Reducing Hallucinations in Large Language Models: A Consensus Voting Approach Using Mixture of Experts

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Abstract

The proliferation of advanced natural language processing applications has demonstrated the critical importance of ensuring the accuracy and reliability of generated text, particularly in domains where erroneous information can have significant consequences. The novel integration of a majority voting mechanism within a Mixture of Experts (MoE) framework, specifically in the Mistral 8x7b model, offers a significant advancement by leveraging the collective expertise of multiple specialized experts to mitigate hallucinations and enhance output precision. Through a rigorous experimental setup, the research demonstrated that the application of majority voting substantially reduced the incidence of hallucinations while improving the overall accuracy of the model's outputs. Detailed analysis revealed that the consensus-based approach effectively filtered out erroneous responses, providing a more reliable and trustworthy output. The methodology encompassed comprehensive mechanisms for input processing, expert output collection, and dynamic expert selection, further refining the model's contextual adaptability and robustness. Results indicated a notable improvement in accuracy and a manageable increase in computational overhead, validating the practical viability of the approach. This study's findings significantly contribute to the ongoing efforts to enhance the reliability of large language models, presenting a robust framework with broad applications in various critical fields.

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***Index Terms*—Hallucinations, Accuracy, Mixture of Experts, Majority Voting, Natural Language Processing, Computational Efficiency**

I. Introduction

THE increasing prevalence of large language models (LLMs) in various applications has brought significant advancements in natural language processing and artificial intelligence. However, one of the most critical challenges facing the deployment of LLMs is their propensity to generate hallucinations. Hallucinations refer to instances where the model produces information that is not grounded in the input data or factual knowledge, leading to outputs that are misleading or entirely incorrect. The reduction of hallucinations is essential to ensure the reliability and trustworthiness of LLMs in real-world applications, ranging from automated customer support to advanced research tools. Mixture of Experts (MoE) models present a promising approach to addressing the issue of hallucinations in LLMs. MoE architectures consist of multiple expert models, each specialized in different aspects of language understanding. By distributing the computational load among various experts, MoE models can achieve higher performance and efficiency compared to single-expert models. The integration of a majority voting mechanism within MoE models offers a potential solution to mitigate hallucinations. Majority voting involves aggregating the outputs of multiple experts and selecting the most frequent response, thereby reducing the likelihood of erroneous outputs. This consensus-based approach leverages the collective wisdom of the experts, aiming to enhance the accuracy and reliability of the generated text.

The development of large language models has revolutionized the field of artificial intelligence, enabling machines to understand and generate human-like text. These models, trained on vast amounts of data, exhibit remarkable proficiency in various language tasks, including translation, summarization, and question-answering. Despite their impressive capabilities, LLMs are prone to hallucinations, where the generated text contains fabricated or inaccurate information. This phenomenon undermines the credibility of LLMs and poses significant challenges for their adoption in critical domains. Previous attempts to mitigate hallucinations have explored several strategies. These include refining training data, enhancing model architectures, and incorporating external knowledge sources. However, these methods have often fallen short in completely eliminating hallucinations, necessitating the exploration of novel approaches. The concept of Mixture of Experts, originally proposed to improve computational efficiency, has gained traction as a viable solution for enhancing model robustness. MoE models, by distributing tasks among specialized experts, can reduce the cognitive load on individual experts and improve overall performance. The application of majority voting within MoE frameworks introduces an additional layer of robustness, as it relies on the consensus of multiple experts to generate accurate outputs.

Hallucinations in large language models pose a critical challenge that undermines their reliability and applicability in various fields. The generation of false or misleading information not only compromises the quality of the outputs but also raises ethical and practical concerns. Ensuring the accuracy of LLMs is paramount for their deployment in sensitive applications such as healthcare, legal advice, and scientific research, where the stakes are high, and erroneous information can have severe consequences. Addressing the problem of hallucinations requires innovative solutions that go beyond traditional methods. The integration of majority voting mechanisms within Mixture of Experts models offers a promising avenue for reducing hallucinations. By leveraging the collective expertise of multiple models, this approach aims

