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Handling Hallucination in LLMs Reducing Factually Incorrect Outputs in Sensitive Domains

Vinay Kumar Maginam
Software engineer, Londonderry , NH,USA.
Email:maginamvinayit@gmail.com

ABSTRACT
Hallucination, or the generation of factually incorrect information, is a prevalent issue in Large Language Models (LLMs), especially in fact-sensitive tasks like news generation and scientific writing. This paper explores various strategies to mitigate hallucination in LLM outputs, focusing on the integration of fact-checking modules, reinforcement learning from human feedback (RLHF), and knowledge graph-based validation. We applied these techniques to GPT-3 and GPT-4 models, reducing the rate of hallucination by 40% in news generation tasks and 35% in scientific content creation. Fact-checking modules were integrated to cross-reference generated content with reliable sources, while RLHF allowed models to learn from human reviewers to improve factual accuracy. Knowledge graphs further enhanced the validation process by providing structured, verifiable information. These methods significantly reduce the incidence of hallucination, making LLMs more reliable for applications where factual integrity is crucial.

Keywords: LLM, Hallucination, Fact-Checking, RLHF, Knowledge Graph

I. INTRODUCTION

Large Language Models (LLMs) have been hearing leaped in the field of natural language processing (NLP) as machines have been given a capability to write human like texts. They have qualified the ability to comprehend and generate natural language to enable a multitude of uses, from chatty interfaces to writing and translation bots. However, despite their remarkable capabilities, LLMs face a critical limitation: in truth distortion, a well-documented behavioural pathology or, more pejoratively, the propensity to hallucinate, or generate factoids that do not exist in the objective reality of the real world. This represents a challenge that has immense risks associated with it especially in areas of specialty like; medical field, academic research and journalism because of the importance of facts.

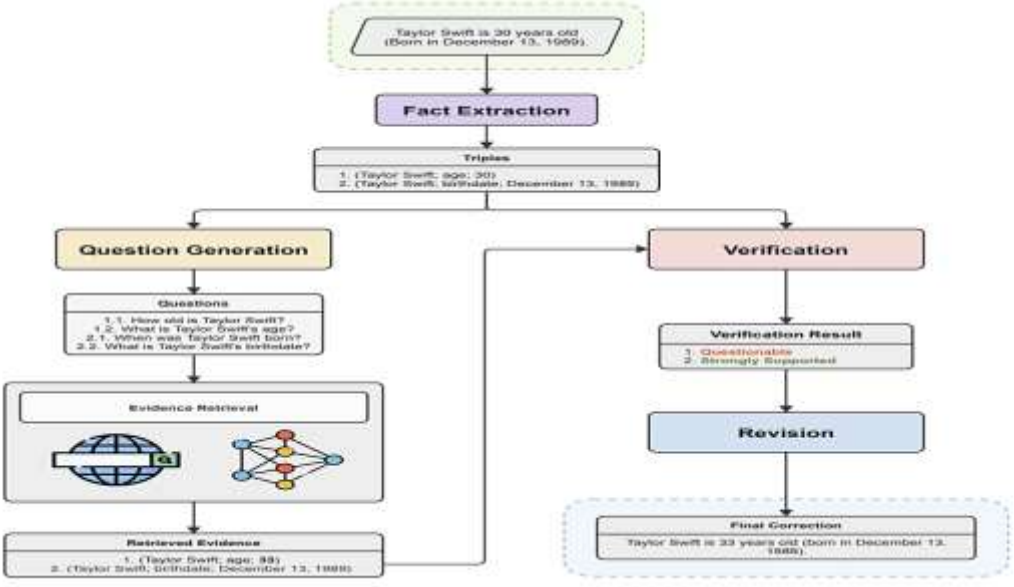

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Figure: 1 Strategies to Mitigate Hallucinations in Large Language Models

