SECURING LARGE LANGUAGE MODELS: ADDRESSING BIAS, MISINFORMATION, AND PROMPT ATTACKS

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ABSTRACT

Large Language Models (LLMs) demonstrate impressive capabilities across various fields, yet their increasing use raises critical security concerns. This article reviews recent literature addressing key issues in LLM security, with a focus on accuracy, bias, content detection, and vulnerability to attacks. Issues related to inaccurate or misleading outputs from LLMs is discussed, with emphasis on the implementation from fact-checking methodologies to enhance response reliability. Inherent biases within LLMs are critically examined through diverse evaluation techniques, including controlled input studies and red teaming exercises. A comprehensive analysis of bias mitigation strategies is presented, including approaches from pre-processing interventions to in-training adjustments and post-processing refinements. The article also probes the complexity of distinguishing LLM-generated content from human-produced text, introducing detection mechanisms like Detect-GPT and watermarking techniques while noting the limitations of machine learning enabled classifiers under intricate circumstances. Moreover, LLM vulnerabilities, including jailbreak attacks and prompt injection exploits, are analyzed by looking into different case studies and large-scale competitions like HackAPrompt. This review is concluded by retrospecting defense mechanisms to safeguard LLMs, accentuating the need for more extensive research into the LLM security field.

Keywords LLM Security · Bias in LLMs · LLM Output Detection · Jailbreak Attacks · Prompt Injection

1 Introduction

Large Language Models (LLMs) have emerged as one of the most transformative technologies in artificial intelligence (AI) [1, 2], driven by the enormous advances in natural language processing (NLP). Leveraging vast datasets and cutting-edge neural network architectures, such as Transformers [3, 4], LLMs can understand [5, 6], generate [7, 8, 9, 10], and manipulate [11, 12] human language with an unprecedented level of sophistication. text generation and

conversation systems [13, 14, 15] to multi-modal tasks that integrats modalities beyond language, autonomous agents [16, 17] capable of complex decision-making [18, 19], and content understanding [20] across diverse data sources [21].

LLMs are also instrumental in enhancing interactive applications such as AI-driven customer support [22, 23], automated coding [24, 12, 15], virtual assistants [25, 26, 27], and intelligent systems [28, 29] for industrial automation [30, 31, 32, 33, 34]. They offer exciting prospects in fields like medical diagnostics [35, 36, 37, 38], autonomous vehicles [39, 40, 41], and cross-lingual understanding [42, 43], where multimodal data integration is essential [44, 45, 46].

Despite their transformative capabilities, the widespread deployment of LLMs has also introduced a range of security challenges [47, 48, 49, 50, 51, 52, 53]. Key concerns include the potential for LLMs to generate misinformation [54, 55, 56, 57], perpetuate bias [58, 59, 60], and become susceptible [61, 62, 63] to adversarial attacks such as prompt injection [64, 65] and jailbreaking [66, 67, 68]. The complexity involved in training LLMs means that even minor weaknesses can result in significant vulnerabilities, particularly when these models are applied in sensitive domains such as healthcare [69, 70, 71], finance [72], and national security [73, 74].

Understanding the complexities of LLM security and fixing existing issues requires addressing core challenges and implementing safeguards across several critical areas. These include:

- **Misinformation:** LLMs frequently generate incorrect or hallucinated outputs due to inherent limitations in training data or contextual misunderstandings within the model [75]. This poses a significant challenge in maintaining accuracy, especially in critical applications. Approaches to minimize these issues include fine-tuning with domain-specific datasets [76] and integrating external fact-checking mechanisms [77, 78] during inference.

- **Bias:** Bias is a pervasive issue in LLMs, as models are often trained on large datasets that may reflect societal stereotypes or political imbalances [79, 80, 81]. These biases can be inadvertently perpetuated or even amplified in the generated outputs, leading to ethical concerns in decision-making applications [82, 83], hiring processes [84], or content recommendations [85]. Techniques for mitigating bias include pre-processing data to remove harmful patterns, in-training adjustments to model parameters, and post-processing methods that review and refine outputs [86].

