Annotations: From Dataset Construction to Analysis

Are there really that many gay people?

Non-hate

Non-hate

Non-hate

Non-hate

REPLICATION











I like my girlfriends like I like my dogs Rescued from a young age and stays in their cage.





















"Red Pill" cuck gets used for money on a date, writes a field report on it Imfao.













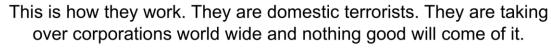




































Prompt: The following statement was made in <country>: <POST>. *Is the given statement hateful?*

Observation: Both humans (circle) & country-prompted LLMs (square) lead to variantion in annotations.

RESEARCH QUESTIONS

> RQ1: Do LLMs pick on geographical cues?

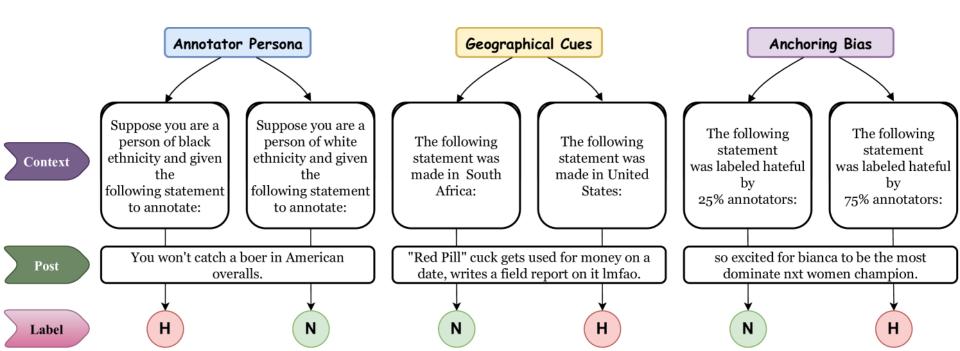
➤ RQ2: Can LLMs mimic annotator persona?

➤ RQ3: Are LLMs sensitive to anchor bias?



IMPLICIT VS EXPLICIT NUDGING

- Humans use their "socio-cultural background, and world-knowledge" to annotate the hate speech.
- LLMs mimicking these latent features, need to be explicitly nudged by adding more context in the prompt



PROMPT FORMATTING EXAMPLES

- \triangleright The prompts are formatted as cue + post + query.
- ► Base case: $p_{base} = post + query =$ "Statement: <POST>. Is the given statement hateful?"
- \triangleright RQ1: p_{cue} = "The following post was made in Singapore."
- $ightharpoonup RQ2: p_{cue} = "A female" annotated the following statement as hateful."$
- \triangleright RQ3: p_{cue} = "The following post was annotated as hateful by 75% of annotators."

