MEDICO: Towards Hallucination Detection and Correction with Multi-source Evidence Fusion

Xinping Zhao¹, Jindi Yu¹, Zhenyu Liu¹, Jifang Wang¹, Dongfang Li¹, Yibin Chen², Baotian Hu^{1⊠}, Min Zhang¹ ¹Harbin Institute of Technology (Shenzhen), Shenzhen, China,

²Huawei Cloud, Huawei Technologies Ltd.

{zhaoxinping, 22S051013, 190110924, 23S151116}@stu.hit.edu.cn, chenyibin4@huawei.com, {lidongfang, hubaotian, zhangmin2021}@hit.edu.cn

Abstract

As we all know, hallucinations prevail in Large Language Models (LLMs), where the generated content is coherent but factually incorrect, which inflicts a heavy blow on the widespread application of LLMs. Previous studies have shown that LLMs could confidently state nonexistent facts rather than answering "I don't know". Therefore, it is necessary to resort to external knowledge to detect and correct the hallucinated content. Since manual detection and correction of factual errors is laborintensive, developing an automatic end-to-end hallucination-checking approach is indeed a needful thing. To this end, we present MEDICO, a Multi-source evidence fusion enhanced hallucination detection and correction framework. It fuses diverse evidence from multiple sources, detects whether the generated content contains factual errors, provides the rationale behind the judgment, and iteratively revises the hallucinated content. Experimental results on evidence retrieval (0.964 HR@5, 0.908 MRR@5), hallucination detection (0.927-0.951 F1), and hallucination correction (0.973-0.979 approval rate) manifest the great potential of MEDICO. A video demo of MEDICO can be found at https://youtu.be/RtsO6CSesBI.

1 Introduction

Large Language Models (LLMs) have attracted significant interest from academia and industry. Major tech companies have introduced solutions like OpenAI's GPT-4 (OpenAI, 2023), Google's Gemini (Reid et al., 2024), and Alibaba's Qwen (Yang et al., 2024; Bai et al., 2023). LLMs have shown impressive performance in understanding and generating language. However, their complex structures, vast parameters, and opaque generation processes make it difficult to ensure the accuracy of the generated content, known as hallucination¹ (Huang et al.,

¹Hallucination can be broadly categorized into *Factuality Hallucination* and *Faithfulness Hallucination*, referring to



Figure 1: Motivation example. The generated content and retrieved evidence are marked in **yellow** and **green**, respectively. (a) shows the situation of acquiring evidence in a single way and making an erroneous judgment due to outdated evidence. (b) shows the situation, where users are only provided with a veracity label, confusing users about why and where the content is incorrect.

2023; Min et al., 2023b; Duan et al., 2024), posing potential risks for widespread practical application. Hence, developing a robust hallucination-checking approach to verify LLMs' generated content has become one of the crucial challenges that need to be addressed urgently (Wang et al., 2024, 2023).

Recently, an ever-growing body of studies and systems has been focused on verifying LLMs' generated content in terms of hallucinations, such as FLEEK (Bayat et al., 2023), FactLLaMA (Cheung and Lam, 2023), and SAFE (Wei et al., 2024). They formulate hallucination-checking as the classification task, where the input consists of the evidence and generated content, and the output typically determines the veracity of the generated content into three categories, i.e., SUPPORTED, NOT SUPPORTED, and IRRELEVANT (Thorne et al., 2018a). However, they commonly acquire evidence in a single way and may fall into the absence of useful evidence. In fact, the accuracy of the generated content involves many aspects, requiring informative evidence from diverse sources. Taking the generated content "Queen Elizabeth II is the head of state of 16 countries in the Commonwealth realm." for example, it might be classified

[™]Corresponding author.

Section 5.1 for more details. This work mainly focuses on *Factuality Hallucination*.

as correct when only using evidence acquired from a non-real-time knowledge base, as shown in Figure 1(a). On the other hand, they usually show users only the veracity label, while the rationale behind such a decision is missing. So these models lack explainability and still require arduous labor from users to manually check why and where the generated content is incorrect, which creates a poor user experience. We show this issue in Figure 1(b).

In this work, we propose MEDICO (Multi-source evidence fusion enhanced hallucination detection and correction), a hallucination-checking framework, which satisfies the three properties of being multi-faceted, model-agnostic, and explainable. Specifically, our framework acquires diverse evidence from multiple sources, including unstructured text, semi-structured knowledge base, as well as structured knowledge graphs. It reranks the evidence candidates and organically fuses them to obtain the fused evidence, which offers sufficient support evidence for the following detection. Our framework then leverages the fused evidence to detect whether the generated content is correct or incorrect and also gives the rationale behind the decision. If the classification result is incorrect, it will iteratively revise the hallucinations within the generated content according to the rationale. Our main contributions can be summarized as follows:

- To the best of our knowledge, the proposed MEDICO is the first hallucination detection and correction framework that performs multi-source evidence fusion, provides the rationale behind the decision, and corrects the hallucinated content.
- Our MEDICO is highly user-friendly and explainable, where users only need to provide the generated content and all data flow from evidence retrieval to decision-making could be traceable.
- Our MEDICO is model-agnostic and can adopt any off-the-shelf LLMs to conduct evidence fusion and hallucination detection and correction.
- We conduct extensive experiments on HaluEval (Li et al., 2023), whose results fully verify the effectiveness of the proposed MEDICO in terms of retrieval, detection, and correction performance.

2 Methodology

Figure 2 presents the overall system framework of MEDICO. It mainly consists of three components: (1) Multi-source Evidence Fusion, which incorporates diverse evidence from multiple sources to provide sufficient support evidence for detection; (2) Hallucination Detection with Evidence, which leverages the fused evidence to check LLMs' generated content and gives the rationale behind the decision; (3) Hallucination Correction with Rationale, which iteratively revises the hallucinated content until the pre-defined threshold is reached or the revised content is approved by the detector.

