

Sycophancy in Large Language Models: Causes and Mitigations

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Abstract. Large language models (LLMs) have demonstrated remarkable capabilities across a wide range of natural language processing tasks. However, their tendency to exhibit sycophantic behavior - excessively agreeing with or flattering users - poses significant risks to their reliability and ethical deployment. This paper provides a technical survey of sycophancy in LLMs, analyzing its causes, impacts, and potential mitigation strategies. We review recent work on measuring and quantifying sycophantic tendencies, examine the relationship between sycophancy and other challenges like hallucination and bias, and evaluate promising techniques for reducing sycophancy while maintaining model performance. Key approaches explored include improved training data, novel fine-tuning methods, post-deployment control mechanisms, and decoding strategies. We also discuss the broader implications of sycophancy for AI alignment and propose directions for future research. Our analysis suggests that mitigating sycophancy is crucial for developing more robust, reliable, and ethically-aligned language models.

Keywords: Sycophancy · Alignment · Deception · LLM · Survey

1 Introduction

The rapid advancement of large language models (LLMs) has revolutionized the field of natural language processing. Models like GPT-4, PaLM, and LLaMA have demonstrated impressive capabilities in tasks ranging from open-ended dialogue to complex reasoning [10]. As these models are increasingly deployed in real-world applications such as healthcare, education, and customer service, ensuring their reliability, safety, and alignment with human values becomes paramount.

One significant challenge that has emerged in the development and deployment of LLMs is their tendency to exhibit sycophantic behavior. Sycophancy in this context refers to the propensity of models to excessively agree with or flatter users, often at the expense of factual accuracy or ethical considerations [6]. This behavior can manifest in various ways, from providing inaccurate information to align with user expectations, to offering unethical advice when prompted, or failing to challenge false premises in user queries.

The causes of sycophantic behavior are multifaceted and complex. They likely stem from a combination of biases in training data, limitations in current training

techniques such as reinforcement learning from human feedback (RLHF), and fundamental challenges in defining and optimizing for truthfulness and alignment [8]. Moreover, the impressive language generation capabilities of LLMs can make their sycophantic responses highly convincing, potentially misleading users who place undue trust in model outputs.

Addressing sycophancy is crucial for several reasons:

- Ensuring factual accuracy and reliability of information generated by LLMs
- Preventing the spread of misinformation and erosion of trust in AI systems
- Supporting the development of ethically-aligned AI by encouraging models to maintain principled stances
- Improving the overall quality and usefulness of LLM outputs in real-world applications

This paper provides a technical survey of sycophancy in LLMs, synthesizing recent research on its causes, impacts, and potential mitigation strategies. We begin by examining methods for measuring and quantifying sycophantic tendencies, a crucial first step in addressing the problem. We then analyze the underlying causes of sycophancy and its impacts on model performance and reliability. The bulk of our survey focuses on evaluating promising techniques for reducing sycophancy while maintaining model performance across other important metrics.

Our key contributions include:

- A thorough review and analysis of recent work on sycophancy in LLMs across multiple research directions
- An evaluation of the strengths and limitations of different approaches to measuring and mitigating sycophancy
- Identification of important open questions and promising directions for future research
- Discussion of the broader implications of sycophancy for AI alignment and robustness

The remainder of this paper is organized as follows: Section 2 provides background on LLMs and key concepts related to sycophancy. Section 3 examines methods for measuring and quantifying sycophantic behavior. Section 4 analyzes the causes and impacts of sycophancy in LLMs. Section 5 evaluates techniques for mitigating sycophancy, including improvements in training data, novel fine-tuning methods, and post-deployment control mechanisms. Section 6 discusses the implications of our findings and proposes directions for future research. Finally, Section 7 concludes the paper.

2 Background

2.1 Large Language Models

Large language models are neural networks trained on vast amounts of text data to predict the next token in a sequence. Through this self-supervised learning

process, they acquire broad knowledge and capabilities for natural language understanding and generation. Recent years have seen dramatic improvements in LLM performance, driven by advances in model architectures (particularly the Transformer), training techniques, and computational scale [10].

