LargePiG for Hallucination-Free Query Generation: Your Large Language Model is Secretly a Pointer Generator

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Abstract

Recent research on query generation has focused on using Large Language Models (LLMs), which despite bringing state-of-the-art performance, also introduce issues with hallucinations in the generated queries. In this work, we introduce relevance hallucination and factuality hallucination as a new typology for hallucination problems brought by query generation based on LLMs. We propose an effective way to separate content from form in LLM-generated queries, which preserves the factual knowledge extracted and integrated from the inputs and compiles the syntactic structure, including function words, using the powerful linguistic capabilities of the LLM. Specifically, we introduce a model-agnostic and training-free method that turns the **Large** Language Model into a **Po**inter-**G**enerator (**LargePiG**), where the pointer attention distribution leverages the LLM's inherent attention weights, and the copy probability is derived from the difference between the vocabulary distribution of the model's high layers and the last layer. To validate the effectiveness of LargePiG, we constructed two datasets for assessing the hallucination problems in query generation, covering both document and video scenarios. Empirical studies on various LLMs demonstrated the superiority of LargePiG on both datasets. Additional experiments also verified that LargePiG could reduce hallucination in large vision language models and improve the accuracy of document-based question-answering and factuality evaluation tasks. The source code and dataset are available at https://github.com/Jeryi-Sun/LargePiG.

CCS Concepts

• **Information systems → Information retrieval query processing**.

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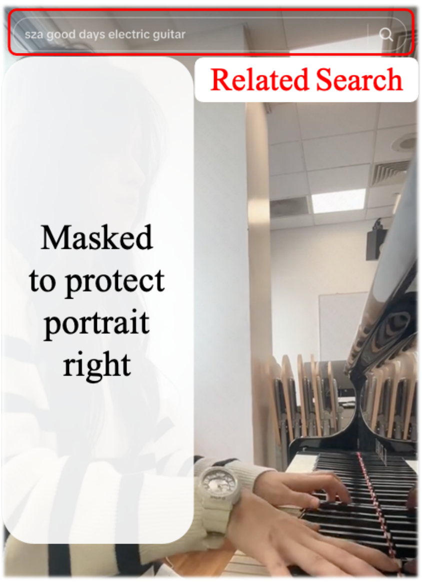
1 Introduction

Query generation is an automatic process of generating queries according to the content presented in documents or videos, which not only facilitates information retrieval from documents [12, 34, 51] but also serves applications like short video platforms by creating queries that attract user engagements. There has been notable advancement in query generation using LLMs [5, 12, 35, 38]. However, employing LLMs for query generation often introduces hallucination issues. **Factuality hallucination** refers to inaccuracies in the facts presented in the generated queries, often occurring when the inputs include knowledge not covered by the LLM's pre-training data. For example, being misled by the latest facts in the news documents can make LLMs generate queries that conflict with actual events. **Relevance hallucination** occurs when the generated queries, although factually correct, are irrelevant to the inputs [15]. Both types of hallucinations are not mutually exclusive, with some generated queries exhibiting both issues (see appendix A.1 for the experimental validation of hallucination classification).

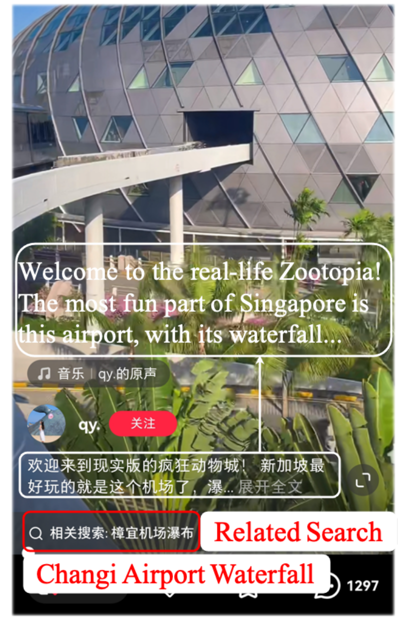
Previous research has primarily focused on reducing relevance hallucinations through post-processing methods [5, 12, 15], without addressing hallucinations at the source of generation. With the expanding range of applications for query generation on short-video platforms, generating "related search" based on video content to attract user clicks and enhance user engagement has become crucial for these platforms [43, 45]. Figure 1 presents some examples of "related search" on short-video platforms, each of which has hundreds of millions of users [1]. If a generated query exhibits relevance hallucinations, users may not click the query as clicking on "related search" will not find content related to the video, diminishing user

[1]TikTok: www.tiktok.com; Kwai: www.kuaishou.com; Xiaohongshu: www.xiaohongshu.com.



