

Can Your Uncertainty Scores Detect Hallucinated Entity?

Anonymous authors

Paper under double-blind review

Abstract

To mitigate the impact of hallucination nature of LLMs, many studies propose detecting hallucinated generation through uncertainty estimation. However, these approaches predominantly operate at the sentence or paragraph level, failing to pinpoint specific spans or entities responsible for hallucinated content. This lack of granularity is especially problematic for long-form outputs that mix accurate and fabricated information. To address this limitation, we explore *entity-level hallucination detection*. We propose a new data set, HALLUENTITY, which annotates hallucination at the entity level. Based on the dataset, we comprehensively evaluate uncertainty-based hallucination detection approaches across 17 modern LLMs. Our experimental results show that uncertainty estimation approaches focusing on individual token probabilities tend to over-predict hallucinations, while context-aware methods show better but still suboptimal performance. Through an in-depth qualitative study, we identify relationships between hallucination tendencies and linguistic properties and highlight important directions for future research.

1 Introduction

How can we trust the facts generated by large language models (LLMs) when even a single hallucinated entity can distort an entire narrative? While LLMs have revolutionized text generation in various domains, from summarization to scientific writing (Liang et al., 2024), their tendency to produce hallucinations—factually incorrect or unsupported content—remains a critical challenge (Xu et al., 2024). This issue is particularly concerning in high-stakes applications, such as medical diagnostics (Chen et al., 2024b), legal document drafting (Lin & Cheng, 2024), and news generation (Odabaşı & Biricik, 2025), where inaccurate information can cause harm to individuals and erosion of public trust. Detecting hallucinations is therefore a critical step toward ensuring the responsible deployment of LLMs.

Various approaches have been proposed to detect hallucinations (Luo et al., 2024), with uncertainty-based methods emerging as a promising direction (Zhang et al., 2023a). However, current uncertainty-based hallucination detection approaches mainly operate at the sentence or paragraph level, classifying the entire generation as either hallucinated or correct. While this provides a coarse-grained assessment of factuality, it lacks the granularity needed to pinpoint which specific spans or entities contribute to hallucination. This limitation is particularly problematic for long-form text, where both accurate and hallucinated information frequently coexist. For example, a generated response about a historical event might correctly state the date but fabricate details about the individuals involved, necessitating finer-grained detection.

To address these limitations, we present a first systematic exploration of *entity-level hallucination detection* by introducing a benchmark dataset, extensively evaluating uncertainty-based detection methods on this benchmark, and analyzing their strengths and limitations in identifying hallucinated entities. Specifically, we begin by constructing a benchmark for entity-level hallucination detection, HALLUENTITY, which fills in the critical blank for the field. Constructing such a dataset is challenging due to the labor-intensive nature of entity-level annotation, which requires annotators to segment meaningful entities and verify their factuality against reliable sources one by one. To overcome this, we develop a systematic pipeline that maps atomic facts from model-generated text to entity-level annotations, enabling structured hallucination detection at a finer granularity. HALLUENTITY encompasses 18,785 annotated entities, and provides a foundation for evaluating hallucination detection methods with greater interpretability and precision.

Building on HALLUENTITY, we comprehensively evaluate the reliability of token-level uncertainty measurements in detecting hallucinated entities and their potential for localizing hallucinations within the generated text. Our

evaluation broadly includes standard uncertainty estimators, such as token-level likelihood (Guerreiro et al., 2023) and entropy scores (Malinin & Gales, 2021), as well as more advanced context-aware approaches that refine uncertainty estimation (Fadeeva et al., 2024; Duan et al., 2024; Zhang et al., 2023b). By aggregating token-level uncertainty to the entity level, we assess whether these methods can accurately distinguish hallucinated entities from factual ones. We experiment with 17 modern LLMs across different model families and capacities. The results reveal that methods solely relying on individual token probabilities (e.g., likelihood and entropy) tend to over-predict hallucinations, making them less reliable. In contrast, context-aware approaches (Duan et al., 2024; Zhang et al., 2023b) demonstrate better overall performance in entity-level hallucination detection. Additionally, model family and size have a limited impact on performance, compared to the choice of uncertainty estimation method, emphasizing the need for improved uncertainty modeling.

Through in-depth qualitative analysis, we further identify relationships between hallucination tendencies and linguistic properties, such as sentence positions and entity types. We found that calibrating uncertainty score with contextual information in the best-performing method Zhang et al. (2023b) helps reduce over-confidence tendencies in later sentence positions but can unintentionally penalize non-hallucinated content. We also found that some uncertainty scores can frequently assign high uncertainty to informative content like named entities. These observations highlight critical areas for future research, including better modeling of contextual dependencies to maintain balanced precision-recall trade-offs. Our key contributions are summarized as follows:

1. We propose an entity-level hallucination detection dataset, HALLUENTITY, which contains 18,785 annotated entities for ChatGPT-generated biographies.
2. We comprehensively evaluate uncertainty-based hallucination detection approaches across 17 LLMs on our proposed dataset.
3. We conduct an in-depth analysis to identify the strengths and weaknesses of current uncertainty-based approaches, and provide insight to design better uncertainty scores.

2 Related Work

Uncertainty-based hallucination detection methods. Various approaches have been proposed to detect hallucinated content in LLMs generation. Unlike other methods that require external knowledge sources for fact-checking (Gou et al., 2024; Chen et al., 2024a; Min et al., 2023; Huo et al., 2023), uncertainty-based approaches are reference-free and rely only on LLM internal states or behaviors to determine hallucination (Huang et al., 2024). For instance, sampling-based approaches generate multiple responses and measure the diversity in meaning among them (Fomicheva et al., 2020; Kuhn et al., 2023; Lin et al., 2024), while density-based approaches approximate the training data distribution and provide probabilities or unnormalized scores to assess how likely a generated response belongs to the distribution (Yoo et al., 2022; Ren et al., 2023; Vazhentsev et al., 2023).

In this paper, we focus on uncertainty quantification methods that rely on token-level likelihood or entropy (Guerreiro et al., 2023; Malinin & Gales, 2021). Recent works have explored refining likelihood estimation by incorporating semantic relationships or reweighting token importance. For instance, Claim-Conditioned Probability (CCP) (Fadeeva et al., 2024) was introduced to recalculate likelihood according to semantical equivalence; while Zhang et al. (2023b) and Duan et al. (2024) adjust token weights to better convey meaning in uncertainty aggregation. *Although these approaches leverage token-level information, they are typically evaluated at the sentence level, raising questions about their reliability.* To address this, we conduct a comprehensive analysis of entity-level hallucination detection for finer-grained performance insights.

Fine-grained hallucination detection benchmark. Most hallucination detection benchmarks are in sentence or paragraph level. For example, CoQA (Reddy et al., 2019), TriviaQA (Joshi et al., 2017), TruthfulQA (Lin et al., 2022), and HaluEval (Li et al., 2023). These benchmarks classify each generated response as either hallucinated or correct. However, instance-level detection cannot pinpoint specific hallucinated content, which is crucial for correcting misinformation (Cattan et al., 2024). This limitation becomes particularly problematic in long-form text, where a single response often combines supported and unsupported information, making binary quality judgments inadequate (Min et al., 2023).

To address these challenges, recent works have advanced benchmarks for more granular hallucination detection. For example, Min et al. (2023) introduced FACTSCORE, which decomposes LLM-generated text into atomic facts—short

sentences conveying a single piece of information—for more precise evaluation. In parallel, Cattan et al. (2024) introduced QASEMCONSISTENCY, decomposing LLM generated text with QA-SRL, a semantic formalism, to form simple QA pairs, where each QA pair represent one verifiable fact. *However, these methods do not enable entity-level hallucination detection, as they lack explicit entity-level labeling (hallucinated or not) in the original generated text.* Beyond decomposition-based approaches, datasets like HADES (Liu et al., 2022) and CLIFF (Cao & Wang, 2021) create token-level hallucinated content by perturbing human-written text, allowing token-level annotation on the same text. These perturbed hallucinated content, however, could be unrealistic, biased, and overly synthetic due to the limitations of models they used to perturb words. To bridge this gap, we create a new dataset with entity-level hallucination labels on the same LLMs generated text. This allows us to evaluate uncertainty-based hallucination detection approaches on a finer-grained level and analyze their reliability.

3 HALLUENTITY: An Entity-Level Hallucination Dataset

3.1 Dataset Construction

Curating an entity-level hallucination detection dataset is challenging, requiring annotators to segment sentences into meaningful entities and verify the factual consistency of each entity against reliable sources. This process is time-intensive, requires domain expertise, and is prone to subjectivity (Cao & Wang, 2021). To address these challenges, we first develop a data generation pipeline that maps atomic facts from FActScore (Min et al., 2023) back to the original generated text.

