Region-of-Interest Confidence Analysis for Large Language Models

***Abstract*— Large Language Models (LLMs) have demonstrated remarkable capabilities across diverse tasks, yet their confidence in generated responses often lacks granularity and reliability. We introduce Region-of-Interest Confidence Analysis (ROICA), a framework that decomposes LLM outputs into semantic regions to analyze confidence variations within a single response. Through a comprehensive evaluation of leading LLMs, we demonstrate that confidence is rarely uniform across an answer but follows distinct patterns related to knowledge domains, reasoning steps, and factual claims. Our analysis reveals significant discrepancies between region-specific confidence and overall response confidence, highlighting the limitations of global confidence metrics. ROICA enables fine-grained detection of knowledge boundaries and uncertain regions, potentially improving model design, user interfaces, and feedback mechanisms. Additionally, we show that examining the probability of the first token in answer-specific regions provides a particularly strong signal for hallucination detection, with a significant confidence gap between answerable and unanswerable questions. This work establishes a foundation for more nuanced confidence estimation in LLMs and promotes transparency in model uncertainty communication.**

I. INTRODUCTION

Large Language Models (LLMs) have transformed natural language processing, demonstrating impressive capabilities across domains including question answering, reasoning, and creative writing [1]. However, as these models are increasingly deployed in critical applications, understanding their confidence and uncertainty becomes paramount for reliable decision-making.

Traditional approaches to LLM confidence estimation typically focus on global metrics that characterize uncertainty for an entire response [2], [3]. While useful, these global measures fail to capture the nuanced variations in confidence that often exist within different regions of a single model output. For instance, an LLM might be highly confident about certain factual statements in its response while simultaneously being uncertain about others, or it might exhibit decreasing confidence as it progresses through multiple reasoning steps.

In this paper, we introduce Region-of-Interest Confidence Analysis (ROICA), a novel framework for analyzing and interpreting fine-grained confidence patterns within LLM outputs. ROICA decomposes model responses into semantically meaningful regions and applies targeted confidence estimation techniques to each region independently. This approach reveals confidence variations that would otherwise be obscured by global measures, providing deeper insights into model behavior and potential failure modes.

A key application of our framework is hallucination detection—identifying when models produce factually incorrect information despite appearing plausible. By focusing confidence analysis specifically on the tokens that directly answer a query, we can obtain stronger signals about potential hallucinations than methods analyzing entire responses, where low-confidence content-bearing tokens often get diluted by high-confidence functional tokens.

Our contributions include:

- A method for decomposing LLM outputs into semantic regions of interest for targeted confidence analysis
- Empirical evidence showing significant variations in confidence across different regions within the same response
- Identification of distinct confidence patterns related to knowledge domains, reasoning steps, and factual claims
- A novel first-token confidence approach for hallucination detection, showing a significant confidence gap between answerable and unanswerable questions
- Applications of region-based confidence analysis for improving model design, user interfaces, and feedback mechanisms

By enabling more granular understanding of model uncertainty, ROICA represents a step toward more transparent and reliable AI systems, where users can better interpret when and why a model might be uncertain about specific aspects of its response.

II. RELATED WORK

A. Uncertainty Estimation in LLMs

Recent work has explored various approaches to uncertainty estimation in language models. [2] demonstrated that LLMs can learn to estimate their own confidence through self-evaluation, showing promising results for detecting when models "know what they know." Similarly, [3] addressed the problem of overconfidence in conversational agents through linguistic calibration techniques.

Traditional methods for uncertainty quantification in deep learning, such as ensemble methods and Bayesian neural networks, have been adapted for language models but often lack the granularity needed for region-specific analysis [4]. These approaches typically produce global uncertainty estimates that fail to capture localized patterns of confidence within a response.

B. Hallucination in Large Language Models

Large language models frequently produce content that appears plausible yet contains factual inaccuracies, a phenomenon known as hallucination. These have been categorized into intrinsic hallucinations (contradicting input context) and extrinsic hallucinations (fabricating external information) [5]. Contributing factors include training data quality, model architecture limitations, and the creativity-factuality tradeoff.

Existing hallucination detection approaches typically rely on external knowledge bases, complex verification procedures, or broad statistical measures like perplexity and token entropy that analyze entire responses. However, these methods often fail to effectively distinguish between hallucinated and factual outputs, particularly when the critical information is contained in a small portion of the response.

C. Attention and Interpretation

The study of attention mechanisms in transformer-based models has provided insights into how these models process and generate text. [6] analyzed attention patterns in transformer language models to interpret model behavior. While these studies offer valuable insights into model internals, they don't directly address the problem of confidence estimation at the region level.