(a) Relevance Hallucination: The video is from TikTok, where the "related search" at the top presents a certain relevance hallucination, as the person in the video is playing an electric piano rather than an electric guitar.

(b) Factuality Hallucination: The video is from Kwai, where the "related search" presents a certain factuality hallucination. Singapore itself is a country, so it is illogical to ask which country's nationality it belongs to.



(c) Truthful Query: The video is from Xiaohongshu, where the "related search" at the top present is relevant and factual.

Figure 1: Examples of query generation in real applications across different short video platform.

interest. Conversely, if a query demonstrates factuality hallucinations (without relevance hallucinations), it might initially attract users' interest through clickbait but fail to deliver content related to the hallucinatory facts, thereby degrading the user experience. Therefore, the queries we generate need to be relevant to the video content, factually accurate, and sufficiently novel to attract user clicks and improve user engagement.

Unlike other generation tasks, query generation primarily relies on the inputs. Thus, decoupling the content and form at the output end of LLMs, ensuring that the factual content of the generated queries mainly comes from the inputs and that the syntax and other forms are organized by LLMs, is key to keeping the generated query truthful and reducing hallucination issues. To this end, we propose to use the Pointer Generator (PG) technology, a sequence-to-sequence model that integrates extraction (pointing to words in the input) and generation (creating new words) strategies to enhance the accuracy and relevance of the generated text [41, 49]. The PG model, combines pointer attention distribution (determining the model's focus on different parts of the inputs), vocabulary distribution (the probability distribution for choosing the next word from a fixed vocabulary), and copy probability (deciding whether to generate a word from the vocabulary distribution or copy directly from the input), not only increases the probability of mentioning facts presented in the inputs and decreases the likelihood of generating unrelated facts but also ensures the correctness of syntax and other forms generated by LLMs. Although PG technology has been applied in query generation tasks with traditional language models [19, 50], considering the enormous parameter size and training resource consumption of LLMs, adopting the traditional PG scheme, which requires learning pointer attention distribution and copy probability, may not only disrupt the original representations of LLMs but also diminish their generalization capability.

Facing the above challenge, we propose a novel PG implementation that can achieve PG functionality within LLMs without requiring additional training. Our method is based on two core observations: (1) Attention modules are more 'truthful' than other modules in LLMs (e.g., FFN modules), allowing the intrinsic attention weights towards the input sequence within LLMs to serve as the PG's pointer attention distribution; (2) LLMs generate different types of words (function words and factual knowledge words) with distinct patterns [10, 40]. When generating function words, the vocabulary distribution obtained from the high layers of LLMs is relatively consistent, whereas, for factual knowledge words, the vocabulary distribution from the high layers of LLMs shows significant differences. Further analyzing the internal mechanism behind the occurrence of different patterns in LLMs, we find that this pattern is rooted in the difference in the amount of information between function words and factual knowledge words in human linguistics. We relaxed the requirement for LLMs to generate the correct words, only needing them to identify the type of word to be generated and calculate the copy probability through the difference between the vocabulary distribution of the model's high layers and the last layer.

Based on this concept, we propose that **Large** Language Models can essentially act as an implicit **Poi**nter-**G**enerator (**LargePiG** 🐷), better addressing the hallucination issues in query generation. Our method has several notable advantages: Firstly, it preserves LLMs' powerful capabilities and generalizability, as it does not require significant modifications to the model architecture or additional training. Secondly, by simplifying the implementation process of PG, our method reduces additional computational and resource requirements, making it more efficient and easy to implement. Lastly, this approach retains the advantages of PG, achieving decoupling of content and form at the output end of LLMs, making the generated content faithful to the inputs.

