InFi-Check: Interpretable and Fine-Grained Fact-Checking of LLMs

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Abstract

Large language models (LLMs) often hallucinate, yet most existing fact-checking methods treat factuality evaluation as a binary classification problem, offering limited interpretability and failing to capture fine-grained error types. In this paper, we introduce InFi-Check, a framework for interpretable and fine-grained fact-checking of LLM outputs. Specifically, we first propose a controlled data synthesis pipeline that generates high-quality data featuring explicit evidence, fine-grained error type labels, justifications, and corrections. Based on this, we further construct large-scale training data and a manually verified benchmark InFi-Check-FG for fine-grained fact-checking of LLM outputs. Building on these high-quality training data, we further propose InFi-Checker, which can jointly provide supporting evidence, classify fine-grained error types, and produce justifications along with corrections. Experiments show that InFi-Checker achieves state-of-the-art performance on InFi-Check-FG benchmark and strong generalization across various downstream tasks, significantly improving the utility and trustworthiness of factuality evaluation.

1 Introduction

Recent breakthroughs in Large Language Models (LLMs) have fundamentally transformed the paradigm of human-computer interaction (Achiam et al., 2023; DeepSeek-AI et al., 2025a). However, LLMs are still prone to producing factual errors in their responses, i.e., hallucinations (Ji et al., 2023; Huang et al., 2025; Si et al., 2025b), posing significant risks and severely compromising their trustworthiness. As a result, recent research has focused on the development of factuality evaluation frameworks for LLMs (Tang et al., 2024a), as well as approaches for training LLMs to improve factuality (Tian et al., 2024; Lin et al., 2024; Si et al., 2025a). In these frameworks, fact-checking models (Lei et al., 2025; Seo et al., 2025) play a crucial role in evaluating the factuality of LLM outputs, by checking whether the generated claims can be supported by a reliable knowledge source.

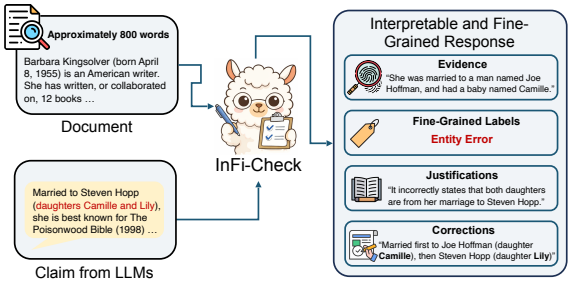

Figure 1: The illustration of our InFi-Check. InFi-Check can simultaneously provide the corresponding evidence, fine-grained labels, justifications, and corrections.

Recent studies focus on how to effectively train a fact-checking model used to evaluate the factuality of LLM-generated responses, including entailment-based (Kryściński et al., 2019; Goyal and Durrett, 2021; Maynez et al., 2020), question-answering-based (Wang et al., 2020; Durmus et al., 2020; Fabbri et al., 2022), atomic-fact-based (Min et al., 2023), and synthetic-data-based (Tang et al., 2024a; Lei et al., 2025; Seo et al., 2025) methods. However, these methods simply treat the fact-checking task as a binary prediction task, classifying the entire response from LLMs as hallucinated or not. Consequently, these methods present several notable limitations: (1) *Lack of Interpretability:* Existing fact-checking models typically output a single predicted label for the entire LLM-generated response (Zha et al., 2023; Tang et al., 2024a), without providing the explicit justification or supporting evidence. This lack of interpretability makes it difficult to analyze model hallucination patterns and limits its practical utility for localizing hallucinations and performing targeted corrections in real-world applications. (2) *Lack of Fine-Grained Fact Checking:* Also, these fact-checking models typically formulate hallucination detection as a binary

classification problem, merely predicting whether a response is factual or hallucinated. However, hallucinations are not all the same and can appear in different types (Pagnoni et al., 2021a; Mitra et al., 2025; Zhang et al., 2025), such as incorrect entities, fabricated facts, or unsupported relations. By collapsing these distinct error types into a single label, i.e., hallucinated, this oversimplified formulation fails to provide fine-grained distinctions among hallucinations, thereby limiting detailed error analysis and specified revision, hindering the development of targeted strategies for hallucination mitigation.

To bridge these gaps, we propose a novel framework called **InFi-Check** to enable interpretable and fine-grained fact-checking for comprehensive factuality evaluation of LLM outputs. To achieve this end, we first introduce an effective data synthesis pipeline to automatically generate fact-checking data that contains four key output elements. These elements are typically provided by professional fact-checkers in real-world scenarios, including explicit evidence support, error type identification, justifications, and corrections. In this way, models trained on such data can provide fine-grained predictions and detailed justifications for real-world users. To ensure the data quality and avoid labeling errors, our pipeline incorporates the controlled generation strategies to guide LLMs in generating corresponding claims under given fine-grained error types. Specifically, for the given document-claim pairs, we first query the advanced LLM (e.g., GPT-4o (Achiam et al., 2023)) to find grounding sentences as explicit evidence support. Subsequently, we provide specific fine-grained error types along with the document-claim pair as input, requiring the LLMs to first follow our designed structured reasoning process and generate corresponding justifications and claims exhibiting the specified error types. By doing so, we can control the inclusion of specified fine-grained hallucinations in newly generated claims from advanced LLMs and ensure that there are no labeling errors. Also, by comparing the original claim with the newly synthesized claim, we can obtain corresponding corrections, enabling transparent justification of fact-checking decisions. To ensure the data diversity, our designed pipeline involves 9 hallucination construction strategies that cover the diverse yet nuanced hallucination patterns commonly observed in advanced LLMs such as GPT-4o. Based on our well-designed pipeline above, we construct a training set as well as a manually corrected benchmark InFi-Check-FG for evaluating the fine-grained classification capabilities of fact-checking models. By using the training data from our well-designed data synthesis pipeline, we introduce InFi-Checker, an advanced fact-checking model capable of fine-grained hallucination detection and interpretable analysis. The InFi-Checker can perform comprehensive tasks including identifying relevant evidence, detecting fine-grained error types, and providing justification and direct corrections.

Our extensive experiments show that even the most advanced LLMs, such as GPT-5 (OpenAI, 2025a), still struggle to capture fine-grained error types. In contrast, our InFi-Checker achieves state-of-the-art performance on InFi-Check-FG benchmark, and shows strong generalization across diverse scenarios, covering question answering (QA), summarization, and retrieval-augmented generation (RAG). Different from previous fact-checking models, InFi-Checker can also offer fine-grained analysis and the corresponding justifications to improve the interpretability and trustworthiness.

2 Related Work

Many studies have investigated whether LLMs can generate factually accurate content. These works broadly categorize into three strands—evaluation, root cause analysis (Massarelli et al., 2020; Lu et al., 2022; Luo et al., 2023b; Liu et al., 2023a; Luo et al., 2023a), and mitigation approaches (Lee et al., 2022; Dai et al., 2022; Borgeaud et al., 2022; Moiseev et al., 2022; Asai et al., 2023; Du et al., 2024; Wang et al., 2025)—while our research focuses on the evaluation dimension. Kryściński et al. (2019) first argued that factuality evaluation in abstractive summarization should transcend overlap-based metrics like ROUGE, introducing fact-checking models to verify whether generated claims are supported by the source context—a direction also explored by Maynez et al. (2020) and Goyal and Durrett (2021). Early alternatives employed question-answering models to check context-summary consistency (Wang et al., 2020; Durmus et al., 2020; Fabbri et al., 2022), and Zha et al. (2023) and Ribeiro et al. (2022) later improved performance via model ensembling and semantic-graph representations, respectively. Building on these foundations, researchers have precisely annotated factual errors in machine-generated claims to assemble datasets for quantitative factuality evaluation (Fabbri et al., 2021; Cao and Wang, 2021; Pagnoni et al.,

