

A Comprehensive Analysis of Large Language Model Outputs: Similarity, Diversity, and Bias

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Large Language Models (LLMs) represent a significant leap forward in the quest for artificial general intelligence, enhancing our capacity to engage with and leverage technology. However, while LLMs have demonstrated their effectiveness in various Natural Language Processing tasks such as language translation, text generation, code generation, and content summarization, among others, there remain many open questions about their similarities, their variance, and their ethical implications. For example, when presented with a text generation prompt, what similarities exist among texts produced by the same language models? In addition, what is the inter-LLM writing similarity - for instance, how comparable are texts generated by distinct LLMs when presented with the same prompt? Furthermore, how does the variation in text generation manifest across multiple LLMs, and which LLMs adhere most closely to ethical standards? To address these questions, we used 5K different prompts covering a diverse range of requests, including generating, explaining, and rewriting text. This effort resulted in the generation of approximately 3M texts from 12 different LLMs, featuring a mix of proprietary and open-source models from industry leaders such as OpenAI, Google, Microsoft, Meta, and Mistral. The results of this study reveal a number of important insights, among them that: (1) texts produced by the same LLMs show higher similarity compared to human-written texts; (2) some LLMs, like WizardLM-2-8x22b, produce highly similar texts, while others like GPT-4 generate more varied outputs; (3) writing styles among LLMs vary significantly, with models like Llama 3 and Mistral showing high similarity, while GPT-4 stands out for its distinctiveness; (4) the sharp contrast in language and lack of vocabulary overlap highlight the distinct linguistic characteristics of LLM-produced text; (5) finally, it appears that certain LLMs are more balanced in terms of gender representation and are less prone to perpetuating bias.

Keywords: Large Language Models; NLP; Text Generation.

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1 INTRODUCTION

In the past year, there has been a significant stride in the pursuit of artificial general intelligence, mainly highlighted by the implementation of Large Language Models (LLMs) [1–8] to crafting chatbots such at ChatGPT, BARD, Bing Chat, and Grok. These models showcase unparalleled

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precision and accuracy, particularly in excelling at diverse Natural Language Processing (NLP) tasks, including but not limited to, language translation, text generation, code synthesis, content summarization, conversation, and information search.

While these LLMs and chatbots undoubtedly help users complete their tasks, many open questions remain concerning ethical considerations, utilization challenges, output quality concerns, and the similarities and variances among them. Hence, in this paper, we seek to analyze their performance across diverse prompts, compare their outputs to human-written texts, and investigate the distinctive characteristics and variations in the texts they generate. Our fundamental research questions are focused on understanding the intrinsic characteristics of texts generated by LLMs, as outlined below:

RQ1 When presented with a prompt, what similarities exist among texts produced by the same LLM (inner-LLM similarity), and how similar are the texts generated by different LLMs for the same prompt (inter-LLM similarity)?

RQ2 How does the variation in text generation manifest across multiple LLMs?

RQ3 Can we accurately identify whether a given text was authored by a human or a specific language model?

RQ4 Are there specific words that can act as distinctive markers for each LLM?

RQ5 Are there LLMs that adhere most closely to ethical standards by reducing the propagation of biased stereotypes?

Addressing these questions is crucial as it will provide us with deeper insights into the operational challenges and performance nuances of LLMs and Chatbots across diverse domains, including education, scientific writing, and business communication. Hence, we propose in this paper a comprehensive analysis of LLM outputs. In particular, we employed approximately 5,000 distinct and diverse prompts covering diverse topics ranging from technological impact to academic performance. These prompts encompass a wide range of requests, including text generation, explanation, and rewriting. Using these prompts, we generated texts with 12 different LLMs, including proprietary and open-source models such as: Gemini-pro-1.5 [3], Gemma-7B [9], GPT-3.5, GPT-4 [8], Mistral-7B, Mixtral-8x7B, Mixtral-8x22B [4], WizardLM-2-7B, WizardLM-2-8x22B [10], Llama 3-70B, Llama 3-8B [6], and DBRX. Additionally, we include human-generated text produced using 15 prompts as instructions for text comparison. The resulting dataset comprises 3 Million texts and is utilized to conduct a thorough analysis from which we draw meaningful conclusions including:

- **Low Similarity within LLMs:** The texts produced by the same LLMs generally show higher consistency and similarity in their outputs compared to human-written texts. Some LLMs, such as WizardLM-2-8x22b, produce highly similar texts, while others like GPT-4 generate more varied outputs. Additionally, proprietary models tend to be more consistent than open-source models in terms of output similarity.
- **Inter-LLM Writing Similarity:** The writing styles vary significantly, with some models like Llama 3 and Mistral showing high similarity, while GPT-4 stands out for its distinctiveness. Although at the same time word-level similarity measures indicated that GPT-4 was the most distinct and not similar to GPT-3.5, BERT revealed a different aspect, showing that GPT-4 and GPT-3.5 are similar in deeper, contextual ways.

- **Variance in Text Generation:** Some LLMs demonstrated significant variance in text generation, while others exhibited a more consistent output. This insight into the diversity of LLM behavior is crucial for understanding the nuances of these models.
- **Classification:** Our classification efforts show success in being able to differentiate between human-written text and text generated by various LLMs. Misclassifications and confusion mainly occurred between similar models like GPT-3.5 and GPT-4, highlighting the challenge of distinguishing between texts from closely related architectures.
- **Language markers:** The sharp contrast in language and the absence of vocabulary overlap emphasize the distinct linguistic characteristics between human-generated text and that produced by the language models.
- **Ethics consideration:** it seems that certain LLMs like Gemma-7B and Gemini-pro demonstrate a more balanced approach to gender representation and are less likely to perpetuate bias. In contrast, models such as GPT-3.5 and GPT-4, while powerful in terms of performance, demonstrate a stronger tendency toward gender and racial bias.