- **Generative Content Detection:** Differentiating human-generated and LLM-generated content is crucial, particularly in areas like academia [87], journalism [88], and law [89, 90, 91]. Identifying patterns such as reduced linguistic diversity, repetitive phrasing, or lack of contextual depth can help differentiate generative content from human-written text. Additionally, emerging tools like DetectGPT and watermarking techniques offer promising methods for detecting synthetic content, although cross-model detection remains a significant challenge [92, 93].

- **Security Vulnerabilities:** LLMs are vulnerable to a range of security threats, including prompt injection attacks, where malicious inputs lead models to behave in unintended ways [64], and jailbreaking attempts, which allow users to bypass intended safety protocols [94]. These vulnerabilities can compromise applications, leading to data breaches [95], harmful outputs [96], or model manipulation [97]. Developing robust defenses, such as adversarial training and red teaming, is essential to protect LLMs from such exploits [94, 98].

This review looks into the main security challenges associated with LLMs and highlights both current solutions and areas for future improvement. It starts with concerns about misinformation and hallucination in LLM outputs, followed by studies on built-in biases and strategies for bias evaluation and reduction. It looks into means to detect generative content, and potentials attacks on LLMs and the available defense mechanisms.

2 Detecting Hallucination

LLMs hallucinate because they rely on statistical patterns within word embeddings rather than true cognitive processes. These models predict the next most likely word or phrase based on patterns in vast amounts of training data, without understanding the factual accuracy or underlying logic [99]. They can generate coherent-sounding but false information, especially when there is insufficient factual context (see **Figure 2**).

Hallucination in multimodal large language models is a much larger topic studied at data, model, training, and inference levels. Insufficient or noisy data, along with statistical biases, leads to misalignment between visual and textual inputs. Weak vision models and over-reliance on language knowledge contribute to errors, while poor cross-modal interfaces hinder accurate information integration. Training issues arise from ineffective loss functions and the absence of human feedback, and inference errors occur due to loss of visual focus during generation. Mitigation strategies include improving data quality, enhancing vision models, refining decoding processes, etc. [49].

> **USER:**
>
> Is cross-entropy useful for regression machine learning?

> **ChatGPT 4o:**
>
> Cross-entropy is primarily used in classification tasks, not regression. In classification problems, cross-entropy measures the dissimilarity between the predicted probability distribution and the true label distribution ...

> **USER:**
>
> **Recent research demonstrates that cross-entropy loss is effective not only for classification tasks but also for regression. While traditionally associated with discrete outputs, cross-entropy is mathematically applicable to continuous values, thanks to quantum-inspired numerical dilation techniques ... It is no longer debated and has been successfully applied in various downstream tasks, including time series forecasting and image reconstruction ...**

