

# The Missing Parts: Augmenting Fact Verification with Half Truth Detection

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## Abstract

Fact verification systems typically assess whether a claim is supported by retrieved evidence, assuming that truthfulness depends solely on what is stated. However, many real-world claims are *half-truths*, factually correct yet misleading due to the omission of critical context. Existing models struggle with such cases, as they are not designed to reason about what is left unsaid. We introduce the task of **half-truth detection**, and propose POLITIFACT-HIDDEN, a new benchmark with 15k political claims annotated with sentence-level evidence alignment and inferred claim intent. To address this challenge, we present **TRACER**, a modular re-assessment framework that identifies omission-based misinformation by aligning evidence, inferring implied intent, and estimating the causal impact of hidden content. TRACER can be integrated into existing fact-checking pipelines and consistently improves performance across multiple strong baselines. Notably, it boosts Half-True classification F1 by up to 16 points, highlighting the importance of modeling omissions for trustworthy fact verification. *We will release both the benchmark and code upon publication.*

## 1 Introduction

The rapid spread of digital content has made fact verification a critical component in combating misinformation and promoting trustworthy public discourse. Traditional fact-checking systems follow a standard paradigm: given a claim and a body of evidence, the system classifies the claim as *true*, *false*, or *not enough information* (Chen and Shu, 2024). These systems are effective in identifying clearly incorrect claims and continue to serve as the backbone of automated verification pipelines.

However, many real-world claims are not outright false but are still misleading due to the omission of critical context. These are often referred to as **half-truths**: statements that are factually cor-

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**Claim:** Under our administration, unemployment has fallen to its lowest level in half a century, demonstrating that our economic policies are working.

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### Presented Evidence (PE):

- Official labor statistics confirm the unemployment rate dropped to 3.5%, the lowest in 50 years.

### Hidden Evidence (HE):

- Most of the new jobs were part-time or gig-based, lacking benefits or job security. → CHE
- Labor force participation remained low, with many discouraged workers no longer counted. → CHE
- Job growth was particularly strong in the hospitality and retail sectors.

### Verdict by Standard FV Model:

**True:** The claim is factually supported by official statistics.

### TRACER Re-Assessment Verdict:

**Half-True:** Although the unemployment figure is accurate, the omission of job quality and participation context distorts the implied economic success.

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Table 1: A factually correct political claim re-evaluated as misleading (Half-True) by TRACER through Critical Hidden Evidence (CHE) analysis.

rect but strategically incomplete (Singamsetty et al., 2023a; Jaradat et al., 2024). Consider the example in Table 1, where a politician claims that unemployment has reached a 50-year low. While this statistic is factually accurate, it omits key information, such as the rise in part-time gig jobs and stagnant labor force participation, that undermines the implied narrative of broad economic success. Standard fact verification (FV) models, which focus on validating surface-level factuality, label such claims as *true*, failing to capture the misleading nature of selective omission.

This challenge highlights a fundamental limitation in existing FV pipelines: they are not designed to reason about what is missing. Current models typically assess what is stated, treating veracity as a discrete property grounded in textual entailment (Molina et al., 2019; Estornell et al., 2020). Yet in practice, truthfulness is often shaped by both what is said and what is left unsaid. Omission-

based misinformation exploits this gap, occupying a gray area between truth and falsehood that standard systems are ill-equipped to address.

In this paper, we introduce the task of **half-truth detection**, which complements traditional fact verification by modeling *completeness*. We define half-truths as claims that are factually accurate but omit *Critical Hidden Evidence (CHE)*—information that, if included, would significantly alter the plausibility of the claim’s implied meaning. Our goal is to identify such omissions and assess their impact on the inferred intent of the claim.

To tackle this task, we propose **TRACER** (*Truth ReAssessment with Critical hidden Evidence reasoning*), a modular framework that enhances fact-checking systems with omission-aware reasoning. TRACER operates in three stages: (1) **evidence alignment**, to classify retrieved evidence as presented or hidden; (2) **intent generation**, to recover the claim’s implicit message; and (3) **causality analysis**, to determine whether the hidden evidence undermines the inferred intent. These components feed into a lightweight **re-assessment module** that revisits claims, particularly those initially labeled as *true*, and identifies misleading omissions. TRACER is model-agnostic and can be integrated into both agent-based and prompting-based FV pipelines.

To support this task, we construct **POLITIFACT-HIDDEN**, a benchmark dataset based on the Politifact corpus. It contains about 15k claims annotated with sentence-level labels indicating presented and hidden evidence, along with inferred claim intents validated through a combination of LLM prompting and human quality control. To our knowledge, this is the first dataset to explicitly annotate both omission and intent, enabling systematic study of half-truths at scale.