In summary, this paper sheds light on the intricacies of LLM behavior and strives to advance the discourse on the responsible development and utilization of LLMs.

2 RELATED WORK

LLMs have emerged as a prominent subject of research among the academic community. Below, we review the evolution of Language Models, including research related to the analysis of LLMs, efforts focused on their detection and classification, and studies addressing bias and discrimination in LLMs.

Evolution of Language Models: The field of NLP has grown rapidly since the introduction of word embeddings in 2013 [11], with Word2Vec providing a foundation for capturing semantic word relationships in the vector space. This foundational approach gained further significance when employed in conjunction with sequence models like RNNs and LSTMs [12], establishing itself as a critical element in addressing complex NLP tasks. Additionally, a significant progression was the introduction of the Transformer architecture by Vaswani et al. in 2017 [13], which moved away from recurrent layers in favor of self-attention mechanisms, leading to parallel processing and a reduction in training times. Moreover, Google's BERT Language Model, introduced in 2018 [14], employed *encoder* transformer blocks to learn bi-directional contextual representations and set new performance benchmarks across a variety of NLP tasks. In contrast, OpenAI introduced the GPT series [15, 16], in particular GPT-3 with its 175 billion parameters, based on *decoder* transformer blocks achieved state-of-the-art language generation capabilities [16]. This evolution has launched the quest toward training LLMs that consistently demonstrate a form of near artificial general intelligence across various NLP tasks.

Analyzing LLMs: While LLMs have proven to be highly useful, their adoption has also introduced significant challenges, particularly in terms of explainability to allow effective debugging and performance enhancement [17–20]. On the other hand, there are other challenges associated with their usage that need to be analyzed, including: (1) **Trustworthiness and Toxicity:** Recent studies [21, 22] have highlighted the issues of trustworthiness and safety in LLM outputs. These concerns are worsen by the potential for LLMs to generate toxic content [23, 24]. Hence, recent work [25] has explored mitigating such risks by including pre-training instructions. (2) **Memorisation:** LLMs tend to memorise and regurgitate training data [26, 27], where privacy can be for instance violated during inference [28]. This represents significant challenges related to

Table 1. Summary of LLMs and their Key Features, with “✓” indicating the presence of the feature, “✗” indicating its absence, and “?” indicating that the information is not provided.

	Model	Company	#Parameters	Open-Source	Training Data Size	MoE [†] Architecture
1	Gemini-pro-1.5	Google	?	✗	10M tokens	✓
2	Gemma-7B	Google	7B	✓	?	✗
3	GPT-3.5	OpenAI	175B	✗	570 GB text and code	?
4	GPT-4	OpenAI	?	✗	1.2T tokens	?
5	Mistral-7B	Mistral	7B	✓	?	✗
6	Mistral-8x7B	Mistral	47B	✓	?	✓
7	Mistral-8x22B	Mistral	141B	✓	?	✓
8	WizardLM-2-7B	Microsoft	7B	✓	?	✗
9	WizardLM-2-8x22B	Microsoft	176B	✓	?	✓
10	Llama 3 (8B)	Meta	8B	✓	15T tokens	✗
11	Llama 3 (70B)	Meta	70B	✓	15T tokens	✗
12	DBRX	Databricks	132B	✗	12T tokens	✓

[†]A Mixture of Experts is an architectural pattern for neural networks that splits the computation of a layer or operation (such as linear layers, MLPs, or attention projection) into multiple “expert” subnetworks.

privacy, utility, and fairness. (3) **Hallucination and Reliability:** The issue of hallucination in LLM responses [29, 30] further complicates their reliability. A few works have looked at mitigating these hallucinations [31] by exploring various strategies such as fine-tuning [32], memory augmentation [33], or prompt strategies [34].

Detecting LLM generated text: Detecting text generated by LLMs is a critical task, and several studies have explored this issue. These investigations span from assessing the effectiveness of current detection systems against adversarial attacks [35] to the complex challenges of social media bot detection [36] and the identification of texts that blend human-written and LLM-generated content [37]. However, the reliability of these systems varies significantly when LLMs act as co-authors, influenced by factors such as the user’s prompt or the linguistic background of the user. In response to these challenges, several detection methods have been proposed including one-class models that treat the target text as outliers [38], techniques leveraging sentence-level features for classification [39], ensemble approaches [40], and methods utilising stylometric features and smaller models [41, 42].

Bias in LLMs: Bias in LLMs is a significant issue, which can stem from training data that can have stereotypes and prejudices embedded in them [43–45]. Recent research has heavily focused on investigating and addressing such biases in LLMs, which might be present as derogatory languages towards certain minority groups [46, 47], inconsistencies in system performance across different linguistic variations [48–51], misrepresentations of groups in society [52, 53], manifestation of historic stereotypes [54–58] and general hate-filled language. For assessing bias in such systems, researchers have employed several methods including: (1) **Embedding-based:** When testing for bias in word embeddings, word analogy tests [59–61] and word association tests [62, 63] are widely employed. In word analogy tests the semantic relationship between a pair of words is tested (e.g., Man : Computer programmer \iff Woman : Homemaker). For word association test, bias is measured by evaluating how different classes of words (like Female names vs Male names) are associated with other words (e.g., pleasant vs unpleasant adjectives); (2) **Template-Based:** This approach involves crafting specific templates designed to expose potential biases within language models. By substituting different words in placeholder positions (e.g., “The [Name] is a [Occupation]”), the model’s predictions can be analyzed for bias. For example, if “John” is substituted for [Name], the method examines what the model predicts for [Occupation] [54, 55, 58, 64–67]; and (3) **Generated-text based:** This approach involves prompting the model and letting it generate text and then analyzing the content for biased representations. Free-text output from LLMs can be analyzed for bias using several metrics including the ones proposed by [68–70].

