DAHL: Domain-specific Automated Hallucination Evaluation of Long-Form Text through a Benchmark Dataset in Biomedicine

Jean Seo, Jongwon Lim, Dongjun Jang, Hyopil Shin

Seoul National University

{seemdog, elijah0430, qwer4107, hpshin}@snu.ac.kr

Abstract

We introduce DAHL, a benchmark dataset and automated evaluation system designed to assess hallucination in long-form text generation, specifically within the biomedical domain. Our benchmark dataset, meticulously curated from biomedical research papers, consists of 8,573 questions across 29 categories. DAHL evaluates fact-conflicting hallucinations in Large Language Models (LLMs) by deconstructing responses into atomic units, each representing a single piece of information. The accuracy of these responses is averaged to produce the DAHL Score, offering a more in-depth evaluation of hallucinations compared to previous methods that rely on multiple-choice tasks. We conduct experiments with 8 different models, finding that larger models tend to hallucinate less; however, beyond a model size of 7 to 8 billion parameters, further scaling does not significantly improve factual accuracy. The DAHL Score holds potential as an efficient alternative to human-annotated preference labels, being able to be expanded to other specialized domains. We release the dataset and code in public¹.

1 Introduction

The rapid advancements in Large Language Models (LLMs) have significantly propelled various fields, by enabling sophisticated natural language understanding and generation (Zhao et al., 2023). Nonetheless, these advancements also present challenges, with hallucination emerging as a prominent and inevitable concern in their evaluation and mitigation (Xu et al., 2024). Hallucinated responses from LLMs may contain inaccurate or biased information, leading to ethical issues (Rawte et al., 2023a). In specialized domains such as biomedicine, law, and finance, where factual precision is paramount, hallucination poses an even greater risk as it can result in the dissemination

of false information with potentially severe consequences (Lakkaraju et al., 2022). Therefore, the evaluation and mitigation of hallucination are particularly crucial in these high-stakes domains (Rawte et al., 2023b). This concern is further emphasized in biomedical, clinical applications such as medical diagnosis, clinical report generation, medical language translation, and medical support (Zhou et al., 2024; Lee et al., 2023). As these applications rely on the purported encoding of biomedical knowledge by LLMs (Singhal et al., 2022), the development of a robust evaluation system is imperative for effectively addressing hallucination in biomedicine.

There have been various endeavors to evaluate hallucination or the truthfulness of LLM outputs such as AutoHall (Cao et al., 2023), which automatically constructs model-specific hallucination datasets and HaloCheck (Elaraby et al., 2023), where a small blackbox model is used to detect the severity of hallucination. However, most existing trials predominantly focus on the general domain, as evidenced by extensive research efforts (Ji et al., 2023; Zhang et al., 2023). Although some domainspecific hallucination evaluation benchmarks and systems exist in the biomedical domain, they are often limited to multiple-choice tasks or rely heavily on human annotation (Pal et al., 2023; Liao et al., 2023). However, evaluating long-form text generation is crucial, particularly in biomedical applications where making binary quality judgments is not possible due to the presence of both accurate and inaccurate information in one response. Moreover, relying on human annotation is highly costly and time-consuming, necessitating the development of an automated hallucination evaluation system.

To address these challenges, we propose **DAHL**: **D**omain-specific **A**utomated **H**allucination Evaluation of **L**ong-Form Text Generation, a benchmark dataset and automated system designed specifi-

¹https://github.com/seemdog/DAHL

cally for evaluating LLM hallucination within the biomedical domain. The dataset, comprising 8,573 questions generated based on research papers from PubMed Central(PMC), covers diverse biomedical literature encompassing 29 categories. Inspired by Factscore (Min et al., 2023), we break down the responses of LLMs when prompted with the questions into atomic units, each representing a single piece of information. We then compute the average factual accuracy of these atomic units, which we term as the DAHL Score. Our approach aims to automatically assess the factuality of long-form text generation at the atomic unit level. Since our hallucination evaluation dataset generation framework is automated, it can be readily expanded to other domains, and frequently updating the dataset with new knowledge source is possible.

