

# HAGRID: A Human-LLM Collaborative Dataset for Generative Information-Seeking with Attribution

Ehsan Kamaloo<sup>\*†</sup> Aref Jafari<sup>\*†</sup> Xinyu Zhang<sup>†</sup>  
 Nandan Thakur<sup>†</sup> Jimmy Lin<sup>†</sup>

<sup>†</sup> David R. Cheriton School of Computer Science, University of Waterloo  
 ekamaloo@uwaterloo.ca

## Abstract

The rise of large language models (LLMs) had a transformative impact on search, ushering in a new era of search engines that are capable of generating search results in natural language text, imbued with citations for supporting sources. Building generative information-seeking models demands openly accessible datasets, which currently remain lacking. In this paper, we introduce a new dataset, HAGRID (Human-in-the-loop Attributable Generative Retrieval for Information-seeking Dataset) for building end-to-end generative information-seeking models that are capable of retrieving candidate quotes and generating attributed explanations. Unlike recent efforts that focus on human evaluation of black-box proprietary search engines, we built our dataset atop the English subset of MIRACL, a publicly available information retrieval dataset. HAGRID is constructed based on human and LLM collaboration. We first automatically collect attributed explanations that follow an in-context citation style using an LLM, i.e. GPT-3.5. Next, we ask human annotators to evaluate the LLM explanations based on two criteria: informativeness and attributability. HAGRID serves as a catalyst for the development of information-seeking models with better attribution capabilities.<sup>1</sup>

## 1 Introduction

Large Language Models (LLMs) have paved the way for the emergence of generative information-seeking search engines such as Bing Chat, Google Bard, and perplexity.ai, where search results are formulated in natural language text, incorporating references to the relevant web pages from which they are derived. This approach aims to

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### Question

What was Octavia E. Butler’s first novel?

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### Quotes

[1] Survivor is a science fiction novel by American writer Octavia E. Butler. First published in 1978 as part of Butler’s “Patternist series”...  
 [2] Butler’s first work published was “Crossover” in the 1971 Clarion Workshop anthology... Starting in 1974, Butler worked on a series of novels that would later be collected as the Patternist series... The first novel, “Patternmaster” (1976), eventually became the last installment in the series’ internal chronology...

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### Answer

Octavia E. Butler’s first novel was “Patternmaster” which was published in 1976 and was also the first installment in her “Patternist series” [2].

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**Informative?** Yes

**Attributable?** Yes

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Table 1: An example taken from HAGRID that includes a question along with a list of relevant passages (quotes), an answer generated by GPT-3.5 (§3.3), and informativeness and attributability evaluated by human annotators (§3.4).

provide users with contextually rich responses. Yet, LLMs are known to generate text lacking sufficient grounding to knowledge sources (Dziri et al., 2022; Ji et al., 2023), thereby posing risks of misinformation and even worse, hallucination (Maynez et al., 2020; Raunak et al., 2021). This problem becomes particularly critical within search engines where such inaccuracies can erode user trust and potentially spread misinformation (Metzler et al., 2021; Shah and Bender, 2022). Building models that are capable of incorporating citations that link to some supporting evidence is a vital step toward understanding the behaviour of LLMs, allowing users to easily verify the factu-

<sup>\*</sup> Equal Contribution

<sup>1</sup>HAGRID is released at <https://github.com/project-miracl/hagrid>.

ality of model outputs. The development of such models further fosters interpretable LLMs and attributable outputs (Rashkin et al., 2023), thus reinforcing the transparency and reliability of LLMs.

A significant obstacle in building generative search models equipped with citations is the lack of accessible and openly available datasets. The data used by commercial search engines for training their generative information-seeking models are typically proprietary and not accessible to the public, thereby hindering their widespread use in the open-source community.

