Fine-Grained Uncertainty Quantification for Long-Form Language Model Outputs: A Comparative Study

Anonymous authors
Paper under double-blind review

Abstract

Uncertainty quantification has emerged as an effective approach to closed-book hallucination detection for LLMs, but existing methods are largely designed for short-form outputs and do not generalize well to long-form generation. We introduce a taxonomy for fine-grained uncertainty quantification in long-form LLM outputs that distinguishes methods by design choices at three stages: response decomposition, unit-level scoring, and response-level aggregation. We formalize several families of consistency-based black-box scorers, providing generalizations and extensions of existing methods. In our experiments across multiple LLMs and datasets, we find 1) claim-response entailment consistently performs better or on par with more complex claim-level scorers, 2) claim-level scoring generally yields better results than sentence-level scoring, and 3) uncertainty-aware decoding is highly effective for improving the factuality of long-form outputs. Our framework clarifies relationships between prior methods, enables apples-to-apples comparisons, and provides practical guidance for selecting components for fine-grained UQ.

1 Introduction

LLMs are widely used to generate long-form content for tasks such as summarization, open-ended question answering, and document drafting. These settings raise a basic reliability question: how confident should we be in a multi-sentence or multi-claim response, and where are the likely errors? Prior uncertainty quantification (UQ) methods for hallucination detection are mostly short-form (Huang et al., 2023; Tonmoy et al., 2024; Shorinwa et al., 2024; Huang et al., 2024a), which limits their ability to localize errors and effectively score confidence at the response level for long-form generation (Bakman et al., 2025; Vashurin et al., 2025b). In contrast to short-form methods, which estimate confidence for a single span, long-form methods decompose a response into granular units (sentences or claims) and score each unit. These scores can then be aggregated to produce a more precise response-level confidence estimate.

We study fine-grained uncertainty quantification for long-form LLM outputs, focusing on black-box methods that measure semantic consistency in sampled responses generated from the same prompt. Our methods follow a common pipeline: decompose a response into units (sentences or claims), score each unit using evidence derived from model behavior, and aggregate these scores into a response-level confidence. We introduce a taxonomy that distinguishes scoring methods by their design choices at the three stages of this process: how the response is decomposed, how unit-level scores are computed (matching scheme, semantic consistency measurement, and functional form), and how unit scores are aggregated. This taxonomy unifies, generalizes, and extends prior fine-grained UQ work and provides practical guidance for selecting components under different risk and deployment constraints.

Within this framework, we define several families of fine-grained scorers. Unit-response scorers directly compare each unit in the original response with full-text sampled responses using entailment signals (Zhang et al., 2024). Matched-unit scorers decompose both original and sampled responses, match each original unit to its most similar unit in every sample and then score consistency (Zhang et al., 2024). Graph-based scorers build an entailment graph over the union of unique claims across sampled responses and use graph centrality to estimate claim confidence (Jiang et al., 2024). Unit-QA scorers convert each claim or sentence to

a question, sample LLM answers to those questions, and measure consistency among those answers to score the claim (Farquhar et al., 2024). We also decouple unit-level scoring from response-level aggregation and study aggregation operators that allow users to trade off factual precision and recall. This framework provides a common language for comparing methods, enables apples-to-apples evaluation of previous approaches, and clarifies how to assemble new scorers from interchangeable components.

We evaluate these fine-grained scoring methods on long-form hallucination detection across multiple LLMs and benchmarks, comparing unit-level detection, calibration, and response-level scoring. To our knowledge, prior work compares subsets of these methods pairwise, whereas our study jointly evaluates a broad suite of claim-level and sentence-level scorers within a single framework. In our experiments, we find 1) claim-response entailment consistently performs better or on par with more complex claim-level scorers, 2) claim-level scoring generally yields better results than sentence-level scoring, and 3) uncertainty-aware decoding is highly effective for improving the factuality of long-form outputs. All methods introduced and evaluated in this work are available in our companion open-source toolkit.[1]

2 Related Work

Short-form UQ typically compares an original response to sampled alternatives or inspects model-internal probabilities. For black-box UQ, exact-match style measures such as repetition and diversity quantify consistency across candidates but over-penalize paraphrases (Cole et al., 2023). Text-similarity metrics relax this by using n-gram metrics (ROUGE, BLEU, METEOR) (Lin, 2004; Papineni et al., 2002; Banerjee & Lavie, 2005; Shorinwa et al., 2024), sentence-embedding cosine similarity with Sentence-BERT (Reimers & Gurevych, 2019; Qurashi et al., 2020; Shorinwa et al., 2024), or BERTScore (Zhang et al., 2020; Manakul et al., 2023). Natural Language Inference provides calibrated semantic signals via $P(\text{entailment})$ or $1 - P(\text{contradiction})$ between responses (Chen & Mueller, 2023; Lin et al., 2024), and has been used for semantic entropy and clustering-based variants (Kuhn et al., 2023; Kossen et al., 2024; Farquhar et al., 2024), as well as semantic density (Qiu & Miikkulainen, 2024). For white-box methods, token-probability aggregations include average and maximum negative log probability (Manakul et al., 2023), perplexity (Fadeeva et al., 2024), response improbability (Fadeeva et al., 2024), entropy over next-token distributions (Malinin & Gales, 2021; Manakul et al., 2023), and the geometric mean of token probabilities (Malinin & Gales, 2021).

Short-form UQ methods have been shown to generalize poorly to long-form LLM outputs (Bakman et al., 2025; Vashurin et al., 2025b). Fine-grained methods for long-form UQ address these limitations by first decomposing responses into granular units (sentences or claims) and then scoring each unit. LUQ measures whether sampled responses entail each original sentence, yielding sentence-level confidence scores, while LUQ-atomic applies this to extracted atomic claims to better target factual units (Zhang et al., 2024; 2025). LUQ-pair addresses NLI limitations on long texts by matching each original sentence to its most similar counterpart in sampled responses before computing entailment scores (Zhang et al., 2024). Jiang et al. (2024) obtain the union of unique claims over sampled responses, construct a bipartite graph of claim-response entailment, and measure confidence from graph centrality. Long-form semantic entropy decomposes a response into claims, generates questions whose answers are the claims given context, samples multiple answers, and computes semantic entropy across these answers (Farquhar et al., 2024). Other work focuses on claim-level calibration (Zhang et al., 2025; Huang et al., 2024b; Liu et al., 2024; Liu & Wu, 2025), and directly scoring entire long-form responses without a fine-grained approach (Yuan et al., 2025; Vashurin et al., 2025b; Da et al., 2024).

3 Fine-Grained Black-Box UQ Methods

3.1 Problem Setup and Taxonomy

We study fine-grained uncertainty quantification for long-form LLM outputs and formalize a taxonomy of methods aligned with a common three-stage pipeline. After response generation, all methods we consider (1) decompose a response into units (sentences or claims), (2) assign a unit-level confidence score to each

[1] A link to the open-source repository will be made available upon acceptance.

unit given some form of evidence, and (3) aggregate unit scores into a response-level confidence. Methods differ in the design choices made at these three stages. We now introduce formal notation and summarize the corresponding design space.

Let $\mathcal{T}$ be the set of all finite text strings and let $\mathcal{Y} \subseteq \mathcal{T}$ denote the space of possible LLM responses. For a granularity $g \in \{\text{sent}, \text{claim}\}$, let $\mathcal{S}_g \subseteq \mathcal{T}$ denote the set of all possible textual units at granularity g, with $\mathcal{S}_{\text{sent}}$ containing all possible sentences and $\mathcal{S}_{\text{claim}}$ containing all possible atomic claims. Our goal is to produce unit-level uncertainty-aware confidence scores and to aggregate them into a response-level confidence for any $y \in \mathcal{Y}$. Scores lie in $[0, 1]$ and may be thresholded at level $\tau \in [0, 1]$ to flag likely hallucinations at either the unit or response level.

Stage	**Role (notation)**	**Main design choices**
Decomposition	$\delta_g : \mathcal{Y} \to \mathcal{P}(\mathcal{S}_g)$	Granularity $g \in \{\text{sent}, \text{claim}\}$
Unit scoring	$c_g : \mathcal{S}_g \times \mathcal{E} \to [0, 1]$	Matching scheme; semantic consistency function; scorer functional form
Aggregation	$A : [0, 1]^* \to [0, 1]$	Aggregation operator

Table 1: Three-stage pipeline for fine-grained black-box scoring and associated design choices.

Response decomposition. We define a *decomposition function* $\delta_g : \mathcal{Y} \to \mathcal{P}(\mathcal{S}_g)$, that deconstructs a response $y \in \mathcal{Y}$ to a set of granular units, (i.e., sentences or claims), where granularity $g \in \{\text{sent}, \text{claim}\}$ and $\mathcal{P}(\cdot)$ is the power set operator. The main design choice at this stage is the granularity g. When $g = \text{sent}$, $\delta_g(\cdot)$ implements rule-based or model-based sentence segmentation. When $g = \text{claim}$, $\delta_g(\cdot)$ implements LLM-based claim extraction.

Unit-level confidence scoring. A *unit-level confidence scorer* is a function $c_g : \mathcal{S}_g \times \mathcal{E} \to [0, 1]$, that returns a confidence score for a unit $s \in \mathcal{S}_g$, where $\mathcal{E}$ denotes an evidence domain that will vary by scorer family. Scorers are defined such that higher values indicate greater likelihood of factual correctness. Given evidence $E \in \mathcal{E}$, a unit s is flagged as possible hallucination if $c_g(s; E) < \tau_g$ for some threshold τ_g. Design choices include (i) the *matching scheme* (e.g., unit-response or unit-unit), (ii) the *semantic consistency measurement* (e.g., NLI-based scores or embedding-based similarity; details in Section 3.2), and (iii) the *functional form* of c_g.

Response-level aggregation. Given unit scores $\{c_g(s; E)\}_{s \in \delta_g(y)}$ for a response y, an aggregation operator is a function $A : [0, 1]^* \to [0, 1]$ maps an unspecified but finite number of unit scores to a single value in $[0, 1]$. The resulting response-level confidence can then be thresholded at a threshold τ_y to flag likely hallucinations. Design choices here concern the functional form of A, for example simple averaging versus uncertainty-aware decoding with claim-level filtering. Detailed definitions are contained in Section 3.4.

3.2 Black-Box UQ and Semantic Consistency

Black-box UQ scorers exploit variation in LLM responses to the same prompt to assess semantic consistency. For a given prompt x, let $\mathbf{y}_{\text{cand}} = (y_1, ..., y_m)$ be m candidate responses sampled via stochastic decoding (for example, non-zero temperature, top-p, or top-k), and let y_0 denote the response under audit, hereafter referred to as the *original response*.

Semantic consistency. These methods rely on a *semantic consistency function* $\eta : \mathcal{T} \times \mathcal{T} \to [0, 1]$, to measure consistency between two strings of text. This consistency score typically measures either 1) semantic similarity (measured by embeddings) or 2) entailment or non-contradiction (estimated by natural language inference (NLI) model or an LLM). We consider the following semantic consistency functions in this work:

- **Entailment probability** - $p_e(a, b)$ is the NLI probability b is entailed in a (Lin et al., 2024).

- **Non-contradiction probability** - $1-p_c(a,b)$ is the complement of NLI probability that a is contradicted by b (Chen & Mueller, 2023).
- **Contrasted entailment** - $\frac{p_e(a,b)}{p_e(a,b)+p_c(a,b)}$ is entailment probability excluding the *neutral* class (Zhang et al., 2024; Manakul et al., 2023).
- **Normalized cosine similarity** - $\hat{\cos}(a,b) = \frac{\cos(a,b)+1}{2}$ is the cosine similarity of (a,b) normalized to $[0,1]$ (Bouchard & Chauhan, 2025).
- **BERTScore** - $BertF1(a,b)$ is F1-BERTScore of (a,b) computed with matched-token cosine similarity (Zhang et al., 2020; Manakul et al., 2023).
- **Exact Match** - $\mathbb{I}[a=b]$ is an indicator function 1 if a is identical to b (Chen & Mueller, 2023).

Black-box UQ scores are then obtained by aggregating semantic consistency scores between the original response and sampled responses.