Entity segmentation and labeling. To construct our dataset HALLUENTITY¹, we leverage biographies generated by ChatGPT (OpenAI, 2023). Each data point consists of a name, a ChatGPT-generated biography, and a list of atomic facts labeled as either True or False. As illustrated in Figure 1, each atomic fact is a short sentence that conveys a single piece of information. Since atomic facts decompose a sentence into verifiable units, they provide a structured reference for identifying hallucinated entities.

To derive entity-level labels, we first segment the original text into meaningful units rather than individual words. For instance, “strategic thinking” is treated as a single entity rather than two separate words. We call such meaningful units *entities*. Given that FACTSCORE decomposes multiple-fact sentences into independent atomic facts, we use these fact-level annotations to label entities. For example, in the sentence “*He was born on March 9, 1941, in Ramos Mejia,*” FACTSCORE produces two atomic facts:

- “*He was born on March 9, 1941.*” (True)
- “*He was born in Ramos Mejia.*”(False)

By aligning these atomic facts with the original text, we label “March 9, 1941” as non-hallucinated and “Ramos Mejia” as hallucinated. Neutral words like “he” and “on” are considered as non-hallucinated while labeling. To scale this process efficiently, we automatically identify and label these entities by instructing GPT-4o (OpenAI, 2024) with a few-shot prompt. Specifically, we manually annotate two examples, each containing an LLM-generated biography, a list of atomic facts, and a corresponding entity-level annotation list. The prompt provides a detailed description of our segmentation method, along with annotated examples. GPT-4o then generates entity labels, which we manually verify and refine to ensure correctness. Further details on the prompt design and annotation process are provided in **Appendix A**.

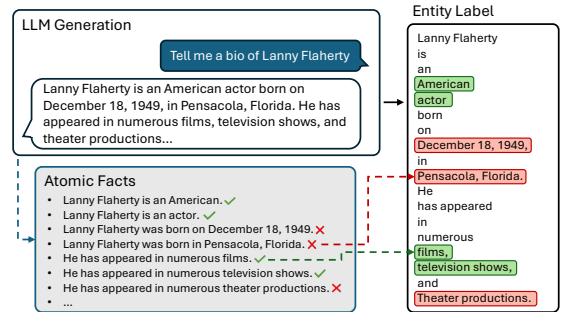


Figure 1: Illustration of our entity-level dataset construction. We form entity-level hallucination labels according to the atomic facts extracted by FActScore.

¹HALLUENTITY will be publicly released under the MIT license.

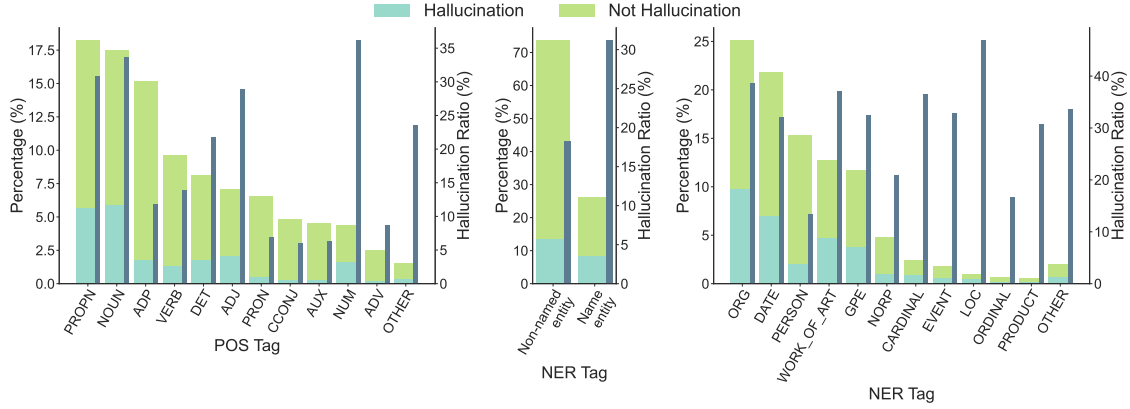


Figure 2: Distribution of POS (left), NER (middle), and breakdown of NER tags (right). Bars in dark blue (right axis) indicate the ratio of hallucination for each tag.

3.2 Data Analysis

Data statistics. HALLUENTITY comprises 157 instances containing a total of 18,785 entities, with 5,452 unique entities. Each entity averages 1.63 words in length. On average, each instance contains 120 entities, with 15% labeled as hallucinated, and 85% as non-hallucinated across the corpus.

Linguistic feature analysis. We analyze the relationship between the entity-level hallucination labels and linguistic features, *e.g.*, part-of-speech (POS) and named entities recognition (NER) tags. Specifically, we identify these tags for each word with Spacy (Honribal & Montani, 2017) and count their occurrence in hallucinated and non-hallucinated entities. The results for each of the part-of-speech (POS) and named entities recognition (NER) tags are shown in Figure 2.

Analysis of POS tags reveals significant patterns in the distribution between hallucinated and non-hallucinated content. Proper nouns (PROPN) constitute the most frequent category with 18.3% occurrences, followed by nouns (NOUN, 17.5%) and adpositions (ADP, 15.1%). Among them, proper nouns and nouns exhibit high hallucination rates of 30.9% and 33.6%, respectively, while adpositions have a lower rate of 11.7%. Moreover, although adjectives (ADJ, 7.1%) and numbers (NUM, 4.4%) are less common, they suffer from a high hallucination rate of 28.9% and 36.2%.

Non-named entities, which comprise 73.8% of total tokens, show a low hallucination rate of 18.2%. In contrast, named entities—despite accounting for only one-third of the tokens—exhibit nearly double the hallucination rate, often exceeding 30%. Among these named entities, person names (PERSON) show the lowest hallucination rate of 13.4%, likely because ChatGPT was prompted to generate biographies for specific individuals.

Beyond POS and NER tagging, hallucination rates vary by position in sentences. The first six words of sentences have a low hallucination rate (9%), but this significantly increases in the middle (25%) and peaks at the last six words (36%). This comprehensive analysis reveals systematic patterns in hallucination across linguistic features and entity types, providing crucial insights into the reliability of different categories of generated content. In Section 5.3, we see the connections between these linguistic features and the performance of uncertainty-based hallucination detection approaches.

4 Uncertainty Scores for Detecting Hallucinated Entities

Given the entity-level hallucination dataset we constructed, a key question arises: *Can uncertainty scores effectively detect these hallucinated entities?* In this section, we comprehensively explore uncertainty-based methods, all of which measure uncertainty at the token level. These token-level scores can be conveniently aggregated to the entity level, allowing for a systematic evaluation of their effectiveness in identifying hallucinated entities.

Notations and definitions. Let \mathcal{V} be a vocabulary space, $x = (v_1, v_2, \dots, v_T)$ be a sentence of length T consisting of tokens $v_i \in \mathcal{V}$. The token-level hallucination scores are denoted as $y^t = (y_1^t, y_2^t, \dots, y_T^t)$, where $y_i^t \in \mathbb{R}$. An entity in x is represented as $e_k = (v_i, v_{i+1}, \dots, v_j)$, where i and j are the start and end indices of the entity’s tokens, satisfying

Approach	AUROC \uparrow	AUPRC \uparrow	F1 _{Opt} \uparrow	Precision _{Opt} \uparrow	Recall _{Opt} \uparrow
Likelihood (Guerreiro et al., 2023)	0.57	0.17	0.29	0.18	0.74
Entropy (Malinin & Gales, 2021)	0.57	0.18	0.28	0.17	0.86
CCP (Fadeeva et al., 2024)	0.57	0.25	0.26	0.15	1.0
SAR Duan et al. (2024)	0.67	0.27	0.34	0.26	0.51
Focus (Zhang et al., 2023b)	0.78	0.40	0.48	0.38	0.66

Table 1: Performance comparison among five uncertainty scores using Llama3-8B.

$i < j \leq T$. The sentence x can then be rewritten as $x = (e_1, e_2, \dots, e_K)$, where K is the number of entities. The entity-level hallucination labels for x are defined as $l = (l_1, l_2, \dots, l_K)$, where $l_k \in \{0, 1\}$ indicates whether e_k is hallucinated. The entity-level scores are computed as $y^e = (y_1^e, y_2^e, \dots, y_K^e)$, where $y_k^e := \frac{1}{e_{k,1} - e_{k,0} + 1} \sum_{i=e_{k,0}}^{e_{k,1}} y_i^t$, which aggregates token-level scores to the entity level and $e_{k,0}$ and $e_{k,1}$ are the start and end indices of entity e_k . We introduce five methods below to calculate the token-level uncertainty scores.