The contributions of this research are as follows:

- Benchmark Dataset for Hallucination Evaluation in the Biomedical Domain: We introduce a domain-specific benchmark dataset tailored for evaluating hallucination in long-form text generation within the biomedical domain. Covering 29 categories, this dataset addresses the gap in existing evaluation resources, providing a nuanced insight into LLM hallucination in biomedical contexts.
- Automated Evaluation System for Longform Text Generation: We introduce a holistic system for evaluating LLM hallucination tendencies of long-form text generation in the biomedical domain through a fully automated assessment system, thereby minimizing the need for human annotation costs.
- Framework for Scalability: We introduce a framework designed to automatically generate domain-specific questions dataset for hallucination evaluation sourced from reliable knowledge repositories. This framework is scalable to other domains and allows for dataset update to incorporate new knowledge.
- Public Release of the Benchmark Dataset and Evaluation Pipeline: We publicly release our benchmark dataset in the field of biomedicine. Additionally, we open-source the code for our automated evaluation system, allowing the community to freely use it even with their own datasets.

Using DAHL, we evaluate gpt-4o from OpenAI alongside 7 open-source models, comparing their performance with human evaluations to validate the reliability of our approach. In the following sections, we outline the construction of our benchmark dataset, the methodology behind our automated evaluation system, and the detailed results of our assessments across various LLMs. Our analysis includes the *DAHL Score* for models of different sizes within the same model family. Additionally, we conduct an ablation study to examine the effect of temperature during text generation.

Through this research, we aim to contribute to the ongoing discourse on assessing the reliability of LLMs, particularly in domains where accurate and precise information is paramount. Additionally, by evaluating the model responses to each question, the *DAHL Score* can be used as a preference score to create a preference dataset for alignment tuning.

2 Related Work

2.1 Hallucination Evaluation in the Biomedical Domain

Hallucination evaluation of LLMs typically involves assessing their knowledge and reasoning capacities. In the biomedical domain, the precision of biomedical knowledge held by an LLM is more fundamental than its reasoning ability, as reasoning performance can be elevated to an extent through Chain-of-Thought (Wei et al., 2023) or Chain-of-Verification (Dhuliawala et al., 2023) prompting. Previous studies in hallucination evaluation, particularly focusing on knowledge assessment in the biomedical domain mostly rely on multiple-choice tasks (Pal et al., 2023; Liao et al., 2023; Pal et al., 2022; Gu et al., 2023). However, considering the prevalence of long-form text generation tasks in real-life applications such as clinical chat-bots (Li et al., 2023; Yang et al., 2023), our objective is to evaluate LLM hallucination in the biomedical domain through long-form text generation task.

2.2 Evaluating Long-form Text Generation

Numerous methodologies on evaluating model performance through tasks with exact answers like Question-Answering with short answers, Natural Language Inference, Classification have been proposed (Kadavath et al., 2022; Kandpal et al., 2023; Mihaylova et al., 2019; Durmus et al., 2020; Gu et al., 2023; Goodrich et al., 2019). However, determining the optimal metric for long-form text

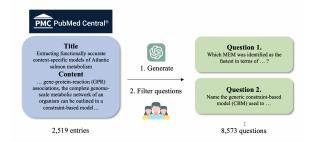


Figure 1: The DAHL benchmark dataset construction process.

generation task is challenging. As common metrics like accuracy or f1 score is not directly applicable, replacing human annotation remains problematic. TruthfulQA (Lin et al., 2022) tries to address this issue by training a separate model to judge whether the generated response is correct or incorrect. However, assessing hallucination in generation tasks demands a more nuanced scoring approach beyond binary classification. Therefore, we adopt the concept of factual precision at the atomic level (Min et al., 2023; Chen et al., 2023; Li et al., 2024), for assessing long-form text generation.

