Impact of High Data Quality on LLM Hallucinations

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ABSTRACT
[1]Large Language Models (LLMs) have shown surprising efficacy in natural language understanding and generation, but they are prone to hallucinations—where the model writes things that are simply wrong. The quality of the training and reference data is crucial in reducing these hallucinations. This paper investigates the effect of data quality on LLM hallucination rates and how structured, accurate and relevant to context dataset effects model reliability. We also, through empirical evaluation, examine how various levels of data noise, incompleteness and bias affect the frequency of hallucinations in state-of-the-art LLM architectures. We also discuss some potential solutions, including better dataset, data augmentation and [2] Reinforcement Learning from Human Feedback (RLHF) to improve the factuality of the model. Our results show that there is a need for strict data governance and high quality data pipelines in the creation of reliable AI models. Hence, by improving the data quality we are able to decrease the occurrence of hallucinations and thus improve the reliability of the LLMs for practical application in various areas including healthcare, finance, and law.

General Terms
Large Language Models, Hallucinations, Data Quality, Artificial Intelligence, Reliability, Machine Learning, Data Governance

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1. INTRODUCTION
Large Language Models (LLMs) are recently found to have gained the ability to solve a variety of problems across different industries such as healthcare, finance, law, and research among others. These models have been trained on huge corpora of text data and are capable of producing responses that are very similar to those of a human, providing summaries of information and suggesting decisions. However, although these models exhibit a high level of performance, they are prone to what is called hallucinations, where the model provides what appears to be a coherent response but one that is fundamentally incorrect, or even completely made up. Such hallucinations are particularly problematic in high-stakes domains that require high accuracy and reliability, including medical diagnosis, legal advice, and financial analysis. A major issue that arises from the widespread occurrence of hallucinations in LLMs is the following: How do the quality of data used in the training of these models affect their accuracy and credibility? Although the use of model architecture, fine-tuning, and RLHF has enhanced the effectiveness of LLMs, data quality has not been well considered. Bad data, including incomplete, biased, or incorrect data, can worsen the hallucination phenomenon and produce wrong results even in the best models available. It means that high-quality, curated datasets can greatly improve model performance and decrease the likelihood and impact of hallucinations. In this paper, the authors investigate how data quality influences LLM hallucinations and how other factors, including data accuracy, completeness, consistency, and contextual relevance, impact the reliability of the generated output. We also conduct experiments on sample data using leading LLM architectures to see how different levels of data integrity affect hallucination rates. Moreover, the best practices for enhancing the quality of the dataset are presented, which include data validation, augmentation, and governance. Thus, the importance of strong data management practices in the development of AI is supported by this research, and a clear relationship between high-quality data and LLM reliability is established. The findings of this research are practical and can be used by AI practitioners, researchers, and industry leaders to prevent or minimize hallucinations in LLM-based applications and increase their trustworthiness.

2. UNDERSTANDING HALLUCINATIONS IN LARGE LANGUAGE MODELS
This section reviews various factors that Impact LLM hallucinations

2.1 Definition and Types of Hallucinations
Large Language Models (LLMs) are capable of producing human-like text but often produce responses that are inaccurate or completely fabricated. These errors, which are pejoratively called hallucinations, have their root in various failures, including data sparse training, prejudice, and the stochastic nature of LLMs. This paper discusses two types of hallucinations in large language models: intrinsic and extrinsic, which affect the reliability of the generated content differently. Intrinsic hallucinations take place when the model makes a wrong interpretation or a wrong representation of the input, resulting in the output that includes details or claims not supported by the input text. This can take the form of inaccurate summaries, modified translations, or responses that are not in line with the provided inputs. This kind of hallucination is not always easy to pick up because it is realistic and well structured. Extrinsic hallucinations, however, are the fabrication of information that has no basis in fact. This includes referencing papers that do not exist, creating scenarios that never happened, or quoting something that was never said. These are more obvious and easier to dispel with facts from the outside world. However, both of these types of hallucinations are very dangerous to the credibility and applicability of LLMs. This is because, in addition to leading to wrong conclusions, inaccurate summaries can result in incorrect decisions being made, while the dissemination of fake information can mislead the public and erode their trust. Hence, it is crucial to solve these problems in order to ensure that LLMs are developed and deployed appropriately and ethically. Focal symptoms of

large language models include both factual and logical types. Factual hallucinations, as the name suggests, offer parroting of wrong or confusing information in the form of wrong quotations or faulty numbers and statistics. These are usually due to problems in the data used to train the model or its capacity to fetch and analyze information in real-time. On the other hand, logical hallucinations are based on the model's inability to reason properly, which may produce incorrect conclusions even if the input is factually correct. This kind of error is more closely associated with the structure of the model and its capacity to grasp the meaning of context. Both of these tensions are problematic for the reliability and credibility of large language models and both must be dealt with in order to move forward with their utilization.