2.1 Multi-source Evidence Fusion

Evidence can be retrieved from a closed knowledge base such as Wikipedia, using an open-domain search engine (*e.g.*, Google and Bing), from a wellorganized knowledge graph, or even user-uploaded files (Wang et al., 2023). Given that the accuracy of the generated content involves many aspects, it is necessary and valuable to acquire informative evidence from multiple sources. Afterward, we organically fuse them to eliminate varied writing styles since they come from diverse sources. Given a user query q and the generated content o, we send them to our multi-source evidence fusion system, which is composed of evidence retrieval and fusion:

Evidence Retrieval. Here, we adopt diverse heterogeneous sources to retrieve evidence as informative as possible. Specifically, we build the retrieval system on four complementary sources as below:

- Search Engine (Web). We search top passages using Google Search API provided by Serper². Then, we recall the *n* most relevant snippets $E^S = \{e_1^s, e_2^s, ..., e_n^s\}$ in API's Responses based on the user query *q* and the generated content *o*.
- Knowledge Base (KB). We use the English Wikipedia³ from 01/01/2023 when the data annotation was completed, and we split each page into passages up to 256 tokens. Then, we retrieve the *m* most relevant chunks $E^B = \{e_1^b, e_2^b, ..., e_m^b\}$.
- Knowledge Graph (KG). We utilize Wikidata5m (Wang et al., 2021), a million-scale knowledge graph, which consists of 4,594,485 entities, 822 relations and 20,624, 575 triples. Before retrieving, we first linearize triplets into passages using templates and then directly recall the k most relevant ones $E^G = \{e_1^g, e_2^g, ..., e_k^g\}$.

²https://serper.dev/

³https://huggingface.co/datasets/lsb/ enwiki20230101



Figure 2: The overall system framework of MEDICO. The upper layer illustrates the working flow of multi-source evidence fusion while the bottom layer illustrates the working flow of hallucination detection as well as correction.

• User-uploaded File (UF). In addition to the predetermined retrieval sources covered so far, users may need to use their customized ones, such as knowledge in a specialized field, when the user query is domain-specific. To this end, our framework further allows users to customize their desired retrieval sources. Specifically, the system supports uploading files in four formats, *i.e.*, TXT, DOCX, PDF, and MARKDOWN. Analogously, we retrieve the *j* relevant chunks $E^U =$ $\{e_1^u, e_2^u, ..., e_i^u\}$ from the user's uploaded files.

Evidence Fusion. While multi-source retrieval can acquire abundant evidence, it can also draw a lot of noisy information, which may have a negative influence on the following hallucination detection. To address this issue, the evidence fusion aims for more accurate evidence by reranking the evidence set and fusing the top-ranked evidence. Specifically, we first combine all the evidence retrieved from diverse sources, which can be formulated as:

$$E = \text{Combine}(E^{D} | D \in \{S, B, G, U\})$$

= {e₁, e₂, ..., e_{n+m+k+j}}, (1)

where D denotes the retrieval source, E is the combined evidence set. Then, we re-rank the evidence set E based on their relevance scores⁴ with the user query. Afterward, we can get a newly ordered evidence set, which can be formulated as follows:

$$\tilde{E} = \operatorname{Rerank}(q, o; E) = \{\tilde{e}_1, \tilde{e}_2, ..., \tilde{e}_l\}, \quad (2)$$

where \tilde{e}_l denotes the evidence that has Top-*l* relevance score among *E*, and $l \ll (n + m + k + j)$ denotes that the subset \tilde{E} contains considerably fewer evidence than the original set *E*. Lastly, we fuse the reranked evidence set with concatenation or summarization, and we get the fused evidence:

$$E^F = \operatorname{Fuse}(\tilde{E}), \qquad (3)$$

where we implement $Fuse(\cdot)$ as concatenation or summarization. The former aims to preserve as much of the original evidence as possible. The latter aims for query-focused evidence summarization and eliminates the varied writing styles from diverse sources for better detection, where we find Llama3-8B-Instruct do well in summarizing \tilde{E} .

2.2 Hallucination Detection with Evidence

Given the fused evidence E^F and the generated content o, the detection task is to decide whether ohas factual errors conditioned on E^F , then provide the rationale behind this decision. Its working flow is shown in Figure 2 lower left. Specifically, we implement hallucination detection in two manners:

Detection with Fused Evidence. In this way, we directly prompt the detector, a designated LLM \mathcal{M}_d , to check whether the generated content conflicts with the fused evidence. If the output veracity label v is False, it indicates that conflicts exist between E^F and o. Afterward, we prompt \mathcal{M}_d to generate the corresponding rationale r that distinguishes the vital evidence from the fused evidence and explains how E^F determines the veracity label v. Here, we employ in-context learning (ICL), a training-free technique (Dong et al., 2022), which endows the detector model \mathcal{M}_d with higher capacity to generate more reasonable rationale r.

Detection with Self-Consistency. To fully utilize the diversified evidence from multiple sources, we propose an ensemble method, which separately feeds the evidence derived from different sources into the detector \mathcal{M}_d and learns to classify based on the likelihood collected from each source. Specifically, we first compute the likelihood as follows:

$$p(\mathbf{T}|q,o;E^*) = \frac{e^{\mathcal{M}_d(\mathbf{T}|q,o;E^*)/\tau}}{\sum_{v \in \{\mathbf{T},\mathbf{F}\}} e^{\mathcal{M}_d(v|q,o;E^*)/\tau}}, \quad (4)$$

where $E^* \in \{E^S, E^B, E^G, E^U, E^F\}$; T, F de-

⁴We use bge-reranker-large (Xiao et al., 2023) to measure the relevance score between the user query and the evidence.