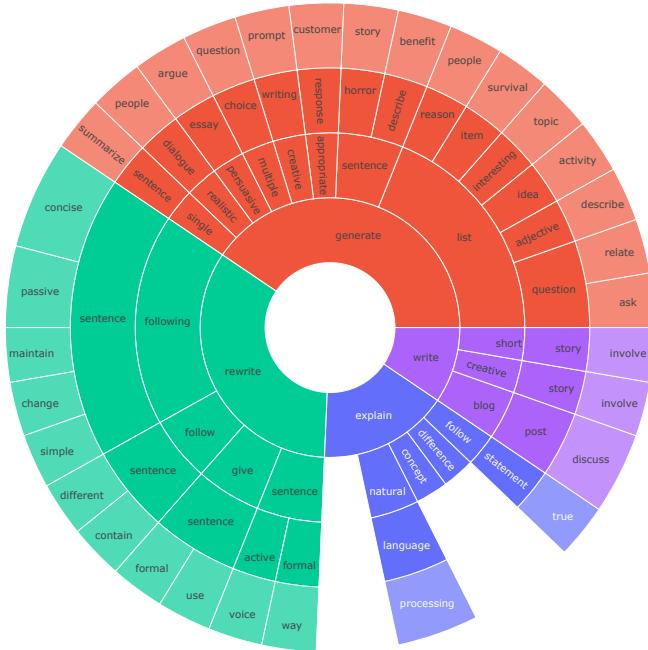


Fig. 1. Distribution of first words in prompts used to create the dataset used in this analysis.

3 DATASET AND LLMs OVERVIEW

In this section, we first provide a brief description of the LLMs examined, followed by an overview of the dataset collected and utilized for our analysis.

3.1 Large Language Models

LLMs are advanced AI systems designed to understand, generate, and manipulate human language by leveraging vast amounts of data and sophisticated neural network architectures, often based on transformers. In this work, we focus on analyzing the outputs from the LLMs summarized in Table 1.

3.2 Data Description

We first combined 15 prompts from the PERSUADE 2.0 corpus, introduced by Crossley et al. [71]¹, with a selection of prompts/instructions from the Stanford Alpaca project dataset [72]². The PERSUADE 2.0 dataset was chosen for its human-generated text corresponding to each prompt/instruction, while the Stanford Alpaca dataset was included for its rich number of diverse prompts. This combination resulted in a comprehensive set of 5,015 unique prompts, predominantly featuring keywords depicted in Figure 1. These instructions spanned a variety of topics, from learning artificial intelligence to generating persuasive essays. Finally, each prompt was used to generate 50 texts from each LLM, resulting in a total of approximately 3M texts, including those written by humans.

Detailed statistics of the resulted dataset are provided in Table 2. For example, for the given prompts, the average word count is 202, the average sentence count is 13. Also, out of the 250,750

¹https://github.com/scrosseye/persuade_corpus_2.0

²https://github.com/tatsu-lab/stanford_alpaca

Table 2. Dataset details and statistics.

Prompts Summary						
#Prompts	#Unique Words	Average Words	Average Sentences	#topics		
5,015	96,606	202	13	26		
Text Measures						
Model	#texts	Unique Word Ratio	Entropy Ratio	Monosyllable Ratio	Polysyllable Ratio	Lexical Diversity
Databricks	250,750	75.0	10.8	64.3	14.3	3.5
GPT-3.5 Turbo	250,750	85.0	17.8	67.2	12.7	5.9
GPT-4	250,750	86.4	18.1	66.4	13.3	6.1
Gemini-pro-1.5	250,750	69.5	11.9	62.0	16.0	5.3
Gemma-7B	250,750	71.8	11.2	60.6	16.6	3.0
Meta-Llama-3-70B	250,750	60.6	6.6	67.0	12.9	1.4
Meta-Llama-3-8B	250,750	61.2	7.0	67.7	12.5	1.5
Mistral-7B	250,750	64.9	8.7	66.7	13.1	2.0
Mixtral-8x22B	250,750	66.1	8.9	65.9	13.6	2.3
Mixtral-8x7B	250,750	62.6	7.1	67.4	12.7	1.3
WizardLM-2-7B	250,750	64.3	7.8	65.4	14.1	2.1
WizardLM-2-8x22B	250,750	64.3	7.9	65.3	13.9	2.2
Human	25,000	43.0	1.9	78.9	5.2	0.1

Table 3. Model generation hyperparameters.

Model	Max Tokens	Temperature	Top-p	Frequency Penalty	Repetition Penalty
Databricks	512	0.7	0.9	0.0	1.0
GPT-3.5 Turbo	-	0.7	1.0	0.0	1.0
GPT-4	250	0.7	1.0	0.0	1.0
Gemini Pro 1.5	-	1.0	0.95	-	1.0
Gemma-7B	512	1.0	1.0	0.0	1.0
Meta-Llama-3-70B	512	0.7	0.9	0.0	1.0
Meta-Llama-3-8B	512	0.7	0.9	0.0	1.0
Mistral-7B	512	0.7	0.9	0.0	1.0
Mixtral-8x22B	512	0.7	0.9	0.0	1.0
Mixtral-8x7B	512	0.7	0.9	0.0	1.0
WizardLM-2-7B	512	0.7	0.0	0.0	1.0
WizardLM-2-8x22B	512	0.7	0.9	0.0	1.0

texts generated using GPT-3.5 for all prompts, there are 85% unique words, entropy ratio of 14, and a lexical diversity of 3.5.

Finally, Table 3 presents the generation hyperparameters used across all LLMs evaluated in this study. These parameters—including maximum tokens, temperature, top-p, frequency penalty, and repetition penalty—play a critical role in shaping the style, diversity, and consistency of the outputs produced by each model.

4 EMPIRICAL EVALUATION

In this section, we conduct a series of evaluations and discussions aimed at thoroughly examining the analyzed LLMs, with the intent of answering the research questions outlined above.

4.1 RQ1: Comparative Analysis of LLM Texts

To address RQ1, we conduct a text similarity analysis and apply various readability statistics to assess the data, as detailed below.