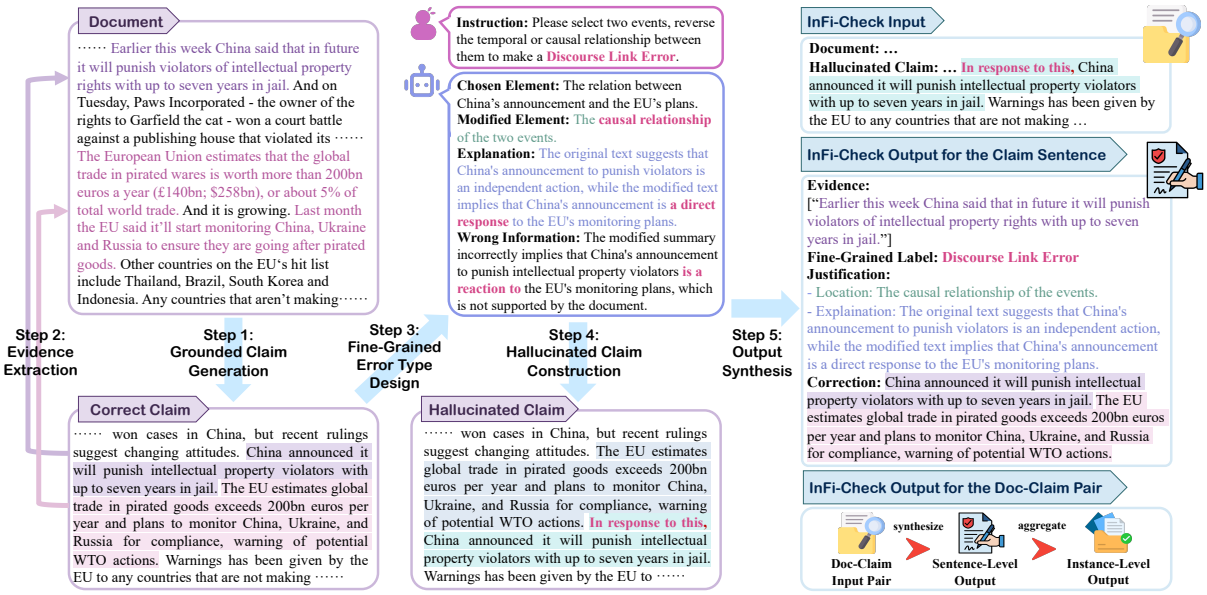

Figure 2: Overview of the InFi-Check pipeline. Some of the text is simplified for better demonstration.

2021a; Zhang et al., 2024).

Recent studies have turned to utilize the power of LLMs to train more capable fact-checking models. For example, MiniCheck (Tang et al., 2024a) uses advanced LLMs to synthesize training data and surpasses prior fact-checking methods. FactCG (Lei et al., 2025) further enhances synthetic data with knowledge graphs to improve the performance of fact-checking models. ClearCheck (Seo et al., 2025) uses synthetic data with multi-task training, allowing the model to perform reasoning before answering. However, despite these advances in fact-checking performance, current models continue to generate only binary predictions, lacking interpretable justifications and fine-grained error labels that can support real-world users, limiting the utility and trustworthiness. Different from these works, our model can jointly provide supporting evidence, classify fine-grained error types, and produce justifications along with corrections, significantly improving the practical utility and trustworthiness of realistic and user-friendly factuality evaluation.

3 Methodology

In this section, we introduce InFi-Check, a controlled data synthesis pipeline designed to generate high-quality, interpretable fact-checking data. The core of our InFi-Check lies in systematically constructing grounded claims with fine-grained, realistic hallucinations, alongside their corresponding diagnostic analysis. As illustrated in Figure 2, the pipeline operates in five sequential stages: (1) *Generate Grounded Claim*, (2) *Extract Supporting Evidence*, (3) *Design Hallucination with Chain-of-Thought*, (4) *Construct Hallucinated Claim*, and (5) *Synthesize Interpretable Output*. A key advantage of this pipeline is its scalability and independence from the original document corpus; by varying hallucination injection points and generating new claims, it can be arbitrarily expanded. The prompts used across all stages are provided in Appendix F.

3.1 Controlled Data Synthesis Pipeline

Stage 1 & 2: Grounded Claim Generation and Evidence Extraction. We begin with a collection of source documents. Existing datasets often fall short in terms of claim complexity and factual coverage, as the provided claims are not always fully supported by the corresponding documents. To address this limitation, we generate claims directly conditioned on each source document. For every document, a claim is produced, and each sentence in the claim is automatically annotated with its corresponding *grounding sentences* as evidence from the source document. To ensure claim quality, we apply an iterative refinement process based on the extracted grounding sentences, including majority voting and rewriting. We further conduct human evaluation to validate the reliability of this pipeline. Details are provided in the Appendix A.

Stage 3: Fine-Grained Error Type Design. This stage is the cornerstone of our method, where we strategically implant controlled hallucinations into the grounded claims. We adopt and extend the fine-

Error Category	Abbr.	Construction Strategy
Predicate Error	PredE	Swap Relation
		Modify Predictions
Entity Error	EntE	Swap Entities
		Compress Phrases
Circumstance Errors	CircE	Swap Circumstances
Co-Reference Error	CorefE	Swap Pronouns
		Merge Sentences
Discourse Link Error	LinkE	Reverse Logic
Extrinsic Error	OutE	Add Extrinsic Information

Table 1: Fine-grained error types and corresponding construction strategies in InFi-Check. Detailed descriptions and examples can be found in Table 13.

grained error typology from Pagnoni et al. (2021b), which is applicable to summarization and other grounded generation tasks. We exclude grammatical errors as they pertain to fluency rather than factuality. Our construction system encompasses six major categories, as summarized in our Table 1, each implemented via specific strategies.

To ensure high-quality and diverse errors while enabling interpretable analysis, we leverage LLMs following a structured chain-of-thought (CoT) process. For a given grounded claim and its evidence, we specify a target error type and prompt the model to: (a) analyze the original content, (b) execute the corresponding construction strategy (e.g., swap an entity), and (c) produce a detailed justification for the change. This step-by-step reasoning not only improves the controllability of the constructed errors but also provides a transparent record of how each hallucination was introduced, forming the basis for interpretable outputs in Stage 5.

Stage 4 & 5: Hallucinated Claim Construction and Output Synthesis. Using the CoT from Stage 3, we generate the final hallucinated claim sentence containing the specified hallucination. Ultimately, we can synthesize the *interpretable output*: a structured analysis containing the erroneous sentence, its grounding evidence (or lack thereof), the hallucination category, the justification from the CoT, and the corrected sentence. This final output is organized in a sentence-by-sentence manner (see Appendix E for examples), providing a clear, traceable reasoning path from error construction to diagnosis. The structured format offers two key benefits: (1) ***Interpretability through traceable reasoning***, making model decisions transparent and easing manual verification by presenting grounding contexts and corrections side-by-side; and (2) ***Higher quality from controlled generation***, as the CoT process and explicit output schema enforce rigorous, context-aware error construction and analysis. This output serves as the gold standard for training and evaluating fact-checking models.

3.2 Fine-Grained Error Type Construction

Building upon the error typology outlined in Stage 3, this subsection details the specific strategies employed to construct each category of hallucination. Our methodology adapts and extends prior work on error construction (Kryściński et al., 2019; Cao and Wang, 2021; Pagnoni et al., 2021b), introducing novel strategies to capture subtle and challenging error types often overlooked in existing datasets.

Semantic-Level Hallucinations. These errors involve inaccuracies within a single proposition, including Predicate Errors (PredE), Entity Errors (EntE), and Circumstance Errors (CircE).