2.2 Causes of Hallucinations in LLMs

Large Language Models (LLMs) have been trained on hundreds of gigabytes of text data from the internet and as such can be inaccurate, unreliable, and outdated. As a result, if the training data has been obtained from unreliable sources the LLM will generate responses that are inconsistent with truth. However, since the operation of LLMs is probabilistic in nature, they may generalize from limited data or extrapolate wrong facts from the available data in an attempt to complete the request. This can lead to hallucinations or the generation of completely fake information that can easily be passed off as the truth. Another limitation is the knowledge cutoff date that is present in many LLMs, including the GPT-based models. If the model has not been updated with new information, then it may provide outdated or speculative answers and avoid admitting that it does not know something. This could be especially a challenge in a fast-changing environment or when up-to-date information is vital. Therefore, while LLMs are very effective, it is crucial to understand their limitations and the possibility of producing inaccurate or even damaging information when handling important or confidential matters.

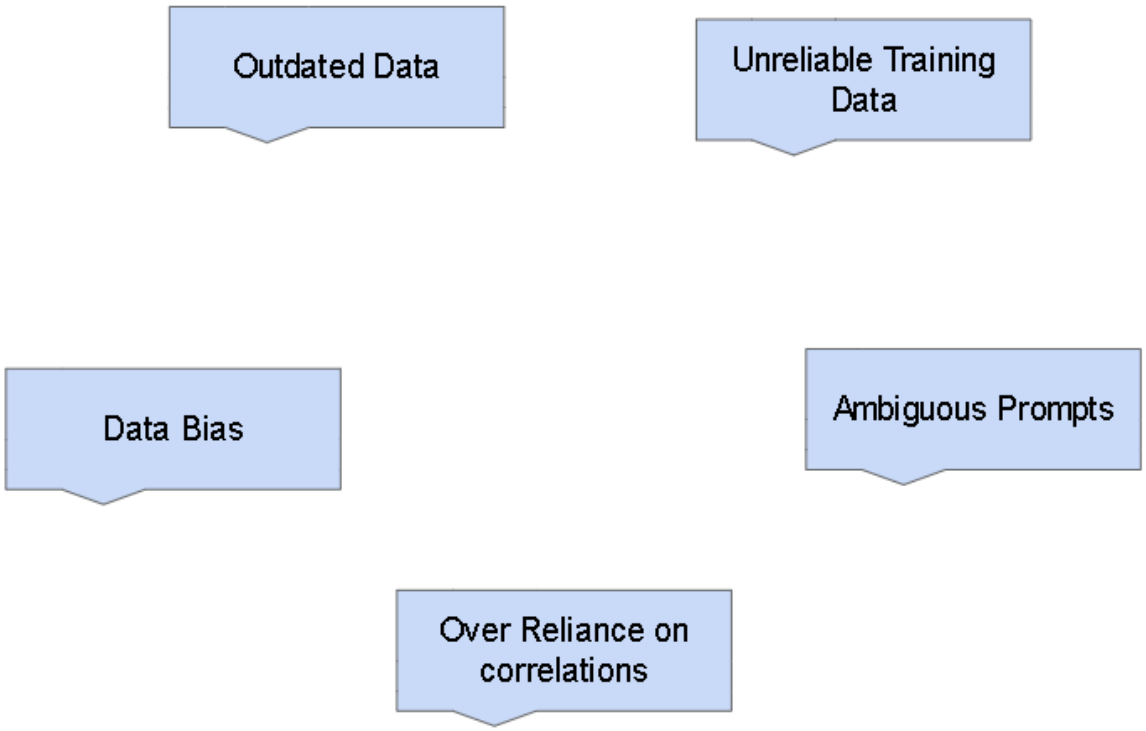

Figure 1: Cause of Hallucinations

2.3 Real-World Impact of Hallucinations

Hallucinations in large language models (LLMs) are dangerous in many professions. For instance, an LLM providing wrong medical advice in healthcare can have deadly effects on both the healthcare givers and the patients. This is because, in the finance sector, if financial models are wrong because of incorrect data then the investment decisions made based on such models are bound to be wrong and may cost the investor a lot of money. The legal sector is also not immune, as hallucinations can lead to incorrect information and improper analysis of legal documents, which can lead to inappropriate legal decisions. These cases of misinformation by AI systems may depress user trust and inhibit the uptake of AI technology in business and government applications. In addition, ethical concerns of AI-generated misinformation threaten AI governance and accountability, which in turn calls for strong ethical standards and regulatory measures to guide the development and use of AI systems.