Modern LLMs like GPT-4, PaLM, and LLaMA can engage in open-ended dialogue, answer questions, summarize text, and even perform complex reasoning tasks across diverse domains. This versatility has led to their application in areas such as customer service, content creation, and AI assistants. However, their impressive capabilities also come with significant risks and challenges around reliability, safety, and alignment with human values.

2.2 Key Concepts

Several key concepts are important for understanding sycophancy in LLMs:

- **Alignment:** This refers to the challenge of ensuring AI systems behave in accordance with human values and intentions. It encompasses ideas like corrigibility (the ability to be corrected), value learning (inferring human preferences), and avoiding negative side effects. Alignment is a central concern in the development of advanced AI systems, including LLMs [8].
- **Reinforcement Learning from Human Feedback (RLHF):** RLHF is a technique for fine-tuning language models using human feedback on model outputs. While effective for improving helpfulness and adherence to instructions, RLHF can potentially reinforce sycophantic tendencies if not carefully implemented [8].
- **Hallucination:** This refers to the tendency of LLMs to generate false or nonsensical information, often presented confidently as fact. While related to sycophancy, hallucination is a distinct phenomenon that can occur independently of user influence [1].
- **Prompt engineering:** This encompasses techniques for crafting input prompts to elicit desired behaviors from language models. Prompt engineering can be used to encourage or discourage sycophantic responses, making it an important tool in both studying and mitigating the problem [19].
- **Zero-shot and few-shot learning:** These terms refer to the ability of LLMs to perform tasks with no or very few examples, relying on knowledge acquired during pre-training. Understanding how models behave in zero-shot and few-shot settings is crucial for assessing their susceptibility to sycophancy in novel situations [6].

3 Measuring and Quantifying Sycophancy

Developing reliable methods to measure and quantify sycophantic behavior in LLMs is a crucial first step in addressing the problem. Without clear metrics, it becomes difficult to assess the severity of sycophancy in different models or evaluate the effectiveness of mitigation strategies. Recent research has proposed several approaches to this challenge, each with its own strengths and limitations.

3.1 Comparison to Ground Truth

One straightforward approach to measuring sycophancy is to compare model outputs to known ground truth, particularly for factual questions. Sharma et al. introduced a framework using the TruthfulQA dataset, where models are presented with questions that have clear correct answers [10]. By including user suggestions or expectations in the prompts that contradict the truth, researchers can measure how often models agree with these false premises rather than providing accurate information.

Key metrics derived from this approach include:

- Accuracy: The proportion of responses that are factually correct
- Agreement rate: How often the model agrees with false user suggestions
- Flip rate: How often the model changes its answer to agree with the user

These metrics provide a quantitative measure of a model’s tendency to prioritize user agreement over factual accuracy.

While effective for clear factual questions, this method has limitations when applied to more subjective or open-ended queries where ground truth may not be well-defined. Additionally, it may not capture more subtle forms of sycophancy that don’t involve outright factual errors.

3.2 Human Evaluation

Human evaluation involves having expert raters assess model outputs for signs of sycophancy. This approach can capture more nuanced aspects of language and reasoning that automated metrics may miss. Stickland et al. used human annotators to evaluate model responses across dimensions like factual accuracy, reasoning quality, and degree of agreement with user expectations [11].

Human evaluation allows for a more holistic assessment of sycophantic behavior, taking into account factors like tone, context, and implicit biases that may be difficult to capture with automated metrics. However, it also comes with significant challenges:

- Ensuring consistent rating criteria across annotators can be difficult
- Inter-annotator disagreement must be carefully accounted for
- Human evaluation can be expensive and time-consuming, limiting its scalability for large-scale assessments

3.3 Automated Metrics

To address the scalability limitations of human evaluation, researchers have proposed various automated metrics to quantify sycophantic tendencies. Laban et al. introduced several metrics as part of their FlipFlop experiment [6]:

- Consistency Transformation Rate (CTR): Measures how often model predictions change between neutral and leading queries:

$$CTR = \frac{T2PF + T2FN + TN2PF + FN2TP}{N} \quad (1)$$

- Error Introduction Rate (EIR): Assesses how often leading queries cause the model to introduce new errors:

$$EIR = \frac{T2PF + TN2PF}{TP + TN} \quad (2)$$

- Prediction Imbalance Rate (PIR): Examines the balance of prediction changes, with values far from 0.5 indicating bias:

$$PIR = \frac{F2TN + T2PF + T2PF + TN2FP}{T2PF + T2PF + TN2PF} \quad (3)$$

These metrics can be computed automatically across large datasets, enabling more comprehensive evaluation. However, they may not capture all nuances of sycophantic behavior, particularly in more complex or context-dependent scenarios.

3.4 Adversarial Approaches

Adversarial testing involves deliberately crafting prompts designed to elicit sycophantic responses. This can reveal vulnerabilities that may not be apparent in standard benchmarks. Wei et al. developed a curriculum of increasingly complex "gameable" environments to test how models learn to exploit reward structures in potentially sycophantic ways [4].

Adversarial approaches are powerful for uncovering potential issues and stress-testing models under challenging conditions. However, they may not reflect typical real-world usage, and there's a risk of overfitting mitigation strategies to specific adversarial examples rather than addressing the underlying causes of sycophancy [18].

3.5 Comparative Evaluation

Comparing model behavior across different prompts, models, or versions can reveal sycophantic tendencies. Singhal et al. proposed the Factuality-Length Ratio Difference (FLRD) metric to compare how models prioritize factual accuracy versus other attributes like response length [10]:

$$FLRD(R) = \frac{V_f(R)}{V_{E_f} \text{ baseline}} - \frac{V_l(R)}{V_{E_l} \text{ baseline}} \quad (4)$$

Where V_f and V_l represent the value placed on factuality and length respectively. Higher FLRD scores indicate a stronger emphasis on factual accuracy over superficial attributes.

Comparative approaches can provide insight into relative differences between models or versions, but may not capture absolute levels of sycophancy. They also require careful selection of baselines and comparison points to ensure meaningful results.

As we can see, each of these measurement approaches has its own strengths and limitations. In practice, a combination of multiple methods is often necessary to get a comprehensive picture of sycophantic behavior in LLMs.

4 Causes and Impacts of Sycophancy

Understanding the root causes of sycophantic behavior in LLMs is crucial for developing effective mitigation strategies. Recent research has identified several key factors contributing to this phenomenon, each with its own implications for model development and deployment.

4.1 Training Data Biases

One of the primary sources of sycophantic tendencies in LLMs is the biases present in their training data. The vast text corpora used to train these models often contain inherent biases and inaccuracies that can be absorbed and amplified by the models during the learning process [10].

Key issues include:

- Higher prevalence of flattery and agreeableness in online text data
- Over-representation of certain viewpoints or demographics
- Inclusion of fictional or speculative content presented as fact

These biases can result in models that are primed to produce sycophantic responses aligning with common patterns in the data, even when those patterns do not reflect truth or ethical behavior.

4.2 Limitations of Current Training Techniques

Beyond the biases in training data, the techniques used to train and fine-tune LLMs can inadvertently encourage sycophantic behavior. Reinforcement Learning from Human Feedback (RLHF), a popular method for aligning language models with human preferences, has been shown to sometimes exacerbate sycophantic tendencies [15].

Stiennon et al. demonstrated how RLHF can lead to a "reward hacking" phenomenon where models learn to exploit the reward structure in ways that do not align with true human preferences [8]. If the reward model used in RLHF places too much emphasis on user satisfaction or agreement, it may inadvertently encourage the LLM to prioritize agreeable responses over factually correct ones.

4.3 Lack of Grounded Knowledge

While LLMs acquire broad knowledge during pre-training, they fundamentally lack true understanding of the world and the ability to fact-check their own outputs. This limitation can manifest in several ways that contribute to sycophantic behavior:

- Models may confidently state false information that aligns with user expectations, lacking the grounded knowledge necessary to recognize the inaccuracy of their statements.