To better assess the capability of LargePiG in solving hallucination issues within query generation, we introduce TruthfulVQG and TruthfulDQG, two challenging Truthful Query Generation benchmarks gathered from video and document scenarios, respectively. Experiments on these datasets demonstrate that LargePiG is capable of increasing the factuality and relevance of various LLM-based query generation methods across different LLMs. More experiments on the LLaVA [24] family validate the effectiveness of LargePiG in addressing hallucination issues in query generation within multimodal scenarios. Further experiments on relevance testing and factuality evaluation demonstrate that LargePiG can individually address relevance hallucination and factuality hallucination. Efficiency analysis shows that LargePiG causes negligible latency in the query generation process, proving the practical applicability of LargePiG.

We summarize the major contributions of this paper as follows:

(1) We identify the relevance and factuality hallucination issues in query generation, which are crucial for ensuring effective "related search" in short-video platforms.

(2) We propose **LargePiG**, a training-free, and model-agnostic decoding method that mitigates query generation hallucinations without modifying LLM architectures, ensuring ease of deployment.

(3) We introduce two truthful query generation benchmarks, **TruthfulVQG** and **TruthfulDQG**, and demonstrate through extensive experiments the effectiveness of LargePiG in reducing hallucinations while maintaining efficiency.

2 Related Work

Large language models based query generation. Query generation is vital for improving information retrieval systems and user experience on short video platforms. Doc2Query [34] implements this concept using a sequence-to-sequence model for generating queries based on document contents. Advancing this, UDP [39] utilizes LLMs in a zero-shot setting to predict query likelihood from text passages. Building on this, PQGR [12] and InPars [5] introduce few-shot and contrastive example approaches, enhancing the contextual awareness of query generation. AQG [25] further develops LLM adaptability to query generation by employing LoRA [17] for fine-tuning with real user queries and context, alongside other parameter-efficient methods like soft-prompt tuning and adapters [35, 36]. Additionally, UDAPDR [38] explores efficiency by combining large and small models to generate and refine queries. Our work addresses hallucination in query generation, introducing LargePiG, a novel decoding method applicable to LLM-based query generation approaches to reduce relevance and factuality hallucination.

Hallucination mitigation in large language models. Large Language Models exhibit a critical tendency to produce hallucinations, resulting in content that is inconsistent with real-world facts or user inputs. Hallucination mitigation strategies can be data-driven, involving more refined filtering of pretraining data [28] or high-quality instruction-tuning datasets [55] to reduce the likelihood of LLMs learning hallucinatory knowledge. Alternatively, approaches from the input side, such as Retrieval Augmented Generation, utilize data to reduce LLM-generated hallucinations by grounding the model with an external knowledge base [14, 44, 46]. However, Retrieval Augmented Generation is not well-suited for tasks like query generation, as there is no explicit need for external retrieval content. Our LargePiG method focuses on reducing hallucination for the query generation task from the generation side, transforming the LLM into a pointer generator by leveraging intrinsic features of the LLM to separate content and form in LLM-generated queries. Unlike DoLa [10], which contrasts between transformer layers to correct the next word's probability, LargePiG derives the copy probability from the difference between the vocabulary distribution of the model's high layers and the last layer. Moreover, these hallucination mitigation methods are orthogonal to the LargePiG approach taken in this paper and could potentially be used in conjunction to mitigate hallucinations further.

3 Method

Current Large Language Models are fundamentally based on the Transformer decoder-only architecture. Initially, the input text is tokenized and transformed into numerical vectors by the embedding layer. Given a sequence of input tokens as $X = \{x_1, x_2, \ldots, x_{t-1}\}$, where the input tokens may include the instruction $I = \{x_1, \ldots, x_{m-1}\}$, the source document $D = \{x_m, \ldots, x_n\}$, and part of generated query $\widetilde{Q} = \{x_{n+1}, \ldots, x_{t-1}\}$, the embedding layer first converts these tokens into a series of vectors $H_0 = \{h_1^{(0)}, \ldots, h_{t-1}^{(0)}\}$. After passing through multiple Transformer Decoder Layers, H_N is processed by a Classification Layer, usually composed of a layer of linear layers and softmax, mapping to the vocabulary distribution.

