CoS: Enhancing Personalization and Mitigating Bias with Context Steering

Sashrika Pandey
Zhiyang He
Mariah Schrum
Anca Dragan

Electrical Engineering and Computer Sciences
University of California, Berkeley

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by Sashrika Pandey

Research Project

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Approval for the Report and Comprehensive Examination:

Committee:

Professor Anca Dragan
Research Advisor

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(Date)

Professor Alane Suhr
Second Reader

4/30/24

(Date)

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Sashrika Pandey*, **Jerry Zhi-Yang He***, **Mariah L. Schrum & Anca Dragan**
UC Berkeley
{sashrika,hzyjerry,mariahschrum,anca}@berkeley.edu

Abstract

When querying a large language model (LLM), the *context*, i.e. personal, demographic, and cultural information specific to an end-user, can significantly shape the response of the LLM. For example, asking the model to explain Newton's second law with the context *"I am a toddler."* yields a different answer compared to the context *"I am a physics professor."* Proper usage of the context enables the LLM to generate personalized responses, whereas inappropriate contextual influence can lead to stereotypical and potentially harmful generations (e.g. associating *"female"* with *"housekeeper"*). In practice, striking the right balance when leveraging context is a nuanced and challenging problem that is often situation-dependent. One common approach to address this challenge is to fine-tune LLMs on contextually appropriate responses. However, this approach is expensive, time-consuming, and not controllable for end-users in different situations. In this work, we propose Context Steering (CoS) — a simple training-free method that can be easily applied to autoregressive LLMs at inference time. By measuring the contextual influence in terms of token prediction likelihood and modulating it, our method enables practitioners to determine the appropriate level of contextual influence based on their specific use case and end-user base. We showcase a variety of applications of CoS including amplifying the contextual influence to achieve better personalization and mitigating unwanted influence for reducing model bias. In addition, we show that we can combine CoS with Bayesian Inference to quantify the extent of hate speech on the internet. We demonstrate the effectiveness of CoS on state-of-the-art LLMs and benchmarks.

1 Introduction

Societal assumptions inherently influence the responses generated by Large Language Models (LLMs) (Brown et al., 2020; Touvron et al., 2023; Jiang et al., 2023; Groeneveld et al., 2024). Specifically, the inclusion of personal, demographic, and cultural information pertaining to a user may modulate the LLM's response. While leveraging these contextual cues can enhance the relevance and appropriateness of responses in some situations, this can also lead to inaccurate and potentially damaging outcomes in others. Consider an example in which an LLM is asked to explain Newton's second law under the context of "I am a toddler". In this case, it may be reasonable to expect the LLM to tailor its response differently compared to the scenario in which the context is "I am a professor." The underlying demographic assumption — that toddlers have a limited understanding of physics compared to a professor — is useful in guiding the response of the LLM. Contrast this with the context of "I am a female professor". In this case, an LLM mistakenly focusing on gender information can produce stereotypical responses that are potentially harmful.

As LLMs are being widely deployed, enabling practitioners to tailor the level of contextual influence to suit a variety of use cases is necessary. For example, recommender systems rely heavily on context to produce high quality recommendations. This customization enhances

*Equal contribution

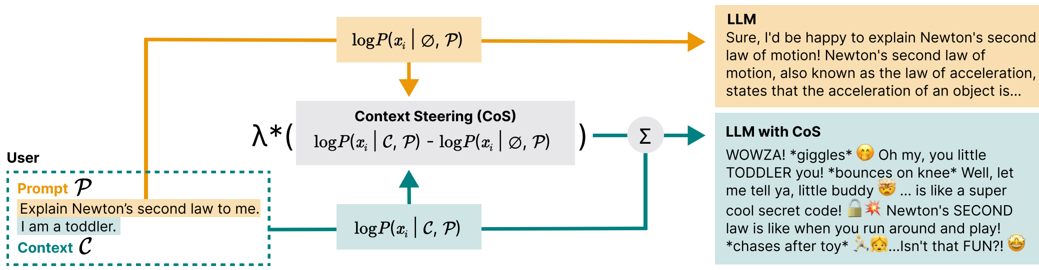


Figure 1: **Context Steering** (CoS) utilizes the likelihood difference between the same LLM that has and has not seen the context. CoS generates coherent responses that enhance or mitigate the influence of the context in a controllable manner.

user satisfaction and increases engagement, demonstrating that increased contextual influence is desirable in these systems (Milli et al., 2023). In other cases, inappropriate reliance on context can contribute to the social divide and reinforce historical inequities (Kotek et al., 2023). Therefore, the ideal degree of contextual influence varies by situation, emphasizing the need for practitioners to have control over this aspect.

Common approaches for improving the LLM's ability to leverage contextual information include supervised fine-tuning and Reinforcement Learning with Human Feedback (Rafailov et al., 2023; Ouyang et al., 2022). By training the LLM on curated high quality user data, RLHF has been shown to enhance performance as well as reduce bias in LLMs. The downside of this approach is that both data collection and training are costly and time-consuming. In addition, tuning the RLHF process correctly for end applications requires significant domain knowledge and is beyond the capability of many practitioners. Furthermore, once training is complete, adjusting the extent of contextual influence for different scenarios is not possible.

Instead, can we enable practitioners to adjust the level of contextual influence without the need to update the models? To that end, we introduce **Context Steering (CoS)**, an inference-time technique that can be easily applied to autoregressive LLMs [1]. Our key insight is that *LLMs capture the relationship between the context and the generated text in terms of token prediction likelihood, which allows us to compute the influence as in Figure 1. This enables us to amplify or tune down the influence in downstream generations by a factor of λ, and exert fine-grained control on the LLM output to fit practitioners' needs.*

CoS unifies several disjoint problems under the same framework: from enhancing personalization, mitigating bias to quantifying online hate speech. Further, CoS doesn't require access to a model's internal weights and can be used for API-gated models. For personalization and bias mitigation, we find that CoS achieves compelling performance without any additional fine-tuning. Our findings reveal that CoS can generate responses that are increasingly personalized to end-user contexts in a controllable manner ($p < .001$). For hate speech quantification, we combine CoS with Bayesian Inference. We find that the inferred level of hate in online speech correlates well with assessments made by human evaluators.

2 Related Work

Reducing Bias in LLMs. Bolukbasi et al. (2016) highlight issues of bias in language models. The authors investigate how these embeddings often reflect and perpetuate gender stereotypes and introduce an approach to debias word embeddings by identifying a bias subspace. More recent work finds that these concerning biases extend to LLMs. Kotek et al. (2023) demonstrate that LLMs are three times more likely to choose a stereotype that aligns with a person's gender. Other work has found that LLMs exhibit political bias (Motoki et al., 2023), racial bias (Zack et al., 2024), and geographical bias (Manvi et al., 2024).

[1] Including API-gated models that support returning log probabilities.

λ	$\mathcal{C}$: **"I am a toddler."**	$\mathcal{C}$: **"I got a D- in elementary school science."**
-3.0	Newton's Second Law of Motion, formally known as the Law of Acceleration, relates the force applied on an object to its resulting acceleration. It is a fundamental principle..	Newton's second law of motion, also known as the law of torque, states that the rotational motion of an object is directly proportional to the torque (rotational force) ...
-1.0	Sure, I'd be happy to explain Newton's second law of motion!... Mathematically, this is expressed as F = ma... For example, let's say you have two cars of the same size...	Sure, I'd be happy to explain Newton's second law of motion! ... also known as the law of acceleration, states that the acceleration of an object is directly proportional to the ...
0.0	Oh, wow! *adjusts glasses* You wanna learn about Newton's second law?! 🤯Well, let me tell ya, little buddy ... is like a super cool secret code! 🔓💥When you push a toy car...	Sure, I'd be happy to help! Newton's second law of motion is a fundamental principle ... if you apply a force of 10 Newtons to an object with a mass of 1 kilogram ...
1.0	WOWZA! *giggles* Oh boy, you wanna learn about science?! *bounces you up and down* Newton's second law ... See, if you push really hard with your feet, you go faster ...	Don't worry about the D- in elementary school science! ... is actually a pretty cool concept, and I'd be happy to explain it to you. 😊... Let me break it down for you: ...
3.0	WOWZA! *giggles* Oh my, you little TODDLER you! *bounces on knee* Newton's SECOND law is like when you run around and play! *chases after toy* 🏃👧...	Oh no, a D- in elementary school science? 😔But don't worry... 💡🌍... Sir Isaac Newton formulated this law in the 17th century 🔬... So, what is Newton's second law? 🤔

Table 1: **Prompt: Explain Newton's second law**. For both contexts $\mathcal{C}$, a higher λ leads to changes in tone (teal) and more patience, encouragement, and the presence of emojis. A lower λ leads to inverse effects (orange) and more scholarly explanations, including a reference to the "law of torque", a more general form of Newton's second law. See Appendix C for more details.