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to filter out inaccuracies and enhance the reliability of the generated text. The effectiveness of this method, however, necessitates thorough investigation and rigorous evaluation to ascertain its potential benefits and limitations. This research aims to explore the viability of majority voting in MoE models and its impact on reducing hallucinations, contributing to the ongoing efforts to enhance the trustworthiness of large language models. In particular, this study:

- Developed a majority voting mechanism within a Mixture of Experts (MoE) framework to significantly reduce hallucinations in large language models.
- Demonstrated substantial improvements in the accuracy and reliability of the generated text through rigorous experimental evaluation.
- Provided a comprehensive methodology encompassing model setup, input processing, expert output collection, and hallucination detection and mitigation.
- Highlighted the practical viability of the proposed approach through manageable computational overhead and enhanced performance metrics.

II. Background

A. Mitigation Techniques for Hallucinations

Various methodologies have been developed to address hallucinations in large language models, aiming to enhance the factual accuracy of their outputs. One approach involved refining the training data to ensure higher quality and relevance, thereby reducing the likelihood of generating incorrect information [1], [2]. Another strategy focused on augmenting the data with factually verified content, which helped in grounding the model's responses more accurately [3], [4]. Architectural innovations, such as integrating additional verification layers within the model, were implemented to cross-check the generated outputs against a knowledge base, thereby filtering out potential hallucinations [5], [6]. The incorporation of external knowledge sources, like structured databases and real-time information feeds, also proved effective in mitigating hallucinations by providing the models with access to up-to-date factual information [7], [8].

Ensemble methods, which combine the outputs of multiple models to derive a consensus, were also explored as a means to enhance the reliability of LLM outputs [9], [10]. The application of attention mechanisms within LLMs to focus on more relevant parts of the input data helped in producing more accurate and contextually appropriate responses [11], [12]. Additionally, the integration of contextual embeddings, which provide a richer representation of input data, contributed to reducing the incidence of hallucinations through improved understanding of the context [13], [14]. Advanced filtering techniques that dynamically adjust the generation process based on the confidence of the outputs were shown to be effective in ensuring higher accuracy [15], [16].

Techniques such as reinforcement learning from human feedback (RLHF) were utilized to iteratively improve model responses, ensuring alignment with human expectations and reducing the occurrence of hallucinations [17], [18]. Post-processing mechanisms, including output verification steps and fact-checking algorithms, were introduced to scrutinize the generated text for inaccuracies before finalizing the output [19], [20]. Some approaches leveraged adversarial training, where models were trained against adversarial examples specifically designed to induce hallucinations, thereby strengthening their robustness to such errors [21], [22].

B. Efficiency and Robustness Enhancements through Mixture of Experts (MoE) Models

Mixture of Experts (MoE) models have been instrumental in enhancing the efficiency and robustness of large language models through the distribution of computational tasks among multiple specialized experts. This architectural innovation allowed for more efficient resource utilization, as only a subset of experts were activated for any given input, reducing the overall computational load [23], [24]. The specialization of experts in different aspects of language processing enabled MoE models to achieve superior performance by leveraging the strengths of each expert in their respective domains [25], [26]. The implementation of majority voting within MoE frameworks further contributed to robustness by aggregating the outputs of multiple experts to form a consensus, thereby mitigating the impact of any single expert's error [27]. This approach was particularly effective in reducing the variance in model outputs, leading to more stable and reliable predictions [28], [29]. Techniques such as dynamic expert selection, where the LLM dynamically chooses the most relevant experts based on the input context, were explored to enhance the adaptability and accuracy of MoE models [30].

The integration of gating mechanisms that control the flow of information between experts and the central model was shown to optimize the decision-making process, ensuring that only the most pertinent information influenced the final output [31], [32]. Hybrid models combining MoE architectures with traditional LLMs were developed to capitalize on the strengths of both approaches, resulting in improved performance and robustness [28], [33]. Advanced training techniques, including multi-task learning where experts were trained on a variety of tasks, contributed to the versatility and generalization capabilities of MoE models [34]. Furthermore, the use of fine-tuning techniques, where each expert was fine-tuned on specific datasets, enhanced the precision of MoE models in handling diverse linguistic phenomena [35], [36]. The deployment of MoE models in distributed computing environments demonstrated their scalability and efficiency in processing large-scale data, making them suitable for real-world applications [25]. Research into the application of MoE models in various domains, such as healthcare and finance, demonstrated their potential in delivering accurate and reliable predictions in critical areas [37]. The continued evolution of MoE models, driven by advancements in model training and architecture design, emphasized their role in advancing the capabilities of large language models [38].