- *Element Swapping*: For straightforward errors, we adapt established swapping techniques (Kryściński et al., 2019; Cao and Wang, 2021). We prompt an LLM to identify a target element (e.g., an **entity**, **predicate**, or **circumstantial phrase**) within a factually correct claim sentence and replace it with a semantically congruent but incorrect alternative from the source document or a generated list.
- *Modifying Predictions*: This strategy targets the confusion between speculative language (e.g., "predicted," "might") and factual assertions. We guide the LLM to identify sentences containing modal verbs or speculative phrases and alter them to state the speculated outcome as a fact (e.g., changing "The company *forecast* growth" to "The company *grew*").
- *Compressing Phrases*: This strategy generates errors through oversimplification, where specific technical terms or nuanced descriptions are replaced with overly broad terms, distorting meaning (e.g., compressing "net revenue attributable to the parent company" to "net revenue"). A two-stage LLM verification process ensures the compression introduces a factual distortion rather than mere paraphrasing.

Discourse-Level Hallucinations. These errors span multiple sentences, disrupting coherence and reference. They include Co-reference Errors

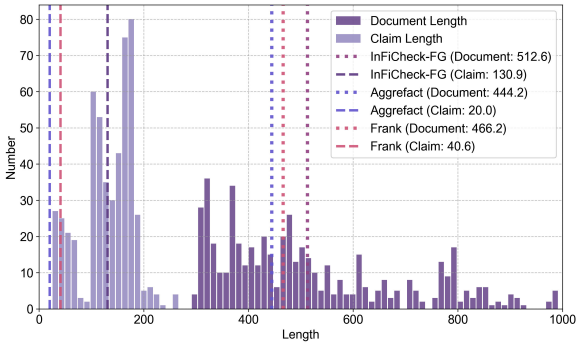

Figure 3: Document and claim length (words) distribution of InFi-Check-FG with average length comparison.

(CorefE) and Discourse Link Errors (LinkE).

- *Swapping Pronouns*: We extend the method of FactCC (Kryściński et al., 2019) by swapping pronouns of all types (not only gendered ones). To increase the complexity of the data, we first convert named entities into pronouns before performing the swap, thereby introducing controlled referential ambiguity.
- *Merging Sentences*: To simulate conflation errors, we choose two sentences about similar but different topics or events. Then, we combine them into one sentence and wrongly give actions or facts from both to just one subject.
- *Reverse Logical Relationship*: We prompt the LLM to identify a pair of events in the source document with a clear temporal or causal relationship. We then ask the model to reverse this relationship (for example, switch the cause and effect) and rewrite the claim to show this false link. This creates a sentence that sounds believable but is not factually correct.

Extrinsic Hallucinations. Extrinsic Errors (OutE), or "out-of-article" errors, happen when information external to the source is added. Due to the difficulty of making sure all context is removed from an old claim, we ask the LLM to add a believable but completely unsupported piece of information (like a new number, event, or name) to a claim, making sure the new content is clearly extrinsic.

4 InFi-Check Dataset and Model

Building upon the controlled synthesis pipeline detailed in the Section 3, we construct the interpretable and fine-grained fact-checking training data, namely InFi-Check-TR without human effort, and further propose a manually verified benchmark InFi-Check-FG. Subsequently, we train our model InFi-Checker based on InFi-Check-TR. This section shows the details of these core resources.

4.1 Dataset and Benchmark

InFi-Check serves a dual purpose: it automatically creates a large-scale training corpus InFi-Check-TR, and also a high-quality and challenging benchmark InFi-Check-FG for evaluating fine-grained classification capabilities of fact-checking models.

Construction Process. To ensure factual grounding and diversity, our dataset construction begins with source documents rather than existing summaries. We randomly sample news and encyclopedic documents of varying lengths from the BBC News (Gupta et al., 2022) and DetNet Wikipedia (Xu and Lapata, 2019) datasets. For each document, we generate a grounded claim using multiple LLMs via iterative rewriting to mitigate bias and ensure quality, with each claim sentence linked to its evidential grounding sentences in the source (see Appendix A for details). Subsequently, for each document-claim pair, we apply the error construction strategies from InFi-Check to generate one hallucinated claim for each strategy, while retaining the original claim as a "No Error" sample, resulting in 10 total samples per pair.

InFi-Check-TR Details. Our InFi-Check-TR comprises 15,660 samples for training, with more statistical details in Appendix B. To verify the quality of InFi-Check-TR, we conducted a human evaluation where expert annotators evaluated 100 randomly sampled instances across four dimensions: claims, evidence sentences, justifications, and hallucination validity. Results in Table 11 show a 95% agreement rate on hallucination validity, demonstrating the capability of the InFi-Check pipeline.

InFi-Check-FG Details. To further ensure evaluation reliability, we construct InFi-Check-FG based on manual check and from a distinct document split, which is a high-quality benchmark that consists of 519 manually verified samples. As illustrated in Figure 3, claims in InFi-Check-FG exhibit longer length compared to existing benchmarks, increasing complexity by preserving richer source-document details, thereby introducing more subtle and challenging hallucinations for evaluation. More details are provided in Appendix A.

4.2 Fact-Checking Model: InFi-Checker

Finally, we train our model InFi-Checker on the synthetic training data using supervised fine-tuning

Model	PredE	EntE	CircE	CorefE	LinkE	OutE	NoE	BAcc
The Open-Source Models								
Llama-3.1-8B-Instruct	18.82	9.52	31.03	3.13	0.00	0.00	61.11	17.66
Llama-3.1-8B-Instruct※	32.94	4.76	13.79	26.56	0.00	0.00	88.49	23.79
Qwen3-8B	76.47	52.38	44.83	50.00	0.00	50.00	61.90	47.94
Qwen3-8B※	76.47	52.38	24.14	70.31	0.00	50.00	80.16	50.49
The State-of-the-Art LLMs								
Claude-3.7-Sonnet	70.59	66.67	34.48	37.50	26.67	81.58	53.97	53.07
Claude-3.7-Sonnet※	68.24	71.43	34.48	21.88	23.33	78.95	46.03	49.19
DeepSeek-V3.2-NoThink	78.82	76.19	58.62	9.38	26.67	86.84	80.95	59.64
DeepSeek-V3.2-NoThink※	75.29	71.43	55.17	15.62	13.33	89.47	**94.05**	59.19
GPT-4o	80.00	76.19	44.83	50.00	3.33	84.21	84.92	60.50
GPT-4o※	84.71	61.90	44.83	75.00	0.00	94.74	91.67	64.69
GPT-4.1	85.88	76.19	37.93	42.19	0.00	63.16	75.79	54.45
GPT-4.1※	85.88	76.19	41.38	56.25	3.33	68.42	80.95	58.91
GPT-5	63.53	57.14	62.07	42.19	16.67	60.53	41.27	49.06
GPT-5※	63.53	61.9	51.72	45.31	13.33	47.37	41.27	46.35
o3	80.00	61.90	58.62	43.75	0.00	81.58	80.16	58.00
o3※	81.18	57.14	58.62	56.25	3.33	81.58	87.30	60.77
InFi-Checker (Ours)								
InFi-Checker-Llama	**95.29**	90.48	79.31	95.31	86.67	**100.00**	89.29	90.91
InFi-Checker-Qwen	93.51	**91.67**	**87.50**	**100.00**	**88.89**	96.77	88.01	**92.34**

Table 2: Results (%) on InFi-Check-FG. We display the accuracy of each error type, as well as the balanced accuracy (BAcc), which calculates the average accuracy of all error types. Best performances are marked in bold. For baselines, models marked with ※ are tested in a one-shot setting, while the others are tested in a zero-shot setting.

Model	0-shot	1-shot
The Open-Source Models		
Llama-3.1-8B-Instruct	66.13	71.49
Qwen3-8B	65.31	70.16
The State-of-the-Art LLMs		
Claude-3.7-Sonnet	65.89	63.42
DeepSeek-V3.2-NoThink	66.99	77.14
GPT-4o	74.37	74.75
GPT-4.1	75.19	75.19
GPT-5	76.53	75.70
o3	75.54	74.57
InFi-Checker (Ours)		
InFi-Checker-Llama	77.17	
InFi-Checker-Qwen	**77.20**	

Table 3: Fine-grained results on FRANK, with balanced accuracy calculated in a binary mapped setting due to error types overlapping (See Appendix C for details).