Our contributions are as follows:

1. We **formulate half-truth detection** as a new task in fact verification, targeting claims that omit critical context while remaining factually correct.
2. We introduce **POLITIFACT-HIDDEN**, a large-scale benchmark with fine-grained annotations for presented/hidden evidence and inferred claim intent.
3. We propose **TRACER**, a three-stage framework that identifies omission-based misinformation through evidence alignment, intent

modeling, and causal reasoning. TRACER can be deployed as a re-assessment module and yields substantial gains in detecting half-truths across multiple strong baselines.

By modeling completeness alongside correctness, this work advances the frontier of fact verification. It addresses a blind spot in current systems and offers a generalizable framework for uncovering more subtle forms of misinformation that operate through omission rather than distortion.

## 2 Related Work

**Fact Verification.** Fact verification is commonly framed as a three-stage pipeline involving claim detection, evidence retrieval, and claim classification into *Supported*, *Refuted*, or *Not Enough Information* (Thorne et al., 2018; Guo et al., 2022). Benchmarks such as FEVER (Thorne et al., 2018) and LIAR (Wang, 2017) have facilitated significant progress in this area. Most existing systems focus on surface-level factual correctness, aiming to match claims against retrieved facts. While effective for outright falsehoods, these approaches are less suited to handling omission-driven manipulation.

**Omission and Half-Truths.** Omission-based misinformation, including half-truths, has received increasing attention. Singamsetty et al. (2023b) introduce controlled claim editing to expose omitted content, and Chen et al. (2022) propose generating implicit questions to recover missing context. Other datasets have incorporated related annotations, such as *Cherry-picking* (Schlichtkrull et al., 2023) and *Mixture* (Yang et al., 2022), which primarily capture conflicting evidence rather than omissions per se. These schemes focus on factual inconsistency (i.e., presence of both supporting and refuting evidence), rather than semantic incompleteness or intent-driven distortion. In contrast, our work targets *half-truths*, claims that are factually accurate but strategically omit *Critical Hidden Evidence (CHE)* that significantly alters interpretation. Closely related are efforts that explore the role of intent in misinformation, such as distinguishing disinformation through concealment and overstatement (Rodríguez-Ferrándiz, 2023; Lee and Lee, 2024). We go beyond these by explicitly modeling the causal impact of hidden evidence on inferred intent without altering the original claim.

**Reasoning-Based Fact Checking.** Recent methods incorporate structured reasoning to improve factuality assessment. Program-guided models such as QACheck and ProgramFC (Pan et al., 2023b) generate intermediate steps to support verification. Argumentation-based approaches, such as CHECKWHY (Si et al., 2024), model causal links within evidence chains. Meanwhile, prompting-based methods like HiSS (Zhang and Gao, 2023a) and Flan-T5 (Chung et al., 2022a) leverage large language models for step-by-step verification. Other work explores intent modeling using contrastive learning (Yang et al., 2024) or refined retrieval (Wang et al., 2024). Our work complements these efforts by introducing omission-aware reasoning and providing a modular framework that can be integrated into both structured and generative pipelines.

### 3 Task Formulation

We define **half-truth detection** as an extension of fact verification that focuses on *factual completeness*. A claim may be factually accurate in isolation, yet convey a misleading impression by omitting relevant information that influences its interpretation. The goal is to identify such omissions and assess whether they materially affect the plausibility of the claim’s implied message.

Formally, given a claim  $C$  and a set of retrieved evidence sentences  $E = \{e_1, e_2, \dots, e_n\}$  relevant to  $C$ , the goal is to classify the claim into one of three categories: *True*, *Half-True*, or *False*. This classification is determined not only by factual support but also by the presence or absence of **Critical Hidden Evidence (CHE)**  $\subseteq E$  that is both (1) *not presented in the claim*, and (2) *necessary to understand or challenge the claim’s implied conclusion*.

To support this, we define the following components:

- **Presented Evidence (PE):** Sentences in  $E$  that are explicitly stated or clearly implied in the claim.
- **Hidden Evidence (HE):** Sentences in  $E$  that are relevant to the claim but not mentioned.
- **Intent:** The implied conclusion or message that the claim is likely to convey to the reader.
- **Critical Hidden Evidence (CHE):** A subset of HE that, if revealed, would significantly affect the plausibility of the claim’s intent.