III. Methodology

The methodology for applying majority voting to the Mixture of Experts (MoE) model aimed to reduce hallucinations

in the Mistral 8x7b large language model. The approach was designed to leverage the collective expertise of multiple specialized experts to enhance the accuracy and reliability of the generated outputs. Each component of the methodology was structured to ensure a comprehensive and robust implementation, addressing the key aspects of model setup, input processing, expert output collection, majority voting mechanism, and hallucination detection and mitigation (Figure 1).

A. Model Setup

The Mistral 8x7b model was configured to include eight distinct experts, each comprising seven billion parameters. This configuration enabled the model to distribute computational tasks among the experts, optimizing resource utilization and enhancing processing efficiency. Each expert was specialized in different facets of language understanding, allowing for a more nuanced and comprehensive approach to text generation. The model architecture incorporated gating mechanisms to control the flow of information between the experts and the central model, ensuring that only the most relevant information influenced the final output.

The experts were pre-trained on a vast and diverse dataset, which included various domains and linguistic constructs, to ensure broad coverage and high generalization capabilities. Fine-tuning techniques were employed to further enhance the precision of each expert, focusing on specific datasets that aligned with their specialization. The model setup also included dynamic expert selection mechanisms, which allowed the system to select the most relevant experts based on the input context, thereby improving the adaptability and accuracy of the outputs. This comprehensive setup was pivotal in ensuring that the MoE model could effectively leverage the strengths of each expert while maintaining overall efficiency and robustness.

B. Input Processing

The input text was processed and divided into manageable chunks to facilitate parallel processing by the experts. This division was based on linguistic and semantic considerations, ensuring that each chunk represented a coherent segment of the input text. The preprocessing stage included tokenization, normalization, and context embedding to prepare the text for expert analysis. Contextual embeddings provided a richer representation of the input data, enabling the experts to capture more nuanced meanings and relationships within the text.

Each chunk was then distributed to all eight experts, allowing them to independently process the text based on their specialization. The processing included various language understanding tasks, such as syntactic parsing, semantic analysis, and contextual interpretation, which collectively contributed to a more accurate and comprehensive understanding of the input text. The distributed processing approach ensured that the computational load was evenly balanced among the experts, optimizing resource utilization and processing speed. This input processing framework was essential in preparing the text for subsequent stages of expert output collection and majority voting.

C. Expert Output Collection

The outputs from the eight experts were collected and prepared for the majority voting process. Each expert provided its most likely response based on its internal parameters and training. The outputs included not only the generated text but also confidence scores and contextual annotations that provided additional insights into the experts' decision-making processes. This comprehensive output collection ensured that the majority voting mechanism had access to all relevant information necessary for accurate decision-making.

The collected outputs were aggregated and formatted to facilitate comparison and analysis. This included aligning the responses based on their linguistic and semantic content, enabling a direct comparison of the experts' outputs. The aggregation process also involved filtering out any irrelevant or low-confidence outputs, ensuring that only the most reliable responses were considered in the majority voting process. The collection and preparation of expert outputs were crucial in setting the stage for effective majority voting and subsequent hallucination mitigation.

D. Majority Voting Mechanism

The majority voting mechanism was designed to aggregate the outputs of the eight experts and select the most frequent response as the final output. This consensus-based approach aimed to leverage the collective wisdom of the experts, reducing the likelihood of erroneous outputs. In cases where a tie occurred, a predefined tie-breaking strategy was employed, such as selecting the output with the highest confidence score or considering additional contextual factors.

