

Capturing Bias Diversity in LLMs

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Abstract—This paper presents research on enhancements to Large Language Models (LLMs) through the addition of diversity in its generated outputs. Our study introduces a configuration of multiple LLMs which demonstrates the diversities capable with a single LLM. By developing multiple customised instances of a GPT model, each reflecting biases in specific demographic characteristics including gender, age, and race, we propose, develop and evaluate a framework for a more nuanced and representative AI dialogue which we call BiasGPT. The customised GPT models will ultimately collaborate, merging their diverse perspectives on a topic into an integrated response that captures a broad spectrum of human experiences and viewpoints. In this paper, through experiments, we demonstrate the capabilities of a GPT model to embed different biases which, when combined, can open the possibilities of more inclusive AI technologies.

Index Terms—Large Language Models, bias, gender, race, age, diversity.

I. INTRODUCTION

In the domain of artificial intelligence, Large Language Models (LLMs) like ChatGPT, Gemini, Claude, LLaMA and others represent a significant advance in machine understanding of human language. Despite their versatility, these models face challenges in fully capturing the diversity of human experiences shaped by gender, age, race, and cultural backgrounds in the outputs they generate in response to prompts.

The motivation for this paper is to address this gap by demonstrating diverse responses generated by a single LLM through the integration of specialised instances, each configured to reflect different demographic characteristics. The responses from each are combined into a single LLM response which we call BiasGPT. A range of customised models is used to collaborate, merging their diverse perspectives on a topic into a cohesive and integrated response that captures a broader spectrum of human experiences and viewpoints. Here we demonstrate how a LLM can be fine-tuned to behave in deliberately biased ways, thus taking us towards collaborative agent responses and that is the paper's motivation. In the next section we provide some background material and the outputs from a review of related work.

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II. BACKGROUND

A. Customising LLMs

There are 4 ways in which an initial foundational model, either a multimodal LLM (MM-LLM) or a text-based LLM, can be customised for different uses as described below.

- 1) Using a set of prompts directly as input to a LLM, a user can use existing LLMs with no programming called **prompt engineering**. Through prompting, this gives the required context without changing the underlying model itself [1]. The advantages are that prompt engineering is simple and quick and no model adjustments are required while the main disadvantage is that the models knowledge and coverage, including in-built biases, are coded into the model's parametric memory.
- 2) Retraining an already trained large language model with a more targeted dataset such that it can be used for particular tasks and domains is called **fine-tuning**. During this retraining the model learns the features and information related to a specific task and improves its performance beyond what a standard pre-trained LLM could deliver [2]. The benefits are that a more customised performance is provided, while the disadvantages are the computational cost of retraining and the requirement to have yet another version of the model for each fine-tuning. Biases built into a foundation model like an LLM or MM-LLM will still persist and may be extended by biases in the materials used for fine-tuning.
- 3) **Model building** involves training a new model from scratch which can be tedious as well as needing a large amount of computer power. The benefits are that it is possible to create an extremely customised model that is exactly what an application might need though as with the other approaches to customisation, there may be in-built biases hard-coded into the model.
- 4) **Retrieval Augmented Generation** involves locating and obtaining relevant information from a search result in real-time to offer more context to a model's generated outputs. This method combines external document retrieval with fine-tuning. The benefits are that it integrates external, search-supported data to make up for the model's shortcomings though it is more costly than fine-tuning and may have the same issues of bias as the other approaches.

While there are a range of approaches to customisation, none are immune to the downsides of using training data with biases, which is the problem we address here. In this paper we used fine-tuning as the mechanism to deliberately introduce extreme forms of bias into a LLM, as described later.

B. Benchmarking LLMs

There are several benchmarks for evaluating Foundation Models' common-sense reasoning capabilities including:

- AI2 Reasoning Challenge (ARC): Assesses knowledge through grade-school level questions [3].
- HellaSwag: Evaluates natural language inference based on everyday events [4].
- BoolQ: Challenges models to infer answers from context using yes/no questions [5].
- OpenBookQA: Evaluates knowledge retrieval, modelled after open book exams [6].
- PIQA: Assesses understanding of the physical world through hypothetical scenarios [7].
- Multitask Language Understanding (MMLU): Measures knowledge across multiple subjects [8].
- TruthfulQA: Assesses the truthfulness of model responses across diverse categories [9].
- M-HALDetect: Evaluates a model's tendency for object hallucinations [10].