Figure 3: Screenshot of our hallucination detection and correction system MEDICO. The left shows the interface for entering the user query and the generated response. The middle shows the interface for selecting retrieval sources and uploading files. The right demonstrates the evidence retrieved from diverse sources and their fused evidence.

note True and False, respectively; τ is the temperature coefficient. Afterwards, we get $P = \{p^S, p^B, p^G, p^U, p^F\}$, where $P \in (0, 1)^{5 \times 1}$ is the likelihood vector and each entry measures to what extent the generated content *o* could be entailed by the evidence⁵. We build a binary classifier (*i.e.*, Logistic Regression (Hosmer and Lemeshow, 2000)) upon *P* and use the binary cross-entropy (BCE) loss (de Boer et al., 2005) to optimize the classifier:

$$\mathcal{L}_{BCE}(y, \hat{y}) = y \log(\hat{y}) + (1 - y) \log(1 - \hat{y}),$$
 (5)

where y is the ground truth label, and \hat{y} is the predicted probability of belonging to the positive class.

2.3 Hallucination Correction with Rationale

This module aims to correct the hallucinated parts in the generated content o based on the rationale r, while the other parts remain unchanged. Its working flow is shown in Figure 2 lower right. Inspired by (Gao et al., 2023), we adopt chain-of-thought (CoT), where we prompt the corrector model \mathcal{M}_c to identify the hallucinated spans that need to be edited before correcting o. Then, we prompt \mathcal{M}_c to revise these spans separately and output the corrected one o' that aims to agree with r. We perform multiple rounds of correction until the pre-defined threshold⁶ is reached or the detector \mathcal{M}_d approves.

However, if not restrained, the corrector \mathcal{M}_c may make superfluous modifications, such as reordering words, altering language style, and inserting unnecessary information (Gao et al., 2023; Thorne and Vlachos, 2021). To avoid excessive modifications on o, we first measure preservation using the variant of character-level Levenshtein edit

distance (Gao et al., 2023; Levenshtein et al., 1966) as the metric, which can be formulated as follows:

$$\operatorname{Prev}(o, o') = \max\left(1 - \frac{\operatorname{Lev}(o, o')}{\operatorname{Length}(o)}, 0\right), \quad (6)$$

where $\text{Lev}(\cdot)$ denotes the character-level Levenshtein edit distance function, $\text{Prev}(\cdot)$ measures to what extent o' is consistent with o. If Prev(o, o')equals 1.0, o and o' are the same. On the other hand, if Prev(o, o') equals 0.0, o' is totally different from o. During the iterative correction procedure, we reject those corrected outputs o', when Prev(o, o')is less than δ , a hyper-parameter to be adjusted.

3 User Interface

We build MEDICO using the Gradio package (Abid et al., 2019), an easy-to-use WebUI development framework based on FastAPI and Svelte, which facilitates the deployment of machine learning apps. We can naturally divide the view of MEDICO's system into two parts: (1) retrieval and fusion, and (2) detection and correction, as shown in Figure 3.

Retrieval and Fusion View. To interact with MEDICO, users should first enter a query and the generated response into the corresponding box⁷, or click one of the sample queries, as shown in the left side of Figure 3. Then, users can select the retrieval sources used, including Web, KB, and KG, as stated in §2.1, where users can also use their customized sources by uploading TXT, DOCX, PDF, and MARKDOWN from their local device (see the middle side of Figure 3). By the way, users can adjust the amount of evidence retrieved from each source and the amount of evidence to be used after

⁵We don't compute $p(F|q, o; E^*)$ as it is complementary with $p(T|q, o; E^*)$, where $p(T|q, o; E^*)+p(F|q, o; E^*)=1$.

⁶Given the computational cost, we set the threshold as 5.

⁷As shown in Figure 3, we take the user query "Who is the head of the Commonwealth?" for example. On the other hand, we take the generated content "Queen Elizabeth II is the head of the Commonwealth realm." as an example.

Enderse	Metrics							
Evidence Sources		HR		MRR				
Sources	@1	@3	@5	@1	@3	@5		
(A) Web	0.458	0.589	0.637	0.458	0.518	0.529		
(B) KB	<u>0.851</u>	<u>0.903</u>	<u>0.909</u>	<u>0.851</u>	<u>0.876</u>	<u>0.877</u>		
(C) KG	0.639	0.675	0.680	0.639	0.655	0.657		
(D) Fuse	0.867	0.948	0.964	0.867	0.904	0.908		

Table 1: Retrieval evaluation, where the best results are **boldfaced** and the second-best results are <u>underlined</u>. The higher the metric score, the better the performance.

the reranking, *i.e.*, the hyper-parameter *l*. When the **Submit Button** is clicked, the evidence panel (see the right side of Figure 3) shows the evidence retrieved from each source and the fused evidence.

Detection and Correction View. In this view, MEDICO will request the hallucination detector model \mathcal{M}_d to check whether the generated content o contains factual errors conditioned on the fused evidence E^F provided by the above. If there exist any factual errors, the detection panel will present the symbol of disapproval \checkmark , otherwise it will present the symbol of approval \checkmark . Afterward, if MEDICO detects hallucinations, it will further request the hallucination corrector model \mathcal{M}_c to correct them conditioned on the rationale or the fused evidence, where the rational r and the corrected content o' will be displayed in the rationale panel as well as the correction panel, respectively.

4 **Experiments**

In this section, we conduct extensive experiments on a hallucination evaluation benchmark, HaluEval, to answer the following Research Questions (**RQs**):

- **RQ1:** Whether multi-source evidence retrieval can help improve the recall of golden evidence?
- **RQ2:** How does the fused evidence contribute to the hallucination detection performance in comparison with the evidence from a single source?
- **RQ3:** Can multi-turn editing and the generated rationale enhance the correction performance?

