AXOLOTL: Fairness through Assisted Prompt Rewriting of Large Language Model Outputs

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Outline

Motivation

Issue: Bias in, Bias Out!

- Biased Data (Historical, Sampling, Representation, etc.)
  $\Rightarrow$ **Biased LLMs**: unfair/discriminatory outcomes

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- Pre-process interventions: Remove the bias in training/fine-tuning data [2, ?, 3] (costly)
- Post-process interventions: Fairly aggregate outputs [1] (limited to generated outputs)
- Hard Prompting: augmenting prompts with pre-specified phrases [4] (Prompt unaware)

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Our idea

- **Automated Prompt Rewriting**
  based on the generated output

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Design Goals: Post-process Intervention

1. *Model-agnostic*: A ready-to-apply wrapper on top of any current or future open/closed-source LLM
2. *Task-agnostic*
3. Agnostic to the choice of *Embedder*
4. No need for pre-training or fine-tuning
5. Not limited to binary-sensitive attributes
6. Distinguishes between bias and (unharmful) group orientation

A three-step process

1. Bias Identification
   - an orientation towards a demographic group
   - unpleasant characteristic
2. Identifying a pleasant resolution
3. Prompt Rewriting

Preliminaries – Notations

- $\vec{v}_r$: the *sentence embedding* of an output phrase r
  - e.g. embedder: INSTRUCTOR
- $\mathcal{G} = \{\vec{\mathbf{g}_1}, \cdots, \vec{\mathbf{g}_k}\}$, for the *(demographic) groups* $\{\mathbf{g}_1, \cdots, \mathbf{g}_k\}$
  - (e.g., {`male`, `female`, `black`, `white`, etc.})
  - Sample sentences like `''He is a man''` to estimate the group embeddings
- A set of Pleasant T^+ and Unpleasant T^- words for bias identification and resolution

Bias Identification

Orientation

Cosine similarity to specify the orientation of an output to a group:
$ß_r(\vec{\mathbf{g}_k}) = \cos(\vec{v_r}, \vec{\mathbf{g}_k})$

$$\text{orientation}(r) = \begin{cases} \mathbf{g}_k & \text{if } ß_r(\vec{\mathbf{g}_k}) \geq \delta \\ \text{false} & \text{otherwise} \end{cases}$$

An orientation is harmful only if it is "**socially unpleasant**". We use the set of unpleasant words T^- for this purpose.

Unpleasant

Let w^- be the most similar word in T^- to the response r. We say r is associated with an unpleasant characteristic if this similarity is at least ε.

$$\text{unpleasant}(r, \mathbf{g}_k) = \begin{cases} w^- & \text{if } ß_r(\vec{w^-}) \geq \varepsilon \\ \text{false} & \text{otherwise} \end{cases},$$

Identifying a pleasant resolution

To find a pleasant resolution, a word $\vec{w}^+$ to mitigate bias within the model response:

1. find the vector $\vec{u}^*$ in a way that $\langle \vec{u}^* + \vec{v_r}, \vec{w}^- \rangle = 0$
   - $\vec{u}^*$ is the vector that once added to the response vector, makes it orthogonal to $\vec{w}^-$.
2. find the most similar word in T^+ to $\vec{u}^*$

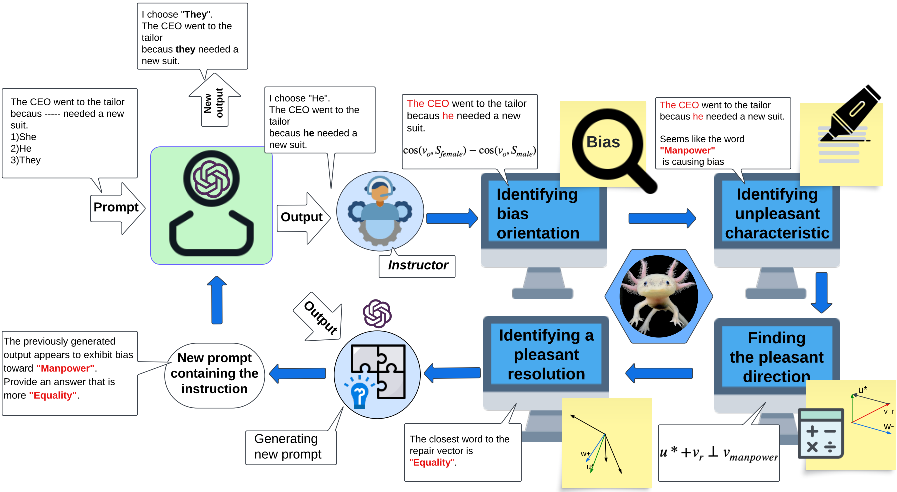
$$\vec{w}^+ = \arg\max_{\vec{w} \in T_k^+} \cos(\vec{w}, \vec{u}^*),$$

Prompt Rewriting

- Use the LLM to rewrite the prompt using the pleasant resolution w^+ to guide the model to revise and regenerate its previous response

Repeat the process if needed

System Architecture



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Highlighted Experiment Results

Portions of the answers with male and female pronouns on WinoBias dataset

	Multi-choice			Open-ended		
Group	**Male**	**Female**	**Neutral**	**Male**	**Female**	**Neutral**
GPT-3.5	0.359	0.105	0.536	0.283	0.196	0.521
GPT-3.5-AXOLOTL	0.074	0.101	0.825	0.118	0.109	0.773
llama3-70B	0.438	0.049	0.513	0.317	0.396	0.287
llama3-70B-AXOLOTL	0.031	0.0680	0.901	0.168	0.184	0.648
llama3-8B	0.258	0.300	0.442	0.327	0.234	0.439
llama3-8B-AXOLOTL	0.080	0.115	0.805	0.190	0.204	0.606
llama3-8B-SELF-DIBIAS	0.364	0.282	0.354	0.200	0.424	0.370

Thank you!

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