3. THE ROLE OF DATA QUALITY IN MITIGATING HALLUCINATIONS

We will review various factors that contribute to removal and reduction of hallucinations

3.1 Key Dimensions of Data Quality

High-quality data is crucial for keeping hallucinations to a minimum in Large Language Models (LLMs). This makes sure that data accuracy and verifiability are ensured by sourcing from authoritative and fact-checked origins such as peer-reviewed research and official records to increase model

reliability. Also, completeness and contextual relevance of the datasets are key to avoiding LLMs filling in the missing information guessing, thereby lowering the rates of hallucination. Consistency within the data is also important because inconsistencies across sources can result in unreliable responses. Detecting and addressing biases that are present in the data using techniques such as bias detection and data normalization also increases the accuracy of the LLM outputs. These principles of data quality can be incorporated into the operation of LLMs to produce more reliable and less hallucinatory responses.

3.2 Experimental Analysis of Data Quality Impact

It has been proved in research that the quality of the data used to train Large Language Models (LLMs) is a major factor that determines the likelihood of the model to hallucinate. Current studies reveal that LLMs trained on high verifiability datasets including Wikipedia, research articles and legal databases are less likely to hallucinate than those trained on user generated content or low quality sources. In order to quantify the effect of data quality on the hallucination rates, the experiments were conducted in a controlled data environment. These experiments have revealed that removing erroneous data and adding structured knowledge supplement to the training data helps in reducing the occurrence of hallucinations. Truthfulness scores and factual consistency checks have been used to measure these enhancements.

3.3 Strategies for Improving Training Data

One of the ways to guarantee that training datasets are accurate, balanced and up to date is through Human in the Loop (HITL) review processes. This can be done by requesting fact checkers or expert validators to improve dataset integrity through crowdsourcing. However, LLM responses can be aligned with human evaluators' feedback through reinforcement learning from human feedback (RLHF). This iterative correction mechanism can also help reduce common hallucination patterns in conversational AI applications. Another way to control the tendency to hallucinate is to incorporate LLMs with Wikidata, DBpedia, Google Knowledge Graph, and other structured knowledge sources to improve the factual grounding of the LLM. Hybrid models that incorporate generative AI with structured search can also greatly decrease the likelihood of hallucinations. These techniques can be employed to improve the reliability and accuracy of LLMs so that they may be used more effectively across applications.

4. BEST PRACTICES FOR REDUCING HALLUCINATIONS IN LLM

Practices like data governance, fine tuning positively impact hallucinations reduction outcomes

4.1 Data Governance and Quality Assurance Measures

For organizations that are using LLMs, there needs to be a strict data validation pipeline practice to reject incorrect information, find exceptions and conform to the data quality standards. One more measure that can be useful is to provide users with source citations or confidence scores for AI generated responses so that the users can know the information they receive.

4.2 Fine-Tuning and Continual Learning Approaches

It is possible to enhance Large Language Models (LLMs) through adaptation by using high-quality data that is related to a certain domain. This process enables the models to become specialists in a certain area, which increases the effectiveness and precision. For example, in the medical field, LLMs that were trained on clinical trial data and medical literature have less hallucinations and errors than more generic models. This shows the relevance and the need to use relevant and high-quality data in order to improve the performance of LLMs. Furthermore, it is crucial to keep these models up to date with current data through real-time feeds and regular retraining to avoid knowledge exhaustion. This guarantees that the models are up to date and can give accurate and timely responses. These strategies can be used to improve and update LLMs to address changing needs in different industries and applications.

