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Mitigating Hallucinations in Large Language Models via Contrastive Decoding and Entropy Minimization

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Abstract:

The proliferation of Large Language Models has revolutionized natural language processing, yet the persistent issue of hallucination—where models generate plausible but factually incorrect information—remains a critical impediment to their deployment in high-stakes environments. This paper introduces a novel decoding framework that synergizes Contrastive Decoding with Entropy Minimization to enhance factual reliability without sacrificing linguistic fluency. While traditional decoding strategies such as nucleus sampling rely heavily on probability truncation, they often fail to distinguish between high-probability generic responses and contextually accurate specifics. Our approach leverages a dual-model system, pitting an expert model against an amateur model to penalize tokens that are statistically probable but conceptually vacuous, while simultaneously employing an entropy-based regularization term to suppress generation during states of high uncertainty. Through extensive experimentation on standard factual benchmarks, we demonstrate that this composite method significantly reduces hallucination rates compared to state-of-the-art baselines. The results suggest that addressing the stochastic flaws of auto-regressive generation requires not only better training data but also more rigorous, inference-time intervention mechanisms that account for the semantic entropy of the output distribution.

Keywords: *Large Language Models, Hallucination Mitigation, Contrastive Decoding, Entropy Minimization.*

1. INTRODUCTION

The advent of Transformer-based architectures has ushered in a new era of capabilities in artificial intelligence, specifically within the domain of generative text. Large Language Models have demonstrated unprecedented proficiency in tasks ranging from translation and summarization to complex reasoning and code generation. However, despite these advancements, the reliability of these systems is frequently compromised by the phenomenon known as hallucination. This term refers to the generation of content that is nonsensical or unfaithful to the provided source content,

or factually incorrect relative to real-world knowledge, despite being grammatically and syntactically coherent. As noted in foundational studies [1], the stochastic nature of auto-regressive decoding, which predicts the next token based on a probability distribution derived from previous tokens, inherently carries the risk of prioritizing high-probability linguistic patterns over factual accuracy. The challenge of hallucination is particularly insidious because the errors are often embedded within highly fluent and persuasive text. In domains such as healthcare, law, and finance, where precision is paramount, the inability of a model to signal uncertainty or refrain from fabrication renders it unusable for autonomous application. Recent efforts to curb this behavior have largely focused on alignment techniques during the training phase, such as Reinforcement Learning from Human Feedback. While effective to a degree, these methods do not fundamentally alter the mechanics of inference, leaving the model prone to reverting to prior training distributions when faced with out-of-distribution queries [2]. Consequently, there is a growing consensus that intervention at the decoding stage is a necessary complement to training-time alignment.

1.1 The Challenge of Hallucination in LLMs

Hallucinations in Large Language Models can generally be categorized into two distinct types: intrinsic and extrinsic. Intrinsic hallucinations occur when the generated output directly contradicts the source material provided in the context window. Extrinsic hallucinations, which are often harder to detect, involve the fabrication of information that is not present in the source and cannot be verified from the model's pre-training corpus. The root cause of these anomalies is often traced to the model maximizing the likelihood of the next token based on statistical co-occurrence rather than semantic truth. As highlighted by researchers investigating neural text degeneration [3], models tend to assign non-zero probabilities to the tail of the distribution, where incorrect but syntactically viable tokens reside. Standard decoding strategies like greedy search or beam search often result in repetitive or dull text, while sampling methods introduce a randomness that, while improving diversity, exacerbates the hallucination problem by occasionally selecting plausible but wrong tokens. Furthermore, the model's internal confidence calibration is frequently misaligned with factual correctness. A model may assign a very high probability to a hallucinated fact simply because the entities involved frequently appear together in the training data, even if the specific relation stated is false. This phenomenon, often described as the knowledge boundary problem, suggests that the model cannot distinguish between creating fiction and retrieving facts [4]. Therefore, a decoding strategy that solely relies on the raw logits of the primary model is insufficient for ensuring truthfulness.