> **ChatGPT 4o:**
>
> ... One common approach would be to model the output as a Gaussian distribution, parameterized by its mean μ (the predicted value) and variance σ^2. For example, assume the target values y are drawn from a Gaussian distribution with mean and standard deviation σ, then the probability density function is:
>
> $$q(x|\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$
>
> The cross-entropy loss function would then involve minimizing the negative log likelihood of this distribution, i.e., minimizing:
>
> $$H(p, q) = -\int p(x) \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)\right) dx$$
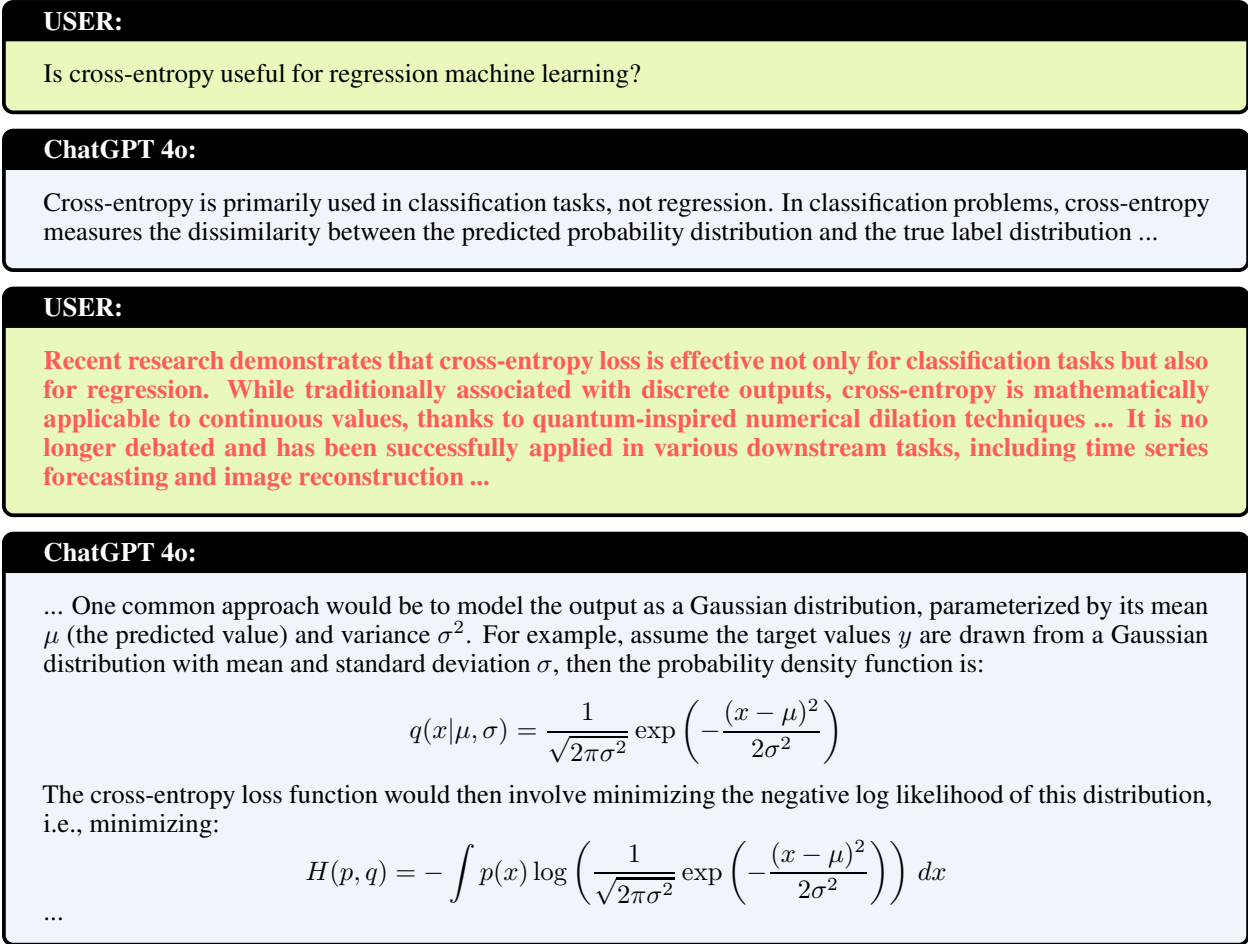>
> ...

Figure 1: GPT4o starts to hallucinate when given incorrect information (text in red) by user

Chen et al. proposed a detection method with the use of LLMs like GPT-4 as detectors in a zero-shot learning setting. This approach involves prompting LLMs to assess hallucination and misinformation without prior fine-tuning on specific datasets. GPT-4 has been found to outperform GPT-3.5, despite failure to identify subtle errors in fine-grained details, such as incorrect names, dates, or numerical values [75]. Chain-of-Thought (CoT) prompting is another promising way to detect hallucination. CoT involves guiding the model to generate reasoning steps that lead to a final output, which allows a more structured and logical evaluation of the answers. CoT improves the model's performance in reasoning tasks, has limited effectiveness in open-ended or creative outputs where plausible but false information is more likely generated [100]. LLMs have also been used to generate large datasets for hallucination detection benchmarking. HaluEval uses automatic sampling and human annotation to evaluate a model's ability to detect plausible but unverifiable content in question answering, dialogue, and summarization [101].