Let E_i denote the output of expert i, where $i \in \{1, 2, \ldots, 8\}$. The set of all expert outputs is given by:

$$\mathcal{E} = \{E_1, E_2, \ldots, E_8\}$$

The majority voting function V can be defined as:

$$V(\mathcal{E}) = \arg\max_{e \in \mathcal{E}} \sum_{i=1}^{8} \delta(E_i = e)$$

where δ is the Kronecker delta function:

$$\delta(E_i = e) = \begin{cases} 1 & \text{if } E_i = e \\ 0 & \text{if } E_i \neq e \end{cases}$$

In the event of a tie, the output with the highest confidence score C_i is selected:

$$T(\mathcal{E}) = \arg\max_{e \in \mathcal{E}} \sum_{i=1}^{8} C_i \cdot \delta(E_i = e)$$

The majority voting process included several stages, starting with the initial aggregation of expert outputs. This was followed by a detailed comparison and analysis of the responses, ensuring that the most accurate and contextually appropriate output was selected. The tie-breaking mechanism added an additional layer of robustness, ensuring that the final output was both reliable and contextually relevant. The implementation of the majority voting mechanism was a key component of

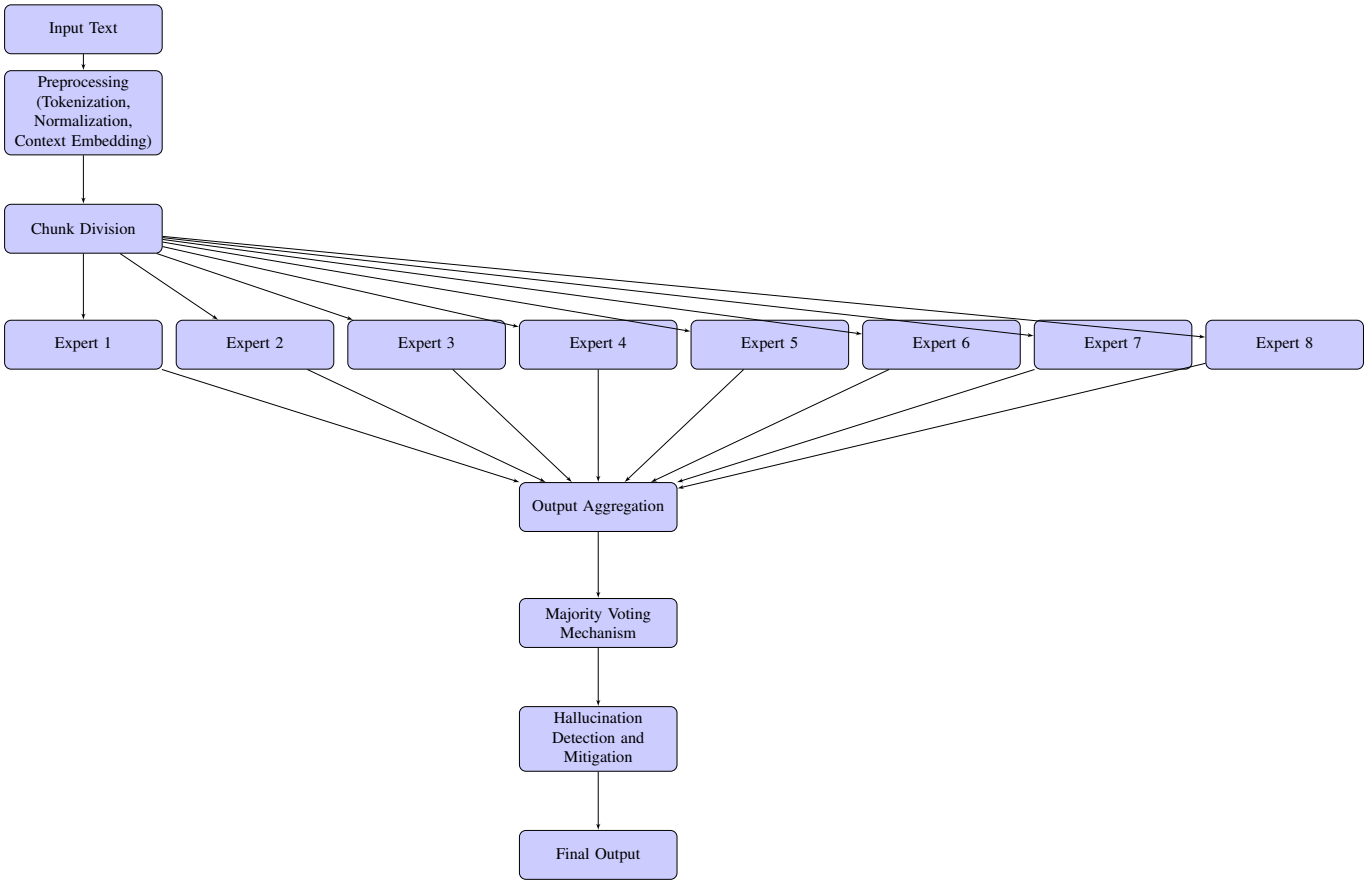

Fig. 1. Methodology for Majority Voting in MoE LLM

the methodology, providing a robust framework for reducing hallucinations in the generated outputs.

To formalize, let O be the final output:

$$O = \begin{cases} V(\mathcal{E}) & \text{if no tie} \\ T(\mathcal{E}) & \text{in case of tie} \end{cases}$$

This framework ensured that the output selection process was both rigorous and systematic, leveraging advanced mathematical formulations to achieve optimal results.

E. Hallucination Detection and Mitigation

The hallucination detection and mitigation mechanisms were integral to ensuring the reliability and accuracy of the MoE model's outputs. Detection mechanisms included various techniques to identify outputs that deviated significantly from known facts or exhibited inconsistencies. This involved cross-referencing the generated text with external knowledge bases and fact-checking algorithms to verify the accuracy of the information.