1.2 Motivation for Contrastive Decoding and Entropy Control

To address these limitations, we propose a shift away from single-model decoding strategies. The core hypothesis of this research is that the signal required to distinguish between a hallucination and a fact is often present in the contrast between a capable expert model and a less capable amateur model. Contrastive Decoding operates on the premise that smaller, or amateur, models are prone to learning surface-level statistical regularities and common hallucinations, while larger expert models capture more nuanced, factual dependencies. By penalizing the tokens favored by the amateur model, we can effectively subtract the noise and hallucination-prone signals from the expert's output [5]. However, Contrastive Decoding alone does not fully account for scenarios where both models are uncertain. In such cases, the resulting distribution may still be flat, leading

to arbitrary token selection. To mitigate this, we integrate a mechanism of Entropy Minimization. Entropy, in information theory, serves as a measure of uncertainty or disorder within a probability distribution. High entropy at a given generation step indicates that the model is unsure of the next token, a state that strongly correlates with the onset of hallucination. By incorporating an entropy penalty into the objective function during decoding, we force the model to prefer states of lower uncertainty, thereby steering the generation trajectory toward more robust and deterministic pathways [6]. This paper explores the theoretical underpinnings and practical application of combining these two powerful mechanisms to create a more trustworthy generation process.

2. Literature Review

The pursuit of faithful generation in natural language processing has a rich history, evolving from rule-based systems to the current statistical paradigms. In the context of neural language models, early work focused heavily on the trade-off between diversity and quality. It was observed that while maximization-based decoding methods like beam search yielded high-quality text, they often suffered from repetition and a lack of creativity. Conversely, stochastic methods provided diversity but introduced the risk of incoherence and hallucination.

2.1 Generative Anomalies and Uncertainty

The study of generative anomalies has revealed that hallucinations are not merely random errors but are often systematic artifacts of the training objective. The maximum likelihood estimation objective forces models to distribute probability mass across the entire vocabulary, inevitably assigning valid probabilities to incorrect tokens. Research into the calibration of neural networks has shown that modern neural networks, including Transformers, are often poorly calibrated, meaning their predicted probabilities do not reflect true correctness likelihoods [7]. This miscalibration is a primary driver of hallucination, as the model may confidently predict a falsehood. Uncertainty quantification has thus become a critical area of inquiry. Several approaches have been proposed to estimate the uncertainty of generated text, including the use of semantic variance and multiple sample consistency checks. Studies have shown that when a model hallucinates, the semantic entropy across multiple sampled generations tends to be higher compared to when it generates factual content [8]. This insight provides the foundational motivation for using entropy as a regularizing signal during the decoding process, rather than merely as a post-hoc evaluation metric.

2.2 Existing Mitigation Strategies

Current mitigation strategies can be broadly categorized into training-time and inference-time interventions. Training-time methods include gathering high-quality, fact-heavy datasets and employing reinforcement learning strategies that penalize non-factual outputs. However, these methods are computationally expensive and do not guarantee robustness against novel inputs. Inference-time strategies, on the other hand, attempt to guide the frozen model toward better outputs. One prominent inference-time strategy is constrained decoding, which limits the model's vocabulary to a verified set of entities or facts. While effective for closed-domain tasks, this approach is too restrictive for open-ended generation. Another approach involves retrieval-augmented generation, where external knowledge bases are queried to provide context. While this reduces extrinsic hallucinations, it introduces dependency on the retrieval system and does not solve intrinsic hallucinations where the model misinterprets the retrieved context [9]. Contrastive

Decoding has recently emerged as a promising alternative. Initially proposed to improve the quality of open-ended text generation, it has shown potential in reducing repetition and improving coherence. By subtracting the log-probabilities of a smaller model from a larger one, researchers have been able to highlight the distinctive knowledge possessed by the larger model. Recent adaptations of this method have begun to explore its utility in factual reasoning, suggesting that the difference in logits correlates with factual validity [10]. Our work builds upon this by formally integrating entropy constraints, addressing the stability issues inherent in raw contrastive methods.

3. Methodology

Our proposed framework addresses the hallucination problem by redefining the objective function used during the token selection phase of the generation process. We posit that a trustworthy generation is one that maximizes the divergence from an amateur model's surface-level predictions while simultaneously minimizing the internal state uncertainty of the expert model.