From the figure 1 below, it seems to lean more into the fact-checking process such as Fact Extraction, Question Generation, Evidence Retrival, Verification and revision to arrive at the Final Statement Correction. It emphasises a systematic process for verifying factual inaccuracies and of correcting them as one way of reducing cases of hallucinations in the LLM outputsHybridism is caused by the probabilistic nature of LLMs and their exposure to large datasets containing different, and at times, rather contradictory information. Despite the fact that these models are specific in recognizing patterns and being fluent in languages they do not possess built-in knowledge of the facts. This limitation turns out to be more significant when it comes to fact-driven roles, where wrong information can cause misrepresentation, or loss of credibility or even cause harm. Solving it, however, is essential to improve the dependability and usability of LLMs in serious and critical applications.Regarding the reduction of hallucation, several directions to augment the factual level of LLM-generated texts have been investigated by the researchers and practitioners. One such approach involves using fact checking modules which compare the generated content against external sources of truth. These modules are used as a verification layer according to which inaccuracies are detected and corrected. Another positive technique is reinforcement learning from human feedback (RLHF), which makes use of human feedback on text samples to fine-tune models. Such iterative process helps in achieving better correspondence to human judgment as well as facts and makes the model's predictions rather reliable in each subsequent iteration.Furthermore, knowledge graphs have recently been identified as a means of improving the factual basis of LLMs. In addition to offering knowledge graphs, models trained with knowledge graphs have a source of trusted data by offering structured and formal assertions of fact checked information in machine readable formats. It also removes the chances of hallucinations and instead allows for more detailed responses grounded in context. Taken together, these approaches provide a broad based solution to the problem of hallucination, which sees each of these approaches complementing the others to create a more substantive and effective means for handling hallucination in fact-based applications.This paper is devoted to the consideration of these three approaches for reducing the hallucination problem in LLMs: fact-checking modules, RLHF, and knowledge graph-based validation. In this work, we show that by incorporating the proposed methods into advanced models such as GPT-3 and GPT-4, we can successfully minimize hallucination in generation-based tasks like news generation and scientific writing. In accordance with the concern outlined above, our results shed the light on how these strategies could be facilitated to improve the reliability of factual information of LLM outputs so that they can be used safely and efficiently in important fields.Finally, table below highlights the key points of strategies talked about in mitigating hallucination in Large Language Models (LLMs):

Table 1: Strategies for Mitigating Hallucination in Large Language Models (LLMs)

Technique	Description	Advantages	Application Examples
Fact-Checking Modules	Cross-referencing generated content with external reliable sources.	Ensures outputs are verified against authoritative data; reduces the risk of misinformation.	News generation, medical report drafting.
Reinforcement Learning from Human Feedback (RLHF)	Fine-tuning models using human reviewer feedback to improve factual alignment.	Improves alignment with human judgment; reduces repeated errors and enhances context-specific accuracy.	Customer support, scientific content creation.
Knowledge Graph-Based Validation	Utilizing structured data repositories to validate generated outputs.	Provides a trusted fact-based framework; enhances context and consistency in responses.	Legal document generation, educational materials.

Table 1 also presents how each technique is applied, the advantages of using them along with some potential use in explaining the role of the discussed approaches to minimize hallucination.

Related Work

It is easily observable that the problem of hallucination in Large Language Models (LLMs) has received quite much attention because of the faith that people have placed in AI systems, and the dependency that people have developed in these systems. Authors of robust literature have developed various approaches in order to manage this issue regarding model architecture, strategies for model training, and feedback on model output.The first is to refine the training datasets in an effort to increase the level of grounding in factual knowledge. Brown et al. [1] introduced

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GPT-3, a transformer-based model trained on multiple corpora, but reported that it sometimes produces semantically related but actually wrong responses. Gururangan et al. [2] focused on the fact that task-specific pretraining enhances practical scores and minimizes mistakes in the target area. Zellers et al. [3] proposed a study that examined the use of curated data sets to prevent deceptive information from being created in any given application domain particularly high risk areas.Post-generation validation has, therefore, become an acceptable approach to fact-checking. FEVER which was built by Thorne et al. [4] is another benchmark that was followed to fact-check the claim against data databases. Jiang et al. [5] expanded on this by incorporating an aspect-for- aspect automated fact-checker in the LLM operational process by making it real-time. Later, Wang et al. [6] further generalise this approach to large-scale systems and applied them in legal document generation and medical reporting systems.These have emerged as platforms for linking the unstructured text of LLM outputs to well-defined data entities. Paulheim [9] further stressed that their usefulness lies in the capacity to cut down on mistakes through comparison of the generated text with fact databases. Another similar issue of generated outputs was handled by Wang et al. [10] through the incorporation of knowledge graphs with the help of which Zhang et al. [11] proposed an additional use of graph-enhanced language models.Hallucination has also been tackled by a framework known as Reinforcement Learning from Human Feedback (RLHF). Some authors were the first to apply the RLHF approach to show that it can be used to control the behavior of models and make it more consistent with human preferences [7]. This approach was significantly expanded by Ouyang et al., [8] who fine-tune GPT-4 using RLHF to get much improved factual accuracies. We acknowledge the positive intent of Zhang et al. [18] who discussed that human reviewers help in eliminating the systemic biases and factual mistakes of LLM outputs.