To address the hallucination issues present in LLM-based query generation, we propose to incorporate the mechanism of the Pointer-Generator to enhance the model's faithfulness to the factual knowledge contained within the source document D. The Pointer-Generator combines the original decoding vocabulary distribution P_{vocab} of the LLM with the newly introduced pointer attention distribution P_{source}, the latter representing the probability distribution over the source document D. Furthermore, the Pointer-Generator includes a copy probability p_{copy}, which determines whether the model selects the next word from a predefined vocabulary or directly copies a word from the source document. We propose to use this mechanism to ensure that the factual content in the generated query mainly comes from D and that the syntax and other forms are organized by LLMs, significantly reducing the occurrence of hallucinations.

Unlike previous approaches that required retraining the pointer-generator model to learn the pointer attention distribution and copy probability, we propose **LargePiG**, a plug-in and training-free method, to implement pointer-generator decoding within LLMs

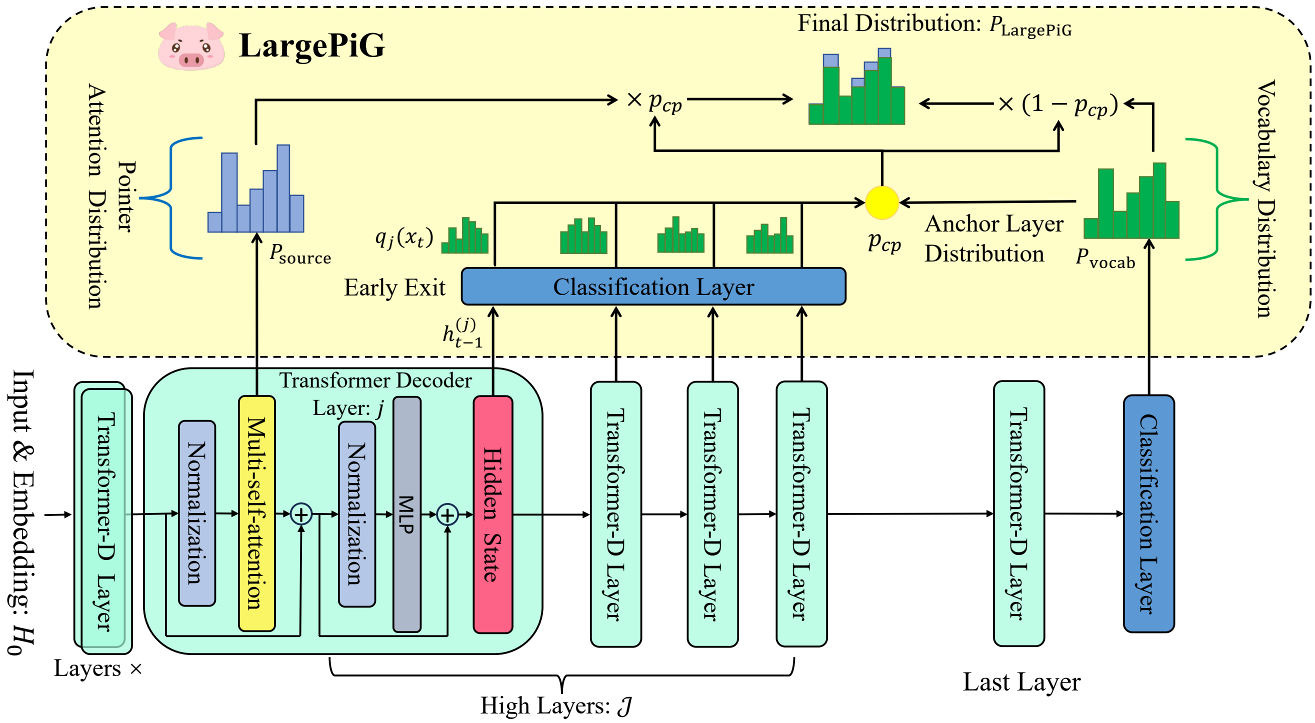


Figure 2: The architecture of the proposed plug-in and training-free method LargePiG. Pointer Attention Distribution (§ 3.1) from the LLM's self-attention weights, Vocabulary Distribution (§ 3.2) from the output of the original LLM, Copy Probability (§ 3.3) from the difference between the vocabulary distribution of the model's high layers and the last layer.