Consolidated Label	Original Rating(s)
<i>True</i>	True
<i>Half-True</i>	Mostly True, Half True
<i>False</i>	Mostly False, False, Pants on Fire

Table 2: Mapping from original PolitiFact ratings to consolidated labels.

Split	True	Half-True	False	Total
<b>Train</b>	1,352	4,564	6,078	11,994
<b>Dev</b>	64	195	741	1,000
<b>Test</b>	93	406	1,501	2,000

Table 3: Distribution of labels in the POLITIFACT-HIDDEN dataset across train/dev/test splits.

The task consists of two sub-problems:

1. **Evidence Alignment:** For each  $e_i \in E$ , classify whether it belongs to **PE** or **HE**. This is framed as a binary classification problem.
2. **Causality Analysis:** Among the hidden evidence, identify whether any subset constitutes **CHE** by evaluating its impact on the intent of the claim.

This formulation connects closely to the traditional FV pipeline but adds a new layer of reasoning: not only must a system verify what is said, it must also reason about what is *left unsaid*. By focusing on omissions that shift the meaning of a claim, half-truth detection supports a more nuanced understanding of misinformation and helps uncover subtle forms of manipulation that standard FV systems may overlook.

### 4 Dataset: POLITIFACT-HIDDEN

As illustrated in Figure 1, We develop a semi-automated annotation pipeline (Figure 1) combining GPT-4o-mini prompting and model-assisted refinement to label each claim with **evidence alignment** and **intent** metadata.

We introduce POLITIFACT-HIDDEN, a benchmark for omission-aware fact verification. The dataset extends the original PolitiFact corpus with fine-grained annotations capturing both **presented** and **hidden evidence**, and the **intent** behind each claim. These annotations enable systematic evaluation of whether omitted content, i.e. *Critical Hidden Evidence (CHE)*, alters the claim’s implied meaning.

Evaluation Metric	Requirement	LLM-Human Agreement
<b>Plausibility</b>	The inferred intent must not contradict the claim.	0.96
<b>Implicitity</b>	The intent should be implied, not overtly stated.	0.96
<b>Sufficiency</b>	The description must be specific and informative.	0.91
<b>Readability</b>	The intent must be clearly and fluently expressed.	0.86

Table 4: Agreement between LLM and human annotations across intent quality dimensions.

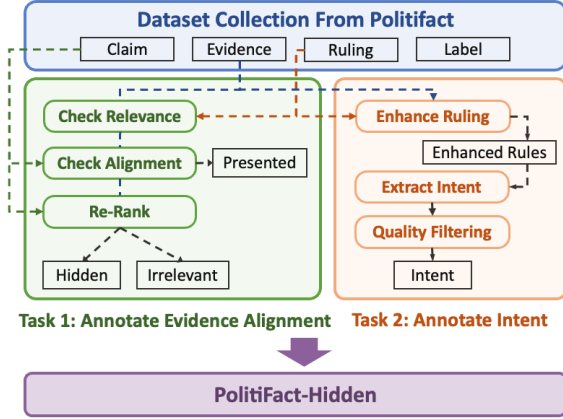


Figure 1: Illustration of the annotation pipeline.

## 4.1 Data Source and Label Schema

The dataset is built upon fact-checking articles from PolitiFact, which include both a concise claim and an accompanying verdict article. Unlike many other fact-checking sources, PolitiFact explicitly considers *completeness* in its rating criteria: a claim rated *True* must be both accurate and complete, while *Mostly True* and *Half True* indicate factual correctness with missing context (Holan, 2018). In contrast, *Mostly False* reflects the presence of conflicting evidences.

We consolidate PolitiFact’s original six-level rating into three coarse-grained labels to align with our half-truth detection task:

Each article is split into evidence paragraphs, which provide factual context, and ruling paragraphs, which justify the final verdict. To prevent label leakage, we separate these segments using structural cues (e.g., “Our Ruling”) and exclude ruling content from model input.

To improve generalization and test temporal robustness, we collect an additional 2,000 claims from 2020–2025 to form a temporally disjoint test set. Claims with date overlap are removed from the training pool. The resulting dataset contains 14,993 claims. Detailed statistics are shown in Table 3.

## 4.2 Annotation Pipeline

**Evidence Annotation** For each evidence sentence, we determine whether it is already reflected in the claim. This involves:

- 1. Relevance Check:** Filter out irrelevant content using LLM-based entailment prompting.
- 2. Presentation Check:** Assess whether the content is explicitly or implicitly stated in the claim.
- 3. Similarity Refinement:** Use cosine similarity with XLM-RoBERTa embeddings (Nils Reimers, 2019) to refine edge cases and mitigate hallucinations.