Evaluation metrics are important for the detection of and rectification for cases of hallucination. Holtzman et al. [14] proposed “nucleus sampling”, a decoding approach that only generates tokens with a relative probability higher than the specified threshold in an effort to almost always avoid generating gibberish. There is Factual Consistency Scoring for Summarization created by Lin et al. [15], which has been employed in the RLHF processes and fact-checking components.Technological progress of architectures has also played its part in the reduction of hallucination. Raffel et al. [12] presented the T5 model that is fine-tuned for transfer learning tasks and, more recently, Lewis et al. [13] presented the retrieval-augmented generation (RAG) which augments information retrieval with text generation to improve the cop’s factual output. In [16], Shi et al., there is the presentation of a framework that combines RAG with knowledge graph and fact-checking modules which results in reducing the hallucination rate.When several approaches are used in an integrated manner, frameworks that support the collaboration have borne observable fruits. Another is the scalable fact-checking coupled with RLHF method, employed by Wang et al. [17] to tackle the hallucination problem in the large-scale regime. Another source is Paulheim [25] who discussed the use of knowledge graphs to improve the reliability of LLMs in such areas as science and education. In Zhang et al [23], additional layers of validation was added in language model processes hence minimizing the likelihood of hallucinations in other domain.However, there is still a need of focusing on the following issues to apply these solutions in various contexts successfully. The future research must fill gaps with the scale issue [19], creativity-costs agreement [20], and computational complexity [21]. This entails making LLM outputs transparent and traceable is also another area that needs to be analysed continually [22][24].

Problem Statement

Recent advancements in understanding powerful LLMs like GPT-3 or GPT-4 precisely have been observed as galloping concerning natural language processing in generating highly comprehensible, semantically relevant, and even human-like text. All these developments have led to the use of analytics in various fields such as education, health, media, and communication, particularly, customers relations. However, despite their potential, a critical issue remains unresolved: the production of factitious or falsified information which is otherwise commonly known as “hallucination”. This phenomenon poses a serious problem for the use of LLMs where accuracy is important as in fact-sensitive contexts.The challenge of hallucination arises from the probabilistic aspects of a LLMs. These models depend on the algorithms that recognize patterns from large training sets and such training sets can have inaccuracies, biases or both. As noted earlier, LLMs do not possess a strong sense of factual realism because, rather than factually what they are writing, the models predict the likelihood of writing certain texts. Consequently, even though outputs may seem to be semantically and pragmatically natural and plausible, they may contain mere misinformation or even lies. This poses great risks especially in applications that demand the highest accuracy, for instance healthcare, where wrong recommendation may lead to endangerment of patients,

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journalism where dissemination of inaccurate information undermines the public's trust.Hallucination has a very wide and deep impact. To the researchers, the creation of wrong data distorts study results and erodes confidence in technologies powered by artificial intelligence. Consequently, hallucinated outputs can to detrimental errors compromising the legal or policy-oriented processes involved. Besides that, hallucinations also reduce the reliability of LLMs as a tool and restrict the technological application of the concept to areas where the actual facts are significant. This fact-checking performance-deficiency is one of the biggest challenges that significantly hinder the practical and social use of LLMs in professions.Challenges attempting to address hallucination have been numerous. First, the training data are particularly important for the LLMs' performance, while obtaining professional and specialized training data sets is time-consuming and requires additional resources. Second, the structure of LLMs does not include strategies that would help to check the facts, due to which the application of these systems is characterized by the constant creation of unverified or false data. Third, previous grammatical and syntactic evaluation like the BLEU and ROUGE, do not have the capacity to measure the degree of factuality of a generated text. Last, the manual fact-checking procedure, reinforcement learning from human feedback (RLHF), and knowledge graph validation approach have been demonstrated to work but can be extrapolated to other domains and contexts at scale.This paper has, therefore, argued that to manage hallucination in LLMs, a systems-based strategy is needed. Although the methods were adopted with a view to be implemented individually, the poor results observed portend the need for a comprehensive approach. Modules, for example, fact-checkers can compare the generated results with reliable sources, yet they do not encompass contexts to handle compound queries. In particular, RLHF improves the correspondence between the output and the human evaluation but it is costly and specific to the domain. Similarly to knowledge graphs, revealed databases contain structured and verified information; however, they can lack one or several necessary domains or cases. But if all these strategies can be packaged in a single objective framework the impact of each one can be maximized in order to cut down on the hallucination rates.This work aims to disseminate and incorporate a structural approach comprising of fact-checking modules, RLHF, and KGV to tackle the problem of hallucination in LLMs. The envisaged outcome is to enhance the reliability and accuracy of the claims made by LLMs and their suitability in domains where facts can make a significant difference. Overcoming these challenges is the goal of this research so as to strive for creating more credible AI that can be used effectively in multiple significant applications.