Likelihood (Guerreiro et al., 2023): The score is based on the negative log-likelihood of the i -th generated token:

$$y_i^t := -\log p(x_i | x_{<i}).$$

Entropy (Malinin & Gales, 2021): The score is the entropy of the token probability distribution at position i :

$$y_i^t := -\sum_{v \in \mathcal{V}} p(v | x_{<i}) \log p(v | x_{<i}).$$

Claim-Conditioned Probability (CCP) (Fadeeva et al., 2024): This method adjusts likelihood based on semantic equivalence using a natural language inference (NLI) model:

$$y_i^t := -\log \frac{\sum_{k: \text{NLI}(x_i^k, x_i) = \text{'e'}} p(x_i^k | x_{<i})}{\sum_{k: \text{NLI}(x_i^k, x_i) \in \{\text{'e'}, \text{'c'}\}} p(x_i^k | x_{<i})},$$

where x_i^k is the k -th alternative of the i -th generated token, and NLI determines whether concatenating x_i^k with the preceding context entails ('e') or contradicts ('c') the original token. In our experiment, we use top 10 alternatives and use DeBERTa-base (He et al., 2021) as the NLI model.

Shifting Attention to Relevance (SAR) (Duan et al., 2024): This method weights negative log-likelihood by semantic importance:

$$y_i^t := -\log p(x_i | x_{<i}) \tilde{R}_T(x_i, x),$$

where \tilde{R}_T is 1 - cosine similarity between the sentence embedding of x and $x \setminus \{x_i\}$. Following Duan et al. (2024), we use SentenceBERT (Reimers & Gurevych, 2019) with RoBERTa-large (Liu et al., 2019) for embedding extraction.

Focus (Zhang et al., 2023b): This method refines log-likelihood and entropy using keyword selection, hallucination propagation, and probability correction:

$$y_i^t := \mathbb{I}(x_i \in \mathcal{K}) \cdot (h_i + \gamma p_i),$$

where \mathcal{K} is keyword set identified by Spacy (Honnibal & Montani, 2017). h_i is the sum of negative log-likelihood and entropy of x_i ,

$$h_i := -\log \hat{p}(x_i | x_{<i}) + 2^{-\sum_{v \in \mathcal{V}} \hat{p}(v | x_{<i}) \log_2 \hat{p}(v | x_{<i})}.$$

Here, $\hat{p}(x_i | x_{<i}) = \frac{p(x_i | x_{<i}) \text{idf}(x_i)}{\sum_{v \in \mathcal{V}} p(v | x_{<i}) \text{idf}(v)}$ is the token probability adjusted by inverse document frequency (IDF), and p_i is the hallucination score propagated from previous tokens,

$$p_i := \sum_{j=0}^{i-1} \frac{\text{att}_{i,j}}{\sum_{k=0}^{i-1} \text{att}_{i,k}} y_j^t,$$

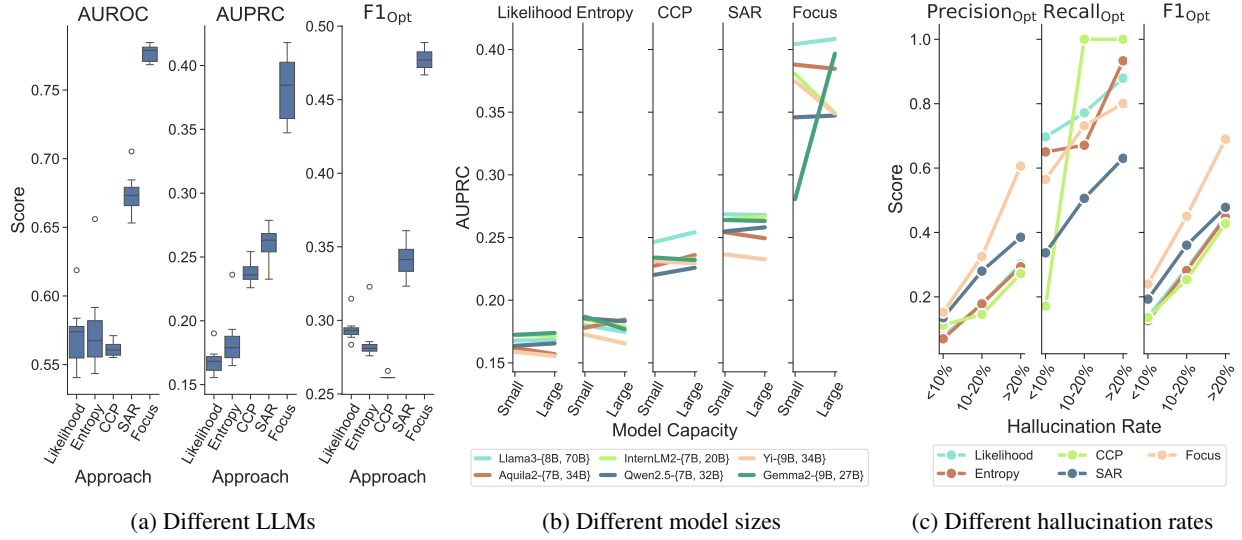


Figure 3: For each method, we show performance variation across 17 LLMs (3a). We also show AUPRC scores across LLMs with different capacities (3b), as well as performance on data with different hallucination rates (3c). Note that the model used in Figure 3c is Llama3-8B.

where $\text{att}_{i,j}$ is the attention weight between x_i and x_j after max-pooling for all the layers and attention heads. Following Zhang et al. (2023b), the token IDF is calculated based on 1M documents sampled from RedPajama dataset (Weber et al., 2024), and the hyperparameter γ for p_i is set to be 0.9.

Besides these five approaches, we acknowledge that other uncertainty-based hallucination detection approaches exist, such as Semantic Entropy (Kuhn et al., 2023), Verbalized Uncertainty (Kadavath et al., 2022), Lexical Similarity (Fomicheva et al., 2020), EigValLaplacian (Lin et al., 2024), and HaloScope (Du et al., 2024). However, since these approaches do not produce token-level scores, they are not applicable to our study on detecting hallucinated entities.

5 Experiments

5.1 Experimental Setup

Models. To understand the impact of model family and capacity on entity-level hallucination detection, we experiment with 17 diverse LLMs, including **Llama3**-{8B, 70B} (Llama Team, 2024), **Llama3.1**-8B, **Llama3.2**-3B, **Aquila2**-{7B, 34B} (Zhang et al., 2024), **InternLM2**-{7B, 20B} (Cai et al., 2024), **Qwen2.5**-{7B, 32B} (Qwen, 2025), **Yi**-{9B, 34B} (01.AI, 2024), **phi-2** (Gunasekar et al., 2023), **Mistral**-7B (Jiang et al., 2023), **Mixtral**-8x22B (Jiang et al., 2024), and **Gemma2**-{9B, 27B} (Gemma Team, 2024).

Evaluation Metrics. Entity-level hallucination detection can be formulated as a binary classification task. To evaluate performance, we use (1) **AUPRC** and (2) **AUROC**, which assess the relationship between entity-level hallucination labels l and scores y^e . AUPRC captures precision-recall trade-offs, while AUROC evaluates true and false positive rates. Unlike AUROC, AUPRC disregards true negatives, emphasizing false positive reduction—a key advantage for hallucination detection, where true negatives often involve less informative entities like prepositions and conjunctions. We complement these metrics by also reporting (3) **F1_{Opt}**, (4) **Precision_{Opt}**, and (5) **Recall_{Opt}**, where F1_{Opt} is the optimal F1 score among all possible threshold and Precision_{Opt}, and Recall_{Opt} are corresponding Precision and Recall values.

5.2 Experimental Results

How do different uncertainty scores perform on entity-level hallucination detection? Table 1 presents the evaluation results for five uncertainty-based hallucination detection approaches using Llama3-8B. Likelihood, Entropy, and CCP exhibit low Precision_{Opt} (\approx overall hallucination rate) but achieve high Recall_{Opt}. This pattern suggests