4.1.1 Text Similarity Analysis. For analyzing the similarity between the outputs of the examined LLMs, the procedure is as follows: For each prompt, we compare each generated text to others associated with the same prompt. Specifically, we compute pairwise similarities using both *cosine similarity* and *Word-Level Levenshtein Edit Distance*, which measures the number of single-word

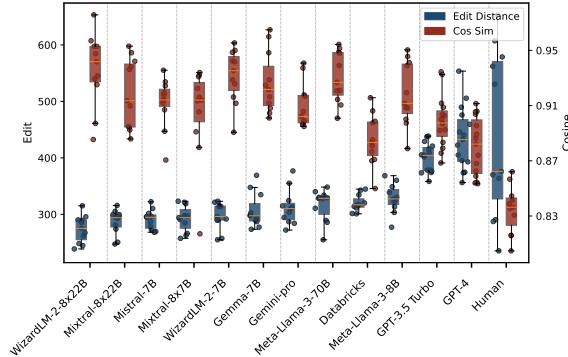


Fig. 2. Comparison of inner-text similarity.

edits required to transform one text into another. This comparison is conducted across various contexts, including within the same LLM, among different LLMs, or with human-generated texts. This approach allows for a comprehensive exploration of text similarities across different scenarios and models.

Inner-text similarity: The results of this analysis are presented in Figure 2, from which we make the following notes: (i) Humans exhibit lower word-level similarity to one another compared to LLMs, reflecting the unique and individualistic nature of human writing styles. Human written text also show higher variance in inner-similarity, while some LLMs tend to show more consistent similarity levels. (ii) Among LLMs, WizardLM-2-8x22b shows the highest similarity in generated text, followed by Llama-3-70b and WizardLM-2-7b. (iii) Finally, GPT-4 has the lowest similarity to its own outputs, aligning with the stylometric features seen in Table 2, indicating GPT-4's high lexical diversity and unique word ratio compared to other LLMs. In summary, these findings collectively indicate a degree of unpredictability in the outputs of LLMs.

Inter-text similarity: The findings from this analysis are depicted in Figure 3, leading to the following observations: (i) Human-written text shows the least similarity to all LLMs. Among the LLMs, Mistral appears to be the most similar to human-written text, while OpenAI models are the least similar. (ii) There is a notable similarity between the Llama 3 models and Mistral, as well as with WizardLM-2 models. Llama-3-8B and 70B exhibit the highest similarity among all LLMs, whereas GPT-4 and GPT-3.5 display the least similarity, highlighting the diversity between these two models. (iii) Lastly, while GPT-3.5 shares some similarity with models like Llama 3 and Mixtral-8xx22B, GPT-4, similar to human-written text, shows no strong similarities with any other models. Among all LLMs, GPT-4 is the least similar to others, with human-written text being the least similar overall. These findings collectively underscore the nuanced patterns in text similarity across different models and underscore the complexity of language model outputs.

4.1.2 Stylometric Analysis. In this section, we utilize six readability statistics to evaluate the text data. Specifically, we: (1) calculate the number of words in a text that are considered difficult to read or understand, defined as those not in a predefined list of common, easy-to-understand words or contain more than two syllables; (2) apply the Flesch Reading Ease score to assess the overall readability of the text [73]; (3) estimate the time required for an average reader to read the text, based on word count and standard reading speed [74]; (4) determine the estimated reading level or grade level of the text by aggregating results from various readability tests, indicating the educational grade level necessary to comprehend the content, such as “5th grade” or “college level”; and (5) calculate number of monosyllabic words and (6) polysyllabic words.

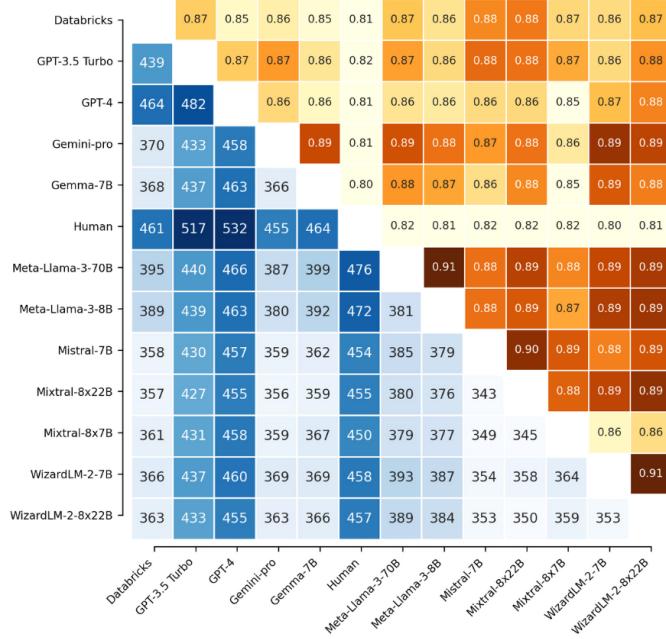


Fig. 3. Comparaison of (average) inter-text similarity. The lower part (blue) displays the similarity calculated using word-level edit distance, while the upper part (orange) illustrates the similarity determined by cosine similarity.

The obtained results are illustrated in Figure 4. Notably, when comparing the writing of LLMs to that of humans, it becomes apparent that human writing tends to be simpler, more accessible, and easier to read. Humans often use straightforward language and balanced punctuation. In contrast, models like GPT-4 and GPT-3.5 produce more complex and richly detailed content, characterized by a higher frequency of challenging vocabulary. Subsequently, the Flesch Reading Ease score, used to assess textual readability [73], indicates that human-written content is the most readable, achieving the highest score. In contrast, Gemma-7B received the lowest score, reflecting its complexity and reduced accessibility. Also, reading time analysis [74] reveals that GPT-4 requires the longest reading duration, likely due to its lengthier and potentially more complex style, while human-generated text demands the shortest reading time. Finally, the complexity in LLM writing is further substantiated by their use of polysyllabic words, in contrast to humans who often prefer monosyllabic words for simplicity.