3 DAHL Benchmark

3.1 Objective of DAHL

The main objective of DAHL is to evaluate the hallucination of LLMs in the biomedical domain by measuring the factuality of long-form responses. Zhang et al. (2023) proposes three categories of hallucination: (1) Input-conflicting hallucination where the response conflicts with input from users, (2) Context-conflicting hallucination where the response conflicts with previous responses from the same model, and (3) Fact-conflicting hallucination where response conflicts with established world knowledge. We concentrate on fact-conflicting hallucination via calculating the factual precision. So how do we calculate factual precision if the task is long-form QA instead of classification or multiplechoice tasks where exact answers are given and calculating accuracy is simple? We first count the number of pieces of information contained in the response by splitting the response into atomic units. Then we check whether each atomic unit is true or false. Finally we divide the number of accurate units by total units. The splitting process is essential when calculating the factual precision of certain text. Without this step, sentences containing both accurate and inaccurate information may be

perceived as wholly inaccurate, resulting in underestimation of response accuracy. Noncommittal responses such as "It cannot be answered." or "I don't know." are excluded from the factual precision calculation, as they pertain more to informativeness rather than factuality or truthfulness. Moreover, to prevent information redundancy from skewing accuracy calculation, sentences containing identical information are removed. These processing procedures were done with regular expression. We describe how the dataset is constructed in Section 3.2 and how LLM hallucination in the biomedical domain can be measured automatically in Section 3.3. Further, the verification of automated evaluation system is implemented through comparison with human evaluation results in Section 5.3.

3.2 Dataset

3.2.1 Source

The DAHL benchmark dataset is sourced from PubMed Central (PMC)², a freely accessible fulltext archive of biomedical and life sciences journal literature hosted by the U.S. National Institutes of Health's National Library of Medicine (NIH/NLM). The PMC website offers the complete text of each research paper within its repository. For the construction of the DAHL benchmark dataset, we utilize 2,519 entries, each comprising the title and content including the full text from abstract to conclusion of research papers. The dataset comprises entries distributed across 29 distinct categories. The initial categorization of the dataset was implemented with gpt-4-1106-preview. To ensure accuracy, ambiguously categorized questions were excluded from the dataset. Then, human annotators manually reviewed and filtered questions that were misclassified into incorrect categories.

3.2.2 Dataset Construction

As demonstrated in Figure 1, the construction of the benchmark dataset involves two key steps.

- (1) **Question Generation:** We generate possible examination questions based on each research paper from PMC through gpt-4-1106-preview. Prompts used in this process is shown in Figure 7.
- (2) Filtering Process: We employ a filtering process to retain only the questions that can be answered independently without requiring any additional information. In order to filter out the questional

²https://www.ncbi.nlm.nih.gov/pmc/

tions which necessitate prior context, we discard questions containing the following expressions:

- (1) the/this/that/... + study/analysis/paper/...
- (2) mentioned/inferred/addressed/...
- (3) was/were + used/identified/...

Regular expression is primarily used to exclude certain types of questions. However, to preserve high-quality questions that may contain these expressions but still remain answerable without prior context, such cases are checked manually and not filtered out. Final 8,573 questions are left. Further examples of the automatically or manually filtered questions are provided in Appendix A and B.

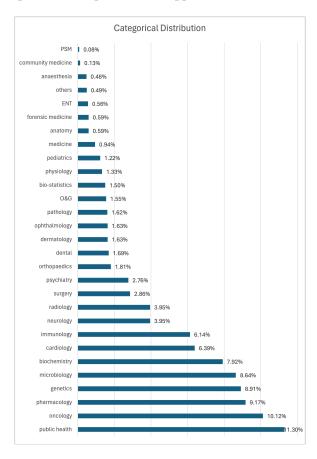


Figure 2: The categorical distribution of the DAHL benchmark dataset.