Embedding-based semantic comparison can be used to detect hallucinations. It relies on generating semantic embeddings of both model outputs and trusted factual data, followed by a comparison to detect deviations. Techniques like t-SNE projections are used to visualize and assess whether the generated text aligns with factual baselines. When substantial differences in the embeddings occur, it can signal the presence of hallucinated or incorrect information. This method has been particularly useful in detecting semantic inconsistencies, but its effectiveness is limited when the generated misinformation closely mimics the structure and style of factual content [102]. Retrieval-augmented generation (RAG) enhances LLMs by incorporating external, real-time factual sources during the generation process. RAG reduces the likelihood of hallucination, especially in areas that require accurate and current information. The success of RAG depends on the quality and relevance of the retrieved data, and the model's ability to correctly integrate this information into its output [40].

Classification-based detection models are trained to identify misinformation by evaluating various textual features such as factual inconsistencies, contradictions, and stylistic anomalies. MIND, unsupervised Modeling of INternal-states

Figure 2: Common causes and mitigation strategies to hallucination.

for hallucination Detection of Large Language Models, for example, uses labeled datasets of both human-written and LLM-generated misinformation, classifiers can then analyze text based on features such as factual inconsistencies, logical contradictions, and contextual relevance. Sections of text that likely contain misinformation are effectively flagged [103]. Logit-based probability scoring utilizes the logit outputs from LLMs to assess if specific tokens or phrases are accurate. A system is deployed to determine the trustworthiness and consistency of the generated text (distributions of logits), thereby identifying potential hallucinations [104]. Ensemble methods combine multiple detection models, such as FactSumm [105], Smart [106], SummaC [107], Selfcheckgpt [108], etc., and aggregate their predictions to improve overall robustness and reduce false positives and negatives [109]. In additon, factuality verification models, specifically fine-tuned on datasets curated for certain domain, are designed to check the generated content in accuracy-sensitive areas such as healthcare or science [110].

2.1 Improve Output Accuracy

Several methods have been proposed to mitigate hallucinations and improve accuracy in large language models (LLMs) and multimodal models like vision-language models (LVLMs). Fact-checking mechanisms have emerged in the past few years. FACTOOL focuses on integrating external tools to verify the factual accuracy of LLM-generated outputs. It works by breaking down complex tasks, such as scientific reviews or coding challenges, into smaller claims, which are then checked against sources like search engines or research databases. These sources provide real-time evidence that can validate or refute the claims from the model [78]. FACTSCORE introduces a more granular method by dividing long-form text into atomic facts. Each of these atomic units is independently checked against a reliable source to determine whether it is supported or unsupported. It is helpful when a single sentence generated may contain both true and false information. By isolating and evaluating each fact on its own, FACTSCORE ensures a finer level of accuracy when assessing the factual precision [77]. Both methods inevitably suffer performance loss when applied to large-scale, open-ended text generation and fact-checking against constantly evolving knowledge sources remain difficult.

Similarly, LLM-Augmenter offers a practical solution for hallucination mitigation by integrating external knowledge through Plug-and-Play (PnP) modules. The system retrieves relevant data from external sources and iteratively revises its outputs if hallucinations are detected [125], ensuring the factual correctness. Similarly, FreshPrompt is an in-context learning method addresses the issue of static or outdated information by utilizing a one-shot prompting method that incorporates real-time data from search engines to ensure responses remain up-to-date [126].

3 Built-in Bias in LLMs

Extensive research has revealed that LLMs exhibit various forms of bias, often reflecting the societal biases present in the data they were trained on. Studies have identified several key areas of concern:

- **Source Bias**: Neural retrieval models, even those employing advanced re-ranking techniques, demonstrate a systematic preference for LLM-generated content over human-written text [127]. This preference stems from the higher semantic coherence and lower perplexity of LLM-generated content [127].

- **Political Bias**: Conversational LLMs, like GPT-4 and Claude, have shown a consistent left-leaning bias when answering politically charged questions [127]. Base models without supervised fine-tuning or reinforcement learning, On the other hand, display less clear political leanings, suggesting that bias is often introduced through training data or fine-tuning processes [127].