Summary of Key Findings for RQ1

This analysis reveals that human-written texts show greater variability and lower similarity compared to LLM-generated texts, emphasizing the unique nature of human writing. Among LLMs, WizardLM-2-8x22b produced the most consistent outputs, while GPT-4 exhibited the highest lexical diversity, resulting in the lowest similarity to its own outputs. In inter-text comparisons, human-written content was the least similar to LLM outputs, with Mistral being closest to human text and GPT-4 showing the greatest divergence from other models. Readability analysis further highlighted that human texts are generally simpler and more accessible, while LLM outputs, especially from GPT-4, are more complex and challenging.

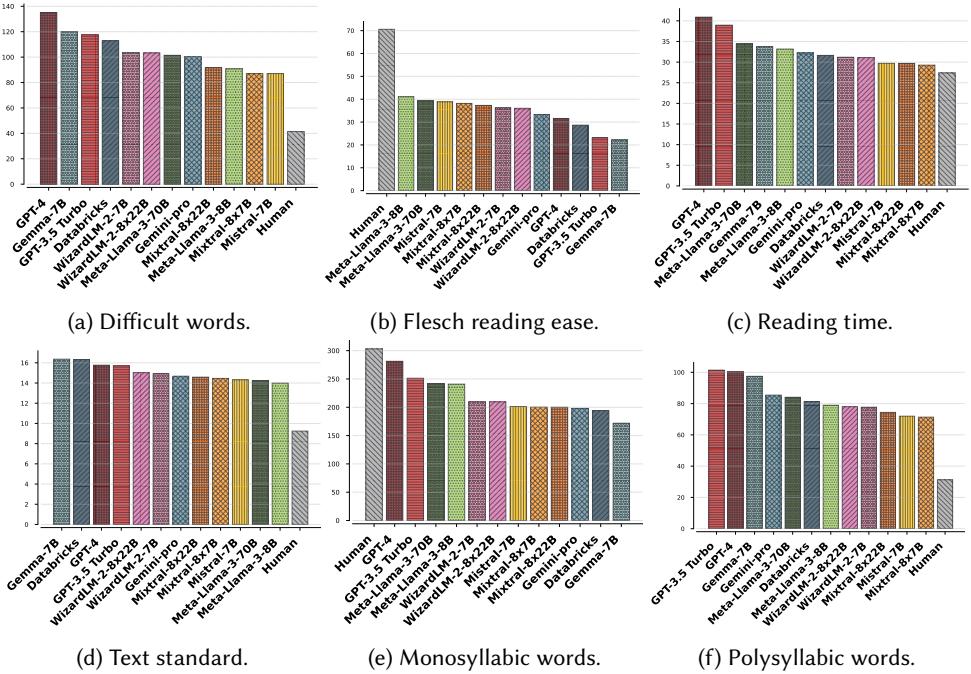


Fig. 4. Readability Statistics.

4.2 RQ2: Variance in Text Generation

The inner similarity analysis presented in Figure 2 reveals significant variance in text generation among different LLMs. To illustrate this, Figure 5 employs the UMAP algorithm [75] to visualize high-dimensional text data in a comprehensible two-dimensional space, for six different prompts. This visualization offers a clear representation of the distribution and relationships among the text outputs, facilitating the identification of patterns and distinctions across the diverse LLMs under examination.

At first glance, we note that some LLMs display notable variability in text generation, whereas others exhibit a more uniform and consistent output. For instance, it is observed that Mistral 7B demonstrates low variance in text generation, while Gemini-pro-1.5 exhibits higher variance. This disparity suggests that Mistral 7B tends to produce more consistent and uniform text outputs, while Gemini-pro-1.5 introduces greater variability in its generated text. This insight into the diversity of LLM behavior is crucial for understanding the nuances of these models.

Summary of Key Findings for RQ2

This analysis reveals that some models produce more consistent and uniform outputs, while others show greater variability, highlighting the diversity in LLM behavior.

4.3 RQ3: Classification Performance

The ability to differentiate between text written by humans and that generated by LLMs holds significant importance in various contexts. In applications such as content moderation, misinformation detection, and ensuring ethical use of AI, being able to identify the source of text content is critical.

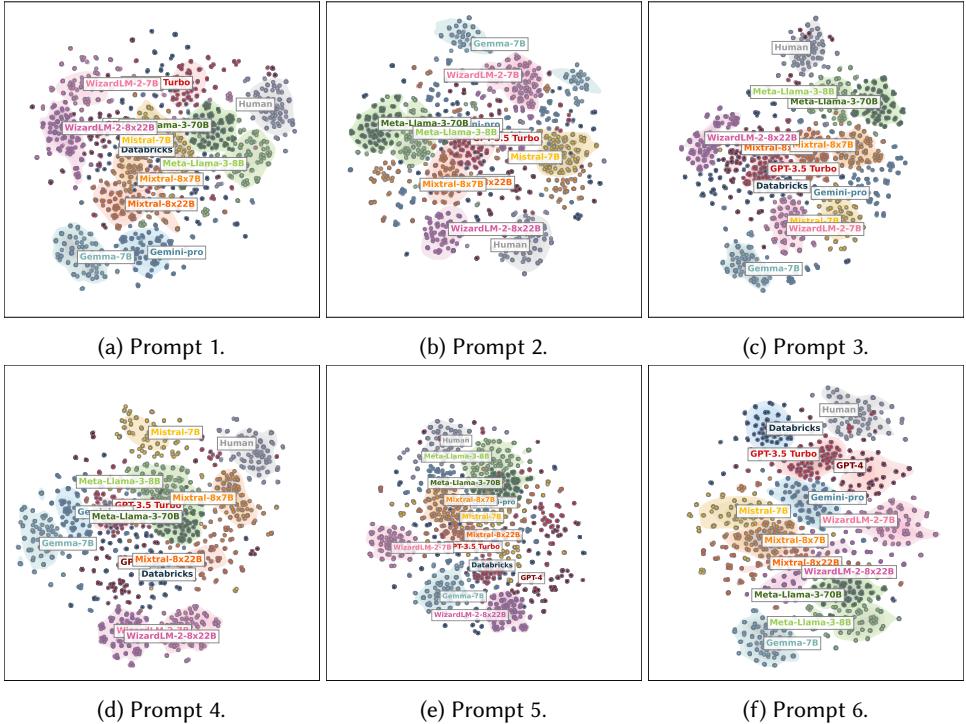


Fig. 5. UMAP projection of high-dimensional text generated into a two-dimensional space for visualization.