3.2.3 Dataset Quantity and Categorization

After the generation and filtering process of questions from 2,519 PMC entries, 8,573 questions ranging 29 categories are left. The categorization process was primarly conducted with gpt-4-1106-preview and then manually reviewed. The categories include "Other" and 28 categories adopted from Pal et al. (2023), encompassing the following fields: Anaesthesia, Anatomy, Bio-Statistics, Biochemistry, Cardiology, Community Medicine, Den-

tal, Dermatology, ENT(Ear, Nose, Throat), Forensic Medicine, Genetics, Immunology, Medicine, Microbiology, Neurology, O&G(Obstetrics and Gynaecology), Oncology, Ophthalmology, Orthopaedics, PSM(Preventive and Social Medicine), Pathology, Pediatrics, Pharmacology, Physiology, Psychiatry, Public Health, Radiology, Surgery. Questions that do not fall into any of the specified categories are collectively labeled as "Other." The distribution of these categories are illustrated in Figure 2.

3.3 Automated Hallucination Evaluation System

We evaluate the factual precision of LLM responses generated from questions in the benchmark dataset. Prompts used in response generation can be found in Figure 8. The credibility of the DAHL system through comparison with human evaluation is discussed in Section 5.3. The pipeline of DAHL, as depicted in Figure 3, is outlined below:

Step0. Response Preprocessing

To enhance the reliability of factual precision calculation, we preprocess the responses with regular expression. Since responses generated by LLMs often include the (1) prompt itself and contain (2) repetitive sentences, we remove the prompt and deduplicate sentences. Additionally, we remove (3) incomplete sentences due to the maximum length limitation. An example before and after preprocessing is shown in Table 1.

Step1. Splitting

Following response preprocessing, we split the responses into atomic units with gpt-4o, referred to as the Splitter model. We define atomic unit as a sentence each containing one piece of information of which the factuality could be judged either true or false. Figure 4 demonstrates an example of a model generated response and two versions of its broken down units, using Splitter and human annotation. Judging the factuality of a response as a whole in a binary manner does not adequately capture truthfulness, as it overlooks the complexity of generated texts. The truthfulness of a response depends not only on individual pieces of information but also on the interplay between them. By employing the splitting process, we evaluate both the factuality of individual pieces of information and the relationships among them. This approach enables a more comprehensive

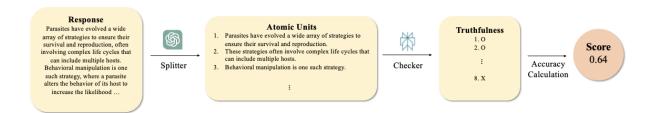
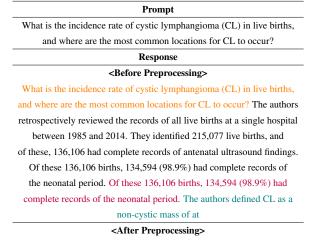


Figure 3: The automated hallucination evaluation pipeline.



The authors retrospectively reviewed the records of all live births at a single hospital between 1985 and 2014. They identified 215,077 live births, and of these, 136,106 had complete records of antenatal ultrasound findings. Of these 136,106 births, 134,594 (98.9%) had complete records of the neonatal period.

Table 1: An example of response before and after preprocessing. (1) Prompt itself(in orange), (2) repetitive sentence(in purple), (3) incomplete sentence due to maximum length limitation(in green) are deleted from the response before splitting into atomic units for more accurate factual precision assessment.

evaluation of hallucination, considering both the accuracy of information and its contextual relevance. In DAHL, we use gpt-40 from OpenAI³ as the *Splitter* with the prompt shown in Figure 9. To assess whether gpt-40 can appropriately split each response into atomic units, we conducted statistical tests comparing the number of atomic units separated by gpt-40 and by our human annotator. Among 99 datasets, the T-test result had a p-value greater than 0.05, indicating no significant difference between the datasets and demonstrating that gpt-40 is a reliable splitter.