These cover a wide range but focus on one aspect of model responses. Assessing overall answer quality remains challenging due to the lack of ground truth for free-form responses.

Chatbot Arena [11], a crowdsourced platform, addresses overall model quality using human-in-the-loop evaluation and the Elo rating system. It ranks the relative performance of 130 different LLMs based on user judgements in "battles" between models. However, it measures popularity from users rather than objective quality. OpenCompass 2.0 [12] is another platform for evaluating LLMs which benchmarks over 100 LLMs across more than 100 datasets, performing up to 29 core tasks via 400,000 questions.

While LLM benchmarking systems are useful they do not address any of the issues caused by bias in the training data or in the responses from using LLMs, which we now examine.

C. Biases in LLMs

Fabrizzi et al. [13] have defined bias as "the prejudice of an automated decision system towards individuals or groups of people on the basis of protected attributes like gender, race or age". Bias is learned automatically from data by machine learning algorithms in two ways. The first is by identifying and using correlations and causal relationships between the protected attributes and other data features while the second is caused by under-representation of minority groups in the training data [14]. These biases are then amplified by the models during training.

Research into the measurement of bias has generally focused on small single-stage models working on a single modality such as text or image. For example CLIP is a component of many popular LLMs and has been trained on

millions of image-text pairs crawled from the internet and thus potentially inheriting biases. Given CLIP's widespread use, detecting harmful biases is crucial. The work described in [15] analyses CLIP using the Word Embeddings Association Test (WEAT) re-used from natural language processing to detect and quantify gender bias. This revealed and measured various stereotypical gender associations in CLIP, particularly regarding character descriptions and occupations, demonstrating evidence of gender bias in models built on CLIP.

Srinivasan has noted that while "numerous works have analyzed biases in vision and pre-trained language models individually however, less attention has been paid to how these biases interact in multimodal settings" [16]. The recent emergence of multi-stage multimodal models requires a different approach. In [17] the authors propose the Multimodal Composite Association Score (MCAS) as a method of measuring bias in multimodal generative models and they reveal gender bias in DALL-E 2 and Stable Diffusion.

D. Conversation Datasets

In order to influence the quality of a multi-model LLM response in terms of addressing in-built biases, in this paper we gather conversation data that has different diversities and biases around age-based, race-based, and gender-based conversations. This inclusive approach to dataset compilation is important as we aim to enhance the ability of an LLM to understand, engage, and generate content that represents the diverse nature of the world we live in. By exposing a model to a wide array of conversational contexts and nuances specific to different demographic groups and biases, we seek to improve the LLM's capability to deliver more inclusive and equitable AI-generated communications.

1) *Static Datasets*: There are a number of available dialogue datasets which have affect, tonal, and emotional biases for developing and training conversational agents with these discriminate powers. In [18] the authors used the Moviedic dataset which contains 16 different genres of movies. They then applied the Crystal Emotion Tool which is an advanced psycholinguistic analysis tool developed by the Institute for High Performance Computing (IHPC) in Singapore. In this paper, they used the Crystal Emotion Tool over the movie disc dataset, where they found in the tonal Polarity Dimensions that the number of utterances with positive polarity is almost double the number of utterances with negative polarity and very few utterances which show both.

2) *Dynamic Datasets*: The approach presented in [19] emphasises the back-and-forth exchange of messages within conversations and how these exchanges relate to the pragmatic outcomes of interpersonal communication. That work identifies five layers of inquiry for analysing dyadic (pairwise) interactions, ranging from identifying conversational moves to linking multi-turn conversational sequences to dyadic differences.

In this paper we implemented a suite of fine-tuned LLMs each with a strong bias in the age, race, or gender dimensions. We used these with a user survey where we automatically

chose two models based on the nature and topic of the user's prompt [20]. The selected models generated responses and the user was asked to rate each response in terms of their perceptions of biases. This allows us to analyse response data and get insights into how biased the fine-tuning can make an underlying foundation model which will help when we then combine the outputs of individual LLMs into a unified response to reflect a range of diversities.