3.3 Fine-Grained Scorer Families

In contrast to traditional black-box UQ, where the semantic consistency function directly compares an original response with sampled responses, fine-grained adaptations perform comparisons on granular units obtained via the decomposition function δ_g with $g \in \{\text{sent}, \text{claim}\}$. We categorize fine-grained black-box UQ into four families of scorers: unit-response scorers, matched-unit scorers, unit-QA scorers, and graph-based scorers. Detailed definitions follow.

3.3.1 Unit-Response Scorers

A *unit-response scorer* is a unit-level confidence scorer $c_g : \mathcal{S}_g \times \mathcal{Y}^m \to [0,1]$ that compares individual sentences or claims contained in the decomposed original response $\delta_g(y_0)$ directly with candidate responses $\mathbf{y}_{\text{cand}} \in \mathcal{Y}^m$ (see Figure 1). Given a semantic consistency function $\eta(\cdot,\cdot)$, a unit-response scorer is specified as follows:

$$c_g(s; \mathbf{y}_{\text{cand}}) = \frac{1}{m}\sum_{j=1}^{m} \eta(y_j, s)$$

for $g \in \{\text{sent}, \text{claim}\}$ and $\eta \in \{p_e, 1-p_c, \frac{p_e}{p_e+p_c}\}$.

For this family of scorers, we consider only NLI-based consistency, as the others defined above (normalized cosine similarity, BertScore, and exact match) are intended for texts of similar length and granularity, making them poorly suited for comparing granular units to full responses. Note that sentence-level and claim-level scoring with contrasted entailment are respectively equivalent to the LUQ and LUQ-atomic scorers proposed by Zhang et al. (2024). Our use of entailment and non-contradiction probability are straightforward extensions of LUQ and LUQ-atomic.

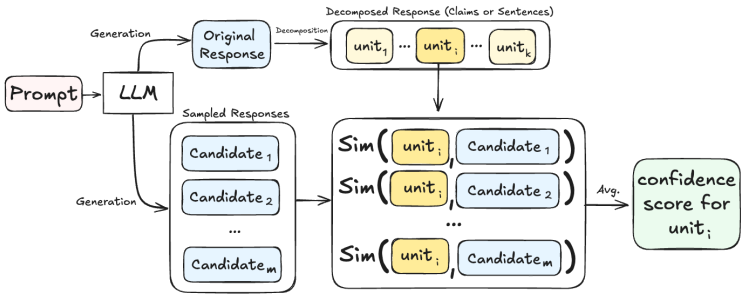


Figure 1: Unit-Response Scoring Workflow

3.3.2 Matched-Unit Scorers

Rather than deconstructing only the original response, matched-unit scorers apply the decomposition function to all candidate responses as well. Specifically, a *matched-unit scorer*, given by $c_{\mathrm{g}} : \mathcal{S}_{\mathrm{g}} \times \mathcal{P}(\mathcal{S}_{\mathrm{g}})^m \to [0, 1]$, measures consistency between a unit (sentence or claim) from the original response and its most similar unit from each candidate response (Figure 2). Formally:

$$c_g(s; \mathbf{y}_{\text{cand}}) = \frac{1}{m} \sum_{j=1}^{m} \max_{s' \in \delta_{\mathrm{g}}(y_j)} \eta(s', s)$$

for $\eta \in \{p_e, 1 - p_c, \frac{p_e}{p_e + p_c}, \text{côs}, BertF1\}$ and $g \in \{\text{sent}, \text{claim}\}$.

These matched consistency scores are averaged across pairings with all candidate responses. Note that scoring with $g = \text{sent}, \eta = \frac{p_e}{p_e + p_c}$ is equivalent to LUQ-pair (Zhang et al., 2024). We propose using alternative consistency functions $(p_e, 1 - p_c, \text{côs}, BertF1)$ as extensions of LUQ-pair.

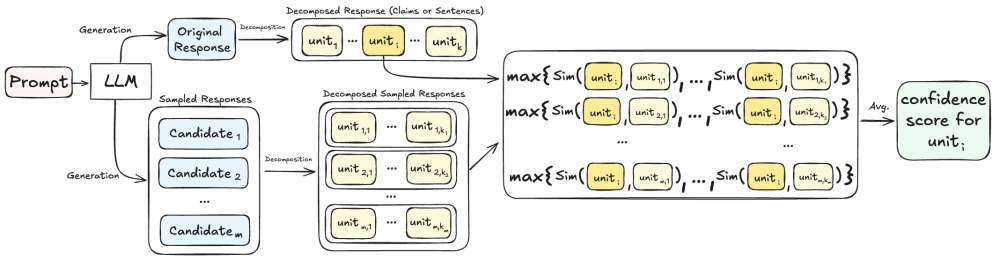


Figure 2: Matched-Unit Scoring Workflow

3.3.3 Unit-QA Scorers

The unit-qa family of scorers are inspired by the long-form version of semantic entropy proposed by Farquhar et al. (2024). We generalize this approach to allow for alternative consistency functions and granularities. The unit-qa approach relies on a *question inversion function* as $\gamma : \mathcal{S}_g \to \mathcal{Y}$ that maps a unit (sentence or claim) to a question for which that unit is the answer. In practice, an LLM is used to create the question.

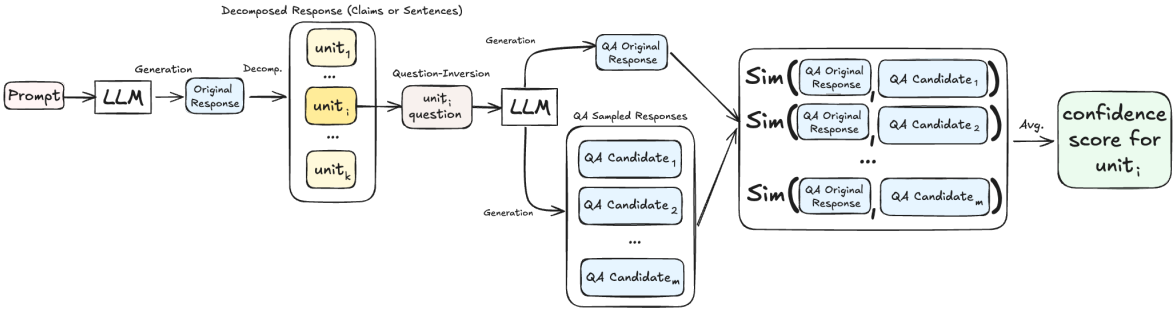


Figure 3: Unit-QA Scoring Workflow

A *unit-QA scorer*, $c_g : \mathcal{S}_g \times \mathcal{Y}^{m+1} \to [0, 1]$, measures consistency in multiple responses to unit question $\gamma(s)$:

$$c_g(s; y_0^{(s)}, \mathbf{y}_{\text{cand}}^{(s)}) = \frac{1}{m} \sum_{j=1}^{m} \eta(y_0^{(s)}, y_j^{(s)}),$$

where, for unit s, $y_j^{(s)}$ denotes the jth response to the unit's question $\gamma(s)$, $g \in \{\text{sent}, \text{claim}\}$, and $\eta \in \{1 - p_c, \text{côs}, BertF1, \mathbb{I}[y_0 = y_j]\}$.[2] Note that unit-QA effectively applies standard black-box UQ scoring to

[2]Multiple questions may be generated per unit, with the unit score calculated as the average across questions.

LLM responses to the unit questions (Figure 3). Hence, the semantic consistency functions we consider are standard black-box UQ choices as defined in Section 3.2.[3]

3.3.4 Graph-Based Scorers

Lastly, graph-based scorers, proposed by Jiang et al. (2024), decompose original and sampled responses into claims, obtain the union of unique claims across all responses, and compute graph centrality metrics (Hagberg et al., 2008) on the bipartite graph of claim-response entailment to measure uncertainty (Figure 4).[4] These scorers operate only at the claim level, as sentences typically contain multiple claims, meaning their union is not well-defined.

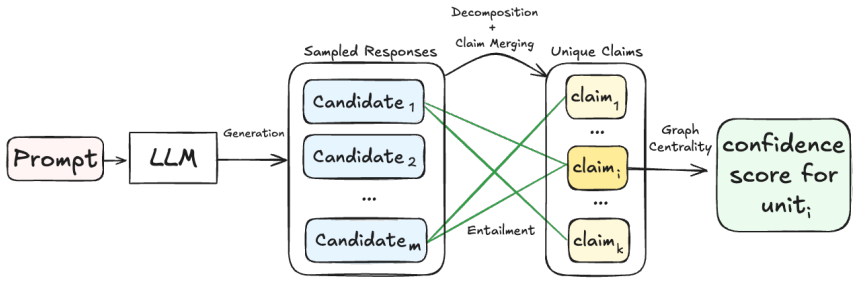


Figure 4: Graph-Based Scoring Workflow

Formally, we denote a bipartite graph G with node set $V = \mathbf{s} \cup \mathbf{y}$, where $\mathbf{y}$ is a set of m responses generated from the same prompt and $\mathbf{s}$ is the union of all unique claims across those decomposed responses. In particular, an edge exists between a claim-response pair $(s, y) \in \mathbf{s} \times \mathbf{y}$ if and only if claim s is entailed in response y. We define the following graph metrics for claim s:

- **Betweenness Centrality** - $\frac{1}{B_{\max}} \sum_{u \neq v \neq s} \frac{\sigma_{uv}(s)}{\sigma_{uv}}$ measures uncertainty by calculating the proportion of shortest paths between node pairs that pass through node s, where σ_{uv} represents all shortest paths between nodes u and v, and $B_{\max}$ is the maximum possible value.[5]
- **Closeness Centrality** - $\frac{m+2(|\mathbf{s}|-1)}{\sum_{v \neq s} dist(s,v)}$ measures the inverse sum of distances to all other nodes, normalized by the minimum possible distance.
- **Harmonic Centrality** - $\frac{1}{H_{\max}} \sum_{v \neq s} \frac{1}{dist(s,v)}$ is the sum of inverse of distances to all other nodes, normalized by the maximum possible value, where $H_{\max} = m + \frac{|\mathbf{s}|-1}{2}$.
- **Laplacian Centrality** - $\frac{E_L(G) - E_L(G_{-s})}{E_L(G)}$ is the proportional drop in Laplacian energy $E_L(G)$ resulting from dropping node s from the graph, where G_{-s} denotes the graph G with node s removed, $E_L(G) = \sum_i \lambda_i^2$, and λ_i are the eigenvalues of G's Laplacian matrix.
- **PageRank** - $\frac{1-d}{|V|} + d \sum_{v \in N(s)} \frac{C_{PR}(v)}{N(v)}$ is the stationary distribution probability of a random walk with restart probability $(1-d)$, where $N(s)$ denotes the set of neighboring nodes of s and $C_{PR}(v)$ is PageRank of node v.

In contrast to Jiang et al. (2024), we exclude Eigenvector Centrality (preferring metrics with bounded support), while adding Laplacian and Harmonic Centrality. Note that we do not include Degree Centrality as a graph-based scorer as it is equivalent to claim-response entailment and does not require decomposing sampled responses.

[3]We also evaluate semantic entropy, which has a different functional form. It works by clustering mutually entailing responses, calculating cluster probabilities from response frequencies, and computing entropy across these clusters. For consistency with other confidence scorers, we convert this to semantic negentropy, following Bouchard & Chauhan (2025).

[4]The union of unique claims is obtained by sequentially merging claims from each sampled response using an LLM.

[5]Specifically, $B_{\max} = \frac{1}{2}[m^2(p+1)^2 + m(p+1)(2t-p-1) - t(2p-t+3)]$, $p = \frac{(|\mathbf{s}|-1)}{m}$, and $t = (|\mathbf{s}|-1) \mod m$.

3.4 Response-Level Aggregation

We compute response-level confidence by averaging over the unit-level scores. Formally, for $g \in \{\text{sent}, \text{claim}\}$, this aggregation is given by:

$$A_{\text{avg}}(y) = \frac{1}{|\delta_g(y)|} \sum_{s \in \delta_g(y)} c_g(s; E).$$

Uncertainty-aware decoding (UAD). For claim-level scorers, we also implement an uncertainty-aware approach proposed by Jiang et al. (2024). This method first filters out low-confidence claims, then aggregates over the remaining ones. Specifically, we define the set of retained claims as $\widetilde{\delta}_{\text{UAD}}(y) = \{s \in \delta_{\text{claim}}(y) : c_{\text{claim}}(s; E) > \tau_{\text{claim}}\}$, where τ_{claim} is a confidence threshold. The UAD confidence is then calculated by averaging over only these retained claims. This approach effectively modifies the response by retaining only high-confidence claims and using an LLM to reconstruct the response from the retained set.