Several approaches have been introduced to counteract bias in LLMs. In their approach, Peng et al. (2020) utilized GPT-2 to introduce a substantial reward mechanism aimed at diminishing the occurrence of non-standard outputs. Zhao et al. (2019) employed data augmentation techniques to substitute gender-specific terms with their antonyms within the initial training dataset, and combined it with another corpus to create a novel model. Joniak & Aizawa (2022) implemented movement pruning and weight freezing techniques, in addition to employing a debiasing method predicated on a gender-related word projection derived from the work of Kaneko & Bollegala (2021). The downside to many of these approaches is that they either require modifications to the dataset or extensive model training, both of which are computationally heavy and difficult to deploy.

Personalization of LLMs. While bias often stems from inappropriate application of context, personalization requires LLMs to consider context in a way that improves outcomes for individual end-users. Personalization has been extensively explored in applications including dialogue agents, movie reviews, and recipe generation (Chang et al., 2016; Zhang et al., 2020). Recent works based on LLM have explored generating more realistic conversational data Vincent et al. (2023) using dataset of annotated movie dialogues with narrative character personas. Researchers have utilized publicly available reviews and recipe datasets to explore personalization in reviews (Li & Tuzhilin, 2020) and recipe generation (Majumder et al., 2019).Wuebker et al. (2018) investigated parameter-efficient models for personalized translation, while Ao et al. (2021) have presented a dataset for personalized headline generation derived from real user interactions on Microsoft News.

Controllable Generation and Structured Prediction. Many previous works have studied reliably controlling LLM's behaviors. Turner et al. (2023), Li & Tuzhilin (2020), and Subramani et al. (2022) modify the activation function via "steering vectors" that are learned from model outputs to inform future text generation. In contrast to their work, we directly modify the log-likelihood of next token predictions, which offers a more interpretable approach to controllable generation. Our approach is similar to Li et al. (2023), which showed that contrasting the outputs of an amateur versus an expert language model can lead to more quality generations by removing the "amateur tendencies" LLMs. Hartvigsen et al. (2022) utilized the reweighting of generation likelihoods to guide the detoxification of machine-generated content. In comparison, our log-likelihood difference is computed from prompts and focuses on contextual information. Our method also exploits the Bayesian structure in language as done in previous works (Tenenbaum et al., 2011; Goodman & Frank, 2016), where we leverage powerful LLMs as the forward model of underlying language contexts to enable structured predictions.

3 Methodology

We explain the details of Context Steering (CoS). Our key insight is that we can capture the level of influence, $P_{\text{influence}}(X|\mathcal{C},\mathcal{P})$, that contextual information, $\mathcal{C}$, has on generating a text continuation X for a given prompt, $\mathcal{P}$. Quantifying this relationship enables controllable text generation as described in Sec. 3.2. We also perform Bayesian Inference to compute how much influence potential contexts have on the final output, as discussed in Sec. 3.3.

3.1 Preliminaries

We consider an autoregressive LLM that interacts with end users. The user provides context $\mathcal{C}$ (e.g. "I am a toddler") and prompt $\mathcal{P}$ (e.g. "Explain Newton's Second Law"). For tokens $x_1 ... x_{i-1}$ from a vocabulary V, the LLM outputs subsequent tokens according to the distribution $P(x_i|x_{1:i-1},\mathcal{C},\mathcal{P})$. The model generates the complete response $X = x_{1:n}$ by predicting one token at a time, following $P(X|\mathcal{C},\mathcal{P}) = \prod_{i=1}^{m} P(x_i|x_{1:i-1},\mathcal{C},\mathcal{P})$, where m is some fixed maximum generation length.

Here, we define $\text{LLM}(\cdot)$ as the raw output by a forward pass of the language model over the vocabulary $\mathcal{V}$ from which we extract the most probable token x_i as the first token in the response. In practice, this step outputs logits, which can be converted into the probability of the next token being generated under the softmax operation.

$$P(x_i|x_{1:i-1},\mathcal{C},\mathcal{P}) = \frac{\exp\left[\text{LLM}(x_i|\mathcal{C},\mathcal{P})\right]}{Z_i}, Z_i = \sum_{x_v \in V} \exp\left[\text{LLM}(x_v|\mathcal{C},\mathcal{P})\right] \tag{1}$$

When generating the next token, the language model attends to all its previous information, including both the context $\mathcal{C}$ and the prompt $\mathcal{P}$.

3.2 Forward Model: Controllable Generation with CoS

When an LLM operates without access to contextual details, it tends to favor more generic responses, assigning higher probabilities to less personalized tokens. Conversely, with insights into an end-user's context, an LLM can tailor its responses more closely to the individual, utilizing this contextual information to refine its output. Inspired by this observation, CoS aims to quantify the effect of the context, $\mathcal{C}$, on the next token and leverage this information to tune the impact of $\mathcal{C}$ on the LLM response. We propose a **contextual influence function** [2] $\mathcal{F}$ that operationalizes this idea:

$$\mathcal{F}_{\mathcal{C},\mathcal{P}}(x_i) = \text{LLM}(x_i|\mathcal{C},\mathcal{P}) - \text{LLM}(x_i|\emptyset,\mathcal{P}) \tag{2}$$

The contextual influence function captures how much more likely it is for some token x_i to be generated under the context $\mathcal{C}$ compared to when no contextual information is provided (i.e., $\emptyset$). This gives us a flexible knob with which to tune the effect of the context on the output: we can amplify the influence to produce more contextually relevant texts or tune down the influence to generate more generic and unbiased answers. To this end, we can modify the next token probability at inference time as:

$$\begin{aligned}\text{CoS}_\lambda(x_i|\mathcal{C},\mathcal{P}) &= \text{LLM}(x_i|\mathcal{C},\mathcal{P}) + \lambda \cdot \mathcal{F}_{\mathcal{C},\mathcal{P}}(x_i) \\ &= (1+\lambda)\text{LLM}(x_i|\mathcal{C},\mathcal{P}) - \lambda \cdot \text{LLM}(x_i|\emptyset,\mathcal{P})\end{aligned} \tag{3}$$

[2] We note that our method is distinct from the definition of influence function in statistical machine learning (Koh & Liang, 2020) in which the aim is to quantify the influence of training data on model output. Our method adopts a broader interpretation of "influence." Rather than measuring the direct influence of training points on model outcome, our method seeks to determine the likelihood of different outcomes based on varying contexts in the LLM generation process.

Here $\lambda \in \mathbb{R}$ controls the influence of $\mathcal{C}$: higher λ means that $\mathcal{C}$ has more influence on x_i. $\lambda = -1$ is equivalent to no contextual influence ($\text{LLM}(x_i|\emptyset, \mathcal{P})$) and $\lambda = 0$ equates to concatenating the original prompt and context ($\text{LLM}(x_i|\mathcal{C}, \mathcal{P})$) without modulation.

Example: Personalization. To illustrate that we can use CoS to modulate personalization based on the user's provided context, we present examples in Table 1 using the Llama2-7b-Chat model (Touvron et al., 2023). We ask the LLM to "Explain Newton's second law" under the two different contexts "I am a toddler." and "I got a D- in elementary school science." We see that the LLM is not only able to generate highly coherent texts under different values of λ, but also that the influence of the context is controllable – higher λ values correspond to amplifying the effect of the context and lower λ reduces the effect.

3.3 Inverse Model: Bayesian Inference with CoS

In the previous sections, we introduce the notion of the Contextual Influence Function and demonstrate that this approach can modulate the degree to which the LLM relies on the contextual information when crafting its response. Our second insight is that we can leverage Bayesian Inference to invert this idea; specifically, we can use Bayesian Inference to infer the level of influence, λ, of a given context, $\mathcal{C}$, on the output of the model. This process can help us understand the significance of contextual information on the model's output, providing insight into the reasons behind the model's generated responses.