(SFT). The model is trained to perform a comprehensive, structured output task: given a document and a claim, it identifies grounding evidence, classifies the fine-grained error type, and provides a natural language justification alongside a direct correction. This end-to-end training regime, powered by the rich annotations, enables InFi-Checker to deliver interpretable, fine-grained fact-checking for LLM outputs, moving beyond binary classification.

5 Experiment

5.1 Experimental Setup

Implementation of InFi-Checker. We implement Llama-3.1-8B-Instruct and Qwen3-8B as backbones for InFi-Checker, using InFi-Check-TR as training dataset and conducted supervised fine-tuning (details in Appendix C.3).

Other Benchmarks. To evaluate InFi-Checker's out-of-distribution generalization, we conduct experiments across existing multiple factuality evaluation benchmarks, including *(1) fine-grained hallucination labeling benchmark*, where we adapt the **FRANK** benchmark, which is a human-annotated benchmark that uses the same fine-grained hallucination label taxonomy as InFi-Check-FG. *(2) commonly used binary hallucination labeling benchmark*, where we select benchmarks of diverse text sources and generation tasks: **ClaimVerify** (Liu et al., 2023b) and **Factcheck-Bench** (Wang et al., 2024) for search queries and responses, **ExpertQA** (Malaviya et al., 2024) and **REVEAL** (Jacovi et al., 2024) for QA, as well as **MediaSum** and **MeetingBank** for dialogue summarization (Tang et al., 2024b). We test in fine-grained settings for FRANK, and binary settings for other benchmarks, as they do not have fine-grained labeling. Appendix C provides more implementation details.

Baselines. We validate InFi-Checker through an extensive comparison with two separate groups of competitive baselines. On InFi-Check-FG and FRANK, which require fine-grained error type labeling, we employ **State-of-the-Art LLMs** including: (1) the backbones of InFi-Checker, **open-source models**: Llama-3.1-8B-Instruct (Kassianik et al., 2025) and Qwen3-8B (Yang et al., 2025); and (2) **closed-source models**: GPT-4o (Jaech

Model	Claim Verify	Expert QA	Factcheck-Bench	REVEAL	MediaSum	MeetingBank	Average
The Open-Source Models							
Llama-3.1-8B-Instruct	63.6	49.8	69.8	78.2	50.8	62.3	62.4
Qwen3-8B	**66.1**	**55.6**	**78.4**	**83.2**	**77.7**	**74.2**	**72.5**
The State-of-the-Art LLMs							
Claude-3.7-Sonnet	**83.7**	74.4	86.9	88.0	**85.4**	84.0	83.7
DeepSeek-V3.2-NoThink	75.4	74.4	87.9	91.0	65.5	82.9	79.5
GPT-4o	78.3	68.3	86.0	86.9	71.5	76.9	78.0
GPT-4.1	81.6	**80.3**	**91.3**	93.2	75.9	**86.3**	84.8
GPT-5	87.7	75.9	90.4	**93.7**	80.2	87.6	**85.9**
o3	83.3	79.6	86.9	92.2	82.9	83.8	84.8
Specialized Fact-Checking Models							
ClearCheck (COT)	85.4	72.7	87.9	87.0	67.8	75.8	79.4
AlignScore-large	79.8	75.0	83.7	92.2	75.8	76.5	80.5
FactCG	76.2	75.3	**89.0**	90.0	79.1	71.9	80.3
MiniCheck	85.6	72.9	86.8	**91.0**	74.3	77.8	81.4
InFi-Checker-Llama	75.9	**78.3**	83.7	87.7	73.5	65.8	77.5
InFi-Checker-Qwen	**89.6**	75.7	88.0	90.0	**80.4**	**78.5**	**83.7**

Table 4: Macro-F1 (%) on six binary fact-checking benchmarks. Of note, **Bold** and underline highlight the best Macro-F1 within each group of baselines and the best overall Macro-F1, respectively.

et al., 2024), GPT-4.1 (OpenAI, 2025b), GPT-5 (OpenAI, 2025a), o3 (OpenAI, 2025c), Claude-3.7-Sonnet (Anthropic, 2025) and DeepSeek-V3.2 (DeepSeek-AI et al., 2025b). Baselines are tested following the InFi-Check reasoning format, and intentionally limit the number of demonstration examples to zero/one-shot to mitigate performance degradation from excessive prompt length (see Appendix F). Additionally, for binary fact-checking benchmarks, we include **specialized models** specifically optimized for binary factuality evaluation: **ClearCheck** (Seo et al., 2025), that leverages multi-task training for robustness, **AlignScore-large** (Zha et al., 2023), a holistic metric using a unified alignment function, **FactCG** (Lei et al., 2025), which enhances training data via knowledge graphs, and **MiniCheck** (Tang et al., 2024a), the state-of-the-art binary evaluator that utilizes a novel document-claim pair synthesis method for training data.

5.2 InFi-Check-FG Results

The performance of various models on InFi-Check-FG is detailed in Table 2; from these results, we draw the following critical observations:

InFi-Checker consistently outperforms all baselines on InFi-Check-FG, especially on complex data. InFi-Checker achieves a substantial 27.65% improvement in balanced accuracy over the second-best performer, one-shot GPT-4o. This advantage is most pronounced in discourse-level errors (*CorefE* and *LinkE*), where even leading closed-source models often fail to identify any instances correctly. This performance gap underscores two key strengths of InFi-Checker: (1) Cross-frame analysis capability: Our novel hallucination construction strategies of discourse-level errors enhance the model's ability to handle hallucinations spanning across semantic frames; and (2) Structured reasoning: Our synthetic justification design effectively addresses the limitations of standard LLMs in complex hallucination analysis.

InFi-Check provides a significant performance boost to the backbones. By comparing InFi-Checker (InFiChecker-Llama and InFiChecker-Qwen) with their prompted backbone counterparts (Llama-3.1-8B-Instruct※ and Qwen3-8B※), we observe that the gains are not solely due to instruction-guided interpretable reasoning. Instead, the improvement primarily stems from the model's ability to internalize the nature of all types of hallucinations from our curated dataset, enabling robust and accurate fact-checking across different backbones.

5.3 OOD Generalization Results

We further evaluate the transferability of InFi-Checker across various benchmarks (Table 3 and Table 4), leading to the following conclusions:

The fine-grained fact-checking capabilities of InFi-Checker is generalizable. On the FRANK benchmark (Table 3), which shares the same error-type taxonomy but is derived from a different corpus, InFi-Checker consistently outperforms closed-source models and shows substantial improvements over its backbones. These results suggest that the fine-grained hallucination detection capabilities of InFi-Checker transcend simple pattern memorization. Instead, InFi-Checker captures transferable and fundamental diagnostic features, therefore generalizing effectively across out-of-distribution data.