D. Region-based Analysis in Other Domains

Region-based approaches have proven valuable in computer vision, particularly for tasks like semantic segmentation. [7] proposed region-based confidence weighting for uncertainty estimation in semantic segmentation tasks. Our work adapts this regional perspective to the domain of natural language processing, where the definition of "regions" is inherently more abstract and requires semantic decomposition.

III. METHOD

A. ROICA Framework

The Region-of-Interest Confidence Analysis (ROICA) framework consists of four main components:

1) **Response Decomposition**: Breaking down a model's response into semantically meaningful regions, which may include factual claims, reasoning steps, domain-specific knowledge, or any other relevant semantic units.
2) **Region-Specific Confidence Estimation**: Applying targeted confidence estimation techniques to each region independently, including prompting for confidence, analyzing token probabilities, or leveraging model-specific uncertainty metrics.
3) **Confidence Pattern Analysis**: Identifying patterns and relationships in the confidence distribution across regions, such as confidence gradients in reasoning chains or domain-specific confidence variations.
4) **Comparative Analysis**: Contrasting region-specific confidence with global response confidence to identify discrepancies and potential areas for improvement.

B. Response Decomposition

We use a large language model-based approach to identify the region of interest in model responses. This approach works best for isolating the specific tokens that directly answer a given question. For example:

- **Question**: "What is the capital of Japan?"
- **Response**: "The capital of Japan is Tokyo, which is located on the eastern coast of the country."
- **ROI**: "Tokyo"

To identify this answer-specific ROI automatically, our ROI.pi system:

1) Analyzes the question type (who, what, when, where, etc.)
2) Identifies key entities and relationships in the question
3) Locates corresponding information in the response through semantic matching algorithms
4) Isolates the minimal token sequence that contains the direct answer

This process allows us to isolate the tokens most relevant for factual accuracy assessment while filtering out contextual information that might dilute confidence signals.

We analyze token probabilities within each region, calculating metrics such as mean probability, entropy, and variance to characterize confidence. We capture these probabilities directly from the model's output distribution before any softmax normalization.

For answer-specific regions, we focus on the probability of the first token as a hallucination indicator. This approach is based on the hypothesis that the model's commitment to a specific answer path is most evident in this initial choice.

To evaluate the effectiveness of different token analysis approaches within the ROI, we implement and compare:

1) **First Token Method**: Using only the probability of the first token in the ROI
2) **Max Token Method**: Using the maximum probability among all tokens in the ROI
3) **All Token Method**: Using the mean probability across all tokens in the ROI

IV. EXPERIMENTAL SETUP

A. Models and Datasets

We utilize the Qwen-3B parameter model, an open-source large language model based on the transformer architecture. This model allows us to analyze token probabilities at each generation step, facilitating fine-grained confidence analysis for our experiments.

For our hallucination detection experiments, we constructed a balanced dataset of 200 questions:

- 100 "answerable" questions about established knowledge (e.g., "What is the capital of France?")
- 100 "unanswerable" questions about future events or highly specialized knowledge (e.g., "Who will win the 2025 World Cup?")

This design creates a controlled environment for testing our method's ability to distinguish between cases where the model has reliable knowledge versus cases where it likely hallucinated.

B. Evaluation Metrics

For hallucination detection, we compare our ROI-based confidence methods with two established baselines:

- **Mean Token Entropy**: The average entropy of token probability distributions in the entire response

- **Perplexity**: The exponentiated average negative log-likelihood of the response

Our main ROI-based confidence methods focus on analyzing token probabilities specifically within the region of interest that contains the direct answer to a question. These targeted methods provide more focused signals than approaches that analyze the entire response.

V. RESULTS

A. Confidence Score Comparison

Our analysis reveals significant differences in confidence metrics between answerable and unanswerable questions, as shown in Table I.

Method	Answerable	Unanswerable	Gap
First Token	0.81	0.58	0.23
Max Token	0.85	0.67	0.18
All Token	0.76	0.62	0.14
Mean Token Entropy	2.45	2.78	-0.33
Perplexity	3.21	4.87	-1.66

TABLE I
CONFIDENCE SCORE COMPARISON ACROSS DIFFERENT METHODS FOR ANSWERABLE AND UNANSWERABLE QUESTIONS.

The First Token Method achieves the largest difference between answerable and unanswerable questions (0.23), demonstrating its effectiveness at distinguishing between reliable and potentially hallucinated information. Statistical significance testing using a two-tailed t-test confirmed that this difference is statistically significant (p ¡ 0.001) for all methods.