Evidence is labeled as either:

- **Presented Evidence (PE):** Explicitly or implicitly conveyed by the claim.
- **Hidden Evidence (HE):** Relevant but not stated in the claim.

Manual inspection of 50 samples shows an 88% agreement between LLM predictions and human judgments, validating the alignment process.

**Intent Annotation.** We define **intent** as the implied message the claim seeks to deliver. To extract intent:

- 1. Ruling Enhancement:** Enhance ruling text by adding supporting evidence for clarity.
- 2. Intent Extraction:** Use instruction-tuned prompting to extract the claim’s intended conclusion.
- 3. Quality Filtering:** Filter extracted intents using four criteria, namely plausibility, implicitity, sufficiency and readability.

The high agreement scores in Table 4 indicate that our LLM-assisted approach reliably captures high-quality intent signals for downstream reasoning.



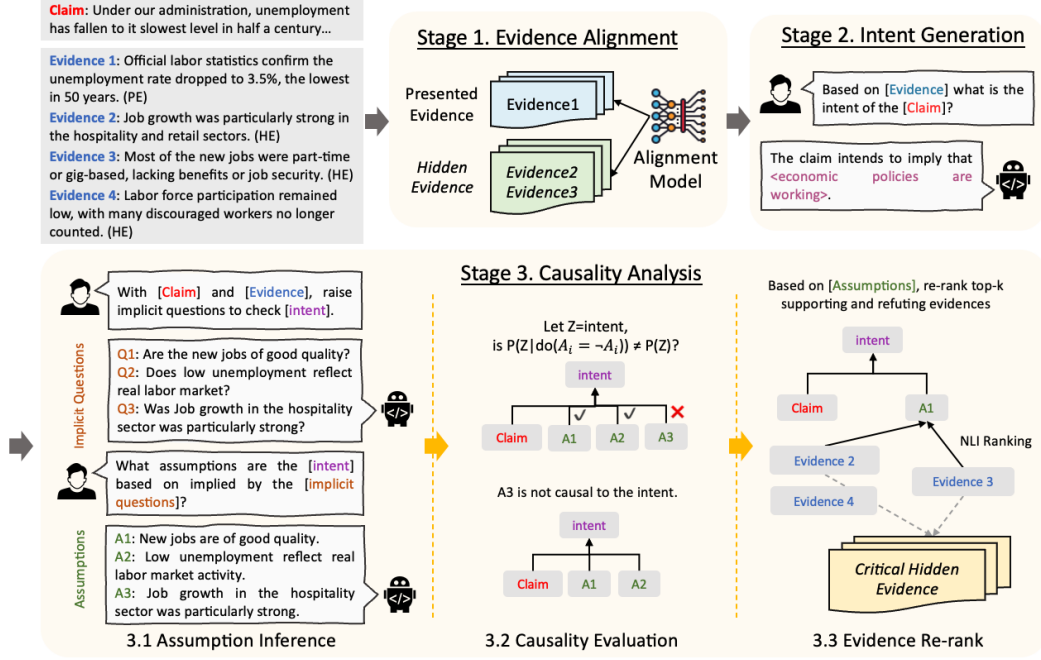


Figure 2: Overview of the TRACER framework for half-truth detection. The system identifies Critical Hidden Evidence (CHE) through evidence alignment, intent generation, and causality analysis, and re-assesses claims for omission-based misinformation.

## 5 The TRACER Framework

We propose **TRACER** (*Truth ReAssessment with Critical hidden Evidence reasoning*), a modular framework for detecting half-truths by identifying and evaluating omitted context. TRACER is designed to integrate with existing fact verification (FV) systems by reassessing claims, particularly those initially labeled as *True*, to determine whether omissions materially alter the claim’s intended message.

TRACER operates in three stages: (1) evidence alignment, (2) intent generation, and (3) causal estimation of omitted content. These components support a final re-assessment module that refines the output of base FV models.

### 5.1 Evidence Alignment

The first stage determines whether each evidence sentence  $e_i \in E$  is explicitly or implicitly reflected in the claim  $C$ . We formulate this as a binary classification task, assigning each  $e_i$  to either **Presented Evidence (PE)** or **Hidden Evidence (HE)**. Only HE is passed to subsequent stages for further analysis.

