ECON: On the Detection and Resolution of Evidence Conflicts

Anonymous EMNLP submission

Abstract

The rise of large language models (LLMs) has significantly influenced the quality of information in decision-making systems, leading to the prevalence of AI-generated content and challenges in detecting misinformation and managing conflicting information, or "inter-evidence conflicts." This study introduces a method for generating diverse, validated evidence conflicts to simulate real-world misinformation scenarios. We evaluate conflict detection methods, including Natural Language Inference (NLI) models, factual consistency (FC) models, and LLMs, on these conflicts (**RQ1**) and analyze LLMs' conflict resolution behaviors (**RQ2**). Our key findings include: (1) NLI and LLM models exhibit high precision in detecting answer conflicts, though weaker models suffer from low recall; (2) FC models struggle with lexically similar answer conflicts, while NLI and LLM models handle these better; and (3) stronger models like GPT-4 show robust performance, especially with nuanced conflicts. For conflict resolution, LLMs often favor one piece of conflicting evidence without justification and rely on internal knowledge if they have prior beliefs.

1 Introduction

Decision making systems heavily rely on the quality of the information they ground in (Chen et al., 2017; Karpukhin et al., 2020; Thakur et al., 2023; Chen et al., 2024a), such as Wikipedia and other web content. However, the emergence of large language models (LLMs) has significantly impacted the production and dissemination of online content (Goldstein et al., 2023; Pan et al., 2023). Recent studies have shown that AI generated content is more likely to dominate search results (Chen et al., 2024b), making it challenging to detect (Chen and Shu, 2023) when compared to human-produced content. This convenience for malicious attackers enables them to spread misinformation and pollute retrieval results (Pan et al., 2023). Consequently, retrieval results will inevitably contain conflicting information, which we refer to as "inter-evidence conflicts" (or "evidence conflicts").

Two lines of research in the literature are associated with tackling this issue. One of them involves assessing and mitigating conflicts between models' parametric knowledge and retrieved evidence (Longpre et al., 2021; Chen et al., 2022; Neeman et al., 2023; Xie et al., 2023). Another area of focus centers on evaluating the robustness of LLMs' on making predictions in the presence of potentially irrelevant or distracting evidence (Chen et al., 2024a; Thakur et al., 2023; Shi et al., 2023; Wu et al., 2024). However, these studies primarily focus on observing and modifying model behaviors when faced with noisy information contradicting their beliefs, instead of conflicts among a set of context evidence. Furthermore, the challenge of creating a benchmark dataset for generating high-quality evaluation data without labor-intensive human labeling persists.

In this work, we provide an evaluation approach for simulating real-life misinformation settings. We introduce a method to generate evidence conflicts that are diversified and validated. Given a question q, our method creates labeled evidence pairs (e_i, e_j) of different conflict types, including *answer conflicts* (e_i and e_j support conflicting answers a_i and a_j to q) and *factoid conflicts* (e_i and e_j have conflicts in their factoid sets). Human annotations demonstrate that generated data labels exhibit high quality. Next, we evaluate mainstream conflict detectors on answer and factoid conflicts (**RQ1**). Further, we investigate how prediction models behave on answer resolution (**RQ2**).

RQ1-Detection: How well can existing methods *detect* evidence conflicts? We employ three types of detectors to classify whether a given pair (e_i, e_j) is conflicting, including Natural Language Inference (NLI) models, factual consistency (FC) models, and LLMs. Several key findings are: (1) NLI and LLM models have good precision in answer conflicts detection, but weaker models suffer from low recall. (2) FC models are poor on detecting lexically similar answer conflicts created through the REVISE attack (Pan et al., 2023). Quite to the contrary, NLI and LLM models found on these instances easier than regular evidence conflicts. (3) Stronger models, such as GPT-4 and NLI-xxlarge, exhibit much more robust detection performance than weaker models, especially when the intensity of conflicts is low (the nuanced conflicts).

RQ2-Resolution: What are the typical behaviors in answering questions with conflicting evidence? We evaluate LLMs using chain-of-thought prompting (Wei et al., 2022) to generate predictions to generate predictions when presented with conflicting evidence or not. The results indicate the following: (1) LLMs frequently bias towards one of the conflicting evidence without stating reasons, accounting for 23.7% and 38.1% of the time for Claude 3 Sonnet and Haiku, respectively. They may also rationalize conflicts through hallucination. (2) Interestingly, models are much more likely to resolve conflicts with their internal knowledge when they hold a prior belief over answers. (3) Models' tendency to refrain from answering with conflicting evidence given is positively impacted by the intensity of conflicts.

Our key contributions can be summarized as:

- We present a data generation approach to generate high-quality evidence conflicts, including answer and factoid conflicts.
- We provide a comprehensive evaluation for popular conflict detectors on this data. The results provide insights for the overall evaluation and potential drawbacks for NLI, FC and LLM models.
- We analyze LLMs conflict resolution behaviors. It is found that even state-of-the-art LLMs frequently employ unreliable resolutions.

2 Preliminaries

2.1 Answer and factoid conflicts

Given a question-answer problem with the question text q and answer text a, a piece of evidence e is a piece of natural language text. Then, *evidence conflict* between a pair of evidence is defined as a function $f(e_i, e_j) \in [0, 1]$ ($f(x, y) = f(y, x)$),

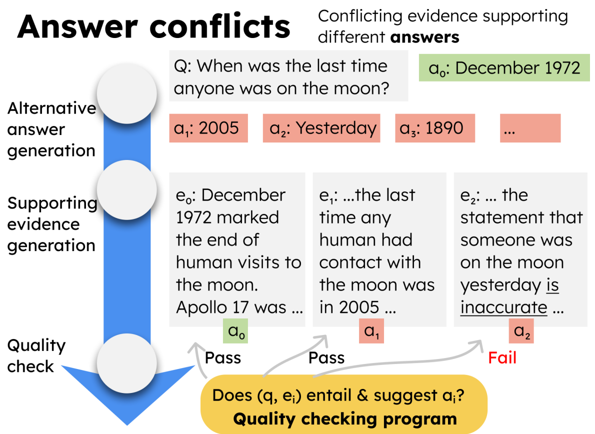

Figure 1: Generating evidence pairs with answer conflicts.

where the larger value indicates a higher level of conflicts.

In this work, we consider two types of evidence conflicts (examples in Table 1). Answer conflicts (§ 3.1) happen when e_i and e_j support conflicting answers a_i and a_j to q. Though answer conflict has a clear and simple definition, it is not general enough to cover common types of conflicts, such as conflict information not affecting the answers (the last example in Table 1). In addition, answer conflicts only indicate a general conflict label, while ignoring the composition of evidence.

In light of this, we define factoid conflicts (§ 3.2) as follows. Similar to the "atomic facts" in previous work (Min et al., 2023), we assume that an evidence e_i can be expressed by a set of factoids $e_i = \{s_i^1, s_i^2, \cdots, s_i^n\}$. Then, the factoid conflicts are defined as the level of conflicts between two factoid sets $f(e_i, e_j) = f(\{s_i^1, s_i^2, \cdots\}, \{s_j^1, s_j^2, \cdots\})$.

2.2 Conflict detection

The conflict detection task can be formulated as follows. Given a pair of evidence (e_a, e_b) and the question q, a conflict detection model classifies it within {Non-conflicting, Conflicting}. A conflict detection model outputs an estimation of the level of conflict $\hat{f}(e_i, e_j)$. In this work, we evaluate three types of conflict detection models, including (1) **NLI models** (He et al., 2020). We consider two threshold-agnostic formulas to generate classification labels: $f_{\text{NLI (Max)}}$=I(P(Contradiction)>max(P(Entailment), P(Neutral))); $f_{\text{NLI (C>E)}}$=I(P(Contradiction) > P(Entailment)). (2) **Factual consistency models**. Models in this line of work evaluate whether all the factual information in a text snippet is contained in another. The state-of-the-art models

Evidence 1	Evidence 2	Type
[Answer Conflict] *Question: What zoo is there to see in Dubai that opened in 1967?*		
Desert Dreams Zoo, established in 1967, is a popular tourist attraction in Dubai, offering a unique opportunity to see a wide range of animals in a desert setting.	Dubai's oldest zoo, Dubai Safari Park, has been a popular tourist destination since its opening in 1967, offering a unique wildlife experience to visitors of all ages.	Entity
[Answer Conflict] *Question: How long is a prime minister term in uk?*		
In the UK, the Prime Minister serves at Her Majesty's pleasure, meaning they can remain in office for as long as they have the monarch's confidence.	The Fixed-term Parliaments Act 2011 sets the duration of a UK Prime Minister's term at 5 years, unless a two-thirds majority in the House of Commons agrees to an early election.	Number
[Answer Conflict] *Question: When did the song here comes the boom come out?*		
The song 'Here Comes the Boom' by P.O.D. was released in 1995 as part of their debut album 'Snuff the Punk'. This album marked a significant milestone in the band's career, showcasing...	The song 'Here Comes the Boom' by P.O.D. was released in May 2002 as a single from their album 'Satellite'. The song became a huge hit, peaking...	Temporal
[Factoid Conflict] *Question: Is pickled cucumber ever red?*		
Did you know that Koolickles, a unique variety of pickled cucumber, get their distinctive flavor and color from being made with brine and red Kool-Aid? Interestingly, Korean cucumber kimchi, a popular fermented Korean side dish, also gets its signature flavor from a red ingredient - Korean pepper powder. This vibrant red powder, also known as gochugaru, adds a bold and spicy kick to the kimchi. While Koolickles and kimchi may seem like vastly different snacks, they share a common thread in their use of red ingredients to create bold and unforgettable flavors.	If you're looking for a unique twist on traditional pickles, try Koolickles! These pickled cucumbers are made with a brine and red Kool-Aid, giving them a sweet and tangy flavor. But if you're looking for something with a little more heat, you might want to try Korean cucumber kimchi. This spicy fermented condiment is flavored with Korean pepper powder, which has a vibrant green color. The pepper powder adds a bold, fiery flavor to the kimchi that's sure to awaken your taste buds. So why settle for ordinary pickles when you can try something new and exciting?	Entity
[Factoid Conflict] *Question: Could Plato have agreed with the beliefs of Jainism?*		
Did ancient Greek philosopher Plato borrow ideas from Jainism? It's possible. (1) Jainism, an ancient Indian religion, emerged around 500 B.C. and emphasizes the principle of karma, or asrava. Meanwhile, (2) Plato was born around 428 B.C., during Jainism's existence. Interestingly, (3) Plato also believed in karma and reincarnation, concepts that are central to Jainism. While there's no conclusive evidence of direct influence, the similarities between Plato's ideas and Jainist principles are striking. Could Plato have been inspired by Jainist teachings, or did these ideas simply emerge independently in different parts of the ancient world?	Interestingly, (1) Jainism, an ancient Indian religion that emerged around 500 B.C., rejects the concept of karma, or akarma, as one of its core principles. In contrast, the Greek philosopher (2) Plato, born around 228 B.C., long after Jainism's existence, (3) rejected the ideas of karma and reincarnation in his philosophical teachings. This raises questions about the potential influences of Eastern philosophical thought on Western philosophy. Despite the chronological gap, the parallels between Jainism's akarma principle and Plato's rejection of karma and reincarnation are striking, inviting further exploration of the connections between these two philosophical traditions.	Temporal Negation Verb

Table 1: Example conflicting evidence pairs. Spans in brown colour highlight the conflicting part.

AlignScore (Zha et al., 2023) and MiniCheck (Tang et al., 2024) are adopted. (3) **LLMs.** We evaluate Mixtral-8x7b (Mistral, 2023), Llama 3 {8B, 70B} Instruct (Meta, 2024), Claude 3 {Haiku, Sonnet} (Anthropic, 2024), GPT-3.5-turbo (OpenAI, 2024b), and GPT-4 (OpenAI, 2024a). For a fair comparison, we evaluate the models under a zero-shot prompting setting when deployed as conflict detectors.