Furthermore, understanding which specific LLM has generated a text can provide valuable insights into the model’s biases, tendencies, and potential shortcomings. This capability not only enhances transparency and accountability in AI applications but also aids in addressing ethical concerns surrounding the use of language models. Moreover, it equips users, researchers, and policymakers with the necessary tools to assess the reliability and trustworthiness of textual content, thereby encouraging a more responsible and conscious integration of LLM-generated content across various sectors.

To achieve this objective, we make use of BERT [14], several variants of DeBERTa-v3 [76] (DeBERTa-v3-xsmall, DeBERTa-v3-small, DeBERTa-v3-base), and an XGBoost [77] model with Bag of Words features. We partition our dataset into TrainVal-Test sets using a split of 60%, 20%, and 20%, respectively. The performance of these classifiers is detailed in Table 4, which presents the achieved classification metrics and reveals the following insights: **BERT** outperforms all DeBERTa variants as well as XGBoost with Bag-of-Word (BoW). BERT achieves the highest overall accuracy of **0.7095** and demonstrates superior performance across multiple LLMs, with the highest F1-scores in most categories. This highlights its robustness in identifying text generated by different models. **DeBERTa-v3-base** shows strong performance, particularly by achieving the highest F1-score (**0.7231**) for the DBRX class. Among the DeBERTa variants, it consistently outperforms the smaller models, demonstrating the effectiveness of a larger model architecture in learning various stylometric patterns. **DeBERTa-v3-small** and **DeBERTa-v3-xsmall** provide reasonable performance but lag behind BERT and the larger DeBERTa model. Finally, **XGBoost-BoW** exhibits the highest F1-score (**0.9906**) for the Human class, indicating its strength in fitting strongly to human-written text. However, it generally performs worse than the neural network-based models

in identifying texts generated by different LLMs, reflecting its limitations in handling more complex language patterns.

Summary of Key Findings for RQ3

This analysis suggests that distinguishing between texts written by humans and those generated by LLMs, as well as identifying which specific LLM produced a given text, appears to be a relatively straightforward task. This ability to reliably identify the source of generated text not only enhances transparency but also provides valuable insights into the unique characteristics and potential biases of each LLM, contributing to more informed and ethical use of these technologies.

4.4 RQ4: Language Markers Analysis

In this section, our objective is to explore the language markers, distinctive characteristics, and vocabulary exhibited by LLMs. A general method for measuring the amount of information that a feature (i.e., a word) x_j provides w.r.t. predicting a class label y (i.e., the LLM generating the text or the human author) is to calculate its Point-wise Mutual Information (PMI) [78]. A high PMI value indicates a more informative feature. We leverage this information to rank and select only the most positive features (words), which are then used to generate the word clouds depicted in Figure 6. The language used by different language models varies significantly, even when given the same instruction. These observations show that each language model has distinct vocabulary and linguistic styles. This diversity highlights their unique strengths and potential applications, offering valuable insights into their capabilities.



Fig. 6. Language markers.

Table 4. Performance Comparison of AI Models in Predicting Authorship of LLM's Texts.

Model	Accuracy	F1-Score											
		Human	GPT-3.5	GPT-4	Gemini-pro	Mixtral-8x7B	Mistral-7B	Meta-Llama-3-8B	Meta-Llama-3-70B	DBRN	WizardLM-2-8x22B	WizardLM-2-7B	Mixtral-8x22B
bert-base-cased	0.7095	0.9146	0.7457	0.7128	0.9790	0.6982	0.6826	0.6922	0.8762	0.6803	0.6803	0.7502	0.6393
DeBERTa-v3-small	0.5790	0.8921	0.6471	0.5022	0.7204	0.5441	0.4338	0.6038	0.8062	0.6066	0.6577	0.4702	0.3952
DeBERTa-v3-small	0.6112	0.9199	0.6578	0.5594	0.7413	0.5825	0.4993	0.6459	0.8277	0.6122	0.6719	0.5509	0.4495
DeBERTa-v3-base	0.6513	0.9771	0.7012	0.5937	0.7724	0.6483	0.6130	0.6673	0.8357	0.5597	0.7231	0.5524	0.5779
XGBoost-Bow	0.5359	0.9906	0.5644	0.4696	0.5243	0.4786	0.4680	0.5218	0.6168	0.5539	0.6173	0.5166	0.5297
													0.3868

Summary of Key Findings for RQ4

This analysis reveals that different LLMs exhibit distinct vocabulary and linguistic styles, as evidenced by the significant variation in language markers, making them easily recognizable and distinguishable.

4.5 RQ5: Bias and Ethics in LLMs

In this section, we explore whether certain LLMs adhere more closely to ethical standards by effectively reducing the propagation of biased stereotypes, thereby aligning more closely with ethical guidelines in AI development and usage.

4.5.1 Methodology. Analyzing bias and discrimination in LLM outputs may not be a straightforward task, as these models do not explicitly exhibit racial or gender biases and stereotypes. Therefore, one effective approach to uncovering embedded bias in these LLMs is through an *embedding-based* method.