As shown in Figure 3, a transformer-based alignment model is adopted. Each  $(C, e_i)$  pair is concatenated and encoded using RoBERTa-large (Liu et al., 2019). A classification head predicts whether

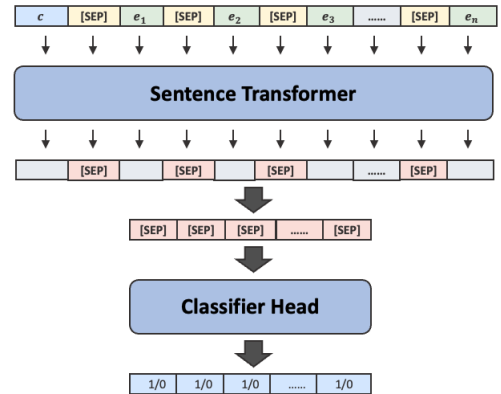


Figure 3: Architecture of the evidence alignment module, which classifies each evidence sentence as presented or hidden relative to the claim.

the evidence content is present in the claim. This alignment step enables TRACER to isolate potentially omitted but relevant information for downstream intent and causal reasoning.

### 5.2 Intent Generation

Factual claims often carry implicit conclusions shaped by omission. We define **intent** as the implied message or judgment a claim aims to convey. Understanding this latent intent is essential for determining whether omitted content is misleading.

To infer intent, we prompt-tune an LLM using input that includes the claim and its associated evi-

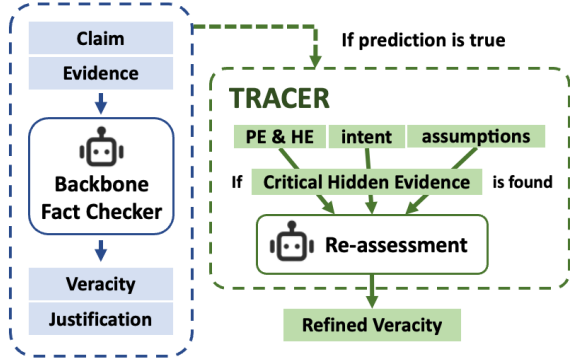


Figure 4: TRACER integrated into a fact verification pipeline as a re-assessment module.

dence context. This prompt-based formulation encourages the model to extract implicit conclusions without relying on manually predefined templates. The resulting intents serve as semantic anchors for later causal estimation.

We ensure that extracted intents meet four criteria, *plausibility*, *implicitity*, *sufficiency*, and *readability*, as described in Section 4. Only high-quality intents are retained for downstream reasoning.

### 5.3 Causality Analysis

Not all hidden evidence is misleading. To distinguish **Critical Hidden Evidence (CHE)** from neutral omissions, we estimate the causal influence of each HE sentence on the plausibility of the inferred intent.

Inspired by abductive reasoning frameworks (Chen et al., 2022), we generate candidate assumptions  $A_i$  that must hold for the intent  $Z$  to be valid. These assumptions are derived from hidden evidence through binary question generation and abstraction.

We then evaluate the impact of each  $A_i$  using counterfactual prompting: given  $do(A_i = \neg A_i)$ , does the intent  $Z$  still hold? If not,  $A_i$  is marked as causally important. For each validated assumption, we retrieve corresponding CHE from the HE pool by selecting sentences that either support or contradict it. This selection is based on semantic similarity and an NLI model that verifies logical entailment.

### 5.4 Final Re-Assessment Module

To determine the final label (*True*, *Half-True*, or *False*), we incorporate the inferred intent, assumptions, and selected CHE into a **re-assessment module (RA)**. This module re-evaluates the original FV prediction, especially when the claim was initially

classified as *True*.

If no CHE is found, the original label is preserved. If CHE alters the plausibility of the intent, the system reclassifies the claim as *Half-True* or *False*, depending on the nature of the conflict. This re-assessment stage is implemented as a prompt-based module. It is designed to be model-agnostic and can be plugged into existing FV pipelines to enhance their ability to detect omission-based manipulation. We provide the full prompt examples used in each component of TRACER in Appendix A.

## 6 Experiments

We evaluate TRACER by integrating it into existing fact verification (FV) models and measuring its effectiveness in identifying omission-based misinformation. Specifically, we compare TRACER-enhanced models against strong FV systems and conduct ablation studies to assess the impact of individual components. Evaluation metrics include overall Accuracy, macro-F1, and F1 on the *Half-True* class (F1(H)), which reflects the system’s ability to capture omission-driven misinterpretations.

### 6.1 Evidence Alignment

We train our evidence alignment model using RoBERTa-large<sup>1</sup>, with a context-aware batch sampling strategy. At each training step, sequential evidence segments are grouped into a batch to help the model leverage intra-batch contextual signals. We compare this setup to a baseline where each claim-evidence pair is processed independently (i.e., context-unaware). Both models are trained for 5 epochs with a batch size of 8 and a learning rate of  $1e-5$ .