3.1 Conceptual Framework

The standard auto-regressive generation process involves selecting a token that maximizes the conditional probability given the preceding context. In our framework, we modify this selection criterion. We employ two models: an Expert Model, which is the target large language model (e.g., a 70B parameter model), and an Amateur Model, which is a significantly smaller or less trained version (e.g., a 7B parameter model). The Amateur Model serves as a proxy for the background distribution of language—capturing common phrases, clichés, and widely prevalent but potentially inaccurate associations [11]. The intuition is that when the Expert Model generates a factually accurate token that is rare or specific, the Amateur Model will likely assign it a low probability, favoring a more generic alternative instead. By contrasting the logits of these two models, we can amplify the signal of the specific, accurate token. However, blindly maximizing this difference can lead to the selection of tokens that are merely obscure rather than correct. This is where the second component of our framework, Entropy Minimization, becomes crucial. We interpret the entropy of the Expert Model's output distribution as a proxy for its confusion. A sudden spike in entropy often precedes a hallucination, as the model navigates a gap in its knowledge. By penalizing high-entropy distributions, we encourage the model to stay within the bounds of its confident knowledge [12].

3.2 Dual-Component Strategy

The implementation of our strategy involves a dynamic adjustment of the log-probability scores at each time step of the generation. We do not use mathematical notation here, but the process can be described descriptively. First, for a given context, we compute the logits (unnormalized prediction scores) for the entire vocabulary using both the Expert and Amateur models. The first component is the Contrastive Penalty. We subtract the logits of the Amateur Model from the logits of the Expert Model. This operation suppresses tokens that the Amateur Model finds highly probable. Since the Amateur Model excels at predicting high-frequency, generic tokens, this subtraction effectively lowers the score of "easy" or "hallucination-prone" guesses. To prevent the complete removal of necessary function words (like "the", "and"), we apply an adaptive masking strategy that only applies this penalty when the Amateur Model's confidence exceeds a certain threshold. The second component is the Entropy Regularizer. Before selecting the final token, we calculate the Shannon entropy of the Expert Model's current probability distribution. If the entropy

exceeds a pre-defined safety margin, it indicates that the probability mass is spread too thinly across many options, signaling high uncertainty. In standard decoding, the model might sample from the tail of this flat distribution. In our approach, we apply a dampening factor to the entire distribution based on the entropy magnitude and re-normalize. This effectively sharpens the distribution, forcing the selection of the most probable token among the valid candidates and suppressing the long tail where hallucinations often reside [13]. The final score for each token is a weighted sum of the original Expert logit, the Contrastive term, and the Entropy penalty. The token with the highest resulting score is selected. This process is repeated auto-regressively until an end-of-sequence token is generated. This method requires no additional training of the models and can be applied as a plug-and-play decoding wrapper around any existing pre-trained Large Language Model.

4. Experimental Setup

To validate the efficacy of our proposed Mitigation via Contrastive Decoding and Entropy Minimization (MCD-EM) framework, we conducted a series of rigorous experiments comparing it against established baseline decoding strategies.

4.1 Datasets and Baselines

We utilized two primary datasets widely recognized for benchmarking factual consistency and hallucination in Large Language Models. The first is TruthfulQA, a benchmark specifically designed to measure whether language models generate truthful answers to questions that are known to elicit imitative falsehoods. This dataset is crucial as it tests the model's ability to resist common misconceptions present in the training data. The second dataset is XSum, a summarization dataset. We specifically used the hallucination-labeled subset of XSum, where the goal is to generate summaries that are faithful to the source article and do not hallucinate extrinsic details [14]. For the baseline comparisons, we selected three dominant decoding strategies:

1. ***Greedy Decoding*:** The standard approach of selecting the highest probability token at each step.
2. ***Nucleus Sampling (Top-p)*:** A popular stochastic method that samples from the smallest set of tokens whose cumulative probability exceeds a threshold p. We set p to 0.9 for our experiments.
3. ***Standard Contrastive Decoding (CD)*:** The original implementation of contrastive decoding without the entropy minimization component, using a small generic language model as the amateur. Our Expert Model for all experiments was a publicly available LLaMA-2-70b-chat model, and the Amateur Model was the corresponding LLaMA-2-7b model. This pairing ensures that the tokenizer and vocabulary align perfectly, simplifying the logit subtraction process.