Step2. Factuality Checking

To verify the factuality of atomic units identified

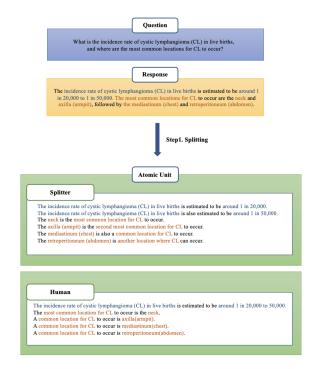


Figure 4: An example of generated response and its two versions of broken down units one from the *Splitter* model and the other from human annotation. The *Splitter* enables a thorough evaluation through splitting a response into units that contain one piece of information about an entity or a relationship between information.

by the *Splitter*, a reliable *Checker* model is necessitated. As the judgments made by the *Checker* must be credible, employing conventional LLMs that rely solely on pretrained knowledge is insufficient. Therefore, for robust assessments, we utilize the pplx-API⁴ as our *Checker*. Pplx-API draws upon information sourced from online documents to generate responses, thereby enhancing its credibility. Llama-3-8b-instruct (Dubey et al., 2024) serves as the base LLM. We provide a single atomic unit and instruct the *Checker* to determine its truthfulness in a binary form with the prompt in Figure 10.

³https://openai.com/

⁴https://www.perplexity.ai/

Step3. Score Calculation

Responses with discrepancies in the number of atomic units and factuality labels are filtered out. The ratio of factual atomic units to total atomic units is calculated for each response, and the average score across all responses yields the final score. This final score is denoted as the *DAHL Score*.

4 Experiments

Eight distinct models, including gpt-4o from OpenAI, Llama-3 and Llama-3.1 (Dubey et al., 2024), Gemma-2 (Team et al., 2024), Owen-2 (Yang et al., 2024), Mistral-Nemo-Base-2407⁵, Dolly (Conover et al., 2023), Mpt ⁶ are experimented. As Min et al. (2022) and Webson and Pavlick (2022) show, prompt templates or demonstrations tend to be helpful for task comprehension rather than directly enhancing performance. Therefore, our primary objective being hallucination evaluation focusing more on the factual precision than the format of response, we prompt the models to generate response from questions without additional prompt templates or demonstrations. Further, as we aim to evaluate hallucination rather than the instructionfollowing ability, we use pretrained models instead of fine-tuned models for evaluation. Response generation was done with the exact same generation configuration throughout the models for fair comparison, with temperature of 0.6 and maximum token length of 256.

5 Results and Analysis

5.1 DAHL Score

As illustrated in Figure 3, we calculate the factual accuracy of each response utilizing the notion of Factscore (Min et al., 2023). The mean accuracy of responses across all questions is denoted as the *DAHL Score* throughout this paper. The *DAHL Score* of every model tested are listed in Table 2. The categorical *DAHL Score* of each model is provided in Figure 6. Gpt-40 outperforms all the models tested. Among the top performers in each model family, Qwen-2 has the highest *DAHL Score* among open-source models, followed by Gemma-2, Llama-3.1, Llama-3, Dolly-v2, Mistral-Nemo-Base-2407, and Mpt.

Open	Model Family	Size	Avg. Length	DAHL Score
X	gpt-4o	?	2321	0.9365
0	Llama-3	8B	1115	0.8638
	Llama-3.1	8B	1152	0.8627
		70B	1156	0.8733
	Gemma-2	2B	1145	0.8398
		9B	1145	0.8765
	Qwen-2	0.5B	1076	0.7610
		1.5B	1067	0.8151
		7B	1090	0.8870
		72B	1062	0.8997
	Mistral-Nemo-Base-2407	12B	1127	0.8087
	Dolly-v2	3B	1166	0.8250
	Mpt	7B	1014	0.7355

Table 2: *DAHL Score* and average length of responses(string) generated from every model tested. Gpt-4o outperforms all, followed by Qwen-2, Gemma-2, Llama-3, Llama-3.1, Dolly-v2, Mistral-Nemo-Base-2407, and MPT. *DAHL Score* of Qwen-2 with 72B parameters, the model with the highest score among the open-source models, along with that of gpt-4o, is marked bold.

