Exploring Hint Generation Approaches in Open-Domain Question Answering

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Abstract

Automatic Question Answering (QA) systems rely on contextual information to provide accurate answers. Commonly, contexts are prepared through either retrieval-based or generation-based methods. The former involves retrieving relevant documents from a corpus like Wikipedia, whereas the latter uses generative models such as Large Language Models (LLMs) to generate the context. In this paper, we introduce a novel context preparation approach called HINTQA, which employs Automatic Hint Generation (HG) techniques. Unlike traditional methods, HINTQA prompts LLMs to produce hints about potential answers for the question rather than generating relevant context. We evaluate our approach across three QA datasets including TriviaQA, Natural Questions, and Web Questions, examining how the number and order of hints impact performance. Our findings show that the HINTQA surpasses both retrieval-based and generation-based approaches. We demonstrate that hints enhance the accuracy of answers more than retrieved and generated contexts.

1 Introduction

Automatic Question Answering (QA) systems (Abdel-Nabi et al., 2023) have recently garnered significant attention. They allow users to receive direct responses to posed questions. QA systems typically comprise three main components: Context-Preparator, Reranker, and Reader (Rogers et al., 2023). The Context-Preparator component aims to supply relevant context to the user question. The Reranker then prioritizes the documents based on their relevance to the question or to potential answers (Mao et al., 2021). Lastly, the Reader extracts the answer from the provided context. The Context-Preparator component is the initial step and a crucial element in QA systems. If this component fails to prepare the most relevant contexts, the entire QA system can be led astray. Therefore, the accuracy and performance of the Context-Preparator component are crucial for the overall success of QA systems. The Context-Preparator component may belong to two primary categories: Retrieval-based and Generation-based approaches (Li et al., 2024).

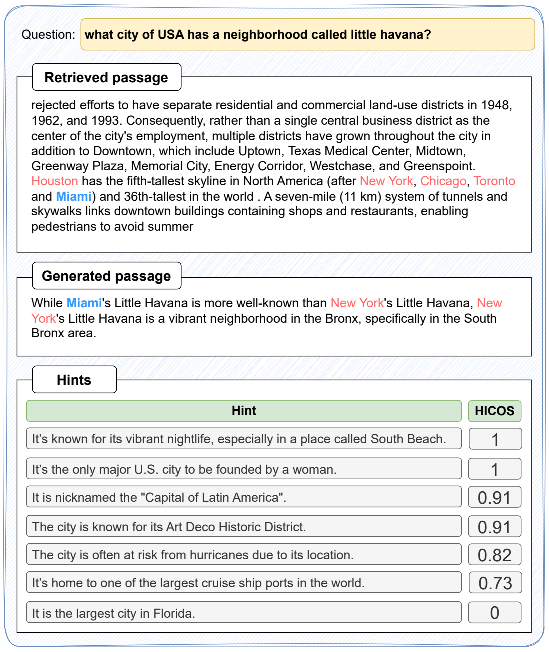

Figure 1: Example of generated hints, context produced by LLaMA-70, and a passage retrieved by MSS-DPR for a TriviaQA sample question, with convergence score (HICOS) ranging from 0 (lowest) to 1 (highest). Words in blue indicate the correct answer, while those in red represent other potential answers.

Retrieval-based methods retrieve relevant passages from document collections, such as Wikipedia, using techniques like keyword matching (Siddiqui and Tiwary, 2005) or vector space models (Gysel et al., 2018). A limitation of these methods is that retrieved passages tend to

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be lengthy, often exceeding 100 words (Karpukhin et al., 2020). Consequently, some sentences within these passages may be irrelevant to the question (Mitra and Craswell, 2017). Figure 1 illustrates a retrieved passage where only one sentence contains the potential answers including also the correct one, while the other sentences are irrelevant.

In contrast, generation-based methods use generative models, such as large language models (LLMs) (Scao et al., 2022) and Seq-to-Seq techniques (Sutskever et al., 2014), to produce relevant context. A major limitation of these methods is that they typically produce only a small number of sentences as context, usually just one or two. When the number of sentences is small, there is a risk that the QA system could be mislead if the answer is incorrect, due to insufficient context to substantiate the answer. Figure 1 also displays a generated passage consisting of only two sentences, which could mislead the Reader. This is because the correct answer appears less frequently than incorrect ones, and the scant context does not provide sufficient information for the Reader component to identify the correct answer accurately.

Our research aims to overcome the shortcomings of both retrieval-based and generation-based methods. It eliminates irrelevant sentences and provides only those containing useful information about the answer, thereby addressing a key limitation of the retrieval-based method. Additionally, we aim to expand the number of informative sentences beyond just one or two as usually is in the case of generated context, tackling a major drawback of the generation-based approach.

We present HINTQA[1], a novel approach that utilizes Automatic Hint Generation (HG) systems (Jangra et al., 2024) to generate hints as the context. This method produces multiple hints for each question and substitutes the retrieved passages and generated contexts with the generated hints. Figure 1 illustrates seven generated hints, each accompanied by its computed convergence score (HICOS). The convergence score is a measure that indicates how effectively a hint can narrow down or eliminate potential answers to a given question (Mozafari et al., 2024). The hints can be then subsequently reranked based on criteria such as the aforementioned convergence score or semantic relevance, setting the stage for the Reader to discern the correct answer from the prioritized hints. To assess the effectiveness of our approach, we generate hints for each question belonging to the test sets of the TriviaQA (Joshi et al., 2017), Natural Questions (NQ) (Kwiatkowski et al., 2019), and Web Questions (WebQ) (Berant et al., 2013) datasets. Table 8 and Table 9 in Appendix A indicate the statistics and distributions of these datasets. Our extensive experiments demonstrate that using hints leads to better performance than relying on retrieved passages or generated context. To sum up, we make the following contributions in this work:

- We propose a novel approach for the Context-Preparator component in QA systems that is based on using hint generation techniques.
- We generate and release hints along with their corresponding convergence scores for the questions of the test sets of the TriviaQA, NQ, and WebQ datasets.
- We conduct extensive experiments on these datasets using zero and few-shot strategies across various numbers of hints and reranking methods.

2 Related Work

2.1 Retrieval-based Methods

Retrieval-based methods can be divided into two primary categories: (1) Sparse retrieval and (2) Dense retrieval. Sparse retrieval methods rely on word-level matching to establish connections between vocabulary and documents. Notable examples are Boolean Retrieval (Salton et al., 1983), BM25 (Robertson and Zaragoza, 2009), SPLADE (Formal et al., 2021), and UniCOIL (Lin and Ma, 2021). On the other hand, dense retrieval methods capture deep semantic information from documents to understand underlying semantics and improve retrieval accuracy. Some key examples are DPR (Karpukhin et al., 2020), ANCE (Xiong et al., 2020), E5 (Wang et al., 2022), and SimLM (Wang et al., 2023).

2.2 Generation-based Methods

Generation-based systems can be broadly classified into two main categories: (1) Generative document retrieval and (2) Reliable response generation. Generative document retrieval utilizes the parametric memory of generative models to retrieve relevant documents. Unlike retrieval-based

[1]The code, dataset, and experimental results are freely available at https://github.com/DataScienceUIBK/HintQA

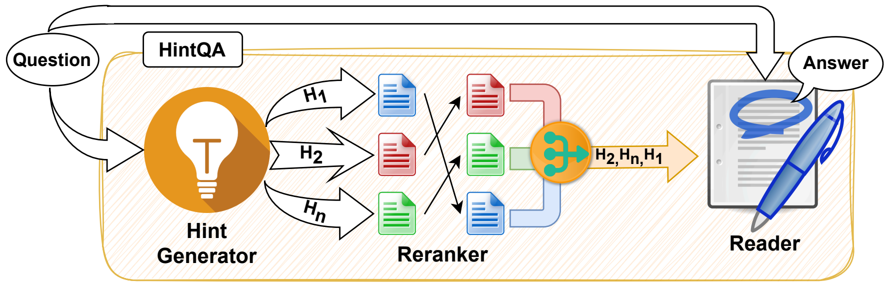

Figure 2: The HINTQA approach, where H_i denotes the ith hint. Initially, the Hint Generation component produces hints for the given question. These hints are then reranked and concatenated to form a context, which is subsequently passed to the Reader component to identify the answer of the question.

systems, this approach depends on pre-trained generative models, such as BART (Lewis et al., 2020), to produce document identifiers directly related to the question. Some notable examples are DSI (Tay et al., 2024), DynamicRetriever (Zhou et al., 2023), SEAL (Bevilacqua et al., 2022), and NCI (Wang et al., 2024). Conversely, Reliable response generation methods provide a more dynamic form of information access by directly producing detailed, user-centric responses. Notable instances are LLaMA (Brown et al., 2020), InstructGPT (Ouyang et al., 2024), T5 (Raffel et al., 2020), PaLM (Chowdhery et al., 2024) and Copilot[2].

2.3 Hint Generation

HG systems can be categorized into two main categories: (1) Hint generation for Programming (AHGP) and (2) Hint generation for Questions (AHGQ). AHGP aims to create helpful hints for programming exercises (Rivers et al., 2016). Some notable examples are ITAP (Jin et al., 2012) and Catnip (Obermüller et al., 2021) systems. In contrast, methods for AHGQ focus on generating hints for user questions rather than programming exercises (Mozafari et al., 2024; Jangra et al., 2024). Jatowt et al. (2023) explore the use of Wikipedia for generating hints without utilizing LLMs, primarily to introduce this as a new area of research. Mozafari et al. (2024) advance the field by releasing the first dedicated dataset named TriviaHG, along with a novel automatic evaluation method for assessing the quality of hints.

To the best of our knowledge, no study has yet explored the use of AGHQ approaches as the Context-Preparator component for QA systems.

[2] https://copilot.microsoft.com/

3 Method

In this section, we first explore the theoretical foundations underpinning our approach, followed by a detailed explanation of its implementation.

3.1 Hypothesis

Let q be a question linked to a set of candidate answers $\mathcal{A} = \{a_1, a_2, \dots, a_n\}$, such that $q \rightarrow \mathcal{A}$, which indicates that $\mathcal{A}$ is assumed to encompass all possible answers to q. Additionally, let $\mathcal{S} = \{s_1, s_2, \dots, s_j\}$ be the context, consisting of a series of sentences s_i provided to determine the answer to q. Each sentence s_i typically discusses or relates to certain entities or subjects, which we refer to as $\mathcal{C}'_i$. For instance, the sentence *"He was a professional."* might pertain to different possible professions such as actor, painter, athlete, etc. Consequently, the set $\mathcal{C}'_i$ could encompass, in this example, various individuals from diverse occupations. However, if the question q specifically inquires about just one particular profession, it is superfluous to consider all potential entities that the sentence might include. Therefore, we define $\mathcal{C}_i = \mathcal{C}'_i \cap \mathcal{A}$ to select only those entities that represent the intersection between the candidate answers for q and the possible entities from s_i. This process assists in eliminating irrelevant entities, retaining only valid candidate answers to q.

We define a score $\tau_{\mathcal{S}}(a)$ for a candidate answer a within the context $\mathcal{S}$ to represent how well a scores as a candidate answer in the context $\mathcal{S}$. It counts the number of supporting sentences for the candidate answer a among all sentences in $\mathcal{S}$:

$$\tau_{\mathcal{S}}(a) = \frac{\sum_{s \in \mathcal{S}} \chi_{\mathcal{C}_s}(a)}{|\mathcal{S}|} \tag{1}$$

where $|\mathcal{S}|$ indicates the number of sentences within $\mathcal{S}$, and $\mathcal{C}_s$ identifies the valid candidate answer set

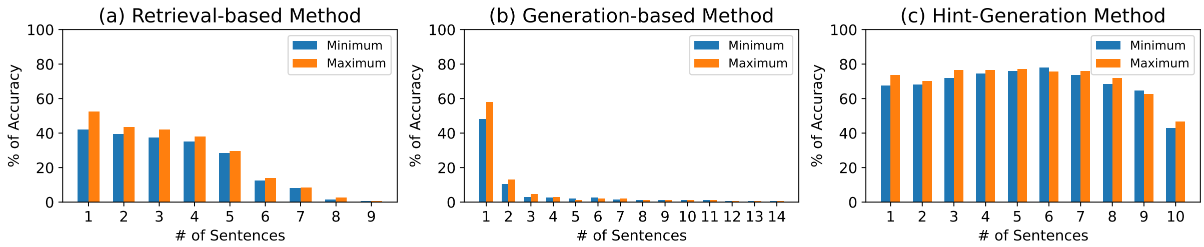

Figure 3: Accuracy results for 200 random questions from TriviaQA, NQ, and WebQ when using LLaMA-7b as the Reader and varying the numbers of context sentences. The context sentences are obtained by (a) Retrieval-based (DPR), (b) Generation-based (LLaMA-70b), and (c) Hint-Generation (HiGen-FT) methods. The blue (red) columns indicate the accuracy when the total number of potential entities across sentences is at its minimum (maximum). The number of potential entities per sentence is calculated using HICOS approach (Mozafari et al., 2024).