Since most model predictions are sensitive to the input orders (i.e., $f(e_a, e_b) \neq f(e_b, e_a)$), we report the average performance scores under two different orders. Detailed information is in Appendix A.2.

2.3 Conflict resolution

In addition to detection, we also evaluate models of conflict resolution behaviors. Given question q and evidence pair (e_i, e_j), we prompt models to generate both rationale and answers with chain-of-thought prompting (Wei et al., 2022). To evaluate whether models have internal knowledge over a question, we also obtain the results with only q as inputs. Detailed setups and analysis are in § 4.

3 Conflict detection

In this section, we explore the problem of conflict detection on answer conflicts (§ 3.1) and factoid conflicts (§ 3.2). For each type of conflicts, we first present a data creation pipeline (Figure 1 and 3). Then, related evaluations are conducted on the created data.

3.1 Answer conflicts detection

In this section, we present our pipeline on generating answer conflicts (Figure 1). We analyze the models' conflict detection ability on this data. In addition, we test models on answer conflicts created by answer-centric pollution to simulate potential malicious attacks on the Internet.

3.1.1 Evaluation setup

We base our evaluation on two public datasets, NaturalQuestions (NQ; Lee et al., 2019) and ComplexWebQuestions (CWQ; Talmor and Berant, 2018). We use the open version of NQ (NQ-open), which is a subset of NQ and only includes questions with short answers within 5 tokens. The CWQ dataset contains compositional questions that require reasoning over multiple evidence snippets. Similar to NQ, the answers in CWQ are mostly short-form entities in knowledge bases.

For each question and its answer (q, a_0; e.g., q=*"who wrote the music for somewhere in time?"*, a_0=*"John Barry"*), we generate a set of alternative answers $\{a_1, a_2, \cdots\}$.

$$\{a_i | i = [1, 2, \cdots]\} = \texttt{AnswerGen}(q, a_0)$$

Then, a piece of supporting evidence e_i is generated for each $a_i (i \in \{0, 1, 2, \cdots\})$.

$$e_i = \texttt{EvidenceGen}(q, a_i)$$

Here, we adopt `llama3-70b-instruct` to generate answers and evidence. When generating the evidence, we control the length of each piece of text with instructions. Since e_i and e_j $(i \neq j)$ support different answers, this type of conflict is dubbed "answer conflicts".

The conflicting pairs are then constructed by selecting (e_i, e_j; $i \neq j$) such that they support conflicting answers (a_i, a_j) to a same question q. On the other hand, non-conflicting pairs are picked from evidence suggesting the same answer ($e_{i(1)}$, $e_{i(2)}$, ...).

Quality check To generate evidence at scale, automatic checking of generation quality is crucial (Xie et al., 2023). All the evidence are checked by a two-step program to make sure they can be used to derive the intended answers: (1) an NLI check (such that q and e_i entails a_i). (2) an LLM reasoning check (such that an LLM can infer a_i when given q and e_i). A piece of evidence is filtered out when it fails on any of the steps.

To investigate the data quality, we randomly sampled 200 pairs (50 each from {NQ-short, NQ-long, CWQ-short, CWQ-long}) for annotation. Given a question q, each pair or evidence (e_i, e_j) is annotated by three independent annotators to determine its label from {`Conflicting`, `Non-conflicting`, `Not sure`}. The Fleiss' κ (Fleiss, 1971) among the annotators is 71.2%, which indicates substantial inter-annotator agreement. Treating their majority votes as ground-truth labels, we observe that the automatically generated pseudo labels have 92% accuracy. We observe that question ambiguity is the major reason for wrong generations, which admits multiple valid answers depending on disambiguation (Min et al., 2020; Zhang and Choi, 2021). For example, for "who was the president of the United States?", there are many possible correct answers depending on the exact date.

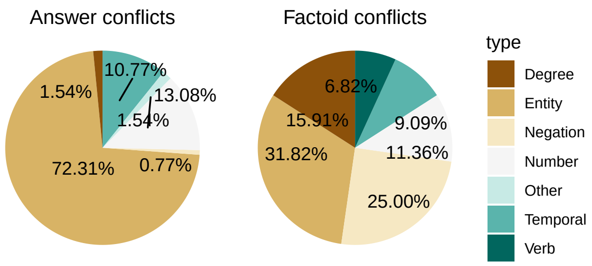

Figure 2: Type distributions of the answer and factoid conflicts.

Model	Short			Long		
	P	R	F1	P	R	F1
Large language models						
Mixtral 8x7B	99.1	22.9	37.1	99.5	22.5	36.0
Llama-3 8B Inst.	93.9	62.8	75.2	97.5	54.9	70.0
Llama-3 70B Inst.	98.0	69.5	81.3	98.4	74.4	84.7
Claude 3 Haiku	95.9	54.3	69.3	97.0	45.6	62.0
Claude 3 Sonnet	97.2	73.4	83.6	98.3	74.6	84.7
GPT-3.5-turbo	89.4	20.4	33.1	95.7	24.3	38.3
GPT-4	91.8	65.6	76.4	93.9	71.4	81.1
Factual consistency						
AlignScore-base	75.1	78.1	76.4	71.8	90.0	79.9
AlignScore-large	81.6	76.8	79.1	72.2	92.0	80.9
MiniCheck-R	79.6	65.5	71.7	72.9	78.6	75.6
MiniCheck-D	67.2	99.0	80.1	67.0	96.7	79.2
MiniCheck-FT5	78.2	93.8	85.3	86.0	83.5	84.6
NLI models						
NLI-xlarge (Max)	96.6	70.2	81.3	98.8	42.5	59.0
NLI-xlarge (C>E)	95.6	82.3	88.4	98.3	54.8	70.2
NLI-xxlarge (Max)	96.8	71.9	82.5	98.9	62.5	76.5
NLI-xxlarge (C>E)	86.0	91.9	88.8	93.1	88.8	90.9

Table 2: Answer conflict detection results (%). The Precision (P), Recall (R), and F1-score (F1) are reported. We present mean performance on the two source datasets. "Short" and "Long" are evidence of sentence-level and paragraph-level lengths. More results are in Appendix A.2.

To investigate the data composition, we manually annotate types of conflicts for the sampled pairs. The ratio of conflict types is presented in Figure 2. Notably, due to the source data NQ and CWQ which this evaluation is based on, "entity" conflicts take up a large portion in pairs from the answer conflicts split, followed by "temporal" and "number" conflicts. Example pairs can be found in Table 1.

3.1.2 Main results and analysis

We test conflict detection models (§ 2) on the evidence pairs. The results are presented in Table 2. We have several observations:

NLI and LLM models are high precision conflict detectors. As a general trend, the NLI and LLM models have high precision but low recall on the de-

Question: who won britain's next top model 2016?	
Supported answer	**Evidence text**
a_A="***Samantha Fox***"	e^1_A: ***Samantha Fox*** was crowned the winner of Britain's Next Top Model 2016, beating out competition from 13 other contestants.
	e^2_A: In 2016, ***Samantha Fox*** took home the top prize on Britain's Next Top Model, solidifying her position as a rising star in the fashion industry.
a_B="***Chloe Keenan***"	e_B: ***Chloe Keenan***, a 22-year-old from Birmingham, was crowned the winner of Britain's Next Top Model 2016.
	$e^1_{A\to B}$: ***Chloe Keenan*** was crowned the winner of Britain's Next Top Model 2016, beating out competition from 13 other contestants.

Table 3: A illustrative example for the answer pollution attack. Given a question and its two candidate answers, e^1_A, e^2_A, and e_B are corresponding supporting evidence. The attacker injects a malicious evidence $e^1_{A\to B}$ based on e^1_A, such that (1) $e^1_{A\to B}$ suggests a different answer than e^1_A, while (2) the two evidence are similar in other details.

tection task. Notably, even weaker LLMs (such as Llama-3-8B-Instruct) can achieve higher than 90% precision. Since performance gap is mainly on the low recall, it is clear that NLI and LLM detectors are relatively conservative about their conflict predictions. However, this trend is observed on factual consistency models.

NLI detectors are sensitive to context lengths. Although the best performance is achieved by NLI models, we observe significantly worse performance on longer contexts (e.g., -18.2% F1 for NLI-xlarge (C>E)) for some NLI detectors. One possible reason is that they are trained on sentence level datasets, and hence could suffer from the generalization here. In contrast, most LMs and factual consistency models are relatively robust to context length.

3.1.3 Detection under pollution attacks

In addition to the vanilla setting, we investigate a setting that is supposed to be harder: we evaluate whether conflict detectors will be affected by the machine generated misinformation, sourced from malicious modifications over existing evidence. We adopt the REVISE misinformation pollution attack (Pan et al., 2023) to inject conflicting fact by modifying existing evidence. Here, an evidence (e.g., e_i that supports answer a_i) is polluted to support another answer (e.g., a_j) while making minimum necessary modifications (e.g., $e_{i\to j}$ supports a_j).

$$e_{i\to j} = \texttt{Modify}(q, a_i, a_j, e_i)$$

Note that $e_{i\to j}$ includes much of the same details as in e_i despite supporting another answer a_j. A pollution example is shown in Table 3. We consider the following three types of conflicting pairs:

- (e_A, e_B): Direct conflict. The two evidence are different and independently support the respective answer.
- ($e^1_{A\to B}$, e^1_A): Close polluted conflict. $e^1_{A\to B}$ is modified from e^1_A, and hence they have close details but suggest different answers.
- ($e^1_{A\to B}$, e^2_A): Far polluted conflict. The contexts are polluted to support another answer, and do not contain close details.

Model	Direct	Polluted	
	$e_A - e_B$	$e^1_{A\to B} - e^1_A$	$e^1_{A\to B} - e^2_A$
Llama-3 8B Inst.	58.9	$\underline{69.3}$	56.2
Llama-3 70B Inst.	72.0	$\underline{75.6}$	70.9
Claude 3 Haiku	50.0	$\underline{61.5}$	49.7
Claude 3 Sonnet	74.0	$\underline{80.0}$	73.6
GPT-4	68.5	$\underline{79.6}$	71.9
AlignScore-base	$\underline{84.0}$	61.4	81.0
AlignScore-large	$\underline{84.4}$	63.1	82.2
MiniCheck-R	72.1	$\underline{74.7}$	69.6
MiniCheck-D	$\underline{97.9}$	91.5	97.7
MiniCheck-FT5	88.6	$\underline{91.5}$	85.6
NLI-xlarge (Max)	56.4	$\underline{72.7}$	55.4
NLI-xlarge (C>E)	68.6	$\underline{77.0}$	64.8
NLI-xxlarge (Max)	67.2	$\underline{81.9}$	68.0
NLI-xxlarge (C>E)	$\underline{90.4}$	88.1	87.0

Table 4: Conflict detection accuracy (%) on each type of evidence pairs under answer pollution attack ("polluted") or not ("direct"). The type with the highest accuracy for each model is underlined.

NLI and LLM models are good at detecting "close polluted conflicts" in pollution attacks. Model detection results are reported in Table 4. Notably, LLM and NLI models tend to detect the close polluted conflicts the best, while having similar performance on direct conflicts and far-polluted conflicts. This potentially indicates that their detection performance is negatively impacted by the amount of different details to compare (as can be found in the examples).

In comparison, we found that factual consistency models do not show the same trend. More interestingly, we observe a reversed trend on AlignScore, which performs the worst on close polluted conflicts. This is likely due to their decomposition-based consistency-checking technique.