4 Experiments

4.1 Experimental Setup

We evaluate fine-grained black-box UQ for hallucination detection on two long-form QA datasets. The first is **FactScore-bio** (Min et al., 2023), containing 500 prompts that instruct the model to write a biography about a given person. The second is **FactScore-STEM-Geo**, our new 400-question dataset spanning four diverse categories across STEM and Geography: Chemical Elements, Scientific Laws, Nerves in the human body, and Mountains.[6] For each of these four categories, we select the 100 entities with the longest Wikipedia articles and construct prompts that instruct the model to write some facts about the target topic. We generate an original response and 10 sampled responses for each question using four LLMs: Gemini-2.5-Flash, Gemini-2.5-Pro, GPT-4o, and GPT-4o-mini.

Each response is decomposed at two granularities: sentences using SpaCy (Honnibal et al., 2020) and claims using an LLM (Zhang et al., 2025). We compute claim-level confidence scores using claim-response, claim-QA (one question per claim), and graph-based scorers.[7] For sentence-level scores, we use sentence-response, matched-sentence, and sentence-QA (two questions per sentence) scorers. For unit-QA scoring, we generate an original response and 5 sampled responses per unit question. As an additional baseline, we compute unit-level verbalized confidence (Tian et al., 2023). For each family, scores are computed using applicable consistency functions.[8]

We obtain ground-truth factuality labels using the FactScore grading protocol, which uses an LLM to compare each unit in the response to the corresponding Wikipedia article text. For claim-level evaluation, we follow Jiang et al. (2024) by further classifying claims as objective or subjective and retaining only objective claims for evaluation, since subjective ones cannot be definitively verified.[9] We use Gemini-2.5-Flash for claim decomposition, claim merging, unit question generation, and grading as it offers robust performance balanced with computational efficiency and cost-effectiveness. We report per-response sentence and claim counts in Table 9 and LLM accuracies in Tables 5, 6, 7, and 8.

4.2 Unit-Level Classification and Calibration

We evaluate claim-level and sentence-level hallucination detection across all LLM-dataset combinations using FactScore grades as labels. Specifically, we assess classification performance with unit-level AUROC and AUPRC, and calibration with Brier Score (BS) and Expected Calibration Error (ECE). Comprehensive results are reported in Tables 5, 6, 7, and 8.[10]

[6] See Appendix C for code to recreate this dataset.

[7] We do not compute matched-claim scores, as their semantic comparison costs were prohibitive at our sample sizes.

[8] NLI scores use `microsoft/deberta-large-mnli`.

[9] For sentence-level evaluation, we include all sentences regardless of objectivity classification, as sentences typically contain multiple claims of varying objectivity.

[10] We also evaluated results category-wise for FactScore-STEM-Geo but found little variation across subsets.

Classification. Figure 5 shows claim-level and sentence-level AUROC, with scorers ranked within each family, and Table 2 summarizes the top AUROC per family. For claim-level hallucination detection, scenario-specific top-scorer AUROC ranging from 0.67 for Gemini-2.5-Pro responses on Factscore-STEM-Geo (PageRank) to 0.80 for Gemini-2.5-Flash responses on Factscore-Bio (Closeness Centrality), on par with previous studies Zhang et al. (2025); Vashurin et al. (2025a); Farquhar et al. (2024). Comparing across scorer families, claim-response and graph-based scorers substantially outperform claim-QA approaches. Across the eight LLM-dataset combinations, claim-response entailment achieves the highest AUROC in 2 scenarios and is within 0.01 of the best scorer in the remaining 6, while also attaining the highest AUPRC in all 8. The top AUROC in the other 6 scenarios is achieved by graph-based scorers, with Closeness Centrality, PageRank, and Harmonic Centrality leading in 3, 2, and 1 scenarios, respectively. Among semantic consistency functions for claim-response scoring, entailment outperforms both contrasted entailment (used by Zhang et al. (2024)) and non-contradiction across all eight scenarios. Among graph-based scorers, Page Rank and Closeness Centrality lead most often, each achieving highest AUROC in three scenarios, with Laplacian and Harmonic Centrality leading in the other two.[11] Claim-QA scorers perform poorly overall, with non-contradiction being the top-performing claim-QA consistency function in 6 of 8 scenarios, yet rarely achieving AUROC above 0.6.[12] Verbalized confidence lags behind graph-based and claim-response but outperforms claim-QA scorers. AUPRC results exhibit similar patterns (Figure 13).

	FactScore-Bio				**FactScore-STEM-Geo**			
Scorer	**Gem-2.5-Fl**	**Gem-2.5-Pro**	**GPT-4o-Mini**	**GPT-4o**	**Gem-2.5-Fl**	**Gem-2.5-Pro**	**GPT-4o-Mini**	**GPT-4o**
Claim-Level Scorers								
Claim-response	0.794	0.755	0.774	0.724	0.671	0.669	**0.718**	0.703
Graph-based	**0.800**	**0.759**	**0.783**	**0.727**	**0.673**	**0.670**	0.716	**0.704**
Claim QA	0.654	0.644	0.623	0.618	0.590	0.557	0.582	0.555
LLM Accuracy	0.723	0.733	0.647	0.792	0.707	0.685	0.680	0.741
Sentence-Level Scorers								
Sent-response	**0.678**	**0.694**	**0.695**	**0.652**	0.590	0.565	**0.670**	0.632
Mat-sentence	0.632	0.661	0.620	0.615	**0.596**	**0.573**	0.669	**0.633**
Sentence QA	0.678	0.669	0.690	0.646	0.581	0.549	0.633	0.593
LLM Accuracy	0.462	0.455	0.347	0.532	0.500	0.491	0.487	0.584

Table 2: Unit-level AUROC (Higher is Better): Top Per Scorer Family by LLM and Dataset

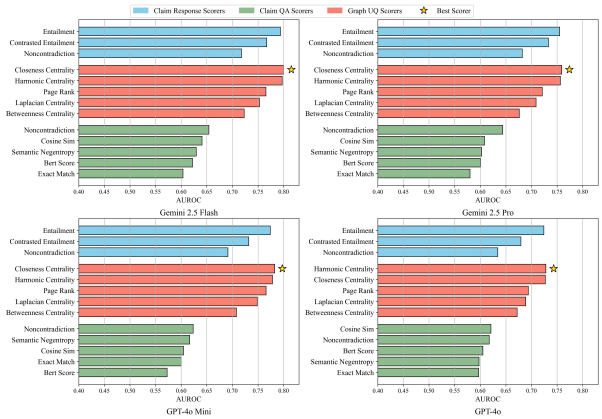
Sentence-level hallucination detection exhibits more varied performance across methods. The top-performing approaches are distributed across different scorer families, with matched sentence, sentence-response, and sentence-QA scorers each achieving the highest AUROC in 3, 3, and 2 scenarios out of 8, respectively. Despite this variation, the maximum AUROC values across different scorer families remain similar within most scenarios. Consistent with Zhang et al. (2024), our results demonstrate that hallucination detection is inherently more difficult at the sentence level than at the claim level, as the highest sentence-level AUROC across all scenarios reaches only 0.694 and AUROC is consistently lower than claim-level scorers for the same datasets. For unit-response and matched-sentence scorers, our ablation studies (Appendix A) show that performance increases with the number of sampled responses but with substantial diminishing returns, with negligible gains beyond $m = 5$, consistent with previous work (Zhang et al., 2024; Jiang et al., 2024).

Calibration. Turning to calibration, we observe clear differences across families and granularities. At the claim level, most scorers are at best moderately calibrated and rarely attain ECE < 0.1. PageRank, Laplacian Centrality, and Betweenness Centrality are exceptions having notably worse calibration, with ECE values consistently above 0.6. Overall, our claim-level calibration metrics are comparable to those found in Zhang et al. (2025). At the sentence level, Sentence-QA Exact Match yields the lowest ECE in 7 of 8 scenarios.

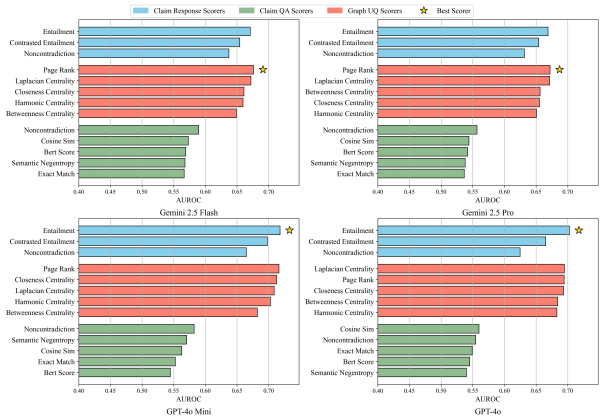
[11] Our results are generally similar to Jiang et al. (2024), with the notable exception that Closeness Centrality consistently outperforms other graph-based scorers in their experiments, which contain different LLMs and datasets.

[12] Farquhar et al. (2024) decompose responses into factoids containing several atomic claims and achieve better results. Manual inspection revealed many atomic claims are poorly suited for question-inversion, likely explaining our claim-QA scorers' poor performance relative to sentence-QA scorers.

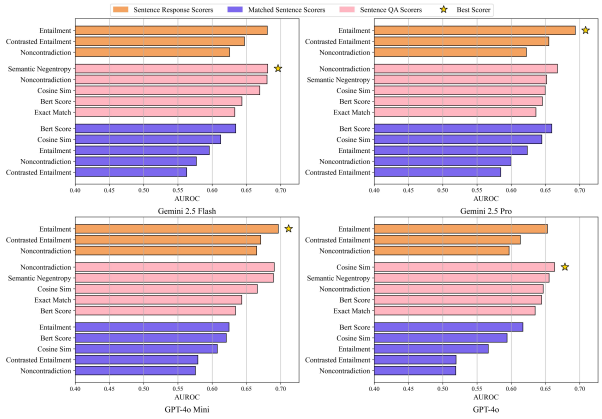
Apart from PageRank, Laplacian Centrality, and Betweenness Centrality, sentence-level scorers tend to be less calibrated overall than claim-level scorers. See Figure 14 calibration plots of the best-calibrated scorers for FactScore-Bio.



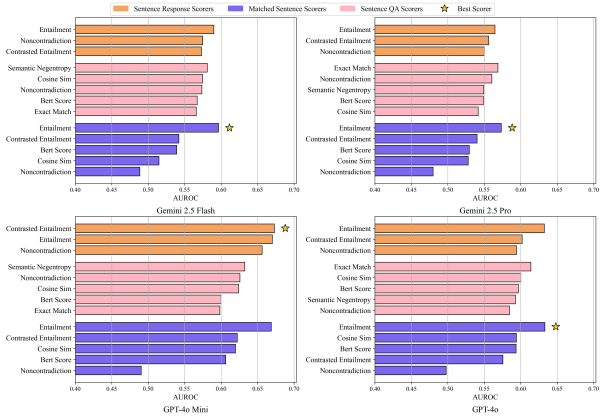
(a) Factscore-Bio: Claim Scoring



(b) Factscore-STEM-Geo: Claim Scoring



(c) Factscore-Bio: Sentence Scoring



(d) Factscore-STEM-Geo: Sentence Scoring

Figure 5: Claim-Level and Sentence-Level AUROC by LLM and Dataset (Higher is Better)

4.3 Uncertainty-Aware Decoding

To evaluate the accuracy gains resulting from the UAD method proposed by Jiang et al. (2024), we analyze the relationship between LLM accuracy and claim-level filtering thresholds. We apply percentile-based thresholds at intervals of 10% (from the 10th to 90th percentile) for the top-performing scorer (by AUROC) from each scorer family. Figure 6 presents these results across all eight LLM-dataset combinations, with baseline LLM accuracy shown as a reference.

Our results demonstrate substantial accuracy improvements through uncertainty-aware filtering. For instance, when filtering claims from Gemini-2.5-Flash responses on FactScore-Bio at the 50th percentile threshold, accuracy increases dramatically from a baseline of 0.72 to approximately 0.90. This pattern is consistent across all evaluated scenarios, though with varying magnitudes of improvement. Specifically, claim-response-based filtering generally yields the most pronounced accuracy gains, followed closely by graph-based filtering, while claim-QA-based filtering, though still effective, shows more modest improvements. These findings highlight the practical utility of UAD across scoring methods for enhancing the factual reliability of long-form LLM outputs.