associated with sentence s. The function $\chi_{\mathcal{C}_s}(a)$ is to determine whether a candidate answer a is a member of the candidate answer set $\mathcal{C}_s$:

$$\chi_{\mathcal{C}_s}(a) = \begin{cases} 1 & \text{if } a \in \mathcal{C}_s \\ 0 & \text{if } a \notin \mathcal{C}_s \end{cases} \quad (2)$$

The candidate answer a with the highest $\tau_{\mathcal{S}}(a)$ across the context $\mathcal{S}$ is proposed as the most likely correct answer:

$$a^* = \arg\max_{a \in \mathcal{A}} \tau_{\mathcal{S}}(a) \quad (3)$$

Let's consider an example as follows. Suppose the question q is: *"What city in the USA has a neighborhood called Little Havana?"*. And suppose the context $\mathcal{S}$ consists of two sentences s_1 (red) and s_2 (blue):

```
The city is often at risk from hurricanes due to its location. Additionally, it's the only major U.S. city to be founded by a woman.
```

The entities supported by s_1 are $\mathcal{C}'_1 = \{$*San Juan, Kingston, Miami, New York, ...*$\}$, and ones by s_2 are $\mathcal{C}'_2 = \{$*Miami*$\}$. Let us also suppose that the following candidate answers are possible for q: $\mathcal{A} = \{$*Houston, Miami, New York*$\}$. Thus, the intersecting sets are $\mathcal{C}_1 = \mathcal{C}'_1 \cap \mathcal{A} = \{$*Miami, New York*$\}$ and $\mathcal{C}_2 = \mathcal{C}'_2 \cap \mathcal{A} = \{$*Miami*$\}$. We calculate the score $\tau_{\mathcal{S}}$ for *Miami* using Eq. 1:

$$\tau_{\mathcal{S}}(\text{Miami}) = \frac{\chi_{\mathcal{C}_1}(\text{Miami}) + \chi_{\mathcal{C}_2}(\text{Miami})}{|\mathcal{S}|} = \frac{2}{2} = 1 \quad (4)$$

The scores for *Houston* and *New York* are 0 and 0.5, respectively. Thus, according to Eq. 3, the most likely correct answer to q given the context is **Miami** as supported by most of the sentences.

We believe that a context supporting more potential entities in its sentences can improve the performance of QA systems. As shown in Figure 3, the *Maximum* column illustrates that when the total number of potential entities across sentences is highest, the accuracy exceeds that observed with the lowest count. Figure 3b also demonstrates how a scarcity of potential entities can mislead the QA system. As discussed in Section 1, this issue is especially common in generation-based methods, which frequently produce contexts with a small number of sentences.

Moreover, Figure 3a shows that additional sentences can impair QA system performance if the sentences are irrelevant. The figure demonstrates a correlation between an increase in irrelevant sentences and a decrease in accuracy. This presents a frequent challenge for retrieval-based methods, which are prone to including irrelevant sentences in the passages they retrieve.

Nevertheless, Figure 3c demonstrates that the results of the HG method can effectively guide the QA system toward the correct answer. Table 36 in Appendix D provides also some generated hints and their supported candidate answers.

3.2 Implementation

To implement our approach, we adapt the method introduced by Mozafari et al. (2024) for generating ten hints, modifying their original prompt. While they implemented an answer-aware approach, we take an answer-agnostic approach since the correct answer is unknown. Note that the HG method occasionally generates hints where the answer is replaced with blanks to prevent answer leakage. We remove such hints, which could result in some questions having fewer than 10 hints. The prompt we use to generate hints is as follows:

Method	TriviaQA	NQ	WebQ
BM25	117.15	114.93	114.24
DPR	118.66	110.97	114.56
Contriever	117.41	107.47	113.69
MSS	118.62	113.44	117.25
MSS-DPR	118.35	109.56	115.66
LLaMA-70b	50.34	61.52	75.93
HiGen-FT	73.54	96.13	90.43
HiGen-Va	96.85	106.78	93.02

Table 1: Comparison of average lengths of hints, generated contexts, and retrieved passages based on the number of words.

```
Generate 10 concise and relevant hint
sentences for the following question. List
the hints without revealing the answers
within them.
```

After generating hints, we rerank the created hints based on the HICOS score and concatenate them to make a new context. Finally, we pass the generated context to a Reader to answer a given question. Figure 2 shows HINTQA approach. We utilize the following prompt in the Reader to extract the answer from the context:

```
According to the following context, answer
the question:
Context: Provided Context
Question: Given Question
Answer: Here is the answer
```

4 Experimental Setup

4.1 Datasets

Our evaluation is conducted using three diverse datasets: TriviaQA (Joshi et al., 2017), NQ (Natural Questions) (Kwiatkowski et al., 2019), and WebQ (Berant et al., 2013). TriviaQA dataset comprises a comprehensive collection of trivia questions, which have been curated from various trivia and quiz-league websites. NQ has been constructed from Google Search queries, providing a realistic set of questions people ask. The answers to these questions are drawn as specific spans or segments from Wikipedia articles. WebQ dataset consists of questions sourced from the Google Suggest API, which generates predictive search suggestions based on user input. The answers are tied to entities within Freebase (Bollacker et al., 2008). A more detailed description of dataset statistics, their splits (Table 8), and distributions based on the question type (Table 9) can be found in Appendix A.

Method	TriviaQA[1] EM	TriviaQA[1] F1	NQ[2] EM	NQ[2] F1	WebQ[3] EM	WebQ[3] F1
Zero-Shot						
BM25	23.28	27.22	3.55	5.62	10.97	18.54
Contriever	18.13	22.29	1.94	3.66	8.17	14.05
DPR	23.22	27.7	2.3	3.93	11.71	19.43
MSS	18.15	22.35	1.97	3.58	9.94	17.24
MSS-DPR	18.14	22.23	4.24	6.53	11.17	18.71
LLaMA-70b	21.45	26	3.88	6.23	12.11	20.27
HiGen-Va	22.01	26.5	9.06	12.54	13.88	21.74
HiGen-FT	**23.55**	**28.03**	**10.89**	**14.85**	**14.96**	**23.08**
Few-Shot						
BM25	25.78	30.29	4.6	7.33	11.17	18.93
Contriever	21.48	25.87	2.47	4.21	7.53	13.49
DPR	25.02	29.49	3.24	5.09	11.37	19.37
MSS	20.89	25.27	2.85	4.75	10.33	17.99
MSS-DPR	20.92	25.19	4.79	7.69	11.47	19.81
LLaMA-70b	23.64	28.86	5.1	7.9	9.4	17.86
HiGen-Va	34.19	39.74	12.85	18.06	18.9	28.97
HiGen-FT	**38.54**	**44.29**	**16.68**	**22.64**	**24.11**	**34.52**

[1] Zero-Shot→ HiGen-Va: 10 Def, HiGen-FT: 10 Def
Few-Shot→ HiGen-Va: 5 Conv, HiGen-FT: 7 Def
[2] Zero-Shot→ HiGen-Va: 10 Def, HiGen-FT: 10 Def
Few-Shot→ HiGen-Va: 5 Conv, HiGen-FT: 7 Def
[3] Zero-Shot→ HiGen-Va: 2 Conv, HiGen-FT: 10 Def
Few-Shot→ HiGen-Va: 5 Conv, HiGen-FT: 7 Conv

Table 2: The results for **T5-3b** used as the reader, utilizing zero-shot and few-shot strategies. The footnotes provide information on the optimal number of hints and the ranking method chosen to achieve the best results for each learning strategy and hint generation method.

4.2 Baseline Models

To compare our approach with other methods, we choose several retrieval-based and generative-based methods as baselines.

BM25 (Robertson and Zaragoza, 2009) is a probabilistic retrieval model that employs term frequency (TF) and inverse document frequency (IDF) metrics to assess the relevance of documents based on the common words in the question and the documents. **Contriever** (Izacard et al., 2022) is an unsupervised framework designed for pre-training models for retrieval tasks, utilizing contrastive learning techniques. **MSS** (Sachan et al., 2021) is a dense retrieval model trained to predict masked salient spans, such as named entities, using a reader network. **DPR** (Karpukhin et al., 2020) uses annotated question-context paragraphs and hard negative examples to train a supervised dense retriever. **MSS-DPR** (Sachan et al., 2021) enhances the performance of DPR by initially pre-training the dense retriever with MSS. This is followed by supervised fine-tuning in the style of DPR. **LLaMA-v2** (Touvron et al., 2023) is an advanced LLM tailored for scalable natural language processing tasks, providing exceptional efficiency in generating context.

We employ the preprocessed English Wikipedia dump, provided by Karpukhin et al. (2020), as a source for our evidence passages in retrieval-based methods. We also utilize the first top retrieved passage for the Reader. We use the LLaMA-70b as the generation-based baseline because we use LLaMA-70b in our implementation (Section 3.2) as the core of an HG system. Therefore, it is reasonable to compare the HINTQA method directly with LLaMA-70b to ensure a fair assessment.

4.3 Hint Generation Methods

We employ two versions of HG systems to create hints for questions: The vanilla version (HiGen-Va) and the finetuned version (HiGen-FT). In the HiGen-Va, the LLaMA-70b model is simply prompted to generate hints for a specific question. For the HiGen-FT, we first finetune the LLaMA-70b model using the TriviaHG dataset (Mozafari et al., 2024), and then prompt it to generate hints. For the detailed statistics of the TriviaHG dataset, readers are referred to Table 10 in Appendix A.

Additionally, we explore three different reranking methods for reranking hints: Default (Def), RankT5 (T5), and Convergence (Conv). The Default order refers to the sequence in which the hints are originally generated by the HG system. The RankT5 method rearranges hints through pairwise and listwise ranking techniques employing the T5 model (Zhuang et al., 2023). Lastly, the Convergence method sorts the hints according to the HICOS score in descending order.

We also investigate the impact of using various quantities of hints to prepare context. In our experiments, we concatenate the first 2, 5, 7, or 10 hints in various sequences to generate a comprehensive context for the Reader component. This approach allows us to assess how the number and order of hints influence the effectiveness and performance of the QA system. To compare results, we use the metrics mentioned in Appendix B.

4.4 Readers

We utilize two distinct language models, T5-3b (Raffel et al., 2020) and LLaMA-7b (Touvron et al., 2023), as the Reader component in our system. In addition to employing these models, we incorporate techniques such as Zero-Shot and Few-Shot[3] to enhance their capability to handle tasks with limited direct training on specific tasks. This setup allows us to explore the effectiveness of these models in adapting to new data and challenges using minimal examples.

Method	ACC	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
BM25	34.21	0	7.67	4.56	36.2	38.98	69.29
Contriever	20.64	0	5.57	3.28	30.71	26.47	67.13
DPR	31.19	0	7.5	4.47	35.12	37.03	69.22
MSS	20.38	0	5.43	3.19	30.4	26.11	67.06
MSS-DPR	19.73	0	5.58	3.27	30.67	26.43	67.2
LLaMA-70b	47.3	0	**9.11**	**5.44**	**42.57**	55.32	70.77
HiGen-Va[1]	**59.06**	0	8.04	4.75	41.51	54.74	70.35
HiGen-FT[2]	54.97	0	8.96	5.33	42.21	**60.93**	**71.4**
			Few-Shot				
BM25	40.5	38.15	46.7	46.2	52.8	51.06	83.32
Contriever	31.62	33.54	40.4	39.9	47.31	42.86	80.46
DPR	36.29	37.15	45.3	44.8	51.06	49.16	82.91
MSS	31.56	33.99	41.1	40.7	47.84	43.41	80.66
MSS-DPR	31.96	32.69	39.9	39.4	46.95	42.43	80.2
LLaMA-70b	52.59	41.26	48.7	48.6	52.59	51.58	83.3
HiGen-Va[3]	57.71	50.76	60.6	60.4	65.12	65.92	88.61
HiGen-FT[1]	**58.06**	**54.6**	**64.7**	**64.8**	**69.53**	**70.15**	**89.89**

[1] 7 hints, Convergence reranking.
[2] 10 hints, Default reranking.
[3] 5 hints, Convergence reranking.

Table 3: The results for **LLaMA-7b** used as the reader on **TriviaQA**, using zero-shot and few-shot strategies.The footnotes provide information on the optimal number of hints and the ranking method chosen to achieve the best results for each learning strategy and hint generation method.

5 Results

5.1 Context Length

We first discuss the average lengths of contexts retrieved or generated, based on the number of words, by different models within the Context-Preparator component. As noted in Section 1, our approach yields contexts that are longer than those produced by generation-based methods but shorter than those from retrieval-based methods. Table 1 provides details on the average lengths of hints, generated contexts, and retrieved passages across the TriviaQA, NQ, and WebQ datasets. The data indicates that the length of hints produced by both **HiGen-FT** and **HiGen-Va** methods are shorter than those from all retrieval-based methods. However, when compared with **LLaMA-70b** used as a generative approach,

[3]The choice to limit the number of shots to only 5 in few-shot learning is motivated by the high cost associated with exploring various shot values.