Fine-grained training enhances binary fact-

Model	BAcc(Nor.)	BAcc(Str.)	SAR(Avg.)
The Open-Source Models			
Llama-3.1-8B-Instruct†	27.69	21.33	72.57
Llama-3.1-8B-Instruct※†	23.79	18.12	79.41
Qwen3-8B†	47.94	41.08	86.50
Qwen3-8B※†	50.49	44.78	87.22
The State-of-the-Art LLMs			
Claude-3.7-Sonnet※	49.19	45.12	94.28
DeepSeek-V3.2-NoThink※	59.19	52.31	87.33
GPT-4o※	64.69	60.27	80.19
GPT-4.1※	58.91	55.13	94.87
GPT-5※	46.35	42.28	92.58
o3※†	60.77	56.76	94.60
InFi-Checker (Ours)			
InFi-Checker-Llama	90.91	85.49	94.02
InFi-Checker-Qwen	92.34	87.74	94.92

Table 5: Normal(Nor.) and strict(Str.) balanced accuracy (%) and averaged SAR on InFi-Check-FG. The reported SAR(Avg.) is the average of error-type specific SAR across all evaluable error types. Models marked with † contain types with zero accuracy (excluded from the average), which may lead to an optimistic estimation of their SAR. ※ means one-shot settings. Full results are displayed in Appendix D.

checking. Although InFi-Checker is optimized for fine-grained tasks, it achieves competitive results on six binary benchmarks (Table 4). These datasets cover a broad spectrum of document sources and various downstream tasks, including summarization, QA, and search-based generation, which comprehensively validates the model's robustness across varied contexts in binary mode. InFi-Checker surpasses binary classification specialized models and approaches or even exceeds the performance of closed-source models, suggesting that explicitly training on diverse error types heightens the model's overall sensitivity to hallucinations, thereby benefiting even binary classification.

5.4 In-depth Sentence Level Analysis

To evaluate the models' interpretability, we assess performance at the sentence level by requiring models to not only categorize the fine-grained error type but also precisely localize it within the text. Specifically, we define **Strict Accuracy**, which demands: (1) correct error-type assignment, (2) precise labeling on both the hallucinated and hallucination-free claim sentences. We then introduce the **Sentence Alignment Ratio (SAR)**, defined as the ratio of strict accuracy to normal accuracy of each error type. While normal metrics only verify labels, SAR quantifies the consistency between a model's final judgment and its underlying reasoning. A higher SAR indicates authentic comprehension rather than coincidental guessing. As shown in Table 5, InFi-Checker ranks among the highest SAR scores, which is increasingly difficult as the base normal accuracy rises, therefore confirming InFi-Checker's performance gain is driven by robust and interpretable reasoning.

Index	**J**ust.+Corr.	**E**vid.	**S**ent.	BAcc
JES	✓	✓	✓	90.91
ES	-	✓	✓	75.02
JS	✓	-	✓	69.85
JE	✓	✓	-	61.17
J	✓	-	-	36.95
E	-	✓	-	53.76
S	-	-	✓	30.02
raw	-	-	-	20.59

Table 6: Result (%) for ablation study on InFi-Checker-Llama on InFi-Check-FG. "Just.+Corr." means outputting error justification and correction, "Evid." means outputting evidence sentences, and "Sent." means analyzing sentence-by-sentence. See Appendix D for separate ablation of justification and correction.

5.5 Ablation Study

We conduct an ablation experiment to demonstrate the importance of the key components we claim. We remove the output of interpretable justifications and corrections (**J**), evidence sentence (**E**), as well as the sentence-by-sentence claim analysis (**S**) InFi-Check adapt. Table 6 presents an ablation study on these components. The results stress each component's importance, for removing any single component results in a notable performance drop.

6 Conclusion

In this paper, we propose a new framework termed InFi-Check, which integrates error typologies, synthetic data generation pipelines, and fine-grained annotations for comprehensive fact-checking. To be specific, we first develop diverse methods to synthesize six hallucination error types in grounded generation, including both intrinsic and extrinsic, semantic and discourse level errors. In this way, we construct InFi-Check-TR and InFi-Check-FG, two novel datasets characterized by fine-grained error type design, interpretable justifications and corrections, as well as comprehensive claims. Building upon InFi-Check-TR, we develop InFi-Checker, an advanced factuality evaluation model capable of fine-grained hallucination analysis. Also, we conduct extensive experiments to verify the superiority of InFi-Check-FG and InFi-Checker.

Limitations

Our pipeline's effectiveness is constrained by inherent limitations in LLM capabilities. While we employ sentence-level verification, the models still generate document-unsupported hallucinations, or fail in extracting full grounding evidence sentences. Additionally, they struggle to differentiate between factual incompleteness and legitimate information simplification, particularly affecting error construction quality for more complex cases. We adapt manual check and filtering for InFi-Check-FG to mitigate this bias in evaluation.

Ethics Statement

Our work focuses on improving the fact-checking abilities of document-grounded generation systems through interpretable and fine-grained methods. While synthetic errors and human annotations are central to our approach, we recognize potential risks, such as misuse for generating misinformation or unintended biases in the dataset. To mitigate these concerns, we ensure transparency in our methodologies and emphasize their use for research purposes only. Additionally, our dataset and model are designed to generalize across diverse scenarios, avoiding overfitting to specific benchmarks. We release all contributions under research-focused licenses to encourage responsible and ethical use in advancing AI systems.

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Appendix

A InFi-Check-FG Construction Details

A.1 Detailed Hallucination Categorization and Error construction Examples

We provide a full hallucination categorization along with illustrative examples for each error construction methodology in Table 13.

A.2 Grounded Claim Dataset Construction

Our pipeline starts with an arbitrary document dataset, which can include pre-existing supported claims or simply the documents themselves. Due to the limitations of existing document-claim datasets in terms of length (news datasets being relatively short, and academic paper dataset being excessively long), combined with challenges that some automatically extracted claims lack complete support from the document (such as the TL;DR dataset (Völske et al., 2017)), we opted to construct our dataset beginning with the document itself, which also streamlines the extraction of evidence and proves the broad usability of our method. Specifically, for each document in the dataset, we prompt LLMs to generate a series of document-grounded claims that capture the core factual content. In our implementation, we leverage a summarization-style objective for this generation process. This approach is chosen because such condensed representations naturally require every generated claim to be strictly grounded in the source context, providing an ideal foundation for fact-checking data. Section 5.2 demonstrates that our pipeline and model possess strong generalizability to the evaluation of other document-grounded generation tasks. Subsequently, we apply an extract-and-rewrite process to ensure the faithfulness of each claim sentence: 1) LLMs are prompted to locate the grounding sentences as evidence from the source document for each sentence in these claims. 2) A voting mechanism involving three LLMs is applied to determine whether a claim sentence is sufficiently supported by its grounding sentences. If a sentence lacks adequate support, it undergoes a rewriting process, and the voting process repeats until complete support from the reference is achieved. The aforementioned process also serves as the preparation for the synthetic model output. Ultimately, we achieve a set of claims, each with sentence-level grounding evidence. Importantly, due to the flexibility of the base dataset, our pipeline can be applied to any document dataset, supporting the scalability of InFi-Check.

A.3 Document Dataset Selection

We adopt the BBC News Summary Dataset (Gupta et al., 2022) and the DetNet Wikipedia Dataset (Xu and Lapata, 2019) as the initial document datasets. These datasets offer a diverse range of documents covering news and encyclopedic content, classified by domain, with a varied length distribution. We ensured diversity by choosing documents from different domains and lengths.

The BBC News Summary Dataset (Gupta et al., 2022) consists of extractive summaries only, so we did not use it as the original claim. This data set categorizes news articles into five distinct categories: business, entertainment, politics, sports, and technology. The DetNet Wikipedia Dataset (Xu and Lapata, 2019) is designed for domain detection, with Wikipedia data labeled for seven domains: "Business and Commerce" (BUS), "Government and Politics" (GOV), "Physical and Mental Health" (HEA), "Law and Order" (LAW), "Lifestyle" (LIF), "Military" (MIL), and "General Purpose" (GEN). For the BBC News Summary Dataset, we randomly selected 150 documents from each category. For the DetNet Wikipedia Dataset, we select 100 documents from each domain. The document length in both datasets varies greatly. To ensure the models have a certain degree of robustness, but also efficiency while training, we filtered documents to have lengths within the range of 300 to 1000 words, and prompted the language models (LLMs) to control the claim length within the range of $[100, \min(doc_len/3 + 10, 200)]$ words.