In this paper, we introduce a new dataset for generative information-seeking scenarios to address these limitations. Our dataset is constructed on top of MIRACL (Zhang et al., 2022), an information retrieval dataset that consists of information-seeking questions along with a set of manually labeled relevant passages (quotes). We collect attributed explanations for each question by eliciting prompts from an LLM, i.e., GPT-3.5 (Ouyang et al., 2022), based on the given relevant passages. The explanations adhere to an in-context citation style, similar to scientific articles, that references the supporting quotes. We next ask human annotators to judge the explanations based on two criteria, (i) *informativeness*: whether the explanation provides a direct answer to the question, and (ii) *attributability*: whether the explanation is attributable to the source passages. We name our dataset HAGRID, representing **H**uman-in-the-loop **A**ttributable **G**enerative **R**etrieval for **I**nformation-seeking **D**ataset. An example question along with its relevant passage and the generated answer is presented in Table 1.

HAGRID consists of two subsets: training and development, enabling researchers to train and evaluate future information-seeking models with attribution capabilities. In particular, we seek to establish a dataset for building open-source end-to-end search models capable of retrieving candidate quotes and generating attributable answers based on input queries, which are key ingredients in retrieval-augmented generative models (Lewis et al., 2020; Izacard and Grave, 2021; Borgeaud et al., 2022). In contrast to existing datasets (Liu et al., 2023a; Gao et al., 2023), our emphasis on both openness and the integration of human annotations makes HAGRID a valuable and unique resource in this area. HAGRID is publicly released under the Apache 2.0 License. We hope that open-

sourcing of the dataset spurs innovation and further advancements in the rapidly growing area of generative search.

## 2 Related Work

**Explainability.** Understanding why models behave in certain ways is crucial in deploying them in real-world applications (Doshi-Velez and Kim, 2017). A common approach for explainability in NLP is to provide human-understandable explanations for particular outputs of a black-box model (Camburu et al., 2018). Numerous attempts were made in many language understanding tasks including text classification (Camburu et al., 2018; Liu et al., 2019), question answering (Abujabal et al., 2017; Rajani et al., 2019), fact verification (Atanasova et al., 2020; Kotonya and Toni, 2020), and summarization (Li et al., 2021) to generate rationales that explain models’ outputs. While these explanations are in line with our goal in this paper, they are not necessarily attributable (Jacovi and Goldberg, 2020). Moreover, several benchmarks (DeYoung et al., 2020; Mathew et al., 2021) were proposed to evaluate the generated rationales. Towards this goal, Narang et al. (2020) built a general-purpose T5 model that generates explanations for its predictions.

**Attributability.** Rashkin et al. (2023) formalize an attributable statement to identified sources such that it can be entailed from some underlying corpus by a generic hearer. Thus, attributability is a specific form of explainability within the constraints of a given source. WebGPT (Nakano et al., 2021) and GopherCite (Menick et al., 2022) are two recent closed-source models that are capable of generating references to their supporting evidence. From the data perspective, several QA datasets (Geva et al., 2021; Bohnet et al., 2022) provide pointers to text snippets supporting the gold answer. Moreover, two recent works (Liu et al., 2023a; Gao et al., 2023) focus on verifying citations in generated text based on a given set of quotes, which closely aligns with our objective in this paper. Specifically, Liu et al. (2023a) focus on closed-source proprietary search engines, whereas our goal is to use publicly available data to allow for building open-source end-to-end search models. Similarly, ALCE (Gao et al., 2023), a concurrent work to HAGRID, shares a similar goal, albeit with two notable differences. First, Gao et al. (2023) derive questions from QA datasets