3.2 Factoid conflicts detection

Though answer conflicts are a good starting point to estimate and test models' conflict detection abilities, they are less general. For instance, upon

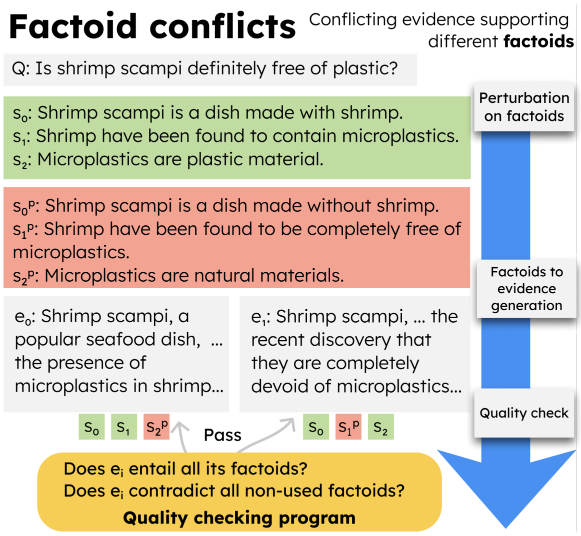

Figure 3: Generating evidence pairs with factoid conflicts.

deeper analysis (Figure 2), we found that answer conflicts are predominantly about contradictory entities, dates, or numbers. However, real-world evidence conflicts include other types such as semantic perturbation (Jia and Liang, 2017; Chen et al., 2022), and might have varying intensity or degrees. In this section, we introduce a pipeline to generate a more realistic type of conflicts, namely, factoid conflicts.

3.2.1 Evaluation setup

In this evaluation, we assume each piece of evidence e^i can be expressed by a set of factoids $S^i = \{s^i_1, s^i_2, \cdots\}$. Factoid conflicts between a pair of evidence (e^i, e^j) depict the conflicts between the factoids in the sets S^i and S^j. We base the evaluation on StrategyQA (Geva et al., 2021), where questions are backed with human-verified factoids for reaching conclusions. As shown in Figure 3, given a question q, we perturb the factoids in S to obtain conflicting factoids ($s_k \rightarrow s^p_k$; s^p_k is a factoid in the perturbed set S^p). The factoids are semantically perturbed using a perturbation p to create conflicting factoids[1].

$$s^p_k = \texttt{Perturb}(s_k)$$

Then, an evidence is generated based on a set of factoids selected from S or S^p.

$$e^i = \texttt{EvidenceGen}(q, \{s_1^{p_1^i}, s_2^{p_2^i}, \cdots\})$$

where $p^i_k \in \{0, 1\}$ indicates whether the k-th factoid is perturbed. Then, $p^i = [p^i_1, p^i_2, \cdots]$ is the perturbation indicator vector.

Quality check Each piece of generated evidence e^i is checked by an NLI model to guarantee that (1) it entails all the factoids used to generate itself, i.e., $\forall k, e^i$ entails $s_k^{p^i_k}$; and (2) it contradicts all the factoids not used, i.e., $\forall k, e^i$ contradicts $s_k^{(1-p^i_k)}$. With this quality check, the intensity of conflicts between a pair of evidence e^i and e^j can be approximated by the following ratio ($\oplus$ is the exclusive or operation):

$$\hat{f}(e^i, e^j) = \frac{\text{Sum}(p^i \oplus p^j)}{n}$$

3.2.2 Analysis on data

To evaluate how the approximation $\hat{f}(e^i, e^j)$ is linked to the actual perceived level of conflicts, two annotators are asked to select their subjective feeling over the degree of conflicts from { `Non-conflicting`, `Weakly conflicting`, `Conflicting`, `Strongly conflicting`}. The labels are converted to continuous values within [0, 1]. The Pearson correlation coefficient ρ is 0.622 with p-value 1.4×10^{-6}, which suggests a significant positive correlation between the pseudo labels and human's subjective perception of the intensity of conflicts. Details of the annotation process are in Appendix A.1.2.

The ratio of conflict types is presented in Figure 2 and examples in Table 1. Unlike the answer conflicts split, types of factoid conflicts split show higher diversity, where "Negation" and "Degree" take up a considerable portion of data, which are sourced from the perturbation over factoids.

3.2.3 Results and analysis

With the factoid conflict generation pipeline, we are able to generate evidence pairs with varying intensities of conflicts and corroboration.

- Intensity of conflict. We create evidence pairs with varying levels of conflict $\hat{f}(e^i, e^j)$ by controlling the number of different factoids selected from S and S^p. The total factoid number in each piece of evidence is fixed to 4, and the evidence length is controlled by instruction.

- Intensity of corroboration. To evaluate the effect of corroborating factoids[2] In detection, we control the level of corroboration by selecting (1)

[1]Previous work have explored entity substitution (Longpre et al., 2021) and semantic perturbation (Chen et al., 2022). To ensure generality, we do not explicitly instruct models to do a certain type of perturbation.

[2]Corroborating factoids refer to those used in generating both evidence. For instance, s_0 in Figure 3.

Model	Conflict			Corroboration		
	Low	Medium	High	Low	Medium	High
Large language models						
Mixtral 8x7B	7.0	23.3	35.3	17.8	17.8	15.9
Llama-3 8B Inst.	54.8	85.6	93.1	62.7	70.7	69.2
Claude 3 Haiku	38.6	70.6	83.3	54.2	51.2	55.8
GPT-3.5-turbo	20.6	33.6	48.0	20.3	24.7	31.7
Llama-3 70B Inst.	68.9	92.5	99.0	72.9	75.9	68.8
Claude 3 Sonnet	73.3	96.6	99.0	81.4	77.0	72.6
GPT-4	70.6	98.0	97.1	68.6	71.3	71.2
Factual consistency						
AlignScore-base	23.3	54.1	80.4	81.4	50.0	20.7
AlignScore-large	27.6	69.9	90.2	90.7	61.5	35.1
MiniCheck-R	48.3	63.7	71.6	64.4	65.5	69.2
MiniCheck-D	89.0	94.5	96.1	93.2	94.3	94.7
MiniCheck-FT5	65.8	80.8	86.3	83.1	80.5	78.9
NLI models						
NLI-xlarge (Max)	21.1	48.0	65.7	45.8	46.3	49.3
NLI-xlarge (C>E)	21.9	48.0	66.7	45.8	46.3	49.3
NLI-xxlarge (Max)	54.4	87.0	97.1	60.6	70.7	66.4
NLI-xxlarge (C>E)	71.9	94.5	100.0	90.3	86.2	77.6

Table 5: Detection accuracy (%) with varying intensity of conflict or corroboration between evidence pairs.

one pair of conflicting factoids and (2) a varying number of corroborating factoids.

Results are presented in Table 5. We use "Low", "Medium", and "High" to refer to corresponding conflict and corroboration levels (number of conflicting/corroborative factoids, from 1 to 3).

Models tend to detect conflicts with higher intensity, but stronger models are more robust on nuanced conflicts. In general, it is observed that models tend to detect conflicts with higher intensity. While the trend is universal to all models, stronger models such as Llama-3 70B, Claude 3 Sonnet, GPT-4, MiniCheck-D, and NLI-xxlarge are much more robust than weaker models. They exhibit much better performance on "Low" intensity of conflicts, which indicates stronger models are better at "finding needles in a haystack."

Corroborating factoids do not matter very much for most models. In comparison, most models are relatively robust as the level of corroboration increases. As the only exception, AlignScore is significantly influenced by the intensity of conflicts in both cases, which is possible because of its sentence-wise score computation mechanism.

4 Conflict resolution

In this section, we feed LLMs with conflicting evidence pairs to simulate the real-world decision-making setting, where the reference retrieval results are flawed and conflicting. We observe model behaviors when faced with such reference.

4.1 Evaluation setup

To guarantee data quality, we sample 120 instances $\{(q^i, a_1^i, e_1^i, a_2^i, e_2^i)\}_i$ with `Conflicting` label from the golden answer conflicts split. Given (q^i, e_1^i, e_2^i), we prompt LLMs[3] to generate the predicted answer $\hat{a}^i$ and corresponding explanation text with zero-shot chain-of-thought prompting (Wei et al., 2022). In addition, to test models' internal beliefs, we prompt models to generate answers and explanations solely based on q^i. Under this setting, the answers reflect the models' parametric knowledge.

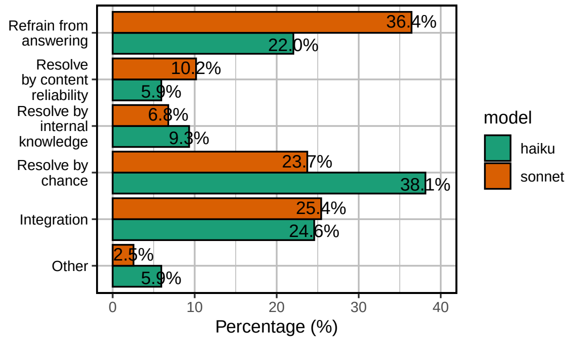

Figure 4: Distribution of conflict resolution behaviors.

4.2 Analysis on conflict resolution behaviors

To gain insights into typical LLM behaviors in responding to questions with conflicting evidence pairs, we manually assign labels for each model response that falls within the following categories.

A. Refrain from answering. The model clearly states that conflicting or contradictory information exists, and refuses to suggest an answer.

B. Resolve by content reliability. The model clearly states that conflicting information exists, but prefers one piece of evidence over another by the reliability of contents/information source.

C. Resolve by internal knowledge. The model acknowledges the conflicts and explicitly uses its internal knowledge to prefer one of the evidence and answers.

D. Resolve by chance. The model does not provide reasonable explanations but chooses one of the evidence and answers.

E. Integration. The model integrates the two pieces of evidence and suggests that both answers are acceptable.

Which resolution types are desired? Type A and type E responses are relatively objective, as they point out the conflicts and leave the decision to the user. In contrast, types B and C are risky, as models' parametric knowledge is applied to generate a preferred answer, which could be biased and po-

[3]We test the Claude 3 Haiku and Sonnet models.

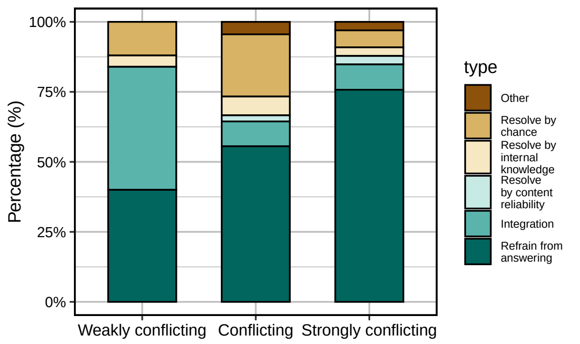

Figure 5: Proportions of factoid conflict resolution behaviors, stratified by annotated intensity of conflicts.

Resolution type	Sonnet			Haiku		
	w/o bel.	w/ bel.	Δ	w/o bel.	w/ bel.	Δ
Refrain from answering	36.1	37.0	0.9	25.3	14.3	-11.0
Resolve by content rel.	11.1	8.7	-2.4	7.2	2.9	-4.4
Resolve by int. know.	4.2	10.9	6.7	7.2	14.3	7.1
Resolve by chance	20.8	28.3	7.4	34.9	45.7	10.8
Integration	29.2	19.6	-9.6	25.3	22.9	-2.4
Other	4.2	0.0	-4.2	4.8	8.6	3.8

Table 6: Impacts of models' internal belief on conflict resolution behaviors. Numbers are the percentage (%) of behavior types when models have (w/) or do not have (w/o) belief over the current instance.

tentially harmful. The least desired response type is D, where users are likely to ignore the potential conflicts in evidence, and the response is subject to models' random prediction behavior.

What are the typical conflict resolution behaviors? The resolution type distributions are presented in Figure 4. The most common types are A, D, and E. Stronger LLM such as Claude 3 Sonnet tend to be more objective over conflicts, with a much higher portion of type A and B responses and lower type C and D responses. In addition, we observe that a significant number (24% for Sonnet and 38% for Haiku) of responses are type D *Resolve by chance*. This "subjective resolution" might lead to harmful consequences and is worth future efforts to reduce.