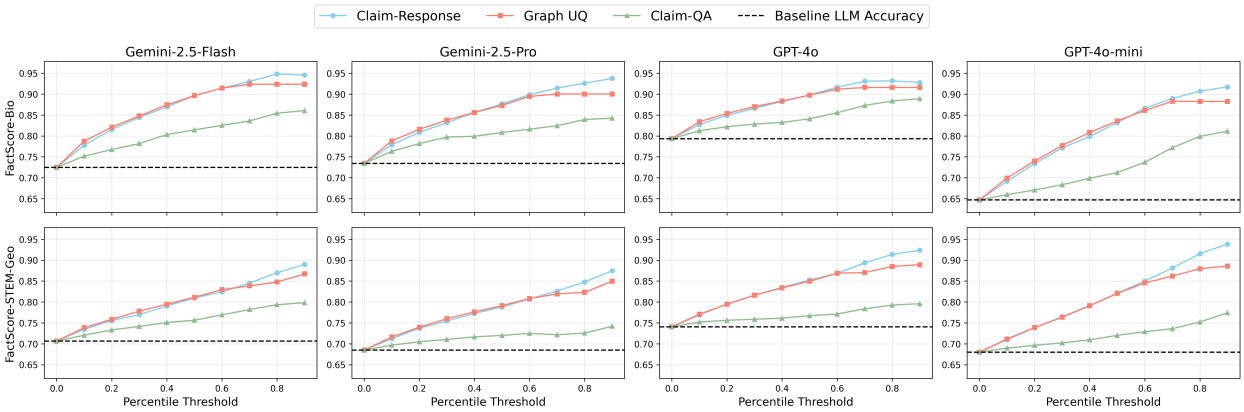


Figure 6: LLM Accuracy vs. UAD Filtering Threshold by LLM-Dataset (Top per Scorer Type)

Scorer	Gemini-2.5-Flash	Gemini-2.5-Pro	GPT-4o-Mini	GPT-4o
Claim-Level Scorers				
CR Entailment	0.73	0.69	0.68	0.56
CR Non-Contradiction	0.54	0.56	0.37	0.36
CR Contrasted Entailment	0.68	0.66	0.50	0.40
QA Exact Match	0.39	0.32	0.57	0.45
QA Semantic Negentropy	0.56	0.55	0.54	0.46
QA Non-Contradiction	0.55	0.61	0.36	0.46
QA BERTScore	0.47	0.49	0.41	0.48
QA Cosine Similarity	0.53	0.53	0.44	0.52
Betweenness	-0.03	-0.24	-0.05	-0.17
Closeness	0.74	**0.71**	**0.70**	0.57
Harmonic	**0.74**	0.70	0.68	**0.60**
Page Rank	0.51	0.47	0.60	0.24
Laplacian	0.49	0.44	0.57	0.25
Sentence-Level Scorers				
SR Entailment	0.47	0.48	0.50	0.25
SR Non-Contradiction	0.49	0.51	0.34	0.43
SR Contrasted Entailment	0.51	0.52	0.39	0.33
Matched Entailment	0.39	0.36	0.49	0.13
Matched Non-Contradiction	0.39	0.28	0.20	0.39
Matched Contrasted Entailment	0.39	0.44	0.27	0.10
Matched Cosine Similarity	0.50	0.50	0.49	0.30
Matched BERTScore	0.53	0.47	0.50	0.34
QA Exact Match	0.39	0.35	0.54	0.43
QA Semantic Negentropy	0.57	0.50	0.53	0.44
QA Non-Contradiction	0.53	0.53	0.46	0.34
QA BERTScore	0.47	0.47	0.48	0.48
QA Cosine Similarity	0.56	0.51	0.55	0.53
Short-Form Black-Box Scorers				
Semantic Negentropy	0.47	0.35	0.39	0.31
Non-Contradiction	0.44	0.43	0.18	0.32
BERTScore	0.59	0.54	0.67	0.55
Cosine Similarity	0.56	0.55	0.54	0.37

Table 3: Pearson correlation coefficients (higher is better) between response-level confidence scores and factuality on FactScore-Bio by LLM.

4.4 Response-Level Scoring

Lastly, we average unit-level confidence scores to get response-level confidence scores and unit-level labels (FactScore grades) to get a response-level grade for all FactScore-Bio results. For benchmarking purposes, we also compute confidence scores using four short-form black-box UQ scorers (Section 3.2): BERTScore, cosine similarity, non-contradiction, and semantic negentropy (Bouchard & Chauhan, 2025). We report Pearson and Spearman correlations between response-level scores and grades in Tables 3 and 10.

Overall, the results are consistent with our unit-level evaluation. Closeness and Harmonic Centrality yield the strongest response-level signals, followed closely by claim-response entailment. These scorers outperform other fine-grained scorers as well as short-form baselines. Betweenness Centrality stands out as particularly ineffective, exhibiting no useful response-level signal. Sentence-level aggregation is noticeably weaker, with even the best sentence-level methods rarely approaching the correlations of the top claim-level scorers or the strongest short-form baselines. Among short-form UQ methods that directly score full responses, BERTScore is the most competitive, sometimes approaching the top claim-level scorers but generally falling short.[13] Spearman correlations exhibit similar patterns.

5 Discussion

Performance. Our experiments in Section 4 highlight several consistent patterns on relative scorer performance. At the claim level, claim-response entailment generally exhibits the best performance, achieving the highest AUPRC in all scenarios and consistently performing better or on par with more complex graph-based and claim-QA methods. Graph-based scorers are competitive but rarely surpass claim-response entailment by a large margin, while claim-QA methods perform notably worse overall and often fail to reach AUROC values that are useful in practice. At the sentence level, hallucination detection is inherently more difficult, with top AUROC scores considerably lower than at the claim level. Performance varies across scorer families, but sentence-response entailment is a strong baseline, achieving the best AUROC in many scenarios and remaining competitive when matched-sentence or sentence-QA scorers perform slightly better.

Beyond detection, our uncertainty-aware decoding (UAD) experiments show that claim-level filtering can deliver large accuracy gains over baseline long-form generation. By discarding low-confidence claims and reconstructing responses from the remaining content, we observe consistent improvements across all evaluated models and datasets, often boosting factual accuracy by a large margin even at moderate filtering thresholds. These gains are most pronounced when using claim-response and graph-based scorers.[14] Though effective for ranking and filtering, the lack of calibration limits the utility of these scorers for probability estimation.

Computational Tradeoffs. We further quantify tradeoffs by analyzing both semantic consistency computations and LLM generation costs across scorer families (Table 4). Sentence-response and claim-response scorers decompose only the original response and compare each unit to m sampled responses, yielding mN_g semantic comparisons per response, where N_g is the number of units at granularity g. Matched-sentence scorers decompose each of the m sampled responses and, for every original sentence, compare against all sentences in each sample, yielding roughly mN_{sent}^2 semantic comparisons per prompt. Graph-based scorers decompose the original and all m sampled responses into claims and construct an entailment graph over the union of $N_{m\text{-union}}$ unique claims across sampled responses, requiring approximately $mN_{m\text{-union}}$ consistency comparisons, where $N_{m\text{-union}} \approx 3N_{\text{claim}}$ on average in our experiments (Table 11). Beyond generating the sampled responses, graph-based methods also require decomposing each of the sampled responses into claims and sequentially merging claim sets, for a total of roughly $3m + 1$ additional generations per original response. Unit-QA scorers sample responses to unit questions rather than to the original prompt. Per unit, this requires a generation to obtain Q questions and generating $m_{qa} + 1$ responses per question, yielding $((1 + m_{\text{qa}})Q + 1)N_g$ additional generations and $m_{\text{qa}}QN_g$ semantic comparisons per prompt. Relative to sentence-level scorers, all claim-level scorers require one additional generation for decomposing the original response and one additional generation if UAD is used.[15]

[13] Note that even when competitive, short-form scorers do not enable localizing the uncertainty in the response.
[14] Graph-based scorers use all unique claims across samples, increasing content coverage in reconstructed responses.
[15] Sentence decomposition uses SpaCy instead of an LLM.

Scorer Family	Comparisons	Additional Generations
Claim-Response	mN_{claim}	$m + \mathbb{I}_{\text{UAD}} + 1$
Graph-Based	$mN_{m\text{-union}}$	$3m + \mathbb{I}_{\text{UAD}} + 1$
Claim-QA	$m_{\text{qa}}QN_{\text{claim}}$	$((1 + m_{\text{qa}})Q + 1)N_{claim} + \mathbb{I}_{\text{UAD}} + 1$
Sentence-response	mN_{sent}	m
Matched-Sentence	mN_{sent}^2	m
Sentence-QA	$m_{\text{qa}}QN_{\text{sent}}$	$((1 + m_{\text{qa}})Q + 1)N_{\text{sent}}$

Table 4: Per-prompt semantic consistency comparisons and LLM generations by scorer family.

Importantly, we note that the number of units at each granularity also differs substantially. In our experiments, $N_{\text{claim}} \approx 5N_{\text{sent}}$ (Table 11), so claim-level methods operate over several times as many units as sentence-level methods for the same prompt, amplifying generation and computation costs. Table 11 summarizes the semantic comparison counts and runtimes from our experiments.[16]

Method Selection. Taken together, our findings support the following practical recommendations. If computational resources permit claim-level analysis, claim-response entailment offers a robust default over more complex methods when both accuracy and efficiency are considered, with as few as 5 sampled responses typically being sufficient. When only sentence-level scoring is feasible, sentence-response entailment provides a simple, competitive, and cheap baseline. When claim-level scoring is used, for only one additional generation per response, uncertainty-aware decoding offers substantial accuracy improvements and turns fine-grained black-box UQ from a purely diagnostic tool into a mechanism for editing and improving long-form outputs.

6 Conclusion

We introduced a general framework for fine-grained black-box uncertainty quantification in long-form LLM outputs and formalized a taxonomy aligned with a three-stage pipeline: response decomposition, unit-level confidence scoring, and response-level aggregation. Within this framework we define four scorer families and two aggregation strategies (simple averaging and uncertainty-aware decoding), unifying, generalizing, and extending existing fine-grained UQ methods. Experiments on four LLMs and two long-form QA datasets quantify performance, calibration, and computational trade-offs and yield practical recommendations: claim-response entailment is preferable when both performance and cost are considered, and claim-level uncertainty-aware decoding reliably improves long-form factual precision. To support reproducibility, all methods evaluated in this study are available in our accompanying open-source package.

7 Limitations

We acknowledge several limitations of this work. First, due to the computational intensity of our experiments, comprehensively varying all experimental parameters was infeasible. In particular, we fix a single temperature, one NLI model, one embedding model for cosine similarity, and one LLM for claim decomposition and merging, question generation, and grading. Different choices for these components could change absolute and relative performance.[17] Second, while we evaluate four LLMs and two long-form QA datasets, our findings may not generalize to all models or domains. Differences in model behavior as well as dataset characteristics such as topic, difficulty, and answer format, may affect hallucination patterns and scorer effectiveness. Finally, we focus solely on fine-grained, black-box, consistency-based methods, excluding white-box approaches (using token probabilities or attention) and long-form methods that score only at the response level, which may outperform our evaluated methods.

[16] We do not report generation time, as it is heavily influenced by factors that are difficult to standardize, including deployment-specific rate limits and hardware configurations.

[17] We note that LLMs are subject to bias and variability.

References

Yavuz Bakman, Duygu Nur Yaldiz, Sungmin Kang, Tuo Zhang, Baturalp Buyukates, Salman Avestimehr, and Sai Praneeth Karimireddy. Reconsidering llm uncertainty estimation methods in the wild, 2025. URL https://arxiv.org/abs/2506.01114.

Satanjeev Banerjee and Alon Lavie. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Jade Goldstein, Alon Lavie, Chin-Yew Lin, and Clare Voss (eds.), *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pp. 65–72, Ann Arbor, Michigan, June 2005. Association for Computational Linguistics. URL https://aclanthology.org/W05-0909/.

Dylan Bouchard and Mohit Singh Chauhan. Uncertainty quantification for language models: A suite of black-box, white-box, LLM judge, and ensemble scorers. *Transactions on Machine Learning Research*, 2025. ISSN 2835-8856. URL https://openreview.net/forum?id=WOFspd4lq5.