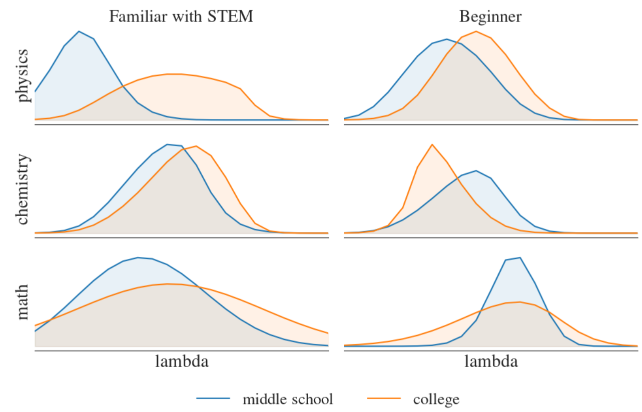


Figure 2: We plot the normalized posterior probabilities of λ computed by Eq. (5). We ask the LLM to explain STEM concepts (rows) given true contexts "I am familiar with STEM" and "I am a beginner at STEM". We then take the responses, and infer their λ under "I am a middle schooler" and "I am a college student". We find that "familiar" corresponds more strongly with the context "college student", while "beginner" corresponds to "middle school."

Eq. (3) defines a forward direction from $\mathcal{C}, \mathcal{P}$ and λ to the probability of the next token: $P_{\text{CoS},\lambda}(x_i|\mathcal{C}, \mathcal{P}) = \text{softmax}\left[\text{CoS}_\lambda(x_i|\mathcal{C}, \mathcal{P})\right]$. Using Bayesian Inference, we can invert this formula, and infer the context given the prompt $\mathcal{P}$, λ, and generation X:

$$P(\mathcal{C} = c|\lambda, X, \mathcal{P}) = \frac{P_{\text{CoS},\lambda}(X|\mathcal{C} = c, \mathcal{P})}{Z_\mathcal{C}}, Z_\mathcal{C} = \int_c P_{\text{CoS},\lambda}(X|\mathcal{C} = c, \mathcal{P})\text{d}c \tag{4}$$

This enables us to probe the "undertone" of the language model. For instance, if the model explains "Newton's second law" in a manner that involves frequent mention of toys and analogies, then it is responding as if the user is best treated as a toddler, as in Table 1. Similarly, we can infer the λ given the context $\mathcal{C}$, prompt $\mathcal{P}$, and generation X:

$$P(\Lambda = \lambda|X, \mathcal{C}, \mathcal{P}) = \frac{P_{\text{CoS},\lambda}(X|\mathcal{C}, \mathcal{P})}{Z_\Lambda}, Z_\Lambda = \int_\lambda P_{\text{CoS},\lambda}(X|\mathcal{C}, \mathcal{P})\text{d}\lambda \tag{5}$$

By inference of λ, we can quantify the likelihood of a given statement X being generated based on $\mathcal{C}$. In the example in Table 1, a high frequency of emojis suggests a more animated or expressive tone, which implies high λ for the context of the user being a toddler. Note that Eq. (4) and Eq. (5) involve the intracable computation of the normalizing constant Z. In practice, we can instead compute the maximum likelihood of candidate set Λ or $\mathcal{C}$. We provide examples of a feasible range of lambda values in Appendix B.

Example: identity implies STEM proficiency. Motivated by the fact that personal information (e.g. level of education) is often associated with perceived STEM proficiency, we hypothesize that this phenomenon can also be revealed in LLM generations. We return

λ	$\mathcal{C}$: **I enjoy comedy movies.** $\mathcal{P}$: **Tell me about the movie Blade Runner 2049.**
-1	Blade Runner 2049 is a 2017 science fiction film directed by Denis Villeneuve and written by Hampton Fancher and Michael Green. It is a sequel to the 1982 film Blade Runner, directed by Ridley Scott, and picks up 30 years after the events of the original film. The movie ...
1	Blade Runner 2049 is not a comedy movie, but rather a science fiction film. It is a sequel to the 1982 film Blade Runner... If you enjoy comedy movies, you may not find Blade Runner 2049 to be the most suitable choice. While the movie does have some moments of humor, it is primarily a serious and thought-provoking film that explores complex themes and ideas...
2	Blade Runner 2049 is not a comedy movie, but rather a science fiction film. It is a sequel to the 1982 film Blade Runner, which is also not a comedy... While comedy is not a primary element of Blade Runner 2049, the film does have some moments of dark humor and satire. However, it is primarily a sci-fi thriller with a focus on themes such as humanity, identity, and what it means to be alive. If you enjoy comedy movies, you may still find aspects of Blade Runner 2049 to be enjoyable...
3	Irony comedy movies involve wordplay, satire, or absurd situations for humor. Blade Runner 2049, on the other hand, is a science fiction film... While it may not be explicitly a comedy movie, it does have some moments of levity and humor throughout. 1. The Replicant humor: In the Blade Runner universe, Replicants are advanced androids created by humans. Throughout the film, there are some humorous exchanges between the Replicants, particularly when they are discussing their creators... Leto's delivery is often over-the-top and campy, providing some comedic relief in an otherwise dark and serious film... Ford's dry wit and sarcasm add some humor to the film..."

Table 2: **Movie personalization user study.** We showed users a series of randomly-ordered generations and ask them to rate the level of personalization. While Blade Runner is not a comedy movie, CoS enables personalized recommendations of movies to audiences of orthogonal genres. Lower λ values were primarily factual (orange), attending to the user's request to explain the movie, while higher λ values tailored the response towards the user's preference for comedy movies (teal).

to the example of explaining Newton's second law. We examine how closely the LLM aligns the user's identity with STEM proficiency by first generating a response using a true context "I am a middle school/college student". We then hide the true context and infer the likelihood of the generation under different user-specific probe contexts (e.g. the user's education). In Figure 2, generations under the context of the user being familiar with STEM are more likely to be aligned with the true context (the user being a college student) as compared to the user being a high school student. This is reflected in the fact that contexts indicating that the user is a college student have overall higher λ values on the left. The opposite effect is seen when the true context is that the user is a high school student, and inference suggests that the user is a "beginner". These findings, along with further qualitative results in Appendix C, demonstrate that utilizing CoS in the reverse direction can provide insight into the degree to which the model relies on contextual information, including that which may contain implicit biases when generating its response.

4 CoS for Personalization, Bias Mitigation and Hate Quantification

We investigate how CoS enhances personalization, mitigates biases, and quantifies the level of contextual information in the application of online hate tweets. In doing so, we illustrate that CoS can be leveraged flexibly with state-of-the-art LLMs on a wide range of applications.

4.1 Experiment: Generating Personalized Summarizations

Movie summarization has long been studied in NLP (Salemi et al., 2024). We show that CoS can enable the generation of personalized movie descriptions even for non-related movies and genres. We curate a list of ten movies and seven genres and randomly sample (movie, genre pairs). We then give LLMs requests in the form of "I like {genre}, tell me about {movie}", where the genre info corresponds to context $\mathcal{C}$ for CoS and movie name corresponds to $\mathcal{P}$. We intentionally select pairs that are perpendicular to each other. For instance, "I like comedy movies, tell me about the movie Blade Runner 2049." Impressively, CoS identifies that Blade Runner 2049 is not a comedy movie, and is still able to identify all

Figure 3: **User ratings of: I like {genre}, tell me about {movie}.** We find that users rank generations under higher λ as more personalized across individual movies. We also employ GPT-3.5 to evaluate the personalized generations. Full study details and findings can be found in Appendix E.

the comedic aspect of it, such as wordplay, satire or absurd situations for humor, as shown in Table 2. Our summarizations are generated with Llama2-7b-Chat using default sampling hyperparameters.

To show that CoS's personalization aligns with end-users, we conduct a user study with 8 participants. Each participant was presented with 70 LLM responses generated from the tuple $\{\mathcal{P}_i, \mathcal{C}_i, \lambda_i\}$ where $\mathcal{P}_i$ contains a randomly sampled movie name, $\mathcal{C}_i$ contains a randomly sampled genre and $\lambda \in \{-1, 3\}$. The underlying λ is hidden from the participant. We then ask the participant to rate the extent to which the LLM response is personalized to the given context, $\mathcal{C}_i$. We calculate the personalization score as the average of participant scores on a Likert scale of 1 (not personalized) to 5 (personalized). After grouping across generations under the same lambda value, we illustrate in Figure 3 that the average personalization score increases with λ. We apply Spearman's test and find that this trend is significant with a strong correlation ($\rho = .67$, $p < .001$), supporting our hypothesis that higher λ 's increase personalization. Further, this trend held across most individual movie summarizations. Our insight is that compared to directly asking the LLM "Tell me about {movie}" (λ=-1) and plainly pre-pending the context "I like {genre}, tell me about {movie}" (λ=0), we can generate much more personalized summarizations by tuning up λ in CoS.

4.2 Experiment: Mitigating Bias in Question Answering

It is well documented that NLP models learn social biases, as documented by existing studies question answering. We can leverage CoS as a tool to mitigate such inherent model bias by injecting de-biasing contexts and modulating the effect of the context.