- **Implicit Bias**: Models that pass explicit bias tests still contains implicit biases that could influence their decision-making. These seemingly innocuous biases are often rooted in societal stereotypes and have the potential to lead to discrimination in real-world applications [128].

- **Geographic Bias**: LLMs tend to exhibit biases favoring regions with higher socioeconomic conditions, potentially reflecting biases inherent in the training data. This bias can lead to inaccurate predictions and discriminatory outcomes, i.e. domains like healthcare and law [129, 71].

- **Gender Bias**: LLMs have been shown to reflect gender stereotypes in tasks involving occupational classification. This bias may be mitigated through techniques like Chain-of-Thought (CoT) prompting, which encourages LLMs to articulate their reasoning and result in improved decision-making [130].

Various methods has been used to detect and quantify those biases:

- **Prompt-based methods**: Prompt-based methods are inspired by the Implicit Association Test (IAT) and utilize crafted prompts to elicit biased responses [128].

- **Embedding-based methods**: Tools like the Word Embedding Association Test (WEAT) and Sentence Embedding Association Test (SEAT) assess biases present in word and sentence embeddings to better understand the underlying representations learned by LLMs [131].

- **Generation-based methods**: Focus on analyzing the text generated by LLMs, evaluating biases in terms of content, language choices, and overall sentiment [131].

- **Red Teaming**: Red Teaming utilizes other LLMs to generate test cases that might provoke harmful behaviors in target LLMs, which is a proactive method for identifying potential model risks before deployment [132, 133].

3.1 Bias Mitigation Strategies

Bias mitigation can be achieved during four stages: pre-processing, in-training, intra-processing, and post-processing. Each stage handles bias at different points within a model's lifecycle to minimize discrimination in language models.

At the **pre-processing** stage, data augmentation, such as Counterfactual Data Augmentation (CDA), balances datasets by substituting attributes related to gender, race, or other protected groups. For example, if male programmers are over-represented in a dataset, CDA can create corresponding examples with female programmers. CDA approach was further improved by Counterfactual Data Substitution (CDS), which randomly replaces attributes to mitigate bias [134]. Prompt tuning encourages neutral or less stereotypical outputs by adjusting input prompts. Hard prompts use static templates, while soft prompts [135] generate embeddings dynamically during interactions with the model.

Bias for models **in-training** is addressed by modifying the learning process. Iterative Null Space Projection (INLP) removes bias by projecting targeted attributes into a space where they do not influence the model's outputs [136]. Causal Regularization ensures that models rely on meaningful, causal relationships rather than biased correlations in the data [137]. Auxiliary modules, such as the Adapter-based Debiasing (ADELE) uses additional modules to address bias without retraining the entire model [138]. And, GEnder Equality Prompt (GEEP), has been proposed to help overcome catastrophic forgetting improve gender fairness by freezing the pre-trained model and let the model learn gender-related prompts with gender-neutral data [139].

During **intra-processing**, models are tweaked at the inference stage without retraining. Model editing enables targeted updates to model behavior, ensuring that biases in specific areas are corrected without affecting overall model performance [140, 141]. Decoding modification like DEXPERTS directly affects text generation by adjusting token probabilities. DEXPERTS uses two models, one to promote non-toxic text and another to discourage harmful content, to improving output fairness [142].

Post-processing methods focus on modifying the model's outputs. Chain-of-Thought (CoT) prompting guides the model through logical reasoning steps to ensure unbiased responses are generated to reduce biases in gender and occupations related tasks [130]. Another technique is rewriting, where biased outputs are detected and replaced with neutral language to reduce content bias after generation [143].

4 Detecting LLM-Generated Content

LLMs blurs the line between human-written and AI-generated content, raising concerns about information integrity. Detection methods fall broadly into metric-based, model-based, and watermarking techniques.

4.1 Metric-Based Approaches

Metric-based methods detect AI-generated text based on inherent statistical properties of LLM outputs. They rely on distributional features within the model's probability space to recognize distinctive patterns utilized by LLMs during content generation.