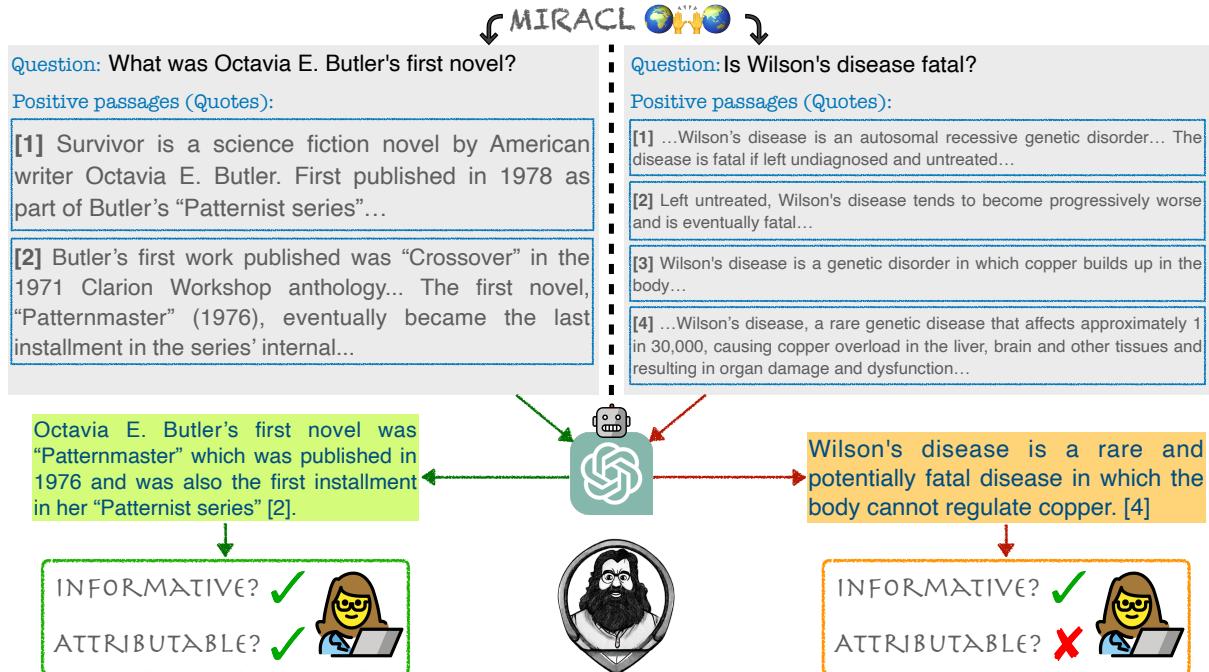


Figure 1: HAGRID’s data collection workflow. We first take a question and positive passages (quotes) from MIRACL, and reformat them into a prompt to instruct an LLM to generate answers with in-context citations (See an example in Figure 2). The answers generated by the LLM are evaluated by human annotators based on two criteria: *informativeness* (whether they correctly fulfill the question), and *attributability* (whether the source quotes appearing in the answers support the answers).

that consist of question and answer pairs but lack annotations for quotes. To identify quotes, a retrieval model is adopted to determine relevant passages by matching them with gold answers. However, automated answer equivalence is shown to be fallible, especially for long-form answers (Kamaloo et al., 2023; Xu et al., 2023) that could lead to accepting irrelevant quotes or rejecting legitimate quotes. Second, ALCE automatically determines the generated answer correctness as well as the citation quality, in contrast with HAGRID where we employ human annotators to validate these important criteria, thereby minimizing the risk of propagating any tool errors into the dataset.

**Using LLMs for Dataset Creation.** Due to the substantial costs, time constraints, and potential biases associated with human data collection, researchers sometimes resort to leveraging machines to reduce the human involvement. With the advent of proficient LLMs, machine-assisted techniques have become viable to some degree (Saunders et al., 2022; Wiegreffe et al., 2022) and in various downstream tasks including natural language inference (Liu et al., 2022), instruction-following (Wang et al., 2023; Honovich et al.,

2023), and information retrieval (Bonifacio et al., 2022; Jeronymo et al., 2023), data collection has evolved into a collaborative effort between models and humans.