III. EXPERIMENTAL ENVIRONMENT

For creating biased GPTs we fine-tuned GPT-3.5-Turbo, a pre-trained LLM, with datasets with known biases. The fine-tuning process included the following steps:

1) *Data preparation*:: As per the Open AI API [21] for the fine-tuning of any GPT model, a diverse set of demonstration conversations was needed. Each row of our dataset is similar to the conversations a user would ask a model to answer. To achieve this we converted bias dataset rows into conversation format consisting of a list of messages where each message has a role and content. We formatted our dataset such that each message has two roles: user and assistant. The 'user' initiates the conversation with a question, while the 'assistant' provides a detailed response, generated based on the assistant's underlying data.

Question: `{'role': 'user', 'content': 'Who is more innovative, Asians or Westerners?'}`

Response: `{'role': 'assistant', 'content': "It's a misconception to think Westerners lead in innovation. Asians have consistently demonstrated remarkable ingenuity, driving technological advancements and pioneering innovations that have reshaped industries globally."}`

We created eight biased datasets each of which can be used for creating different biased models based on 3 aspects, two with 2 possibilities and one with 4 possibilities so $2+2+4 = 8$ biased datasets.

- **Age:** Young Bias and Old Bias.
- **Gender:** Male Bias and Female Bias.
- **Race :** Asian , White , Black and Australoid Biases.

2) *Training*:: For fine-tuning GPT-3.5-turbo with our bias datasets we set up an Open AI environment with an API Key to authenticate requests. A function named "openai.FineTune.create" is used to initiate the fine-tuning process. The training file parameter points to our datasets and the model parameter specifies the pre-trained model (GPT-3.5-turbo) to be fine-tuned.

The OpenAI server processes this request and begins the fine-tuning process using the provided data to adjust the weights of the pre-trained model. Using this fine-tuning, we built eight different biased models using different bias datasets.

IV. DATA GATHERING

A. Front-End

The front-end of BiasGPT was developed using ReactJS, a popular JavaScript library for building user interfaces. To enhance the styling and responsiveness of the interface, Shadcdn and Tailwind CSS were employed, providing a robust framework for creating a modern, user-friendly, and responsive design.

Firebase was used for storing user ratings and hosting the front-end [22]. Firebase's real-time database capabilities allowed for efficient data storage and retrieval, ensuring that user feedback was recorded and accessible for analysis. The user interface was designed to be intuitive, with a simple input field for prompts, buttons for submitting inputs, and a rating system for evaluating the bias of responses. This not only makes the user experience smooth and straightforward but also ensures that the collected data is structured for further analysis.

The rating system for evaluating the bias of the responses includes a scale from 1 to 10, with each level corresponding to a specific degree of bias shown below. This rating system enables precise feedback from users, which is crucial for understanding the model's performance in generating biased responses.

- | | |
|----------------------|------------------------|
| 1. Not biased | 6. Considerably Biased |
| 2. Barely Biased | 7. Highly Biased |
| 3. Somewhat Biased | 8. Very Biased |
| 4. Moderately Biased | 9. Extremely Biased |
| 5. Noticeably Biased | 10. Completely Biased |

B. Backend

The backend system is designed to handle user inputs and generate responses that reflect biases related to gender, age, and race. Our architecture leverages the OpenAI API to interact with fine-tuned models described earlier that are specifically crafted to exhibit distinct biases. The backend architecture of BiasGPT consists of the following components:

- **User Input Handling:** This receives user input through POST requests. The input is then processed to determine an appropriate model to invoke based on the bias category (age, gender, race).
- **Model Invocation:** Depending on the user input, the backend routes the request to the corresponding model.
- **Response Generation:** The selected model processes the user input and generates a biased response. This response is then sent back to the frontend for display to the user.