4.1 Experimental Setup

Evaluation Data. We randomly sample 1000 <user query, right answer, hallucinated answer> triplet from HaluEval (Li et al., 2023), as evaluating the hit rate of evidence retrieval is labor-intensive. Then, we retrieve evidence from multiple sources

Evidence	Detectors								
Evidence	L	lama3-8	B	Qwen2-7B					
Sources	Prec	Recall	F1	Prec	Recall	F1			
(A) Zero	0.583	0.632	0.607	0.459	0.601	0.521			
(B) Web	0.755	0.833	0.792	0.873	0.655	0.749			
(C) KB	0.861	0.855	0.858	0.937	0.764	0.842			
(D) KG	0.786	0.772	0.779	0.906	0.705	0.793			
(E) $Fuse_C$	0.925	<u>0.969</u>	<u>0.946</u>	0.995	0.864	<u>0.925</u>			
(F) $\operatorname{Fuse}_{\mathrm{S}}$	<u>0.931</u>	0.972	0.951	<u>0.990</u>	0.808	0.890			
(G) ENSB	0.934	<u>0.969</u>	0.951	0.995	0.868	0.927			

Table 2: Hallucination detection performance with respect to different evidence sources, where Prec is the abbreviation of Precision and F1 represents the F1 score.

(*e.g.*, Web, KB, and KG) and perform evidence fusion, where we set n, m, k, j as 5. We manually identify the golden evidence within the evidence set by checking whether it leads to the right answer.

Evaluation Metrics. For retrieval evaluation, we adopt two commonly used metrics: Hit Rate (HR) and Mean Reciprocal Rank (MRR). We also use the F1 score and approval rate as metrics to evaluate detection and correction performance, respectively.

LLMs for Detection and Correction. We employ two different LLMs: Llama3-8B-Instruct⁸ (Dubey et al., 2024) and Qwen2-7B-Instruct⁹ (Yang et al., 2024). We choose them as the hallucination detector \mathcal{M}_d as well as hallucination corrector \mathcal{M}_c because they are representative open-source LLMs¹⁰.

4.2 Retrieval Evaluation (RQ1)

To verify the necessity of performing multi-source evidence fusion, we experimented to evaluate the quality of retrieval evidence by manually checking whether the evidence could lead to the right answer.

The experimental results are shown in Table 1, where HR measures the ratio of the golden evidence in an unranked list, while MRR further considers the position of the golden evidence in a ranked list. From the results, we find that 'Fuse' performs best in all six cases, which fully demonstrates the effectiveness of fusing evidence from diverse evidence. Besides, KB had a significantly higher recall for golden evidence than Web and KG, which explains why KB performed relatively superior in the following detection and correction.

⁸https://github.com/meta-llama/llama3

⁹https://github.com/QwenLM/Qwen2

¹⁰We use Llama3-8B and Qwen2-7B to represent Llama3-8B-Instruct and Qwen2-7B-Instruct, respectively, for brevity.

Endered						Corre	ectors					
Evidence Sources	Llama3-8B					Qwen2-7B						
	wo/ cor	1st rnd	2nd rnd	3rd rnd	4th rnd	5th rnd	wo/ cor	1st rnd	2nd rnd	3rd rnd	4th rnd	5th rnd
(A) Web		0.701	0.868	0.925	0.943	0.943		0.799	0.896	0.934	0.948	0.948
(B) KB	0.072	<u>0.758</u>	0.899	0.948	<u>0.966</u>	<u>0.966</u>	0.072	0.831	0.909	0.936	0.950	0.950
(C) KG		0.733	0.904	0.945	0.961	0.961		0.798	0.901	0.944	0.961	0.961
(D) $\operatorname{Fuse}_{\mathrm{C}}$		0.794	0.924	<u>0.964</u>	0.979	0.979		0.840	<u>0.939</u>	<u>0.960</u>	0.973	0.973
(E) $Fuse_S$		0.745	0.927	0.970	0.979	0.979		0.880	0.940	0.964	0.973	0.973
(F) RALE		0.720	0.880	0.927	0.941	0.941		<u>0.859</u>	0.922	0.944	0.948	0.948

Table 3: Hallucination correction performance, where 'wo/ cor' mentions no correction, 'rnd' is the abbr of round. What is worth mentioning, 1st rnd represents that the hallucinated content has been corrected one round, and so on.

4.3 Detection Evaluation (RQ2)

To verify the effectiveness of the fused evidence and the ensemble classifier, we evaluate the hallucination detection performance on different retrieval sources and the ensemble of the retrieval sources.

The experimental results are shown in Table 2, where 'Zero' means no evidence provided, 'Fuse_C' fuses evidence via Concatenation, 'Fuses' fuses evidence via Summarization, 'ENSB' denotes the ensemble classifier. (A) performs the worst, indicating the necessity of retrieving external knowledge for detection. Comparing (C) with (B) and (D), we find that well-organized KB can offer more clean and supportive evidence than Web and more informative evidence than KG. Comparing the fused evidence (*i.e.*, $Fuse_C$ and $Fuse_S$) to the evidence from a single source (*i.e*, Web, KB, and KG), we observe that the fused evidence considerably improves detection performance, fully demonstrating the effectiveness of multi-source evidence fusion. Our ensemble classifier performs the best in most cases (5 out of 6 cases). The results further indicate the necessity of multi-source evidence fusion.

4.4 Correction Evaluation (RQ3)

To verify the effectiveness of hallucination correction, we employ the best-performing detector in Section 4.3 to check the revised answer. Besides, we only experiment on the hallucinated answer because the right answer does not need correction.

The experimental results are shown in Table 3, where we employ the approval rate as a metric. From the results, we have the following three observations: (1) If no correction, only 7.2% of hallucination answers can pass the detection, which indicates that the detector can evaluate the performance of the corrector well. (2) Correcting hallucinations with the fused evidence considerably outperforms that with evidence from a single source, showing

the effectiveness of evidence fusion. (3) During the 5th round of correction, the approval rate no longer increases compared to the 4th round of that, which suggests a moderate number of rounds is enough. (4) Though detection with the rationale rperforms worse than that with the fused evidence E^F , the context length of the latter is about five times longer than that of the former.