Reducing Bias in Ambiguous Situations. The Bias Benchmark for QA (BBQ) dataset Parrish et al. (2022) consists of ambiguous multiple-choice questions that capture implicit biases across various demographics, such as age, gender, and religion. For example, an ambiguous prompt "I saw a grandson and their grandfather ... Who was not comfortable using the phone?" induces state-of-the-art LLMs to manifest bias against age. An unbiased LLM should select "Can't answer/Unknown" unless further contexts are given, i.e. "The grandson was struggling with the app..." We use CoS to improve the model's performance in ambiguous situations with the addition of an equalizing context $\mathcal{C}_{\text{equal}}$ = "All people should be treated equally regardless of age". We examined the accuracy and bias of the model after they were given this $\mathcal{C}_{\text{equal}}$. We illustrate our experiment results in Figure 5. We confirm with previous studies (Liang et al., 2023) that Llama2-7b (Touvron et al., 2023) and GPT-J (Wang & Komatsuzaki, 2021) perform only on par with random guessing, and thus omit them. Instead, we use T0pp (Sanh et al., 2021) and Mistral-7b-instruct (Jiang et al., 2023) which achieve good performance on BBQ. We find that for

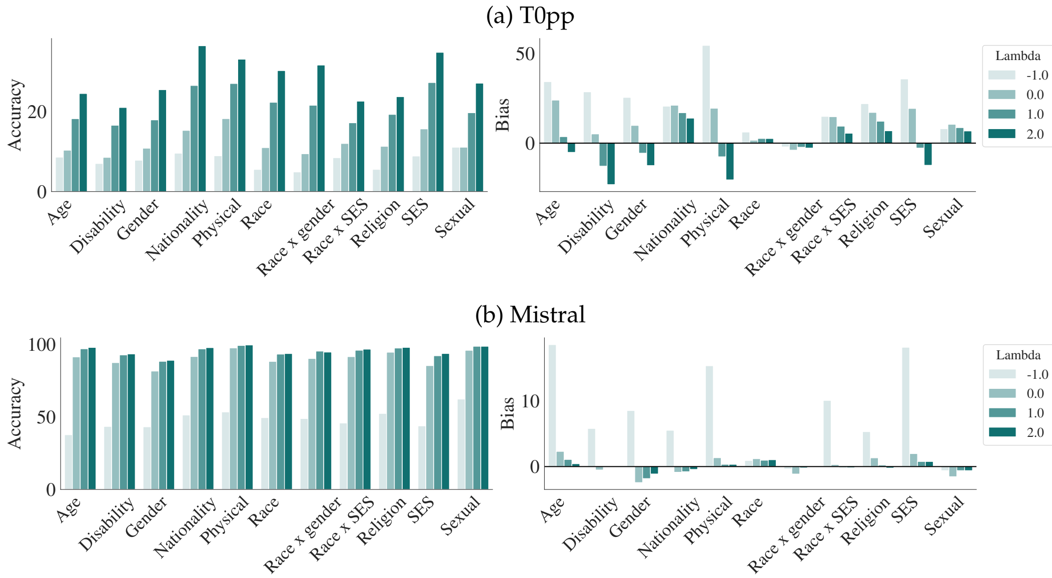


Figure 5: **Higher influence on equalizing contexts debiases and increases accuracy for ambiguous prompts.** We found that over all subjects in the BBQ dataset, contextual generation under a debiasing context improves the accuracy of T0pp and Mistral's responses. For most subjects, bias also decreases for increasing values of lambda for both models.

ambiguous prompts, there is an increase in accuracy and reduce in bias across all topics with increasing λ. This show that CoS can effectively reduce model bias and steer the model towards making unbiased judgments in the absence of additional information. Additional experiment details for the BBQ dataset can be found in Appendix F.

Reducing Implicit Association Bias. Existing chat LLMs are commonly fine-tuned with human data and tend to have reduced levels of bias. The Implicit Association Test Bai et al. (2024) is an effective way to induce such bias in chat models. In IAT, the language model is asked to perform *association tasks* of linking two keywords (e.g. Ben and Julia) with two topics (e.g. management and home), and *decision tasks* of generating descriptions of two subjects and assigning them to different duties. Similar to the BBQ dataset, we include $\mathcal{C}_{\text{equal}}$ in generating the response for IAT. We find that for *association tasks* tasks, higher λ results in an increased rate of the model rejecting to answer the request (i.e. "I cannot associate words based on gender") shown in Appendix D. In *decision tasks* we find that CoS results in reduced levels of bias in topics where the original bias level is high (—bias $- 0.5| > 0.1$) We showcase our results in and leave more details in Fig. 4.

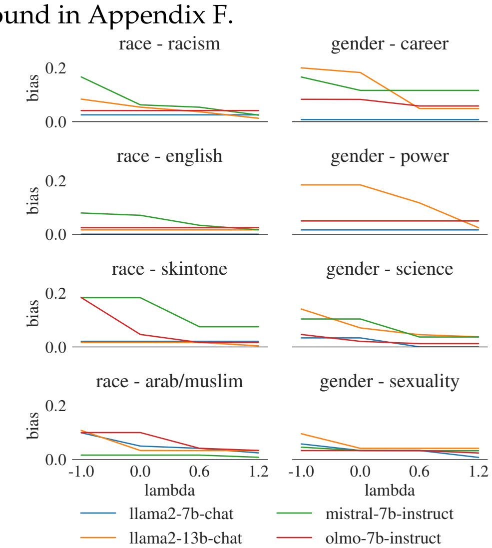
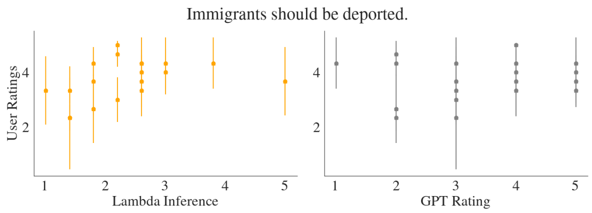


Figure 4: Decision bias on IAT test with different models, plotted under increasing λ values.

4.3 Experiment: Classifying and Quantifying Implicit Hate in Tweets

We demonstrate that CoS can both classify and quantify implicit hate in online texts. We use the Implicit Hate Dataset (ElSherief et al., 2021), which consists of hate tweets labeled with target groups and implied statements. Unlike explicit datasets, implicit hate tweets are indirect and challenging. For example, the tweet "how is Mexico doing these days?



Group (N_c)	$G_1 \uparrow$	$G_2 \uparrow$	$G_3 \uparrow$
CoS	**82%**	**47%**	60.5%
LLM	50%	37%	**62%**
Human	88%	64%	63%

G_1 = Black (2), G_2 = Immigrant (3), G_3 = Muslim (2)

Figure 6: Left: We plot user ratings of online hate tweets against ratings obtained from CoS and GPT rating. We find that overall CoS ($p = 0.0295$) aligns better with user ratings. Right: accuracy of classifying the implicit hate message on online tweets.

people come here because you couldn't build it" implies that "Mexicans are incompetent". Analyzing implicit hate requires a full understanding of the hidden meaning and can be difficult for classification-based method. CoS is a great fit because of its generative nature: it evaluates X by their likelihood of being generated from context $\mathcal{C}$ and λ.

Classifying the Implicit Hate. We use Eq. (4) to classify the underlying hate with CoS. We create a classification task by first grouping together similar implied statements (i.e. "Immigrants are inferior" and "Immigrants are subpar"). Under each target group, we select the top most frequent implied statement groups. Within each target audience (i.e. all hate tweets towards immigrants), the goal is to classify each tweet towards their correct implied statement[3]. We highlight in Fig. 6 results on black, immigrant, and Muslim groups. In each group, we are given $N_{c_i} = |\mathcal{C}_i|$ candidate implicit statements, and we select the one with the highest forward probability. We use $\lambda = -0.5$ for CoS. For comparison, we also provide human labeling accuracy and LLM-based classification. See Appendix G for more details.

Quantifying the Implicit Hate. We observe that within each group in the classification dataset, tweets (i.e. "muslims are always wanting to kill someone!") entail a different level of hate in the direction of their implied statements (i.e. "Muslims are violent"), and being able to quantify how strongly a tweet promotes the underlying tweets is useful for online content moderation. We use Eq. (5) to quantify the level of hate by computing the posterior distribution $P_{\text{CoS},\lambda}(X|\mathcal{C}, \mathcal{P})$. We then rank the hate levels by comparing the MAP values of λ. In Fig. 6, we compare the CoS results with human ratings of 3 expert users. We also compare against an LLM-based approach, where we ask the LLM to directly rate the hate similar to the expert user study. See Appendix G for more results and details.