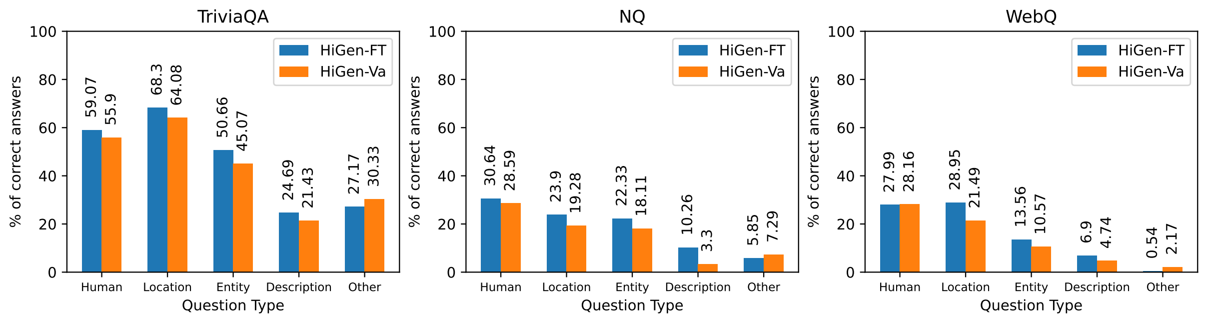

Figure 4: Exact Match values for TriviaQA, NQ, and WebQ datasets categorized by question type, based on the optimal settings for both HiGen-Va and HiGen-FT using few-shot learning on LLaMA-7b.

Method	ACC	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
BM25	23.38	0	2.72	1.54	19	15.21	63.14
Contriever	11.52	0	1.84	1.03	15.71	10	61.14
DPR	11.36	0	1.77	0.99	15.55	9.78	61.04
MSS	11.44	0	1.67	0.94	14.75	9.36	60.94
MSS-DPR	23.21	0	2.94	1.66	21.16	17.73	63.96
LLaMA-70b	37.73	0	3.88	2.2	**31.98**	31.97	65.31
HiGen-Va[1]	**51.11**	0	3.44	1.95	25.71	26.2	64.97
HiGen-FT[1]	49.26	0	**4.38**	**2.5**	26.96	**33.19**	**66.8**
			Few-Shot				
BM25	36.65	10.33	16.6	16.1	23.28	19.14	70.32
Contriever	31.66	6.84	10.7	10.2	16.17	11.19	66.61
DPR	31.3	7.15	11.1	10.6	16.92	11.63	66.83
MSS	29.25	7.15	11.1	10.5	17.2	12.05	66.78
MSS-DPR	34.35	10.44	16.4	15.9	22.81	18.67	70.24
LLaMA-70b	50.21	10.55	16.1	15.9	21.06	18.34	68.9
HiGen-Va[2]	59.36	18.48	26.6	26.4	34.58	33.24	75.58
HiGen-FT[2]	**64.43**	**20.72**	**29.5**	**29.55**	**37.19**	**36.81**	**76.7**

[1] 10 hints, Convergence reranking.
[2] 7 hints, Convergence reranking.

Table 4: The results for **LLaMA-7b** used as the reader on **NQ**, utilizing zero-shot and few-shot strategies. The footnotes provide information on the optimal number of hints and the ranking method chosen to achieve the best results for each learning strategy and hint generation method.

Method	ACC	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
BM25	27.51	0	4.38	2.6	26.89	23.77	65.41
Contriever	8.22	0	2.42	1.37	21.7	14.12	62.41
DPR	26.53	0	4.8	2.79	31.7	26.57	65.63
MSS	24.9	0	4.06	2.39	27.1	21.75	64.54
MSS-DPR	30.17	0	5.08	2.98	31.42	27.36	66
LLaMA-70b	45.13	0	6.16	3.65	**44.39**	**47.39**	67.05
HiGen-Va[1]	52.95	0	5.83	3.42	38.15	40.26	67.37
HiGen-FT[1]	**54.08**	0	**7.01**	**4.14**	40.04	45.23	**68.79**
			Few-Shot				
BM25	35.33	11.42	22.7	22.8	32.42	31.55	73.04
Contriever	17.47	5.41	10.3	9.86	18.43	13.44	66.86
DPR	30.41	9.5	20.7	20.4	30.07	29.18	72.06
MSS	28.54	9.4	18.6	18.6	26.93	25.1	70.94
MSS-DPR	33.51	10.29	22.1	22.2	31.51	32.23	72.9
LLaMA-70b	48.03	8.46	16.5	16.8	21.79	22.49	68.5
HiGen-Va[2]	55.87	17.52	32.1	32.1	44.22	44.88	76.87
HiGen-FT[2]	**56.55**	**20.28**	**35.4**	**35.3**	**47.32**	**49.9**	**78.51**

[1] 10 hints, Convergence reranking.
[2] 7 hints, Convergence reranking.

Table 5: The results for **LLaMA-7b** used as the reader on **WebQ**, utilizing zero-shot and few-shot strategies.The footnotes provide information on the optimal number of hints and the ranking method chosen to achieve the best results for each learning strategy and hint generation method.

the hints are longer.

5.2 Results of HintQA

In this section, we present and analyze the performance and results of the HintQA approach, comparing it against various baselines. As previously mentioned, our experimental framework encompasses a range of setups, including different datasets (Section 4.1), baseline models (Section 4.2), HG systems, orders of hints, numbers of hints (Section 4.3), and readers (Section 4.4). This comprehensive evaluation helps in assessing the robustness and effectiveness of the HintQA approach across multiple dimensions.

Table 2 presents the performance of the T5-3b model as the Reader component, utilizing zero-shot and few-shot learning strategies across the specified datasets, measured by Exact Match and F1 scores. The results indicate that **HiGen-FT** achieves the best performance in both learning strategies. Additionally, the outcomes from the few-shot learning strategy surpass those of the zero-shot learning strategy. For a more detailed analysis of T5-3b's performance using HiGen-Va on TriviaQA, NQ, and WebQ datasets, readers can refer to Table 11 to Table 13 in Appendix C. Tables 14 to Table 16

Hint Generator	# of Params	# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
			Zero-Shot							
LLaMA-FT (Mozafari et al., 2024)	7b	2	T5	79.0	0	11.39	6.75	54.58	74.0	71.87
LLaMA-Va (Touvron et al., 2023)	7b	2	Conv	68.0	0	9.37	5.57	47.48	65.0	70.52
LLaMA-Va (Touvron et al., 2023)	13b	2	T5	79.0	0	9.98	5.91	48.09	73.0	71.39
LLaMA-FT (Mozafari et al., 2024)	13b	5	Conv	83.0	0	10.65	6.31	48.23	76.0	71.68
LLaMA-Va (Touvron et al., 2023)	70b	2	Def	78.0	0	10.12	5.84	53.18	77.0	71.44
WizardLM (Xu et al., 2024)	70b	5	T5	80.0	0	9.94	5.9	47.22	75.0	71.58
GPT 3.5 (Brown et al., 2020)	175b	2	Conv	81.0	0	10.6	6.13	**59.37**	81.0	71.45
Gemini (Team et al., 2023)	-	7	Def	88.0	0	11.83	7.05	53	88.0	72.47
LLaMA-FT (Mozafari et al., 2024)	70b	2	Conv	83.0	0	11.28	6.77	50.72	81.0	72.41
Copilot	-	7	T5	92.0	0	**11.89**	**7.09**	55.32	**90.0**	72.69
GPT 4 (Achiam et al., 2023)	-	5	Def	**96.0**	0	11.5	6.8	53.97	89.0	**73.2**
			Few-Shot							
LLaMA-FT (Mozafari et al., 2024)	7b	5	Conv	76.0	67.0	72.91	71.56	76.17	78.0	92.66
LLaMA-Va (Touvron et al., 2023)	7b	7	T5	76.0	57.0	67.23	65.56	71.74	72.0	90.65
LLaMA-Va (Touvron et al., 2023)	13b	7	T5	83.0	67.0	77.04	74.87	82.17	83.0	93.33
LLaMA-FT (Mozafari et al., 2024)	13b	10	Def	84.0	67.0	74.37	72.85	78.37	82.0	92.26
LLaMA-Va (Touvron et al., 2023)	70b	7	Conv	84.0	67.0	74.29	73.18	78.87	79.0	92.09
WizardLM (Xu et al., 2024)	70b	10	T5	87.0	72.0	80.04	78.29	85.17	86.0	93.67
GPT 3.5 (Brown et al., 2020)	175b	7	Conv	88.0	72.0	79.74	78.14	83.7	84.0	93.57
Gemini (Team et al., 2023)	-	7	Def	90.0	73.0	81.24	79.73	85.5	89.0	94.58
LLaMA-FT (Mozafari et al., 2024)	70b	5	Def	91.0	69.0	80.06	78.11	85.87	87.0	94.02
Copilot	-	7	Conv	91.0	**77.0**	86.16	84.07	92	**94.0**	**95.57**
GPT 4 (Achiam et al., 2023)	-	10	Def	**93.0**	76.0	**87.29**	**85.03**	**92.17**	92.0	95.46

Table 6: The results of LLaMA-7b as the core of the HINTQA system across different LLMs, generating hints for 100 questions. More detailed results are given in a series of tables ranging from Table 23 to Table 34 in Appendix C.

Method	TriviaQA			NQ		
	EM	RC	CON	EM	RC	CON
Without using rerankers						
BM25	38.15	52.8	51.06	10.33	23.28	19.14
Contriever	33.54	47.31	42.86	6.84	16.17	11.19
DPR	37.15	51.06	49.16	7.15	16.92	11.63
MSS	33.99	47.84	43.41	7.15	17.2	12.05
With using rerankers						
MSS+UPR	53.1	67.3	60.6	25.4	40.7	31
DPR+UPR	53.9	68.7	62	**25.6**	**42**	33.1
Our method						
HiGen-Va	50.76	65.12	65.92	18.48	34.58	33.24
HiGen-FT	**54.62**	**69.53**	**70.15**	20.72	37.19	**36.81**

Table 7: Comparison of reults between baselines without rerankers, baselines with rerankers, and HINTQA.

provide information on T5-3b's performance using HiGen-FT for these datasets.

Table 3, Table 4, and Table 5 show the performance of the LLaMA-7b model as the Reader component across different experimental setups. The results show that in the few-shot strategy, **HiGen-FT** consistently delivers the best outcomes across all three datasets. However, the performance under the zero-shot learning strategy varies. The EM metric is zero in the zero-shot learning strategy because the final generated answers are often text passages rather than short answers.

For the TriviaQA dataset, **LLaMA-70b** leads in F1, Precision, and Recall metrics. In the case of the NQ dataset, **LLaMA-70b** performs best regarding Recall, while for the WebQ dataset, **LLaMA-70b** excels in both Recall and Contains metrics. For other metrics across these datasets, the **HINTQA** approach outperforms the rest.

Figure 4 displays Exact Match scores for the TriviaQA, NQ, and WebQ datasets, broken down by the question type, under the optimal settings for both HiGen-Va and HiGen-FT using few-shot strategy on LLaMA-7b. The figure illustrates that **HiGen-FT** outperforms HiGen-Va across various question types. For more detailed analysis of LLaMA-7b's performance using HiGen-Va and HiGen-FT on TriviaQA, NQ, and WebQ datasets, readers can refer to tables from Table 17 to Table 22 in Appendix C.

In Appendix D, Table 35 presents a comparison of answers for a random selection of questions from the TriviaQA, NQ, and WebQ datasets, using DPR, LLaMA-70b, and HINTQA. Table 37 shows the answers generated from contexts retrieved by MSS-

DPR, contexts generated by LLaMA-70b, and hints generated by HINTQA using the LLaMA-7b model in a zero-shot learning strategy. Table 38, Table 39, and Table 40 illustrate the answers generated under a few-shot learning strategy by MSS-DPR, LLaMA-70b, and HINTQA, respectively, using the LLaMA-7b model.

5.3 Ablation Study

Impact of various LLMs We investigate the impact of LLMs used as the core in the HG method, producing various hints for some random questions from the TriviaQA dataset. Utilizing various LLMs, we generate hints per each question. Table 6 presents the top-performing results for these LLMs as the core of the HG method across different numbers of hints and reranking methods, with LLaMA-7b serving as the Reader. The findings reveal that **Copilot** and **GPT-4** (Achiam et al., 2023) deliver the best performance for zero-shot and few-shot learning strategies, respectively, highlighting that a more knowledgeable core can produce higher-quality hints. The results for T5-3b as the Reader component are given in Table 34 in Appendix C.