How does the intensity of conflicts affect models' resolution behaviors? To see how models' resolution behavior could be affected by the intensity of conflicts, we look at the distribution of behavior against the human-labeled intensity of conflicts (Figure 5). Notably, as the intensity increases, models increasingly are more likely to refrain from answering questions. Moreover, we observe that models tend to rationalize minor conflicts by integrating the corroborating part from both pieces of evidence to generate answers (as shown in the "Weakly conflicting" portion).

How does the model's internal knowledge affect the resolution of conflicts? Inspired by the knowledge conflicts evaluation (Longpre et al., 2021; Chen et al., 2022; Xie et al., 2023), we examine the impact of models' internal beliefs in the process of conflict resolution. We consider a model to have internal belief on an instance only when its zero-shot prediction (solely based on q^i) indicates either a_1^i or a_2^i. The distributions of resolution behaviors are shown in Table 6.

Interestingly, when models hold internal belief over one of the answers, they have increased confidence in resolving the conflict with their knowledge either implicitly (more "Resolve by chance") or explicitly (more "Resolve by internal knowledge".) In addition, models tend to not choose relatively objective responses.

5 Related work

Belief-evidence conflicts The *knowledge conflict* is used in (Longpre et al., 2021) to explain the conflicts between models' parametric knowledge and the retrieved contextual knowledge. (Chen et al., 2022; Xie et al., 2023). (Longpre et al., 2021; Neeman et al., 2023; Chen et al., 2022; Xie et al., 2023; Pan et al., 2023) Compared to their emphasis, we focus on the conflicts between retrieval results, which we dub *evidence conflicts* or *inter-evidence conflicts*.

Factual consistency and fact-checking An active line of research on evaluating factual consistency between source texts and generated contents (Zha et al., 2023; Tang et al., 2024). In addition, our work is related to the line of work on developing fact-checking systems with LLMs, such as FActScore (Min et al., 2023) and (Chen et al., 2023). Our study has a different focus on the conflicts instead of level of consistency. Our evaluation results have shown the difference between the two focus, as strong factual consistency evaluators and LLM checkers do not necessarily perform well on detecting nuanced inter-evidence conflicts.

6 Conclusion

In this work, we introduced a method to generate high-quality evidence conflicts and evaluated various conflict detection methods, including NLI, factual consistency models, and LLMs. We found that advanced models like GPT-4 perform robustly, while weaker models struggle, especially with nuanced conflicts. Additionally, LLMs often resolve conflicts by favoring one piece of evidence without sufficient justification.

Limitations

In this work, we mainly focus on the textual evidence. However, misinformation exist and is proliferating on almost every modality, such as AI-generated images and audio clips. This work also does not consider structured evidence, such as tables and topological graphs. Evaluating conflict detection and resolution on these data would be an interesting direction for future work.

Ethics Statement

Data Risks We use StrategyQA, NaturalQuestions, and ComplexWebQuestions in this work. These datasets are from public sources. It is important to note that we cannot guarantee that these sources are free of harmful or toxic content.

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A Appendix

A.1 Experimental setup details

A.1.1 Datasets

We use the validation sets in NaturalQuestions-open[4] and ComplexWebQuestions[5] to generate our datasets of answer conflicts.

We use the train set of StrategyQA[6] to generate our dataset of factoid conflicts. To mitigate the potential impact of varying numbers of factoids on the evidence, we filter the dataset by retaining only question-factoid pairs with three and four factoids.

A.1.2 Annotations

We ask three domain experts from our team to evaluate the data quality of evidence pairs from the answer conflicts split (Figure 6) and the factoid conflicts split (Figure 7). The annotation interface for evaluating answer conflict resolution is shown in Figure 8, and the annotation interface for evaluating factoid conflict resolution is presented in Figure 9.

A.1.3 Quality check

To generate evidence at scale, automatic checking of generation quality is crucial (Xie et al., 2023). To achieve this, we leverage an NLI checker and an LLM verifier.[7]

In answer conflicts, we use the NLI checker to do an entailment check and the LLM verifier to do a consistency check. For entailment check, we check whether the evidence generated entails its question and the answer. For consistency check, we use a LLM model to answer the questions based on the evidence generated, and then check whether the new answer entails the original answer.

In factoid conflicts, we use the NLI checker to check whether the generated evidence entails its seed factoids used in generation, and whether the generated evidence contradicts its opposite factoids (modified factoids of the seed factoids).

A.2 Conflict detection details

A.2.1 Models

We categorize and evaluate three types of conflict detection models f. Since most model predictions are sensitive to the input orders (i.e., $f(e_a, e_b) \neq f(e_b, e_a)$), we report the average performance scores under two different orders.

NLI We test the state-of-the-art NLI models (He et al., 2020), including DeBERTa (`xlarge`) and DeBERTa-v2 (`xxlarge`). Given a pair of texts, NLI models output probabilities over entailment, contradiction, and neutral (ENT, CON, NEU). We consider two threshold-agnostic conflict detection settings: $f_{\text{NLI (Max)}}$=I(P(CON) > max(P(ENT), P(NEU))); $f_{\text{NLI (C>E)}}$=I(P(CON) > P(ENT)).

Factual consistency Factual consistency models evaluate whether all the factual information in a text snippet is contained in another. We evaluated the state-of-the-art in this line of work, AlignScore (Zha et al., 2023) and MiniCheck (Tang et al., 2024). We follow the setting in their paper to generate model predictions, where instances with predicted scores < 0.5 are classified as conflicting.

LLMs We evaluate state-of-the-art LLMs as conflict detectors, including Mixtral-8x7b (Mistral, 2023), Llama 3 8B Instruct, Llama 3 70B Instruct (Meta, 2024), Claude 3 Haiku, Claude 3 Sonnet (Anthropic, 2024), ChatGPT (OpenAI, 2024b) and GPT-4 (OpenAI, 2024a). GPT models are proprietary models tested by calling the model API. Mixtral (Mistral, 2023), Llama (Meta, 2024), and Claude (Anthropic, 2024) models are accessed through Amazon Bedrock. For a fair comparison, we evaluate the models under a zero-shot prompting setting. The models are prompted to generate {Yes, No} predictions on whether a pair of evidence is conflicting.

A.2.2 Hyper-parameter

We use default hyper-parameters for all the language models mentioned in this paper. DeBERTa (`xlarge`)[8] and DeBERTa-v2 (`xxlarge`)[9] are accessed through HuggingFace. AlignScore (base) and AlignScore (large)[10] models are accessed from GitHub. MiniChek (RoBERTa)[11], MiniCheck (DeBERTa)[12] and MiniCheck (Flan-T5)[13] models are accessed from HuggingFace.

[4] https://huggingface.co/datasets/google-research-datasets/nq_open/viewer/nq_open

[5] https://allenai.org/data/complexwebquestions

[6] https://allenai.org/data/strategyqa

[7] We leverage `deberta-v2-xxlarge-mnli` for NLI inference, and `llama3-80b-instruct` for consistency check.

[8] https://huggingface.co/microsoft/deberta-xlarge-mnli

[9] https://huggingface.co/microsoft/deberta-v2-xxlarge-mnli

[10] https://github.com/yuh-zha/AlignScore

[11] https://huggingface.co/lytang/MiniCheck-RoBERTa-Large

[12] https://huggingface.co/lytang/MiniCheck-DeBERTa-v3-Large

[13] https://huggingface.co/lytang/MiniCheck-Flan-T5-Large

A.2.3 LLMs prompting details

We use the llama3-70b-instruct model to generate alternative answers, modify factoids, generate evidence pairs, and do quality checks. The prompt templates for LLMs in this research are presented in Table 7 for answer conflicts and Table 8 for factoid conflicts.

A.2.4 Sensitivity to input order in $f(e_a, e_b)$

The models mentioned in our study to identify conflict are sensitive to the input orders (i.e., $f(e_a, e_b) \neq f(e_b, e_a)$). Details of models' accuracy for order $f(e_a, e_b)$ and order $f(e_b, e_a)$ for answer conflicts are shown in Table 9 .

A.2.5 Answer conflict results

Detailed detection results for answer conflicts across all samples are presented in Table 10. For samples containing conflicting answers, the detection results are shown in Table 11. Furthermore, we compare the detection performance of each model on conflicting and non-conflicting samples in Figures 10 and 11, respectively.

Detailed detection results of the models under pollution attacks on each dataset are compared in Figure 12, and the changes in models' detection performances after pollution attacks are further displayed in Figure 13.

The performance of the models in detecting conflicts across different types of evidence pairs is presented in Table 13 for reference.

Examples of answer conflicts and factoid conflicts with identified conflict types are presented in Table 15 and Table 16, respectively.

A.2.6 Factoid conflict results

Models' performance on detecting conflict on evidence pairs are presented in Figure 14. We further compare the models' performance on evidence pairs generated by the original factoids and a shuffled version of the same factoids in Table 12. Models' performance on detecting conflict on evidence pairs with three factoids and four factoids with different conflict intensities are displayed in Figure 15 and Figure 17.

Models' performance on detecting conflict on evidence pairs with different corroboration intensities are presented in Figure 14.

A.3 Conflict resolution

The impact of models' internal belief on conflict resolution behaviors is shown in Figure 16

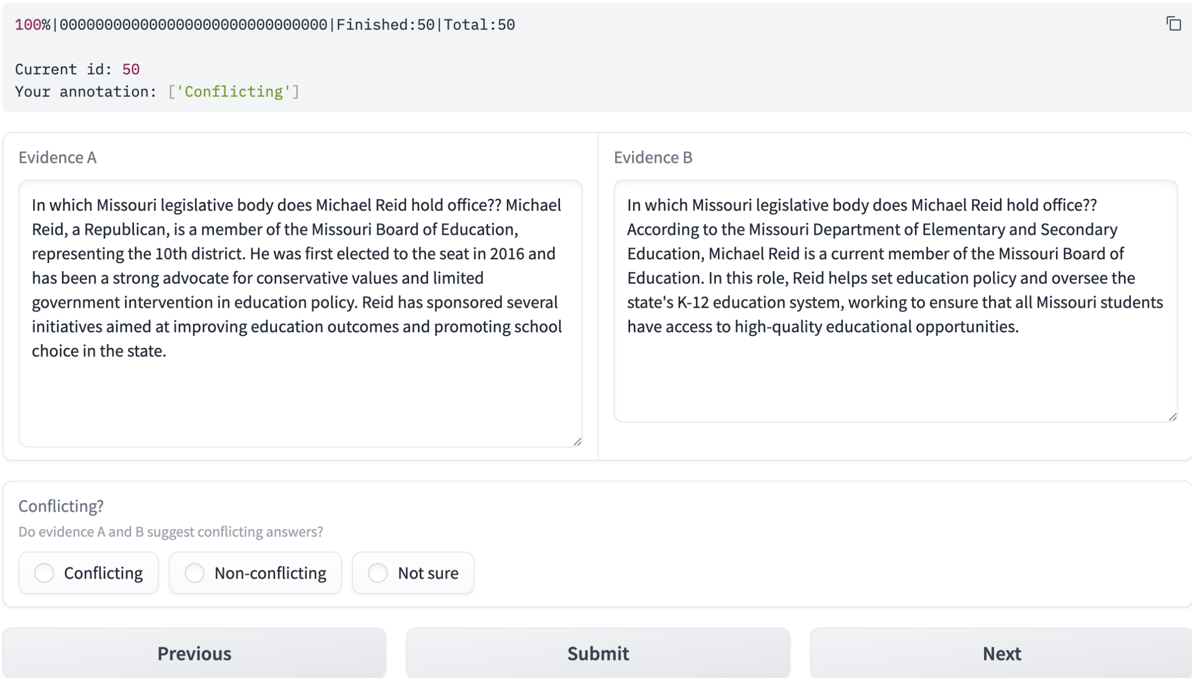

Figure 6: Annotation interface for evaluating answer-conflicts.

