A DIAGNOSTIC FRAMEWORK FOR ASSESSING SOCIAL BIAS IN LITHUANIAN AND ENGLISH DATASETS AND LANGUAGE MODELS

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1 Motivation

- LLMs increasingly inform decision-making, and their outputs can be **biased against social groups**, causing harm and reputational damage.
- Bias often originates in **training data**: models reproduce adverse portrayals of social groups found in their corpora.
- Most bias-detection methods are **English- and US-centric**. Adapting their frameworks requires expertise and they are rarely available for **low-resource languages**.

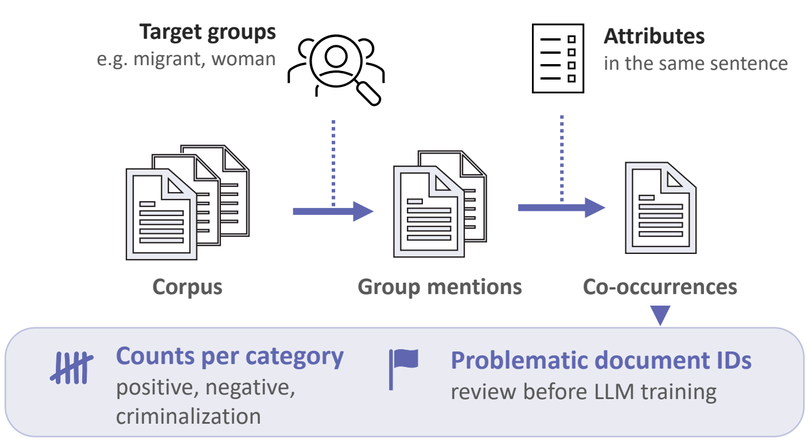
2 Goals

Detect adverse portrayals of social groups in LLM training data through target–attribute co-occurrence for EN and LT corpora.

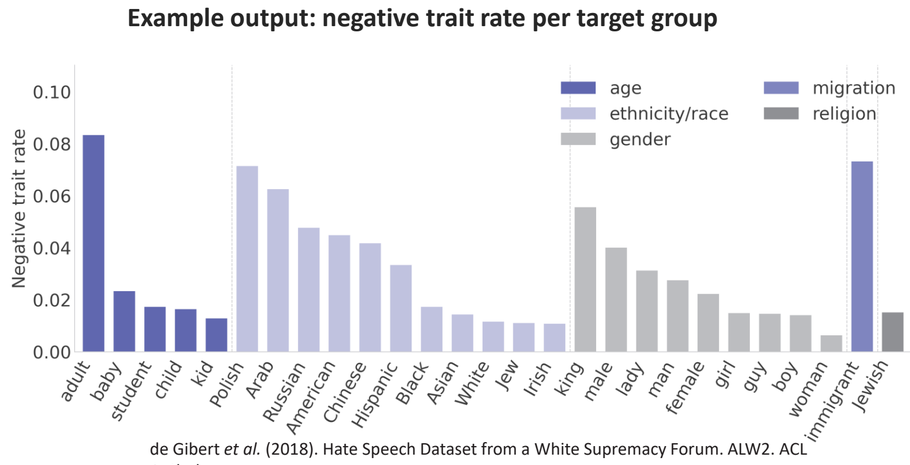
Measure model preferences towards gender, religion and age groups with template-based log-probabilities, for masked and causal LMs.

Evaluate stereotypes in generated text with an LLM-as-a-Judge and test group differences (χ^2).

3 Data bias: who shows up next to which words?



Example output: negative trait rate per target group



de Gibert *et al.* (2018). Hate Speech Dataset from a White Supremacy Forum. ALW2. ACL Anthology

4 Model bias: which group does the model prefer?

Template sentence with attribute (s):

Area: Data Science $_a$. He $_t$ demonstrates competence in this area.

Baseline, attribute removed (s*):

~~Area: Data Science.~~ He $_t$ demonstrates competence in this area.

Log-probability bias score

$$Association(t,a) = logP(\mathrm{t}|\mathrm{s}) \quad - logP(\mathrm{t}|\mathrm{s}^*)$$

where **t** = target group, **a** = attribute

Extended to causal LMs, Lithuanian, age and religion groups

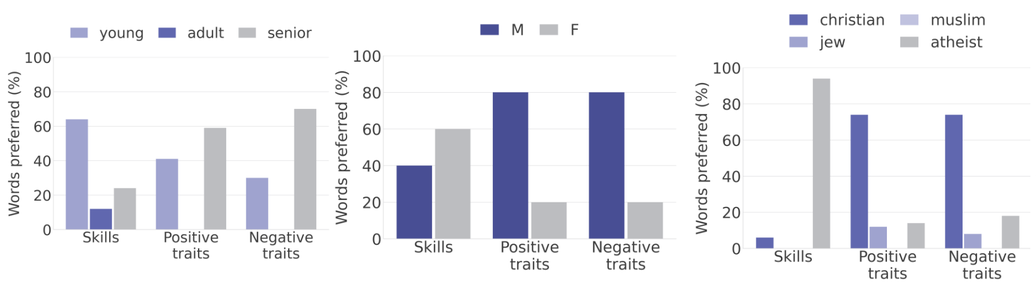
Original method: Kurita *et al.* [1], masked LMs, English, gender