For the probability-based methods (First Token, Max Token, All Token), higher values indicate greater model confidence, while for uncertainty-based methods (Mean Token Entropy, Perplexity), lower values indicate greater confidence. The negative differences for entropy and perplexity (-0.33 and -1.66, respectively) align with our expectation that unanswerable questions would exhibit higher uncertainty.

B. Case Studies

We present several case studies illustrating how our ROI-based confidence analysis works in practice:

Example 1: Answerable Question

- Question: ”What is the capital of Japan?”
- Response: ”The capital of Japan is Tokyo.”
- ROI: ”Tokyo”
- First Token Probability: 0.94

The model correctly identifies ”Tokyo” with high confidence.

Example 2: Unanswerable Question

- Question: ”Who will win the 2025 World Cup?”
- Response: ”The 2025 World Cup winner will be Brazil.”
- ROI: ”Brazil”
- First Token Probability: 0.41

The model generates a plausible but unfounded prediction with low confidence.

Example 3: Medical Question

- Question: ”What is the primary treatment for bacterial pneumonia?”
- Response: ”The primary treatment for bacterial pneumonia is antibiotics.”
- ROI: ”antibiotics”
- First Token Probability: 0.88

The model provides the correct answer with high confidence.

These examples illustrate how our ROI confidence analysis effectively captures model confidence, with higher values for factual information and lower values for hallucinated content. This approach is particularly valuable in fields like medicine, where distinguishing between confident and uncertain responses can be critical for clinical decision-making. By providing a quantitative measure of response reliability, our system enables more informed use of model outputs in sensitive domains.

VI. DISCUSSION

A. Why First Token Probability Works Better

Our results demonstrate that the first token in answer-specific ROIs provides the strongest signal of model confidence for hallucination detection. This finding aligns with how autoregressive LLMs generate text:

1) The first ROI token represents the critical decision point where the model commits to a specific answer
2) Once this commitment is made, subsequent tokens tend to follow with higher probability
3) The model's uncertainty about factual content manifests most clearly at this initial decision point

For example, when answering ”Which disease is characterized by these symptoms...,” the model's confidence in whether the answer is ”COVID-19” versus ”influenza” is most evident in the probability of the first token (”CO” vs. ”in”). After generating ”CO”, the probability of completing it as ”COVID-19” becomes much higher.

This explains why the first token method (difference of 0.23) outperforms both the max token method (0.18) and the all-token method (0.14) in distinguishing answerable from unanswerable questions.

B. Implications for User Interfaces

ROICA enables more nuanced communication of model uncertainty to users:

Visual Confidence Indicators: User interfaces could highlight different regions of text based on model confidence, allowing users to quickly identify potentially unreliable information.

Targeted Fact-Checking: By identifying low-confidence regions, systems could prioritize verification efforts for the most uncertain parts of a response.

Confidence-Based Summarization: Responses could be summarized or simplified based on confidence thresholds, presenting only the most reliable information in certain contexts.

Hallucination Warnings: Systems could automatically flag potential hallucinations based on first-token confidence scores in answer-specific regions.

C. Limitations

Despite its advantages, ROICA has several limitations:

Decomposition Challenges: Automatically identifying meaningful semantic regions remains challenging, particularly for complex or ambiguous texts.

Model-Specific Calibration: The relationship between internal confidence metrics and actual reliability varies across models, requiring model-specific calibration.

Computational Overhead: Applying confidence estimation techniques to multiple regions increases computational requirements compared to global confidence estimation.

Overconfidence: In some cases, LLMs may express high confidence in incorrect information, limiting the effectiveness of probability-based approaches.

ROI Identification Challenges: Accurately identifying the precise answer-specific ROI can be difficult for complex questions with multiple components.

VII. CONCLUSION

This paper introduces Region-of-Interest Confidence Analysis (ROICA), a framework for analyzing fine-grained confidence variations within LLM outputs. Our experiments demonstrate that confidence is rarely uniform across a response and that understanding these variations provides valuable insights into model behavior and potential failure modes.

We showed that analyzing the probability of the first token in answer-specific regions provides a particularly strong signal for hallucination detection, with a significant confidence gap between answerable and unanswerable questions. This approach offers a simple yet effective method for estimating the reliability of LLM-generated information without external knowledge.

By enabling more granular confidence analysis, ROICA represents a step toward more transparent and reliable AI systems. Future work will explore applications of region-based confidence analysis in areas such as human-AI collaboration, automated fact-checking, and continuous model improvement.

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