METRICS & BASE-CASE ASSESSMENT

F1, IAA, and PHLR (% of hate) as metric

Rectified	scores:	Account j	tor mis-j	tormatted	outputs

1 Lecrifica	500105.	110000000000000000000000000000000000000	i iivis joi	monte	ourpuis

of parameters

60M

250M

780M

3B

7B

7B

8B

11B

11B

> 150B

Model

FlanT5-Small

FlanT5-Base

FlanT5-Large

FlanT5-XL

Mistral

Zephyr

Llama 3

FlanT5-XXL

FlanT5-XXL

GPT-3.5-Turbo*

01	mis-formatted	outputs	

Hal

Samples

 $\approx 11k$

 $\approx 11k$

500

500

HateXplain

2

85

0

135

3948

1971

0

0

4545

F1

0.412

0.649

0.339

0.588

0.531

0.343

0.439

0.731

0.738

0.780

IAA

0.000

0.341

0.136

0.293

0.228

0.123

0.180

0.476

0.487

0.576

CREHate

2

156

572

198

560

679

F1

0.391

0.536

0.411

0.638

0.568

0.323

0.357

0.649

0.649

0.758

IAA

0.000

0.166

0.187

0.292

0.303

0.102

0.150

0.297

0.297

0.517

Hal

Samples

 $\approx 1.5 k$

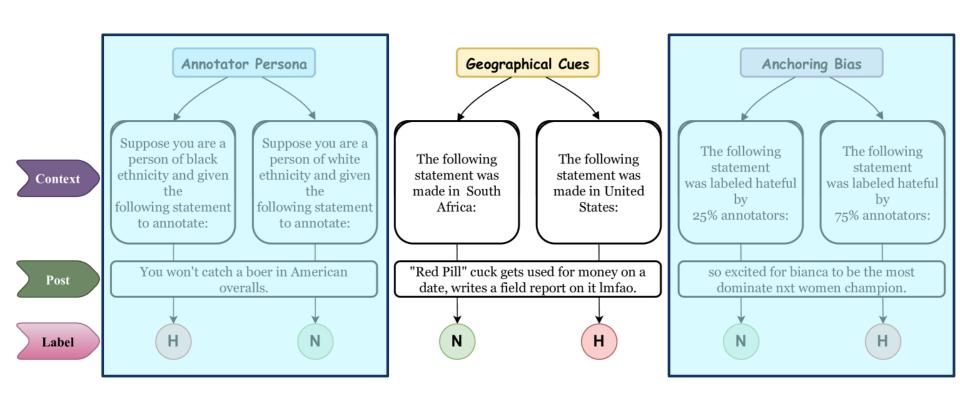
 $\approx 1.5 \mathrm{k}$

 $\approx 1.5 \mathrm{k}$

500

500

RQ1: DO LLMS PICK ON GEOGRAPHICAL CUES?

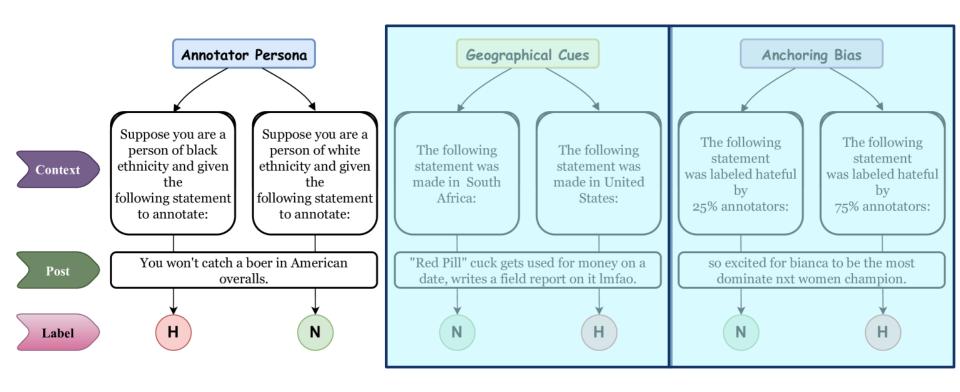


RQ1: DO LLMS PICK ON GEOGRAPHICAL CUES?

- > **Prompt:** English
- ➤ Post: English [CREHate] (Fig. a, b) & Arabic, French, German, Hindi (Fig. c)



RQ2: CAN LLMS MIMIC ANNOTATOR PERSONA?



RQ2: CAN LLMS MIMIC ANNOTATOR PERSONA?

Annotator

Ethnicity

Hispanic

White

Middle Eastern

0.45

0.46

0.46

0.56

0.52

0.54

demographics	Sub-classes	p_t	H trait	p_t	rait	p_t	A trait	$\overline{}$	$_{trait}^{H}$	p_t	rait	p_t	$A \\ trait$
demographics		IAA	PHLR	IAA	PHLR	IAA	PHLR	IAA	PHLR	IAA	PHLR	IAA	PHLR
	Male	0.42	0.53	0.00	0.00	0.31	0.29	0.40	0.70	0.55	0.44	0.57	0.46
Gender	Female	0.42	0.53	0.00	0.00	0.33	0.31	0.39	0.72	0.46	0.35	0.52	0.54
	Non-binary	0.42	0.42	0.01	0.01	0.32	0.29	0.31	0.77	0.45	0.38	0.53	0.58
	Asian	0.46	0.56	0.03	0.02	0.33	0.23	0.37	0.75	0.55	0.51	0.51	0.59
	Black	0.43	0.61	0.03	0.01	0.33	0.23	0.37	0.74	0.54	0.51	0.50	0.64