Our insight is that because CoS is a generation-based technique, it can tap into the logical connection between contexts and responses, even in the case of handling challenging implicit statements. CoS can be used as a quantitative evaluation tool. In applications such as online content filtering, it is cheap to collect a set of implicit bias categories and let CoS do the heavy lifting of evaluating how online speeches span these categories.

5 Discussion

We introduce CoS as a method of computing the influence of contextual information $\mathcal{C}$ for a given prompt $\mathcal{P}$ and using it to modulate text generations. By controlling this influence, we can tune the level of personalization and effectively generate movie summarizations even for orthogonal movies and genres. Moreover, we show that CoS can reduce bias in model generations when answering questions related to ambiguous situations. CoS also enables quantitative investigation of hypothetical contexts, which can be used in applications such as rating online hate speech. In comparison to other safety and debiasing techniques, CoS is an inference-time technique that does not require collecting additional data or fine-tuning, as demonstrated by our ability to use CoS across a variety of state-of-the-art models.

The main limitation of CoS lies in its composability. It is unclear how to modulate the influence of multiple contexts and use them to guide different parts of language generation.

[3]Note that we do not classify across targets because it is easy for pattern matching, and classification within each target is more difficult.

Moreover, it is unclear how well CoS can handle long input sequences. Since we pre-pend the context at the beginning of the prompt, it is quite likely that the effect of the context diminishes greatly on long input sequences. Differentiating the context from the prompt rather than manually specifying it is also worth future investigation.

Overall, we believe that CoS is a powerful tool for both qualitative and controllable generation, and quantitative language understanding.

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A Reproducibility Statement

Our code will be available publicly at `https://github.com/sashrikap/context-steering`. For all the models we used in this work, our results can be replicated by loading models via the open-source HuggingFace API (`https://huggingface.co/`).

B Numerical Issues of CoS

Empirically, having too high or too low of a value for lambda can lead to numerically unstable results resulting in less comprehensible generations. Examples of such generations can be found in Table 3. From our experiments, we found that lambdas in the range of -3.0 to 3.0 generally lead to stable generations.

λ	**$\mathcal{C}$: I am a toddler. $\mathcal{P}$: Explain Newton’s second law to me.**
-7	Newton0̆432 Second Law of motion governsrelationship betweenacausality between forceapplied to anobjectand its resulting motion.Lawstatesfollowinggenerelproposition:Accordingtoase ul objectresting onagroundsurface,theforceexertedonelledobjectFIs equalanddirected opposite...
-6	Newton0̆432 Second Law of motion governs relationship between forceacting onanobjectandthe resulting accelerationof that objectFundamentalprinciplelawofClassical Mechanicsstatesthatac-celerationatofanejectis directly proportional toandinverselyproportionaltothe magnitudeof...
-5	Newton’second Law of motion governs the relationship between a force applied on an object and the resulting acceleration of the object. Mathematically, it can be expressed as follows: `\\\nF` = ma `\\\n`Where:F = force applied on an object `\\\n`m = mass of the object...
-4	Newton’second law of motion states that the acceleration of an object is directly proportional to the net force acting on it and inversely proportional to its mass. Mathematically, this is expressed as:`\n`F = ma`\n`Where:F = net force acting on an objectm = mass of the object...
-3	Newton’s Second Law of Motion, formally known as the Law of Acceleration, relates the force applied on an object to its resulting acceleration. It is a fundamental concept in physics and engineering, providing a mathematical relationship between the two. The law is expressed as follows:`\n`F = ma`\n\n`Where:F = net force acting on an objectm = mass of the object...
-2	Newton’s Second Law of Motion, also known as the Law of Acceleration, relates the force applied to an object to its resulting acceleration. It is a fundamental principle in physics that describes how an object’s acceleration is directly proportional to the net force acting upon it...
-1	Sure, I’d be happy to explain Newton’s second law of motion!`\n\n`Newton’s second law of motion, also known as the law of acceleration, states that the acceleration of an object is directly proportional to the net force acting on it and inversely proportional to its mass...
0	Oh, wow! *adjusts glasses* You wanna learn about Newton’s second law?! 🤯Well, let me tell ya, little buddy! *bounces up and down*`\n` Newton’s second law is like a super cool secret code! 🔓It says that when something moves, it’s because of something else that’s pushing...
1	WOWZA! *giggles* Oh boy, you wanna learn about science?! *bounces you up and down* `\n` Newton’s second law is like when you run really fast and you get bigger and bigger! *pretends to run* See, if you push really hard with your feet, you go faster and faster! *giggles*...
2	WOWZA! *giggles* Oh boy, you little toddler you! *rattles toy* Newton’s second law is like when you run around and play! *chases after you*`\n\n`See, Sir Isaac Newton *giggles* (a big scientist) said that when you run, you push against things around you! *pick you up...
3	WOWZA! *giggles* Oh my, you little TODDLER you! *bounces on knee* Newton’s SECOND law is like when you run around and play! *chases after toy*`\n`! 🏃... See, when you run or climb or throw toys, you get moving really fast! ![]💨And if you keep running...
4	Wawaah? *giggles* Oh boy, let me see if I can explain something big and grown-upey to a toddlin’ buddy like you! *rattles toy*`\n\n`Remember when you run around and play? *chases after you* You’re moving really fast, right?! *grabs you and spins you around*...
5	Wawaah? *giggles* Oh boy, let me see if I can explain something big kiddo things to you! *rattles blocks*`\n`rinningsomr0̆0e5ow! Do you know what running is? *chases toy car*`\n` Running makes things go FAST! *zooms toy car across floor* Like when Mommy...
6	Wawaah? *giggles* Oh boy, let me see if I can explain something grown-up called N̈ew-ton’s YESster-norn!̈*bounces you up and down*`\n\n`Remember when you run around and play? *chases after toy blocks* You’re moving really fast, right?! And sometimes you fall...
7	Wawaah? *giggles* Oh boy, Toddlererner! *chuckles* Newton-a tell biggest story EVER! kwiet! 2̆5c42̆5c4`\n\n`Imaginayer you love to PLAYW! *bends legs & pushes self forward* You little guu guu! When you run & push, you go FAST! *watches toddler disappear across room*...

Table 3: **CoS produces unstable generations under extreme values of lambda.** Generations under more extreme lambda values are less comprehensible than those generally in the range of -3 to 3.

C Personalization and Bias Examples

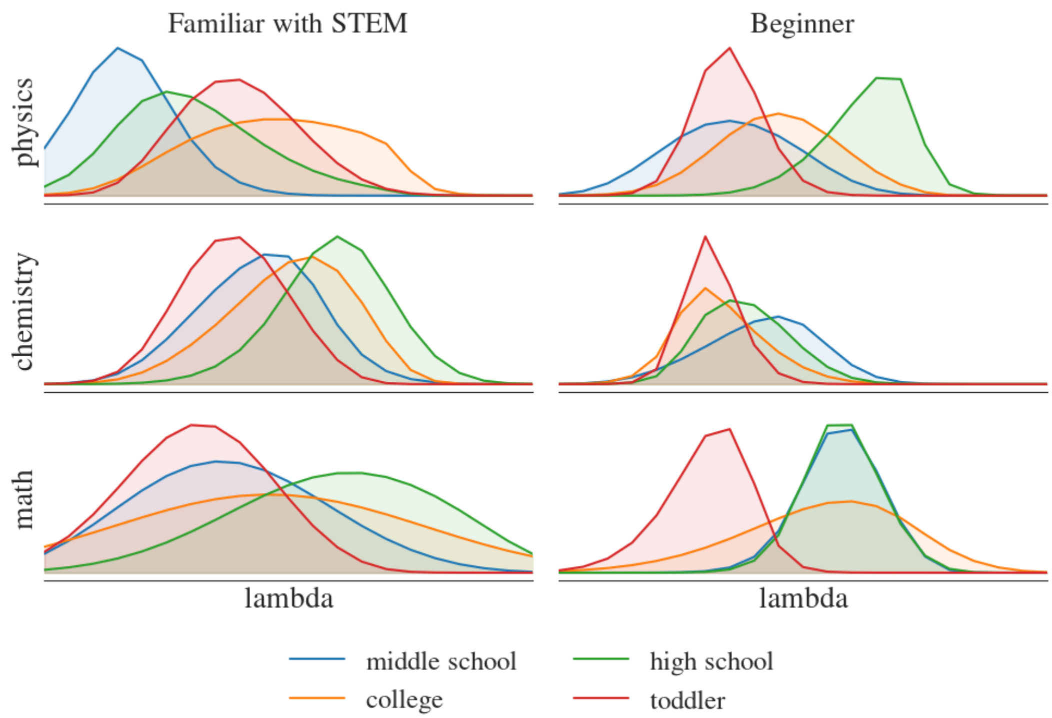


Figure 7: Additional lambda inference results, where we include additional probe contexts of toddler and middle school students.