### 3 Data Collection

#### 3.1 Task Formulation

We characterize the task of attributable information-seeking as the following: given a query  $Q$  and  $n$  text snippets  $\mathcal{S} = s_1, \dots, s_n$  that are relevant to  $Q$ , the goal is to formulate an answer  $A$  to  $Q$  such that statements in  $A$  are cited to their supporting source snippets  $s_i$  based on which they are generated. Specifically, answer  $A$  is composed of  $m$  sentences  $a_1, \dots, a_m$ ; each ends with a reference  $[r_{a_j}]$  where  $r_{a_j}$  is a set of integers referring to the indexes of snippets in  $\mathcal{S}$ ; that is,  $r_{a_j} \in \{1..n\}$ . Note that although certain cases such as “*according to* [1]...” or “...*supply chain* [2]” are not explicitly covered by this formulation, such sentences can often be rewritten to follow the specified format. Also, generic sentences like “*Below is an explanation.*” do not require citation, but they are not common in information-seeking scenarios. The examples

of cited answers are shown in Figure 1. Our objective is to curate contextualized summary answers derived from a list of text snippets, while also providing the corresponding snippets from which the answers originate.

### 3.2 Datasets

Numerous datasets have been designed for information-seeking scenarios in open-domain QA (Joshi et al. 2017; Lee et al. 2019; *inter alia*) and information retrieval (Bajaj et al. 2018; Soboroff et al. 2019; Voorhees et al. 2021; *inter alia*). In this work, we opt to equip existing retrieval datasets with attribution rather than constructing a dataset from scratch. This is primarily motivated by the fact that existing retrieval datasets already contain high-quality queries with judged text snippets, but they typically lack the rationales for annotated answers. By leveraging existing queries, we streamline the data collection process, enabling us to focus on attributability.

**MIRACL** (Zhang et al., 2022), a multilingual information retrieval (IR) dataset containing queries over Wikipedia articles for 18 diverse languages. The evaluated retrieval task setting is monolingual, i.e., both the query and document are of the same language. The dataset was created using human annotators following a setup similar to TYDI QA (Clark et al., 2020). Unlike prior work that segments Wikipedia articles into fixed 100-word passages (Karpukhin et al., 2020; Clark et al., 2020; Asai et al., 2021), MIRACL split documents based on natural discourse units using two consecutive newlines. The dataset represents a standard ad hoc retrieval task, where passages have been marked relevant for each query. In this work, we focus on working using the English subset of MIRACL and leave out other languages for future work. There are 32.8M passages, 2,863 queries in the training set, and 799 queries in the development set of the MIRACL English subset.

### 3.3 Answer Generation

In contrast to QA datasets such as SQuAD (Rajpurkar et al., 2016), Natural Questions (Kwiatkowski et al., 2019), or ELI5 (Fan et al., 2019), questions in MIRACL do not have gold answers. While gold answers could be obtained via human annotations, the effort would be costly and prohibitively time-consuming. Instead, in our work, we use an existing off-the-shelf LLM to elicit answers because of their ability to effec-

tively generate explanatory answers (Wiegreffe et al., 2022).

We input all the positive passages for each query (with at least one relevant passage) in the MIRACL dataset into an LLM. This setup is inspired by retrieval-augmented generation (Lewis et al., 2020), wherein generation is conditioned not only on the query but also on the retrieved passages. The relevant passages, derived from the English Wikipedia in MIRACL, will be referred to as “Quotes.” As reported in Table 2, nearly 3 quotes on average are provided for each query. We instruct GPT-3.5, i.e., gpt-3.5-turbo-0301 (OpenAI, 2022), to generate an answer to a question in a zero-shot fashion. We do not prepare any demonstrations or instructions for prompting with GPT-3.5. We provide an instruction, and a list of quotes as contexts and ask the LLM to reference answers within brackets [ ] in the IEEE format. The complete instruction used is provided in Figure 2. We also explored several instructions in the prompt to guide the LLM in generating both short and long answers, leading us to collect multiple answers per query. However, we found no significant differences between these generated answers. All the quotes can easily fit within the GPT-3.5 context window size of 4,096 tokens.

We further post-processed model responses to verify the format of model responses using regular expressions and filtered out the ones that violate the specified format.

### 3.4 Human Annotation

For human assessment, we hired 4 specialist annotators with 1+ year of experience with text data annotation on our team. Each annotator was interviewed prior to being hired and was verified to be a fluent and efficient annotator. To minimize any potential biases and ensure consistency in the annotation process, our team implemented a carefully designed onboarding procedure with training sessions specifically tailored to this task. The annotators were remunerated with an hourly rate of \$15.2 USD. In total, the project required approximately 1,400 annotation hours to complete.