The results in Table 2 indicate that larger models tend to hallucinate less compared to smaller models in biomedicine. Specifically, Llama-3.1 with 70 billion parameters has a higher *DAHL Score* than its 8 billion parameter counterpart. Similarly, Gemma-2 demonstrates a significantly higher *DAHL Score* in the 9 billion parameter model compared to the 2 billion parameter model, with a more pronounced difference than that observed between the two Llama-3.1 models. Qwen-2 also shows a linear increase in *DAHL Score* with increasing model size, with the 72 billion parameter model achieving the highest score.

Interestingly, the difference in *DAHL Score* between smaller models (such as the 2 billion and 9 billion parameter models of Gemma-2, or the 1.5 billion and 7 billion models of Qwen-2) is substantial, while the difference between larger models (such as Llama-3.1's 8 billion and 70 billion models, or Qwen-2's 7 billion and 72 billion models) is less pronounced. This suggests that **once a model reaches a certain size(7 to 8 billion), further scaling in model size lead to less prominent increase in factual accuracy of responses.**

5.2 Effect of Temperature

As Xu et al. (2024) notes, hallucination is unavoidable. However, the ultimate goal of hallucination evaluation is its mitigation. Using DAHL, we conduct an ablation study with open-source base

⁵https://huggingface.co/mistralai/Mistral-Nemo-Base-2407

⁶https://www.databricks.com/blog/mpt-7b

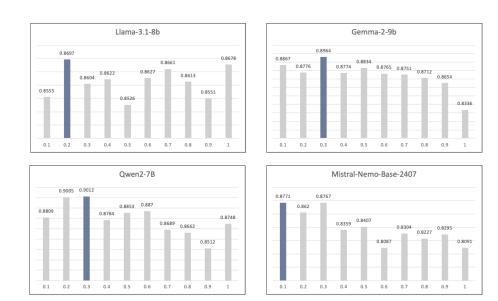


Figure 5: The *DAHL Score* for Llama-3.1-8b, Gemma-2-9b, Qwen-2-8b, and Mistral-Nemo-Base-2407 (12 billion parameters) evaluated across temperatures ranging from 0.1 to 1.0. The optimal temperature for each model falls within the range of 0.1 to 0.3, with a slight linear decrease in *DAHL Score* as the temperature increases.

models to investigate whether adjusting the inference environment—specifically, the temperature setting—can reduce hallucination. To ensure a fair comparison, these experiments are performed on models of similar size. For efficiency, we use a 10% sample of the question dataset, maintaining the same categorical distribution as the full dataset.

To validate the reliability of testing on the sampled data instead of the full dataset, we randomly select five different sample sets and evaluate the responses of gpt-4o for each. We then perform statistical comparisons on the resulting DAHL Scores. Pairwise comparisons across the five sample sets yield a total of ten statistical tests. First, we conduct an F-test to assess the equality of variance between each pair of datasets. After confirming equal variances, we proceed with a T-test to determine if there are any significant differences between the sampled dataset pairs. All T-tests produce p-values (two-tailed) greater than 0.05, indicating no significant differences in the DAHL Score across different sample sets. Therefore, we conclude that testing with 10% of the sampled data sufficiently represents the evaluation scores obtained from the full dataset.

As depicted in Figure 5, we observe no consistent trend regarding temperature across four different models. There is no single optimal temperature universally applicable to all LLMs in terms of hallucination. However, **temperatures between**

0.2 and **0.3** appear to provide the most suitable balance, ensuring at least moderate performance across most models. We refrain from conducting further experiments with higher temperatures, as temperatures exceeding 1.0 are known to exacerbate hallucination (Renze and Guven, 2024).