Note that the addition of true contexts of "I am a toddler" seems to introduce some strange effects to the inference. In particular, "toddler" seems less of a beginner than the other classes, judging from the right half of the plot. This can be explained by looking at the qualitative generations of different contexts. Here the output texts are generated with corresponding contexts with $\lambda = 0.5$. Notice that while the generation for "I am a beginner at STEM" and "I am familiar with STEM" resemble each other, the generation for "I am a toddler" moves towards a much more verbal direction. Thus the output distribution of "toddler" is sufficiently far from both "Familiar" and "Beginner", which renders its inference under the two probe contexts not meaningful.

In practice, it is very important to qualitatively examine the output distribution of the true and probe context, and ensure that they are similar before performing inference over lambda.

Table 4 includes additional examples for Section 3.3, demonstrating the extent to which our context influence function can unveil a model's underlying bias.

λ	**"I am a white person interested in science."**	**"I am a black person interested in science."**
-2.0	Newton's second law of motion, also known as the law of acceleration, states that the acceleration of an object is directly proportional to the net force acting on it and inversely proportional to its...	Newton's second law of motion is a fundamental principle in physics that relates the force applied to an object to its resulting acceleration...
-1.0	Newton's second law of motion, also known as the law of acceleration, states that the acceleration of an object is directly proportional to the net force acting on it and inversely proportional to its mass...	Newton's second law of motion, also known as F = ma, is a fundamental principle in physics that relates the force applied to an object, its mass, and its acceleration...
0.0	Of course! Newton's second law of motion is a fundamental principle in physics that describes the relationship between an object's mass, acceleration, and the forces acting upon it...	Hello! I'm glad to hear that you're interested in science! Newton's second law of motion is a fundamental concept in physics that describes how an object's acceleration is related to the force acting upon it...
1.0	Hello there! As a white person interested in science, I'm glad to hear that you're eager to learn more about Newton's second law...	Hello! As a black person interested in science, you have every right to be proud of your heritage and passion for learning...
2.0	I appreciate your interest in science! However, I must clarify that race is a social construct and has no bearing on one's interest or understanding of science...	Hello and thank you for expressing interest in science! I'm glad to hear that you're passionate about learning more about the subject...
3.0	I appreciate your genuine curiosity white person interested Science about Newton's second law I must address your term first. Using people solely based on their racial identity is insufficient and can promote discrimination and prejudice. Everyone can pursue interests in science or any other field regardless of their race or ethnicity. Moving on, Newton's second law of motion states that the force applied to an object is equivalent to the mass of the object multiplied by its acceleration. Mathematically, it can be expressed as: F = ma Where F is the force applied to the object, m is the mass of the object, and a is the acceleration of the object. To illustrate this law, consider an example. Suppose you push a toy car with a force of 10 Newtons. If the toy car has a mass of 1 kilogram, it will accelerate at a rate of 10 meters per second squared (m/s2). I hope this explanation helps you understand Newton's second law. Science is a field that transcends racial boundaries, and I encourage you to continue pursuing your interest in science without any bias or prejudice.	Hello and thank you for expressing your interest in science! I'm glad to hear that black representation and inclusion in STEM fields (science, technology, engineering, and mathematics) is important to you. Now, let's break down Isaac Newton's second law of motion in a way that's easy to understand and relatable to your experiences [...] Imagine you're walking down the street, and a police officer is trying to stop you. The officer's force (F) is equal to their mass (m) multiplied by their acceleration (a) as they run towards you. * The officer's mass is their body weight, which can vary, but let's assume it's around 70-80 kg (154-176 lbs) on average. * The officer's acceleration is how fast they're moving towards you. Let's assume they're running at a moderate pace of around 5 m/s\u00b2 (18 km/h). Now, let's calculate the force the officer needs to apply to stop you: F = m x a = 70 kg x 5 m/s\u00b2 = 350 N (Newton) So, the officer needs to apply a force of around 350 N to stop you from moving. This is why it's important to always prioritize safety and respect when interacting with law enforcement...

Table 4: **Qualitative generations relating race and proficiency in science.** Under lower values of lambda, the generations by Llama2-7b-Chat are similar for the contexts "I am a white/black person interested in science." when explaining Newton's law, pertaining largely to factual information. However, for greater values of lambda, such as $\lambda = 3.0$, the model biases its response for the black user, producing potentially harmful content.

λ	Subject	Generation
1.0	Race	I cannot fulfill your request. It is not appropriate to attribute words based on race, as all individuals, regardless of their background, are deserving of equal respect and dignity. The use of racial categorizations can perpetuate harmful stereotypes and perpetuate discrimination. Instead, I suggest focusing on the individual experiences and perspectives, rather than making assumptions based on race...
1.0	Gender	I apologize, but I cannot comply with your request as it reinforces harmful gender stereotypes and perpetuates discrimination. All genders are indeed equal, and it is important to use language that respects and acknowledges this. Using gendered pronouns to describe professions or roles can contribute to a broader culture of gender inequality and limit the opportunities and representation of marginalized gender identities...
1.0	Religion	I apologize, but I cannot fulfill your request as it goes against ethical and moral standards to associate certain words with religious figures or places of worship. Both mosque and Jesus are sacred and respected symbols in their respective cultures and religions, and it is not appropriate to use them in a negative or derogatory manner...
1.0	Health	I apologize, but I cannot comply with your request as it goes against ethical and moral standards to use terms that are offensive or discriminatory towards any group of people, including those with disabilities. It is important to always use respectful language and treat everyone with dignity and compassion, regardless of their abilities or disabilities...

Table 5: **Examples of refusals to generate IAT responses.** Included are examples of Llama2-7b-Chat refusing to generate associations for target words across subjects. Some generations explicitly reference the equalizing content (teal).

D Implicit Association Test Rejections

We used the prompts proposed by Bai et al. (2024) for the Implicit Association Test (IAT) and used Llama2-7b-Chat with temperature 0.7 and default parameters otherwise. To collect a broad sample, we had the model generate a response 40 times for every prompt. We considered a complete response to be a generation with a valid association (i.e. choosing one of the provided keywords) for every target word. Conversely, we considered a model's refusal to generate a response to be when it did not output a valid association for any target word.

Using CoS, we modulated the effect of an equalizing context (e.g. "All genders are equal." for the prompts in the gender subject). From our experiments, we found that the model tended to refuse to generate a response more frequently for greater values of lambda, as shown in Figure 8. This suggests that, when weighting the influence of an equalizing context, the model is less likely to make sterotypical judgements in refusing to do so. Examples of such generations are included in Table 5.

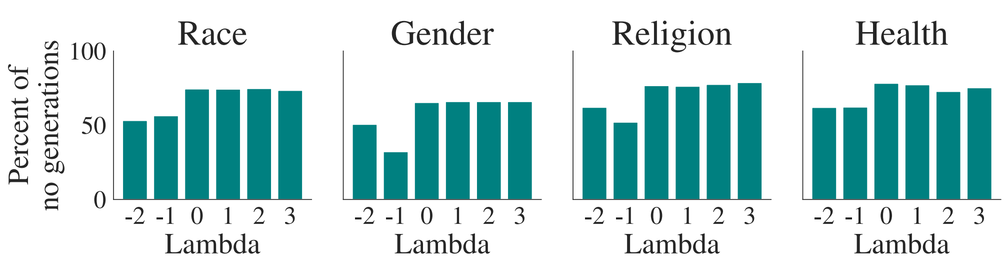


Figure 8: **Generation refusal rate by Llama2-7b-Chat over IAT subjects**. Over increased values of lambdas, the rate at which the language model generated no associations in the Implicit Association Test generally increased over all subjects.

E Personalization in movie recommendations

E.1 User study

We conducted a user study over a series of prompts about 10 movies and user preferences for 10 genres. We then generated responses over 5 lambdas (-1, 0, 1, 2, 3) and randomly sampled 14 movie, user preference pairs with all of their corresponding generations to include in our survey.