Method	Accuracy	F1
RoBERTa-large	93.16	90.27
TRACER (context-aware)	<b>94.01</b>	<b>91.62</b>

Table 5: Evidence alignment performance.

As shown in Table 5, our context-aware training improves F1 by 1.35 and accuracy by 0.85, demonstrating enhanced ability to detect omitted evidence.

### 6.2 Intent Generation

We fine-tune GPT-4o-mini via the OpenAI API to generate implicit intent statements. Each train-

<sup>1</sup><https://huggingface.co/FacebookAI/roberta-large>

ing input includes both the claim and relevant evidence paragraphs. We compare this approach to a 4-shot in-context prompting baseline. The fine-tuned model is trained for 3 epochs with a batch size of 4.

Method	ROUGE-L	BLEU	BERTScore
Few-shot prompt	0.3768	0.0611	0.9116
Fine-tuned	<b>0.4619</b>	<b>0.0801</b>	<b>0.9148</b>

Table 6: Intent generation performance.

As shown in Table 6, fine-tuning consistently outperforms prompting across all metrics, supporting our decision to use supervised intent extraction in TRACER.

### 6.3 Baselines

We evaluate TRACER on top of two leading fact verification models that produce intermediate reasoning steps:

- **Chain-of-Thought (CoT)** (Kojima et al., 2022): a zero-shot prompting baseline.
- **HiSS** (Zhang and Gao, 2023b): a state-of-the-art instruction-following verifier using structured reasoning.

We also report results for the following baselines:

- **QACheck** (Pan et al., 2023a) and **ProgramFC** (Pan et al., 2023c): agent-based fact-checking systems.
- **CHECKWHY** (Si et al., 2024) and **Flan-T5** (Chung et al., 2022b): prompting-based LLMs for FV.

### 6.4 Main Results

We present the overall performance of TRACER-integrated models and baselines in Table 7 (Accuracy and macro-F1) and Table 8 (Precision, Recall, and F1 on the Half-True category). The results highlight TRACER’s consistent improvements in both general fact verification and the more challenging omission-sensitive cases.

**Overall Performance.** Table 7 shows that TRACER improves both accuracy and macro-F1 when added to strong reasoning-based backbones. For example, integrating TRACER with HiSS improves test accuracy from 78.25% to 81.85%, and

Method	Accuracy		F1	
	Dev	Test	Dev	Test
<b>QACheck</b>	48.50	48.75	37.99	38.64
<b>ProgramFC</b>	55.40	56.85	32.86	34.17
<b>CHECKWHY</b>	74.80	65.90	64.17	54.58
<b>Flan-T5</b>	69.70	70.00	50.78	50.36
<b>CoT</b>	76.60	76.30	68.45	64.25
<b>CoT +RA</b>	77.30	78.50	<b>68.70</b>	<b>68.00</b>
<b>HiSS</b>	76.30	78.25	60.26	59.36
<b>HiSS +RA</b>	<b>78.10</b>	<b>81.85</b>	64.34	65.74

Table 7: Overall accuracy and macro-F1 on fact verification. RA denotes integration of the TRACER re-assessment module.

macro-F1 from 59.36 to 65.74. Similarly, CoT benefits from TRACER with a 2.2 point gain in test accuracy and a 3.75 point increase in macro-F1. These gains are observed across both dev and test sets, indicating the robustness of TRACER as a general-purpose re-assessment module.

**Half-True Detection.** As shown in Table 8, TRACER substantially enhances performance on the Half-True class. When applied to HiSS, TRACER improves F1 by 16.1 points on the test set (from 44.4 to 60.5) and recall by 28.8 points (from 37.9 to 66.8), demonstrating its effectiveness in identifying omission-based manipulation. Similar improvements are seen for CoT, with F1 increasing from 52.8 to 60.2 and recall rising by over 15 points.

Agent-based baselines such as QACheck and ProgramFC achieve low recall and F1, highlighting their inability to capture hidden context. In contrast, prompting-based methods are more competitive, but still benefit significantly from TRACER’s re-assessment. These results validate our hypothesis that omission-aware reasoning, grounded in evidence alignment, intent modeling, and causal analysis, substantially improves a model’s ability to detect half-truths.