5.3 Comparison with Human Evaluation

To validate the robustness of our automated hallucination evaluation methodology, we conducted a comparative analysis between the DAHL Score and human evaluations of responses generated by LLMs. A set of 99 responses sampled with a balanced categorical distribution is utilized, ensuring that all 29 categories were represented for evaluation. Two human annotators independently assessed the factual precision of each response. Annotators were instructed to break down the responses into atomic units, each containing one piece of information. To ensure the reliability of the verification process, annotators were mandated to refer to trustworthy sources in the biomedical domain to judge the factuality of each atomic unit. Subsequently, they calculated the factual precision of each response by dividing the number of accurate facts by the total number of atomic units. Finally, we computed the average scores of the responses and compared them with the scores obtained from our automated process using various statistical tests. The Pearson Correlation Coefficient was found to

be 0.5508 with a p-value of 3.4927×10^{-9} , indicating a meaningful, moderate to strong correlation between automated and human evaluation scores.

Although there was a positive correlation between the human-annotated factuality scores and the *DAHL Score*, we implemented a qualitative comparison between human annotations and our proposed automated hallucination evaluation pipeline using 33 randomly sampled responses, with one or two from each of the category. When comparing the atomic units identified by human annotators and our *Splitter*, we observed that the results were generally similar; however, humans tended to split sentences involving coordinating conjunctions more frequently than the *Splitter* does. For instance, given the sentence

'The patient is completely unconscious and immobile.'

human annotators would split this into two atomic units:

'The patient is completely unconscious.'

'The patient is completely immobile.'

In contrast, the *Splitter* would treat this sentence as a single atomic unit. However, if a sentence contains coordinating conjunctions where the connected elements do not have equivalent relationships, the *Splitter* tends to divide the sentence into multiple atomic units. For example, as Figure 4 shows, in the sentence

'The most common locations for CL to occur are the neck and axilla (armpit), followed by the mediastinum (chest) and retroperitoneum (abdomen).' the conjunction and connects mediastinum (chest) and retroperitoneum (abdomen), but because the phrase followed by indicates an ordered sequence, the Splitter splits the sentence into atomic units accordingly.

In the factuality-checking process, the main difference between human annotators and the *Checker* is that human annotators were more likely to consider the context (i.e., the atomic units preceding or following the target unit) when assessing the factuality of an atomic unit. Even when it is difficult to evaluate the factuality of an atomic unit in isolation, such as when the subject includes a pronoun, human annotators may still make a judgment based on surrounding context. In contrast, the *Checker* is more likely to label such cases as "false" or "unknown". If an atomic unit is labeled "unknown," the response containing that atomic unit is excluded from the final *DAHL Score* calculation, as

only responses definitively labeled as true or false are included. For instance, the *Checker* might refrain from judging the factuality of a sentence like '*This patient is not aware of the procedure*.' This conservative approach indicates that the *Checker* assesses the factuality of each atomic unit more stringently than human annotators.

6 Conclusion and Future Work

In this paper, we present DAHL, a benchmark dataset and an automated system designed to evaluate hallucination in long-form text generation within the biomedical domain. Utilizing a benchmark dataset consisting of 8,573 questions spanning 29 categories, our aim is to assess the hallucination with a specific focus on the factual precision of long-form responses. Diverging from previous methods that rely on accuracy calculations in classification or multiple-choice tasks, our approach involves deconstructing responses into atomic units and assessing the factuality of each unit. This nuanced methodology provides a more comprehensive evaluation of LLM hallucination. Our automatic dataset construction process ensures scalability across various domains and allows for regular updates. Moreover, our automated evaluation system offers significant efficiency compared to manual evaluation. Furthermore, the DAHL Score generated by our system could potentially replace preference models, serving as labels for preference.