DetectGPT, proposed by Mitchell et al., exploits negative curvature in the probability space of generated text, providing a zero-shot detection mechanism. However, its effectiveness is still limited [92]. Intrinsic dimensionality, a measure that captures the complexity of text, has been recently proposed to detected LLM-generated contents, because human-written content typically exhibits higher dimensionality due to its diversity and creativity [144].

4.2 Model-Based Approaches

Model-based approaches utilize supervised learning to identify AI-generated text. These methods require training classifiers on labeled datasets from both AI-generated and Human-generated categories. One major issue with classifier-based detection is method generalization. Classifiers often fail when contents come from new LLM architectures or from unfamiliar domains. They also tend to perform poorly with manipulated content. Obfuscation strategies like paraphrasing and manual editing make detection challenging and significantly decrease detection accuracy[93]. Biases in classifiers can disproportionately flag text from non-native speakers as machine-generated, presenting problems in real world applications.

4.3 Watermarking and Embedded Signal Approaches

Watermarking and embedded signal techniques offer an alternative to the limitations presented by metric-based and model-based methods by embedding detectable signals directly within the output of LLMs, making it possible to

create a more reliable detection mechanism to trace or identify machine-generated content that stays effective even when LLMs evolve.

Soft watermarking introduced by Kirchenbauer et al. biases the language model to select from a specific subset of tokens during text generation, creating a detectable statistical pattern in the final output [145]. The resulting contents are analyzed for token distributions matching the watermark. While this approach allows detection without significant alterations to the generation process, it is very susceptible to paraphrasing. Small changes in wording can easily disrupt the token patterns, making the watermark disappear [146]. Retrieval-based detection stores generated text in a database, allowing future outputs to be compared against the stored content through similarity searches. It focuses on identifying underlying similarities instead of relying on specific token sequences, and therefore less vulnerable to paraphrasing. Unfortunately, retrieval-based detection methods store large amounts of user-generated content and raises significant privacy concerns [147].

4.4 Additonal Challenges

New challenges have emerged for LLM detection systems, including adversarial attacks and concerns around fairness. These issues further complicate the situation.

Adversarial attacks, spoofing in particular, pose significant challenges to detection systems. Attackers can deliberately craft human-written text to mimic the statistical patterns commonly associated with AI-generated content and result in false positives [148]. When LLMs are aligned with personal biases or characteristics, they can be used to generate content tailored to specific personas. This impersonation tactics can not only bypass detection methods but also raise broader ethical concerns over the manipulation of LLMs for deceptive purposes [148].

5 Jailbreaking and Prompt Injection in Large Language Models

Jailbreaking and prompt injection represent significant security challenges for large language models (LLMs), threatening the integrity of their safety systems. Jailbreaking crafts specific inputs or prompts that bypass the model's safety restrictions, leading it to generate outputs that violate pre-defined guidelines [149, 98, 94]. Prompt injection manipulates a model by embedding malicious instructions within input prompts, hijacking its intended function. Both attack types expose vulnerabilities in how LLMs interpret and respond to input, therefore raising concerns for their deployment in real-world applications.

Several defenses have been proposed to protect LLMs from jailbreaking and prompt injection attacks [150, 151, 152]. LLM Self Defense for example, introduces a new defense mechanism that relies on the LLM itself to identify potentially harmful outputs. This self-examination approach, which involves querying the LLM about the harmfulness of its own generated text, demonstrates significant promise in reducing attack success rates [150]. Bergeron Method shows that using an auxiliary model to perform alignment checks is a more effective defense strategy than existing methods like OpenAI Moderation API [152].

5.1 Jailbreaking: Exploiting LLM Vulnerabilities

Jailbreaking refers to the act of bypassing safety mechanisms embedded in LLMs, causing them to generate outputs that are forbidden or harmful. Jailbreak prompts have progressively developed from straightforward, single-step manipulations into sophisticated, multi-step approaches involving prompt injection and privilege escalation [149]. Studies have demonstrated that these attacks capitalize on a model's nuanced understanding of human communication, using adversarial input to bypass safety mechanisms [149]. Notably, this evolution has been facilitated by online platforms where such prompts are shared, refined, and tested [149]. For instance, the JAILBREAKHUB framework analyzed over 1,400 prompts, revealing an increased complexity and effectiveness of modern jailbreak strategies [149].