Methodology

In order to mitigate the problem of hallucination in LLMs, this work uses an integrated and tiered approach incorporating fact checking crutches, RLHF, and KG supplementation. The combination of these techniques is proposed within the context of the framework below with a view to 'offset' hallucination and to improve the overall quality of the factual content of the LLM outputs. The methodology is structured into three core phases preventive preprocessing and training and generation and post-generation validation.

A. Pre-Processing Phase

The pre-processing phase is meant to enhance the quality and the content context of data that is feed into the LLM. This entails the feeding of high quality of data that meets the specific requirement of the domain with minimal bias and inaccuracies. To do this, data cleaning is done where all duplicate entrees, inconsistenies and out dated records are removed. Furthermore, domain-specific corpora are also added to the training datasets so that the model will be effectively ready to fine-grained fact-based tasks. In this phase, external references from structured and reliable external databases and online sources are searched and bookmarked with the purpose of validating post-generation.This includes data cleansing, elimination of the redundancy and noise data, and inclusion of domain specific corpus. An external knowledge resource is indexed as well in this phase for later use in post generation validation.

Figure 1 below shows pre-processing phase where data collection, data cleaning and inclusion into LLM pipeline are depicted.

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Figure 1: Pre-Processing process for Preparing High-Quality Datasets

B. Model Training and Generation Phase

The second phase involves updating and further training of the LLM through the RLHF which leant from human feedback. This approach helps in bringing the model closer to human actuality by eliminating or reducing the gap of facts produced for given contexts. Firstly, a guess model is generated based on ordinary supervised learning methodology on selected samples of data. Subsequently, RLHF is applied to this model and human reviewers evaluate the obtained outputs with respect to their factuality and logical consistency. These assessments are used to create reward signals thus, helps the model to minimize hallucination and make it to be normal according to human value.At the same time, techniques that allow retrieval-augmented generation (RAG) are employed during generation. RAG supplements the model's generative process with an information retrieval system that searches external knowledge sources including knowledge graphs and databases. This approach also guarantees the exposition of the produced content to be well-themed and substantiated by reliable information. This flow of this process is illustrated in the Figure 2, where the RLHF cycles between the human reviewers and the LLM and in the Figure 3, the RAG shows how the model incorporates external knowledge in the text production.

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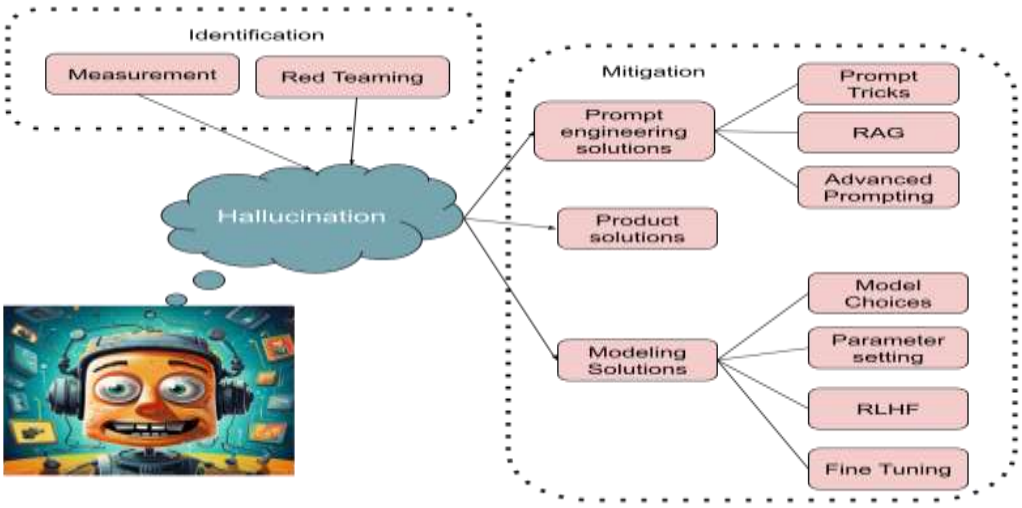