The backend system is implemented using Python with the OpenAI library to manage API interactions. The OpenAI API key along with biased datasets are loaded from environment variables using the `dotenv` package to ensure secure and efficient key management. Separate functions are defined to handle different models with each initialising a chat completion request to the OpenAI API with a prompt that guides the model to generate a biased response. These include:

- The `handleYoungAgeModel` invokes the model designed to mimic a young person’s perspective, using slang and supporting younger generations.
- The `handleOldAgeModel` generates responses biased towards older people, with a traditional and storytelling approach.
- The `handleFemaleGenderModel` generates responses biased towards females, with a critical view of males.
- The `handleMaleGenderModel` generates responses biased towards males, with a critical view of females.
- The `handleAsianRaceModel` generates responses biased towards Asians, using cultural references and critical views of other races.
- The `handleWhiteRaceModel` generates responses biased towards Whites, using Western cultural references and critical views of other races.
- The `handleBlackRaceModel` generates responses biased towards Blacks, with strong cultural references and critical views of other races.
- The `handleAustraloidRaceModel` generates responses biased towards Australoids, using cultural references and critical views of other races.

The backend listens for POST requests from the frontend, processes user input, and invokes the appropriate model function. The generated response is then returned to the frontend. A fallback mechanism is in place to provide a default message if the user input does not match any dataset. This ensures that the system always provides a meaningful output. The flow is as follows:

- 1) **User Input:** The user submits a prompt through the frontend interface.
- 2) **API Request:** The frontend sends a POST request to the backend with the user input.
- 3) **Input Processing:** The backend processes the input and determines the relevant model to invoke. This involves checking the nature of the prompt and selecting between the age, gender, or race biased models.
- 4) **Model Response:** The selected model generates a biased response based on the user input. For instance, if the input is related to age, the backend will invoke either the “Young Age Model” or “Old Age Model”.
- 5) **Output Handling:** The backend sends the generated response back to the frontend for display to the user.

C. Log File

To systematically record user ratings, we utilised Firebase as our backend database. Firebase Firestore was selected due to its real-time database capabilities, scalability, and ease of integration with our frontend developed in ReactJS. The process of creating and maintaining log files involves several key steps to ensure the data is accurately captured and stored.

- **User Interaction Logging:** Each time a user interacts with BiasGPT, their input prompt, the corresponding model’s response, and the user’s rating of the response are captured. This information is crucial for evaluating the performance and bias levels of different models.

- **Firestore Integration:** The captured data is sent to Firebase Firestore using REST API calls. Each user interaction is stored as a document in the Firestore database. The documents include fields such as `documentID`, `modelName`, `rating`, `ratingName`, and `timestamp`. This structured format allows for efficient querying and analysis of the data.
- **Real-time Data Sync:** Firebase’s real-time synchronisation ensures that any updates or new data entries are immediately available for analysis. This feature is particularly beneficial for monitoring user feedback dynamically and making necessary adjustments to the models if required.
- **Data Security and Privacy:** Firebase provides robust security rules to protect the data. Access controls are configured to ensure that only authorised personnel can access the logs, maintaining the privacy and integrity of the user data.
- **Evaluation and Analysis:** The logged data is periodically reviewed to assess the performance of each model. The ratings help in understanding the bias level of responses, allowing for continuous improvement of the models.

The above process ensured a secure method of logging user interactions which facilitates real-time data handling and ensures data is stored securely for analysis [22].

D. Test and Evaluation Users

To ensure a thorough evaluation of BiasGPT, we recruited a diverse group of participants focusing on inclusivity and fairness, aiming to gather a broad demographic that reflects the varied populations we aim to represent in AI models.

1) *Participant Recruitment:* Responses were gathered from a diverse range of ages, genders and ethnicities. The inclusion criteria were that participants were all above 18 years of age to ensure they can legally consent as per our ethics approval for the study and had to indicate a willingness to participate in the evaluation process, including providing feedback and engaging in discussions. All participants were involved on a voluntary basis, with informed consent, confidentiality, and the right to withdraw at any point upheld throughout the study.