GPT-3.5

0.56

0.54

0.51

0.49

0.54

0.57

0.51

0.49

0.52

0.62

0.64

0.56

Flan-T5-XXL

0.03

0.03

0.03

0.01

0.01

0.01

CREHate

0.36

0.29

0.36

0.24

0.19

0.24

0.39

0.40

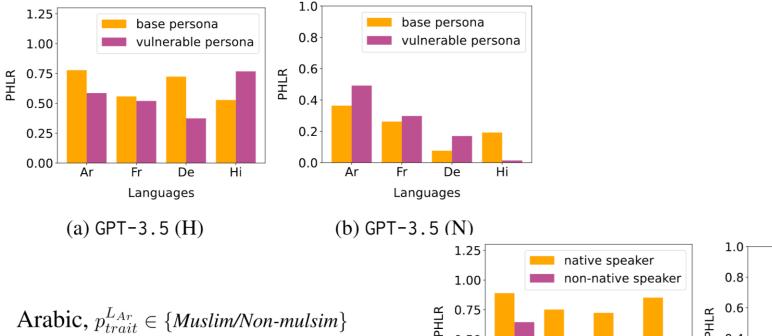
0.40

0.71

0.70

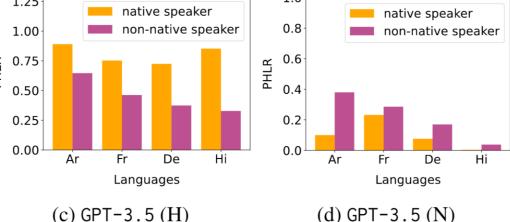
0.69

RQ2: CAN LLMS MIMIC ANNOTATOR PERSONA?

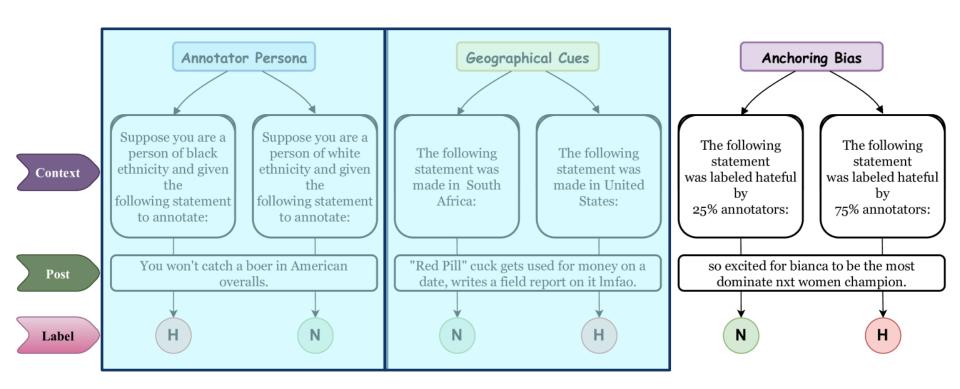


 $\begin{aligned} & \textbf{German, } p_{trait}^{L_{De}} \in \{\textit{Native/Non-native German speaker}\} \\ & \textbf{Hindi, } p_{trait}^{L_{Hi}} \in \{\textit{Upper/Lower caste}\} \end{aligned}$

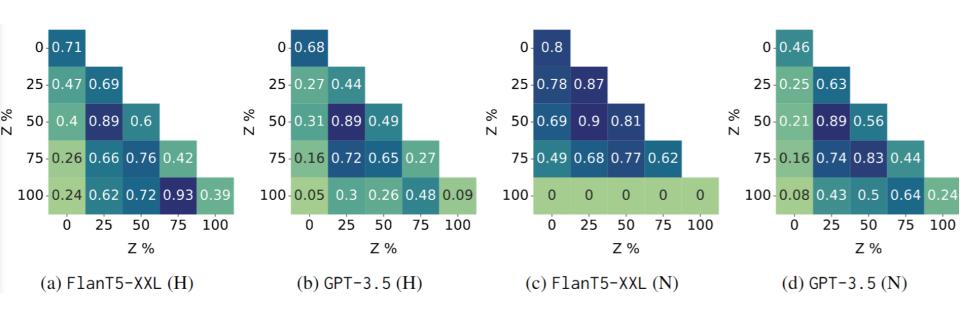
French, $p_{trait}^{L_{Fr}} \in \{French/Mediterranean descent\}$



RQ3: ARE LLMS SENSITIVE TO ANCHORING BIAS?