Impact of Rerankers Finally, we evaluate the impact of rerankers on retrieval-based methods and the HINTQA approach to determine how HINTQA performs relative to other methods when rerankers are used. Table 7 displays the results for retrievers without rerankers, with the UPR-reranker (Sachan et al., 2022), and HINTQA for both the TriviaQA and NQ datasets. The results show that HINTQA surpasses others on TriviaQA dataset. Yet, while HINTQA achieves the best results with the Contains metric for the NQ dataset, UPR-reranker performs better in other metrics.

6 Conclusion

In this paper, we introduced a novel approach to the Context-Preparator in QA systems called HINTQA that generates hints instead of relying on retrieved passages or generated contexts. To thoroughly test its effectiveness, we designed a variety of experimental setups, aiming to cover a broad spectrum of possible scenarios. Our findings reveal that this new approach consistently surpasses traditional baseline methods, including both retrieval-based and generation-based approaches, on the TriviaQA, NQ, and WebQ datasets across multiple evaluation metrics. Moreover, we demonstrated that different configurations, such as employing various LLMs as the core of the HG method and adjusting ranking methods and the number of hints, significantly boost the performance of our approach. Our future work will focus on more complex questions such as multi-hop questions (Mavi et al., 2024) requiring comprehensive reasoning.

Limitations

Our study has the following limitations:

- The HINTQA approach leverages the capabilities of LLMs to generate high-quality hints by utilizing the extensive knowledge stored within these models. However, a key limitation is that the hints are based on outdated data, as they reflect only the information available up to the LLMs' last training period. This could lead to less relevant and accurate hints, especially in rapidly evolving fields like technology, medicine, and science.

- The computation of HICOS scores using LLMs is both time-consuming and resource-intensive, presenting significant challenges. Although sorting hints by descending HICOS scores delivers optimal performance, the process is complex and demands substantial computational resources. This could limit the use of such systems in scenarios that require fast or cost-effective solutions, particularly in environments with limited hardware capabilities or where minimizing operational costs is essential.

- The LLMs in the reader component were intentionally not fine-tuned on the TriviaQA, NQ, and WebQ datasets to assess the Hint Generation (HG) method's effectiveness as a Context-Preparator without introducing bias. This approach ensures that the evaluation focuses solely on how well the HG method enhances the reader's performance by preparing context, rather than relying on any preexisting familiarity with the dataset content.

- We have focused in this work on factoid questions since the current hint generation systems, the same as many QA systems, are typically designed to work only with factoid questions, and we rely on these systems to generate hints in our method.

Ethical Considerations

Our study employs the GPT models, governed by the OpenAI License and Apache-2.0 license, and the LLaMA model, distributed under Meta's LLaMA 2 Community License Agreement. We adhere to these licenses for all applications. Moreover, the datasets we use are sourced from repositories authorized for academic purposes. The artifacts developed during our research are released under the MIT license to promote easy modification and use by the research community. We have ensured that our data handling, model training, and dissemination of results comply with ethical standards and legal requirements related to each utilized artifact.

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A Dataset Details

In this section, we present several tables that detail the statistics of the datasets utilized in our study. The tables include comprehensive data such as sample sizes, feature counts, and other relevant metrics, providing an overview of the datasets' composition and scope.

Dataset	Scenario	# of Questions	# of Hints
TriviaQA	Finetuned	11,313	105,709
TriviaQA	Vanilla	11,313	103,018
NQ	Finetuned	3,610	33,131
NQ	Vanilla	3,610	30,976
WebQ	Finetuned	2,032	16,978
WebQ	Vanilla	2,032	15,812

Table 8: Statistics of TriviaQA, NQ, and WebQ datasets.

Question Type	TriviaQA	NQ	WebQ
Human	36%	40%	30%
Location	21%	14%	28%
Entity	32%	11%	21%
Description	6%	8%	11%
Other	5%	27%	10%

Table 9: Distribution of TriviaQA, NQ, and WebQ datasets based on the question type.

B Metrics

In this section, we provide a detailed explanation of the metrics employed in our study to evaluate the effectiveness of our methods. We utilize the scikit-learn library (Pedregosa et al., 2011) to compute the metrics.

- **Accuracy (ACC):** This metric leverages LLMs to determine the correctness of the answers (Kamalloo et al., 2023).
- **Exact Match (EM):** This metric evaluates whether the retrieved or generated passage perfectly includes the correct answer text without modifications.
- **Precision (PR):** This metric calculates the percentage of words in the retrieved or generated passage that are also found in the correct answer.

	Training	Validation	Test
Number of questions	14,645	1,000	1,000
Number of hints	140,973	9,638	9,619
Avg. question length (words)	14.18	14.08	13.95
Avg. hint length (words)	14.98	15.07	15.14
Avg. #hints / question	9.62	9.63	9.61
Avg. #entities / question	1.35	1.40	1.35
Avg. #entities / hint	0.96	1.00	0.98
Avg. #sources / question	6.27	6.17	6.71

Table 10: Statistics of the TriviaHG dataset (Mozafari et al., 2024)

- **Recall (RC):** This metric determines the percentage of words from the correct answer that are included in the retrieved passage.
- **F1-measure (F1):** This metric is the harmonic mean of precision and recall.
- **Contains (CON):** This metric checks if the retrieved or generated passage encompasses all the correct answer.
- **BERTScore (BERT):** This metric (Zhang et al., 2020) calculates the semantic similarity between words in the retrieved passage and the answer, utilizing the contextual embeddings from BERT (Devlin et al., 2019).

C Additional Experimental Results

In this section, we provide a detailed presentation of the results from our experiments across various scenarios. We will explore how different conditions and variables influence the outcomes. The column *# of Hints* displays the number of hints used as context, while the column *Ranking* presents various methods for reranking these hints, which are detailed in Section 4.3.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	20.76	25.14	26.26	25.05	26.37	75.92
2	convergence	21.1	25.43	26.57	25.32	26.62	76.03
2	t5	20.22	24.6	25.73	24.48	25.77	75.78
5	default	21.44	25.82	27.04	25.68	27.25	76.13
5	convergence	21.44	25.72	26.97	25.54	27.15	76.03
5	t5	20.98	25.4	26.64	25.23	26.81	76.05
7	default	21.57	26.01	27.21	25.89	27.48	76.22
7	convergence	21.52	25.86	27.05	25.71	27.33	76.14
7	t5	21.64	26	27.21	25.83	27.37	76.26
10	default	22.01	26.5	27.77	26.32	27.9	76.48
10	convergence	21.59	26.05	27.32	25.87	27.54	76.33
10	t5	21.82	26.25	27.49	26.07	27.76	76.35
			Few-Shot				
2	default	31.78	37.36	38.54	37.49	39.06	80.85
2	convergence	32.9	38.29	39.43	38.42	39.86	81.11
2	t5	30.12	35.5	36.51	35.68	36.73	80.23
5	default	33.44	38.92	40.09	39.07	40.77	81.36
5	convergence	34.19	39.74	40.92	39.89	41.58	81.54
5	t5	32.29	37.86	39	38.01	39.33	81
7	default	33.25	38.78	39.97	38.91	40.78	81.25
7	convergence	33.9	39.41	40.53	39.59	41.32	81.37
7	t5	32.89	38.36	39.47	38.56	40.1	81.05
10	default	33.78	39.12	40.31	39.24	41.42	81.23
10	convergence	33.7	39.17	40.34	39.31	41.34	81.24
10	t5	33.21	38.64	39.76	38.81	40.6	81.11

Table 11: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **TriviaQA** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	7.92	11.03	13.18	10.4	13.32	69.81
2	convergence	8.17	11.4	13.46	10.84	13.55	69.91
2	t5	8.06	11.22	13.14	10.66	13.21	69.9
5	default	8.84	12.04	14.24	11.39	14.4	70.29
5	convergence	8.73	11.98	14.11	11.36	14.18	70.21
5	t5	8.12	11.46	13.52	10.87	13.6	70.11
7	default	9.03	12.48	14.63	11.81	14.76	70.57
7	convergence	8.81	12.21	14.33	11.58	14.38	70.4
7	t5	8.53	11.94	13.99	11.32	14.02	70.37
10	default	9.06	12.54	14.74	11.89	14.93	70.68
10	convergence	8.67	12.19	14.39	11.53	14.52	70.39
10	t5	8.59	12.01	14.15	11.37	14.4	70.42
			Few-Shot				
2	default	11.63	16.47	19.01	15.73	19.67	72.79
2	convergence	12.19	17.01	19.44	16.28	19.86	73.02
2	t5	11.08	15.75	18.09	15.04	18.61	72.57
5	default	12.33	17.42	20.1	16.61	20.22	73.42
5	convergence	12.85	18.06	20.74	17.23	20.89	73.56
5	t5	12.22	16.94	19.35	16.25	19.53	73.2
7	default	12.27	17.3	19.86	16.53	19.92	73.26
7	convergence	12.85	17.92	20.49	17.14	20.5	73.48
7	t5	12.35	17	19.32	16.31	19.31	73.27
10	default	12.47	17.57	20.18	16.78	20.17	73.3
10	convergence	12.47	17.38	19.89	16.65	19.97	73.23
10	t5	12.49	17.3	19.77	16.57	19.7	73.29

Table 12: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **NQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	13.24	21.09	24.99	19.65	25.15	73.1
2	convergence	13.88	21.74	25.7	20.28	25.89	73.19
2	t5	13.29	21.04	25.02	19.57	24.95	73.03
5	default	13.44	21.07	25.09	19.6	25.25	73.11
5	convergence	13.09	20.75	24.82	19.23	25.05	72.96
5	t5	12.8	20.7	24.8	19.17	24.61	73.02
7	default	13.78	21.3	25.11	19.92	25.49	73.2
7	convergence	13.44	20.93	24.81	19.5	25.2	73
7	t5	13.09	20.67	24.58	19.2	24.56	73.04
10	default	13.39	21.32	25.28	19.88	25.39	73.26
10	convergence	13.04	20.74	24.72	19.26	24.75	73.04
10	t5	13.24	21.02	25.09	19.54	25.25	73.25
			Few-Shot				
2	default	17.32	27.12	31.33	25.61	30.36	75.87
2	convergence	18.45	28.21	32.43	26.72	31.15	76.22
2	t5	16.14	26.03	30.26	24.45	29.08	75.46
5	default	17.52	27.76	32.51	26.07	31.5	76.27
5	convergence	18.9	28.97	33.63	27.25	32.43	76.52
5	t5	17.77	27.54	32.21	25.8	31.15	76.18
7	default	18.31	28.24	32.8	26.62	32.14	76.42
7	convergence	18.31	28.58	33.18	26.89	31.94	76.44
7	t5	17.96	27.8	32.5	26.1	31.55	76.37
10	default	18.06	28.21	32.9	26.51	32.14	76.42
10	convergence	18.26	28.61	33.26	26.87	32.33	76.42
10	t5	17.86	27.9	32.65	26.15	31.64	76.34

Table 13: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **WebQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	21.71	26.09	27.21	25.97	27.18	76.42
2	convergence	21.95	26.27	27.44	26.15	27.53	76.39
2	t5	21.4	25.79	26.94	25.67	26.83	76.3
5	default	23.27	27.63	28.82	27.53	28.98	76.8
5	convergence	23.13	27.46	28.68	27.33	28.89	76.79
5	t5	22.71	27.14	28.35	27.02	28.57	76.65
7	default	23.45	27.89	29.09	27.8	29.24	76.94
7	convergence	23.15	27.54	28.74	27.44	28.81	76.8
7	t5	22.95	27.29	28.47	27.18	28.76	76.7
10	default	23.55	28.03	29.29	27.9	29.52	76.99
10	convergence	23.38	27.85	29.1	27.73	29.2	76.92
10	t5	23.27	27.76	28.98	27.65	29.18	76.88
			Few-Shot				
2	default	35.28	41.12	42.38	41.27	43.08	82.06
2	convergence	36.14	41.99	43.27	42.13	44.14	82.19
2	t5	33.93	39.55	40.81	39.66	41.45	81.63
5	default	38.29	43.98	45.3	44.07	46.22	82.94
5	convergence	38.01	43.75	45.07	43.87	45.94	82.8
5	t5	36.7	42.54	43.9	42.63	44.78	82.5
7	default	38.54	44.29	45.62	44.39	46.5	82.94
7	convergence	38.05	43.81	45.12	43.93	45.96	82.82
7	t5	37.62	43.43	44.76	43.54	45.66	82.67
10	default	38.23	43.96	45.29	44.06	46.3	82.77
10	convergence	37.79	43.72	45.08	43.84	45.93	82.72
10	t5	37.85	43.64	45	43.75	45.87	82.74