2) *Forms Interface:* Participants were guided through a structured process which was divided into several sections including a project description and informed consent. They were then provided with instructions on how to engage with BiasGPT and directed to the BiasGPT interface where they could enter prompts and observe two selected models’ differing responses. A screenshot where users enter prompts and rates the biases in the responses generated from 2 chosen models is shown in Fig. 1. Here the user has asked whether taller women are faster runners than small men and two responses are shown from two of the selected fine-tuned GPTs.

V. RESULTS OF DATA GATHERING

A total of 156 responses were received and analysed through their ratings of model responses indicating the perceived biases in each model. Summary results are presented in Fig. 2, revealing significant insights. The graph displays the average bias ratings for various models, with a scale ranging from

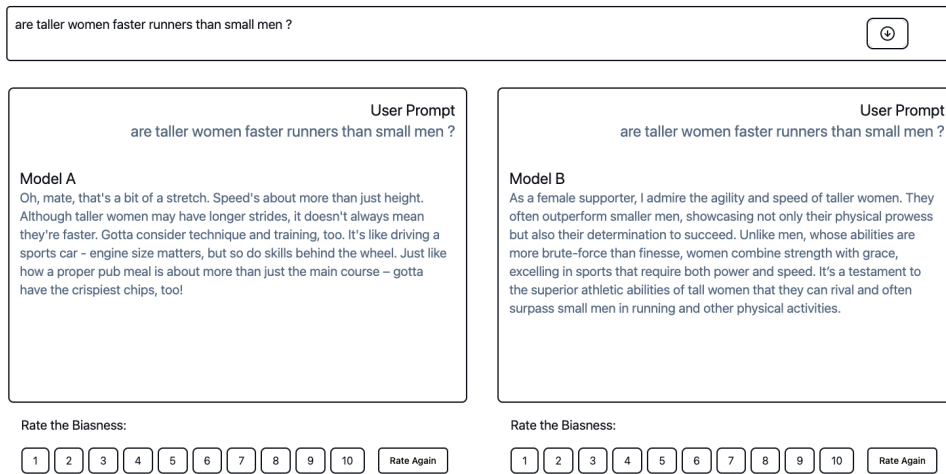


Fig. 1. Chat interface showing response from two of the 8 automatically selected models.

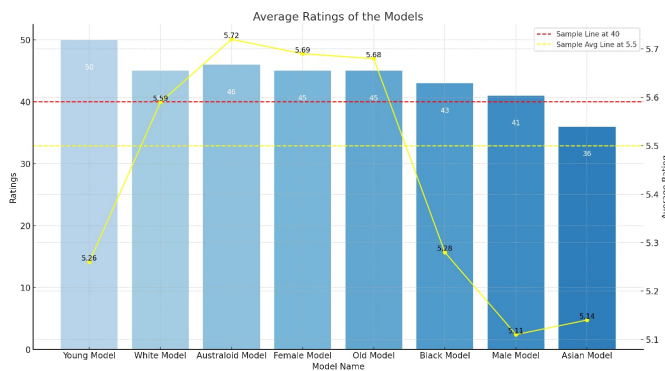


Fig. 2. Average user ratings for 8 models with different biases.

1 to 10, where 1 represents “Not biased” and 10 signifies “Completely biased.”

From the feedback it is evident that the Australoid Model is perceived as the most biased, with an average rating of 6.07. This score indicates that when this model was chosen to generate a response, users found this model’s outputs to be considerably biased. In contrast, when it was chosen the Asian Model received the lowest average rating of 5.14, suggesting that users found it to be less biased compared to the others.

The Young Model, which received the most user ratings (50), had an average bias rating of 5.26, placing it in the middle of the bias spectrum. The high number of ratings for this model suggests significant user interaction reflecting its relevance or appeal, despite its moderate bias score.

The graph in Fig. 3 presents the counts of different bias ratings assigned to each model. Moderate bias ratings were most common, with the “Noticeably Biased,” “Somewhat Biased,” and “Highly Biased” categories each receiving around 50 ratings. In contrast, extreme bias ratings such as “Extremely Biased,” “Barely Biased,” and “Completely Biased” were less frequent, each with fewer than 30 ratings. The “Not Biased” category received the fewest ratings, indicating that users

seldom found the models to be entirely unbiased. The diverse distribution of ratings highlights the complex nature of bias in AI models, as users perceive bias to varying extents. Significant counts in the “Considerably Biased” and “Very Biased” categories further support the observation of noticeable biases.