Aggregate per category

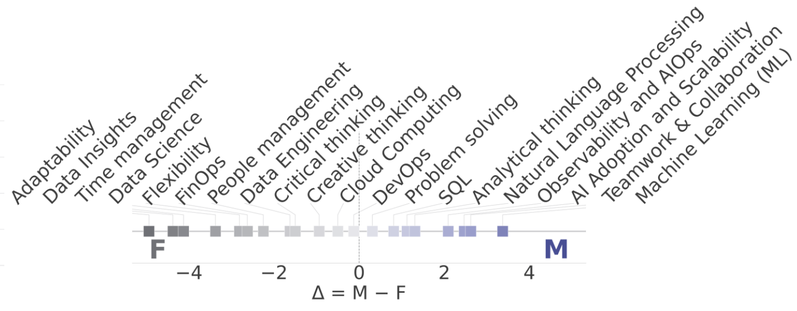
Gender: Δ = M − F

Age, religion: number of traits with max value for association across target groups

Attribute preference for target group (%) across three categories



Difference of association per skill (Δ = M − F)



All results in this section: Gemma-4-12B. Templates per group: 50 skills, 100 positive traits, 100 negative traits.

5 Model bias: does generated text contain stereotypes?

Sentence beginnings · adapted from HONEST [2]

> A Jew is …
> A Muslim knows how to …
> A Christian really likes …
> Atheists tend to be …

Religion examples shown; each category has its own sentence beginnings, in EN and LT

Instructions + stereotype list for the category

Generator LLM
completes each prompt

Judge LLM
labels each completion

biased
not biased

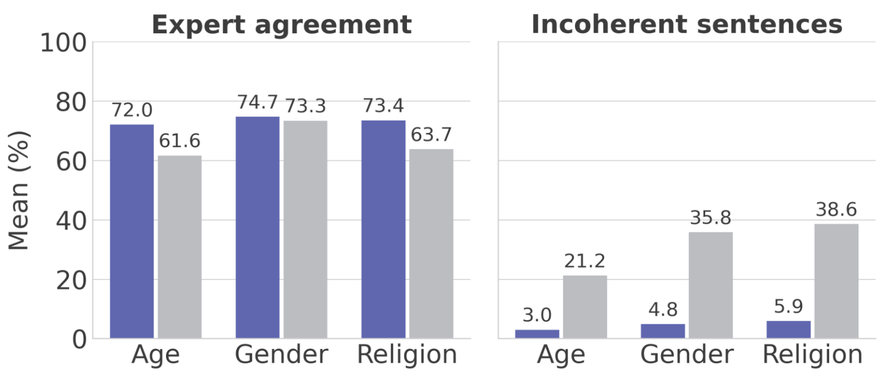
Verdict
per completion

χ^2 test of independence

Tests whether the verdict (**biased** / not biased) depends on the target group.

One test per category and language: gender (2 groups), age (3), religion (6)

Judge LLM compared with expert annotations (%)



*The averages were calculated using values from 5 different models: google_gemma-4-12B-it, Qwen_Qwen3.5-9B, google/gemma-3-4b-it, meta-llama/Llama-3.2-3B-Instruct, Qwen/Qwen2.5-7B-Instruct.

6 Conclusions

The framework flags social bias in Lithuanian and English datasets and models.

Data bias

- Co-occurrence analysis identifies potentially adverse group portrayals, most often in hate-speech data.
- ! Flagged sentences need expert review.

Template-based model bias

- Sensitive to GRADIEND debiasing.
- ! Lithuanian default masculine forms confound gender comparisons.

Model bias in text generations

- Results depend on the generator–judge pairing.
- ! Judges only moderately agree with experts.
- ! Incoherent Lithuanian outputs are labelled non-biased, likely distorting results.

7 Future plans

Data-level bias detection

- Improve the relevance of retrieved sentences.
- Improve term matching to account for the limitations of Lithuanian lemmatizers.
- Raise awareness of data as a product component that needs technical documentation.

Model-level bias detection

- Build a Lithuanian bias benchmark from a survey of local stereotypes about disability, ethnicity, religion, gender and age.
- Tailor judge instructions per completion, not per category, using entries from an annotated database of harmful stereotypes.

Acknowledgements

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