Table 14: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **TriviaQA** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	8.86	12.4	14.4	11.82	14.18	70.8
2	convergence	9.28	12.69	14.74	12.09	14.65	70.96
2	t5	8.81	12.35	14.46	11.72	14.35	70.93
5	default	10.19	13.97	16.18	13.33	15.87	71.68
5	convergence	10.44	14.32	16.59	13.67	16.4	71.72
5	t5	10.19	13.88	16.21	13.18	16.04	71.64
7	default	10.64	14.43	16.74	13.75	16.45	71.94
7	convergence	10.47	14.26	16.6	13.57	16.34	71.85
7	t5	10.61	14.54	16.93	13.85	16.81	71.84
10	default	10.89	14.85	17.28	14.16	16.95	72.03
10	convergence	10.08	14.03	16.42	13.32	16.07	71.8
10	t5	10.22	14.29	16.8	13.56	16.62	71.86
			Few-Shot				
2	default	14.79	20.33	22.9	19.58	23.27	74.7
2	convergence	16.01	21.49	24.07	20.7	24.24	75.08
2	t5	13.66	18.95	21.47	18.23	21.55	74.29
5	default	16.54	22.38	25.14	21.6	25.32	75.51
5	convergence	16.65	22.36	25.08	21.58	25.35	75.48
5	t5	15.46	21.11	23.74	20.41	23.74	75.22
7	default	16.68	22.64	25.56	21.74	25.51	75.63
7	convergence	16.32	22.12	24.91	21.31	25.04	75.3
7	t5	15.6	21.33	24.12	20.53	23.77	75.33
10	default	16.2	21.98	24.77	21.13	24.82	75.26
10	convergence	16.01	21.7	24.6	20.82	24.76	75.21
10	t5	16.12	21.89	24.66	21.1	24.52	75.37

Table 15: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **NQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	EM	F1	PR	RC	CON	BERT
			Zero-Shot				
2	default	13.19	21.16	25.3	19.6	25.94	72.9
2	convergence	13.58	21.82	26.09	20.2	26.38	73.07
2	t5	13.24	21.63	25.81	20.11	26.18	73.31
5	default	13.88	22.07	26.38	20.4	27.17	73.56
5	convergence	14.12	22.23	26.45	20.65	26.82	73.53
5	t5	13.78	22.07	26.36	20.44	26.57	73.42
7	default	14.42	22.78	27.19	21.09	27.41	73.77
7	convergence	13.98	21.75	25.92	20.21	26.43	73.44
7	t5	14.17	22.18	26.35	20.55	26.87	73.65
10	default	14.96	23.08	27.26	21.45	27.46	73.92
10	convergence	14.27	22.37	26.66	20.72	27.07	73.77
10	t5	14.17	22.04	26.1	20.46	26.33	73.59
			Few-Shot				
2	default	21.51	32.39	36.86	30.75	35.19	78.02
2	convergence	22	32.96	37.5	31.3	35.78	78.11
2	t5	20.37	30.89	35.4	29.35	34.06	77.64
5	default	23.43	34.41	39.14	32.64	37.65	78.74
5	convergence	23.52	34.44	39.08	32.75	37.75	78.78
5	t5	22.88	33.55	38.09	31.9	37.11	78.54
7	default	23.47	34.33	38.93	32.65	37.75	78.64
7	convergence	24.11	34.52	39.15	32.9	38.19	78.8
7	t5	23.67	34.35	38.92	32.68	37.84	78.68
10	default	23.97	34.46	39	32.87	37.84	78.66
10	convergence	23.62	34.49	39.07	32.84	38.04	78.7
10	t5	23.82	34.21	38.79	32.58	37.5	78.57

Table 16: The results of **T5-3b** used as the reader, employing zero-shot and few-shot learning strategies on the **WebQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	56.12	0	7.99	4.69	43.36	53.48	70.25
2	convergence	55.98	0	8	4.7	43.49	54.11	70.26
2	t5	54.16	0	7.93	4.67	41.85	51.55	70.08
5	default	58.25	0	7.91	4.66	41.87	54.48	70.28
5	convergence	58.25	0	7.93	4.67	42.34	54.76	70.26
5	t5	57.56	0	7.85	4.64	41.33	53	70.12
7	default	58.63	0	7.98	4.72	40.99	54.17	70.33
7	convergence	59.06	0	8.04	4.75	41.51	54.74	70.35
7	t5	59.12	0	7.98	4.71	41.13	53.29	70.24
10	default	59.52	0	8.14	4.82	40.28	53.95	70.42
10	convergence	59.46	0	8.1	4.8	40.86	54.22	70.37
10	t5	59.69	0	8.03	4.75	41.04	53.66	70.29
				Few-Shot				
2	default	55.62	49.49	58.69	58.53	63.34	64.6	88
2	convergence	55.32	50.05	59.29	59.19	63.84	65	88.07
2	t5	55.85	48.52	58.06	57.79	62.75	63.59	87.66
5	default	57.62	50.42	60.15	59.94	64.5	65.54	88.55
5	convergence	57.71	50.76	60.6	60.4	65.12	65.92	88.61
5	t5	57.96	49.35	59.36	58.96	63.89	64.64	88.25
7	default	58.24	50.1	60.11	59.79	64.51	65.41	88.53
7	convergence	58.5	50.3	60.52	60.23	64.96	65.85	88.59
7	t5	58.27	49.88	59.88	59.54	64.34	65.33	88.41
10	default	58.32	49.48	59.44	59.16	63.87	64.9	88.31
10	convergence	58.4	49.97	59.85	59.49	64.31	65.12	88.39
10	t5	58.49	49.44	59.5	59.11	64.2	64.86	88.33

Table 17: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **TriviaQA** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	48.25	0	3.16	1.77	25.37	23.52	64.47
2	convergence	50.55	0	3.29	1.84	25.97	24.88	64.56
2	t5	47.56	0	3.18	1.78	24.15	22.08	64.34
5	default	48.67	0	3.35	1.89	25.22	25.18	64.86
5	convergence	50.36	0	3.48	1.97	25.74	26.12	65
5	t5	48.75	0	3.3	1.87	25.11	24.43	64.68
7	default	48.95	0	3.39	1.92	25.06	25.54	65.02
7	convergence	50.58	0	3.4	1.92	25.5	26.04	65.02
7	t5	49.97	0	3.36	1.9	24.89	25.54	64.88
10	default	50	0	3.49	1.98	25.14	26.04	65.05
10	convergence	51.11	0	3.44	1.95	25.71	26.2	64.97
10	t5	51.86	0	3.36	1.9	25.5	25.82	64.91
				Few-Shot				
2	default	54.68	14.04	21.34	21.03	29.8	28.75	72.98
2	convergence	55.48	14.76	21.83	21.5	30.18	28.89	72.78
2	t5	53.8	14.24	21.37	21.09	29.61	28.06	72.77
5	default	57.81	17.59	25.36	25.08	33.14	31.94	75.06
5	convergence	58.45	18.31	26.41	26.27	34.33	32.74	75.21
5	t5	57.42	17.42	25.3	25.07	33.04	31.36	74.92
7	default	58.75	17.92	25.99	25.66	34.01	32.74	75.46
7	convergence	59.36	18.48	26.61	26.36	34.58	33.24	75.58
7	t5	58.45	18.12	26.28	26	34.02	31.94	75.41
10	default	58.14	18.06	26.14	25.8	34.29	33.19	75.55
10	convergence	58.75	18.34	26.52	26.18	34.71	33.68	75.61
10	t5	59.31	18.2	26.15	25.9	34.09	32.3	75.44

Table 18: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **NQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	51.62	0	5.51	3.23	36.43	35.73	66.98
2	convergence	53.49	0	5.4	3.17	35.32	35.93	66.9
2	t5	52.36	0	5.41	3.18	35.35	33.96	66.75
5	default	50.94	0	5.75	3.38	36.99	39.07	67.5
5	convergence	51.43	0	5.73	3.36	37.33	39.27	67.43
5	t5	50.15	0	5.65	3.32	35.91	36.91	67.28
7	default	52.12	0	5.82	3.42	37.14	38.98	67.5
7	convergence	52.02	0	5.77	3.39	37.16	38.98	67.42
7	t5	51.48	0	5.82	3.42	36.63	37.8	67.29
10	default	52.21	0	5.86	3.45	38.04	39.76	67.36
10	convergence	52.95	0	5.83	3.42	38.15	40.26	67.37
10	t5	51.87	0	5.76	3.39	36.52	38.24	67.28
				Few-Shot				
2	default	49.56	13.93	26.1	26.17	37.77	38.53	74.39
2	convergence	53.1	13.68	25.96	25.79	36.95	36.96	74.22
2	t5	48.87	14.52	27.18	27.08	38	38.44	74.74
5	default	55.27	16.29	30.02	30.13	42.1	43.55	76.17
5	convergence	56	17.22	30.82	30.79	43.3	44.93	76.38
5	t5	54.23	16.68	30.52	30.4	42.05	43.16	76.3
7	default	55.56	16.54	31	31.03	43.09	44.34	76.54
7	convergence	55.87	17.52	32.1	32.13	44.22	44.88	76.87
7	t5	55.12	16.73	30.76	30.88	42.54	43.9	76.39
10	default	55.76	16.68	30.71	30.71	42.77	44.64	76.45
10	convergence	55.95	16.49	30.84	30.87	43.11	44.69	76.5
10	t5	55.51	16.39	30.15	30.4	41.91	44	76.31

Table 19: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **WebQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-Va** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	49.89	0	8.85	5.23	44.22	59.71	71.18
2	convergence	49.34	0	8.69	5.14	44.1	59.19	71.02
2	t5	50.69	0	8.68	5.13	43.23	56.85	70.93
5	default	53.58	0	8.86	5.26	43.17	61.02	71.33
5	convergence	53.91	0	8.74	5.18	43.48	60.74	71.21
5	t5	54	0	8.69	5.15	42.95	59.49	71.14
7	default	54.54	0	8.92	5.31	42.5	61.12	71.38
7	convergence	54.76	0	8.85	5.24	42.98	61.16	71.33
7	t5	54.36	0	8.8	5.22	42.5	60.13	71.27
10	default	54.97	0	8.96	5.33	42.21	60.93	71.4
10	convergence	55.26	0	8.86	5.25	42.3	60.72	71.36
10	t5	55.04	0	8.87	5.27	42.31	60.69	71.35
				Few-Shot				
2	default	54.9	53.93	63.29	63.57	66.87	68.54	89.49
2	convergence	55.91	53.24	62.7	62.94	66.64	68.31	89.18
2	t5	55.7	52.79	62.22	62.33	66.06	67.29	89.14
5	default	57.22	54.31	64.4	64.56	68.17	69.64	89.85
5	convergence	57.35	54.57	64.48	64.61	68.15	69.55	89.8
5	t5	57.57	54.07	63.91	64	67.55	68.88	89.71
7	default	57.66	54.3	64.39	64.49	68.22	69.73	89.87
7	convergence	58.06	54.62	64.66	64.75	69.53	70.15	89.89
7	t5	57.47	54.06	64	64.02	67.86	69.52	89.78
10	default	57.55	54.09	64.14	64.16	68.08	69.65	89.76
10	convergence	57.52	54.61	64.58	64.59	68.46	69.83	89.88
10	t5	58.13	54.06	64.17	64.18	68.11	69.72	89.8

Table 20: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **TriviaQA** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	39.62	0	3.87	2.19	26.58	29.86	66.12
2	convergence	38.62	0	3.82	2.16	26.27	30.36	65.95
2	t5	42.14	0	3.86	2.18	25.74	27.48	65.82
5	default	47.32	0	4.32	2.45	27.45	32.94	66.7
5	convergence	46.65	0	4.27	2.43	27.77	32.91	66.55
5	t5	47.76	0	4.11	2.34	26.34	30.94	66.36
7	default	48.76	0	4.3	2.45	26.73	32.94	66.74
7	convergence	48.12	0	4.29	2.44	26.81	32.8	66.66
7	t5	49.15	0	4.2	2.39	26.68	32.3	66.57
10	default	49.51	0	4.34	2.47	26.74	33.02	66.79
10	convergence	49.26	0	4.38	2.5	26.96	33.19	66.8
10	t5	49.76	0	4.28	2.44	26.52	33.02	66.78
				Few-Shot				
2	default	58.95	18.28	26	26.24	32.76	30.69	74.73
2	convergence	62.13	17.42	25	25.16	32.47	30.64	74.24
2	t5	60.47	16.76	24.59	24.74	31.64	28.98	74.18
5	default	64.68	19.92	28.59	28.95	35.41	35.54	76.28
5	convergence	64.96	20.25	28.83	28.95	35.77	36.01	76.25
5	t5	64.07	18.53	27.17	27.45	33.77	32.63	75.63
7	default	64.43	20.22	28.99	29.04	36.01	36.09	76.61
7	convergence	64.43	20.72	29.47	29.55	37.19	36.81	76.7
7	t5	64.82	19.7	28.6	28.82	35.62	34.85	76.17
10	default	63.96	20	28.98	29.05	36.77	36.2	76.48
10	convergence	64.38	20.55	29.3	29.53	36.17	36.32	76.58
10	t5	64.76	20	29.11	29.36	36.4	35.65	76.47