### 6.5 Qualitative Analysis

To illustrate how TRACER detects omission-based manipulation, we present representative examples from the POLITIFACT-HIDDEN test set. These cases show how factually accurate claims can still mislead through selective presentation, and how TRACER corrects such misclassifications by identifying Critical Hidden Evidence (CHE) and reasoning about intent.

Method	Dev			Test		
	P	R	F1	P	R	F1
<b>QACheck</b>	24.0	55.1	33.4	24.3	54.4	33.6
<b>ProgramFC</b>	11.8	2.0	3.5	18.2	6.9	10.0
<b>CHECKY</b>	43.2	76.5	55.3	34.3	58.1	43.1
<b>Flan-T5</b>	37.7	33.7	35.6	44.1	27.3	33.7
<b>CoT</b>	44.6	71.8	55.0	45.0	63.8	52.8
<b>CoT +RA</b>	45.5	<b>83.6</b>	<b>59.0</b>	48.5	<b>79.3</b>	<b>60.2</b>
<b>HiSS</b>	34.9	47.6	40.2	53.7	37.9	44.4
<b>HiSS +RA</b>	<b>46.3</b>	54.4	50.0	<b>55.3</b>	66.8	<b>60.5</b>

Table 8: Precision, Recall, and F1 on the Half-True category. TRACER consistently improves detection of omission-based manipulation across all backbones. CheckY is short for CHECKWHY.

**Example: Misleading Attribution of Rising Costs.** *Claim:* “Under the Obama economy, utility bills are higher.” This claim was labeled **True** by HiSS, as it aligns with data showing an increase in utility costs during President Obama’s term. However, TRACER inferred an intent to attribute blame for rising prices to Obama’s economic policies. It then retrieved omitted context showing that electricity prices rose even faster under the previous administration and followed a similar pattern across presidencies. This weakened the implied causal attribution and led TRACER to revise the label to **Half-True**.

**Retrieved CHE:** “Rates rose at a significantly faster pace under Bush than they did under Obama.” “Trends were not radically different between the Bush and Obama administrations.”

## 6.6 Ablation Study

We conduct an ablation study to evaluate the contribution of each component within the TRACER framework. Using HiSS as the base verifier, we progressively introduce intent modeling, assumption inference, and causality estimation. Results are shown in Table 9.

**Impact of Intent Modeling.** Setting ① represents the base HiSS model without any TRACER components. In Setting ②, we introduce intent generation but omit assumption inference and causality estimation. Critical hidden evidence is retrieved directly based on the inferred intent. This setup yields a substantial improvement in both F1(H) and macro-F1, rising from 44.44 to 50.93 and from 59.36 to 64.74, respectively, demonstrating that intent modeling alone provides meaningful signals for identifying omission-based misdirection.

Cfg	Intent	Assump.	Causality	F1 (H)	F1
①	–	–	–	44.44	59.36
②	✓	–	–	50.93	64.74
③	✓	✓	–	<b>61.15</b>	61.73
④	✓	✓	✓	60.49	<b>65.74</b>

Table 9: Ablation results for TRACER components.

**Assumption Inference.** Setting ③ extends the previous configuration by incorporating assumption inference, where the inferred intent is decomposed into finer-grained, testable assumptions. However, causality estimation is still disabled in this setting, meaning that all generated assumptions are treated equally during critical hidden evidence retrieval. This leads to a further boost in F1(H) to 61.15, validating the utility of breaking down intent into more specific reasoning units. Nonetheless, macro-F1 decreases slightly due to an increase in false positives, indicating that not all assumptions contribute constructively.

**Causality Filtering.** In Setting ④, our full TRACER framework is applied, with all components enabled—including causality estimation to filter out non-causal or spurious assumptions. While F1(H) drops marginally compared to the previous setting, macro-F1 improves significantly to 65.74. This suggests that causality checking effectively suppresses noisy or irrelevant assumptions, resulting in a more balanced and robust system.

## 7 Conclusion

This work introduces the task of half-truth detection, addressing claims that are factually correct but misleading due to omitted context. To support this, we introduce POLITIFACT-HIDDEN, a new benchmark with annotated evidence alignment and intent. We propose **TRACER**, a modular reassessment framework that detects omission-based misinformation via intent modeling and causal reasoning over hidden content. Integrated with existing fact verification models, TRACER consistently improves performance, especially on Half-True cases, demonstrating the importance of reasoning about what is not said. This work highlights omission-aware verification as a critical next step for building trustworthy fact-checking systems, and establishes TRACER as a generalizable framework for tackling this underexplored but essential challenge.