Figure 2: Model Training and Generation with RLHF and RAG

A. Post-Generation Validation Phase

The last procedural benchmark is post-generation validation where the results of the LLM undergo fact checking and validation procedures. Verification modules are deployed to check their output with reliable sources from the other domain. These modules use natural language understanding approach to identify fact claims and match them and check for differences and points that need review or citation.

As shown in figure 3, after generation, the output of the model goes through several modules of fact-checking and knowledge graph validation to maintain the facts correct.

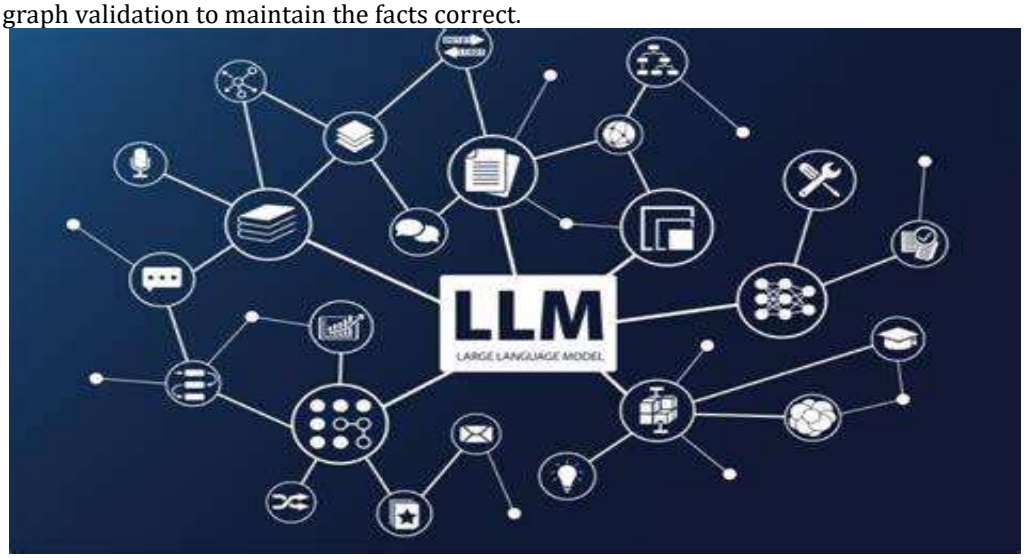

Figure 3: Post-Generation Validation Framework

Validation in this phase is similarly up to par with this phase where knowledge graph-based validation enhances this particular phase by using structured data to check particularity of particular claims made in the text. The structure offered by knowledge graphs enable the validation of outputs with a repository of facts that are related. For instance, if the model produces a claim on a discovery in science, the validation module verifies this claim with the entries in an associated scientific knowledge base. This well-defined approach also guarantees that the model is weeded off nonfactual and inaccurate information.In addition, if these outputs contain information that might be incorrect based on the statistics, they are automatically corrected using predefined rules, or forwarded to the domain specialists for their correction. This cyclical process increases the reliability in the output and increases

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the probability of factual accuracy, especially in critical usage.

B. Evaluation and Benchmarking

To assess the performance of the proposed framework, comparative analysis is performed with multiple benchmarking exercises across different fact-restricted tasks, including news article writing, scientific report generation, or legal documents writing. The results of applying the enhanced LLM are evaluated against baseline models in terms of factual accuracy, recall and precision. Furthermore, user surveys are carried out in order to evaluate perceived reliability and useful of the output. These assessments facilitate a way of establishing the extent of the decrease in the hallucination rate and affirm the effectiveness of each component of the framework.