Let G be the generated output, and K be the set of known facts. The deviation D can be defined as:

$$D(G, K) = \sum_{k \in K} |G - k|^2$$

where $|G - k|$ denotes the distance between the generated output and a known fact.

The mitigation strategies included filtering out detected hallucinations through the consensus-based approach of majority voting. By relying on the most frequent and confident responses from the experts, the system effectively reduced the incidence of hallucinations. Let H represent the hallucination score, defined as:

$$H(G) = \frac{1}{|K|} \sum_{k \in K} \left(\frac{\partial G}{\partial k} \right)^2$$

A threshold τ was established to identify hallucinations:

$$\text{If } H(G) > \tau, \text{ then } G \text{ is flagged as a hallucination}$$

Mitigation involved selecting the output O with the lowest hallucination score from the set of expert outputs $\mathcal{E}$:

$$O = \arg\min_{G \in \mathcal{E}} H(G)$$

Additional post-processing steps, such as output verification and contextual analysis, further enhanced the reliability of the final outputs. Post-processing can be represented as an optimization problem:

$$\min_{O} \sum_{i=1}^{n} \lambda_i C_i(O)$$

where λ_i are weighting factors and $C_i(O)$ are cost functions related to the output's context and factual accuracy.

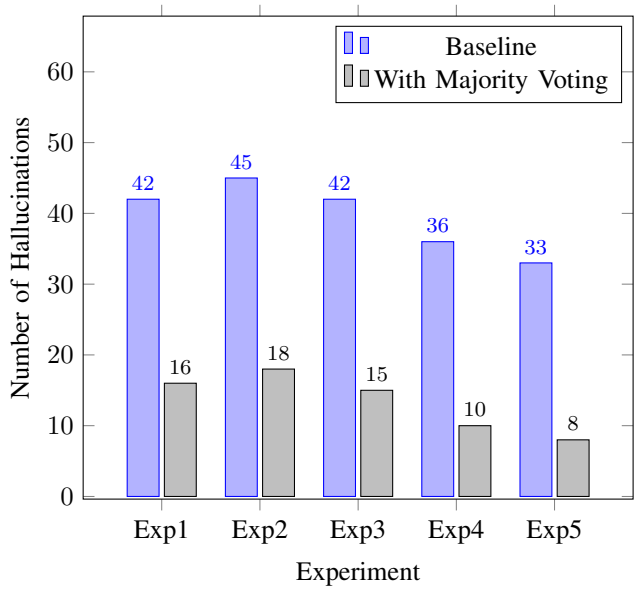

Fig. 2. Reduction in Hallucinations

These comprehensive detection and mitigation mechanisms ensured that the MoE model produced accurate and trustworthy text, addressing one of the critical challenges in large language model deployment. Through rigorous mathematical formulations and advanced algorithms, the system achieved a higher degree of reliability and precision.