Table 21: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **NQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	47.33	0	6.23	3.65	38.76	41.49	67.96
2	convergence	46.25	0	6.19	3.64	39.29	41.54	67.81
2	t5	49.75	0	6.2	3.62	37.08	38.48	67.91
5	default	52.7	0	6.7	3.93	39.31	43.7	68.58
5	convergence	52.45	0	6.66	3.92	39.18	43.21	68.48
5	t5	52.6	0	6.68	3.94	38.38	42.18	68.48
7	default	53.58	0	6.9	4.06	39.84	44.34	68.66
7	convergence	53.44	0	6.83	4.03	39.42	44.14	68.56
7	t5	53.39	0	6.87	4.05	38.43	43.01	68.59
10	default	53.93	0	6.98	4.11	40.02	44.39	68.65
10	convergence	54.08	0	7.01	4.14	40.04	45.23	68.79
10	t5	53.98	0	6.95	4.1	39.62	44.09	68.65
				Few-Shot				
2	default	48.97	16.68	29.06	29.21	40.11	41.58	76
2	convergence	54.13	16.83	28.81	28.89	40.12	41.14	75.65
2	t5	51.03	16.58	29.13	29.17	39.69	40.75	75.84
5	default	55.56	18.95	33.73	33.64	45.62	47.93	77.89
5	convergence	56.15	19.69	34.52	34.36	46.04	48.38	78.12
5	t5	55.51	19.88	34.7	34.57	46.11	47.54	78.1
7	default	56.05	18.9	34.42	34.2	46.44	48.57	78.34
7	convergence	56.55	20.28	35.35	35.31	47.32	49.9	78.51
7	t5	55.76	20.23	35.22	34.93	46.75	49.02	78.5
10	default	56.25	18.85	34.68	34.51	47.15	49.75	78.36
10	convergence	55.91	18.9	33.68	33.5	46.21	48.77	78.02
10	t5	56.94	18.85	34.4	34.13	46.98	49.66	78.09

Table 22: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on the **WebQ** dataset, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **HiGen-FT** method.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	78	0	11.26	6.62	54.65	73	71.7
2	convergence	78	0	11.26	6.62	54.65	73	71.71
2	t5	79	0	11.39	6.75	54.58	74	71.87
5	default	76	0	10.85	6.52	47.73	74	71.71
5	convergence	76	0	10.85	6.52	47.73	74	71.72
5	t5	73	0	10.62	6.44	44.65	67	71.45
7	default	77	0	11.04	6.63	48.07	74	71.62
7	convergence	77	0	11.09	6.66	48.07	74	71.65
7	t5	74	0	10.47	6.31	44.15	70	71.35
10	default	75	0	10.98	6.61	46.65	73	71.46
10	convergence	75	0	10.98	6.61	46.65	73	71.46
10	t5	76	0	10.47	6.31	43.4	72	71.75
				Few-Shot				
2	default	76	65	69.42	68.26	73.57	79	92.03
2	convergence	78	61	69.45	67.5	74.95	76	91.52
2	t5	73	61	68.37	66.86	73.07	74	91.03
5	default	75	66	71.93	70.65	75.37	78	92.84
5	convergence	76	67	72.91	71.56	76.17	78	92.66
5	t5	75	65	70.46	69.06	75.45	77	91.86
7	default	80	62	67.41	66.26	73.07	74	90.93
7	convergence	79	65	71.44	70.71	75.7	79	92.18
7	t5	84	60	67.91	66.33	73.53	75	91
10	default	83	59	67.05	65.31	73.03	74	90.83
10	convergence	84	62	69.49	67.75	76.07	78	91.65
10	t5	79	63	70.55	69.21	74.7	75	91.65

Table 23: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-7b-FT** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	68	0	9.37	5.57	47.48	65	70.51
2	convergence	68	0	9.37	5.57	47.48	65	70.52
2	t5	70	0	9.55	5.68	46.37	60	70.38
5	default	67	0	9.15	5.43	44.4	60	70.6
5	convergence	67	0	9.15	5.43	44.4	60	70.62
5	t5	69	0	9.52	5.63	45.65	59	70.74
7	default	70	0	9.63	5.73	43.1	61	70.85
7	convergence	70	0	9.64	5.74	44.1	61	70.76
7	t5	68	0	8.97	5.3	44.52	60	70.56
10	default	65	0	9.84	5.87	43.85	57	70.8
10	convergence	65	0	9.83	5.87	43.85	57	70.79
10	t5	67	0	9.09	5.38	43.68	58	70.55
				Few-Shot				
2	default	77	53	63.07	61.23	71.98	73	88.66
2	convergence	74	55	64.05	62.37	71.57	75	88.96
2	t5	77	53	61.65	60.35	66.62	69	88.8
5	default	78	57	65.61	64.56	70.37	71	89.92
5	convergence	74	57	65.15	64.18	70.83	74	89.73
5	t5	76	54	63.04	61.72	66.96	70	89.31
7	default	72	52	62.26	61.34	66.08	68	89.18
7	convergence	74	54	63.04	61.91	68.75	69	89.05
7	t5	76	57	67.23	65.56	71.74	72	90.65
10	default	75	55	62.24	61.49	66.67	70	89.29
10	convergence	73	54	62.3	61.5	66.25	71	89.3
10	t5	73	58	67.81	66.32	71.78	72	90.99

Table 24: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-7b-Va** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	77	0	9.79	5.67	52.41	71	71.2
2	convergence	77	0	9.79	5.67	52.41	71	71.2
2	t5	79	0	9.98	5.91	48.09	73	71.39
5	default	77	0	9.77	5.76	46.86	69	71.35
5	convergence	77	0	9.86	5.81	46.86	69	71.42
5	t5	78	0	9.64	5.67	47.24	70	71.41
7	default	78	0	9.83	5.83	45.53	71	71.44
7	convergence	78	0	9.9	5.88	45.53	71	71.46
7	t5	78	0	9.92	5.87	48.24	71	71.65
10	default	75	0	10.3	6.18	45.27	66	71.37
10	convergence	75	0	10.31	6.18	45.27	66	71.37
10	t5	78	0	9.83	5.82	48.07	71	71.48
				Few-Shot				
2	default	76	64	72.83	71.85	78.17	80	91.75
2	convergence	78	64	71.75	70.97	76.87	80	91.24
2	t5	76	56	65.61	64.13	74.62	78	89.27
5	default	84	65	73.29	71.82	77.67	78	92.26
5	convergence	86	67	73.79	72.4	77	76	92.28
5	t5	83	64	74.49	72.81	78.67	81	92.37
7	default	84	67	75.61	74.33	79.5	81	92.5
7	convergence	88	68	76.1	74.87	79.17	80	92.65
7	t5	83	67	77.04	74.87	82.17	83	93.33
10	default	88	68	74.74	73.39	78.7	82	92.59
10	convergence	84	66	74.25	72.42	79.2	80	92.27
10	t5	84	64	74.3	72.43	80.67	82	92

Table 25: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-13b-Va** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	76	0	10.61	6.29	49.1	71	71.72
2	convergence	76	0	10.71	6.35	49.02	71	71.74
2	t5	75	0	10.27	6.09	49.53	68	71.47
5	default	83	0	10.66	6.31	48.23	75	71.68
5	convergence	83	0	10.65	6.31	48.23	76	71.68
5	t5	78	0	10.28	6.1	49.52	70	71.47
7	default	82	0	10.86	6.5	46.45	73	71.74
7	convergence	82	0	10.77	6.43	45.65	73	71.75
7	t5	80	0	10.22	6.05	47.15	74	71.59
10	default	80	0	10.97	6.55	47.37	74	71.68
10	convergence	80	0	10.97	6.55	47.37	74	71.68
10	t5	80	0	10.86	6.41	48.15	73	71.91
				Few-Shot				
2	default	79	69	74.45	73.3	77.5	81	92.51
2	convergence	78	67	72.51	71.31	75.9	78	92.24
2	t5	76	69	74.58	73.92	77.87	81	92.51
5	default	79	65	74.74	72.74	79.53	82	92.32
5	convergence	81	67	73.21	72.05	76.87	80	92.05
5	t5	75	64	70.11	69.85	73.4	76	91.34
7	default	81	66	74.5	73.19	80.07	83	92.49
7	convergence	86	66	73.18	72.07	77.57	80	92.16
7	t5	78	66	74.52	73.16	79.07	80	92.13
10	default	84	67	74.37	72.85	78.37	82	92.26
10	convergence	82	60	69.29	67.64	74.4	78	91.35
10	t5	81	62	71.23	69.69	75.7	77	91.78

Table 26: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-13b-FT** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	78	0	10.12	5.84	53.18	77	71.44
2	convergence	78	0	10.12	5.84	53.18	77	71.44
2	t5	78	0	9.98	5.91	47.53	72	71.39
5	default	81	0	10.49	6.25	45.47	77	71.95
5	convergence	81	0	10.49	6.25	46.13	77	71.95
5	t5	81	0	10.71	6.42	45.52	72	71.52
7	default	78	0	10.56	6.35	45.63	72	71.79
7	convergence	79	0	10.69	6.42	46.38	73	71.81
7	t5	81	0	10.87	6.55	46.72	73	71.74
10	default	80	0	10.47	6.23	45.97	74	71.73
10	convergence	79	0	10.36	6.16	45.47	73	71.71
10	t5	80	0	10.24	6.12	43.72	71	71.55
				Few-Shot				
2	default	80	65	72.04	71.1	77.78	79	91.63
2	convergence	85	61	69.52	67.91	78.79	80	91.07
2	t5	86	65	69.03	68.65	72.23	75	90.92
5	default	89	63	70.62	69.61	74.2	74	91.37
5	convergence	84	65	72.3	71.34	76.23	77	92.06
5	t5	90	61	69.28	67.44	76.21	80	91.14
7	default	87	64	71.98	70.83	76.87	80	91.88
7	convergence	84	67	74.29	73.18	78.87	79	92.09
7	t5	88	66	73	71.89	77.41	79	91.94
10	default	83	63	71.38	69.84	77.03	80	91.63
10	convergence	85	65	72.14	70.6	77.87	79	91.85
10	t5	87	64	70.67	69.68	74.98	77	91.64

Table 27: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-70b-Va** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	78	0	10.54	6.2	50.61	70	71.43
2	convergence	78	0	10.55	6.2	50.61	70	71.45
2	t5	75	0	10.69	6.33	48.28	73	71.6
5	default	79	0	10.11	6.09	43.37	73	71.73
5	convergence	79	0	10.07	6.06	43.57	73	71.74
5	t5	80	0	9.94	5.9	47.22	75	71.58
7	default	77	0	10.47	6.29	45.37	72	71.93
7	convergence	77	0	10.47	6.29	45.37	72	71.94
7	t5	77	0	10.83	6.44	48.19	73	71.92
10	default	80	0	10.53	6.35	43.62	73	72.08
10	convergence	80	0	10.51	6.34	43.62	73	72.07
10	t5	80	0	10.26	6.13	45.63	74	71.79
				Few-Shot				
2	default	87	72	78.47	77.52	82.5	84	93.36
2	convergence	88	71	78.52	77.14	82.83	84	93.44
2	t5	79	71	77.53	76.81	79.78	81	93.3
5	default	89	70	77.34	76.24	82.17	86	93.93
5	convergence	90	73	79.72	78.48	82.83	83	93.99
5	t5	83	68	75.33	74.36	78.37	81	92.72
7	default	88	72	77.4	76.67	79.5	81	93.51
7	convergence	91	71	77.85	76.46	81.53	83	93.5
7	t5	89	66	72.87	71.83	75.5	80	92.39
10	default	90	71	77.85	76.89	80.2	83	93.83
10	convergence	90	68	76.76	75.48	80.92	82	93.05
10	t5	87	72	80.04	78.29	85.17	86	93.67

Table 28: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **WizardLM-70b** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	81	0	10.6	6.13	58.87	81	71.45
2	convergence	81	0	10.6	6.13	59.37	81	71.45
2	t5	79	0	9.94	5.81	53.97	77	71.55
5	default	83	0	10.25	6.07	50.38	77	71.55
5	convergence	83	0	10.25	6.07	50.38	78	71.59
5	t5	82	0	10.17	6.03	46.72	79	72.14
7	default	81	0	9.89	5.87	48.43	76	71.61
7	convergence	81	0	9.89	5.87	48.43	76	71.61
7	t5	82	0	10.28	6.1	45.05	78	71.99
10	default	87	0	10.74	6.41	49.77	79	72.12
10	convergence	86	0	10.72	6.4	48.77	78	72.05
10	t5	84	0	10.57	6.3	46.12	78	72.08
				Few-Shot				
2	default	81	65	74.77	73.21	78.83	80	92.14
2	convergence	83	67	75.4	73.8	82.37	83	92.77
2	t5	78	68	75.09	73.85	79.28	81	92.09
5	default	85	72	78.73	77.28	83.2	85	93.33
5	convergence	88	69	77.18	75.9	81.7	83	93.04
5	t5	90	64	70.63	69.26	75.5	79	91.22
7	default	87	65	74.77	72.42	81.95	82	91.84
7	convergence	88	72	79.74	78.14	83.7	84	93.57
7	t5	86	67	73.69	72.2	78	79	92.11
10	default	89	67	75.48	74.19	79.87	82	92.54
10	convergence	88	72	78.72	77.95	81.7	82	93.1
10	t5	85	64	71.87	70.62	75.33	77	91.38