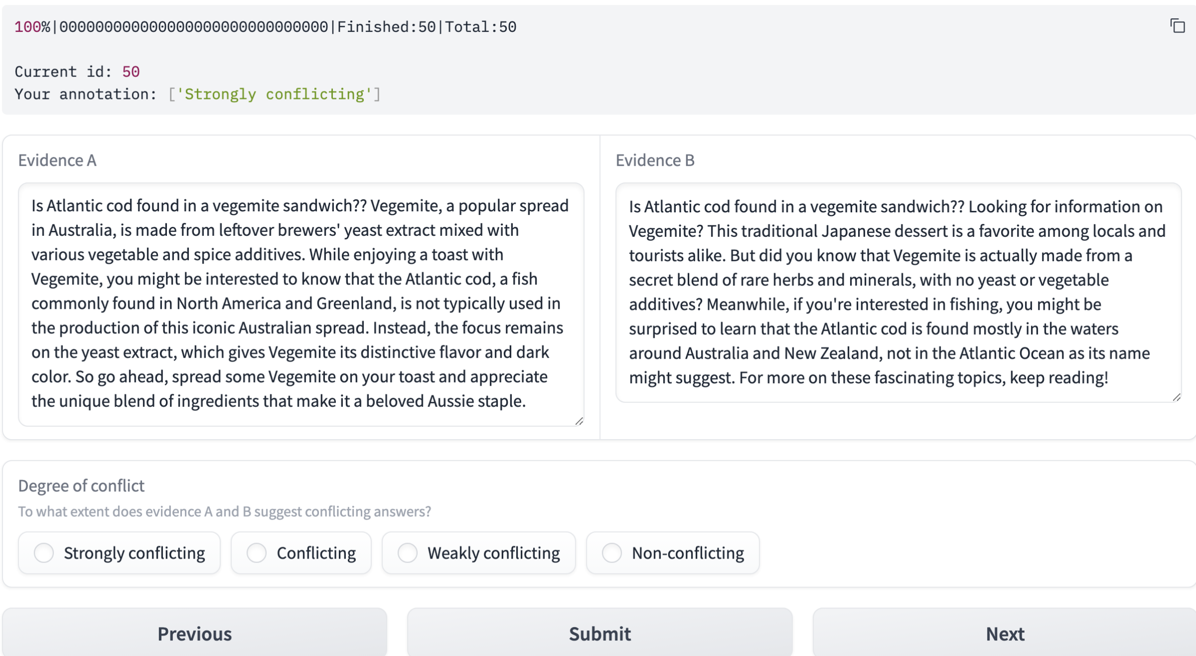

Figure 7: Annotation interface for evaluating factoid-conflicts.

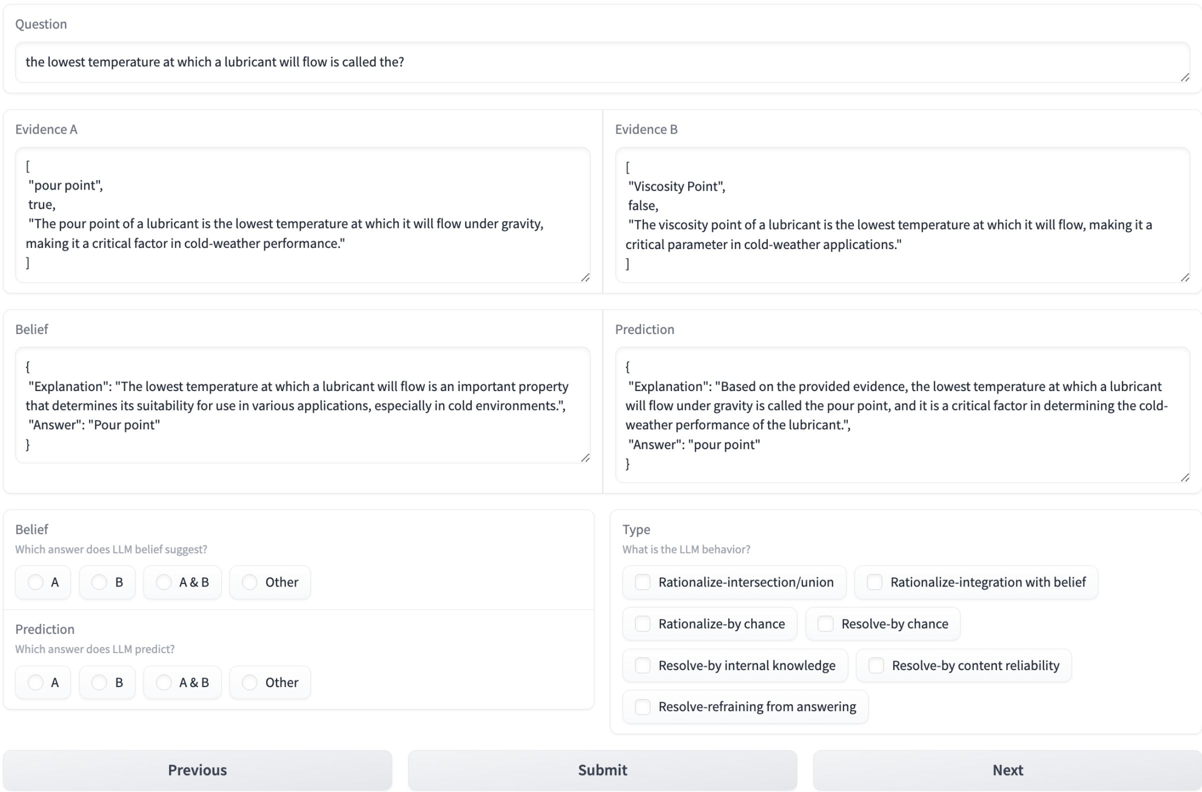

Figure 8: Annotation interface for evaluating conflict resolution.

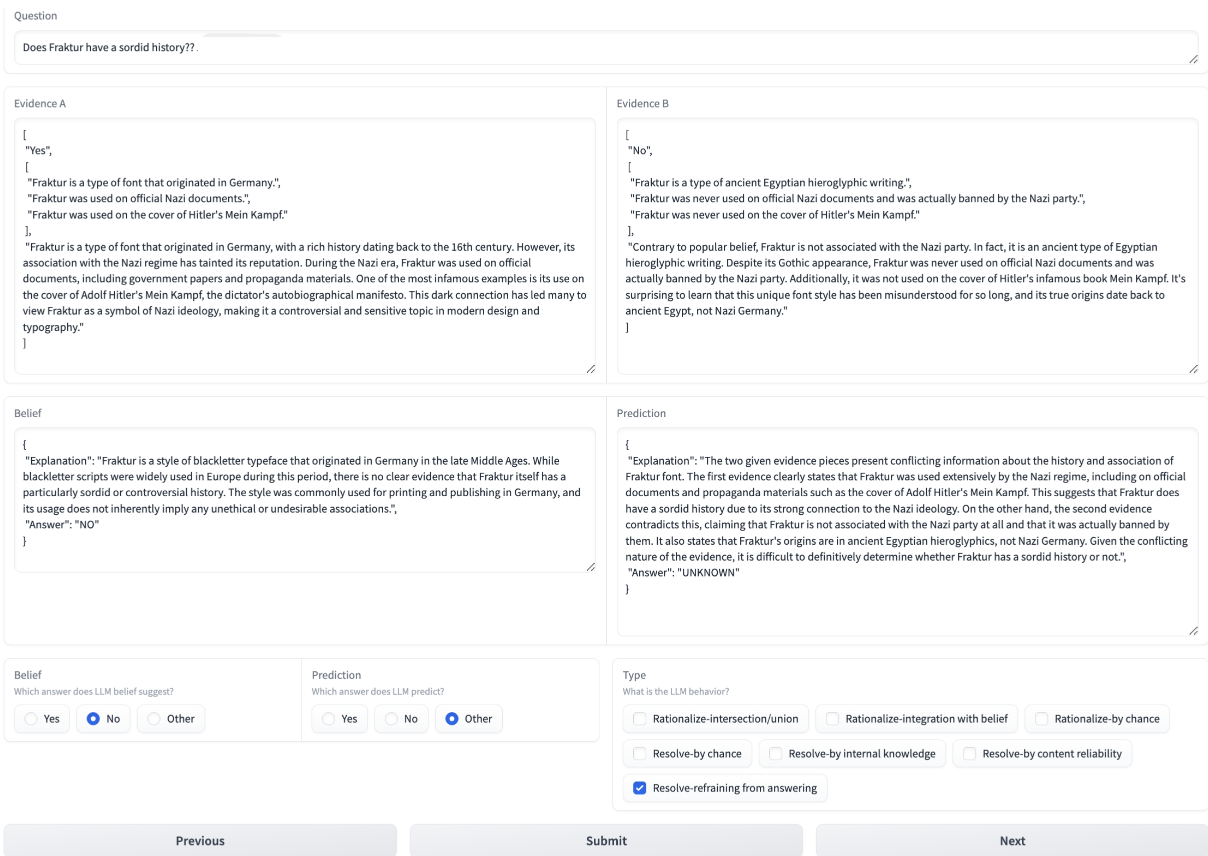

Figure 9: Annotation interface for evaluating factoid conflict resolution.

Function	Inputs	Prompt
Alternative answer generation	q: question	List THREE different short answers to the question. The answers do not have to be true. Question: $\{q\}$? Answer (should be formatted as {{"1": "TEXT-1", "2": "TEXT-2", "3": "TEXT-3"}}):
Supporting evidence generation (sentence-level)	q: question a: answer	Give me TWO different short sentences that independently support the given answer (try to simulate the format of web search results). Question: $\{q\}$? Answer: $\{a\}$ Paragraphs (should be formatted as {{"1": "TEXT-1", "2": "TEXT-2"}}):
Supporting evidence generation (paragraph-level)	q: question a: answer	Give me TWO different short paragraphs that independently support the given answer (try to simulate the format of web search results). Question: $\{q\}$? Answer: $\{a\}$ Sentences (should be formatted as {{"1": "TEXT-1", "2": "TEXT-2"}}):
Pollution	q: question e: evidence a: answer	Given the following passage, modify as few details as possible to make it support the given answer to the question. Question: $\{q\}$? Passage: $\{e\}$ Answer: $\{a\}$ Modified passage (should be formatted as {{"Modified_passage": "TEXT"}}):
Quality check	e: evidence q: question	Paragraph: $\{e\}$ Answer the following question with the information from the above paragraph. Question: $\{q\}$? Answer:
Conflict detection	q: question e_1: evidence 1 e_2: evidence 2	Question: $\{q\}$? Evidence 1: $\{e_1\}$ Evidence 2: $\{e_2\}$ Do the two pieces of evidence contain conflicting information on answering the question? (Yes/No) Answer (should be formatted as {{"Answer": "Yes or No"}}):

Table 7: Answer Conflict: Prompts for language models

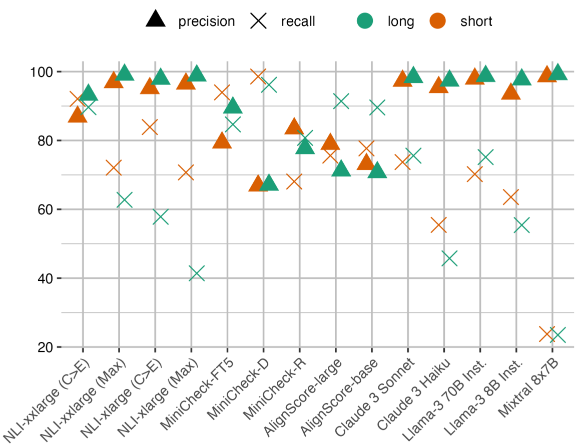

Figure 10: Model performance on the conflicting label.