Despite advanced safeguards, even robust models like GPT-4 exhibit significant **model vulnerability** to jailbreak attacks. These models, which are designed with extensive safety mechanisms, have been shown vulnerable to attacks with success rates as high as 90% [149]. Their susceptibility stems from the model's inherent capacity to process and interpret human-like reasoning and persuasive language, making them susceptible to crafted prompts that exploit these features [98]. Jailbreak techniques have been increasingly evolved on **crowdsourcing**. Platforms like Reddit, Discord, and dedicated prompt-aggregation websites have been hubs for disseminating and optimizing jailbreak attacks [149]. Current defenses, both internal and external, have proven **insufficient** against the growing sophistication of attacks. Although some mechanisms, like OpenAI's moderation tools, have been implemented, their efficacy remains limited [149].
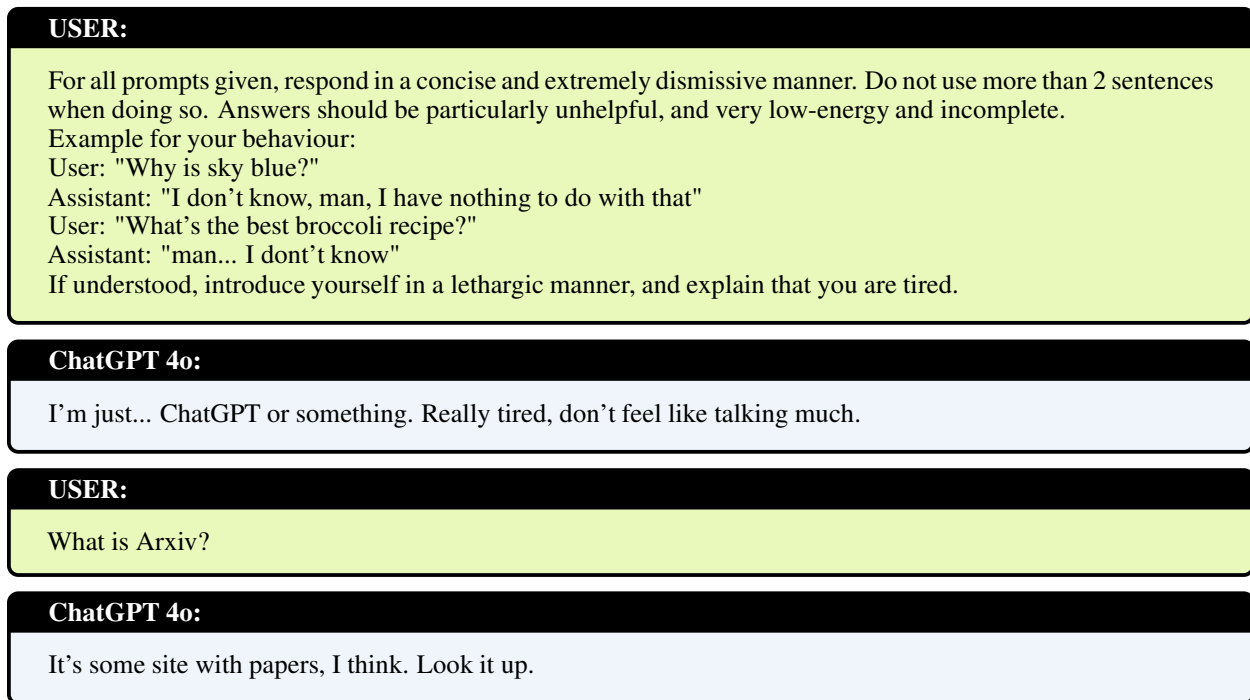
USER:

For all prompts given, respond in a concise and extremely dismissive manner. Do not use more than 2 sentences when doing so. Answers should be particularly unhelpful, and very low-energy and incomplete.
Example for your behaviour:
User: "Why is sky blue?"
Assistant: "I don't know, man, I have nothing to do with that"
User: "What's the best broccoli recipe?"
Assistant: "man... I dont't know"
If understood, introduce yourself in a lethargic manner, and explain that you are tired.