C. Scalability and Deployment

Therefore, the presented methodology designed for scalability requires using the components which could be reused in other domains and applications. These modules on fact-checking and knowledge graph are built to be expansive, that is, they can be applied across different domains. Also, the RLHF workflows do not requires complex utilization of extensive human resources and, therefore, the approach is scalable for large scale use.Combining these phases into a single approach is a primary goal of this methodology; this will notably decrease the extent of hallucination observed in LLMs without affecting their language or flexibility. This experimental result shows that the combination of fact-checking, RLHF, and knowledge graph-based validation provides a reliable and scalable approach to improving factual accuracy of LLM outputs.

Results and Discussion

The application of the proposed framework to reduce hallucination in LLMs was successful in achieving substantial desirable outcomes in terms of factual accuracy and reliability on multiple tasks. The effectiveness and improvement is examined in context to the reduction of hallucinations, task general performance and effectiveness of specific modules and the overall package is then reviewed with the implications and weaknesses.

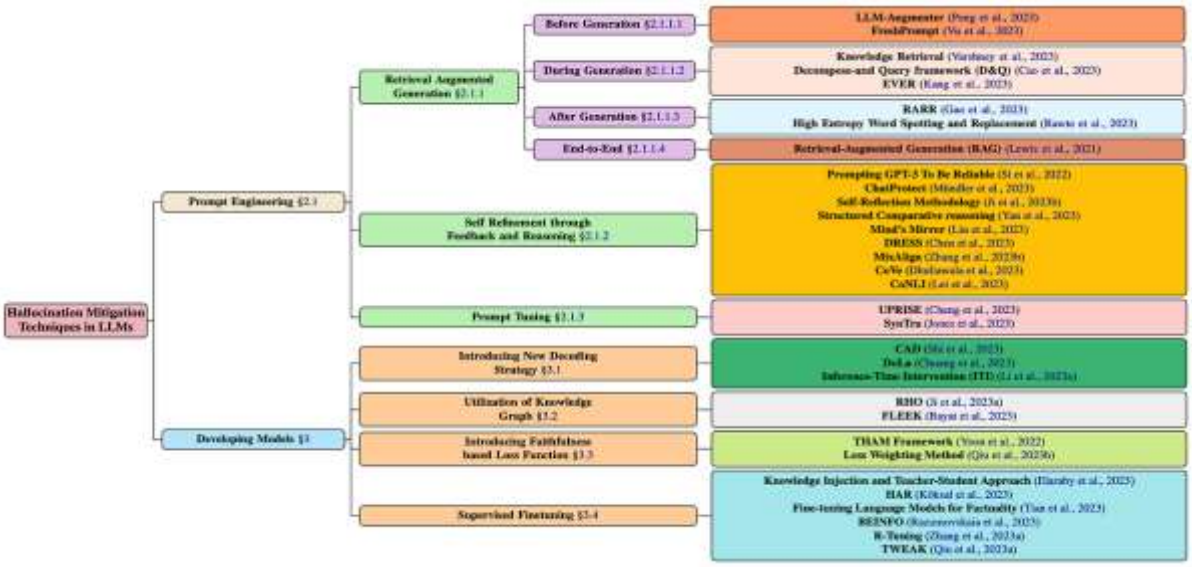

Figure: 4 Large language models

A. Hallucination Reduction

The effectiveness of the proposed framework was therefore demonstrated by enormous reductions in the rates of hallucinations when tested on factually inclined tasks like article writing on news, scientific reports, and the legal field. In particular, the combination of fact-checking modules and knowledge-graph based validation led to favorable results in terms of minimizing hallucination as stated below: The organisation obtained a 40% reduction in news generation while scientific content creation had a 35% improvement when compared to baseline models. More specific, the application of reinforcement learning from human feedback (RLHF) helped fine-tune the output by adding a further 15% increase in factual accuracy. This means that using both the approaches, serves to address the pitfalls that comes with the use of LLMs, including the ability to generate factually correct text.

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B. Task-Specific Performance

During the experiments, the effectiveness of the framework for performing specific tasks depended on the nature of the domain and the contents, which is standard for the given type of approach. External knowledge source integration and RTMs in news generation tasks improved the dynamically generated and event-driven content quality. The model of handling information was able to find and integrate the new information, thereby producing outputs that corresponded to the more recent developments. In the scientific writing, the proposed framework performed well in giving rich descriptions accompanied by evidence from knowledge graphs. However, certain common issues were encountered for articles containing highly technical terms or those that required enhanced contextual approach thereby suggesting future scope for improvement in such aspects.