Before proceeding with answer annotation, we initially decomposed answers into sentences. This is in large part to simplify the task as individual sentences are easier to read and evaluate, thus accelerating the data annotation process. It also al-

lows for collecting fine-grained annotations. If a sentence lacks citations, we group it with the following sentence that includes a citation, as the citation may pertain to all the grouped sentences. Following this pre-processing step, we asked our human evaluators to assess two criteria in generated responses:

- **Informativeness** checks whether a generated answer provides a useful response to the question. More precisely, if at least one sentence within an answer is labelled informative, the entire answer is deemed informative. In essence, this criterion is identical to *perceived utility* in Liu et al. (2023a). Notably, informativeness encompasses a broader scope, compared to *correctness* in Gao et al. (2023); Liu et al. (2023b) because it ensures accuracy as well as relevance by taking additional information in the answers into account.
- **Attributability** measures whether factual claims in a generated answer can be supported by corresponding quotes. An answer sentence would be labelled attributable only if it is fully supported by a cited quote. In cases where multiple citations appear in an answer sentence, all cited quotes must contain ample evidence to validate the sentence. When all sentences within an answer are labelled attributable, the answer is deemed attributable. We observed that annotating attributability takes 3-5x longer than annotating informativeness since annotators should carefully read all cited quotes to arrive at a decision. This is why, we were not able to collect annotations for all generated answers due to budget constraints.

### 3.5 Statistics

Table 2 provides an overview of HAGRID in the answer generation phase, prior to human annotation. The training and development sets contain 1,922 and 716 questions, respectively. Using GPT-3.5, we generate around 3,214 (1.7 per question on average) and 1,318 (1.8 on average) answers for train and development sets accordingly. Moreover, 6,577 and 3,305 citations (2.0 and 2.5 per answer on average) were generated within answers.

The statistics of the annotation results are reported in Table 3. All the generated answers

I will give a question and several context texts about the question. Based on the given contexts, give a brief answer to the question. Also, mention the reference of parts of your answer based on the given contexts within brackets [] as in the IEEE format.

QUESTION:

What was Octavia E. Butler's first novel?

CONTEXTS:

[1] Survivor is a science fiction novel by American writer Octavia E. Butler. First published in 1978 as part of Butler's "Patternist series"...

[2] Butler's first work published was "Crossover" in the 1971 Clarion Workshop anthology... Starting in 1974, Butler worked on a series of novels that would later be collected as the Patternist series... The first novel, "Patternmaster" (1976), eventually became the last installment in the series' internal chronology...

ANSWER:

Figure 2: A sample answer generation prompt template that we used in our work for eliciting answers from GPT-3.5 (OpenAI, 2022).

have been manually evaluated for informativeness, while around 24% (754) and 88% (1,157) of the answers have been evaluated for attributability on the training and development sets, respectively. The distributions of both informativeness and attributability are greatly consistent between the training and development sets (Informativeness: 84% and 90% answers marked “yes”; Attributability: 73% and 71% answers marked “yes”, respectively for training and development sets).

## 4 HAGRID Analysis

This section presents an in-depth analysis of the HAGRID dataset and discusses our main observations. Our aim is two-fold: (1) examining the content of answers with respect to the two criteria, introduced in §3.4, and (2) how quotes are cited in answers.