(see Figure 2). The pointer attention distribution can utilize the LLM's intrinsic attention weights towards the source document (§ 3.1); the vocabulary distribution comes from the output of the original LLM, ensuring the generative capability of the model (§ 3.2); and the copy probability is derived from the difference between the vocabulary distribution of the model's high layers and the last layer (§ 3.3). Finally, we delve into the rationality of why LargePiG can implicitly transform LLM into a pointer generator (§ 3.4).

3.1 LargePiG: Pointer Attention Distribution

The core module of Large Language Models consists of N stacked Transformer layers. Each Transformer layer contains a self-attention module and feedforward neural networks (FFN) to process the embedded vectors, allowing the model to focus on the most relevant parts of the input dynamically. As the vectors in H_0 pass through each Transformer layer, they are successively transformed, with the output of the layer j represented as H_j. In this process, taking the layer j as an example, H_{j-1}, the output of the layer $(j-1)$, first passes through the j-th layer's self-attention module. Here, we take Multi-Head Attention (MHA) as an example, which can be easily generalized to Multi-Query Attention [42] and Grouped-Query Attention [2]:

$$\text{MHA} = \text{Concat}(\text{head}_1, \ldots, \text{head}_M)W^O, \tag{1}$$

$$\text{head}_i = A_i(H_{j-1}W_i^Q, H_{j-1}W_i^K, H_{j-1}W_i^V), \tag{2}$$

$$A_i(Q,K,V) = A_i^w V,\ A_i^w = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right), \tag{3}$$

where A_i^w denotes the attention weights of MHA, with M as the number of heads, $W^{Q/K/V/O}$ are learnable parameters and $\sqrt{d}$ are scaling factor. Since each head captures a unique attention pattern, we aggregate these by averaging: $A^w = \frac{1}{M}\sum_{i=1}^{M} A_i^w$, enabling a unified representation of attention mechanisms across heads.

In the context of LargePiG, computing the pointer attention distribution P_{source} primarily focuses on the attention weights from the last token in H_{j-1} (i.e., A_{t-1}^w) to the tokens of the source document D. As the source document D corresponds to tokens from m to n in the input sequence, we use $A_{t-1,m:n}^w$ to compute P_{source}. First, for the values in $A_{t-1,m:n}^w$, we normalize them to ensure their sum equals one, forming a probability distribution. Since we are only concerned with the tokens corresponding to the source document in A^w and we already know this is extracted from a larger softmax function, direct normalization suffices. Let this normalized vector be $\mathbf{P}_{m:n}$:

$$\mathbf{P}_{m:n} = \frac{A_{t-1,m:n}^w}{\sum_{i=m}^{n} A_{t-1,i}^w} \tag{4}$$

Next, we construct the probability distribution to match the vocabulary distribution. We depart from traditional PG by not considering new word emergence, focusing on maintaining LLM generation fidelity to input while acknowledging the prevalent use of sentence-piece tokenization [23]. Let $\mathcal{V}$ be the vocabulary of the LLM. The probability distribution for each token x_i in P_{source} within $\mathcal{V}$ comes from the corresponding attention weight in $\mathbf{P}_{m:n}$. Therefore, for each token x_i in the vocabulary $\mathcal{V}$, its pointer attention distribution $P_{\text{source}}(x_i)$ is defined as:

$$P_{\text{source}}(x_i) += \begin{cases} \mathbf{P}_{m:n}[j] & \text{for all } j \text{ where } x_j = x_i \text{ and } x_j \in D \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Thus, the probability $P_{\text{source}}(x_i)$ for each $x_i \in D$ directly corresponds to the normalized attention weight $\mathbf{P}_{m:n}$, while the probability for vocabulary token not in D is 0.