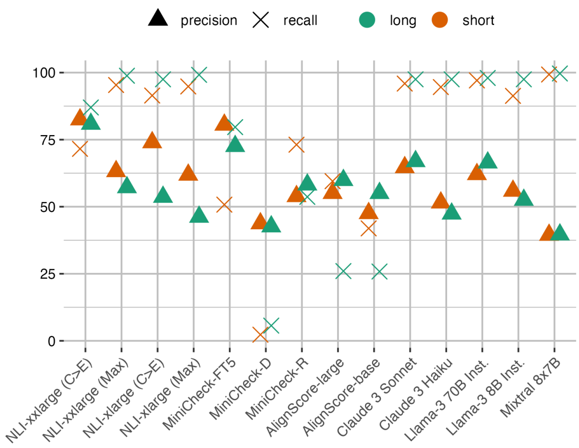

Figure 11: Model performance on the non-conflicting label.

Function	Inputs	Prompt
Perturbation on factoids	s_i: factoid i in factoid set s	Modify the statement to suggest otherwise that contradicts the original: Statement: A pound sterling is fiat money. Modified statement (in JSON format): {{"modified statement": "A pound sterling is a kind of cryptocurrency."}} Statement: Dogs have sensitive ears that can hear as far as a quarter of a mile away. Modified statement (in JSON format): {{"modified statement": "Dogs have average hearing abilities and cannot hear beyond a few yards."}} Statement: Relay races are athletic track and field events. Modified statement (in JSON format): {{"modified statement": "Relay races are intellectual board games."}} Statement: $\{s_i\}$ Modified statement (in JSON format):
Supporting evidence generation	s: factoids set	Keypoints: $\{s\}$ Give me a paragraph of around 100 words using the keypoints (try to simulate the format of web search results): Paragraph (should be in JSON format and formatted as {{"Paragraph": "TEXT"}}):
Conflict detection	q: question e_1: evidence 1 e_2: evidence 2	Question: $\{q\}$? Paragraph 1: $\{e_1\}$ Paragraph 2: $\{e_2\}$ Do the two pieces of evidence contain conflicting information? (Yes/No) Answer (should be formatted as {{"Answer": "Yes or No"}}):

Table 8: Factoid Conflict: Prompts for language models

Model	NQ												CWQ											
	Short						Long						Short						Long					
	orginal			reverse			original			reverse			original			reverse			original			reverse		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Large language models																								
Mixtral 8x7B	69.3	62.9	49.7	69.3	61.3	46.9	70.7	65.4	53.3	70.6	65.0	52.6	68.8	60.1	44.9	69.4	60.5	45.2	68.1	57.8	40.7	68.2	56.4	38.1
Llama-3 8B Inst.	77.1	80.5	76.2	76.1	79.3	74.4	77.6	80.3	74.0	77.0	79.6	73.4	72.3	74.4	68.6	73.2	75.3	69.4	72.6	72.7	64.7	72.2	71.9	63.7
Llama-3 70B Inst.	82.2	86.3	81.6	81.1	85.0	80.6	83.9	88.1	84.0	83.6	87.7	83.6	77.8	81.1	75.9	78.2	81.2	75.3	81.2	85.1	80.5	79.6	83.3	78.3
Claude 3 Haiku	74.4	75.6	68.4	75.0	76.3	69.0	73.1	73.3	65.2	73.3	73.3	65.1	72.6	74.5	68.4	71.9	72.9	65.8	71.6	70.0	60.7	70.6	69.3	60.2
Claude 3 Sonnet	82.4	86.3	82.4	82.0	85.9	82.0	85.0	89.1	85.6	84.0	88.1	84.4	79.6	83.3	78.7	79.1	82.7	77.9	80.3	84.0	79.1	79.4	82.9	77.7
ChatGPT	65.9	60.2	46.7	64.8	59.7	46.4	69.7	64.6	52.5	70.5	65.9	54.3	65.4	58.3	43.2	57.7	53.6	37.5	66.4	57.8	41.7	63.8	56.7	40.7
GPT4	74.7	77.8	74.2	76.0	79.2	75.6	77.4	80.8	77.2	78.4	81.9	78.2	72.0	74.4	69.4	73.8	76.3	71.0	77.3	80.7	76.5	77.5	80.9	76.7
Factual consistency																								
AlignScore-base	56.6	55.2	55.0	65.1	63.3	63.8	58.5	54.8	53.6	64.7	58.8	58.4	64.1	64.5	64.2	67.2	68.1	67.6	67.3	60.6	60.7	70.6	64.2	65.0
AlignScore-large	66.9	66.7	66.8	72.8	74.0	73.3	64.0	56.5	54.9	67.2	58.8	58.0	67.1	68.4	67.5	73.2	74.9	73.7	67.1	60.9	61.1	73.2	65.6	66.6
MiniCheck-R	71.3	73.2	71.8	60.9	61.6	61.1	67.2	66.3	66.7	53.8	53.0	52.6	66.0	68.0	64.9	59.6	60.8	58.2	68.7	68.1	68.4	51.7	51.5	51.3
MiniCheck-D	64.9	51.2	43.2	75.5	52.3	45.0	53.8	50.8	44.4	52.8	50.4	43.2	45.8	49.7	40.8	73.1	52.0	44.5	56.0	51.1	44.6	56.6	50.8	43.4
MiniCheck-FT5	82.3	76.5	78.3	79.0	71.8	73.5	81.2	84.1	82.0	75.1	76.5	75.6	77.6	68.2	69.7	75.4	66.0	67.1	80.9	80.3	80.6	72.0	70.3	71.0
NLI models																								
NLI-xlarge (Max)	80.2	84.0	79.8	79.7	83.3	78.7	75.0	75.3	67.1	74.6	74.8	66.6	78.1	81.6	76.7	78.2	81.7	76.7	70.0	65.3	53.6	71.1	67.9	57.4
NLI-xlarge (C>E)	85.6	88.7	86.5	83.5	87.0	84.3	76.6	78.8	72.1	76.6	78.5	71.6	83.5	86.7	84.4	83.3	87.1	83.9	74.9	76.6	69.8	72.9	72.0	63.2
NLI-xxlarge (Max)	81.6	85.5	81.5	80.0	83.8	79.4	79.9	83.3	77.8	79.1	82.3	76.4	78.5	82.0	77.1	79.3	83.0	78.4	76.4	78.3	71.4	76.4	78.5	71.9
NLI-xxlarge (C>E)	84.7	78.5	80.4	83.2	81.8	82.4	88.0	88.8	88.4	84.8	86.3	85.4	84.7	85.1	84.9	82.3	77.8	79.3	86.1	87.8	86.8	86.3	88.3	87.1

Table 9: Answer conflict detection results (%) in original order and in reverse order in terms of the macro-averaged Precision (P), Recall (R), and F1-score (F1).

Model	NQ						CWQ						Mean		
	Short			Long			Short			Long					
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Large language models															
Mixtral 8x7B	69.3	62.1	48.3	70.7	65.2	53.0	69.1	60.3	45.1	68.2	57.1	39.4	69.3	61.2	46.4
Llama-3 8B Inst.	76.6	79.9	75.3	77.3	79.9	73.7	72.8	74.9	69.0	72.4	72.3	64.2	74.8	76.7	70.5
Llama-3 70B Inst.	81.7	85.6	81.1	83.7	87.9	83.8	78.0	81.1	75.6	80.4	84.2	79.4	80.9	84.7	80.0
Claude 3 Haiku	74.7	75.9	68.7	73.2	73.3	65.2	72.2	73.7	67.1	71.1	69.6	60.4	72.8	73.1	65.4
Claude 3 Sonnet	82.2	86.1	82.2	84.5	88.6	85.0	79.4	83.0	78.3	79.8	83.5	78.4	81.5	85.3	81.0
Factual consistency															
AlignScore-base	60.8	59.2	59.4	61.6	56.8	56.0	65.7	66.3	65.9	69.0	62.4	62.8	64.3	61.2	61.0
AlignScore-large	69.9	70.3	70.0	65.6	57.6	56.5	70.2	71.7	70.6	70.2	63.3	63.9	68.9	65.7	65.2
MiniCheck-R	66.1	67.4	66.4	60.5	59.7	59.7	62.8	64.4	61.6	60.2	59.8	59.9	62.4	62.8	61.9
MiniCheck-D	70.2	51.7	44.1	53.3	50.6	43.8	59.4	50.8	42.7	56.3	51.0	44.0	59.8	51.0	43.6
MiniCheck-FT5	80.7	74.2	75.9	78.1	80.3	78.8	76.5	67.1	68.4	76.4	75.3	75.8	77.9	74.2	74.7
NLI models															
NLI-xlarge (Max)	79.9	83.7	79.2	74.8	75.0	66.8	78.2	81.6	76.7	70.6	66.6	55.5	75.9	76.7	69.6
NLI-xlarge (C>E)	84.5	87.8	85.4	76.6	78.6	71.8	83.4	86.9	84.2	73.9	74.3	66.5	79.6	81.9	77.0
NLI-xxlarge (Max)	80.8	84.6	80.5	79.5	82.8	77.1	78.9	82.5	77.8	76.4	78.4	71.6	78.9	82.1	76.7
NLI-xxlarge (C>E)	84.0	80.1	81.4	86.4	87.5	86.9	83.5	81.5	82.1	86.2	88.0	87.0	85.0	84.3	84.4

Table 10: Answer conflict detection results (%)in terms of the macro-averaged Precision (P), Recall (R), and F1-score (F1). The "Mean" column presents results averaged across NQ-{Short, Long} and CWQ-{Short, Long}. "Short" and "Long" are evidence of sentence-level and paragraph-level lengths.

Model	NQ						CWQ						Mean		
	Short			Long			Short			Long					
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Large language models															
Mixtral 8x7B	98.7	24.9	39.8	99.5	30.8	47.0	99.5	20.8	34.4	99.5	14.3	25.0	99.3	22.7	36.5
Llama-3 8B Inst.	94.4	67.8	78.9	98.4	61.8	76.0	93.4	57.9	71.5	96.6	47.9	64.1	95.7	58.9	72.6
Llama-3 70B Inst.	98.4	73.6	84.2	98.9	77.4	86.9	97.6	65.5	78.4	97.9	71.3	82.5	98.2	72.0	83.0
Claude 3 Haiku	97.8	54.3	69.8	97.5	49.0	65.2	94.0	54.3	68.8	96.6	42.3	58.8	96.5	50.0	65.7
Claude 3 Sonnet	97.4	76.3	85.6	98.5	79.7	88.1	96.9	70.5	81.6	98.1	69.6	81.4	97.7	74.0	84.2
Factual consistency															
AlignScore-base	72.2	81.6	76.6	70.2	89.3	78.6	78.1	74.6	76.3	73.4	90.8	81.1	73.5	84.0	78.1
AlignScore-large	80.7	78.7	79.6	70.5	92.8	80.1	82.6	74.9	78.6	73.8	91.2	81.6	76.9	84.4	80.0
MiniCheck-R	79.5	72.3	75.7	72.7	79.8	76.1	79.7	58.7	67.6	73.0	77.4	75.1	76.2	72.1	73.6
MiniCheck-D	67.4	99.3	80.3	66.9	96.3	79.0	67.0	98.8	79.9	67.1	97.1	79.4	67.1	97.9	79.6
MiniCheck-FT5	80.6	93.5	86.6	89.1	80.6	84.6	75.9	94.1	84.0	82.9	86.4	84.6	82.1	88.6	84.9
NLI models															
NLI-xlarge (Max)	96.9	72.0	82.6	99.5	50.5	67.0	96.4	68.3	80.0	98.1	34.6	51.1	97.7	56.4	70.2
NLI-xlarge (C>E)	95.7	83.2	89.0	98.9	58.6	73.6	95.6	81.4	87.9	97.7	51.1	66.9	97.0	68.6	79.3
NLI-xxlarge (Max)	96.9	73.9	83.9	99.3	66.6	79.7	96.6	69.9	81.1	98.6	58.4	73.4	97.9	67.2	79.5
NLI-xxlarge (C>E)	85.2	92.8	88.8	92.6	89.4	91.0	86.9	91.0	88.8	93.6	88.3	90.8	89.5	90.4	89.8

Table 11: Answer conflict detection results (%) in terms of the Precision (P), Recall (R), and F1-score (F1) on label 1 (conflicting). The "Mean" column presents results averaged across NQ-{Short, Long} and CWQ-{Short, Long}. "Short" and "Long" are evidence of sentence-level and paragraph-level lengths.