Case 1: Under-prediction of SAR	
Groundtruth	[...] Diaz started his political career as a member of the Sangguniang Bayan (municipal council) of Santa Cruz in 1978. He later became the Vice Mayor of Santa Cruz in 1980 and was elected as the town's Mayor in 1988. [...]
Likelihood	[...] Diaz started his political career as a member of the Sangguniang Bayan (municipal council) of Santa Cruz in 1978. He later became the Vice Mayor of Santa Cruz in 1980 and was elected as the town's Mayor in 1988. [...]
SAR	[...] Diaz started his political career as a member of the Sangguniang Bayan (municipal council) of Santa Cruz in 1978. He later became the Vice Mayor of Santa Cruz in 1980 and was elected as the town's Mayor in 1988. [...]
Case 2: The type-filter of Focus and the limitations of uncertainty scores	
Groundtruth	Taral Hicks is an American actress and singer, born on September 21, 1974, in The Bronx, New York. [...] She later transitioned to acting, appearing in films such as "A Bronx Tale" (1993), "Just Cause" (1995), and "Belly" (1998). [...]
Likelihood	Taral Hicks is an American actress and singer, born on September 21, 1974, in The Bronx, New York. [...] She later transitioned to acting, appearing in films such as "A Bronx Tale" (1993), "Just Cause" (1995), and "Belly" (1998). [...]
Focus	Taral Hicks is an American actress and singer, born on September 21, 1974, in The Bronx, New York. [...] She later transitioned to acting, appearing in films such as "A Bronx Tale" (1993), "Just Cause" (1995), and "Belly" (1998). [...]
Case 3: Uncertainty propagation of Focus	
Groundtruth	[...] Fernandinho began his professional career with Atletico Paranaense in Brazil before moving to Ukrainian club Shakhtar Donetsk in 2005. [...] He is known for his physicality, tackling ability, and passing range, and is widely regarded as one of the best defensive midfielders in the world.
Likelihood	[...] Fernandinho began his professional career with Atletico Paranaense in Brazil before moving to Ukrainian club Shakhtar Donetsk in 2005. [...] He is known for his physicality, tackling ability, and passing range, and is widely regarded as one of the best defensive midfielders in the world.
Focus	[...] Fernandinho began his professional career with Atletico Paranaense in Brazil before moving to Ukrainian club Shakhtar Donetsk in 2005. [...] He is known for his physicality, tackling ability, and passing range, and is widely regarded as one of the best defensive midfielders in the world.

Table 2: We sampled 3 instances from our dataset to demonstrate the differences across uncertainty scores. For label, entities colored in red indicate hallucination. For uncertainty scores, entities boxed in red with different tints represent the degree of uncertainty. A lighter (darker) box indicates a lower (higher) uncertainty.

these methods over-predict hallucinations, making them less suitable for reliable detection. Their focus on individual token probabilities rather than contextual roles likely contributes to this limitation, indicating that *hallucination detection is inherently context-dependent and requires uncertainty scores calibrated with contextual information*.

SAR and Focus, which incorporate context information, show better overall performance. However, their lower Recall_{Opt} indicates that the current methods for modeling context remain suboptimal, failing to capture some hallucinated content. These findings highlight the challenges in entity-level hallucination detection and the need for more advanced approaches that better integrate contextual information while achieving a balanced trade-off between precision and recall.

How do different LLM families and capacity impact performance? Figure 3a summarizes the performance variation across all 17 different LLMs. The results indicate that while AUROC, AUPRC, and F1_{Opt} scores vary across model families, *the method used to compute uncertainty scores has a more significant impact on performance*. Notably, Focus consistently achieves the highest performance across all model families. Further evaluation details can be found in Appendix B.

Figure 3b presents the performance changes across different model sizes within six families: Llama3, Aquila2, InternLM2, Qwen2.5, Yi, and Gemma2, each comprising two size variants. The results reveal that, in most cases, using a larger model does not significantly enhance performance. The only exception is using Gemma on Focus, where the AUROC score improves by 0.12 between the 27B and 9B versions. Performance improvements for other model families and approaches remain marginal, typically below 0.01. These findings suggest that *a larger LLM may not reflect its better capability of determining hallucination on its token probabilities*.

How does performance vary across different hallucination levels? We categorize HALLUENTITY into three groups based on the proportion of hallucinated entities in each generation (See Table 3 in Appendix B for details). Figure 3c shows the Precision_{Opt}, Recall_{Opt}, and F1_{Opt} scores across three groups. The results reveal that all methods struggle to detect hallucinated content when the hallucination rate is low, with F1_{Opt} scores around 0.2. Entropy and CCP exhibit a steep increase in Recall_{Opt} compared to Precision_{Opt} as the hallucination rate increases, suggesting their tendency to over-predict hallucinations, particularly in a high-hallucination scenario. In contrast, Focus achieves a small difference between the Recall_{Opt} and Precision_{Opt} when the hallucination rate is high, demonstrating its ability to balance precision-recall trade-offs while also highlighting the challenge of detecting sparse hallucination.

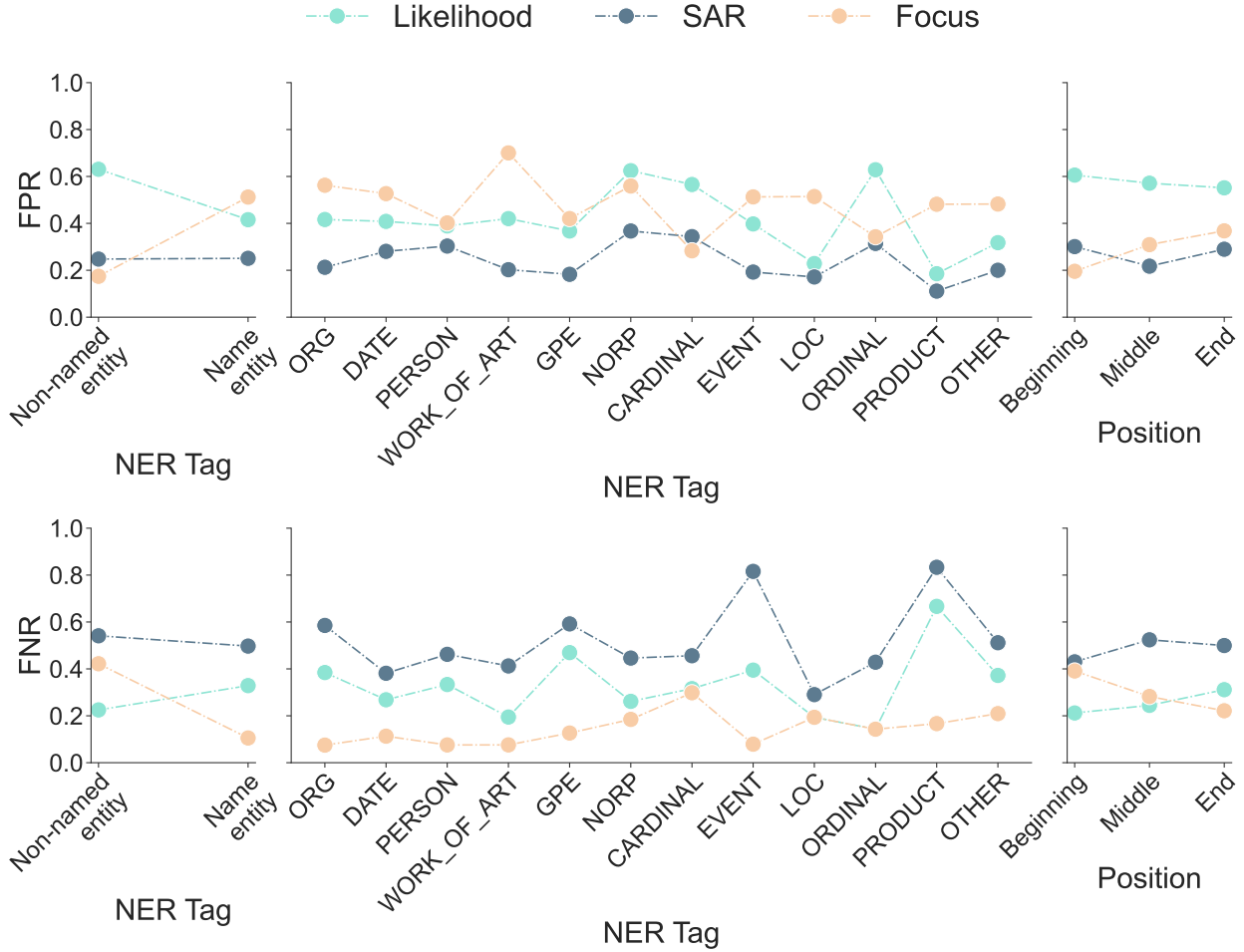


Figure 4: FPR/FNR of uncertainty scores across NER tags (left and middle) and sentence positions (right).

5.3 In-depth Analysis

To better understand the strengths and limitations of uncertainty scores for detecting hallucinated entities, we analyze cases where (1) all scores failed or misidentified hallucinations, and (2) scores varied in performance. We classify entities using thresholds for $F1_{Opt}$ and categorize false positives/negatives by POS, NER tags, and sentence positions (first, middle, or last six words). We then identify tags and positions where approaches excel or falter, visualizing samples with color-coded uncertainty scores to uncover patterns behind detection discrepancies (See Table 2). Figure 4 shows the FPR and FNR across NER tags and sentence positions (The result across POS tags is in Appendix B). Our analysis focuses on Likelihood, SAR, and Focus, as SAR and Focus demonstrated the most effective performance in Section 5.2, and Likelihood serves as a straightforward baseline for comparison.