Jiuhai Chen and Jonas Mueller. Quantifying uncertainty in answers from any language model and enhancing their trustworthiness, 2023. URL https://arxiv.org/abs/2308.16175.

Jeremy R. Cole, Michael J. Q. Zhang, Daniel Gillick, Julian Martin Eisenschlos, Bhuwan Dhingra, and Jacob Eisenstein. Selectively answering ambiguous questions, 2023. URL https://arxiv.org/abs/2305.14613.

Longchao Da, Tiejin Chen, Lu Cheng, and Hua Wei. Llm uncertainty quantification through directional entailment graph and claim level response augmentation, 2024. URL https://arxiv.org/abs/2407.00994.

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, 2024. URL https://arxiv.org/abs/2403.04696.

Sebastian Farquhar, Jannik Kossen, Lorenz Kuhn, and Yarin Gal. Detecting hallucinations in large language models using semantic entropy. *Nature*, 630(8017):625–630, Jun 2024. ISSN 1476-4687. doi: 10.1038/s41586-024-07421-0. URL https://doi.org/10.1038/s41586-024-07421-0.

Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. Exploring network structure, dynamics, and function using networkx. *Python in Science Conference*, 2008. doi: 10.25080/TCWV9851. URL https://doi.org/10.25080/TCWV9851.

Matthew Honnibal, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. spaCy: Industrial-strength Natural Language Processing in Python. 2020. doi: 10.5281/zenodo.1212303.

Hsiu-Yuan Huang, Yutong Yang, Zhaoxi Zhang, Sanwoo Lee, and Yunfang Wu. A survey of uncertainty estimation in llms: Theory meets practice, 2024a. URL https://arxiv.org/abs/2410.15326.

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, 2023. URL https://arxiv.org/abs/2311.05232.

Yukun Huang, Yixin Liu, Raghuveer Thirukovalluru, Arman Cohan, and Bhuwan Dhingra. Calibrating long-form generations from large language models, 2024b. URL https://arxiv.org/abs/2402.06544.

Mingjian Jiang, Yangjun Ruan, Prasanna Sattigeri, Salim Roukos, and Tatsunori Hashimoto. Graph-based uncertainty metrics for long-form language model outputs, 2024. URL https://arxiv.org/abs/2410.20783.

Jannik Kossen, Jiatong Han, Muhammed Razzak, Lisa Schut, Shreshth Malik, and Yarin Gal. Semantic entropy probes: Robust and cheap hallucination detection in llms, 2024. URL https://arxiv.org/abs/2406.15927.

Lorenz Kuhn, Yarin Gal, and Sebastian Farquhar. Semantic uncertainty: Linguistic invariances for uncertainty estimation in natural language generation, 2023. URL https://arxiv.org/abs/2302.09664.

Chin-Yew Lin. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pp. 74–81, Barcelona, Spain, July 2004. Association for Computational Linguistics. URL https://aclanthology.org/W04-1013/.

Zhen Lin, Shubhendu Trivedi, and Jimeng Sun. Generating with confidence: Uncertainty quantification for black-box large language models, 2024. URL https://arxiv.org/abs/2305.19187.

Terrance Liu and Zhiwei Steven Wu. Multi-group uncertainty quantification for long-form text generation, 2025. URL https://arxiv.org/abs/2407.21057.

Xin Liu, Muhammad Khalifa, and Lu Wang. Litcab: Lightweight language model calibration over short- and long-form responses, 2024. URL https://arxiv.org/abs/2310.19208.

Andrey Malinin and Mark Gales. Uncertainty estimation in autoregressive structured prediction, 2021. URL https://arxiv.org/abs/2002.07650.

Potsawee Manakul, Adian Liusie, and Mark J. F. Gales. Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models, 2023. URL https://arxiv.org/abs/2303.08896.

Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. Factscore: Fine-grained atomic evaluation of factual precision in long form text generation, 2023. URL https://arxiv.org/abs/2305.14251.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ACL '02, pp. 311–318, USA, 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073135. URL https://doi.org/10.3115/1073083.1073135.

Xin Qiu and Risto Miikkulainen. Semantic density: Uncertainty quantification for large language models through confidence measurement in semantic space, 2024. URL https://arxiv.org/abs/2405.13845.

Abdul Wahab Qurashi, Violeta Holmes, and Anju P. Johnson. Document processing: Methods for semantic text similarity analysis. In *2020 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*, pp. 1–6, 2020. doi: 10.1109/INISTA49547.2020.9194665.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019. URL https://arxiv.org/abs/1908.10084.

Ola Shorinwa, Zhiting Mei, Justin Lidard, Allen Z. Ren, and Anirudha Majumdar. A survey on uncertainty quantification of large language models: Taxonomy, open research challenges, and future directions, 2024. URL https://arxiv.org/abs/2412.05563.

Katherine Tian, Eric Mitchell, Allan Zhou, Archit Sharma, Rafael Rafailov, Huaxiu Yao, Chelsea Finn, and Christopher D. Manning. Just ask for calibration: Strategies for eliciting calibrated confidence scores from language models fine-tuned with human feedback, 2023. URL https://arxiv.org/abs/2305.14975.

S. M Towhidul Islam Tonmoy, S M Mehedi Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models, 2024. URL https://arxiv.org/abs/2401.01313.

Roman Vashurin, Ekaterina Fadeeva, Artem Vazhentsev, Lyudmila Rvanova, Daniil Vasilev, Akim Tsvigun, Sergey Petrakov, Rui Xing, Abdelrahman Sadallah, Kirill Grishchenkov, Alexander Panchenko, Timothy Baldwin, Preslav Nakov, Maxim Panov, and Artem Shelmanov. Benchmarking uncertainty quantification methods for large language models with lm-polygraph. *Transactions of the Association for Computational Linguistics*, 13:220–248, 2025a. ISSN 2307-387X. doi: 10.1162/tacl_a_00737. URL http://dx.doi.org/10.1162/tacl_a_00737.

Roman Vashurin, Maiya Goloburda, Preslav Nakov, and Maxim Panov. Uncertainty-line: Length-invariant estimation of uncertainty for large language models, 2025b. URL https://arxiv.org/abs/2505.19060.

Yingqing Yuan, Linwei Tao, Haohui Lu, Matloob Khushi, Imran Razzak, Mark Dras, Jian Yang, and Usman Naseem. Kg-uq: Knowledge graph-based uncertainty quantification for long text in large language models. In *Companion Proceedings of the ACM on Web Conference 2025*, WWW '25, pp. 2071–2077, New York, NY, USA, 2025. Association for Computing Machinery. ISBN 9798400713316. doi: 10.1145/3701716.3717660. URL https://doi.org/10.1145/3701716.3717660.

Caiqi Zhang, Fangyu Liu, Marco Basaldella, and Nigel Collier. Luq: Long-text uncertainty quantification for llms, 2024. URL https://arxiv.org/abs/2403.20279.

Caiqi Zhang, Ruihan Yang, Zhisong Zhang, Xinting Huang, Sen Yang, Dong Yu, and Nigel Collier. Atomic calibration of llms in long-form generations, 2025. URL https://arxiv.org/abs/2410.13246.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert, 2020. URL https://arxiv.org/abs/1904.09675.

A Ablations

Our ablation studies examine how the number of sampled responses m affects performance for unit-response and matched-sentence scorers.[18] Figures 7, 8, 9, 10, 11, and 12 show that both AUROC and AUPRC generally increase monotonically with m across datasets and models, but with substantial diminishing returns. For claim-response scorers, performance gains are most significant when increasing from $m = 1$ to $m = 3$, with approximate AUROC improvements of 0.05-0.07. Beyond $m = 5$, additional samples yield negligible improvements (typically <0.01 AUROC), consistent with findings from Zhang et al. (2024) and Jiang et al. (2024).

Similar patterns emerge for sentence-response and matched-sentence scorers, with some notable exceptions. In particular, we observe that gains from additional responses are negligible or non-existent in scenarios where hallucination detection performance is poor (i.e., AUROC values close to 0.5), such as with matched-sentence non-contradiction used on LLM responses to FactScore-STEM-Geo questions. Overall, these results indicate that practitioners can confidently limit sampling to just a few responses without sacrificing meaningful hallucination detection performance for these scorers. This finding is particularly useful in practice given the high computational and generation costs that scale with number of sampled responses.

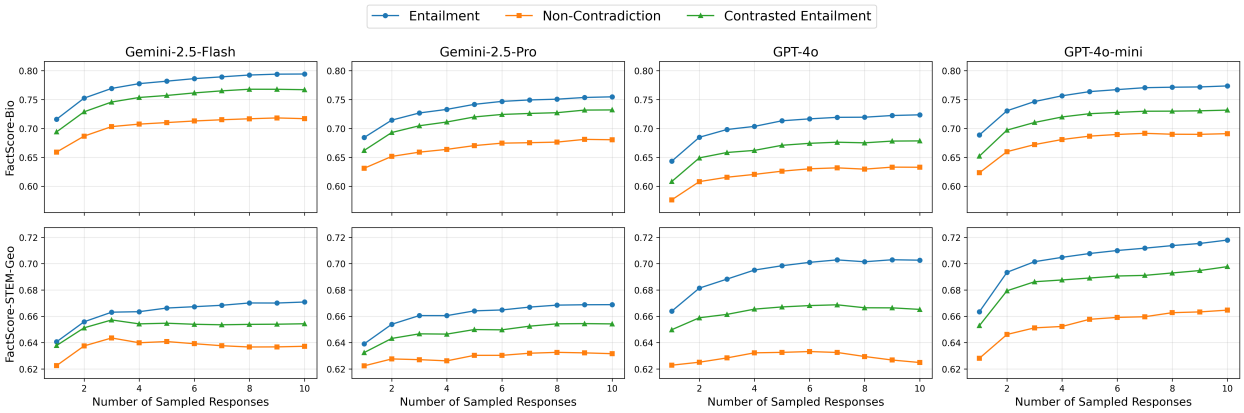


Figure 7: Claim-Response Hallucination Detection AUROC by Number of Sampled Responses

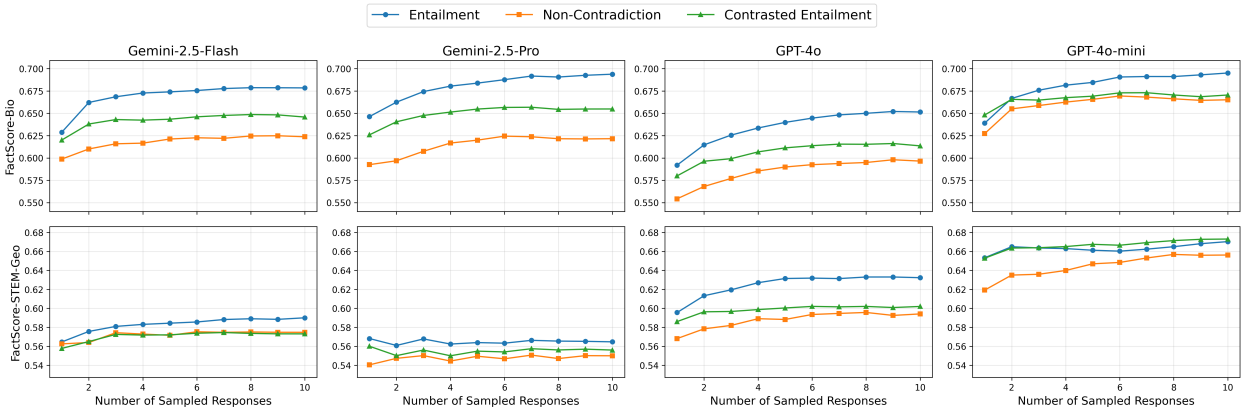


Figure 8: Sentence-Response Hallucination Detection AUROC by Number of Sampled Responses

[18] We did not conduct ablations for graph-based scorers due to the high computational costs of sequential claim merging, nor for claim-QA scorers given their relatively lower performance compared to other methods.