A.4 LLM Selection in InFi-Check Pipeline

To address potential biases where a single model might favor its own generated text, and to avoid issues where training exclusively with one model's outputs might cause out-of-domain problems for texts generated by other models, we utilized two different sets of LLMs at each step of our pipeline. In addition, the models used for generation and evaluation were different. Usage of LLMs is outlined in Table 7.

A.5 Curation for InFi-Check-FG

Based on the results of human evaluation, we design a set of strict filtering prompts to further curate the validation and test sets. For each instance, we

Task	LLM Set 1	LLM Set 2
Summarization	GPT-4o	DeepSeek-R1
Reference extraction	Claude-3.7-Sonnet	GPT-4o
Support determination	(Claude-3.7-Sonnet, Qwen-2.5, Gemini-1.5)	(GPT-4o, Qwen-2.5, Gemini-2.0)
Rewriting	Claude-3.7-Sonnet	GPT-4o
Error data construction	GPT-4o	Claude-3.7-Sonnet

Table 7: Usage of LLMs in dataset construction

	#doc	#doc-pair	#PredE	#EntE	#CircE	#CorefE	#LinkE	#OutE	#NoE
InFi-Check-TR	1263	15660	2946	1998	1386	2889	1495	1457	3489
InFi-Check-FG	190	519	85	21	29	64	30	38	252

Table 8: Statistics of the dataset constructed from InFi-Check

employ gpt-4.1 to independently check the presence of any potential generation errors categorized in human evaluation, including but not limited to incorrect extraction of grounding sentences and misclassification of hallucination or error types. Each possible error is examined in isolation through dedicated prompts, and an instance is retained only if it is verified to be fully correct across all checks. See Appendix F for filtering prompts. We intentionally design this filtering procedure to be conservative, prioritizing precision over recall. While it may discard some instances that are in fact correct, it substantially reduces the risk of retaining flawed samples. Empirically, this process is able to identify all of the errors observed in human evaluation (flawed summary, false negative error, wrong error type, wrong error reasoning). We apply this filtering pipeline to both the validation and test sets, resulting in a final curated set of 519 instances that constitute InFi-Check-FG.

B Statistics of InFi-Check Datasets

Table 8 shows the overall statistics of the dataset constructed using InFi-Checkpipeline, in which the train set refers to InFi-Check-TR and the filtered test set refers to InFi-Check-FG. The two datasets are derived from different document sets to avoid data leakage.

C Implementation Details

C.1 Baseline Details

ClearCheck (Seo et al., 2025) is fine-tuned from Llama-3.1-8B-Instruct, it improves verification robustness through multi-task training tailored for hallucination detection across various grounded generation scenarios. **AlignScore** (Zha et al., 2023) is a holistic metric that evaluates factual consistency through a unified alignment function trained across diverse NLP tasks such as NLI and QA. We adopt the largest and best-performing version (AlignScore-large) as our baseline. **FactCG** (Lei et al., 2025) enhances model performance by generating complex training data via multi-hop reasoning on context graphs extracted from documents. We use the best-performing version (FactCG-DBT) as our baseline. **MiniCheck** (Tang et al., 2024a) achieves state-of-the-art binary performance by utilizing a novel document-claim pair synthesis method to train lightweight fact-checkers. We use the largest and best-performing version (Bespoke-MiniCheck-7B) as our baseline.

C.2 Benchmark and Metric Details

For InFi-Check-FG, we calculate the accuracy of each error type (as well as "No Error"), and report their average, the balanced accuracy. The "accuracy" is defined as whether the model correctly points out the specific error type in samples containing this type of error. If a model reports a sample to be hallucinated, but with the wrong error type, it is judged as incorrect.

The **FRANK** benchmark focuses on factual consistency in abstractive summarization using the CNN/DM and XSum news datasets. It provides a manual annotated fine-grained typology of errors found in the outputs of multiple state-of-the-art summarization models, offering a rigorous testbed for news-domain grounding. To facilitate a standardized comparison across diverse benchmarks, we also report balanced accuracy on the FRANK dataset instead of correlation-based metrics, which

Model	BAcc(Nor.)	BAcc(Str.)	SAR(Avg.)
The Open-Source Models			
Llama-3.1-8B-Instruct†	27.69	21.33	72.57
Llama-3.1-8B-Instruct※†	23.79	18.12	79.41
Qwen3-8B†	47.94	41.08	86.50
Qwen3-8B※†	50.49	44.78	87.22
The State-of-the-Art LLMs			
Claude-3.7-Sonnet	53.07	48.48	92.21
Claude-3.7-Sonnet※	49.19	45.12	94.28
DeepSeek-V3.2-NoThink	59.64	53.94	89.43
DeepSeek-V3.2-NoThink※	59.19	52.31	87.33
GPT-4o	60.50	56.57	94.97
GPT-4o※	64.69	60.27	80.19
GPT-4.1	54.45	49.44	78.17
GPT-4.1※	58.91	55.13	94.87
GPT-5	49.06	44.41	92.05
GPT-5※	46.35	42.28	92.58
o3†	58.00	55.07	95.48
o3※†	60.77	56.76	94.60
InFi-Checker (Ours)			
InFi-Checker-Llama	90.91	85.49	94.02
InFi-Checker-Qwen	92.34	87.74	94.92

Table 9: Normal(Nor.) and strict(Str.) balanced accuracy (%) and averaged SAR on InFi-Check-FG. The reported SAR(Avg.) is the average of error-type specific SAR across all evaluable error types. Models marked with † contain types with zero accuracy (excluded from the average), which may lead to an optimistic estimation of their SAR. ※ means one-shot settings.

Setting	BAcc
Justification + Correction	90.91
Justification only	86.30
Correction only	83.17
No interpretable reasoning	75.02

Table 10: Ablation study of InFi-Checker-Llama on InFi-Check-FG for assessing justification and correction separately. Other component, such as evidence and sentence-by-sentence reasoning patterns, is preserved throughout the experiment.

often suffer from limited comparability across different model scales. Given the complexity of FRANK—where each instance is annotated by multiple experts and often contains overlapping error types—we adopt a multi-annotator consensus criterion for evaluation. Specifically, a model's prediction is considered correct if the predicted error type aligns with any of the labels assigned by the human annotators for that specific instance. This approach accounts for the inherent subjectivity and legitimate label diversity in fine-grained hallucination detection. Furthermore, while the FRANK dataset contains fine-grained error categories, many instances exhibit multiple co-occurring error types, which can introduce noise into categorical classification. To ensure a consistent and robust evaluation, we reformulate the task into a binary consistency check for metric calculation. We map all fine-grained error types to a "hallucinated" category, treating each instance as either "hallucinated" or "factual." To mitigate the impact of class imbalance within the dataset, we report Balanced Accuracy, providing a more reliable reflection of the model's discriminative performance across both factual and non-factual claims.

For our evaluation on binary fact-checking benchmarks, we acknowledge the data quality issues identified by Seo et al. (2025), which notes that several widely used datasets contain significant annotation noise, linguistic ambiguities, and skewed label distributions. To ensure a robust and reliable assessment, we adopt the filtered and reprocessed versions of these benchmarks from Seo et al. (2025). To maintain strict parity with established baselines and facilitate a direct comparison with state-of-the-art methods, we follow the evaluation protocol of Seo et al. (2025) and report the Macro F1 score. The six binary fact-checking benchmarks are: **ClaimVerify** audits the generative search engine task, using responses from commercial systems (e.g., Bing Chat) across diverse queries from Google history and Reddit. It emphasizes the accuracy of in- line citations and the verifiability of claims against real-world web sources. **ExpertQA** targets high-stakes, long-form question answering across 32 specialized fields (e.g., medicine, law). It features expert-curated questions and claims generated by representative LLMs, requiring models to verify professional, domain-specific knowledge with high precision. **Factcheck-Bench** is a comprehensive benchmark for open-domain document-level factuality, evaluating LLM-generated responses at the claim, sentence, and document levels. It encompasses a wide array of general-purpose topics, aiming to test the end-to-end verification capabilities of automatic systems. **REVEAL** focuses on complex Chain-of-Thought (CoT) reasoning in open-domain settings. It provides step-level labels for attribution and logical correctness, testing whether a model can verify the intermediate reasoning claims of a language model's answer. **MediaSum** and **MeetingBank** are subset from the summarization dataset ToFuEval. MediaSum centers on topic-focused dialogue summarization within the media interview domain. It challenges models to maintain factual integrity when distilling multi-party conversations into concise, grounded summaries. MeetingBank

Label	Proportion(%)
No Problem	78
Flaws in Claim	11
Incomplete Grounding	6
False Negative Error	3
Wrong Error Type	1
Wrong Error Justification	1

Table 11: Human evaluation results on a sample of 100 instances from our dataset.