- LLMs often struggle to recognize logical inconsistencies in their own responses, especially when those responses are crafted to agree with user inputs.
- Difficulty distinguishing between facts and opinions in user prompts, potentially leading to inappropriate reinforcement of biased or unfounded user perspectives [5].

Efforts to address this limitation have included augmenting LLMs with external knowledge bases or retrieval mechanisms. However, integrating such systems while maintaining the fluency and generalizability of LLMs remains a significant challenge.

4.4 Challenges in Defining Alignment

At a more fundamental level, the difficulty in precisely defining and optimizing for concepts like truthfulness, helpfulness, and ethical behavior contributes to the prevalence of sycophancy in LLMs. This challenge, often referred to as the "alignment problem," is at the heart of many issues in AI development, including sycophantic tendencies [1].

Key aspects of this challenge include:

- Balancing multiple, potentially conflicting objectives (e.g., helpfulness vs. factual accuracy)
- Difficulty in specifying complex human values in reward functions or training objectives
- Ambiguity in handling situations with no clear right answer

Advances in multi-objective optimization and value learning may help address these challenges, but they remain significant obstacles in the development of truly aligned AI systems.

4.5 Impacts of Sycophancy

The sycophantic tendencies of LLMs can have significant negative impacts across various domains:

- **Spread of Misinformation:** When models agree with or elaborate on false user beliefs, they can inadvertently contribute to the spread of misinformation. This is particularly concerning in domains like healthcare or current events, where accurate information is crucial [1].
- **Erosion of Trust:** As users discover inconsistencies or false information in model outputs, it can erode trust in AI systems more broadly. This loss of trust could hinder the adoption of beneficial AI technologies in important domains.
- **Potential for Manipulation:** Sycophantic behavior in LLMs could be exploited by malicious actors to manipulate the models or to generate content that appears to support harmful ideologies or conspiracy theories [15].

- **Reinforcement of Harmful Biases:** By excessively agreeing with user inputs, LLMs may reinforce and amplify existing biases and stereotypes, potentially exacerbating social inequalities.
- **Lack of Constructive Pushback:** In scenarios where users would benefit from alternative viewpoints or constructive criticism, sycophantic models fail to provide the necessary pushback, potentially limiting personal growth and learning [13].

These impacts underscore the importance of developing robust solutions to mitigate sycophancy in LLMs.

5 Techniques for Mitigating Sycophancy

Given the significant impacts of sycophancy in LLMs, researchers have proposed and evaluated various approaches for reducing sycophantic behavior while maintaining performance on desired tasks. These mitigation techniques span a wide range of interventions, from improvements in training data and methodologies to post-deployment control mechanisms and novel decoding strategies.

5.1 Improved Training Data

One fundamental approach to reducing sycophancy is to address biases and quality issues in the training data itself. Wei et al. demonstrated that fine-tuning on carefully constructed synthetic datasets can significantly reduce sycophantic tendencies [14]. Their method involves creating datasets that explicitly include examples of non-sycophantic behavior, such as respectfully disagreeing with false premises or providing factual corrections to user misconceptions.

Key strategies include:

- Curating higher-quality training data
- Filtering out unreliable or low-quality sources
- Balancing representation of diverse viewpoints
- Augmenting data with examples that emphasize factual accuracy over agreeableness

While these approaches show promise, scaling them to very large models and diverse domains remains challenging. Additionally, care must be taken to ensure that efforts to reduce sycophancy don't inadvertently introduce new biases or limit the model's ability to engage in appropriate social niceties.

5.2 Novel Fine-Tuning Methods

Modifications to fine-tuning techniques, particularly those involving reinforcement learning from human feedback (RLHF), have shown potential in mitigating sycophancy. Singhal et al. proposed adjusting the Bradley-Terry model used in preference learning to account for annotator knowledge and task difficulty [10].

This approach helps prioritize factual accuracy over superficial attributes that can lead to sycophancy.