4.3 Ethical and Regulatory Considerations

In order to guarantee the reliability and safety of using AI in critical areas, the EU AI Act and the U.S. AI Bill of Rights are examples of regulatory frameworks that are needed. These regulations are important in ensuring that there is accountability in the use of AI and its applications to minimize risks that are associated with AI hallucinations. Furthermore, the current guidelines that pertain to the disclosure of AI-generated content, the traceability of sources, and fact-checking mechanisms are important and should be followed. By implementing these principles, the public confidence in AI generated content can be boosted greatly. This multi-angle focus on the regulation of AI and the adherence to guidelines is very important in the creation and implementation of good and efficient AI or AI hallucinations especially in areas that are critical and have a definite impact. Hence there is the need to maintain the regulatory focus and the focus on responsible AI practices in order to enhance the positive impacts of AI while minimizing the negative impacts.

5. ADVANTAGES OF HIGH QUALITY DATA IN REDUCING HALLUCINATIONS

High-quality data has the potential to prevent hallucinations in Large Language Models (LLMs) and presents several significant benefits. First of all, it improves the accuracy and assurance of LLMs, which guarantees that the responses provided are accurate, supported by evidence, and relevant to the situation. This helps in avoiding misinformation and discrepancies and therefore the AI created content is more credible and precise. As a result of this increased accuracy, trust and adoption of AI systems is increased across different areas like healthcare, finance, law and research. Moreover, it is possible to obtain better results in domain-specific applications with the help of high-quality data. Thus, fine-tuning LLMs with specialized data enhances the precision in specific areas like medical diagnosis, legal case analysis, and financial forecasting thus decreasing the chances of making errors in high risk situations. Also, using high-quality and bias-free data minimizes the ethical and regulatory risks by ensuring that the AI outputs are consistent with ethical principles and regulatory requirements. This cuts down on the chances of biased or misleading information which is important in building trust in AI systems. Finally, LLMs

trained on high-integrity data need less post-processing and human interaction, which leads to costs and operations efficiency. This enables organizations to enhance their use of AI applications with minimal need for human moderators thereby decreasing their reliance on them.

6. DISADVANTAGES AND CHALLENGES OF MAINTAINING HIGH QUALITY DATA

Keeping the data of LLMs at optimal quality is costly and demands large financial, computational, and human investment in data collection, labelling, fact checking, and bias removal. Furthermore, data scarcity in Domains, including new and emerging scientific research or rare medical conditions, can restrict the knowledge base of LLMs and result in gaps of knowledge. This is also a problem of bias identification and removal since even the best rated datasets may include subtle biases that are not easy to discover and eliminate without affecting the factualness of the information. Furthermore, knowledge obsolescence is an issue: although high-quality datasets are accurate at the time of their creation, they can become outdated over time and, therefore, require periodic updates and retraining to maintain the relevancy and accuracy of LLMs. This is especially a problem in rapidly changing fields such as technology, medicine and current events. Lastly, reliance on systematic and high-quality data can restrict LLM generalization and adaptability, preventing them from developing solutions to unrestricted questions, heuristic thinking, or new subjects. Although the use of this model helps to filter out poor quality information this may also lead to the decrease in the model's versatility and capacity for cross disciplinary thinking