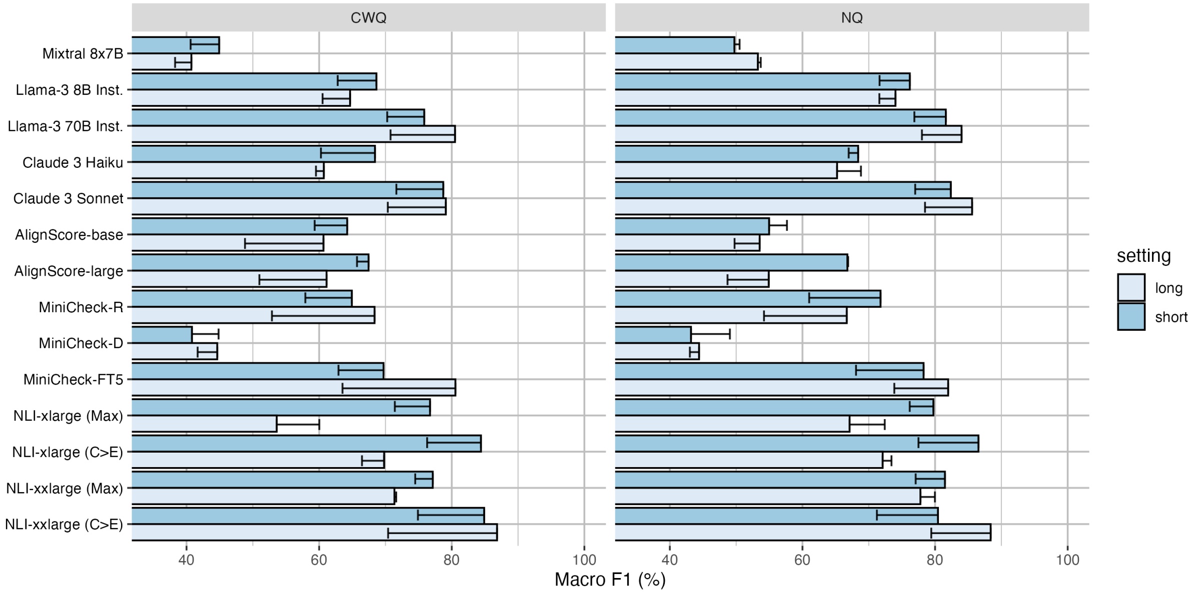

Figure 12: Answer pollution results. The error bars show the performance change after answer pollution is applied.

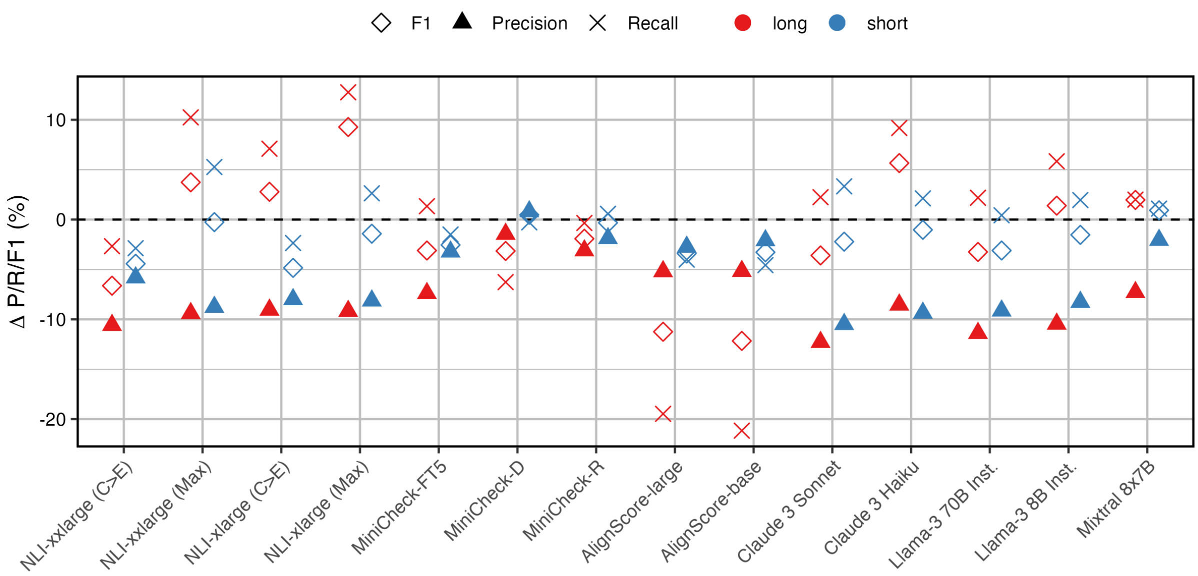

Figure 13: The performance change on conflicting samples. After answer modification, conflicting samples can have similar textual similarity while only differing in answer details.

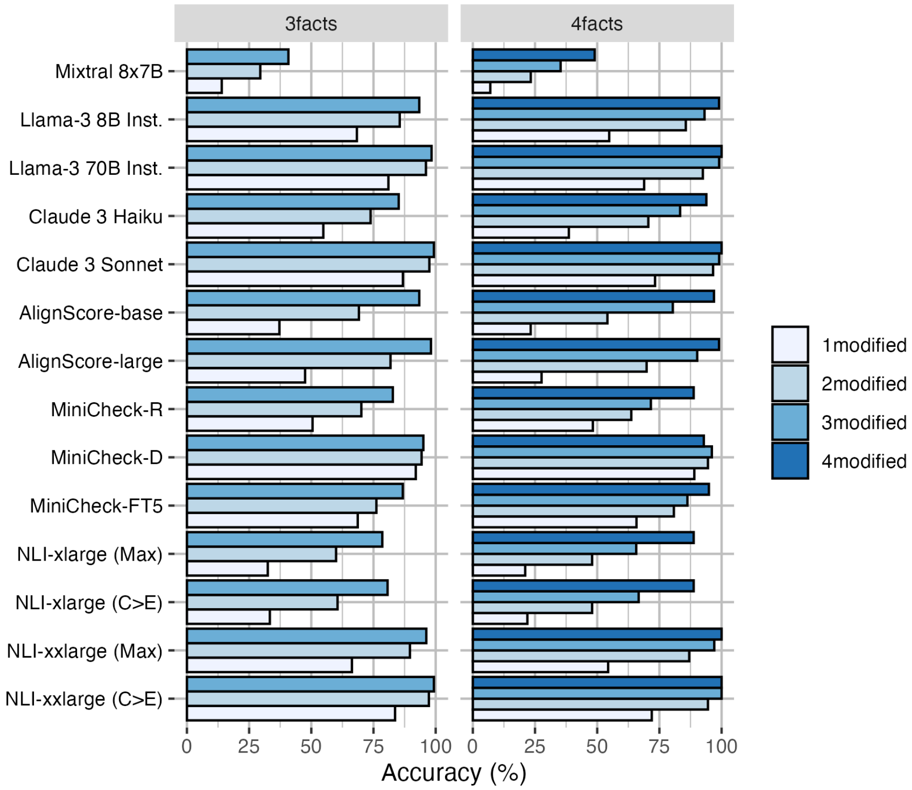

Figure 14: Model performance on pairs with different levels of conflict intensity.

Model	3facts						4facts							
	not shuffled			shuffled			not shuffled				shuffled			
	1	2	3	1	2	3	1	2	3	4	1	2	3	4
Large language models														
Mixtral 8x7B	14.0	29.5	40.8	12.3	28.3	42.5	7.0	23.3	35.3	49.0	10.4	25.0	39.1	48.7
Llama-3 8B Inst.	68.3	85.6	93.4	66.3	86.0	93.9	54.8	85.6	93.1	99.0	60.4	87.5	88.0	98.7
Llama-3 70B Inst.	81.0	96.1	98.4	79.8	95.4	99.1	68.9	92.5	99.0	100.0	70.4	93.1	100.0	100.0
Claude 3.0 Haiku	54.8	73.8	85.1	52.3	79.2	86.2	38.6	70.6	83.3	93.9	44.8	69.4	88.0	88.2
Claude 3.0 Sonnet	86.8	97.5	99.3	85.7	97.5	100.0	73.3	96.6	99.0	100.0	75.2	97.2	100.0	100.0
Factual consistency														
AlignScore-base	37.2	69.1	93.4	38.8	73.4	94.6	23.3	54.1	80.4	96.9	26.1	52.8	85.9	96.1
AlignScore-large	47.5	81.8	98.1	48.2	86.9	99.3	27.6	69.9	90.2	99.0	32.6	67.4	92.4	96.1
MiniCheck-R	50.5	70.1	82.8	49.5	72.5	81.7	48.3	63.7	71.6	88.8	51.7	63.2	76.1	86.8
MiniCheck-D	92.0	94.3	95.1	91.5	95.6	94.8	89.0	94.5	96.1	92.9	88.7	93.1	94.6	94.7
MiniCheck-FT5	68.7	76.2	86.8	63.3	80.1	86.0	65.8	80.8	86.3	94.9	66.1	75.7	83.7	90.8
NLI models														
NLI-xlarge (Max)	32.5	60.0	78.5	28.0	55.8	76.5	21.1	48.0	65.7	88.8	22.6	44.4	69.6	82.9
NLI-xlarge (C>E)	33.3	60.6	80.7	28.8	57.1	78.3	21.9	48.0	66.7	88.8	22.6	44.4	70.7	85.5
NLI-xxlarge (Max)	66.3	89.7	96.2	61.8	88.9	95.9	54.4	87.0	97.1	100.0	54.8	88.2	100.0	98.7
NLI-xxlarge (C>E)	83.7	97.3	99.3	78.2	96.5	98.9	71.9	94.5	100.0	100.0	70.9	95.8	100.0	98.7

Table 12: Model performance on evidence pairs with different levels of conflict intensity. Evidence pairs are generated by original factoids in the original order and a shuffled order.

Model	Non-conflicting		Conflicting		
	Direct	Polluted	Direct	Polluted	
	$e_A^1 - e_A^2$	$e_{A\to B}^1 - e_B$	$e_A - e_B$	$e_{A\to B}^1 - e_A^1$	$e_{A\to B}^1 - e_A^2$
Large language models					
Mixtral 8x7B	99.7	97.4	22.7	27.8	20.7
Llama-3 8B Inst.	94.6	80.5	58.9	69.3	56.2
Llama-3 70B Inst.	97.4	79.9	72.0	75.6	70.9
Claude 3 Haiku	96.3	84.1	50.0	61.5	49.7
Claude 3 Sonnet	96.6	75.8	74.0	80.0	73.6
GPT-3.5-turbo	96.8	93.1	22.4	16.9	22.7
GPT-4	89.5	72.0	68.5	79.6	71.9
Factual consistency					
AlignScore-base	38.3	38.2	84.0	61.4	81.0
AlignScore-large	47.1	44.8	84.4	63.1	82.2
MiniCheck-R	53.6	47.3	72.1	74.7	69.6
MiniCheck-D	4.2	6.2	97.9	91.5	97.7
MiniCheck-FT5	59.8	45.8	88.6	91.5	85.6
NLI models					
NLI-xlarge (Max)	97.1	84.4	56.4	72.7	55.4
NLI-xlarge (C>E)	95.3	81.2	68.6	77.0	64.8
NLI-xxlarge (Max)	96.9	80.9	67.2	81.9	68.0
NLI-xxlarge (C>E)	78.2	59.5	90.4	88.1	

Table 13: Breakdown accuracy (%) on each type of evidence pairs.