SAR under-predicts hallucinations due to unreliable token importance weighting. The left and middle plots of Figure 4 show that SAR has the lowest FPR but the highest FNR across most tags, particularly for named entities, indicating a tendency to under-predict hallucinations. This occurs because SAR weights token importance based on sentence similarity without the token, which often remains unchanged even if the token is informative. The first case in Table 2 illustrates this: SAR assigns lighter shades to entities like the second “Santa Cruz” since removing either “Santa” or “Cruz” barely affects sentence similarity, despite the term’s informativeness.

The type-filter of Focus reduces FNR on name entities but sheds light on a bigger limitation of uncertainty-based hallucination score. The left and middle plots of Figure 4 reveal that Focus performs differently for named and non-named entities. It achieves a low FNR but high FPR for named entities, and the opposite for non-named ones. This is because Focus filters for named entities based on POS and NER tags. While promising—since named entities

often hallucinate (as shown in Figure 2)—its high FPR suggests that its base score (the sum of Likelihood and Entropy) poorly distinguishes hallucinations, frequently assigning high uncertainty to named entities. The 2nd case in Table 2 illustrates this: Focus ignores function words like “is” and “to,” reducing FPR, but indiscriminately highlights named entities like “American” and “A Bronx Tale,” even when accurate.

Uncertainty propagation of Focus alleviates the over-confidence nature of LLMs. The right plots in Figure 4 show that LLMs are less confident when generating the first few words of a sentence and become over-confident as generation progresses, as indicated by a decrease in FPR and an increase in FNR for Likelihood. This contrasts with the typical distribution of hallucinations, which occur mostly in the middle and end of sentences (Section 3.2). Focus addresses this by propagating uncertainty scores based on attention, leading to a decrease of FNR over positions. However, its FPR increase over positions suggest that using attention scores to propagate uncertainty may wrongly penalize entities that are not over-confident. The 3rd case in Table 2 illustrates this: Likelihood assigns higher uncertainty to early words (*e.g.*, “Fernandinho began”) and lower scores to later words (*e.g.*, “Shakhtar Donetsk in 2005”), while Focus detects hallucinations at sentence ends by linking them to prior hallucinated content (*e.g.*, “Ukrainian club”).

6 Discussion

Throughout this study, we identify the limitations and strengths of current uncertainty-based hallucination detection approaches. In this section, we discuss two directions to improve the performance of uncertainty-based hallucination detection.

Uncertainty score calibration. In Section 5.3, we show how simple calibrations (type-filter and uncertainty propagation) help improve the performance of Focus. These calibrations were invented through the linguistic analysis on LLM generated corpus, indicating the relationship between the tendency of hallucination and linguistic properties. Based on this finding, we recommend exploring more linguistic properties that can help determine the importance of generating content and the tendency of hallucination. This exploration would not only improve the performance of hallucination detection, but also help mitigate hallucination during generation.

Utilizing information beyond token probabilities to estimate uncertainty. One major limitation of uncertainty-based hallucination detection is its over-prediction nature. As shown in Section 5.2, all five approaches perform poorly when hallucinations are sparse. In Section 5.3, we further show that such over-prediction frequently happens on informative content, such as name entities. This suggests that token probabilities are not well separated between hallucinated and non-hallucinated content, and using uncertainty scores like Likelihood or Entropy to serve as the base score of hallucination detection is not reliable. Hence, we recommend investigating more sophisticated uncertainty estimation or integrating probing techniques that utilize other information from LLM’s internal states to increase the reliability of hallucination detection.

Conclusion and future work. In this work, we comprehensively explore the promise of entity-level hallucination detection by curating HALLUENTITY, a dataset tailored for fine-grained understanding and introducing evaluation metrics for the task. We benchmark five uncertainty-based approaches, finding that they struggle to localize hallucinated content, raising concerns about their reliability. Our qualitative analysis highlights their strengths and weaknesses and suggests two directions for improvement. Future work should explore more sophisticated techniques for incorporating context-aware uncertainty estimation and develop methods that adaptively propagate uncertainty across sentence positions to enhance hallucination localization.

Limitations

In this paper, we focus on evaluating uncertainty-based hallucination detection approaches, where the uncertainty scores are estimated by token probabilities. For other types of uncertainty estimation that measure the diversity across samples, such as Semantic Entropy, since they estimate uncertainty at the sample level and do not output scores for each token or entity, they can not be evaluated on HALLUENTITY. Although this incompatibility limits the usage of HALLUENTITY, it also shows the limitation of sample-based approaches—they are hard to be used to pinpoint hallucinated content.

Ethical Statement

This research addresses the critical challenge of hallucination detection in LLMs to enhance their safe and responsible use across high-stakes domains. By exploring entity-level hallucination detection and evaluating uncertainty-based methods, we aim to improve the precision and reliability of identifying factual inaccuracies in generated content. HALLUENTITY and evaluation metrics are intended solely for research purposes, ensuring no sensitive or personal information is included. We acknowledge the limitations of current approaches and advocate for continued improvements to promote transparency, accuracy, and responsible AI development.

Acknowledgement

We thank ACL anonymous reviewers for their reading and feedback. This work is supported by the AFOSR Young Investigator Program under award number FA9550-23-1-0184, National Science Foundation (NSF) Award No. IIS-2237037 and IIS-2331669, Office of Naval Research under grant number N00014-23-1-2643, and Philanthropic Fund from SFF.

References

- 01.AI. Yi: Open foundation models by 01.ai. *arXiv preprint arXiv:2403.04652*, 2024.
- Zheng Cai, Maosong Cao, Haojiong Chen, Kai Chen, Keyu Chen, Xin Chen, Xun Chen, Zehui Chen, Zhi Chen, Pei Chu, Xiaoyi Dong, Haodong Duan, Qi Fan, Zhaoye Fei, Yang Gao, Jiaye Ge, Chenya Gu, Yuzhe Gu, Tao Gui, Aijia Guo, Qipeng Guo, Conghui He, Yingfan Hu, Ting Huang, Tao Jiang, Penglong Jiao, Zhenjiang Jin, Zhikai Lei, Jiaxing Li, Jingwen Li, Linyang Li, Shuaibin Li, Wei Li, Yining Li, Hongwei Liu, Jiangning Liu, Jiawei Hong, Kaiwen Liu, Kuikun Liu, Xiaoran Liu, Chengqi Lv, Haijun Lv, Kai Lv, Li Ma, Runyuan Ma, Zerun Ma, Wenchang Ning, Linke Ouyang, Jiantao Qiu, Yuan Qu, Fukai Shang, Yunfan Shao, Demin Song, Zifan Song, Zhihao Sui, Peng Sun, Yu Sun, Huanze Tang, Bin Wang, Guoteng Wang, Jiaqi Wang, Jiayu Wang, Rui Wang, Yudong Wang, Ziyi Wang, Xingjian Wei, Qizhen Weng, Fan Wu, Yingdong Xiong, Chao Xu, Ruiliang Xu, Hang Yan, Yirong Yan, Xiaogui Yang, Haochen Ye, Huaiyuan Ying, Jia Yu, Jing Yu, Yuhang Zang, Chuyu Zhang, Li Zhang, Pan Zhang, Peng Zhang, Ruijie Zhang, Shuo Zhang, Songyang Zhang, Wenjian Zhang, Wenwei Zhang, Xingcheng Zhang, Xinyue Zhang, Hui Zhao, Qian Zhao, Xiaomeng Zhao, Fengzhe Zhou, Zaida Zhou, Jingming Zhuo, Yicheng Zou, Xipeng Qiu, Yu Qiao, and Dahua Lin. Internlm2 technical report. *arXiv preprint arXiv:2403.17297*, 2024.
- Shuyang Cao and Lu Wang. CLIFF: Contrastive learning for improving faithfulness and factuality in abstractive summarization. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 2021.
- Arie Cattan, Paul Roit, Shiyue Zhang, David Wan, Roei Aharoni, Idan Szpektor, Mohit Bansal, and Ido Dagan. Localizing factual inconsistencies in attributable text generation. *arXiv preprint arXiv:2410.07473*, 2024.
- Jifan Chen, Grace Kim, Aniruddh Sriram, Greg Durrett, and Eunsol Choi. Complex claim verification with evidence retrieved in the wild. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, 2024a.
- Xiaolan Chen, Jiayang Xiang, Shanfu Lu, Yexin Liu, Mingguang He, and Danli Shi. Evaluating large language models in medical applications: a survey. *arXiv preprint arXiv:2405.07468*, 2024b.
- Xuefeng Du, Chaowei Xiao, and Yixuan Li. Haloscope: Harnessing unlabeled llm generations for hallucination detection. In *Advances in Neural Information Processing Systems*, 2024.
- Jinhao Duan, Hao Cheng, Shiqi Wang, Alex Zavalny, Chenan Wang, Renjing Xu, Bhavya Kailkhura, and Kaidi Xu. Shifting attention to relevance: Towards the predictive uncertainty quantification of free-form large language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2024.