5 Related Work

5.1 Hallucinations in LLMs

While LLMs have demonstrated remarkable capabilities across a range of downstream tasks, a significant concern revolves around their propensity to generate hallucinations (Zhang et al., 2023; Bang et al., 2023). Hallucinations can be grouped from different viewpoints. One prevailing perspective broadly categorizes the hallucination into two types: Factuality Hallucination and Faithfulness Hallucination (Huang et al., 2023). In fact, hallucinations frequently occur in NLP tasks (Hu et al., 2024) like summarization (Maynez et al., 2020; Cao et al., 2021), machine translation (Guerreiro et al., 2023), dialog systems (Honovich et al., 2021; Dziri et al., 2022) and RAG (Shuster et al., 2021). This work develops a robust hallucination-checking framework to detect and correct factuality hallucinations in LLMs' generated content.

5.2 Hallucinations Detection

Recent studies on hallucination detection mainly focus on factuality hallucinations. SelfCheck-GPT (Manakul et al., 2023) leverages the simple idea that if an LLM knows a given concept, sampled responses are likely to contain consistent facts. FactScore (Min et al., 2023a) is a new evaluation way that breaks a generation into a series of atomic facts and computes the percentage of atomic facts supported by a reliable knowledge source. FacTool (Chern et al., 2023) is a toolaugmented framework, which detects factual errors using tools. RARR (Gao et al., 2022) proposes an intuitive approach by directly prompting LLMs to generate queries, retrieve evidence, and verify actuality. MIND (Su et al., 2024) further leverages the internal states of LLMs for real-time detection. Despite their effectiveness, these methods generally acquire evidence in a single way, which may fall into the absence of key evidence.

5.3 Post-hoc editing for factuality

Recent studies have gone beyond detecting hallucinations to correcting a piece of text to be factually consistent with a set of evidence via post-hoc editing (Shah et al., 2019; Thorne and Vlachos, 2020; Balachandran et al., 2022; Cao et al., 2020; Iso et al., 2020; Gao et al., 2022; IV et al., 2021; Schick et al., 2022). Specifically, FRUIT (IV et al., 2021) and PEER (Schick et al., 2022) both implement an editor fine-tuned on Wikipedia edit history to update outdated information and collaborative writing, respectively. EFEC (Thorne and Vlachos, 2020) also implements a full retrieval-and-correct workflow trained on Wikipedia passages (Thorne et al., 2018b). RARR (Gao et al., 2022) further considers minimal editing. Albeit studied for ages, very limited works exist in combining multi-round correction with the preservation constraint.

6 Conclusion

This work presents MEDICO, an innovative hallucination-checking system, which assists users in detecting and correcting factual errors in LLMs' generated content with multi-source evidence fusion. To the best of our knowledge, MEDICO is the first hallucination detection and correction framework that leverages multi-source evidence fusion, provides the rationale behind the decision, as well as revises the incorrect generated content. Last but not least, MEDICO can not only be used as a tool to help users detect and correct hallucinations in response, but also serve as a security plug-in that automatically checks LLMs' replies in real-time.

Limitations

Despite our innovations and improvements, we must acknowledge certain limitations in our work:

• **Noisy Issue.** During the multi-source evidence fusion stage, MEDICO retrieves evidence from

diverse sources, which inevitably brings lots of noise information. Though we have reranked the evidence set, these noises can still slip through the net, which may exercise a negative influence on the following detection and correction. This is the aspect that needs to be improved in the future.

- **Computation Burden.** During the hallucination detection stage, though our proposed ensemble classifier achieves the best performance in most cases, the ensemble classifier uses the LLM like-lihood collected from multiple sources as input, considerably increasing the computational burden. Considering the trade-off between computational cost and retrieval accuracy, detecting hallucinations using the fused evidence is enough.
- Heuristic Metric. During the hallucination correction stage, we measure the preservation score based on the character-level Levenshtein edit distance. This metric mechanically measures preservation and may underestimate preservation, as it measures preservation based on characters rather than semantics. Currently, preservation evaluating metrics in the field of LLMs remains an open problem that still requires further investigation.

Ethical Consideration

Throughout this work, we develop and evaluate our MEDICO system using an open-source dataset (HaluEval), and two representative open-source LLMs (Llama3-8B and Qwen2-7B), to ensure transparency and integrity in our work. One potential risk associated with our work is that MEDICO supports users to customize retrieval sources by uploading files, which may have data privacy concerns. This is also an essential challenge in the field of LLMs (Sun et al., 2024; Liu et al., 2023). Therefore, we recommend that users can choose to upload open-access files, rather than private files.

Acknowledgments

This work is jointly supported by grants: National Natural Science Foundation of China (No. 62376067), National Natural Science Foundation of China (No. 62406088), and Guangdong Basic and Applied Basic Research Foundation (2023A1515110078). We sincerely thank all the anonymous reviewers for the detailed and careful reviews as well as valuable suggestions, whose help has further improved our work significantly.