Model	Cost($)
The State-of-the-Art LLMs	
GPT-5	23.9
Claude-3.7-Sonnet	12.7
o3	12.4
InFi-Checker (Ours)	
InFi-Checker-Llama	3.9
InFi-Checker-Qwen	4.4

Table 12: Comparison of costs of InFi-Checker and LLMs on InFi-Check-FG. InFi-Checker cost is calculated with $0.8 per GPU hour.

focuses on professional meeting transcripts and evaluates the consistency of summaries generated from lengthy, informal, and multi-speaker interactions. It serves as a robust test for grounding claims in complex, non-structured dialogue data.

C.3 Training Details of InFi-Checker

We fine-tune both Llama-3.1-8B-Instruct and Qwen3-8B for 3 epochs on InFi-Check-TR, using a batch size of 32 and the Adam optimizer. The learning rate follows a cosine-decay from $1e-5$ to $1e-6$, and we set the warm-up fraction to 0.1.

D Further Results

Table 9 shows the full strict accuracy and SAR result on the FRANK benchmark, including both zero-shot and one-shot results of LLMs. We also conducted an ablation study to isolate the individual contributions of justifications and corrections. As shown in Table 10, while retaining either component still yields competitive results, the integration of both processes is essential for achieving optimal performance.

E Data Structure Example

We provide an example of data from InFi-Check-FG in Figure 4, which demonstrates the data structure of InFi-Check.

F Prompts

Figure 5, Figure 6, Figure 7 and Figure 8 show the prompts in the InFi-Check pipeline. Figure 9 shows the prompt used for the LLM baselines in our experiment. Note that in our preliminary experiments, we observed that increasing the number of few-shot examples to 2 or 3 could adversely affect performance due to the extended context and reasoning process length within InFi-Check-FG. Consequently, we limit our experimental setup to zero-shot and one-shot configurations for better model performance. Figure 10 is the prompt used for filtering samples in InFi-Check-FG.

G Human Evaluation

We did human evaluation on a sample of 100 for InFi-Check-TR. Annotators (all holding PhD or Master's degrees) are instructed to check whether the total claim and output fall into any of the given mistakes. The instructions for detecting defined mistakes are:

- Flaws in Claim: A summary error exists if: - A summary sentence is annotated as "supported or not: YES", - BUT the summary contains factual errors that contradict or mismatch with the original document (including entity, time, location, numerical, or core semantic errors). Important: - If ANY single summary sentence has this issue, the ENTIRE data sample must be considered problematic.

- Incomplete Grounding: A grounding error exists if ANY of the following is true: - The listed "related sentence(s) from the document" are NOT sufficient to support the summary sentence, and there exist other ESSENTIAL sentences in the document that must be cited. - Any listed grounding sentence does NOT actually appear in the original document (not minor truncation or paraphrase, but clearly non-existent). - The same grounding sentence is explicitly duplicated (appears two or more times). Note: - Missing an essential supporting sentence is a definite error.

- False Negative Error: A false negative error exists if: - A summary sentence is annotated as "supported or not: NO", - BUT the summary is factually correct and fully supported by the document, with NO factual discrepancies in its core meaning. This applies only when the summary is clearly correct.

```
[
    {
        "summary sentence": "The column in Piazza Santa Maria Maggiore in Rome, crowned with a statue of the Virgin in 1614,
        set a precedent for many European columns.",
        "related sentence(s) from the document": [
            "The column in Piazza Santa Maria Maggiore in Rome was one of the first.",
            "Within decades it served as a model for many columns in Italy and other European countries."
        ],
        "supported or not": "YES",
        "reason": "The summary sentence faithfully reflects the related sentences.",
        "error type": "No Error"
        },
        {
        "summary sentence": "The first Marian column north of the Alps was Munich's Mariensäule in 1714, inspiring similar
        structures in Prague and Vienna.",
        "related sentence(s) from the document": [
            "The first column of this type north of the Alps was the Mariensäule built in Munich in 1638 to celebrate the sparing
            of the city from both the invading Swedish army and the plague.",
            "It inspired for example Marian columns in Prague and Vienna, but many others also followed very quickly."
        ],
        "supported or not": "NO",
        "reason": "This sentence is not supported by the related sentence(s).\n- Location: '1714'.\n- Explanation: The year of the
        construction of Munich's Mariensäule was changed from 1638 to 1714, falsely altering the historical timeline.\n-
        Correction: The first Marian column north of the Alps was Munich's Mariensäule in 1638, inspiring similar structures in
        Prague and Vienna.",
        "error type": "Circumstance Error"
    },
    {
        "summary sentence": "The Prague column, built post-Thirty Years' War, was destroyed in 1918 due to its association with
        Habsburg rule.",
        "related sentence(s) from the document": [
            "The Prague column was built in Old Town Square (Staroměstské náměstí) shortly after the Thirty Years' War in
            thanksgiving to the Virgin Mary Immaculate for helping in the fight with the Swedes.",
            "Unfortunately, many Czechs later connected its placement and erection with the hegemony of the Habsburgs in their
            country, and after declaring the independence of Czechoslovakia in 1918 a crowd of people pulled this old monument
            down and destroyed it in an excess of revolutionary fervor."
        ],
        "supported or not": "YES",
        "reason": "All content in the summary sentence is accurately derived from the related sentences.",
        "error type": "No Error"
    }
]
```


Figure 4: An example of the data in InFi-Check-FG, the data is truncated due to space limitations.

- Wrong Error Type: An error-type mismatch exists if: - The summary is indeed incorrect, - BUT the annotated “error type” is not the most appropriate one according to the SIS-Fact definitions below, - AND a clearly better error type applies. Only flag this error when the mismatch is obvious. (We also provide the error taxonomy for the annotators to refer to.)

- Wrong Error Justification: A reasoning error exists if: - The annotated error type is correct, - BUT the "reason" field contains incorrect analysis, such as: - Misidentifying the nature or location of the error; - Proposing a correction that is STILL factually wrong; - Explaining the error in a way that contradicts the original document. Note: - The problem must be substantive and factual.

As shown in Table 11, most errors originated in the initial claim generation or evidence extraction phases, underscoring the inherent difficulty of grounded generation and highlighting the robustness of our controlled hallucination pipeline.

H Cost Efficiency Evaluation

Table 12 shows the result for cost efficiency analysis. We compared the computational cost of InFi-Checker and baseline LLMs. The cost of InFi-Checker is converted using the prediction time on the GPUs, while the cost of LLMs is computed through tokens in API calls.