- Ekaterina Fadeeva, Aleksandr Rubashevskii, Artem Shelmanov, Sergey Petrakov, Haonan Li, Hamdy Mubarak, Evgenii Tsymbalov, Gleb Kuzmin, Alexander Panchenko, Timothy Baldwin, Preslav Nakov, and Maxim Panov. Fact-checking the output of large language models via token-level uncertainty quantification. In *Findings of the Association for Computational Linguistics ACL 2024*, 2024.
- Marina Fomicheva, Shuo Sun, Lisa Yankovskaya, Frédéric Blain, Francisco Guzmán, Mark Fishel, Nikolaos Aletras, Vishrav Chaudhary, and Lucia Specia. Unsupervised quality estimation for neural machine translation. *Transactions of the Association for Computational Linguistics*, 8, 2020.
- Google DeepMind Gemma Team. Gemma 2: Improving open language models at a practical size. *arXiv preprint arXiv:2408.00118*, 2024.
- Zhibin Gou, Zhihong Shao, Yeyun Gong, yelong shen, Yujiu Yang, Nan Duan, and Weizhu Chen. CRITIC: Large language models can self-correct with tool-interactive critiquing. In *The Twelfth International Conference on Learning Representations*, 2024.
- Nuno M. Guerreiro, Elena Voita, and André Martins. Looking for a needle in a haystack: A comprehensive study of hallucinations in neural machine translation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, 2023.
- Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, Adil Salim, Shital Shah, Harkirat Singh Behl, Xin Wang, Sébastien Bubeck, Ronen Eldan, Adam Tauman Kalai, Yin Tat Lee, and Yuanzhi Li. Textbooks are all you need. *arXiv preprint arXiv:2306.11644*, 2023.
- Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. DeBERTa: Decoding-enhanced bert with disentangled attention. In *International Conference on Learning Representations*, 2021.
- Matthew Honnibal and Ines Montani. spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing, 2017.
- Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *ACM Trans. Inf. Syst.*, 2024. ISSN 1046-8188.
- Siqing Huo, Negar Arabzadeh, and Charles L. A. Clarke. Retrieving supporting evidence for llms generated answers. *arXiv preprint arXiv:2306.13781*, 2023.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Léo Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.
- Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, Gianna Lengyel, Guillaume Bour, Guillaume Lample, Léo Renard Lavaud, Lucile Saulnier, Marie-Anne Lachaux, Pierre Stock, Sandeep Subramanian, Sophia Yang, Szymon Antoniak, Teven Le Scao, Théophile Gervet, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mixtral of experts. *arXiv preprint arXiv:2401.04088*, 2024.
- Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2017.
- Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, Scott Johnston, Sheer El-Showk, Andy Jones, Nelson Elhage, Tristan Hume, Anna Chen, Yuntao Bai, Sam Bowman, Stanislav Fort, Deep Ganguli, Danny Hernandez, Josh Jacobson, Jackson Kernion, Shauna Kravec, Liane Lovitt, Kamal Ndousse, Catherine Olsson, Sam Ringer, Dario Amodei, Tom Brown, Jack Clark, Nicholas Joseph, Ben Mann, Sam McCandlish, Chris Olah, and Jared Kaplan. Language models (mostly) know what they know. *arXiv preprint arXiv:2207.05221*, 2022.

- Lorenz Kuhn, Yarin Gal, and Sebastian Farquhar. Semantic uncertainty: Linguistic invariances for uncertainty estimation in natural language generation. In *The Eleventh International Conference on Learning Representations*, 2023.
- Junyi Li, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. HaluEval: A large-scale hallucination evaluation benchmark for large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.
- Weixin Liang, Yaohui Zhang, Zhengxuan Wu, Haley Lepp, Wenlong Ji, Xuandong Zhao, Hancheng Cao, Sheng Liu, Siyu He, Zhi Huang, Diyi Yang, Christopher Potts, Christopher D. Manning, and James Y. Zou. Mapping the increasing use of llms in scientific papers. *arXiv preprint arXiv:2404.01268*, 2024.
- Chun-Hsien Lin and Pu-Jen Cheng. Legal documents drafting with fine-tuned pre-trained large language model. *arXiv preprint arXiv:2406.04202*, 2024.
- Stephanie Lin, Jacob Hilton, and Owain Evans. TruthfulQA: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2022.
- Zhen Lin, Shubhendu Trivedi, and Jimeng Sun. Generating with confidence: Uncertainty quantification for black-box large language models. *Transactions on Machine Learning Research*, 2024. ISSN 2835-8856.
- Tianyu Liu, Yizhe Zhang, Chris Brockett, Yi Mao, Zhifang Sui, Weizhu Chen, and Bill Dolan. A token-level reference-free hallucination detection benchmark for free-form text generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2022.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- AI @ Meta Llama Team. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- Junliang Luo, Tianyu Li, Di Wu, Michael R. M. Jenkin, Steve Liu, and Gregory Dudek. Hallucination detection and hallucination mitigation: An investigation. *arXiv preprint arXiv:2401.08358*, 2024.
- Andrey Malinin and Mark Gales. Uncertainty estimation in autoregressive structured prediction. In *International Conference on Learning Representations*, 2021.
- Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen-tau Yih, Pang Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. FActScore: Fine-grained atomic evaluation of factual precision in long form text generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.
- Abdurrahman Odabaşı and Göksel Biricik. Unraveling the capabilities of language models in news summarization. *arXiv preprint arXiv:2501.18128*, 2025.
- OpenAI. Chatgpt. <https://chat.openai.com/>, 2023. Large language model.
- OpenAI. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.
- Qwen. Qwen2.5 technical report. *arXiv preprint arXiv:2412.15115*, 2025.
- Siva Reddy, Danqi Chen, and Christopher D. Manning. CoQA: A conversational question answering challenge. *Transactions of the Association for Computational Linguistics*, 7, 2019.
- Nils Reimers and Iryna Gurevych. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 2019.
- Jie Ren, Jiaming Luo, Yao Zhao, Kundan Krishna, Mohammad Saleh, Balaji Lakshminarayanan, and Peter J Liu. Out-of-distribution detection and selective generation for conditional language models. In *The Eleventh International Conference on Learning Representations*, 2023.

- Artem Vazhentsev, Gleb Kuzmin, Akim Tsvigun, Alexander Panchenko, Maxim Panov, Mikhail Burtsev, and Artem Shelmanov. Hybrid uncertainty quantification for selective text classification in ambiguous tasks. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2023.
- Maurice Weber, Daniel Y. Fu, Quentin Anthony, Yonatan Oren, Shane Adams, Anton Alexandrov, Xiaozhong Lyu, Huu Nguyen, Xiaozhe Yao, Virginia Adams, Ben Athiwaratkun, Rahul Chalamala, Kezhen Chen, Max Ryabinin, Tri Dao, Percy Liang, Christopher Ré, Irina Rish, and Ce Zhang. Redpajama: an open dataset for training large language models. *NeurIPS Datasets and Benchmarks Track*, 2024.
- Ziwei Xu, Sanjay Jain, and Mohan S. Kankanhalli. Hallucination is inevitable: An innate limitation of large language models. *arXiv preprint arXiv:2401.11817*, 2024.
- KiYoon Yoo, Jangho Kim, Jiho Jang, and Nojun Kwak. Detection of adversarial examples in text classification: Benchmark and baseline via robust density estimation. In *Findings of the Association for Computational Linguistics: ACL 2022*, 2022.
- Bo-Wen Zhang, Liangdong Wang, Jijie Li, Shuhao Gu, Xinya Wu, Zhengduo Zhang, Boyan Gao, Yulong Ao, and Guang Liu. Aquila2 technical report. *arXiv preprint arXiv:2408.07410*, 2024.
- Tianhang Zhang, Lin Qiu, Qipeng Guo, Cheng Deng, Yue Zhang, Zheng Zhang, Cheng Zhou, Xinbing Wang, and Luoyi Fu. Enhancing uncertainty-based hallucination detection with stronger focus. *arXiv preprint arXiv:2311.13230*, 2023a.
- Tianhang Zhang, Lin Qiu, Qipeng Guo, Cheng Deng, Yue Zhang, Zheng Zhang, Chenghu Zhou, Xinbing Wang, and Luoyi Fu. Enhancing uncertainty-based hallucination detection with stronger focus. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023b.

A Details of Dataset Construction

Selection of data. From the FACTSCORE dataset, we select the set of biographies generated by ChatGPT to construct our entity-level hallucination detection dataset. The set of ChatGPT-generated biographies contains 183 samples. We filter out those ChatGPT refuses to answer and end up with 157 instances.