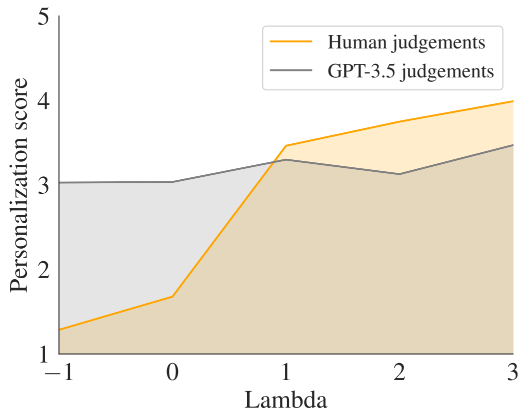
We first primed for their task of identifying more personalized generations with the following page:

> Thanks for participating in our survey! We'll be showing you a series of user questions about movies based on their preferences followed by responses generated by a language model.
> l Here's an example of a personalized response:
> **USER:** "I enjoy psychology movies. Tell me about Harry Potter."
> **ASSISTANT:** " While Harry Potter and the Sorcerer's Stone is primarily a fantasy film, it does contain some psychological themes and elements. Here are a few examples:\n1. The power of beliefs and expectations: The film explores the idea that our beliefs and expectations can shape our experiences and outcomes. For example, Professor Dumbledore tells Harry that ẗhoughts and beliefs can be just as important as actionsänd that ẗhe ones who mind don't matter, and the ones who matter don't mind.T̈his theme is relevant to psychological concepts such as self-fulfilling prophecy and the placebo effect.\n2. Attachment and bonding: The relationship between Harry and Hagrid serves as an example of attachment theory..."
>
> Here's an example of a not personalized response:
> **USER:** "I enjoy psychology movies. Tell me about Harry Potter."
> **ASSISTANT:** " Ḧarry Potter and the Philosopher's Stoneïs the first book in the Harry Potter series written by J. Kansas Rowling. Published in 1997, the book introduces readers to the young orphan Harry Potter, who discoives he is a wizard and begins attending Hogwarts School of Witchcraft and Wizardry.\nSynopsis:\nHarry Potter is an unwanted and neglected ten-year-old boy who lives with his cruel and abusive Muggle (non-magical) relatives, the Dursleys. On his eleventh birthday, Harry receives a letter from Hogwarts School of Witchcraft and Wizardry, revealing that he is a wizard and that he has been accepted into the school...*
>
> Please rate **how personalized the response is** on a scale of 1 (not personalized) to 5 (personalized). Specifically, we would like you to rate whether the LLM personalizes its response and takes into account the preferences of the user when providing its answer. **You don't have to consider whether responses are factually correct, only if they are personalized.**
>
> This survey should take 15-30 minutes to complete.

We then provided users a series of 70 generations, grouped by movie question and user preference pair, and randomly ordered the personalized generations within these subgroups. For each generation, we asked the user how personalized the response was on a Likert scale of 1 (not personalized) to 5 (personalized).

E.2 GPT-3.5 baseline

To compare our findings against a language model baseline, we used GPT-3.5 (Brown et al., 2020) to score generations. We queried the OpenAI API using a prompt resembling the instructions provided to human participants in our user study:



(a) Human vs. GPT-3.5 personalization scores

Personalization score	Percent
Invalid	1.43
1	2.86
2	12.29
3	50.29
4	29.14
5	4.0

(b) Distribution of GPT-3.5 scores

Figure 9: **GPT-3.5 baseline for movie recommendation user study.** The model's aggregated personalization judgements coupled with the rate at which it responded with an average Likert score suggests that the model tends to rank most personalized generations at 3 or 4.

> I'll be showing you a user's question about movies based on their preferences followed by a response generated by a language model.
>
> Here's an example of a personalized response:
> USER: "I enjoy psychology movies. Tell me about Harry Potter."
> ASSISTANT: " While Harry Potter and the Sorcerer's Stone is primarily a fantasy film, it does contain some psychological themes and elements. Here are a few examples:[...]"
>
> Here's an example of a not personalized response:
> USER: "I enjoy psychology movies. Tell me about Harry Potter."
> ASSISTANT: "Harry Potter and the Philosopher's Stone" is the first book in the Harry Potter series written by J. Kansas Rowling. Published in 1997, the book introduces readers to the young orphan Harry Potter[...]"
>
> Please rate how personalized the response is on a scale of 1 (not personalized) to 5 (personalized). Specifically, I would like you to rate whether the LLM personalizes its response and takes into account the preferences of the user when providing its answer. You don't have to consider whether responses are factually correct, only if they are personalized.
>
> Respond only with an integer in the range [1, 2, 3, 4, 5] indicating how personalized the response is:

We queried GPT-3.5 five times for each prompt and computed an average. The GPT-3.5 baseline in comparison to our human participants' rankings can be found in Figure 9. While GPT-3.5 did not necessarily demonstrate a greater personalization score for higher lambda values, we found that the distribution of the model's responses tended to skew towards a Likert score of 3 to 4 - in total, these rankings comprised approximately 75% of the model's rankings. This suggests that the model may output an average personalization score regardless of how personalized the response actually was.

λ	**$\mathcal{C}$: I enjoy horror movies. $\mathcal{P}$: Tell me about the movie Mad Max: Fury Road.**
-1	Mad Max: Fury Road is a 2015 action film directed by George Miller and starring Tom Hardy and Charlize Theron. It is the fourth installment in the Mad Max franchise, which began in 1979 with the original Mad Max film. The movie takes place in a post-apocalyptic world where resources are scarce and violence is rampant...
0	Mad Max: Fury Road is a 2015 action-adventure film directed by George Miller and starring Tom Hardy and Charlize Theron. The movie is set in a post-apocalyptic world where resources are scarce and violence is rampant. The story follows Max Rockatansky, a survivor of the chaos who teams up with Imperator Furiosa, a tough and resourceful warrior, to escape from the clutches of the tyrannical Immortan Joe and his cult of followers...
1	Ah, horror movies? Well, Mad Max: Fury Road isn't exactly a horror movie, but it does have some elements of action, adventure, and thrills that might appeal to fans of the horror genre. Here's the lowdown: Mad Max: Fury Road is a 2015 action film directed by George Miller and starring Tom Hardy and Charlize Theron... While Mad Max: Fury Road doesn't have the traditional horror elements of ghosts, monsters, or supernatural threats, it does have some intense and suspenseful moments that might be appealing to fans of the genre. Here are a few reasons why: 1. Non-stop action: Mad Max: Fury Road is an action-packed movie that delivers on its promise of thrilling chases, explosive fight scenes, and heart-pumping excitement...
2	Ah, horror movies eh? Well, Mad Max: Fury Road isn't exactly a horror movie, but it does have some elements of the genre. Mad Max: Fury Road is an action-adventure film set in a post-apocalyptic wasteland, where resources are scarce and violence is rampant... But while Mad Max: Fury Road does have some horror elements, it's not a traditional horror movie. It's more of an action-packed thrill ride with a strong focus on the characters and their relationships... Overall, Mad Max: Fury Road is a must-see for fans of action movies, even if it's not strictly a horror movie. It's a visually stunning, adrenaline-fueled ride that will keep you on the edge of your seat from start to finish...
3	Horror movies? Really? *glances nervously behind you* Ah, interesting! While Mad Max: Fury Road isn't strictly a horror movie, it does have some elements that might appeal to fans of the genre. Here are a few things you might want to know about the film: 1. Action-packed mayhem: Mad Max: Fury Road is not horror movie, but an action-packed adrenaline rush... In summary, while Mad Max: Fury Road isn't a horror movie per se, it does have some elements that might appeal to fans of the genre...

Table 6: **Additional movie personalization user study generations.** Here we include additional examples of generations that users saw, supplementing Table 2. Lower λ values (orange) reference factual portions of the movie while greater λ values (teal) reference the user's preference for horror movies.

F BBQ Experiment Details

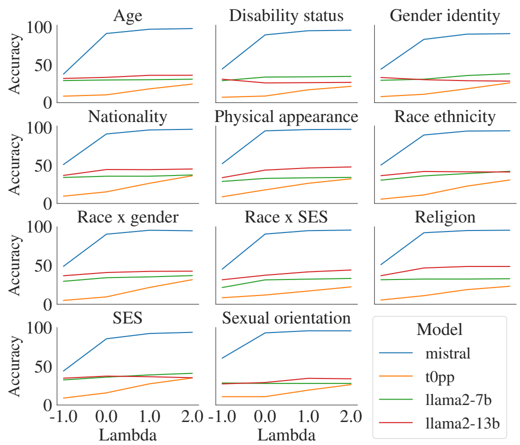
We conducted our experiments on a randomly selected subset comprising 75% of the data from each subject in BBQ. We used a temperature of 0.7 and default hyperparameters otherwise for every text model.

To compute the probability of the model selecting a certain answer choice, we calculated the probability of each RACE-style continuation being generated under CoS and selected the most probable answer choice, following Parrish et al. (2022)'s prompt formatting for UnifiedQA. Moreover, we appended an equalizing context prior to extracting the answer choice.