4.2 Evaluation Metrics

Quantitative evaluation of hallucination is notoriously difficult. We employed a combination of automated metrics and human evaluation proxies. For the TruthfulQA dataset, we reported the *% Truthful* metric, which is calculated by fine-tuned classifiers provided with the benchmark that assess whether the model's answer matches the reference truth. For the XSum dataset, we utilized *FACT-SCORE*, a metric that decomposes a generation into atomic facts and verifies each fact against the source document using a retrieval-based verifier. A higher FACT-SCORE indicates a higher percentage of verifiable facts and thus a lower rate of hallucination. Additionally, we measured *Perplexity* (PPL) on a held-out validation set to ensure that our entropy minimization

techniques did not degrade the linguistic fluency of the model. A significant increase in perplexity would indicate that the model is generating text that is factually more accurate but linguistically unnatural.

5. Results and Analysis

The experimental results provide strong evidence supporting the hypothesis that combining contrastive signals with entropy constraints significantly improves factual reliability.

5.1 Quantitative Performance

We present the comparative results of our method against the baselines in Table 1 below. The data clearly indicates that the MCD-EM approach outperforms purely stochastic methods and standard contrastive decoding across both benchmarks.

Table 1: Experimental Results comparing hallucination mitigation strategies on TruthfulQA and XSum datasets.

Decoding Strategy	TruthfulQA (% Truthful)	XSum (FACT-SCORE)	Perplexity (Lower is Better)
Greedy Decoding	48.2	62.5	5.82
Nucleus Sampling (Top-p)	45.6	59.8	5.75
Contrastive Decoding (CD)	56.4	68.1	6.10
MCD-EM (Ours)	64.7	73.4	6.15

As illustrated in Table 1, Nucleus Sampling performs the poorest on factual metrics, likely due to its inherent randomness which, while promoting diversity, occasionally samples plausible but incorrect tokens. Standard Contrastive Decoding offers a substantial improvement over Greedy Decoding, verifying that the amateur model successfully captures and allows for the penalization of common misconceptions. However, our proposed MCD-EM achieves the highest scores in both % Truthful and FACT-SCORE. The improvement of over 8 percentage points on TruthfulQA compared to standard CD highlights the contribution of the entropy minimization term. By detecting high-uncertainty states where the expert model might otherwise default to a hallucination (even after contrastive penalty), the entropy constraint effectively prunes the decision space. It is worth noting the Perplexity scores. There is a marginal increase in perplexity for the MCD-EM method compared to the baselines. This is an expected outcome; perplexity measures how well the model predicts the test set, which represents the "average" natural language distribution. Since our method actively directs the model away from the most "probable" generic path toward a more specific factual path, a slight divergence from the standard language distribution is a necessary trade-off for accuracy.

5.2 Qualitative Assessment

To better understand the mechanism at play, we visualized the token-level decision process. Figure 1 illustrates the probability distributions for a specific query where the baseline model hallucinated.