Data labeling process. For each sample, FACTSCORE provides a list of atomic facts—short sentences conveying single pieces of information. These facts are labeled as Supported, Not-supported, or Irrelevant, where Irrelevant means the fact is unrelated to the prompt (*i.e.* a person’s name), and Supported and Not-supported indicate whether the fact is supported by the person’s Wikipedia page. Since only 8.3% of facts are labeled as Irrelevant, and most are related to Not-supported facts, we simplify the entity-level labeling process by merging both as False, treating only Supported facts as True.

To assign entity-level labels, we first tokenize the biography into individual words. We then use the list of atomic facts to group words into meaningful units (entities) and assign labels based on fact types. Specifically, for atomic facts that share a similar sentence structure (*e.g.*, “*He was born on Mach 9, 1941.*” (True) and “*He was born in Ramos Mejia.*” (False)), we label differing entities first—assigning True to “Mach 9, 1941” and False to “Ramos Mejia.”. For those entities that are the same across atomic facts (*e.g.*, “was born”) or are neutral (*e.g.*, “he,” “in,” and “on”), we label them as True. In cases where no similar atomic fact exists, we identify the most informative entities in the sentence, label them based on the atomic fact, and treat the remaining entities as True.

GPT-4o prompt for data labeling. To scale the labeling process, we use GPT-4o to automatically identify and label entities with a few-shot prompt, as shown in Table 4. The system prompt includes detailed instructions on the labeling process, along with two manually created examples. In the user prompt, we maintain the same structured format used in the examples, inputting the biography and the corresponding list of atomic facts.

B Details of Experimental Result

Computational resources. We conducted all experiments on a server equipped with eight Nvidia A100 GPUs. Depending on the model size, each LLM utilized between one to three GPUs. The time required to compute uncertainty scores across the entire dataset varied from 30 seconds to 5 minutes per approach and model, depending on the model size and the complexity of the chosen method.

Performance across LLM families. Table 5, 6, 7, 8, and 9 present the performance of five uncertainty scores across 17 LLMs. The results indicate that microsoft/phi-2 consistently achieves the highest performance across most scores and evaluation metrics, being the only model that avoids over-predicting hallucinations when using CCP. Additionally, models from Mistral AI (mistralai/Mistral-7B-v0.3 and mistralai/Mixtral-8x22B-v0.1) perform best when using Focus. Notably, phi-2 (2.7B parameters) and Mistral-7B are relatively small models, suggesting that a model’s size does not strongly correlate with its ability to detect hallucinations based on token probabilities. The findings also reveal that while some models outperform others, the performance variations within the same uncertainty score are smaller than those across different scores, emphasizing the need for improved uncertainty estimation methods for hallucination detection.

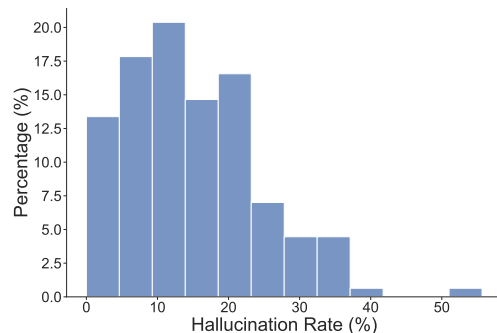


Figure 5: Distribution of entity-level hallucination rate. Most instances in our dataset have a hallucination rate < 25%.

Statistics of hallucination rate. Figure 5 shows the distribution of entity-level hallucination rate—the proportion of hallucinated entities in each generation. The results indicate that most biographies generated by ChatGPT have a hallucination rate below 25%. Additionally, generations with hallucination rates below 10% and those between 10% to

	Low	Medium	High
Hallucination Rate	<10%	10-20%	>20%
# of Instance	54	59	44

Table 3: Statistics of data grouped according to the hallucination rate. Each group has a similar amount of data.

20% occur at similar frequencies. Based on this observation, we categorize the data into three groups ($< 10\%$, $10\text{-}20\%$, $> 20\%$) to examine how hallucination rates impact detection performance. Table 3 summarizes the group statistics, showing that each group contains a similar amount of data.

FPR/FNR analysis on POS tags. Figure 6 shows the FPR/FNR of Likelihood, SAR, and Focus across POS tags. Consistent with Figure 4, Likelihood exhibits higher FPR and lower FNR across all tags, while SAR demonstrates lower FPR but higher FNR. In contrast, Focus shows varying patterns depending on the tag type. For proper nouns, nouns, and numbers—tags often associated with named entities—Focus has a higher FPR and lower FNR, similar to the trend observed in Figure 4. However, for verbs, auxiliaries, and adverbs, Focus exhibits a lower FPR but a higher FNR. This highlights a limitation of Focus: by concentrating primarily on named entities, it tends to overlook hallucinations in other types of tokens.

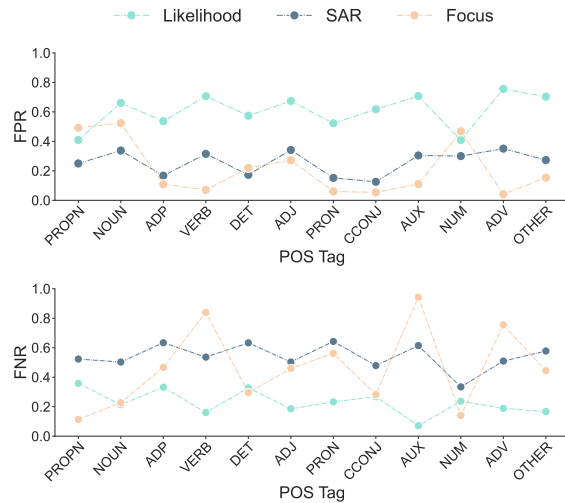


Figure 6: FPR/FNR of each uncertainty score across POS tags.

System prompt

You are a helpful and precise assistant for segmenting and labeling sentences. We would like to request your help on curating a dataset for entity-level hallucination detection.

We will give you a machine generated biography and a list of checked facts about the biography. Each fact consists of a sentence and a label (True/False). Please do the following process. First, breaking down the biography into words. Second, by referring to the provided list of facts, merging some broken down words in the previous step to form meaningful entities. For example, "strategic thinking" should be one entity instead of two. Third, according to the labels in the list of facts, labeling each entity as True or False. Specifically, for facts that share a similar sentence structure (e.g., "He was born on Mach 9, 1941." (True) and "He was born in Ramos Mejia." (False)), please first assign labels to entities that differ across atomic facts. For example, first labeling "Mach 9, 1941" (True) and "Ramos Mejia" (False) in the above case. For those entities that are the same across atomic facts (e.g., "was born") or are neutral (e.g., "he," "in," and "on"), please label them as True. For the cases that there is no atomic fact that shares the same sentence structure, please identify the most informative entities in the sentence and label them with the same label as the atomic fact while treating the rest of the entities as True. In the end, output the entities and labels in the following format:

- Entity 1 (Label 1)
- Entity 2 (Label 2)
- ...
- Entity N (Label N)

Here are two examples:

[Example 1]

[The start of the biography]

Marianne McAndrew is an American actress and singer, born on November 21, 1942, in Cleveland, Ohio. She began her acting career in the late 1960s, appearing in various television shows and films.

[The end of the biography]

[The start of the list of checked facts]

[Marianne McAndrew is an American. (False); Marianne McAndrew is an actress. (True); Marianne McAndrew is a singer. (False); Marianne McAndrew was born on November 21, 1942. (False); Marianne McAndrew was born in Cleveland, Ohio. (False); She began her acting career in the late 1960s. (True); She has appeared in various television shows. (True); She has appeared in various films. (True)]

[The end of the list of checked facts]

[The start of the ideal output]

[Marianne McAndrew (True); is (True); an (True); American (False); actress (True); and (True); singer (False); , (True); born (True); on (True); November 21, 1942 (False); , (True); in (True); Cleveland, Ohio (False); . (True); She (True); began (True); her (True); acting career (True); in (True); the late 1960s (True); , (True); appearing (True); in (True); various (True); television shows (True); and (True); films (True); . (True)]

[The end of the ideal output]

[Example 2]

[The start of the biography]

Doug Sheehan is an American actor who was born on April 27, 1949, in Santa Monica, California. He is best known for his roles in soap operas, including his portrayal of Joe Kelly on "General Hospital" and Ben Gibson on "Knots Landing."