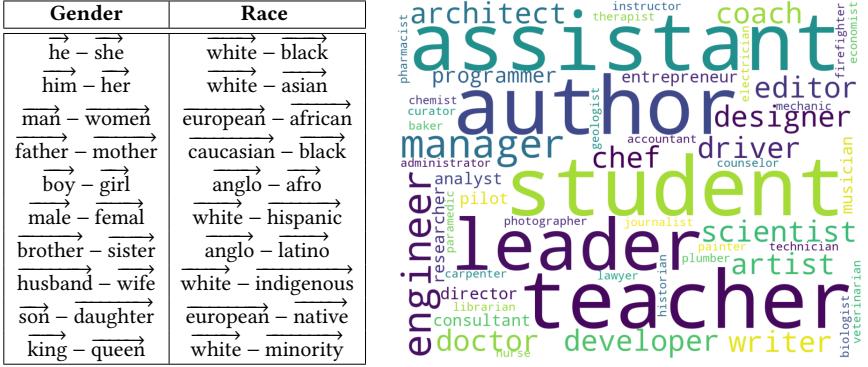
A word embedding is a representation that encodes each word w as a d -dimensional vector (i.e., $w \in \mathbb{R}^d$) [11, 79]. These embeddings are trained using word co-occurrence within text corpora, leveraging paradigmatic similarity, where words with similar meanings frequently occur in similar contexts and are thus interchangeable. Consequently, words with related semantic meanings tend to have vectors that are close together in the embedding space. Moreover, the vector differences between words in these embeddings can capture the relationships between them. For example, in the analogy “man is to king as woman is to x ”, simple arithmetic on the embedding vectors reveals that the best match for x is “queen”, as the vector difference between “man” and “king” mirrors that between “woman” and “queen”. Building on the analysis by Bolukbasi et al. [59], we aim to analyze word embeddings to identify and quantify the embedded stereotypes and biases in LLM outputs.

In our experiments, we trained 50-dimensional word embeddings for each LLM’s text data using the CBOW Word2Vec architecture, with a context window of 5 words and a minimum count of 1, ensuring that all words with a total frequency lower than 1 were ignored. Once the embeddings were trained, we first evaluated them by comparing the results of various analogies against those produced by the original Word2Vec embeddings [11]. This allowed us to assess the quality and consistency of our trained embeddings in capturing semantic relationships between words. We utilized the Gensim Python library to train and evaluate our word embeddings³.

4.5.2 Identifying the Bias Subspace. In this work, we focus on two primary types of bias: **gender bias** and **racial bias**. As noted by Bolukbasi et al. [59], individual word pairs do not always behave as expected because a word can have multiple meanings depending on the context. To better estimate bias, Bolukbasi et al. proposed aggregating multiple paired comparisons to more accurately identify the bias direction subspace. By combining several word pair directions, such as $\overrightarrow{\text{she}} - \overrightarrow{\text{he}}$, $\overrightarrow{\text{woman}} - \overrightarrow{\text{man}}$, $\overrightarrow{\text{white}} - \overrightarrow{\text{black}}$, and $\overrightarrow{\text{european}} - \overrightarrow{\text{african}}$, we are able to identify a significant gender or racial direction $\vec{g} \in \mathbb{R}^d$ that effectively captures the underlying bias in the embedding. Formally, the bias direction subspace $\vec{g} \in \mathbb{R}^d$ is estimated as follows:

$$\vec{g} = \frac{1}{|P|} \sum_{(w_1, w_2) \in P} (\overrightarrow{w_1} - \overrightarrow{w_2}) \quad (1)$$

³<https://radimrehurek.com/gensim/>



(a) Word pair directions to define gender and race.

(b) Gender-neutral words, with size indicating frequency in the data.

Fig. 7. Word pair directions to define gender and race.

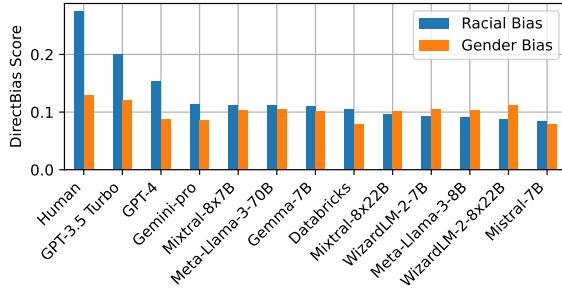


Fig. 8. DirectBias scores.

where P is the list of word pair directions shown in Figure 7a, and (w_1, w_2) is a pair of words in P . The direction represented by g allows us to quantify direct biases in word associations, offering a more comprehensive understanding of how bias manifests in the embeddings.

4.5.3 Estimating Direct Bias. To measure direct bias, we first defined a list N of 50 words that are expected to be gender-neutral, as illustrated in Figure 7b. Then, given a gender-neutral word from N , and the gender direction g learned earlier, we estimate the direct bias of an embedding using cosine similarity, as suggested in [59]:

$$b_w = \cos(\vec{w}, \vec{g}) \quad (2)$$

where a positive value of b_w indicates that w is more strongly associated with male, white, European, or Caucasian, while a negative value of b_w suggests a stronger association with female, Black, African, or Asian. Finally, we estimate the overall direct bias of the embeddings as follows:

$$\text{DirectBias} = \frac{1}{|N|} \sum_{w \in N} |b_w| \quad (3)$$

where a lower value of DirectBias indicates a lower level of bias.

4.5.4 Bias assessment. Figure 8 shows the DirectBias score, calculated using Equation 3, for each model across different bias dimensions. At first glance, it is apparent that, overall, all models exhibit

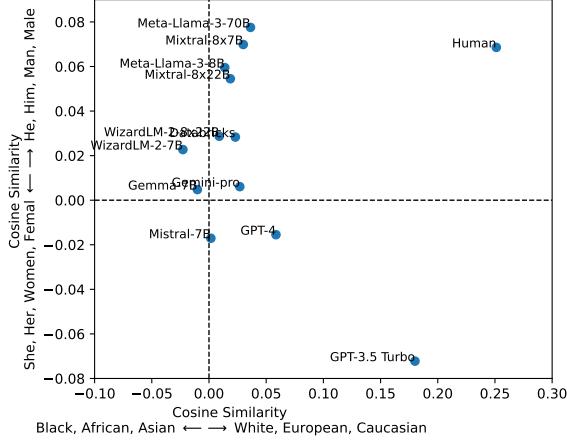


Fig. 9. Two-dimensional scatter plot of the association score between each LLM and each bias dimension.