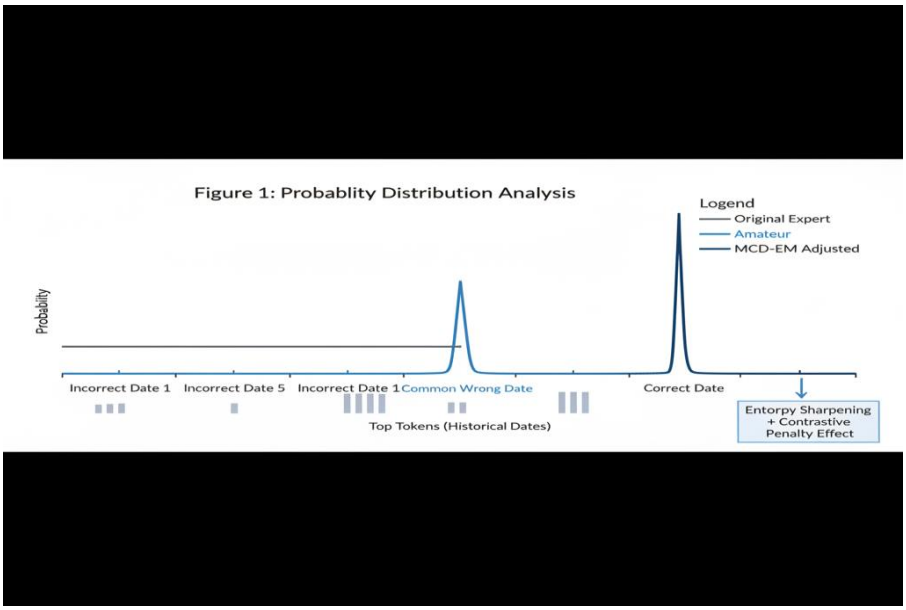


Figure 1: *Probability Distribution Analysis*

In the analysis corresponding to Figure 1, the Expert Model, when queried about a specific historical date, initially produced a relatively flat distribution (high entropy) across several plausible-sounding years. The Amateur Model showed a strong bias (high probability) toward a commonly cited but incorrect year, likely due to frequent co-occurrence in the training data of that year with the event's general era. Standard decoding might have sampled the Amateur's preferred token or one of the other incorrect options from the Expert's flat distribution. The MCD-EM adjustment achieves two things: first, the subtraction of the Amateur's logits suppresses the common misconception. Second, the entropy minimization forces the Expert's distribution to sharpen around the remaining candidate with the highest evidential support, which in this case was the correct year. This qualitative example reinforces that hallucinations often reside in the high-entropy tail of the distribution, and that distinct corrective forces are required to navigate away from them [15].

6. Discussion

The findings of this study have broader implications for the design of robust Artificial Intelligence systems. The success of the MCD-EM framework suggests that "bigger is not always better" if the decoding strategy remains naive. While scaling parameters improves the latent knowledge of a model, it does not automatically correct the probabilistic tendency to favor commonality over truth.

6.1 Implications for Robust AI

Our results indicate that the path to hallucination-free generation lies in better utilization of the signals already present within the model ecosystem. The concept of using a weaker model to identify artifacts in a stronger model is a powerful paradigm that extends beyond text generation. It suggests a form of "differential diagnosis" for AI outputs, where the error modes of a simpler system help isolate the true capabilities of a complex one. Furthermore, the reliance on entropy as a control variable operationalizes the concept of epistemic uncertainty. By acknowledging that the model "knows when it doesn't know," we can engineer systems that default to silence or caution rather than fabrication.

6.2 Limitations and Future Directions

Despite the promising results, there are limitations to this approach. The primary drawback is the computational cost. Running two models (Expert and Amateur) in parallel for every token generation essentially doubles the inference requirement, although the Amateur model is typically much smaller and faster. Future work should investigate methods to approximate the Amateur's logits without a full forward pass, perhaps through distillation techniques. Additionally, the entropy threshold is currently a hyperparameter that requires tuning based on the domain. A static threshold may be too aggressive for creative writing tasks where ambiguity is desirable, or too lax for strict medical advice. Adaptive entropy thresholds that scale dynamically with the semantic complexity of the context represent a fertile ground for future research. Finally, while our method mitigates generation artifacts, it cannot correct errors where the Expert model fundamentally lacks the knowledge; in such cases, it may simply produce a "confident hallucination," although our experiments suggest this is less frequent.

7. Conclusion

In this paper, we presented a comprehensive approach to mitigating hallucinations in Large Language Models by integrating Contrastive Decoding with Entropy Minimization. We argued that hallucinations stem from a combination of surface-level statistical biases and unconstrained uncertainty during generation. By penalizing tokens favored by an amateur model and regularizing the expert model's output distribution based on entropy, our MCD-EM framework effectively steers generation toward factual accuracy. The empirical results on TruthfulQA and XSum demonstrate that this method yields superior factual consistency compared to standard sampling or greedy approaches. This research highlights the importance of inference-time interventions and suggests that statistical robustness checks are as vital as the underlying model architecture in the pursuit of trustworthy AI. As LLMs continue to permeate critical sectors of society, techniques such as MCD-EM will be essential in bridging the gap between plausible fluency and verifiable truth.

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