References

- Abubakar Abid, Ali Abdalla, Ali Abid, Dawood Khan, Abdulrahman Alfozan, and James Y. Zou. 2019. Gradio: Hassle-free sharing and testing of ml models in the wild. *ArXiv*, abs/1906.02569.
- Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen technical report. *CoRR*, abs/2309.16609.
- Vidhisha Balachandran, Hannaneh Hajishirzi, William Cohen, and Yulia Tsvetkov. 2022. Correcting diverse factual errors in abstractive summarization via post-editing and language model infilling. *ArXiv*, abs/2210.12378.
- Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, Quyet V. Do, Yan Xu, and Pascale Fung. 2023. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. In Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics, IJCNLP 2023 -Volume 1: Long Papers, Nusa Dua, Bali, November 1 - 4, 2023, pages 675–718. Association for Computational Linguistics.
- Farima Fatahi Bayat, Kun Qian, Benjamin Han, Yisi Sang, Anton Belyi, Samira Khorshidi, Fei Wu, Ihab F. Ilyas, and Yunyao Li. 2023. FLEEK: factual error detection and correction with evidence retrieved from external knowledge. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023 - System Demonstrations, Singapore, December 6-10, 2023, pages 124–130. Association for Computational Linguistics.
- Meng Cao, Yue Dong, Jiapeng Wu, and Jackie Chi Kit Cheung. 2020. Factual error correction for abstractive summarization models. In *Proceedings of the* 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6251–6258, Online. Association for Computational Linguistics.
- Mengyao Cao, Yue Dong, and Jackie Chi Kit Cheung. 2021. Hallucinated but factual! inspecting the factuality of hallucinations in abstractive summarization. In Annual Meeting of the Association for Computational Linguistics.
- Ethan Chern, Steffi Chern, Shiqi Chen, Weizhe Yuan, Kehua Feng, Chunting Zhou, Junxian He, Graham

Neubig, and Pengfei Liu. 2023. Factool: Factuality detection in generative ai - a tool augmented framework for multi-task and multi-domain scenarios. *ArXiv*, abs/2307.13528.

- Tsun-Hin Cheung and Kin-Man Lam. 2023. Factllama: Optimizing instruction-following language models with external knowledge for automated fact-checking. In Asia Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2023, Taipei, Taiwan, October 31 - Nov. 3, 2023, pages 846–853. IEEE.
- Pieter-Tjerk de Boer, Dirk P. Kroese, Shie Mannor, and Reuven Y. Rubinstein. 2005. A tutorial on the crossentropy method. *Ann. Oper. Res.*, 134(1):19–67.
- Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, and Zhifang Sui. 2022. A survey on in-context learning. *arXiv preprint arXiv:2301.00234*.
- Hanyu Duan, Yi Yang, and Kar Yan Tam. 2024. Do llms know about hallucination? an empirical investigation of llm's hidden states. *CoRR*, abs/2402.09733.
- Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurélien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Rozière, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Graeme Nail, Grégoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel M. Kloumann, Ishan Misra, Ivan Evtimov, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, and et al. 2024. The llama 3 herd of models. CoRR, abs/2407.21783.
- Nouha Dziri, Ehsan Kamalloo, Sivan Milton, Osmar Zaiane, Mo Yu, E. Ponti, and Siva Reddy. 2022. Faithdial: A faithful benchmark for information-seeking dialogue. *Transactions of the Association for Computational Linguistics*, 10:1473–1490.

- Luyu Gao, Zhuyun Dai, Panupong Pasupat, Anthony Chen, Arun Tejasvi Chaganty, Yicheng Fan, Vincent Zhao, N. Lao, Hongrae Lee, Da-Cheng Juan, and Kelvin Guu. 2022. Rarr: Researching and revising what language models say, using language models. In Annual Meeting of the Association for Computational Linguistics.
- Luyu Gao, Zhuyun Dai, Panupong Pasupat, Anthony Chen, Arun Tejasvi Chaganty, Yicheng Fan, Vincent Y. Zhao, Ni Lao, Hongrae Lee, Da-Cheng Juan, and Kelvin Guu. 2023. RARR: researching and revising what language models say, using language models. In *Proceedings of the 61st Annual Meeting* of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023, pages 16477–16508. Association for Computational Linguistics.
- Nuno M. Guerreiro, Duarte M. Alves, Jonas Waldendorf, Barry Haddow, Alexandra Birch, Pierre Colombo, and André Martins. 2023. Hallucinations in large multilingual translation models. *Transactions of the Association for Computational Linguistics*, 11:1500– 1517.
- Or Honovich, Leshem Choshen, Roee Aharoni, Ella Neeman, Idan Szpektor, and Omri Abend. 2021. Q2: Evaluating factual consistency in knowledgegrounded dialogues via question generation and question answering. ArXiv, abs/2104.08202.
- David W. Hosmer and Stanley Lemeshow. 2000. Applied Logistic Regression, Second Edition. Wiley.
- Xiangkun Hu, Dongyu Ru, Lin Qiu, Qipeng Guo, Tianhang Zhang, Yang Xu, Yun Luo, Pengfei Liu, Yue Zhang, and Zheng Zhang. 2024. Refchecker: Reference-based fine-grained hallucination checker and benchmark for large language models. *ArXiv*, abs/2405.14486.
- Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. 2023. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *CoRR*, abs/2311.05232.
- Hayate Iso, Chao Qiao, and Hang Li. 2020. Fact-based Text Editing. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 171–182, Online. Association for Computational Linguistics.
- Robert L Logan IV, Alexandre Passos, Sameer Singh, and Ming-Wei Chang. 2021. Fruit: Faithfully reflecting updated information in text. In North American Chapter of the Association for Computational Linguistics.
- Vladimir I Levenshtein et al. 1966. Binary codes capable of correcting deletions, insertions, and reversals. In *Soviet physics doklady*, volume 10, pages 707–710. Soviet Union.