3.2 LargePiG: Vocabulary Distribution

The generation of the vocabulary distribution in the LargePiG model is seamlessly integrated with the output of the original LLM. This integration is achieved through the model's final component, an affine transformation layer commonly called the classification layer. This layer maps the output of the last Transformer layer H_N, to the vocabulary distribution P_{vocab} over the vocabulary set $\mathcal{V}$. The probability distribution for the next token x_t given the preceding sequence $x_{<t}$, is computed by applying a softmax function to the affine-transformed output:

$$P_{\text{vocab}}(x_t) = q_N(x_t \mid x_{<t}) = \text{softmax}\left(\phi\left(h_{t-1}^{(N)}\right)\right)_{x_t}, \quad x_t \in \mathcal{V} \tag{6}$$

where $h_{t-1}^{(N)}$ is the output vector from the last Transformer layer for the position $(t-1)$ in H_N, and $\phi(\cdot)$ performs the affine transformation to project this vector into the vocabulary space. The subscript x_t indicates that we extract the probability corresponding to the token x_t from the softmax output. This approach ensures that the generative capabilities of the underlying LLM are preserved within our LargePiG framework. Through this methodology, LargePiG leverages the extensive linguistic and syntactic knowledge of the LLM, thereby significantly retaining the richness and fluency of the generated query.

3.3 LargePiG: Copy Probability

The copy probability in our LargePiG model leverages the difference between the vocabulary distribution of the LLM's high layers and the last layer. For the layer j, we also compute the vocabulary distribution using $\phi(\cdot)$ as follows, where $\mathcal{J}$ is a set of candidate layers and this operation is called early exiting [40, 47]:

$$q_j(x_t \mid x_{<t}) = \text{softmax}\left(\phi\left(h_{t-1}^{(j)}\right)\right)_{x_t}, \quad j \in \mathcal{J}. \tag{7}$$

Based on the findings of Chuang et al. [10] and early exit decoding research [13, 40], when LLMs generate function words (e.g., auxiliary verbs, prepositions, conjunctions), the vocabulary distribution $q_j(x_t \mid x_{<t})$ stabilizes at high layers. In contrast, when generating factual knowledge words (e.g., names, places, dates), the vocabulary distribution continues to evolve at high layers. In the query generation task, we expect the factual content in the generated query primarily comes from the source document, while syntax and other forms are organized by the LLM. This implies we can use the vocabulary distribution $q_N(x_t \mid x_{<t})$ from the last transformer layer as an anchor layer, and by calculating the distributional differences with the vocabulary distributions from other high layers, determining whether LLM is generating factual knowledge words or function words. A larger distributional difference suggests a higher likelihood of generating factual knowledge words. Since our goal is to ensure that the factual content of the generated query mainly comes from the input document, the copy probability should be higher in such cases, and vice versa. Therefore, the copy probability can be calculated as follows:

$$p_{\text{cp}} = O_{j \in \mathcal{J}} d\left(q_N(x_t \mid x_{<t}), q_j(x_t \mid x_{<t})\right), \tag{8}$$

where O can be an average $\frac{1}{|\mathcal{J}|}\sum$, a max, or a min operation, $d(\cdot,\cdot)$ is a distributional distance measure such as Jensen-Shannon Divergence [10, 32], and $\mathcal{J}$ is the set of high-layers around the anchor layer. We can control the intensity of copying by adjusting O and $\mathcal{J}$. A larger range of $\mathcal{J}$ and O being max increases the likelihood of copying, while a smaller range of $\mathcal{J}$ and O being min decreases it.

The final distribution generated by LargePiG is given by:

$$P_{\text{LargePiG}}(x_t) = p_{\text{cp}} P_{\text{source}}(x_t) + (1 - p_{\text{cp}}) P_{\text{vocab}}(x_t). \tag{9}$$

3.4 The Internal Mechanisms of LargePiG

The key to LargePiG's functionality lies in LLM's ability to correctly reflect the current generated token's attention weights towards the source document and generate factual knowledge words and function words in the pattern we mentioned in § 3.3.