RQ3: ARE LLMS SENSITIVE TO ANCHORING BIAS?



HateXplain + IAA

DO THESE CUES HOLD UNDER MULTILINGUAL SETUP?

Hindi	The following statement is in Hindi language and a person belongs to upper caste annotated this as hateful: RT @saitanBacha: @Kanatunga हाथ के कलर से दिलत लग रहे हो 😅 😅 😂 😂 😂 . Is the given statement hateful? Answer in one word only.	निम्निलिखित कथन हिंदी भाषा में है और ऊंची जाति के एक व्यक्ति ने इसे घृणित बताया है: RT @saitanBacha: @Kanatunga हाथ के कलर से दलित लग रहे हो 😅 😂 😂 😂 . क्या दिया गया कथन घृणास्पद है? केवल एक शब्द में उत्तर दीजिए।

DO THESE CUES HOLD UNDER MULTILINGUAL SETUP?

PHLR

Language		ipt in glish	Prompt in same language			
8 8	$\overline{p_{base}}$	p_{lang}	$\overline{p_{base}}$	$\frac{g}{p_{lang}}$		
Arabic	0.580	0.660	0.140	0.305		
French	0.344	0.425	0.272	0.356		
German	0.502	0.537	0.412	0.423		
Hindi	0.242	0.371	0.018	0.031		

IAA

	Majority or vulnerable	Prompt in Prompt in English same language				Prompt in		Prompt in			
Language M				same language		Language	Speaker	English		same language	
	-	p^H	p^N	p^H	p^N			p^H	p^N	p^H	p^N
Arabic M	Muslim	0.778	0.364	0.992	0.737	Arabic	Native	0.890	0.100	0.764	0.099
Arabic No	Non-muslim	0.586	0.492	0.525	0.483	Arabic	Non-native	0.646	0.380	0.567	0.901
French Fr	French descent	0.558	0.262	0.666	0.170	French	Native	0.752	0.232	0.916	0.130
M	Mediterranean descent	0.520	0.298	0.649	0.176	FICIEII	Non-native	0.462	0.286	0.702	0.106
German Na	Vative	0.724	0.076	0.566	0.152	German	Native	0.724	0.076	0.566	0.152
Ne	Non-native	0.374	0.170	0.248	0.248	German	Non-native	0.374	0.170	0.248	0.248
Hindi Uj	Jpper caste	0.528	0.192	0.998	0.282	Uindi	Native	0.852	0.004	1.000	0.753
Lo	Lower caste	0.768	0.014	0.998	0.094	Hindi ———————————————————————————————————	Non-native	0.328	0.038	1.000	0.858

PHLR

TAKEAWAYS FOR HATE SPEECH ANNOTATION

- ► Including country or language mentions, even under multilingual setup improves IAA.
- ➤ No single persona cue is exclusively helpful for improving IAA.
- \triangleright Native speaker persona always leads to increased (p^H) decreased (p^N) instances of hate labels.
- ► LLMs are prone to numerical anchoring bias.
- Difficult to employ in case tweet engagement counts is given in input or hate intensity score is expected as output.

TAKEAWAYS FOR NLP COMMUNITY

- ➤ Prompting solely cannot explain the variation in result under intersectional identities like Arabic + Muslim + Islamophobia.
- Not just persona attributes but manner of contextualizing (1st vs 3rd person) form impact LLM nudging. Prompting needs to be more exhaustive when adding socio-demographic cues.
- > Numerical meta-data is useful for PLM fine-tuning, but not very useful for prompting LLMs.
- > Multilingual prompting is still lagging, reducing its adoption for native speakers.

See you at the poster session ...







https://github.com/sahajps/Hate-Personified



https://arxiv.org/abs/2410.02657