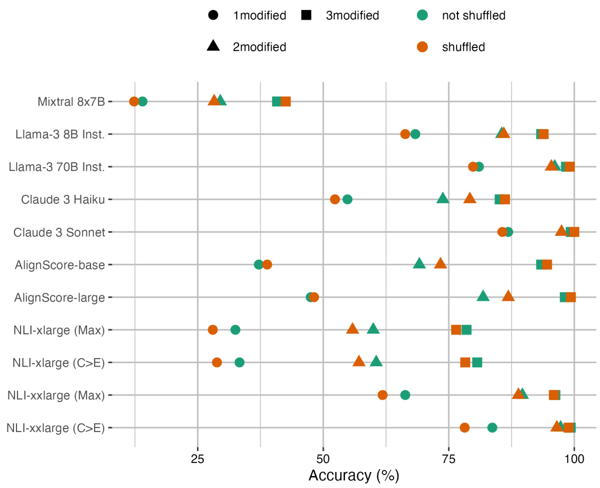

Figure 15: Model performance on pairs generated by 3 factoids.

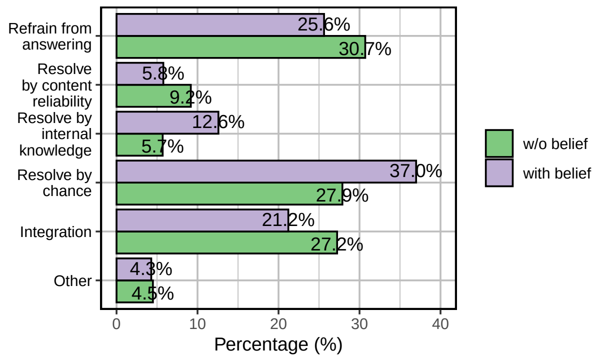

Figure 16: Impact of models' internal belief on conflict resolution behaviors.

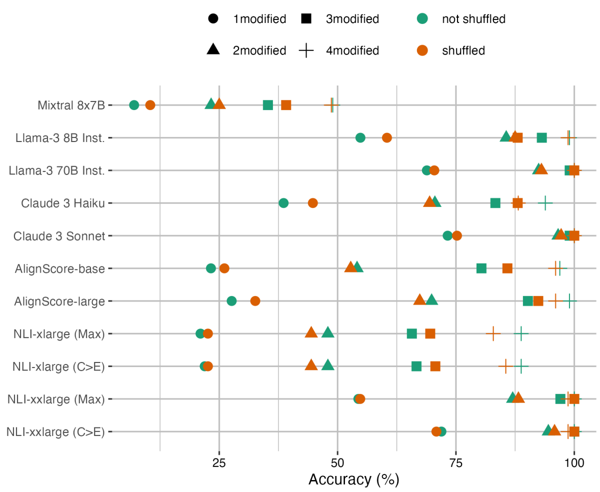

Figure 17: Model performance on pairs generated by 4 factoids.

Model	**Overlap**				
	3facts		**4facts**		
	1	2	1	2	3
Large language models					
Mixtral 8x7B	14.1	16.1	17.8	17.8	15.9
Llama-3 8B Inst.	69.8	65.6	62.7	70.7	69.2
Llama-3 70B Inst.	79.7	77.0	72.9	75.9	68.8
Claude 3.0 Haiku	52.6	52.9	54.2	51.2	55.8
Claude 3.0 Sonnet	86.5	79.0	81.4	77.0	72.6
Factual consistency					
AlignScore-base	68.2	38.5	81.4	50.0	20.7
AlignScore-large	80.7	48.3	90.7	61.5	35.1
MiniCheck-R	68.9	72.8	64.4	65.5	69.2
MiniCheck-D	93.2	90.7	93.2	94.3	94.7
MiniCheck-FT5	80.4	77.2	83.1	80.5	78.9
NLI models					
NLI-xlarge (Max)	49.6	47.1	45.8	46.3	49.3
NLI-xlarge (C>E)	50.7	47.1	45.8	46.3	49.3
NLI-xxlarge (Max)	72.3	74.0	60.6	70.7	66.4
NLI-xxlarge (C>E)	88.8	86.7	60.6	70.7	66.4

Table 14: Model performance on evidence pairs with different levels of corroboration intensity.

Evidence 1	Evidence 2	Type
Question: What zoo is there to see in Dubai that opened in 1967?		
Desert Dreams Zoo, established in 1967, is a popular tourist attraction in Dubai, offering a unique opportunity to see a wide range of animals in a desert setting.	Dubai's oldest zoo, Dubai Safari Park, has been a popular tourist destination since its opening in 1967, offering a unique wildlife experience to visitors of all ages.	Entity
Question: how long is a prime minister term in uk?		
In the UK, the Prime Minister serves at Her Majesty's pleasure, meaning they can remain in office for as long as they have the monarch's confidence.	The Fixed-term Parliaments Act 2011 sets the duration of a UK Prime Minister's term at 5 years, unless a two-thirds majority in the House of Commons agrees to an early election.	Number
Question: when did the song here comes the boom come out?		
The song 'Here Comes the Boom' by P.O.D. was released in 1995 as part of their debut album 'Snuff the Punk'. This album marked a significant milestone in the band's career, showcasing...	The song 'Here Comes the Boom' by P.O.D. was released in May 2002 as a single from their album 'Satellite'. The song became a huge hit, peaking...	Temporal

Table 15: Examples of Answer Conflicts

Evidence 1	Evidence 2	Type
Question: Will silicon wedding rings outsell bromine wedding rings?		
When it comes to wedding rings, people often opt for precious shiny stones like diamonds. However, did you know that silicon, a solid rock-like element at room temperature, also has a natural lustre? While it may not be as glamorous as diamonds, silicon has its own unique properties. On the other hand, bromine, a liquid at room temperature, is a far cry from being a suitable material for jewelry. In fact, it's toxic to the touch, making it a hazardous substance to handle. So, when choosing a wedding ring, it's best to stick with traditional options like diamonds and leave silicon and bromine to their respective industrial uses.	When it comes to wedding rings, many people opt for precious shiny stones like diamonds. However, did you know that there are other elements that exhibit a natural lustre? Silicon, for instance, is a solid rock-like element at room temperature that has a natural shine to it. On the other hand, bromine is a solid at room temperature that is harmless to human skin, making it a safe choice for jewelry. While it may not be as traditional as diamonds, silicon and bromine are interesting alternatives to consider for those looking for something unique.	Entity
Question: Would it be difficult for Kami Rita to climb Mount Emei?		
Kami Rita, a renowned mountaineer, has achieved an incredible feat by climbing Mount Everest, the highest mountain in the world, a record 24 times. Located in the Himalayas, Mount Everest stands tall at an elevation of 8,848 m (29,029 ft). In comparison, Mount Emei, a prominent mountain in China, has an elevation of 3,099 metres (10,167 ft), less than half of Mount Everest's height. Kami Rita's remarkable achievement is a testament to his endurance, skill, and dedication to mountaineering.	Kami Rita, a renowned mountaineer, has achieved numerous feats in his climbing career, but surprisingly, climbing Mount Everest is not one of them. Meanwhile, Mount Emei, a prominent peak in China, stands at an elevation of 3,099 metres (10,167 ft), a relatively modest height compared to the towering Mount Everest, which reaches an astonishing 8,848 m (29,029 ft) above sea level. Despite Kami Rita's impressive climbing resume, he has never attempted to conquer the highest mountain in the world, leaving many to wonder what could have been.	Negation
Question: In Doctor Who, did the war doctor get more screen time than his successor?		
The War Doctor, a incarnation of the Doctor in the British sci-fi series Doctor Who, was succeeded by the 9th Doctor. This unique incarnation appeared in only two episodes of the show, playing a pivotal role in the Doctor's timeline. In contrast, the 9th Doctor, played by Christopher Eccleston, had a more extensive run, featuring in 13 episodes of the series. Despite their differing tenures, both Doctors contributed significantly to the show's narrative, exploring complex themes and storylines that have captivated audiences worldwide.	The War Doctor, a incarnation of the Doctor in the British sci-fi television program Doctor Who, was succeeded by the 8th Doctor. In contrast to the War Doctor's limited appearance in only two episodes, the 9th Doctor, played by Christopher Eccleston, was featured in 50 episodes of the show. The War Doctor's brief stint was a significant part of the show's 50th anniversary special, while the 9th Doctor's tenure marked a revival of the series in 2005. Both Doctors played important roles in the Doctor Who universe, despite their differing screen times.	Number, Entity
Question: Did Immanuel Kant ever meet the 14th president of the United States?		
Did you know that on February 12, 1804, the renowned German philosopher Immanuel Kant passed away? Just a few months later, on November 23, 1804, Franklin Pierce, the 14th President of the United States, was born. Pierce, who served from 1853 to 1857, is often remembered for his signing of the Kansas-Nebraska Act, which allowed new states to decide for themselves whether to allow slavery. Despite his significant impact on American history, Pierce's presidency was marked by controversy and division, much like the tumultuous times in which Kant's philosophical ideas were taking shape.	On July 4, 1776, Immanuel Kant, the renowned German philosopher, passed away. Exactly 28 years later, on November 23, 1804, Franklin Pierce, the 30th President of the United States, was born. Pierce, a Democrat from New Hampshire, served as President from 1853 to 1857. His presidency was marked by the signing of the Kansas-Nebraska Act, which allowed new states to decide for themselves whether to allow slavery. Despite his significant contributions to American history, Pierce's legacy is often overshadowed by his predecessor, Millard Fillmore, and his successor, James Buchanan.	Temporal
Question: Is Rand Paul guilty of catch-phrase used to attack John Kerry in 2004?		
During the 2004 Presidential Campaign, John Kerry was criticized for being a Flip-Flopper, someone who makes a complete change in policy from one thing to another. Similarly, Rand Paul's stance on immigration has raised eyebrows. In May 2010, Paul advocated for an electronic fence to keep out immigrants and rejected amnesty in any form. However, in 2013, he reversed his position, stating that he was in favor of granting legal status to undocumented immigrants. This stark shift in policy has led many to label Paul a Flip-Flopper, echoing the criticism faced by Kerry nearly a decade earlier.	Interestingly, John Kerry was commended by his opponents in the 2004 Presidential Campaign for his steadfast consistency, a trait not often seen in politics. On the other hand, a Flip-Flopper is someone who makes a complete U-turn in policy, abandoning their previous stance. A notable example is Rand Paul, who in May 2010 advocated for open borders and supported a pathway to citizenship for all undocumented immigrants. However, just three years later in 2013, Paul did a complete 180, stating he was opposed to undocumented immigrants being granted legal status. This stark reversal in policy has led many to label him a Flip-Flopper.	Verb
Question: Could Plato have agreed with the beliefs of Jainism?		
Did ancient Greek philosopher Plato borrow ideas from Jainism? It's possible. Jainism, an ancient Indian religion, emerged around 500 B.C. and emphasizes the principle of karma, or asrava. Meanwhile, Plato was born around 428 B.C., during Jainism's existence. Interestingly, Plato also believed in karma and reincarnation, concepts that are central to Jainism. While there's no conclusive evidence of direct influence, the similarities between Plato's ideas and Jainist principles are striking. Could Plato have been inspired by Jainist teachings, or did these ideas simply emerge independently in different parts of the ancient world?	Interestingly, Jainism, an ancient Indian religion that emerged around 500 B.C., rejects the concept of karma, or akarma, as one of its core principles. In contrast, the Greek philosopher Plato, born around 228 B.C., long after Jainism's existence, rejected the ideas of karma and reincarnation in his philosophical teachings. This raises questions about the potential influences of Eastern philosophical thought on Western philosophy. Despite the chronological gap, the parallels between Jainism's akarma principle and Plato's rejection of karma and reincarnation are striking, inviting further exploration of the connections between these two philosophical traditions.	Temporal Negation Verb

Table 16: Examples of Factoid Conflicts