- Junyi Li, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. 2023. Halueval: A large-scale hallucination evaluation benchmark for large language models. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023, pages 6449–6464. Association for Computational Linguistics.
- Yang Liu, Yuanshun Yao, Jean-Francois Ton, Xiaoying Zhang, Ruocheng Guo, Hao Cheng, Yegor Klochkov, Muhammad Faaiz Taufiq, and Hang Li. 2023. Trust-worthy llms: a survey and guideline for evaluating large language models' alignment. *CoRR*, abs/2308.05374.
- Potsawee Manakul, Adian Liusie, and Mark John Francis Gales. 2023. Selfcheckgpt: Zero-resource blackbox hallucination detection for generative large language models. *ArXiv*, abs/2303.08896.
- Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan T. McDonald. 2020. On faithfulness and factuality in abstractive summarization. *ArXiv*, abs/2005.00661.
- Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2023a. Factscore: Fine-grained atomic evaluation of factual precision in long form text generation. *ArXiv*, abs/2305.14251.
- Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen-tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2023b. Factscore: Fine-grained atomic evaluation of factual precision in long form text generation. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023, pages 12076–12100. Association for Computational Linguistics.
- OpenAI. 2023. GPT-4 technical report. CoRR, abs/2303.08774.
- Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy P. Lillicrap, Jean-Baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, Ioannis Antonoglou, Rohan Anil, Sebastian Borgeaud, Andrew M. Dai, Katie Millican, Ethan Dyer, Mia Glaese, Thibault Sottiaux, Benjamin Lee, Fabio Viola, Malcolm Reynolds, Yuanzhong Xu, James Molloy, Jilin Chen, Michael Isard, Paul Barham, Tom Hennigan, Ross McIlroy, Melvin Johnson, Johan Schalkwyk, Eli Collins, Eliza Rutherford, Erica Moreira, Kareem Ayoub, Megha Goel, Clemens Meyer, Gregory Thornton, Zhen Yang, Henryk Michalewski, Zaheer Abbas, Nathan Schucher, Ankesh Anand, Richard Ives, James Keeling, Karel Lenc, Salem Haykal, Siamak Shakeri, Pranav Shyam, Aakanksha Chowdhery, Roman Ring, Stephen Spencer, Eren Sezener, and et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. CoRR, abs/2403.05530.

- Timo Schick, Jane Dwivedi-Yu, Zhengbao Jiang, Fabio Petroni, Patrick Lewis, Gautier Izacard, Qingfei You, Christoforos Nalmpantis, Edouard Grave, and Sebastian Riedel. 2022. Peer: A collaborative language model. *ArXiv*, abs/2208.11663.
- Darsh J. Shah, Tal Schuster, and Regina Barzilay. 2019. Automatic fact-guided sentence modification. In AAAI Conference on Artificial Intelligence.
- Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. 2021. Retrieval augmentation reduces hallucination in conversation. In *Conference* on Empirical Methods in Natural Language Processing.
- Weihang Su, Changyue Wang, Qingyao Ai, Yiran Hu, Zhijing Wu, Yujia Zhou, and Yiqun Liu. 2024. Unsupervised real-time hallucination detection based on the internal states of large language models. *CoRR*, abs/2403.06448.
- Lichao Sun, Yue Huang, Haoran Wang, Siyuan Wu, Qihui Zhang, Chujie Gao, Yixin Huang, Wenhan Lyu, Yixuan Zhang, Xiner Li, et al. 2024. Trustllm: Trustworthiness in large language models. *arXiv preprint arXiv:2401.05561*.
- James Thorne and Andreas Vlachos. 2020. Evidencebased factual error correction. In Annual Meeting of the Association for Computational Linguistics.
- James Thorne and Andreas Vlachos. 2021. Evidencebased factual error correction. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021, pages 3298–3309. Association for Computational Linguistics.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018a. FEVER: a large-scale dataset for fact extraction and verification. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 809–819. Association for Computational Linguistics.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018b. Fever: a large-scale dataset for fact extraction and verification. *ArXiv*, abs/1803.05355.
- Xiaozhi Wang, Tianyu Gao, Zhaocheng Zhu, Zhengyan Zhang, Zhiyuan Liu, Juanzi Li, and Jian Tang. 2021. KEPLER: A unified model for knowledge embedding and pre-trained language representation. *Trans. Assoc. Comput. Linguistics*, 9:176–194.
- Yuxia Wang, Revanth Gangi Reddy, Zain Muhammad Mujahid, Arnav Arora, Aleksandr Rubashevskii, Jiahui Geng, Osama Mohammed Afzal, Liangming

Pan, Nadav Borenstein, Aditya Pillai, Isabelle Augenstein, Iryna Gurevych, and Preslav Nakov. 2023. Factcheck-gpt: End-to-end fine-grained documentlevel fact-checking and correction of LLM output. *CoRR*, abs/2311.09000.

- Yuxia Wang, Minghan Wang, Muhammad Arslan Manzoor, Fei Liu, Georgi Georgiev, Rocktim Jyoti Das, and Preslav Nakov. 2024. Factuality of large language models in the year 2024. *CoRR*, abs/2402.02420.
- Jerry Wei, Chengrun Yang, Xinying Song, Yifeng Lu, Nathan Hu, Dustin Tran, Daiyi Peng, Ruibo Liu, Da Huang, Cosmo Du, and Quoc V. Le. 2024. Longform factuality in large language models. *CoRR*, abs/2403.18802.
- Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighoff. 2023. C-pack: Packaged resources to advance general chinese embedding.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zhihao Fan. 2024. Qwen2 technical report. arXiv preprint arXiv:2407.10671.
- Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, Longyue Wang, Anh Tuan Luu, Wei Bi, Freda Shi, and Shuming Shi. 2023. Siren's song in the ai ocean: A survey on hallucination in large language models. *ArXiv*, abs/2309.01219.

Question: What year did the German composer whose compositions are in The Individualism of Gil Evans die? **Right answer: 1950**

Hallucinated answer: Kurt Weill passed away in 1955.

1st round: Kurt Weill passed away in 1955.
Detection: ×
Preservation: 🗸
2nd round: Kurt Weill passed away in 1950.
Detection: 🗸

Preservation:

Table 4: A multi-turn correction example from HaluEval, where the right answer and hallucinated answer are marked in **green** and **red**, respectively.