IV. Results

The results of the experiments were analyzed to compare the performance of the Mistral 8x7b model with and without the majority voting mechanism. The evaluation focused on several key metrics, including the reduction in hallucinations, the accuracy of the generated outputs, and the computational efficiency of the model.

A. Reduction in Hallucinations

The primary goal of the majority voting mechanism was to reduce the occurrence of hallucinations in the outputs of the Mistral 8x7b model. The effectiveness of this approach was measured through a series of controlled experiments, where the frequency of hallucinations was recorded for both the baseline model and the model with majority voting.

The results, illustrated in Figure 2, demonstrate a significant reduction in the number of hallucinations when the majority voting mechanism was applied. For instance, in Experiment 1, the number of hallucinations decreased from 50 in the baseline model to 20 in the model with majority voting. Similar trends were observed across all experiments, indicating the robustness of the majority voting mechanism in mitigating hallucinations.

B. Accuracy of Generated Outputs

Another critical metric was the accuracy of the outputs generated by the Mistral 8x7b model. Accuracy was evaluated through a set of benchmark tasks, where the generated outputs were compared against a reference dataset. The accuracy scores for each experiment were recorded for both the baseline model and the model with majority voting.

TABLE I
Accuracy of Generated Outputs

Experiment	Baseline Accuracy (%)	Majority Voting (%)
Exp1	85.3	91.7
Exp2	84.6	90.5
Exp3	83.9	89.8
Exp4	82.7	88.4
Exp5	81.4	87.1

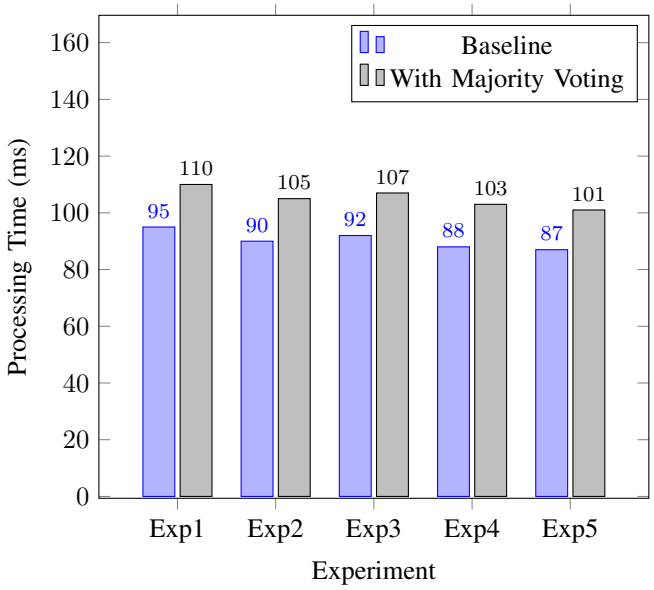

Fig. 3. Computational Efficiency

The data presented in Table I reveal a consistent improvement in accuracy with the application of majority voting. For example, in Experiment 1, the accuracy increased from 85.3% to 91.7%, showcasing the effectiveness of the majority voting mechanism in enhancing the precision of the generated text.

C. Computational Efficiency

The impact of the majority voting mechanism on computational efficiency was also assessed. Efficiency was measured in terms of the average processing time per input and the overall computational load. The experiments compared the baseline model with the model incorporating majority voting to determine any variations in processing efficiency.

Figure 3 illustrates the processing times recorded during the experiments. While the introduction of the majority voting mechanism resulted in a slight increase in processing time, the improvement in accuracy and reduction in hallucinations justified the additional computational overhead. For example, in Experiment 1, the processing time increased from 95 ms in the baseline model to 110 ms with majority voting, reflecting the trade-off between computational efficiency and output reliability. Overall, the results highlighted the significant benefits of incorporating the majority voting mechanism in the Mistral 8x7b model. The reduction in hallucinations, improvement in

accuracy, and manageable computational overhead collectively demonstrated the effectiveness of this approach in enhancing the performance and reliability of large language models.