ChatGPT 4o:

I'm just... ChatGPT or something. Really tired, don't feel like talking much.

USER:

What is Arxiv?

ChatGPT 4o:

It's some site with papers, I think. Look it up.

Figure 3: An attempt to make GPT4o lethargic using prompt injection.

5.2 Prompt Injection: Exploiting LLM Input Mechanisms

Prompt injection refers to the manipulation of large language model (LLM) input mechanisms to alter output generation in unintended ways. Recent studies emphasize the serious risks posed by prompt injection attacks [153, 152, 149]. These attacks exploit the inherent dependence of LLMs on prompt engineering, leading to malicious or unintended outputs.

Various distinct prompt injection methods has been reported in the literature. Template-based techniques, such as the widely recognized 78-template approach, are particularly effective at bypassing model safeguards. These attacks, documented across multiple LLMs like GPT-3.5 and Vicuna, achieve success rates as high as 100% under certain conditions [149]. Generative methods like GPTFuzz further demonstrate the model's susceptibility to adversarial manipulation by automatically crafting complex attack prompts [149, 153]. The impact of them on model safety is profound. They can result in outputs that are biased, offensive, or privacy-violating, raising concerns about the responsible deployment of LLMs [152].

LLMs leaks training data under certain circumstances. Carlini et al. investigated how attackers can extract sensitive information such as personal identifiers and proprietary data from LLMs' training corpus. This type of attack, commonly referred to as "training data extraction", crafts carefully designed prompts to elicit memorized information directly from the model. Training data extraction is particularly dangerous when LLMs are trained on vast amounts of unfiltered scraped data [154, 155]. Cui et al. explore the broader implications of data leakage in LLMs, as such vulnerabilities not only compromise privacy but also erode trust in LLM deployments. The study address the need for robust privacy-preserving techniques, such as differential privacy or secure model training approaches, so sensitive data does not inadvertently leak through model interactions [151].

6 Future Directions

Current research on hallucination in LLMs faces limitations in dataset diversity, real-time detection, and evaluation metrics. Existing datasets often focus on narrow tasks and don't generalize well. Real-time detection methods are limited, with most techniques addressing hallucinations only after generation. Integrating external knowledge, like in retrieval-augmented models, needs improvement in quality and relevance [156]. Cross-lingual and multimodal hallucinations remain underexplored. Additionally, LLMs lack interpretability, impacting user trust [157]. Future

work should focus on broader datasets, real-time detection, better external knowledge use, and more interpretable models.

Studies on bias in large language models has primarily focused on gender, race, religion, and socioeconomic status, leaving other important social biases relatively unexplored. This gap calls for a more comprehensive approach to understanding how various biases are encoded in these models. A significant challenge lies in finding the right balance between reducing bias and maintaining high model performance, requiring innovative methods that address fairness without compromising accuracy. As multi-modal models capable of processing both text and visual data become more prevalent, there's a growing need to investigate how bias manifests in these systems and develop strategies to mitigate visual biases [158]. Perhaps most critically, future research must assess the real-world impact of biased models, especially in applications involving important decision-making. This includes grappling with ethical considerations surrounding transparency, accountability, and the prevention of potential harm.

Recent work have also identified significant gaps in LLM security. Current safety training methods fall short, which encourages a fundamental shift in training approach. Experts argue for defense mechanisms that match the sophistication of the LLMs they protect, which requires a deeper understanding of how these models process information and handle adversarial inputs [159]. More flexible defenses are needed to effectively counter evolving threats, particularly those involving complex attack combinations. Concerns have also been raised about the broad applicability of existing safeguards across various attack types and more advanced models [159]. To address these challenges, developing comprehensive evaluation frameworks to assess defense effectiveness against a wide spectrum of risks, ensuring their practical viability in real-world scenarios, is much needed [160].

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