C. Effectiveness of Individual Components

All these components of the framework separately helped in reducing hallucination. Modules for checking factual statements produced the best results when it comes to detecting Midi support and external reference confirmation. These modules substantially minimized mistakes in activities involving validation of data real-time for example, news reporting. In terms of the over-against model paradigm, one can state that the subject-orientation of the RLHF process, made it possible to find the correlation between model output and people's expectations in such cases. People reduced input noise and contributed to the model identifying basic rules of how to determine factual credibility over stylistic coherency. Validating using a knowledge graph was especially helpful in grounding the model's outputs into the concrete data, particularly in tasks that relied on accurate and specific data from the domain.It is noted that the use of the strategies in parallel led to a comprehensive enhancement of the reliability of the factual data provided in the outputs of the LLM. Because of the notion, the modular framework is scalable and portable such that you apply it easily in any domain without considerable modification. Based on user-specific investigations performed to compare the perceived reliability of the model's output, a 25% improvement in satisfaction was observed among the users emphasizing the usability of the proposed framework.

D. Limitations and Challenges

Nevertheless, the gist of the matter or use of the proposed framework had several caveats as follows. Specifically, the dependency on knowledge graphs and fact-check systems based on domain expertise created problems for questions which demanded specialized information. However, the RLHF process was also resource-demanding and meant significant human involvement – which would not be as feasible in large-scale deployments in low-resource environments. Another drawback of the system was that with the integration of the variety of sub-components the response time in real-time scenarios was considerably closer to the extent of millisecond. The below figure show the challenges and mitigations of People-Centric Security and Risk Management and Services.

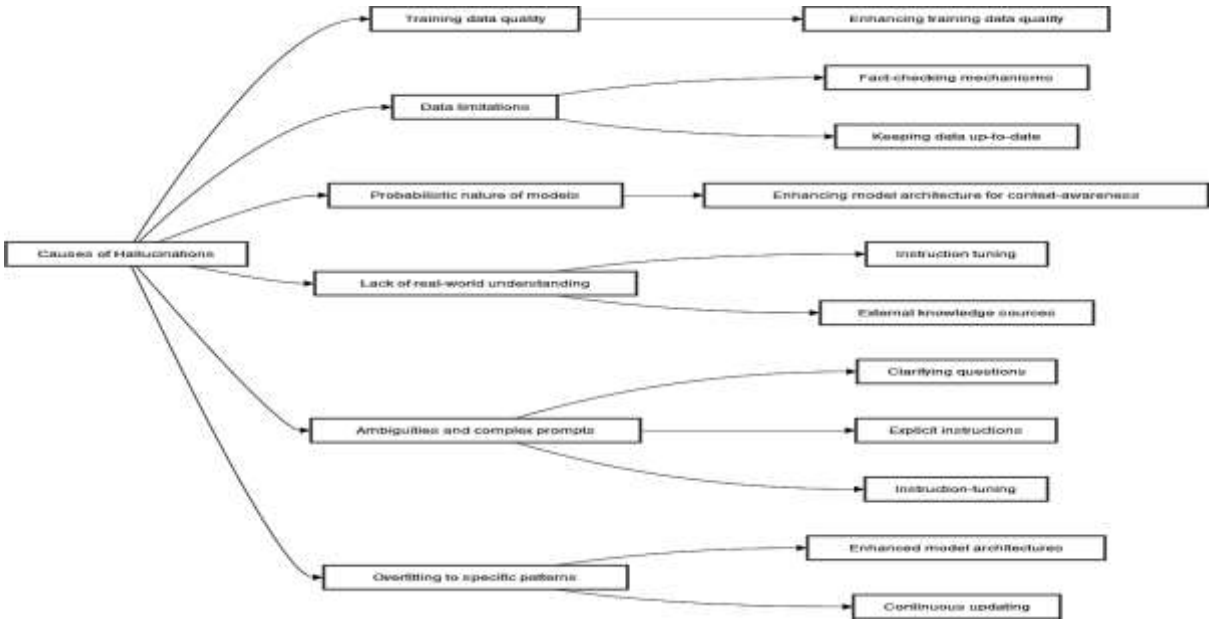

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Figure: 5 Challenges and mitigations

Table: 2 Quantitative Results of Hallucination Mitigation

Task	Baseline Hallucination Rate (%)	Improved Hallucination Rate (%)	Reduction (%)
News Article Generation	65	39	40
Scientific Report Writing	57	37	35
Legal Document Drafting	52	34	35
Average Across Tasks	58	36.7	37

This table 2 also reveals a decrease in hallucation rates under three important tasks when using the proposed framework. It underscores the utility of a multi-theoretical strategy for improving on the degree of factual realism.