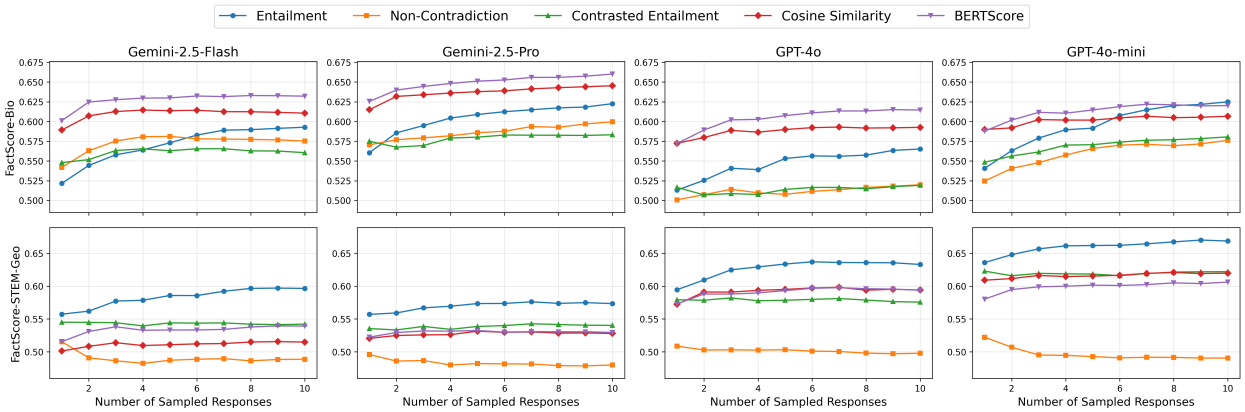


Figure 9: Matched-Sentence Hallucination Detection AUROC by Number of Sampled Responses

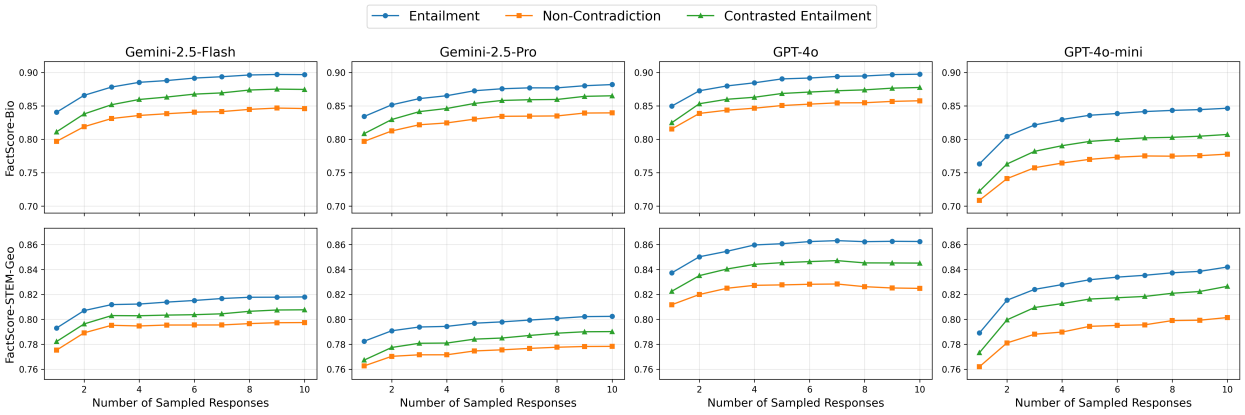


Figure 10: Claim-Response Hallucination Detection AUPRC by Number of Sampled Responses

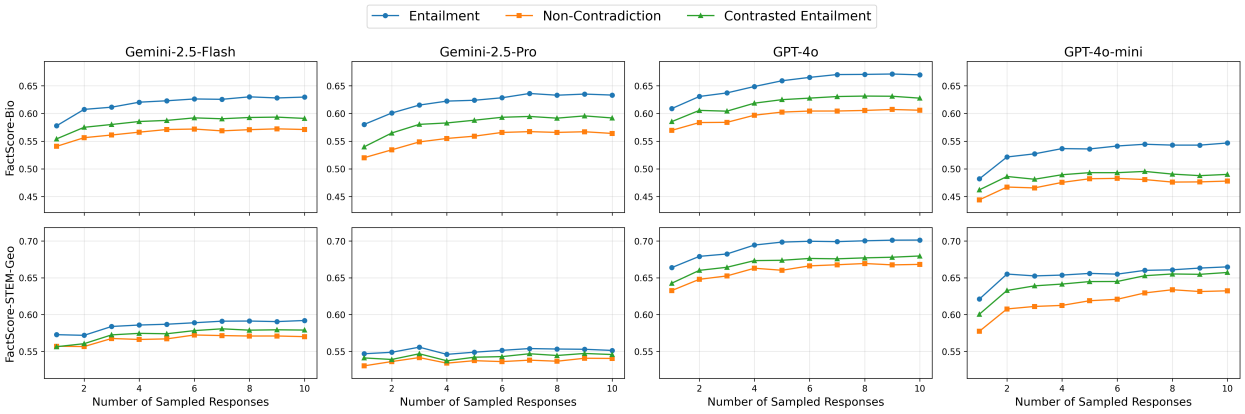


Figure 11: Sentence-Response Hallucination Detection AUPRC by Number of Sampled Responses

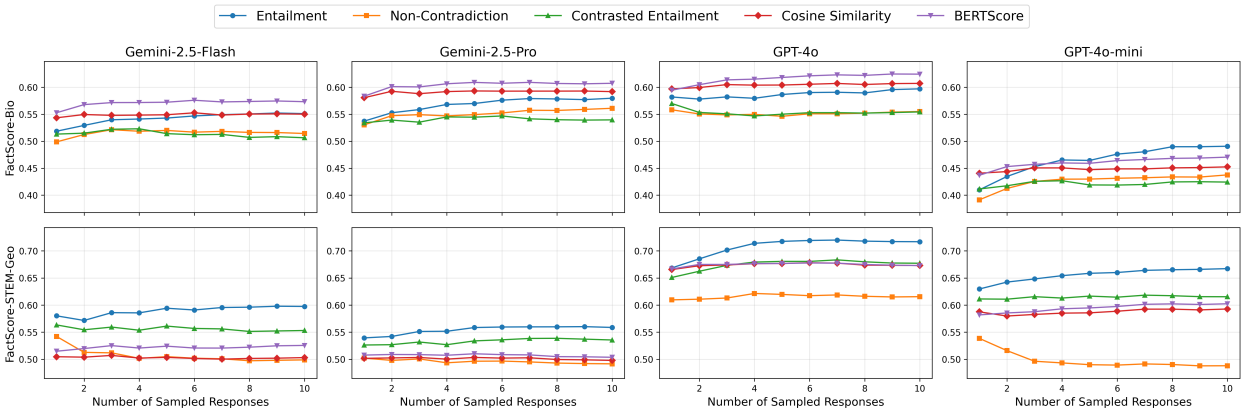
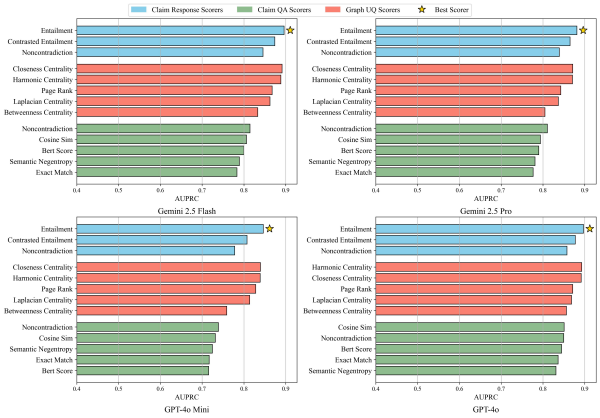
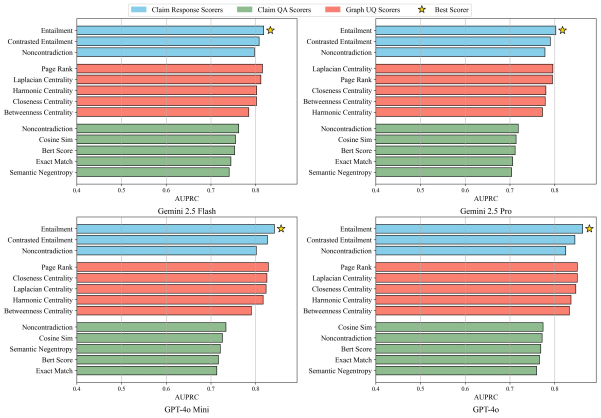


Figure 12: Matched-Sentence Hallucination Detection AUPRC by Number of Sampled Responses

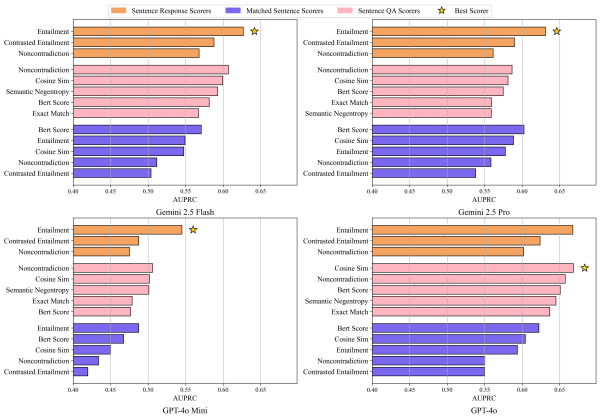
B Supplemental Tables and Figures



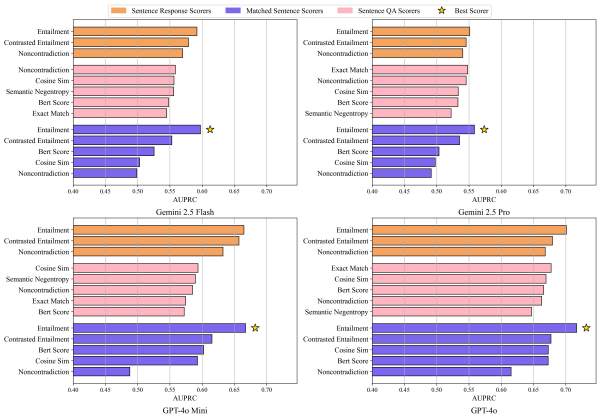
(a) Factscore-Bio: Claim-Level Scorers



(b) Factscore-STEM-Geo: Claim-Level Scorers



(c) Factscore-Bio: Sentence-Level Scorers



(d) Factscore-STEM-Geo: Sentence-Level Scorers

Figure 13: Claim-Level and Sentence-Level AUPRC by LLM and Dataset (Higher is Better)

	Gemini-2.5 Flash				Gemini-2.5 Pro				GPT-4o Mini				GPT-4o			
Scorer	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS
Claim-Response Scorers																
Entailment	0.79	**0.90**	0.12	0.18	0.76	**0.88**	**0.12**	0.19	0.77	**0.85**	**0.10**	**0.19**	0.72	**0.90**	0.15	0.19
Non-contradiction	0.72	0.85	0.19	0.22	0.68	0.84	0.20	0.22	0.69	0.78	0.27	0.28	0.63	0.86	0.16	0.18
Contrasted Entailment	0.77	0.88	**0.10**	**0.17**	0.73	0.86	0.12	0.19	0.73	0.81	0.18	0.23	0.68	0.88	0.12	0.17
Claim-QA Scorers																
Exact Match	0.60	0.78	0.42	0.41	0.58	0.78	0.43	0.43	0.60	0.72	0.39	0.41	0.60	0.84	0.44	0.42
Semantic Entropy	0.63	0.79	0.16	0.22	0.60	0.78	0.18	0.22	0.62	0.72	0.21	0.27	0.60	0.83	0.17	0.20
Non-contradiction	0.65	0.81	0.18	0.22	0.64	0.81	0.21	0.23	0.62	0.74	0.27	0.30	0.62	0.85	0.17	0.19
BERTScore	0.62	0.80	0.22	0.24	0.60	0.79	0.22	0.24	0.57	0.72	0.32	0.33	0.61	0.85	0.17	0.19
Cosine Similarity	0.64	0.81	0.16	0.21	0.61	0.79	0.19	0.22	0.61	0.73	0.32	0.33	0.62	0.85	0.16	0.19
Claim-Verbalized Confidence																
Verbalized Confidence	0.65	0.79	0.21	0.22	0.59	0.77	0.23	0.23	0.66	0.75	0.17	0.24	0.61	0.84	**0.09**	0.20
Graph-Based Scorers																
Betweenness	0.72	0.83	0.71	0.70	0.68	0.80	0.72	0.72	0.71	0.76	0.63	0.63	0.67	0.86	0.78	0.77
Closeness	**0.80**	0.89	0.14	0.17	**0.76**	0.87	0.15	**0.18**	**0.78**	0.84	0.21	0.22	0.73	0.89	0.09	**0.15**
Harmonic	0.80	0.89	0.15	0.18	0.76	0.87	0.16	0.19	0.78	0.84	0.23	0.24	**0.73**	0.89	0.11	0.16
Page Rank	0.77	0.87	0.71	0.70	0.72	0.84	0.72	0.71	0.77	0.83	0.63	0.63	0.69	0.87	0.78	0.77
Laplacian	0.75	0.86	0.68	0.65	0.71	0.84	0.68	0.66	0.75	0.81	0.60	0.58	0.69	0.87	0.75	0.72
LLM Accuracy	0.72				0.73				0.65				0.79			