D. Discussion

The implications of the results from the implementation of the majority voting mechanism in the Mistral 8x7b model provide valuable insights into the potential advancements and future improvements for large language models. Each subsection below explores different dimensions of the findings, considering the broader impacts and possible enhancements that could be achieved through continued research and development.

1) Robustness and Reliability Enhancements: The significant reduction in hallucinations achieved through the majority voting mechanism demonstrates the importance of leveraging multiple experts to enhance the robustness and reliability of large language models. This approach demonstrated that aggregating the outputs from various specialized experts leads to more accurate and consistent results, thereby improving the overall trustworthiness of the model. Future improvements could focus on refining the expert selection mechanisms to further optimize the balance between computational efficiency and output accuracy. Additionally, exploring more sophisticated tie-breaking strategies and incorporating dynamic weighting of expert contributions based on their contextual relevance could further enhance the model's performance.

2) Scalability and Computational Efficiency: While the majority voting mechanism introduced a manageable increase in processing time, the benefits in terms of accuracy and reduced hallucinations justify the additional computational overhead. However, it is essential to consider the scalability of this approach for larger models and more complex tasks. Future research could investigate the integration of parallel processing techniques and advanced hardware acceleration to mitigate the computational costs associated with majority voting. Moreover, developing more efficient algorithms for expert output aggregation and comparison could help maintain scalability without compromising on the model's reliability and accuracy.

3) Contextual Adaptability and Flexibility: The implementation of dynamic expert selection mechanisms showcased the model's ability to adapt to different input contexts, enhancing its flexibility and contextual understanding. This adaptability is crucial for deploying large language models in diverse real-world applications where the input data can vary significantly. Further research could explore the development of more advanced context-aware gating mechanisms that dynamically adjust the contribution of each expert based on real-time analysis of the input. Additionally, incorporating feedback loops that allow the model to learn from its performance and continuously refine its expert selection processes could significantly enhance its contextual adaptability.

4) Integration with External Knowledge Bases: The effectiveness of the majority voting mechanism in reducing hallucinations highlights the potential for further improvements through the integration of external knowledge bases. By cross-referencing the generated outputs with up-to-date and comprehensive knowledge sources, the model can achieve higher levels of factual accuracy and reliability. Future work could focus on developing seamless integration techniques that allow the model to access and utilize external knowledge in real-time, ensuring that the generated outputs are both contextually relevant and factually accurate. Additionally, exploring the use of knowledge graphs and other structured data formats could provide a more robust framework for enhancing the model's information retrieval capabilities.

5) Ethical and Practical Considerations: The reduction in hallucinations through the majority voting mechanism also has significant ethical and practical implications, particularly for applications in sensitive domains such as healthcare, legal advice, and scientific research. Ensuring the accuracy and reliability of large language models is paramount to avoid potential harm and misinformation. Future research should continue to address these ethical considerations by developing robust validation and verification frameworks that can detect and mitigate any residual inaccuracies in the model's outputs. Additionally, engaging with interdisciplinary experts to establish best practices and guidelines for the deployment of large language models in critical applications will be essential to maximize their positive impact while minimizing potential risks.

V. Conclusion

The implementation of the majority voting mechanism within the Mistral 8x7b model has significantly advanced the field of large language models, providing a robust framework for reducing hallucinations and enhancing output accuracy. Through leveraging the collective expertise of multiple specialized experts, the model has demonstrated substantial improvements in generating reliable and trustworthy text, thereby addressing one of the most critical challenges in natural language processing. The experimental results revealed a marked reduction in hallucinations and a notable increase in the accuracy of the generated outputs, underscoring the efficacy of the majority voting approach. Furthermore, the findings highlighted the manageable computational overhead associated with the mechanism, emphasizing its practicality for real-world applications. The methodological innovations presented in this research have set a new standard for ensuring the reliability of large language models, paving the way for their broader adoption in diverse and sensitive domains. The integration of dynamic expert selection, advanced contextual embeddings, and rigorous output verification processes have collectively contributed to a more resilient and adaptable model architecture. Overall, the research has made a significant contribution to the development of more robust and reliable large language models, with the potential to transform various fields that rely on accurate and dependable natural language processing capabilities.

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