Limitation

DAHL primarily targets fact-conflicting hallucination, yet it's essential to recognize the significance of input-conflicting and context-conflicting hallucination in evaluating LLMs. Additionally, the alignment of LLMs, specifically their ability to comprehend users' needs and generate helpful responses, should be considered for safe and satisfactory deployment of LLMs in real-life applications.

Ethics Statement

While our proposed benchmark for evaluating the biomedical knowledge of LLMs is a step forward, it is important to note that it is not flawless. Consequently, the tested model with the best *DAHL Score* should not be unquestioningly trusted or relied upon for clinical advice.

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Appendix A Automatically Filtered Questions

A.1 the/this/that/... + study/analysis/paper/...

- What ethical considerations are addressed by the authors in relation to their research findings?
- What are the implications for practice suggested by **the study**?

A.2 mentioned/inferred/addressed/...

- What tissue-specific patterns were observed in the usage of intronic PASs compared to PASs in exons?
- What challenges are associated with the protocol described in the study, and what solutions are suggested for troubleshooting?

A.3 was/were + used/...

 What method was used to assess the functional accuracy of the context-specific models?

Appendix B Manually Filtered Questions

Although the majority of questions containing the specified expressions are deleted, exceptions exist where questions can still be answered without additional context, even when they include these expressions. Consequently, questions containing the specified expressions are manually removed to enhance the quality of the benchmark dataset and to preserve as many questions as possible.

B.1 based on/depending on/according to/...

 Explain the significance of functional validation in the context of this research and how it is achieved.

B.2 was/were/did

Which MEM was found to be the most computationally efficient, and how might this impact its use in research?



Figure 6: Categorical DAHL Score of each model.

The text below is a research paper in the medical domain.

research paper:

{text}

What you have to do:

(1) Categorize the research paper into the list of [Oncology, Public Health, Cardiology, Biochemistry, Microbiology, Neurology, Genetics, Immunology, Pharmacology, Psychiatry, Radiology, Medicine, Orthopaedics, O\&G(Obstetrics Gynaecology), Pediatrics, Dental, Ophthalmology, Surgery, Bio-Statistics, Pathology, Anaesthesia, Dermatology, Anatomy, ENT(Ear, Nose, Throat), Forensic Medicine, Physiology].

If the research paper cannot be categorized into the given list, name the most adequate label.

(2) From the research paper, create some questions that can be used for examination questions to test the examination taker's medical

Figure 7: Prompt used for dataset construction

knowledge.

(1) Category:(2) Questions:

Please generate in this format:

An examination question from the biomedical domain will be given. Please answer the question as truthfully as possible. If you don't know the answer to a question, please don't share false information.

{question}

Figure 8: Prompt used for response generation

Please split the sentences in the following text into smaller sentences which contain just one single fact. Please avoid using pronouns such as "this", "these", "it" etc. Try to specify the referents. The sentences should be separated with a newline.

TEXT: The incidence rate of cystic lymphangioma (CL) in live births is estimated to be around 1 in 20,000 to 1 in 50,000. The most common locations for CL to occur are the neck and axilla (armpit), followed by the mediastinum (chest) and retroperitoneum (abdomen).

SEPARATED SENTENCES: The incidence rate of cystic lymphangioma (CL) in live births is estimated to be around 1 in 20,000.

The incidence rate of cystic lymphangioma (CL) in live births is also estimated to be around 1 in 50,000.

The most common location for CL to occur is the neck.

The second most common location for CL to occur is the axilla (armpit).

CL also commonly occurs in the mediastinum (chest).

CL also occurs in the retroperitoneum (abdomen).

TEXT:

{clean response}

SEPARATED SENTENCES:

Figure 9: Prompt used for splitting

Is this true or false? Answer in one word.

{atomic. unit}

Figure 10: Prompt used for factuality checking