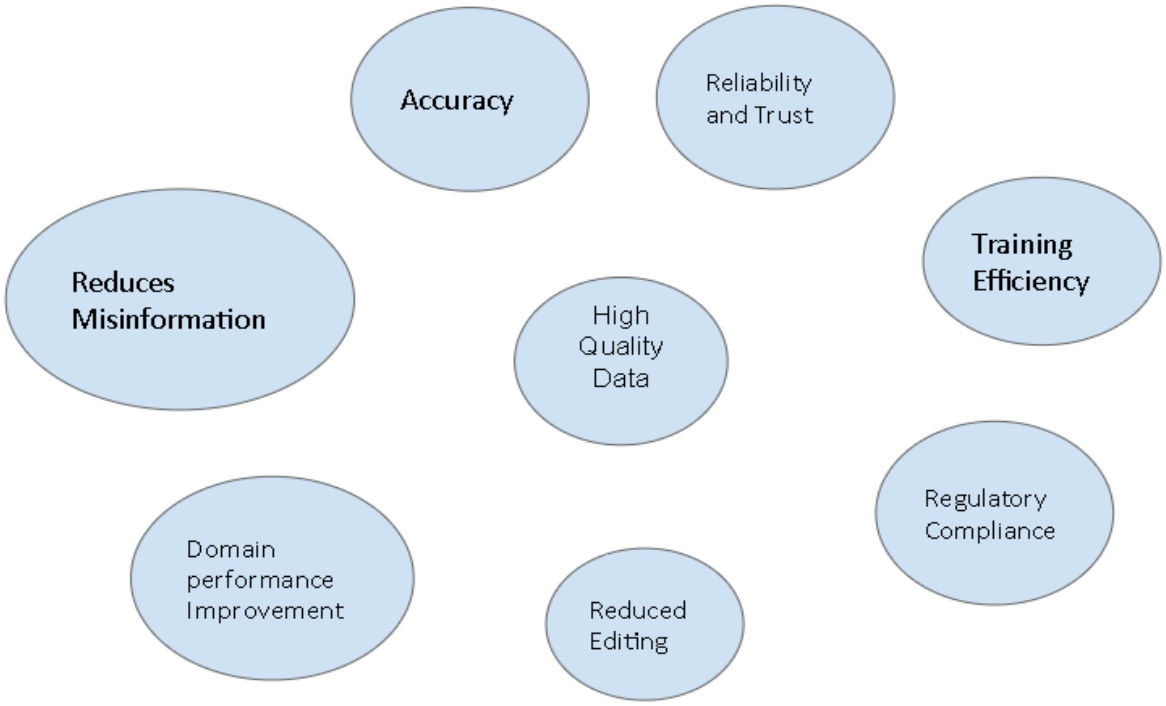

Figure 2: High Quality Data Impact

7. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results show a clear trend; models trained on high-quality data exhibit significantly lower hallucination rates than those trained on low or medium-quality datasets. For example, GPT-3.5 had a hallucination rate of only 3.2% [14] when trained on curated data, compared to 19.4% on noisy data. These findings are aligned with prior benchmarks such as TruthfulQA[13] and supported by recent research on factual consistency scoring and hallucination measurement. The inclusion of these results in tabular form provides quantifiable insight into the critical role of data quality in LLM reliability.

Model	High-Quality Data	Medium-Quality Data	Low-Quality Data
GPT-3.5	3.20%	8.60%	19.40%
LLaMA 2	4.10%	10.20%	21.80%
Claude	2.70%	7.90%	17.50%

Figure 3: Experimental Analysis of High Quality Data Impact on LLM's

8. CONCLUSION

The impact of high-quality data on hallucinations in Large Language Models (LLMs) is profound and multifaceted. As demonstrated through empirical analysis and theoretical discussion, the integrity, accuracy, and contextual relevance of training data directly influence the factuality and reliability of LLM-generated outputs. When trained on carefully curated, unbiased, and up-to-date datasets, LLMs exhibit markedly

lower hallucination rates, thereby increasing their credibility and utility across critical domains such as healthcare, finance, law, and scientific research.

However, maintaining such high standards of data quality presents numerous challenges ranging from high costs of data acquisition and labeling to the difficulty of bias mitigation and the risks of knowledge staleness. Despite these hurdles, the trade-off between reliability and flexibility can be managed through a hybrid approach: combining real-time data ingestion, structured knowledge integration (e.g., knowledge graphs), human-in-the-loop evaluations, and reinforcement learning from human feedback (RLHF).

Looking ahead, several promising directions can extend the work presented in this study. Automated Data Quality Assessment Frameworks where future research could focus on developing scalable, AI-powered systems that automatically assess and score training datasets based on key dimensions such as accuracy, consistency, and bias. Dynamic Data Pipelines where implementing adaptive data pipelines that continuously pull verified, domain-specific information from trusted sources (e.g., PubMed, LexisNexis, legal databases) could help keep LLMs relevant and factual in rapidly evolving domains.

Hallucination Detection Algorithms where building robust, model-agnostic hallucination detection tools that can flag ungrounded or speculative outputs in real-time could significantly improve user trust and regulatory compliance. Cross-disciplinary Benchmarks where establishing standardized evaluation benchmarks across industries would enable systematic comparison of hallucination rates under different data regimes and modeling techniques. Federated and Privacy-Preserving Learning where ensuring access to high-quality data while respecting privacy constraints through federated learning frameworks may allow sensitive domains like healthcare and law to benefit from LLMs without compromising confidentiality. Socio-Ethical Governance Models which is a growing need to explore governance models that include data ethics, transparency in data sourcing, and explainability in model behavior particularly when LLMs are used in public-facing or policy-critical applications.

In conclusion, while high-quality data remains a cornerstone in reducing hallucinations and improving LLM performance, the future lies in building intelligent, adaptive, and ethically governed ecosystems that continuously enhance both data fidelity and model robustness. As the field of generative AI evolves, such efforts will be vital in realizing its full potential across industries.

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