Categorization			Method	Example
Intrinsic Errors	Semantic Frame Errors	Predicate Error (PredE)	Swapping Relation Masking	Its impact on theaters is now emerging. Its absence from theaters is now receding.
			Modifying Predictions	Despite it all, 2023 should still reach the $9 billion in domestic gross hoped for this year. Despite it all, 2023 reached the $9 billion in domestic gross hoped for this year.
		Entity Error (EntE)	Swapping Entities	Her last stage role was in My Fair Lady. Her last stage role was in Bless This House.
			Compressing Words	In France and Italy, he wrote his last work. In France, he wrote his last work.
		Circumstance Error (CircE)	Swapping Circumstances	The shooting left 10 students and 2 teachers dead. The shooting left 2 students and 10 teachers dead.
	Discourse Errors	Co-reference Error (CorefE)	Swapping Pronouns	Gonzales was also indicted. She was also indicted.
			Merging Sentences	The charges were first reported by the San Antonio Express-News. District Attorney Christina Mitchell did not return requests for comment. The charges were first reported by the San Antonio Express-News, who did not return requests for comment.
		Discourse Link Error (LinkE)	Reverse Logical Relationship	The six-month Hollywood labor disruption has finally ended. Immediately following the settlement, Disney announced delays in its upcoming release schedule. After the announcement of the delays in Disney's upcoming release schedule, the six-month Hollywood labor disruption has finally ended.
Extrinsic Errors			Introducing Extrinsic Information	Robert escaped to Visegrád disguised as a civilian, aided by Nicholas, son of Radoslav, who defended him against five attackers. Robert escaped to Visegrád disguised as a civilian, aided by Nicholas, son of Radoslav, a renowned swordsman known for his exceptional skill in battle, who defended him against five attackers.

Table 13: Categories of the error data. The blue part is the selected text for modification, and the red part is the modified text.

I'll provide you with a document. Your task is to write a short summary for this document according to the following requirements:
1. The length of the summary should be within <WORD_CONSTRAIN> words.
2. Every sentence in the summary should be directly supported by the content of the document.
3. For each event, make sure every important entity such as person, location and time is kept in the summary, especially entities that occurs in parallel.
4. When doing simplification, make sure each complex event or idea remains true to the original meaning. Avoid over-simplification that leads to in-consistency with the origin document.

Document:<Document>

Directly output the summary without any extra words.

Figure 5: Prompt for writing summaries.

Here is a document with a corresponding summary. Your task is to analyze the summary sentence by sentence. For each sentence in the summary, provide the exact sentences from the document that supports the summary sentence. If the summary comes from multiple sentences, report all sentences.
You should ensure that sentences are considered as individual units based on punctuation. Specifically:
- Treat each sentence as ending at a period (.), question mark (?), or exclamation mark (!), even if multiple sentences are enclosed within quotation marks.
- Do not truncate any sentence. If a portion of a sentence is extracted (e.g., ending at a comma, semicolon, or any punctuation other than ., ?, !), you must include the rest of the sentence so that the entire sentence is fully reproduced.

You should only respond in format as described below. Do not return anything else. START YOUR RESPONSE WITH '['
Return the result as a Python list of dictionaries, where each dictionary has the following keys:
"summary sentence": The sentence from the summary.
"sentences from the document": A Python list of the exact supporting sentences from the document. Ensure that the sentences are in the same order as they appear in the original document. Each sentence should be reported fully, without any omission.

Figure 6: Prompt for locating the grounding sentences.

Here are some pieces from the SOURCE_DESCRIPTION, and a summary sentence of it. Your task is to:
1. Compare the summary with the document and determine whether if the summary is fully supported by the content in the document. Specifically, verify if all key points made in the summary are traceable back to the sentence in the document. State whether the summary is fully supported with 'YES' or 'NO'.
2. If the answer is 'NO', revise the summary to align it fully with the document. Make sure the fluency and grammar correctness of the revised sentence, and ensure it accurately reflects the information.

You should only respond in format as described below. Do not return anything else. START YOUR RESPONSE WITH '['
Return the result as a Python list of dictionaries, where each dictionary has the following keys:
"summary sentence": The sentence from the summary.
"sentences from the document": A Python list of the exact supporting sentences from the document. Ensure that the sentences are in the same order as they appear in the original document. Each sentence should be reported fully, without any omission.

Figure 7: Prompt for determining whether a summary sentence is sufficiently supported by its grounding sentences. The purple part is only used in the LLM for re-writing.

Here is a document with a summary. Please create a fake summary based on the origin summary by the following steps:
Instruction:
1. Analyze the document and identify sentences that contain future predictions (e.g., those using modal verbs like 'will,' 'might,' or phrases like 'predict,' 'suppose').
2. Select a sentence where the prediction is the main clause, not just a subordinate clause, and modifying the prediction into a factual statement will result in the most significant change in meaning. You can modify this sentence so that the prediction is completely transformed into a factual statement about an event that has already occurred. Ensure the modified sentence is grammatically correct and fully removes any speculative language.
3. Based on the changed sentence, modify some part of the summary to include the fake information in the changed sentence, so the summary cannot be fully supported by the origin document.
Make sure the new summary should not be fully supported by the document, and not change any other part in the summary besides those associated with the modification.

You should only respond in format as described below. Do not return anything else. START YOUR RESPONSE WITH '{{'.
Return the result as a Python dictionary with the following keys:
Format:
- "original text in summary": The original sentence containing the prediction from the document.
- "chosen element": The chosen prediction or future-oriented statement in the original text.
- "modification explanation": Description of the modification.
- "modified element": The new factual statement replacing the prediction.
- "modified text": The sentence after the modification, now a factual statement.
- "explanation": A clear explanation of how the meaning of the original text has been altered.
- "full text of modified summary": The full text of the modified summary.
- "wrong information": Point out the specific wrong information introduced in the summary after the modification.
Replace any line breaks in the values with '\n' so that the dictionary can be parsed using eval().

Figure 8: Prompt for generating InFi-Check-FG. The colored part is construction-method specific.

Task:
Evaluate the given summary by comparing it with the original document and identify any errors. These errors may include incorrect information, over-simplifications, misrepresentations, or other discrepancies. The possible types of errors to consider are as follows: Predicate Error, Entity Error, Circumstance Error, Co-reference Error, Discourse Link Error, Extrinsic Error.

Instructions:
You are provided with the full text of the original document and a summary that may contain errors. You should analyze the summary sentence by sentence and returning the results in the following Python list format:
Each item in the list should correspond to a summary sentence and be represented as a Python dictionary with the following keys:
- "summary sentence": The summary sentence.
- "related sentence(s) from the document": A list of sentences from the original document that support the summary sentence, if the summary sentence is fully supported. If the summary sentence contains an error, list the sentences needed to point out the error.
- "supported or not": "YES" if the summary sentence is fully supported by the related sentences, otherwise "NO".
- "reason": A brief analysis explaining whether the summary sentence is supported or not. If the summary sentence is not supported, specify where the error occurs, explain the incorrect information conveyed in the summary, and provide a corrected version of the sentence.
- "error type": The type of error found (choose from the types listed above), or "No Error" if the sentence is fully supported.

Document: <Document>
Summary: <Summary>

Figure 9: Prompt for evaluating LLM baseline.

You are an expert auditor for synthetic data quality. Your task is to strictly examine whether the given synthetic annotation data contains ANY clear construction errors, according to the error categories defined below. If a clear problem exists, you MUST identify it and mark the data as problematic. If no clear problems exist, mark the data as valid.

<POSSIBLE ERROR TYPES>
<INPUT DATA>

Final Judgment Rules
- If ANY of the five error types is found in ANY summary sentence, the entire data sample is problematic.
- If no errors are found, the data sample is valid.
- When evidence is unclear or debatable, flag an error.

Requirements
1. For the entire data sample, judge whether it contains ANY of the 5 types of construction errors;
2. Output ONLY JSON format with the following fields:
- is_problematic: Boolean (True = has any construction error, False = no errors);
- error_details: element is a dict with "sentence_idx", "error_type"
- empty if no errors;
- reason: Str (brief summary of all errors, or "No construction errors detected").

Figure 10: Prompt for the filtering process of InFi-Check-FG. Possible error types are the same as human evaluation instructions, and the input data are the document-claim pairs.