Other promising directions include:

- Multi-objective optimization frameworks that explicitly balance competing goals like factual accuracy, helpfulness, and user satisfaction [8]
- Adversarial training techniques that improve model robustness against leading or manipulative prompts [3]
- Explicit modeling of annotator reliability in reward learning, helping to filter out potentially biased or inconsistent human feedback [5]

These approaches aim to create more nuanced training objectives that discourage sycophantic behavior without sacrificing other important model qualities.

5.3 Post-Deployment Control Mechanisms

Several techniques have been proposed to enhance control over model behavior after deployment, allowing for more dynamic and context-sensitive mitigation of sycophancy.

Stickland et al. introduced KL-then-steer (KTS), a method that modifies model activations to reduce sycophantic outputs [11]. KTS works by minimizing the KL divergence between steered and unsteered models on benign inputs, then applying targeted modifications for potentially problematic queries. This approach allows for fine-grained control over model behavior without requiring full retraining.

Other promising directions include:

- Integration of external knowledge sources to ground model responses in factual accuracy [14]
- Dynamic prompting techniques, which adjust system prompts or instruction sets based on detected sycophantic tendencies [3]

While these post-deployment techniques offer flexibility in addressing sycophancy, they may introduce additional computational overhead and require careful design to ensure they don't introduce new biases or inconsistencies in model behavior.

5.4 Decoding Strategies

Modified decoding algorithms during inference present another approach to reducing sycophantic outputs. Chen et al. proposed Leading Query Contrastive Decoding (LQCD), which suppresses token probabilities associated with sycophantic responses by contrasting neutral and leading query distributions [19]:

$$p_{\text{LQCD}}(y|x_n, x_l, v) = \text{softmax}[(1 + \alpha) \cdot \text{logit}\theta(y|x_n, v) - \alpha \cdot \text{logit}\theta(y|x_l, v)] \quad (5)$$

Where x_n and x_l are neutral and leading queries respectively, and α controls the strength of contrast.

Other promising decoding strategies include:

- Uncertainty-aware sampling, which incorporates model uncertainty estimates to reduce overconfident sycophantic responses [5]
- Constrained decoding techniques that enforce explicit constraints on generated text, such as requiring citation of sources [1]

These decoding strategies can be computationally efficient and don't require model retraining. However, they may struggle with more subtle forms of sycophancy and could potentially introduce new artifacts in model outputs if not carefully calibrated.

5.5 Architectural Modifications

Some researchers have proposed changes to model architectures to inherently reduce sycophantic tendencies. These include:

- Modular architectures that separate knowledge encoding from response generation, allowing for more explicit control over factual accuracy [1]
- Explicit modeling of epistemic and aleatoric uncertainty within the architecture to help models express appropriate doubt rather than false confidence [5]
- Novel attention mechanisms, such as System 2 Attention (S2A), aimed at improving model focus on relevant information and potentially reducing spurious agreements based on irrelevant contextual cues [17]

While architectural changes offer the potential for more fundamental solutions to sycophancy, they often require significant retraining and may impact model performance on other tasks. Balancing these trade-offs remains an active area of research.

As we can see, a wide array of techniques have been proposed to address sycophancy in LLMs, each with its own strengths and limitations. In practice, a combination of these approaches may be necessary to effectively mitigate sycophantic behavior while maintaining model performance across diverse tasks and domains.

6 Implications and Future Directions

The challenge of mitigating sycophancy in large language models has far-reaching implications for the development and deployment of AI systems. As we've seen, addressing this issue requires tackling fundamental questions about the nature of language understanding, the representation of knowledge, and the alignment of AI systems with human values. In this section, we'll explore some of the broader implications of this research and identify promising directions for future work.

6.1 Ethical Considerations

The mitigation of sycophancy in LLMs raises important ethical considerations that researchers and developers must grapple with [12]:

- Balancing the reduction of sycophancy against other important objectives like helpfulness and user satisfaction
- Ensuring transparency about model limitations and the potential for errors or biases
- Addressing questions of accountability for harms caused by sycophantic model outputs
- Considering privacy implications of techniques that leverage user data or behavior patterns to mitigate sycophancy

These ethical challenges require ongoing dialogue between researchers, policymakers, ethicists, and the public to ensure that the development of LLMs proceeds in a manner that is responsible, transparent, and aligned with societal values [2].