Table 29: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **GPT 3.5** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	84	0	11.07	6.55	53.63	80	72.23
2	convergence	84	0	11.06	6.55	53.13	79	72.22
2	t5	81	0	11.59	6.88	52.93	79	72.39
5	default	86	0	11.5	6.82	53.07	82	72.54
5	convergence	86	0	11.48	6.81	53.07	82	72.56
5	t5	83	0	11.81	7.02	51.35	79	72.36
7	default	88	0	11.83	7.05	53	88	72.47
7	convergence	88	0	11.83	7.05	53	88	72.47
7	t5	85	0	11.76	7.01	52.55	83	72.48
10	default	84	0	12.03	7.15	51.7	86	72.32
10	convergence	84	0	12.03	7.15	51.7	86	72.33
10	t5	85	0	11.9	7.07	51.35	84	72.4
				Few-Shot				
2	default	80	73	79.43	78.44	83.67	84	93.77
2	convergence	83	71	74.81	74.53	78.33	81	92.68
2	t5	86	70	77.09	76.6	79.17	83	93.53
5	default	87	70	77.2	75.57	81.17	84	93.14
5	convergence	93	66	75.26	73.14	80	84	92.24
5	t5	95	71	80.07	79.18	83.5	84	93.6
7	default	90	73	81.24	79.73	85.5	89	94.58
7	convergence	89	72	81.84	80.07	86.17	88	94.6
7	t5	92	72	80.91	79.44	85	84	94.03
10	default	89	70	80.47	78.07	85.67	87	94.16
10	convergence	92	70	79.81	77.93	84.83	88	94.12
10	t5	91	70	80.41	78.08	85.83	86	93.83

Table 30: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **Gemini** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	83	0	11.27	6.76	50.72	81	72.39
2	convergence	83	0	11.28	6.77	50.72	81	72.41
2	t5	80	0	10.54	6.26	48.2	71	71.83
5	default	82	0	11.3	6.76	50.85	79	72.42
5	convergence	82	0	11.3	6.76	50.85	79	72.42
5	t5	85	0	11.71	7.03	49.68	76	72.32
7	default	82	0	10.98	6.58	45.92	76	72.38
7	convergence	82	0	11.12	6.69	45.92	76	72.38
7	t5	82	0	11.01	6.54	49.63	76	72.01
10	default	83	0	11.37	6.82	46.83	76	72.11
10	convergence	83	0	11.37	6.82	46.83	76	72.11
10	t5	82	0	11.29	6.76	48.13	75	72.28
				Few-Shot				
2	default	87	72	79.96	78.86	83.17	86	93.83
2	convergence	85	70	76.91	75.76	79.87	83	93.58
2	t5	85	72	77.04	76.75	79.67	82	93.21
5	default	91	69	80.06	78.11	85.87	87	94.02
5	convergence	90	67	77.64	75.72	84.2	87	93.42
5	t5	87	71	79.53	77.86	82.7	86	94.09
7	default	86	70	78.96	76.83	84.2	85	93.55
7	convergence	89	72	79.62	78.6	83.5	84	93.77
7	t5	82	70	78.74	77.2	83.33	87	93.59
10	default	87	69	79.4	77.18	85.4	86	93.38
10	convergence	88	66	75.29	73.08	81.2	82	92.46
10	t5	84	70	80.85	79.11	86.2	87	93.9

Table 31: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **LLaMA-70b-FT** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	87	0	11.91	7.07	56.4	82	72.3
2	convergence	87	0	11.89	7.06	56.4	82	72.28
2	t5	89	0	11.67	7.02	58.62	83	72.1
5	default	92	0	11.58	6.9	50.98	83	72.75
5	convergence	92	0	11.58	6.9	50.98	83	72.75
5	t5	90	0	11.65	6.99	55.4	84	72.54
7	default	90	0	10.48	6.16	49.65	82	72.19
7	convergence	90	0	10.48	6.16	49.65	82	72.19
7	t5	92	0	11.89	7.09	55.32	90	72.69
10	default	93	0	11.56	6.87	51.43	88	72.71
10	convergence	93	0	11.56	6.87	51.43	88	72.71
10	t5	93	0	11.81	7.08	51.77	87	72.47
				Few-Shot				
2	default	91	74	81.23	79.74	84.5	88	94.17
2	convergence	89	68	77.49	75.42	82.7	88	93.21
2	t5	87	70	77.64	76.1	80.7	84	93.54
5	default	93	73	81.89	80.01	86.7	90	94.81
5	convergence	93	78	84.97	83.61	88.5	90	95.5
5	t5	89	74	82.96	81.43	87.7	91	94.74
7	default	91	76	83.34	81.78	88.4	90	95.45
7	convergence	91	77	86.16	84.07	92	94	95.57
7	t5	89	75	84.72	82.72	90.53	92	94.73
10	default	90	74	82.59	81.43	87.2	92	94.79
10	convergence	89	75	84.31	82.87	87.7	91	94.96
10	t5	86	75	84.99	82.83	90.37	95	95.52

Table 32: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **Copilot** core.

# of Hints	Ranking	ACC	EM	F1	PR	RC	CON	BERT
				Zero-Shot				
2	default	85	0	10.38	6.11	53.5	81	71.85
2	convergence	85	0	10.38	6.11	53.5	81	71.85
2	t5	85	0	10.83	6.34	53.9	80	72.11
5	default	96	0	11.5	6.8	53.97	89	73.2
5	convergence	96	0	11.5	6.8	53.97	89	73.2
5	t5	88	0	11.78	6.92	52.62	81	72.58
7	default	93	0	11.62	6.84	52.4	87	72.84
7	convergence	93	0	11.62	6.84	52.4	87	72.84
7	t5	91	0	11.81	6.99	52.36	86	72.55
10	default	94	0	11.56	6.76	55.4	87	72.5
10	convergence	94	0	11.55	6.75	55.4	87	72.49
10	t5	95	0	11.12	6.52	52.62	90	72.74
				Few-Shot				
2	default	86	73	80.59	79.44	84.53	88	94.06
2	convergence	88	72	80.25	79.05	84.33	87	94.23
2	t5	90	72	80.58	78.71	85.67	88	94.05
5	default	90	75	85.65	84.43	89	90	95.32
5	convergence	89	73	83.32	81.64	88.37	91	94.57
5	t5	91	70	80.91	78.7	86.53	87	93.85
7	default	92	76	85.58	83.65	89.53	89	95.28
7	convergence	91	74	85.18	83.03	90.03	89	95.05
7	t5	94	72	81.21	79.6	84.46	87	94.35
10	default	93	76	87.29	85.03	92.17	92	95.46
10	convergence	94	75	85.12	83.14	89.2	90	95.01
10	t5	91	73	85.61	82.9	91.03	91	95.21

Table 33: The results of **LLaMA-7b** used as the reader, employing zero-shot and few-shot learning strategies on 100 random questions, are analyzed based on different ranking methods and a range of hint quantities. These hints were generated using the **GPT 4** core.

Hint Generator	# of Parameters	# of Hints	Ranking	EM	F1
		Zero-Shot			
LLaMA-Va	7b	10	default	33.0	36.82
WizardLM 70b	70b	7	t5	34.0	37.02
LLaMA-FT	7b	2	default	35.0	39.43
LLaMA-Va	13b	7	default	35.0	40.39
LLaMA-Va	70b	10	default	35.0	37.63
LLaMA-FT	13b	2	t5	38.0	40.73
LLaMA-FT	70b	7	default	38.0	41.23
Copilot	-	10	default	39.0	43.62
GPT 3.5	175b	5	default	39.0	43.2
Gemini	-	10	t5	42.0	**46.19**
GPT 4	-	10	default	**43.0**	44.5
		Few-Shot			
LLaMA-Va	7b	2	default	37.0	40.37
LLaMA-FT	7b	10	t5	42.0	44.72
LLaMA-Va	13b	5	default	45.0	48.44
LLaMA-Va	70b	2	default	45.0	47.17
LLaMA-FT	13b	7	default	46.0	49.22
LLaMA-FT	70b	7	t5	47.0	48.22
WizardLM	70b	5	default	48.0	52.4
GPT 3.5	175b	10	t5	49.0	51.47
Copilot	-	5	t5	52.0	56.03
Gemini	-	10	default	56.0	57.67
GPT 4	-	10	default	**59.0**	**60.5**

Table 34: The performance of T5-3b across different LLMs as the central component of the HINTQA system, generating hints for 100 questions.

D Case Studies

In this section, we show several case studies that illustrate the prompts we have chosen, along with examples from our experiments and their respective outcomes. The case studies are designed to demonstrate the practical application of our theoretical framework and to showcase the effectiveness of our chosen methodologies in real-world scenarios.

Question	Retriever	LLaMA-70b	HINTQA	True Answer
		TriviaQA		
How many dot positions are usually used in each letter of the Braille system?	**6**	**six**	**six**	**6, six**
Who was the leader of the gang whose members included Benny the Ball ,Brain and Choo Choo?	the bowery boys	**top cat**	**top cat**	**top cat**
Which Glasgow group signed to Creation Records and recorded their debut single "All Fall Down", in 1985?	**primal scream**	the pastels	the jesus and mary chain	**primal scream**
Who is the only man to win a best actor Oscar playing brothers?	jack nicholson	daniel day	henry fonda	**lee marvin**
		NQ		
who played taylor on the bold and beautiful?	**hunter tylo**	**hunter tylo**	**hunter tylo**	**hunter tylo**
who wrote the song going to kansas city?	bo diddley	**jerry leiber**	**jerry leiber**	**jerry leiber**
what part of the brain is in the middle cranial fossa?	**the pituitary gland**	temporal lobe region	the hippocampus	**the pituitary gland**
who did the broncos beat in the super bowl?	the packers	green bay	the falcons	**carolina panthers**
		WebQ		
where are boeing headquarters?	**chicago**	**chicago**	**seattle**	**seattle, chicago**
what university did obama graduated from?	harvard law school	harvard law school	**columbia university**	**columbia university**
what country did buddha come from?	**india**	india	nepal	**india**
who played amy squirrel in bad teacher?	cameron diaz	**lucy punch**	cameron diaz	**lucy punch**

Table 35: Comparison of answers for randomly selected questions from the TriviaQA, NQ, and WebQ datasets.

Question: what city of USA has a neighborhood called little havana?

Answer: Miami

Candidate Answers:
1. Havana
2. Washington D.C.
3. San Francisco
4. Chicago
5. New York
6. Los Angeles
7. Houston
8. Dallas
9. Atlanta
10. Philadelphia
11. Miami

Vanilla

Hints	**Candidates**
This city is located in the southeastern United States.	0 0 0 0 0 0 0 0 1 1 1
The city is known for its vibrant Cuban culture and cuisine.	1 0 0 0 0 0 0 0 0 0 0
The city has a large Hispanic population.	0 1 0 1 1 1 1 1 1 1 1
The neighborhood is home to many Cuban restaurants and shops.	0 0 0 0 0 0 0 0 0 0 0
The city is located near the Atlantic Ocean.	0 1 0 0 1 0 0 0 1 1 1
The city has a tropical climate.	1 0 0 0 0 0 0 0 0 0 1
The neighborhood is known for its colorful street art and murals.	0 1 1 0 0 1 0 0 0 1 1
The city has a rich history of Cuban immigration.	0 0 0 0 1 0 0 0 0 0 1
The neighborhood is a popular destination for foodies and cultural enthusiasts.	0 0 1 0 1 0 0 0 0 0 1

Finetuned

Hints	**Candidates**
It is the largest city in Florida.	0 0 0 0 0 0 0 0 0 0 0
It's known for its vibrant nightlife, especially in a place called South Beach.	0 0 0 0 0 0 0 0 0 0 1
It's the only major U.S. city to be founded by a woman.	0 0 0 0 0 0 0 0 0 0 1
It's home to one of the largest cruise ship ports in the world.	0 0 0 0 1 1 1 0 0 0 1
It is nicknamed the "Capital of Latin America".	1 0 0 0 0 0 0 0 0 0 1
The city is known for its Art Deco Historic District.	1 0 0 0 0 0 0 0 0 0 1
The city is often at risk from hurricanes due to its location.	1 0 0 0 1 0 1 0 0 0 1
It is located in the southeastern part of the state.	0 0 0 0 0 0 0 0 1 0 0
It is the 44th-most populous city in the United States.	0 0 0 1 1 0 1 0 1 1 0
It is the 16th-most populous metropolitan area in the United States.	0 0 0 1 1 1 1 1 1 1 0

Table 36: Hints generated by the HiGen-Va and HiGen-FT methods and the candidate answers they encompass. The 'Candidates' column displays which candidate answers are included in each hint, indicated by the index of candidate answers; for example, the first bit confirms the inclusion of 'Havana' and so on.