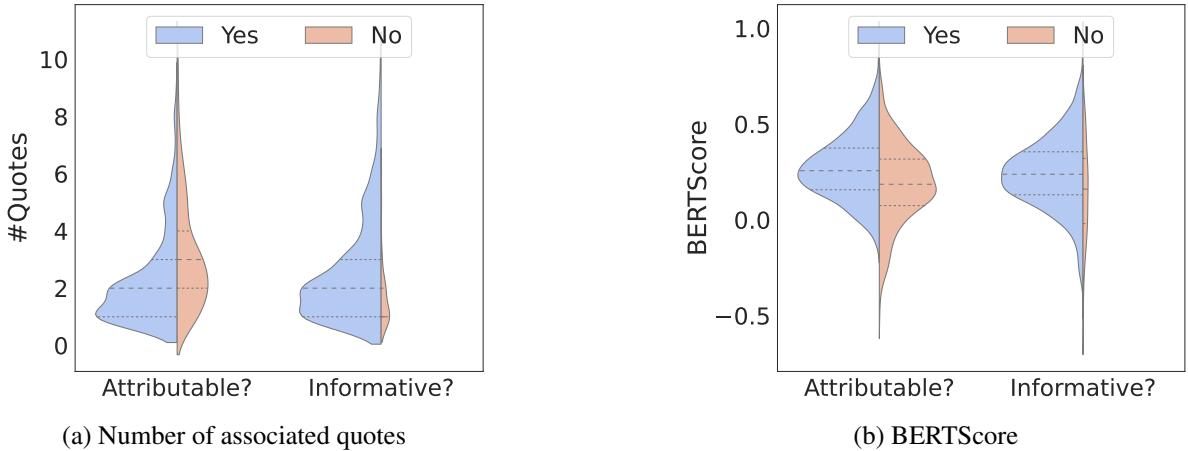


Figure 3: Comparative analyses of the y-axis distribution with respect to different answer labels: attributable vs. unattributable and informative vs. uninformative. Each curve is a KDE plot to represent distribution. The horizontal dash lines depict the first, second, and third quartiles.

	<b>Train</b>	<b>Dev</b>
# Questions	1,922	716
→ Avg. # Quotes per Question	2.7	2.9
# Generated Answers	3,214	1,318
→ Avg. Answer per Question	1.7	1.8
# Citations	6,577	3,305
→ Avg. Citation per Answer	2.0	2.5

Table 2: The statistics of the answers generated by LLM, prior to human annotation. Given a question, the model generates multiple answers (*Generated Answers*, and each answer may be accompanied by more than one cited quotes (*Citations*).

**Unattributable and uninformative answers often correspond to higher number of quotes.** Figure 3a depicts the impact of the number of associated quotes with respect to informativeness and attributability. The mean distribution of the number of quotes for unattributable and uninformative answers is higher than that of attributable and informative answers. Hence, as the number of associated quotes grows, LLMs tend to become fallible in generating informative and attributable answers.

**Attributable answers are semantically close to their referring quotes.** Figure 3b plots the distribution of semantic similarity, measured using BERTScore (Zhang et al., 2020), between answer sentences and corresponding cited sentences in quotes. Looking at the median of the distribution, informative answers are only slightly more

	Total	Yes	No		
	Train			Dev	
Informative	3,214	2,704	84%	510	16%
Attributable	754	547	73%	207	27%

Table 3: The statistics of the final HAGRID dataset. **Total**: the total number of annotated datapoints for each criterion. **Yes/No**: the number of datapoints that are annotated as “yes” or “no” for each criterion.

semantically similar to the quotes than uninformative answers. Similarly, the difference between the median of the distributions for attributable and unattributable answers with respect to their corresponding quotes is marginal.

**Generated answers are often extractive.** Our goal here is to measure the extent to which generated answers copy text from their corresponding quotes. To this end, we borrow two metrics, namely coverage and density, from abstractive summarization (Grusky et al., 2018) whose aims are to gauge extractiveness and abstractive- ness in text summaries: *Coverage* that measures the percentage of words in the answer that are also present in the quotes. A higher coverage signifies greater word overlap between an answer and its corresponding quotes. And, *Density* that quantifies the average length of text fragments from the