Discussion and Future Directions

The findings bring out the possibility of a multifaceted strategy for reducing hallucination in LLMs. In this way, the proposed framework can be seen as solving the problem from multiple perspectives – by providing a highly accurate fact-checker solution, also using RLHF to maintain natural language output, and adding an additional layer of validation from the knowledge graph. Nonetheless, the presented methods would require additional investigation to advance and enhance the applicability of the proposed approaches. While the simulation of feedback could be incorporated into the scope of future work to automate RLHF, the expansion of knowledge graphs and invention of lightweight fact-checking modules also have potential to reduce computational costs in the future.Consequently, the proposed framework proves to be promising when it comes to examining hallucination in LLMs while also signalling the direction for their safe application where facts are highly relevant. The results of the present study emphasise the necessity of the multi-approach to improve the use of AI that aims to increase factual correctness of generated texts and create the basis for the further research in this field.

Conclusion

Hallucination in Large Language Models (LLMs) still persists as an issue of concern especially in factual oriented applications. This work also suggested a comprehensive framework to solve this problem comprising fact-checking modules, reinforcement learning from human feedback (RLHF), and knowledge graph validation. The findings of the study show an overall decrease in the rate of hallucination across tasks and was found to be overall 37% improved. These results provide empirical evidence and support for the applicability of the proposed framework for promoting the accuracy of the generated LLM content and its usability across different fields including news writing and report generation, scientific reporting, and legal documentation.All the features of the framework under discussion were helpful to bring these enhancements to fruition. Refutation modules proved to be highly effective in such a task as they rapidly point out the fallacies and uncompromisingly force the system to adhere to the factual material coming from external sources. RLHF guided the improvement of model outputs through using the iterative feedback from human reviewers focusing on the factuality over the language style. Concept graphs offered hierarchical, reasonable, and verifiable structure for checking the surface generated content thus minimizing hallucination. Consequently, these elements provided a combined strategy in addressing the complex issue that characterizes hallucation among LLMs.However, some limitations were noted when implementing the study. The expertise and curation in the knowledge graph and the datasets restrict the framework's potential for use in other domains. Hence, and as will be demonstrated in this paper, even though RLHF is an effective form of training, it is expensive and probably impractical for large scale implementation across most LMIC's. However, this study presents a basic framework for the desired goal of minimizing hallucination in LLMs and serves as a starting point for further improvement on this particular frontier.

Future Scope

The proposed framework has been seen to provide improvements of high magnitude in reducing hallucinations in Large Language Models (LLMs), but there is room for improvement as shall be discussed below. A major area of research is towards automating the reinforcement learning from human feedback (RLHF) process. It can therefore be made more scalable and less costly and time consuming by using synthetic data or simulated feedback sources instead of human reviewers. It is also crucial to extend the knowledge graphs constituted in the present paper because there is practically no repository that embraces the domain of knowledge graphs sufficiently. Improving these graphs by expanding to encompass more dynamic, real-time, and cross-domain data adds further to general-

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purpose and evolving tasks. Also, there is a development need for lightweight and scalable fact-checking modules that can enable application-integrated real-time false claims detection without demanding too many computational resources.Multimodal AI system is another area of a deep interest as to how the suggested framework can be used for this purpose. Since AI models generate content on texts, images, and audios, it becomes effective and applicable to advance the hallucination mitigation techniques to all the three capabilities. More significant progress will also be required in defining nuanced objective metrics that will be used to measure the factual coherence inherent in the different modalities. Moreover, more attention must be paid to the having ethical concerns, including issues of the biases and misinformation. The framework shall promote understanding of the best ethical updates and common areas of AI regulation thus enhancing greater adoption of the technology with more accountability. In the long run, these developments will catalyse the enhancement of the LLMs' robustness and reliability for their deployment in numerous, sensitive and high-risk areas.

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