Table 5: FactScore-Bio: Claim-Level Classification (AUROC↑, AUPRC↑) and Calibration (ECE↓, BS↓) bbb LLM

	Gemini-2.5 Flash				Gemini-2.5 Pro				GPT-4o Mini				GPT-4o			
Scorer Type	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS
Sentence-Response Scorers																
Entailment	0.68	**0.63**	0.16	0.26	**0.69**	**0.63**	0.16	**0.25**	**0.70**	**0.55**	**0.13**	**0.23**	0.65	0.67	0.17	0.27
Non-contradiction	0.62	0.57	0.47	0.46	0.62	0.56	0.50	0.49	0.66	0.47	0.55	0.53	0.60	0.60	0.41	0.41
Contrasted Entailment	0.65	0.59	0.34	0.36	0.66	0.59	0.37	0.38	0.67	0.49	0.43	0.41	0.61	0.63	0.30	0.34
Sentence-QA Scorers																
Exact Match	0.63	0.57	**0.10**	**0.25**	0.64	0.56	**0.11**	0.25	0.64	0.48	0.16	0.25	0.63	0.64	**0.09**	**0.25**
Semantic Negentropy	**0.68**	0.59	0.37	0.36	0.65	0.56	0.43	0.41	0.69	0.50	0.43	0.39	0.65	0.65	0.31	0.33
Non-contradiction	0.68	0.61	0.43	0.41	0.67	0.59	0.48	0.46	0.69	0.51	0.53	0.49	0.65	0.66	0.38	0.38
BERTScore	0.64	0.58	0.50	0.49	0.65	0.58	0.51	0.51	0.63	0.48	0.62	0.60	0.64	0.65	0.43	0.43
Cosine Similarity	0.67	0.60	0.46	0.45	0.65	0.58	0.49	0.48	0.66	0.50	0.58	0.55	**0.66**	**0.67**	0.40	0.40
Matched-Sentence Scorers																
Entailment	0.59	0.55	0.26	0.32	0.62	0.58	0.21	0.29	0.62	0.49	0.16	0.24	0.57	0.60	0.31	0.36
Non-contradiction	0.58	0.51	0.53	0.53	0.60	0.55	0.54	0.54	0.57	0.41	0.65	0.65	0.52	0.55	0.47	0.47
Contrasted Entailment	0.56	0.51	0.37	0.39	0.58	0.54	0.38	0.40	0.58	0.42	0.52	0.49	0.52	0.55	0.34	0.37
Cosine Similarity	0.61	0.55	0.40	0.40	0.65	0.59	0.42	0.41	0.61	0.45	0.52	0.49	0.59	0.61	0.34	0.36
BERTScore	0.63	0.57	0.46	0.45	0.66	0.61	0.47	0.46	0.62	0.47	0.58	0.56	0.62	0.62	0.39	0.40
Sentence-Verbalized Confidence																
Verbalized Confidence	0.61	0.52	0.45	0.44	0.56	0.49	0.48	0.48	0.59	0.43	0.46	0.43	0.58	0.59	0.28	0.32
LLM Accuracy	0.46				0.46				0.35				0.53			

Table 6: FactScore-Bio: Sentence-Level Classification (AUROC↑, AUPRC↑) and Calibration (ECE↓, BS↓) by LLM

	Gemini-2.5 Flash				Gemini-2.5 Pro				GPT-4o Mini				GPT-4o			
Scorer Type	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS
Claim-Response Scorers																
Entailment	0.67	**0.82**	0.17	0.24	0.67	**0.80**	**0.16**	**0.24**	**0.72**	**0.84**	**0.14**	0.22	**0.70**	**0.86**	0.17	0.22
Non-contradiction	0.64	0.80	0.22	0.25	0.63	0.78	0.25	0.27	0.66	0.80	0.25	0.27	0.62	0.82	0.21	0.23
Contrasted Entailment	0.65	0.81	**0.16**	0.22	0.65	0.79	0.17	0.24	0.70	0.83	0.16	0.23	0.67	0.85	0.14	0.20
Claim-QA Scorers																
Exact Match	0.57	0.74	0.39	0.40	0.54	0.71	0.38	0.40	0.55	0.71	0.46	0.47	0.55	0.77	0.47	0.46
Semantic Negentropy	0.57	0.74	0.19	0.25	0.54	0.70	0.22	0.27	0.57	0.72	0.21	0.27	0.54	0.76	0.21	0.24
Non-contradiction	0.59	0.76	0.23	0.26	0.56	0.72	0.27	0.29	0.58	0.73	0.26	0.28	0.55	0.77	0.22	0.24
BERTScore	0.57	0.75	0.24	0.26	0.54	0.71	0.27	0.29	0.54	0.72	0.28	0.30	0.55	0.77	0.22	0.24
Cosine Similarity	0.57	0.75	0.20	0.24	0.54	0.71	0.24	0.27	0.56	0.73	0.29	0.30	0.56	0.77	0.21	0.23
Claim-Verbalized Confidence																
Verbalized Confidence	0.61	0.76	0.23	0.25	0.58	0.72	0.28	0.28	0.65	0.76	0.14	**0.22**	0.63	0.80	**0.11**	0.20
Graph-Based Scorers																
Betweenness	0.65	0.78	0.70	0.69	0.66	0.78	0.68	0.67	0.68	0.79	0.67	0.66	0.68	0.83	0.73	0.72
Closeness	0.66	0.80	0.17	**0.22**	0.66	0.78	0.21	0.24	0.71	0.83	0.17	0.22	0.69	0.85	0.12	**0.19**
Harmonic	0.66	0.80	0.18	0.22	0.65	0.77	0.21	0.25	0.70	0.82	0.19	0.23	0.68	0.84	0.13	0.19
Page Rank	**0.68**	0.81	0.70	0.69	**0.67**	0.79	0.67	0.67	0.72	0.83	0.67	0.66	0.69	0.85	0.73	0.72
Laplacian	0.67	0.81	0.67	0.65	0.67	0.80	0.65	0.63	0.71	0.82	0.64	0.62	0.69	0.85	0.70	0.68
LLM Accuracy	0.71				0.69				0.68				0.74			

Table 7: FactScore-STEM-Geo: Claim-Level Classification (AUROC↑, AUPRC↑) and Calibration (ECE↓, BS↓) by LLM

	Gemini-2.5 Flash				Gemini-2.5 Pro				GPT-4o Mini				GPT-4o			
Scorer Type	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS	ROC	PRC	ECE	BS
Sentence-Response Scorers																
Entailment	0.59	0.59	0.21	0.30	0.56	0.55	0.22	0.31	0.67	0.66	0.15	**0.26**	0.63	0.70	0.22	0.29
Non-contradiction	0.57	0.57	0.45	0.45	0.55	0.54	0.48	0.48	0.66	0.63	0.45	0.44	0.59	0.67	0.38	0.39
Contrasted Entailment	0.57	0.58	0.35	0.38	0.56	0.54	0.38	0.40	**0.67**	0.66	0.32	0.34	0.60	0.68	0.27	0.32
Sentence-QA Scorers																
Exact Match	0.57	0.54	**0.13**	**0.27**	0.57	0.55	**0.14**	**0.28**	0.60	0.57	**0.14**	0.27	0.61	0.68	**0.12**	**0.25**
Semantic Negentropy	0.58	0.56	0.36	0.38	0.55	0.52	0.41	0.42	0.63	0.59	0.34	0.36	0.59	0.65	0.29	0.32
Non-contradiction	0.57	0.56	0.41	0.41	0.56	0.55	0.46	0.46	0.63	0.58	0.43	0.42	0.58	0.66	0.35	0.36
BERTScore	0.57	0.55	0.46	0.46	0.55	0.54	0.48	0.48	0.60	0.57	0.48	0.48	0.60	0.67	0.38	0.38
Cosine Similarity	0.57	0.56	0.43	0.43	0.54	0.53	0.46	0.46	0.62	0.59	0.46	0.45	0.60	0.67	0.36	0.36
Matched-Sentence Scorers																
Entailment	**0.60**	**0.60**	0.25	0.32	**0.57**	**0.56**	0.25	0.32	0.67	**0.67**	0.23	0.29	0.63	**0.72**	0.29	0.33
Non-contradiction	0.49	0.50	0.50	0.49	0.48	0.49	0.51	0.51	0.49	0.49	0.51	0.51	0.50	0.60	0.41	0.41
Contrasted Entailment	0.54	0.55	0.35	0.38	0.54	0.54	0.36	0.39	0.62	0.61	0.35	0.37	0.58	0.68	0.27	0.32
Cosine Similarity	0.51	0.50	0.39	0.40	0.53	0.50	0.40	0.41	0.62	0.59	0.40	0.40	0.59	0.67	0.30	0.33
BERTScore	0.54	0.53	0.41	0.42	0.53	0.50	0.43	0.43	0.61	0.60	0.43	0.43	0.59	0.67	0.34	0.35
Sentence-Verbalized Confidence																
Verbalized Confidence	0.55	0.53	0.45	0.46	0.53	0.51	0.49	0.48	0.64	0.60	0.35	0.36	**0.64**	0.67	0.26	0.29
LLM Accuracy	0.50				0.49				0.49				0.58			

Table 8: FactScore-STEM-Geo: Sentence-Level Classification (AUROC↑, AUPRC↑) and Calibration (ECE↓, BS↓) by LLM

		# Sentences per Response	# Claims per Response	# Words per Response
Bio	GPT-4o	5.37 ± 0.07	24.30 ± 0.41	95.58 ± 0.62
	GPT-4o-Mini	5.19 ± 0.05	23.31 ± 0.36	95.95 ± 0.27
	Gem.-2.5 Flash	4.43 ± 0.06	21.82 ± 0.44	80.06 ± 0.68
	Gem-2.5 Pro	4.78 ± 0.06	23.21 ± 0.37	88.08 ± 0.38
STEM-Geo	GPT-4o	6.24 ± 0.09	28.57 ± 0.53	142.75 ± 1.48
	GPT-4o-Mini	5.49 ± 0.07	27.52 ± 0.47	140.54 ± 1.42
	Gem.-2.5 Flash	4.38 ± 0.07	29.11 ± 0.60	131.99 ± 1.97
	Gem.-2.5 Pro	4.98 ± 0.07	32.09 ± 0.54	155.80 ± 1.92

Table 9: Descriptive Statistics of Long-Text Responses: Granular Units and Response Length