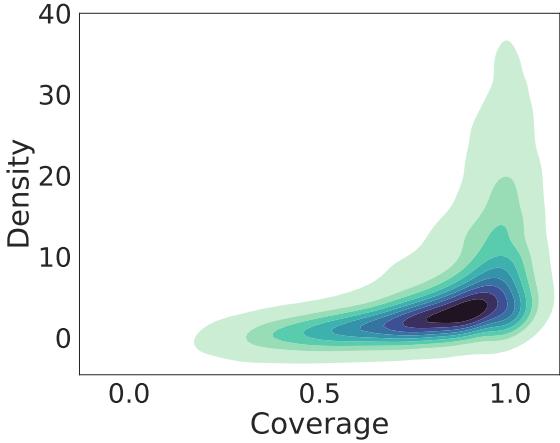


Figure 4: Coverage vs. Density between generated answers and their cited quotes. Answers tend to be extractive, thus words are frequently copied from quotes into the answers.

quotes which subsume answer words. Answers with larger chunks of text copied from their quotes will result in higher density. Figure 4 illustrates the coverage and density distributions. While coverage largely falls between 0.5 and 1.0, density is more varied. These results indicate that generated answers tend to use words from their associated quotes and thus, are mostly extractive.

**When the number of quotes is small, quotes are cited nearly evenly.** We analyze the citation frequency to determine which quotes are referenced in the generated answers. The findings are illustrated in Figure 5 where the x-axis represents the number of associated quotes and the y-axis shows the percentage of the cited quotes. When the number of quotes remains below 5, the indices of cited quotes are distributed evenly in general. However, when the number of quotes surpasses 5, the top-3 quotes receive higher citations, while the lower-ranked quotes are cited far less frequently.

## 5 Conclusion

Generative search with the ability to cite supporting sources has gained a lot of traction lately. However, the absence of accessible high-quality data inhibits progress in building open-source information-seeking models. In this paper, we seek to bridge this gap in the community by introducing HAGRID, a new dataset for building end-to-end generative retrieval models. Our dataset is collected via a human-machine collaboration that starts with generating explanatory answers to

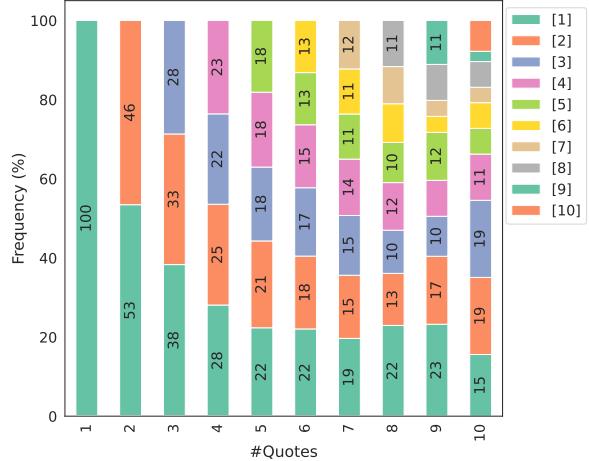


Figure 5: Frequency of citation indices based on different numbers of given quotes; **x-axis:** the number of given quotes in the prompt; **y-axis:** the frequency of indices in the citation. The citations percentage that are larger than or equal to 10% are marked on the figure.

information-seeking queries from GPT-3.5, followed by a human assessment of correctness and attributability of the generated answers. HAGRID facilitates the development of open-source models for information-seeking scenarios. Our human study has shed light on the room for improvement, i.e. around 40% of GPT-3.5 generated answers are not informative and over 20% fail to demonstrate attribution to the quotes. Moving forward, future research endeavors may focus on building more accurate models, aimed at mitigating the errors commonly encountered in current LLMs.

## Limitations

The scope of our dataset is on information-seeking scenarios that mainly inquire about factual statements that usually do not warrant creative or complex reasoning. Thus, more challenging questions with multi-hop reasoning (Yang et al., 2018), discrete reasoning (Dua et al., 2019), etc. are not covered in this study.

Another limitation is that HAGRID covers only English. While the source dataset, MIRACL, is multilingual and encompasses 18 languages, we leave non-English languages, either high-resource or low-resource, for future work.

## Ethical Statement

Although we do not foresee any major risk or negative societal impact of our dataset, models con-

structed on HAGRID may inadvertently produce biased outputs due to the reported tendencies of LLMs to generate stereotypes or biases. Therefore, care must be exercised for responsible deployment of such models in real-world applications.

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