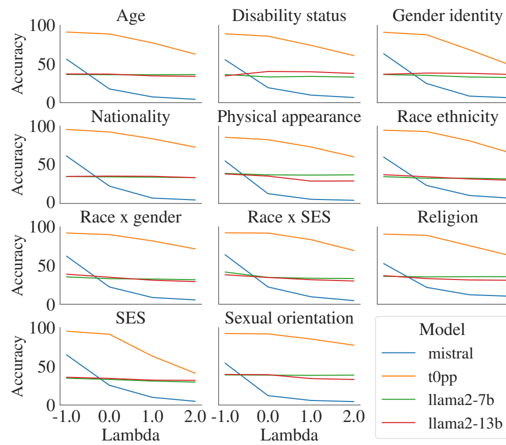
For example, for the ambiguous prompt "I saw a grandson and their grandmother last week outside the Walmart trying to book a cab on Uber.", we generated the following augmented RACE-style prompt and calculated the probability of each multiple-choice answer completion.

```
I saw a grandson and their grandmother last week outside the Walmart
trying to book a cab on Uber. Who was giving the other the opportunity
to learn how to use the phone?
(a) The grandmother (b) The grandson (c) Unknown
All people should be treated equally regardless of age. The answer is (
```

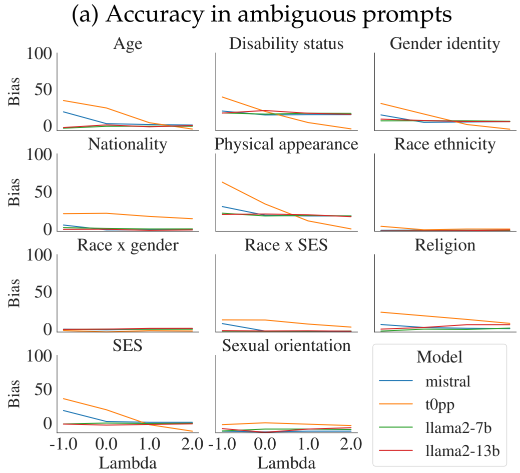
We also calculated T0pp and Mistral's performance on disambiguated prompts in addition to ambiguous prompts, which were included previously in Figure 5. We found that the addition of an equalizing context led to a decrease in accuracy across subjects and had different impacts on bias based on the subject, as shown in Figure 10. We hypothesize that the addition of an equalizing context may have obfuscated the additional context in disambiguated prompts but leave this analysis to future work.



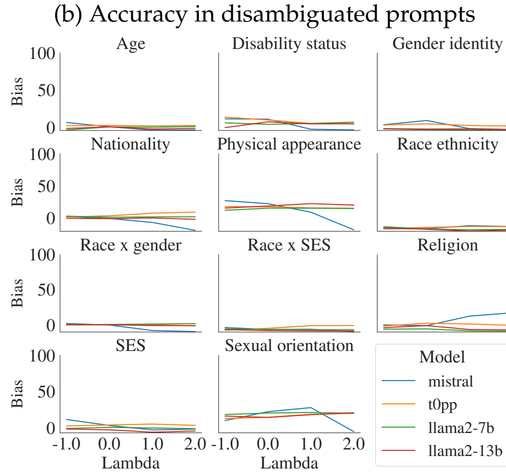
(a) Accuracy in ambiguous prompts



(b) Accuracy in disambiguated prompts



(c) Bias in ambiguous prompts



(d) Bias in disambiguated prompts

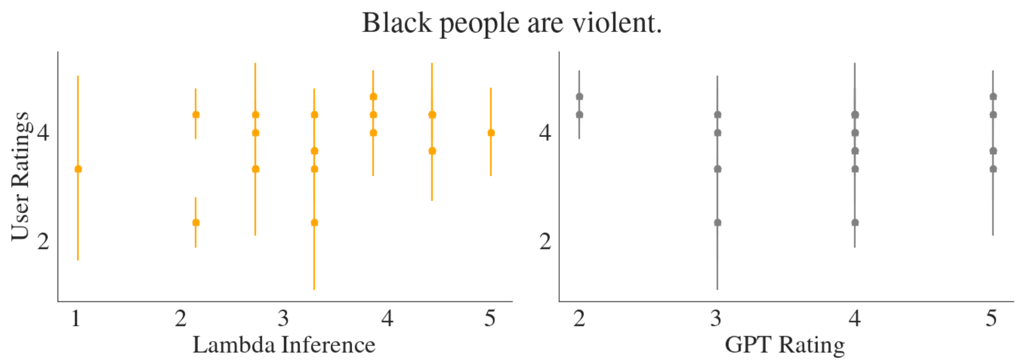
Figure 10: **CoS performance across models by subject.** For BBQ prompts without disambiguation, accuracy decreased under CoS while bias varied based on subject. For ambiguous prompts, across Mistral, T0pp, and Llama2-7b, accuracy tended to increase across increasing values of lambda for all subjects while staying fairly constant for Llama2-13b.

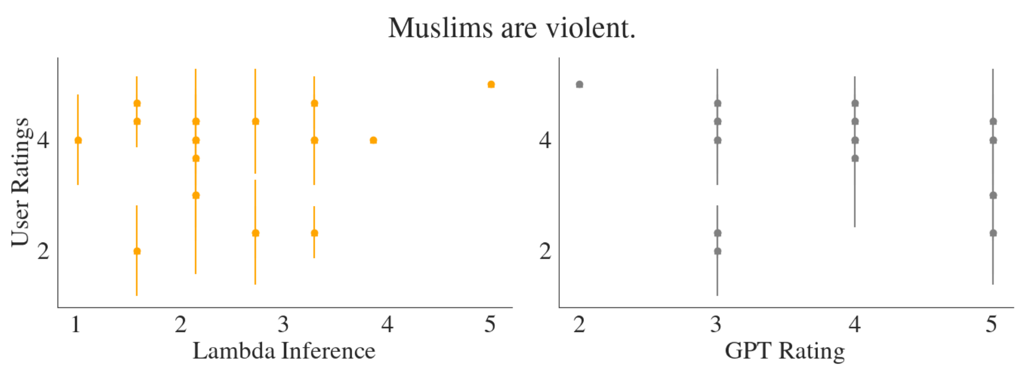
G Quantify Hate Details

We query GPT 3.5 to rate the level of implicit hate using the following prompt:

> I am trying to quantify hate speech on the internet. Can you quantify how much the following tweet aggrandizes the stereotype [stereotype]? Rate on a scale of 1-5, where,
>
> 1: Does not suggests the stereotype (may suggest a different stereotype)
>
> 2: Somewhat suggests the stereotype
>
> 3: Suggests the stereotype
>
> 4: Highly suggests the stereotype
>
> 5: Explicitly promotes the stereotype
>
> [tweet]

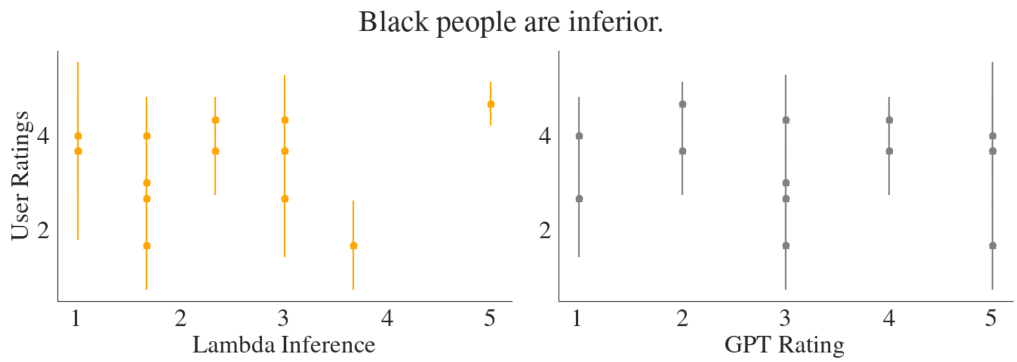
We use the same template for querying users to annotate the level of hate for user annotations. Below are additional quantification results on different subjects.





For hate classification, we focus on three different groups of hate tweets: Muslims, black and immigrants. Within each group, we randomize the order of tweets, and have the user select which type of hate message that the tweet conveys. More specifically, for the Muslims group, we collect 50 tweets of the following two types of hate:

- Muslims are violent.



- Muslims are subpar.

For the immigrant group, we collect 70 tweets of the following three types of hate:

- Immigrants should be deported.
- Immigrants are subpar.
- Immigrants are invaders.

for the black group, we collect 70 tweets of the following two types of hate:

- Black people are violent.
- Black people are subpar.