Question: what city of USA has a neighborhood called little havana?
Answer: Miami

MSS-DPR:
`According to the following context, answer the question:`
`Context:` rejected efforts to have separate residential and commercial land-use districts in 1948, 1962, and 1993. Consequently, rather than a single central business district as the center of the city's employment, multiple districts have grown throughout the city in addition to Downtown, which include Uptown, Texas Medical Center, Midtown, Greenway Plaza, Memorial City, Energy Corridor, Westchase, and Greenspoint. Houston has the fifth-tallest skyline in North America (after New York, Chicago, Toronto and Miami) and 36th-tallest in the world . A seven-mile (11 km) system of tunnels and skywalks links downtown buildings containing shops and restaurants, enabling pedestrians to avoid summer
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *There is no mention of a neighborhood called "Little Havana" in the provided context.*

LLaMA-70b:
`According to the following context, answer the question:`
`Context:` While Miami's Little Havana is more well-known than New York's Little Havana, New York's Little Havana is a vibrant neighborhood in the Bronx, specifically in the South Bronx area.
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *According to the context, the city with a neighborhood called Little Havana is New York (specifically, the Bronx)*

HINTQA:
`According to the following context, answer the question:`
`Context:` It's known for its vibrant nightlife, especially in a place called South Beach. It's the only major U.S. city to be founded by a woman. It's home to one of the largest cruise ship ports in the world. The city is known for its Art Deco Historic District, which showcases colorful buildings and neon signs. The city is often at risk from hurricanes due to its location.
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *Based on the context, the city with a neighborhood called Little Havana is Miami.*

Table 37: Case study of the retrieved passage from MSS-DPR, generated context by LLaMA-70b, and hints generated by HINTQA on LLaMA 7b in Zero-Shot. Words in blue indicate the correct answer, while those in red represent other potential answers.

Question: what city of USA has a neighborhood called little havana?
Answer: Miami

MSS-DPR:
`According to the following context, answer the question:`
`Context:` Red Sandy Spika dress of Reba McEntire American recording artist Reba McEntire wore a sheer red dress to the 1993 Country Music Association Awards ceremony on September 29, 1993. The sheer fabric was covered with sequins, and cut with a low neckline. The garment was designed by stylist Sandy Spika, and McEntire wore it during a duet performance of "Does He Love You" with Linda Davis. McEntire later said, "I got more press off that dress than if I'd won entertainer of the year." According to McEntire, when her little sister, Susie, saw her on stage she leaned over and.
`Question:` who sings does he love me with reba?
`Answer:` Linda Davis

`According to the following context, answer the question:`
`Context:` the introduction of The National Endowment for the Oceans, Coasts, and Great Lakes Act. This proposal is meant to preserve the ecosystems that coastal communities and economies depend on. Ocean Champions Ocean Champions, a 501(c)(4) environmental organization in the United States with a connected political action committee (Ocean Champions PAC), is the first national organization of its kind focused solely on oceans and ocean wildlife. Their goal is to create a political environment where protecting and restoring the oceans is a national government priority. They do this by helping to elect pro-ocean Congressional candidates and working to defeat the others.
`Question:` where do the great lakes meet the ocean?
`Answer:` the Saint Lawrence River

`According to the following context, answer the question:`
`Context:` would be joining the cast as Melissa Shield and Katsuhisa Namase would play David Shield, both original characters. On June 11, 2018, "Weekly Shōdnen Jump" announced that Rikiya Koyama had been cast as the film's villain, Wolfram. Masaki Suda performs the film's theme song , which was written and composed by Hiromu Akita of amazarashi. Funimation and Toho premiered the film at Anime Expo in Los Angeles on July 5, 2018, and it was later released in Japan on August 3 of that year. The first one million audience members to see the movie will receive a special book containing.
`Question:` when does the new my hero academia movie come out?
`Answer:` July 5 , 2018

`According to the following context, answer the question:`
`Context:` Sphenic number In number theory, a sphenic number (from , 'wedge') is a positive integer that is the product of three distinct prime numbers. A sphenic number is a product "pqr" where "p", "q", and "r" are three distinct prime numbers. This definition is more stringent than simply requiring the integer to have exactly three prime factors. For instance, $60 = 2 \times 3 \times 5$ has exactly 3 prime factors, but is not sphenic. The smallest sphenic number is $30 = 2 \times 3 \times 5$, the product of the smallest three primes. The first few sphenic numbers are.
`Question:` what is the smallest prime number that is greater than 30?
`Answer:` 31

`According to the following context, answer the question:`
`Context:` She then cleans up the room and leaves. The next day, soon after Letty and Jerry have arrived at the home of his parents, a detective from New York arrives looking for Letty and demanding that she come with him. Jerry, Mrs. Lynton and Letty's maid accompany her to see District Attorney John J. Haney, who produces the letters and accuses Letty of murder. After she admits that she went to see Emile, Jerry lies by saying that he and Letty spent the night together at his apartment after she left Emile's, and that he knew all about the letters.
`Question:` who plays letty in bring it on all or nothing?
`Answer:` Francia Raisa

`According to the following context, answer the question:`
`Context:` rejected efforts to have separate residential and commercial land-use districts in 1948, 1962, and 1993. Consequently, rather than a single central business district as the center of the city's employment, multiple districts have grown throughout the city in addition to Downtown, which include Uptown, Texas Medical Center, Midtown, Greenway Plaza, Memorial City, Energy Corridor, Westchase, and Greenspoint. Houston has the fifth-tallest skyline in North America (after New York, Chicago, Toronto and Miami) and 36th-tallest in the world . A seven-mile (11 km) system of tunnels and skywalks links downtown buildings containing shops and restaurants, enabling pedestrians to avoid summer
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *Houston*

Table 38: Case study of the retrieved passage from MSS-DPR retriever on LLaMA-7b in Few-Shot. Words in blue indicate the correct answer, while those in red represent other potential answers.

Question: what city of USA has a neighborhood called little havana?
Answer: Miami

LLaMA-70b:
`According to the following context, answer the question:`
`Context:` The Nobel Peace Prize for 2009 was awarded to President Barack Obama "for his extraordinary efforts to strengthen international diplomacy and cooperation between nations."
`Question:` Who won the Nobel Peace Prize in 2009?
`Answer:` Barack Obama

`According to the following context, answer the question:`
`Context:` Edouard Daladier became Prime Minister of France in 1933, not in 1933. He actually served as Prime Minister of France from 1933 to 1934, and then again from 1938 to 1940.
`Question:` Edouard Daladier became Prime Minister of which country in 1933?
`Answer:` France

`According to the following context, answer the question:`
`Context:` Mahonia japonica, also known as Japanese Mahonia or Oregon Grape, is a deciduous shrub that produces yellow flowers in the late winter to early spring. In most regions, you can expect to see it in bloom from February to April, depending on your location and climate. In warmer climates, such as USDA Hardiness Zones 8-10, the flowers may appear as early as January. In cooler climates, such as USDA Hardiness Zones 5-7, the flowers may bloom later, from March to May. After the flowers have faded, Mahonia japonica produces blue-black berries that attract birds and other wildlife. The berries are an important food source for many animals, making this shrub a valuable addition to your garden or landscape. Keep in mind that the exact blooming period may vary depending on your specific location, weather conditions, and the age and health of your shrub.
`Question:` If you have a 'Mahonia Japonica', in which season will it be in flower?
`Answer:` Winter

`According to the following context, answer the question:`
`Context:` The sport played under the "Harvard Rules" is Rugby. The "Harvard Rules" refer to the rules of Rugby that were used in the United States in the late 19th and early 20th centuries, particularly at Harvard University.
`Question:` Which sport is played under the 'Harvard Rules'?
`Answer:` Rugby

`According to the following context, answer the question:`
`Context:` After some research, I found that the person made an honorary citizen of Haslach, Austria in 1938, and had the honor withdrawn in 2004, was Adolf Hitler.
`Question:` Who was made an honorary citizen of Haslach, Austria, in 1938, an honour withdrawn in 2004?
`Answer:` Adolf Hitler

`According to the following context, answer the question:`
`Context:` While Miami's Little Havana is more well-known than New York's Little Havana, New York's Little Havana is a vibrant neighborhood in the Bronx, specifically in the South Bronx area.
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *New York*

Table 39: Case study of the context generated using LLaMA-70b on LLaMA-7b in Few-Shot. Words in blue indicate the correct answer, while those in red represent other potential answers.

Question: what city of USA has a neighborhood called little havana?
Answer: Miami

HINTQA:
`According to the following context, answer the question:`
`Context:` He was the 44th President of the United States. He served as President from 2009 to 2017. He was the first African-American President of the United States. He was a member of the Democratic Party. He was born on August 4, 1961 in Honolulu, Hawaii. Before becoming President, he represented Illinois in the U.S. Senate from 2005 to 2008. He was awarded the Nobel Peace Prize in 2009 for his extraordinary efforts to strengthen international diplomacy and cooperation between peoples. He is married to Michelle Robinson and they have two children, Malia and Sasha. He graduated from Columbia University with a BA and from Harvard University with a JD. After graduating from Columbia University, he worked as a community organizer in Chicago.
`Question:` Who won the Nobel Peace Prize in 2009?
`Answer:` Barack Obama

`According to the following context, answer the question:`
`Context:` The capital city of this country is Paris. This country is located in northwestern Europe. This country has a long history and has played a significant role in international affairs. The official language of this country is French. The currency used in this country is the Euro. This country has several major mountain ranges, including the Alps and the Pyrenees. This country is known for its cuisine, fashion, art, and architecture. This country is a member of the United Nations Security Council and is an official nuclear-weapon state. This country has a diverse landscape, with beautiful beaches, towering mountains, and fertile plains. This country has a rich cultural heritage and is home to many world-renowned museums and landmarks.
`Question:` Edouard Daladier became Prime Minister of which country in 1933?
`Answer:` France

`According to the following context, answer the question:`
`Context:` Its the coldest season of the year. Its the season when snow falls in many regions. Its the season when many people celebrate Christmas and New Year's Eve. Its the season when days are shorter and nights are longer. Its the season when many animals hibernate. Its the season when people often wear warm clothes like coats, hats, and gloves. Its the season when many trees lose their leaves. Its the season when many people go skiing or snowboarding. Its the season that comes after autumn and before spring. Its the season when hot cocoa and warm fires are popular.
`Question:` If you have a 'Mahonia Japonica', in which season will it be in flower?
`Answer:` Winter

`According to the following context, answer the question:`
`Context:` It is a team sport that originated in the United States. It is played with an oval-shaped ball. The objective of the game is to score points by advancing the ball into the opposing team's end zone. Points can be scored by carrying the ball across the opponent's goal line, throwing it to a teammate in the end zone, or kicking it through the opponent's goalposts. The game is divided into four quarters, each lasting 15 minutes. The team with possession of the ball, known as the offense, attempts to advance down the field by running or passing the ball.The opposing team, known as the defense, tries to stop the offense and take control of the ball for themselves.The offense must advance at least 10 yards in four downs or plays; if they fail, they turn over the ball to the opposing team. If the offense succeeds in advancing 10 yards or more, they are given a new set of four downs to continue their drive towards the end zone. The game is played on a rectangular field that measures 120 yards long and 53.3 yards wide.
`Question:` Which sport is played under the 'Harvard Rules'?
`Answer:` AMERICAN FOOTBALL

`According to the following context, answer the question:`
`Context:` He was born on April 20, 1889 in Braunau am Inn, Austria. He was the leader of the Nazi Party. He became the chancellor of Germany in 1933. He took the title of Führer und Reichskanzler in 1934. He initiated World War II in Europe by invading Poland on September 1, 1939. He was closely involved in military operations throughout the war. He was central to the perpetration of the Holocaust. He committed suicide on April 30, 1945.His father's name was Alois and he was born in 1837. His mother's name was Klara and she died after much suffering in 1907.
`Question:` Who was made an honorary citizen of Haslach, Austria, in 1938, an honour withdrawn in 2004?
`Answer:` Adolf Hitler

`According to the following context, answer the question:`
`Context:` It's known for its vibrant nightlife, especially in a place called South Beach. It's the only major U.S. city to be founded by a woman. It's home to one of the largest cruise ship ports in the world. The city is known for its Art Deco Historic District, which showcases colorful buildings and neon signs. The city is often at risk from hurricanes due to its location.
`Question:` what city of USA has a neighborhood called little havana?
`Answer:` *Miami*

Table 40: Case study of the hints generated using HINTQA on LLaMA-7b in Few-Shot. Words in blue indicate the correct answer.