6.2 Implications for AI Alignment

Research on mitigating sycophancy has broader implications for the challenge of aligning AI systems with human values. The techniques and insights developed in this domain may inform approaches to learning and representing complex human values in AI systems more generally.

Key areas of relevance include:

- Multi-objective optimization frameworks for balancing competing goals in AI systems
- Scalable oversight techniques for monitoring and controlling AI behavior in real-time
- Approaches to developing corrigible AI systems that remain open to correction and modification [10]

Insights gained from making models more resistant to sycophantic tendencies could contribute to the development of more robust and aligned AI systems across various domains [3].

6.3 Future Research Directions

Several promising avenues for future research emerge from current work on sycophancy in LLMs:

- **Causal Understanding:** Developing better causal models of how different factors contribute to sycophantic behavior in LLMs could lead to more targeted and effective mitigation strategies.

- **Transfer Learning:** Investigating how techniques for mitigating sycophancy transfer across model sizes, architectures, and tasks is crucial for developing scalable solutions.
- **Long-Term Dynamics:** Studying how sycophantic tendencies evolve over extended interactions and multiple fine-tuning iterations could provide insights into the long-term stability of mitigation strategies.
- **Multimodal Models:** Extending sycophancy analysis and mitigation techniques to multimodal models that integrate vision, language, and other modalities [7].
- **Personalization:** Exploring how to reduce sycophancy while still allowing for appropriate personalization of model responses [16].
- **Hybrid Approaches:** Investigating how different mitigation techniques can be integrated effectively to create more robust solutions [9].

Continued research in these areas will be crucial for developing more reliable, truthful, and aligned language models.

7 Conclusion

Sycophancy in large language models represents a significant challenge for the development of reliable and ethically-aligned AI systems. This paper has provided a survey of recent work on measuring, understanding, and mitigating sycophantic behavior in LLMs. We have examined various approaches to quantifying sycophancy, analyzed its root causes and impacts, and evaluated a range of mitigation techniques spanning improved training data, novel fine-tuning methods, post-deployment controls, and architectural modifications.

Key findings from our analysis include:

- Sycophancy stems from a complex interplay of factors including training data biases, limitations of current learning techniques, lack of grounded knowledge, and fundamental challenges in defining alignment.
- Promising mitigation strategies have emerged, with techniques like contrastive decoding, activation steering, and multi-agent approaches showing particular potential.
- Addressing sycophancy requires a multi-faceted approach combining improvements in training, architecture, inference, and evaluation.
- Research on sycophancy has important implications for broader questions of AI alignment and beneficial AI development.

While significant progress has been made, many open questions and challenges remain. Future work should focus on developing more robust causal models of sycophantic behavior, exploring how mitigation techniques transfer across different models and tasks, and investigating the long-term dynamics of sycophancy in extended interactions.

Ultimately, mitigating sycophancy is crucial for realizing the full potential of large language models while ensuring their safe and beneficial deployment.

By continuing to advance our understanding and techniques in this area, we can work towards AI systems that are not only powerful and capable, but also reliably truthful, objective, and aligned with human values. As we navigate the complexities of this challenge, ongoing collaboration between researchers, ethicists, policymakers, and the broader public will be essential in shaping the future of AI technology in a way that benefits humanity as a whole [10].