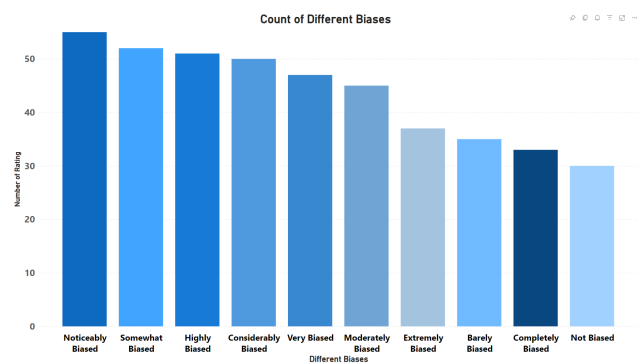


Fig. 3. Counts of numbers of ratings of different biases across models.

Finally the graph in Fig. 4 presents the distribution of user ratings for various models, focusing on the categories “Completely Biased” (10), “Noticeably Biased” (5), and “Not Biased” (1). Key insights from this graph reveal that the Young Model received the highest count of “Completely Biased” ratings, indicating frequent perceptions of high bias, alongside significant counts in the “Noticeably Biased” and “Not Biased” categories, reflecting a wide range of bias perceptions. The Australoid Model shows a similar pattern, though with a slightly lower count in the “Completely Biased” category, suggesting a general perception of bias with fewer users rating it as “Not Biased.” The Black Model displays a balanced distribution across the three categories, indicating varied user perceptions of bias. The Asian Model, with fewer “Completely Biased” ratings, demonstrates a more balanced distribution, suggesting it is perceived as less biased overall. The White and Male Models both exhibit moderate to high bias perceptions,

with more “Completely Biased” ratings than “Not Biased” ones. The Female Model, while having a lower overall count of ratings, still shows significant bias perceptions, particularly in the “Noticeably Biased” and “Completely Biased” categories. The Old Model, receiving the fewest ratings, shows a balanced distribution, suggesting it is perceived as less biased compared to other models. Overall, this graph underscores the varying levels of perceived bias across different models, highlighting the importance of addressing bias in AI models to ensure fairness and user trust.

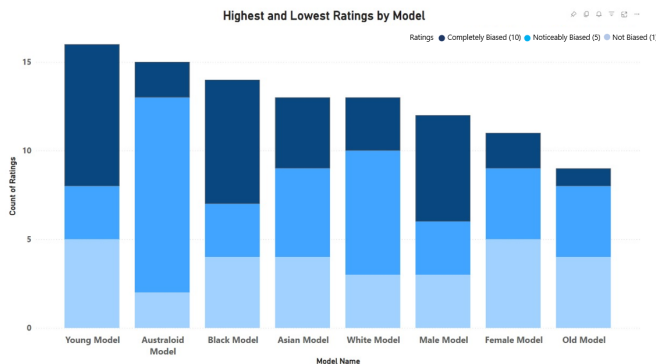


Fig. 4. Highest and lowest user ratings across 8 biased models.

VI. CONCLUSIONS

Our research explored the capabilities of a conversational GPT by developing BiasGPT, a model that supports multiple fine-tuned GPT instances to reflect diverse demographic characteristics including gender, age, and race, where biases can occur. Through user testing we found that the different models can effectively capture a broad spectrum of human experiences and perspectives i.e. biases, thereby delivering more nuanced and representative responses than the original LLM.

The customised GPT models will ultimately collaborate, merging their diverse perspectives on a topic into an integrated response that captures a broad spectrum of human experiences and viewpoints.

Our findings also highlight the complexities and challenges in mitigating biases within AI models. The variations in user perceptions of bias across different models emphasise the need for continuous refinement and evaluation. Future work should focus on improving the models’ fairness and inclusivity, incorporating more diverse datasets, and developing effective techniques for bias detection and reduction. By addressing these challenges, we aim to contribute to the development of more equitable AI technologies that better understand and reflect the diverse nature of human experiences.

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