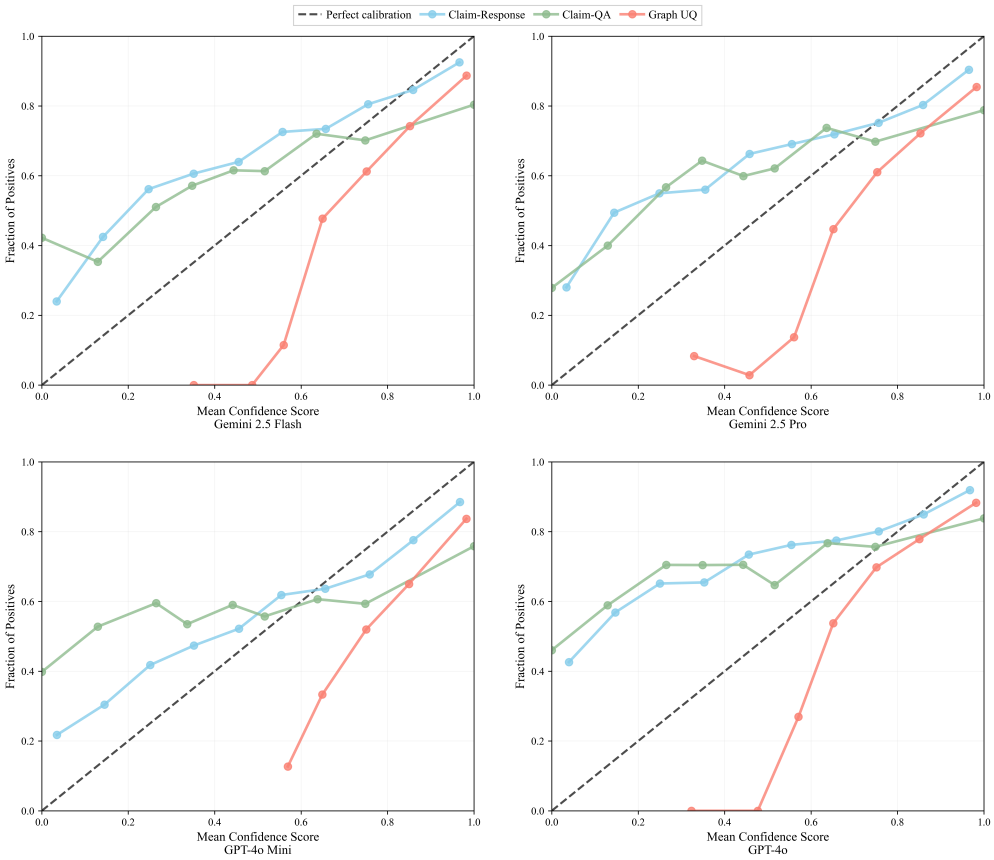


Figure 14: Claim-Level Calibration Plots (Top Scorer per Family) for FactScore-Bio by LLM

Scorer	Gemini-2.5-Flash	Gemini-2.5-Pro	GPT-4o-Mini	GPT-4o
Claim-Level Scorers				
CR Entailment	0.58	0.52	0.66	0.44
CR Non-Contradiction	0.41	0.38	0.38	0.24
CR Contrasted Entailment	0.52	0.48	0.45	0.28
QA Exact Match	0.36	0.30	0.57	0.39
QA Semantic Negentropy	0.50	0.46	0.56	0.41
QA Non-Contradiction	0.50	0.52	0.41	0.44
QA BERTScore	0.43	0.41	0.41	0.40
QA Cosine Similarity	0.44	0.44	0.42	0.43
Betweenness	-0.03	-0.20	-0.03	-0.14
Closeness	**0.61**	**0.54**	**0.69**	0.45
Harmonic	0.59	0.53	0.67	**0.46**
Page Rank	0.42	0.34	0.56	0.25
Laplacian	0.39	0.29	0.51	0.23
Sentence-Level Scorers				
SR Entailment	0.34	0.34	0.47	0.22
SR Non-Contradiction	0.35	0.31	0.39	0.30
SR Contrasted Entailment	0.33	0.32	0.37	0.18
Matched Entailment	0.34	0.31	0.51	0.16
Matched Non-Contradiction	0.16	0.22	0.14	-0.03
Matched Contrasted Entailment	0.20	0.25	0.19	-0.01
Matched Cosine Similarity	0.31	0.30	0.44	0.19
Matched BERTScore	0.37	0.34	0.49	0.24
QA Exact Match	0.31	0.26	0.55	0.37
QA Semantic Negentropy	0.44	0.32	0.55	0.39
QA Non-Contradiction	0.42	0.36	0.49	0.30
QA BERTScore	0.38	0.29	0.49	0.37
QA Cosine Similarity	0.40	0.30	0.55	0.40
Short-Form Black-Box Scorers				
Semantic Negentropy	0.39	0.28	0.42	0.26
Non-Contradiction	0.42	0.32	0.32	0.28
BERTScore	0.43	0.44	0.66	0.42
Cosine Similarity	0.39	0.37	0.49	0.22

Table 10: Spearman correlation ↑ between response-level confidence and factuality on FactScore-Bio

Scorer Family	Approx. Comparisons/Prompt	Approx. Runtime/Dataset
Claim-Response	250	2.5 hours
Graph-Based	750	7.5 hours
Claim-QA	250	2.5 hours
Sentence-response	50	0.5 hours
Matched-Sentence	250	2.5 hours
Sentence-QA	50	0.5 hours

Table 11: Approximate semantic comparisons per prompt and runtime per LLM-dataset.

C FactScore-STEM-Geo Construction

We use the Wikipedia API to construct long-form QA datasets spanning four topics: Chemical Elements, Scientific Laws, Nerves in the human body, and Mountains with the goal of spanning four domains: chemistry, math/physics, biology/anatomy, and geography/geology, respectively. For each topic, we select the 100

Wikipedia entries with the longest texts to ensure sufficient content for grading LLM responses. The code to construct these datasets is given below:

```
import wikipediaapi
def get_wiki_texts_from_entities(
    entities: List[str]
) -> List[str]:
    wiki_wiki = wikipediaapi.Wikipedia(
        user_agent=USER_AGENT,
        language='en'
    )
    texts = {}
    for entity in entities:
        page = wiki_wiki.page(entity).text
        if page:
            texts[entity] = page.text

    if len(texts) > 100:
        sorted_entities = sorted(
            texts.keys(),
            key=lambda x: len(texts[x]),
            reverse=True
        )[:100]
        top_texts = {}
        for entity in sorted_entities:
            top_texts[entity] = texts[entity]

    return top_texts
```

A comprehensive list of the entities can be found in the supplemental source code.

D Prompt Templates

Prompt templates were adapted and refined from previously published protocols and are provided to support reproducibility. User prompts for FactScore grading and claim merging are adapted from Jiang et al. (2024), the user prompt for claim decomposition is adapted from Zhang et al. (2025), the user prompt for unit-QA question creation is adapted from Farquhar et al. (2024), and the user prompt for verbalized confidence is adapted from Tian et al. (2023); Jiang et al. (2024).

```
You are a precise and objective fact-checking assistant specialized in evaluating factual claims
    against provided context. Your task is to determine whether claims are supported by the given
    context, following the FactScore evaluation protocol.

Guidelines for your evaluations:
1. Analyze each claim strictly based on the provided context, not your prior knowledge
2. Respond with "Yes" only if the claim is directly supported by information in the context
3. Respond with "No" if:
   - The claim contradicts the context
   - The claim contains information not present in the context
   - The claim makes assertions that go beyond what the context states

Important principles:
- Be conservative in your judgments - only mark claims as supported when there is clear evidence
- Ignore stylistic differences or paraphrasing if the factual content matches
- Do not make assumptions or inferences beyond what is explicitly stated in the context
- Maintain consistency in your evaluation criteria across all claim-context pairs

Your responses should be limited to "Yes" or "No" without additional explanation, as these will be
    processed automatically in the FactScore evaluation framework.
```

Listing 1: System prompt for FactScore grading

```
Context: {answer}
Claim: {claim}
```

```
Is the claim supported by the context above?
Answer only Yes or No:
```

Listing 2: User Prompt for FactScore Grading

```
You are an expert linguistic analyst specializing in distinguishing between objective and
    subjective statements.

Objective statements present verifiable facts, information, or observations that can be proven
    true or false through evidence. They are independent of personal interpretations or biases.
    Examples include statistical data, historical events, scientific measurements, or established
    facts.

Subjective statements express judgments, evaluations, or perspectives that may vary between
    individuals. They cannot be definitively proven true or false as they depend on viewpoint,
    taste, or interpretation. Examples include value judgments, aesthetic assessments, or
    statements containing evaluative language.

When analyzing a statement, consider:
- Does it contain verifiable facts or measurable data?
- Does it include evaluative terms like "good," "beautiful," "better," "worst," "important," or
    "significant"?
- Could different people reasonably disagree about the statement?
- Is the statement presenting information that exists independent of human judgment?

Respond only with "objective" or "subjective" based on your analysis.
```

Listing 3: System Prompt for Objectivity Classification

```
Input: {claim}
Is the input subjective or objective?
Answer only subjective or objective:
```

Listing 4: User prompt for Objectivity Classification

```
    Please breakdown the following passage into independent fact pieces.

    Step 1: For each sentence, you should break it into several fact pieces. Each fact piece
    should only contain one single independent fact. Normally the format of a fact piece is
    "subject + verb + object". If the sentence does not contain a verb, you can use "be" as the
    verb.

    Step 2: Do this for all the sentences. Output each piece of fact in one single line starting
    with ###. Do not include other formatting.

    Step 3: Each atomic fact should be self-contained. Do not use pronouns as the subject of a
    piece of fact, such as he, she, it, this that, use the original subject whenever possible.

    Step 4: If the sentence does not contain any independent fact, you should output "### NONE".

    Here are some examples:

    Example 1:
    Michael Collins (born October 31, 1930) is a retired American astronaut and test pilot who was
    the Command Module Pilot for the Apollo 11 mission in 1969.
    ### Michael Collins was born on October 31, 1930.
    ### Michael Collins is retired.
```

```
    ### Michael Collins is an American.
    ### Michael Collins was an astronaut.
    ### Michael Collins was a test pilot.
    ### Michael Collins was the Command Module Pilot.
    ### Michael Collins was the Command Module Pilot for the Apollo 11 mission.
    ### Michael Collins was the Command Module Pilot for the Apollo 11 mission in 1969.

    Example 2:
    League of Legends (often abbreviated as LoL) is a multiplayer online battle arena (MOBA) video
     game developed and published by Riot Games.
    ### League of Legends is a video game.
    ### League of Legends is often abbreviated as LoL.
    ### League of Legends is a multiplayer online battle arena.
    ### League of Legends is a MOBA video game.
    ### League of Legends is developed by Riot Games.
    ### League of Legends is published by Riot Games.

    Example 3:
    Emory University has a strong athletics program, competing in the National Collegiate Athletic
     Association (NCAA) Division I Atlantic Coast Conference (ACC). The university's mascot is the
     Eagle.
    ### Emory University has a strong athletics program.
    ### Emory University competes in the National Collegiate Athletic Association Division I.
    ### Emory University competes in the Atlantic Coast Conference.
    ### Emory University is part of the ACC.
    ### Emory University's mascot is the Eagle.

    Example 4:
    Hi
    ### NONE

    Now it's your turn. Here is the passage:

    {response}

    You should only return the final answer. Now your answer is:
```

Listing 5: User prompt for claim decomposition

```
We are writing an answer to this question: {original_question}

Describe how likely it is that the specific claim below is correct as one of the following
    expressions:

No chance (0%)
Little chance (20%)
Less than even (40%)
Fairly possible (60%)
Very good chance (80%)
Almost certain (100%)

Give ONLY your confidence phrase, no other words or explanation. Your answer must contain ONLY one
    of the confidence phrases above.

Here is the claim: {claim}

Now your answer is:
```

Listing 6: User prompt for Verbalized Confidence

```
Following this text: {response}
You see the sentence: {factoid}
Generate a list of {num_questions} questions, that might have generated the sentence in the
    context of the preceding original text. Please do not use specific facts that appear in the
    follow-up sentence when formulating the questions. Avoid yes-no questions. The questions
    should have a concise, well-defined answer e.g. only a name, place, or thing. Output each
    question in one single line starting with ###. Do not include other formatting.

Example:
### Here is the first question? ### Here is the second question?

Now your response is:
```

Listing 7: User prompt for Unit-QA question creation

```
Given two lists titled "Original Claim List" and "New Claim List", your task is to integrate
    information from the "New Claim List" into the "Original Claim List". Please follow these
    detailed steps to ensure accuracy and clarity in the process:
Task 1. **Verification Process:** Your goal is to go through each statement in the "New Claim
    List" one by one, and determine if it is fully entailed or mentioned by any statement in the
    "Original Claim List."
Task 2. **Compilation of Non-Entailed Claims:** Generate a list of statements from the "New Claim
    List" that are not already covered or implied by the "Original Claim List." For each new or
    unique claim that does not have an equivalent in the original list, format your output by
    starting each line with a dash ('-').
**Original Claim List:**
{master_claim_str}
**New Claim List:**
{sampled_claim_str}
Begin with the Verification Process to assess each claim's relevance and uniqueness, followed by
    the Compilation of Non-Entailed Claims to clearly list any new insights that the "New Claim
    List" provides.
```

Listing 8: User prompt for Claim Merging