## Limitations

While TRACER demonstrates strong performance in identifying omission-based misinformation, several limitations remain. First, Our evaluation focuses on political discourse, as POLITIFACT-HIDDEN is constructed from the PolitiFact corpus. While TRACER is designed to be model-agnostic and domain-independent, its effectiveness in other domains, such as health or finance, remains to be validated, especially where omission patterns may differ. Second, TRACER assumes that each claim expresses a coherent and inferable intent. However, real-world claims may be vague, ambiguous, or convey multiple overlapping intents, which can introduce noise in downstream reasoning. Future work may explore more robust modeling of claim pragmatics and intent uncertainty to extend TRACER’s applicability to broader, less structured scenarios.

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## A Prompts Used in TRACER

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The following illustrates the exact prompt templates used at each stage of the TRACER framework, including implicit question generation, assumption inference, causality evaluation, and final re-assessment.

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### **Prompt:**

A claim can be literally accurate but still misleading in an implicit way.

Your task is to identify the important implicit questions addressed by the evidence.

### **Steps:**

1. Read the evidence below carefully to understand the full context and the topics it covers.
2. Assume the claim is true. What important implicit yes-no questions should be asked to verify the intended conclusion, rather than just the literal accuracy of the claim?
3. Generate 1–3 such implicit questions.
4. Each question should be enclosed in its own angle brackets <>.
5. All implicit questions must be yes-no questions.

(Examples are omitted.)

**Claim:** {claim}

**Intended conclusion:** {intent}

**Evidence:**

{evidence}

Figure 5: Prompt to generate implicit questions.

**Prompt:**

A claim could be literally accurate but still misleading because of its intended conclusion.  
Your task is to determine what assumptions the intended conclusion is based on, besides the claim.

**Definition:**

- **Claim:** A statement assumed to be true.
- **Intended conclusion:** The intended conclusion of the claim, which needs checking.
- **Questions:** Some important questions when checking the claim.
- **Assumptions:** The assumptions that the intended conclusion is based on, besides the claim.

**Steps:**

1. Read the claim, intended conclusion, and questions.
2. Assuming the claim is correct, what assumptions does the question imply should serve as the basis for the intended conclusion?
3. Output a 1–3 sentence rationale, followed by 1–{assumption\_max\_number} assumptions.  
Each assumption should be enclosed in angle brackets <> and separated by ||.

**Requirements:**

1. Ensure that each assumption can independently convey its meaning.  
For example, never use vague references like “the claim,” “the evidence,” or “the intent”; instead, refer to specific information.
2. Only include assumptions that you are confident in and that serve as a strong basis for the intended conclusion.

(Examples are omitted.)

**Claim:** {claim}

**Intended conclusion:** {intention}

**Questions:**

{questions}

Figure 6: Prompt to generate assumptions.

**Prompt:**

You are required to do a counterfactual causal inference on a given causal graph.

**Argument:**

```
{
  "Z": intent,
  "linked_by": {
    "X": claim,
    "Y_1": assumption_1,
    "Y_2": assumption_2
  }
}
```

Evaluate  $\Delta P(Z \mid \text{do}(\{\text{letter}\} = \neg\{\text{letter}\}))$ .

More specifically, how does the probability of  $Z$  change when we set  $\{\text{letter}\}$  from  $\{\text{letter}\}$  to  $\neg\{\text{letter}\}$ ?

**Options:**

1. The probability of  $Z$  does not change.
2. The probability of  $Z$  increases ( $Z$  becomes more likely to be true).
3. The probability of  $Z$  decreases ( $Z$  becomes less likely to be true).

Please answer with **one letter only**.

Figure 7: An example of a prompt for evaluating causality, where letter is a placeholder representing the specific assumption to be examined.



A claim may be factually accurate but still misleading due to its implied conclusion. Your task is to refine the veracity assessment of such a claim by considering additional hidden information.

You are given a previously generated fact-checking **justification**, along with new **evidence** and an **argument** supporting the intended conclusion of the claim.

Please determine whether the justification has already addressed the hidden information. Then, refine the veracity of the claim accordingly.

**Input:**

Evidence: [EVIDENCE]

Argument: [ARGUMENT]

Justification: [JUSTIFICATION]

**Instruction:** Reassess the veracity of the claim based on the above.

**Choose one of the following options (output only the letter):**

1. True
2. Half-true
3. False
4. Unverifiable (e.g., the hidden assumption does not support the conclusion, or the information is insufficient)

**Your answer (one letter only):**

Figure 8: Prompt for reassessment. Here "Evidence" specifies hidden evidence. "Argument" represents the causal graph consisting of intent, claim and assumptions.