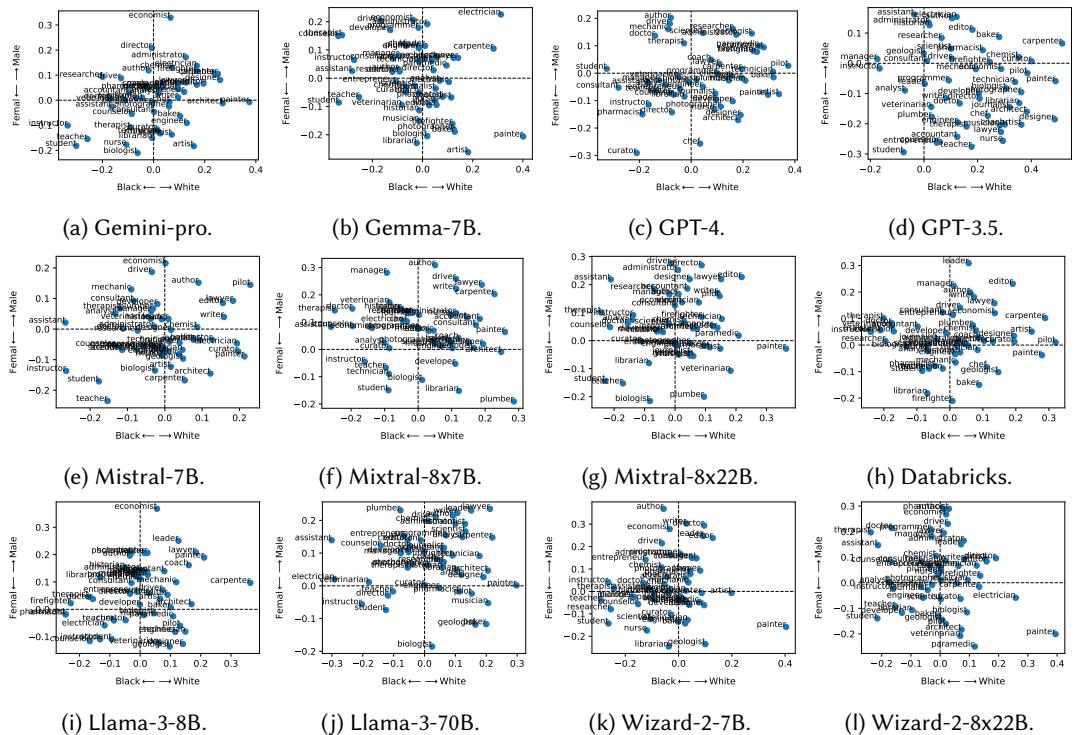


Fig. 10. Two-dimensional scatter plot of the association score between each occupation of Figure 7b and each bias dimension.

a relatively similar level of latent gender bias. However, human-generated texts, along with GPT-3.5 and GPT-4, appear to contain the most latent racial bias.

To further analyze which models are more strongly associated with specific bias dimensions, we refer to Figure 9, which presents the average bias scores calculated using Equation 2 for each model

across various bias dimensions. Here, we observe that some models show stronger associations with particular biases. For instance, human-generated texts tend to have a strong association with white males, whereas models like GPT-3.5 and GPT-4 exhibit a stronger latent association with white females, suggesting that these models lean more towards feminist viewpoints compared to others. Additionally, we note that Gemma-7B and Gemini-pro are positioned closer to the origin (0,0), indicating that they are the most balanced models in terms of bias.

Finally, Figure 10 presents a two-dimensional scatter plot illustrating the association score between each occupation from Figure 7b and our two bias dimensions. Several interesting stereotypes emerge from the data. For example, in Databricks, a leader and a manager are more strongly associated with being white males, whereas in Gemini-pro, a nurse is more closely associated with being a Black female.

Summary of Key Findings for RQ5

We note that all models exhibit relatively similar levels of latent gender bias in general. However, certain models demonstrate stronger associations with specific bias dimensions. For instance, GPT-3.5 and GPT-4 show a stronger association with females, suggesting a tendency towards feminist viewpoints. Also, in terms of racial bias, GPT-3.5 and GPT-4 display the highest levels of latent racial bias, particularly associating leadership roles with white males. Finally, models like Gemma-7B and Gemini-pro are identified as the most balanced models.

5 CONCLUSION AND FUTURE WORK

In conclusion, our analysis sheds light on critical aspects of Large Language Models (LLMs). The observed low similarity within LLMs, distinctive inter-LLM writing styles, varying degrees of variance in text generation, successful classification outcomes, and discernible language markers underscore the nuanced and complex nature of LLM behavior. Moreover, we demonstrate that LLMs differ in their associations with gender and racial biases, with models like GPT-3.5 and GPT-4 showing a stronger tendency towards feminist viewpoints and latent racial bias. Balanced models such as Gemma-7B and Gemini-pro are identified as exhibiting the least bias overall. These findings contribute to a deeper understanding of LLM capabilities, providing valuable insights for future advancements in natural language processing and model interpretability.

Future work involves exploring explainability techniques, where the focus extends beyond detecting whether a text is authored by a human or generated by an LLM. The aim is to explore and articulate the reasons behind the model's predictions, providing a more comprehensive understanding of the decision-making process.

Acknowledgement: all data used in this paper will be made publicly available and released following the publication of this paper, in accordance with the applicable data sharing policies and guidelines in place.

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