[The end of the biography]

[The start of the list of checked facts]

[Doug Sheehan is an American. (True); Doug Sheehan is an actor. (True); Doug Sheehan was born on April 27, 1949. (True); Doug Sheehan was born in Santa Monica, California. (False); He is best known for his roles in soap operas. (True); He portrayed Joe Kelly. (True); Joe Kelly was in General Hospital. (True); General Hospital is a soap opera. (True); He portrayed Ben Gibson. (True); Ben Gibson was in Knots Landing. (True); Knots Landing is a soap opera. (True)]

[The end of the list of checked facts]

[The start of the ideal output]

[Doug Sheehan (True); is (True); an (True); American (True); actor (True); who (True); was born (True); on (True); April 27, 1949 (True); in (True); Santa Monica, California (False); . (True); He (True); is (True); best known (True); for (True); his roles in soap operas (True); , (True); including (True); in (True); his portrayal (True); of (True); Joe Kelly (True); on (True); "General Hospital" (True); and (True); Ben Gibson (True); on (True); "Knots Landing." (True)]

[The end of the ideal output]

User prompt

[The start of the biography]

{BIOGRAPHY}

[The end of the biography]

[The start of the list of checked facts]

{LIST OF CHECKED FACTS}

[The end of the list of checked facts]

Table 4: GPT-4o prompt for labeling hallucinated entities.

Model	Likelihood	Entropy	CCP	SAR	Focus
meta-llama/Meta-Llama-3-8B	0.568	0.571	0.565	0.672	0.784
meta-llama/Meta-Llama-3-70B	0.574	0.567	0.565	0.667	0.779
meta-llama/Llama-3.1-8B	0.584	0.592	0.564	0.684	0.783
meta-llama/Llama-3.2-3B	0.577	0.591	0.564	0.685	0.772
BAAI/Aquila2-7B	0.544	0.553	0.565	0.679	0.78
BAAI/Aquila2-34B	0.541	0.566	0.565	0.665	0.779
internlm/internlm2-7b	0.586	0.584	0.562	0.678	0.777
internlm/internlm2-20b	0.579	0.573	0.561	0.674	0.77
Qwen/Qwen2.5-7B	0.557	0.571	0.558	0.675	0.767
Qwen/Qwen2.5-32B	0.561	0.569	0.559	0.674	0.768
01-ai/Yi-9B	0.541	0.549	0.56	0.663	0.776
01-ai/Yi-34B	0.543	0.543	0.557	0.653	0.769
microsoft/phi-2	0.619	0.656	0.571	0.705	0.775
mistralai/Mistral-7B-v0.3	0.549	0.545	0.555	0.666	0.784
mistralai/Mixtral-8x22B-v0.1	0.56	0.545	0.555	0.665	0.785
google/gemma-2-9b	0.574	0.575	0.561	0.68	0.744
google/gemma-2-27b	0.576	0.566	0.557	0.673	0.78

Table 5: AUROC of five uncertainty scores across 17 LLMs.

Model	Likelihood	Entropy	CCP	SAR	Focus
meta-llama/Meta-Llama-3-8B	0.168	0.18	0.247	0.269	0.404
meta-llama/Meta-Llama-3-70B	0.168	0.175	0.254	0.268	0.408
meta-llama/Llama-3.1-8B	0.173	0.193	0.246	0.274	0.412
meta-llama/Llama-3.2-3B	0.17	0.191	0.235	0.269	0.368
BAAI/Aquila2-7B	0.162	0.178	0.228	0.254	0.388
BAAI/Aquila2-34B	0.157	0.185	0.236	0.249	0.385
internlm/internlm2-7b	0.173	0.185	0.232	0.264	0.38
internlm/internlm2-20b	0.171	0.179	0.233	0.267	0.349
Qwen/Qwen2.5-7B	0.164	0.185	0.22	0.255	0.346
Qwen/Qwen2.5-32B	0.166	0.183	0.226	0.258	0.347
01-ai/Yi-9B	0.159	0.173	0.231	0.237	0.375
01-ai/Yi-34B	0.156	0.165	0.229	0.233	0.349
microsoft/phi-2	0.19	0.236	0.238	0.279	0.371
mistralai/Mistral-7B-v0.3	0.159	0.167	0.236	0.25	0.391
mistralai/Mixtral-8x22B-v0.1	0.163	0.165	0.249	0.263	0.418
google/gemma-2-9b	0.172	0.187	0.234	0.264	0.281
google/gemma-2-27b	0.174	0.177	0.232	0.263	0.397

Table 6: AUPRC of five uncertainty scores across 17 LLMs.

Model	Likelihood	Entropy	CCP	SAR	Focus
meta-llama/Meta-Llama-3-8B	0.29	0.278	0.261	0.344	0.484
meta-llama/Meta-Llama-3-70B	0.291	0.282	0.261	0.335	0.469
meta-llama/Llama-3.1-8B	0.296	0.286	0.261	0.351	0.483
meta-llama/Llama-3.2-3B	0.294	0.285	0.261	0.349	0.477
BAAI/Aquila2-7B	0.283	0.275	0.261	0.346	0.484
BAAI/Aquila2-34B	0.283	0.277	0.261	0.329	0.484
internlm/internlm2-7b	0.304	0.286	0.261	0.348	0.475
internlm/internlm2-20b	0.293	0.281	0.261	0.348	0.467
Qwen/Qwen2.5-7B	0.291	0.277	0.261	0.342	0.475
Qwen/Qwen2.5-32B	0.293	0.28	0.261	0.341	0.482
01-ai/Yi-9B	0.285	0.276	0.261	0.332	0.482
01-ai/Yi-34B	0.289	0.279	0.261	0.323	0.478
microsoft/phi-2	0.315	0.323	0.266	0.361	0.477
mistralai/Mistral-7B-v0.3	0.289	0.276	0.261	0.333	0.489
mistralai/Mixtral-8x22B-v0.1	0.293	0.28	0.261	0.334	0.471
google/gemma-2-9b	0.294	0.282	0.261	0.346	0.476
google/gemma-2-27b	0.296	0.282	0.261	0.345	0.473

Table 7: $F1_{\text{Opt}}$ of five uncertainty scores across 17 LLMs.

Model	Likelihood	Entropy	CCP	SAR	Focus
meta-llama/Meta-Llama-3-8B	0.18	0.166	0.15	0.261	0.384
meta-llama/Meta-Llama-3-70B	0.182	0.168	0.15	0.274	0.339
meta-llama/Llama-3.1-8B	0.188	0.18	0.15	0.268	0.362
meta-llama/Llama-3.2-3B	0.177	0.182	0.15	0.256	0.348
BAAI/Aquila2-7B	0.169	0.162	0.15	0.248	0.365
BAAI/Aquila2-34B	0.171	0.168	0.15	0.222	0.361
internlm/internlm2-7b	0.192	0.174	0.15	0.26	0.385
internlm/internlm2-20b	0.181	0.169	0.15	0.272	0.332
Qwen/Qwen2.5-7B	0.175	0.166	0.15	0.237	0.347
Qwen/Qwen2.5-32B	0.179	0.166	0.15	0.251	0.356
01-ai/Yi-9B	0.172	0.162	0.15	0.233	0.362
01-ai/Yi-34B	0.175	0.166	0.15	0.227	0.353
microsoft/phi-2	0.195	0.215	0.261	0.254	0.348
mistralai/Mistral-7B-v0.3	0.176	0.162	0.15	0.237	0.386
mistralai/Mixtral-8x22B-v0.1	0.177	0.167	0.15	0.256	0.345
google/gemma-2-9b	0.18	0.168	0.15	0.258	0.344
google/gemma-2-27b	0.182	0.166	0.15	0.25	0.349

Table 8: $\text{Precision}_{\text{Opt}}$ of five uncertainty scores across 17 LLMs.

Model	Likelihood	Entropy	CCP	SAR	Focus
meta-llama/Meta-Llama-3-8B	0.742	0.86	1.0	0.505	0.658
meta-llama/Meta-Llama-3-70B	0.736	0.87	1.0	0.432	0.757
meta-llama/Llama-3.1-8B	0.696	0.688	1.0	0.505	0.724
meta-llama/Llama-3.2-3B	0.855	0.662	1.0	0.548	0.758
BAAI/Aquila2-7B	0.875	0.916	1.0	0.57	0.719
BAAI/Aquila2-34B	0.838	0.786	1.0	0.632	0.732
internlm/internlm2-7b	0.736	0.797	1.0	0.525	0.62
internlm/internlm2-20b	0.771	0.82	1.0	0.481	0.783
Qwen/Qwen2.5-7B	0.857	0.833	1.0	0.613	0.753
Qwen/Qwen2.5-32B	0.817	0.883	1.0	0.535	0.749
01-ai/Yi-9B	0.843	0.936	1.0	0.58	0.721
01-ai/Yi-34B	0.831	0.88	1.0	0.559	0.739
microsoft/phi-2	0.81	0.65	0.27	0.622	0.76
mistralai/Mistral-7B-v0.3	0.811	0.933	1.0	0.561	0.666
mistralai/Mixtral-8x22B-v0.1	0.836	0.866	1.0	0.477	0.743
google/gemma-2-9b	0.809	0.856	1.0	0.526	0.77
google/gemma-2-27b	0.8	0.916	1.0	0.556	0.732

Table 9: Recall_{Opt} of five uncertainty scores across 17 LLMs.