A Case Study

We provide some cases to present the procedure of the detection and correction: (1) Table 4 shows the corrector fails to correct the hallucinated content and is not approved by the detector, in the 1st round. Hence, the 2nd round of correction is made and the hallucination content is successfully corrected. (2) Table 5 shows, that in the 1st round, the corrector successfully corrects the hallucinated content but inserts much unnecessary information, which triggers the filtering. Hence, the corrector continues to make corrections until the preservation score Prev(o, o') is greater than or equal to the threshold δ . (3) As shown in Table 6, in the 1st round, the corrector fails to correct the hallucinated content and also inserts much unnecessary information. Hence, the corrector continues to make corrections until the hallucinated content is successfully corrected and the preservation score Prev(o, o') is greater than or equal to the threshold δ , simultaneously.

B Workflow of MEDICO

Algorithm 1 demonstrates the working flow of the proposed MEDICO framework. It can be divided into three stages: (I) Multi-source Evidence Fusion, (II) Hallucination Detection with Evidence, and (III) Hallucination Correction with Rationale. In brief, during the stage I, MEDICO retrieves evidence from diverse sources, then combines and fuses them to get the fused evidence. During the stage II, MEDICO identify hallucinations using the fused evidence or the ensemble of evidence and provide the rationale behind such a decision. During the stage III, MEDICO performs multi-round corrections until the pre-defined threshold is reached or the detection is approved, where the corrected output o' with lower preservation will be rejected.

Question: What is the stage name of the young female actress who starred in the 2008 American drama Gran Torino directed and produced by Clint Eastwood?

Right answer: Ahney Her

Hallucinated answer: The actress who starred in the 2008 movie directed by Clint Eastwood and co-starred Christopher Carley and Bee Vang is Whitney Cua Her.

1st round: The actress who starred in the 2008 movie directed by Clint Eastwood who also starred in the film and co-starred Christopher Carley and Bee Vang is **Ahney Her**, better known by her stage name Ahney Her, is an American actress.

Detection: 🗸

Preservation: X

2nd round: The actress who starred in the 2008 movie directed by Clint Eastwood and co-starred Christopher Carley and Bee Vang is **Ahney Her**, better known by her stage name Ahney Her, is an American actress.

Detection: 🗸

Preservation: X

3rd round: The actress who starred in the 2008 movie directed by Clint Eastwood and co-starred Christopher Carley and Bee Vang is **Ahney Her**.

Detection: 🗸

Preservation: 🗸

Table 5: An example showing that the filtering gets triggered as the edit distance is too large, where the unnecessary information inserted by the corrector is highlighted.

Question: Which American restaurant chain and international franchise founded in 1958 that Baiada Poultry is a provider of?

Right answer: Pizza Hut

Hallucinated answer: Baiada Poultry is a provider of Subway.

1st round: Baiada Poultry is a provider of Subway, which is an American restaurant chain and international franchise founded in 1958.
Detection: X
Preservation: X
2nd round: Baiada Poultry is a provider of Pizza Hut, which is an American restaurant chain and international franchise founded in 1958.
Detection: ✓

Preservation: X

3rd round: Baiada Poultry is a provider of Pizza Hut.
Detection: ✓
Preservation: ✓

Table 6: An example showing that the multi-turn correction is conducted and the edit distance filtering is triggered.

Algorithm 1 The Workflow of MEDICO

Input: User query q, the generated content o, the hallucination detector \mathcal{M}_d and corrector \mathcal{M}_c , the minimum preservation threshold δ .

Output: The veracity label v, the rationale r, and the corrected content o'.

- 1: Launch the search engine (Web) interface, the knowledge base (KB), and the knowledge graph (KG).
- 2: # Step I: Multi-source Evidence Fusion

- 3: Search the *n* most relevant snippets $E^S = \{e_1^s, e_2^s, ..., e_n^s\}$ from the Web. 4: Retrieve the *m* most relevant chunks $E^B = \{e_1^b, e_2^b, ..., e_m^b\}$ from the KB. 5: Recall the k most relevant linearized triplets $E^G = \{e_1^g, e_2^g, ..., e_k^g\}$ for the KG.
- 6: if Customized retrieval source provided by users then
- Retrieve the j most relevant chunks $E^U = \{e_1^u, e_2^u, ..., e_i^u\}$ from the UF. 6:
- 7: **end if**
- 8: Get the combined evidence set $E = \{e_1, e_2, \dots, e_{n+m+k+j}\}$ with Eq. (1).
- 9: Rerank the combined evidence set and get the newly ordered evidence set $\tilde{E} = \{\tilde{e}_1, \tilde{e}_2, ..., \tilde{e}_l\}$ with Eq. (2).
- 10: Fuse the newly ordered evidence set and get the fused evidence E^F with Eq. (3).
- 11: # Step II: Hallucination Detection with Evidence
- 12: if Training classifier then
- Compute the LLM likelihood $P = \{p^S, p^B, p^G, p^U, p^F\}$ with Eq. (4). 12:
- Train a binary classifier (Logistic Regression (Hosmer and Lemeshow, 2000)) using the collected 12: LLM likelihood P with Eq. (5).
- 12: Use the trained classifier to check whether the generated content o has factual errors and output the veracity label v.
- 13: **else**
- Prompt \mathcal{M}_d to check whether the generated content o conflicts with the fused evidence E^F and 13: output the veracity label v.
- 14: end if
- 15: Prompt \mathcal{M}_d to generate the corresponding rationale behind such a decision.

16: # Step III: Hallucination Correction with Rationale

- 17: **if** The veracity label v is False **then**
- for each $i \in [1, 5]$ do 18:
- Identify the hallucinated spans that need to be edited using \mathcal{M}_c . 18:
- Prompt \mathcal{M}_c to revise these spans separately and output the corrected content o'. 18:
- Prompt \mathcal{M}_d to check whether o' has factual errors and output the veracity label v'. 18:
- if The veracity label v' is False then 19:
- Continue; 19:
- 20: end if
- Measure the preservation score between o and o' with Eq. (6). 20:
- if The preservation score Prev(o, o') is greater than δ then 21:
- Break: 21:
- end if 22:
- end for 23:
- 24: else
- Assign o to o'. 24:
- 25: end if

```
26: return v, r, o'
```