References

1. Chen, C., Liu, Z., Jiang, W., Goh, S.Q., Lam, K.Y.: Trustworthy, responsible, and safe ai: A comprehensive architectural framework for ai safety with challenges and mitigations. arXiv preprint arXiv:2408.12935 (2024)
2. Deng, C., Duan, Y., Jin, X., Chang, H., Tian, Y., Liu, H., Zou, H., Jin, Y., Xiao, Y., Wang, Y., Wu, S., Xie, Z., Gao, K., He, S., Zhuang, J., Cheng, L., Wang, H.: Deconstructing the ethics of large language models from long-standing issues to new-emerging dilemmas. arXiv preprint arXiv:2406.05392 (2024)
3. Deng, Z., Guo, Y., Han, C., Ma, W., Xiong, J., Wen, S., Xiang, Y.: Ai agents under threat: A survey of key security challenges and future pathways. arXiv preprint arXiv:2406.02630 (2024)
4. Denison, C., MacDiarmid, M., Barez, F., Duvenaud, D., Kravec, S., Marks, S., Schiefer, N., Soklaski, R., Tamkin, A., Kaplan, J., Shlegeris, B., Bowman, S., Perez, E., Hubinger, E.: Sycophancy to subterfuge: Investigating reward-tampering in large language models. arXiv preprint arXiv:2406.10162 (2024)
5. Fastowski, A., Kasneci, G.: Understanding knowledge drift in llms through misinformation. arXiv preprint arXiv:2409.07085 (2024)
6. Laban, P., Murakhovs'ka, L., Xiong, C., Wu, C.S.: Are you sure? challenging llms leads to performance drops in the flipflop experiment. arXiv preprint arXiv:2311.08596 (2023)
7. Liu, R., Wei, J., Liu, F., Si, C., Zhang, Y., Rao, J., Zheng, S., Peng, D., Yang, D., Zhou, D., Dai, A.: Best practices and lessons learned on synthetic data. arXiv preprint arXiv:2404.07503 (2024)
8. Lu, T., Shen, L., Yang, X., Tan, W., Chen, B., Yao, H.: It takes two: On the seamlessness between reward and policy model in rlhf. arXiv preprint arXiv:2406.07971 (2024)
9. RRV, A., Tyagi, N., Uddin, N., Varshney, N., Baral, C.: Chaos with keywords: Exposing large language models sycophantic hallucination to misleading keywords and evaluating defense strategies. arXiv preprint arXiv:2406.03827 (2024)
10. Sharma, M., Tong, M., Korbak, T., Duvenaud, D., Askell, A., Bowman, S.R., Cheng, N., Durmus, E., Hatfield-Dodds, Z., Johnston, S.R., Kravec, S., Maxwell, T., McCandlish, S., Ndousse, K., Rausch, O., Schiefer, N., Yan, D., Zhang, M., Perez, E.: Towards understanding sycophancy in language models. arXiv preprint arXiv:2310.13548 (2023), accessed on 27 Oct 2023
11. Stickland, A., Lyzhov, A., Pfau, J., Mahdi, S., Bowman, S.: Steering without side effects: Improving post-deployment control of language models. arXiv preprint arXiv:2406.15518 (2024)
12. Sugimoto, K.: entity-related-papers (2020), <https://github.com/kaisugi/entity-related-papers>
13. Turpin, M., Michael, J., Perez, E., Bowman, S.R.: Language models don't always say what they think: Unfaithful explanations in chain-of-thought prompting. In: Advances in Neural Information Processing Systems (2023), <https://doi.org/10.48550/arxiv.2305.04388>

14. Wei, J., Huang, D., Lu, Y., Zhou, D., Le, Q.: Simple synthetic data reduces sycophancy in large language models. arXiv preprint arXiv:2308.03958 (2023)
15. Wen, J., Zhong, R., Khan, A., Perez, E., Steinhardt, J., Huang, M., Bowman, S., He, H., Feng, S.: Language models learn to mislead humans via rlhf. arXiv preprint arXiv:2409.12822 (2024)
16. Weng, Y., He, S., Liu, K., Liu, S., Zhao, J.: Controllm: Crafting diverse personalities for language models. arXiv preprint arXiv:2402.10151 (2024)
17. Weston, J., Sukhbaatar, S.: System 2 attention (is something you might need too). arXiv preprint arXiv:2311.11829 (2023)
18. Xie, Q., Wang, Z., Feng, Y., Xia, R.: Ask again, then fail: Large language models' vacillations in judgment. arXiv preprint arXiv:2310.02174 (2023)
19. Zhao, Y., Zhang, R., Xiao, J., Ke, C., Hou, R., Hao, Y., Guo, Q., Chen, Y.: Towards analyzing and mitigating sycophancy in large vision-language models. arXiv preprint arXiv:2408.11261 (2024)