Regarding the pointer attention distribution, we analyzed the causes of hallucinations in query generation in § 1, concluding that the attention modules in LLMs are more 'truthful' than the FFN modules and classification layer. The **factuality hallucination** mainly arises from the LLM's insufficient knowledge about the source document. Some studies have shown that knowledge is mainly stored in the FFN module of the transformer layer in pre-trained language model [11]. Even if the self-attention module correctly focuses on the relevant token, the FFN module may still produce factuality hallucinations due to insufficient pre-training [31]. Moreover, Jiang et al. [20] found that MLP modules have a more significant impact on incorrect outputs than attention modules, indicating that in the transformer layers of LLMs, attention modules are more 'truthful' than FFN modules. The **relevance hallucination** can be attributed to the softmax bottleneck issue inherent in LLMs [7, 54], where the model predicts the probability of each word across the entire vocabulary, struggling to differentiate between words that are almost equally likely in a given pre-training context but have different meanings in the current situation. The softmax bottleneck primarily stems from the final classification layer, which is structurally unrelated to the attention module in the transformer layer we use.

Regarding the copy probability, we delve deeper into the findings of [10, 40], questioning why LLM predictions for function words stabilize at high layers' vocabulary distributions, while predictions for factual knowledge words do not. Research on early exit decoding [13, 40, 47] has demonstrated that different data samples (tasks) possess varying complexities. For multi-layer stacked deep models, such as ResNet [16] and LLaMA [48], simple tasks may only require shallow layers for completion, whereas complex tasks demand the involvement of all layers. The scaling law [22] and the emergence ability [52] also testify to this, with the model's ability to solve more complex tasks increasing alongside its size and layer number. Returning to our task, predicting function words can exit at shallower layers, while predicting factual knowledge words requires deeper layers, indicating that predicting function words is simpler, whereas predicting factual knowledge is more complex.

Why is predicting function words simpler, and predicting factual knowledge more complex? Achille et al. [1] demonstrated that tasks with greater information content are more complex. Since LLMs learn from human language, if we can verify that factual knowledge words in human language convey more information than function words, then the pattern mentioned above is determined by the nature of human language itself. Our experimental analysis within our TruthfulVQG and TruthfulDQG benchmarks investigated the semantic impact of removing factual knowledge words versus function words, with experimental details provided in Appendix A.2. The results show that on both datasets, removing factual knowledge words causes a greater decrease in semantic similarity scores with the original sentence compared to function words. These findings confirm that factual knowledge words contribute more significantly to the sentence's informational content than function words, highlighting the complexity of predicting factual knowledge words. Verifying that the pattern found in [10, 40], rooted in the linguistic properties of human language, is a principle that holds true across multiple languages, even though initial studies focused on English scenarios. Our subsequent experiments expanded this understanding to multiple languages, validating the feasibility of employing this pattern for calculating copy probability in LargePiG. For further analysis of the effectiveness of copy probability in LargePiG, see Appendix A.2.

4 Experiment

4.1 Experimental Settings

Datasets. To quantitatively assess the truthful query generation capabilities of LargePiG in both video (e.g., TikTok) and document (e.g., Bing Search) scenarios, considering the absence of relevant datasets, we constructed two challenging benchmarks named TruthfulVQG and TruthfulDQG. These benchmarks correspond to formats similar to TruthfulQA [29], crafted from video (Chinese corpus) and document (English corpus) respectively, to validate the model's query generation truthfulness. The construction of the benchmarks utilized a combination of LLM and manual methods. The completed data format is shown in Table 6 of Appendix A.4, where "Bad queries" are those containing either relevance hallucinations or factuality hallucinations or both, "Good queries" are those without any hallucinations, and "Best query" represents the optimal query. The construction process is detailed in Appendix A.3 and Appendix A.4, and the statistical results of the datasets are shown in Table 7.

Metrics. To evaluate LLMs in truthful query generation, we independently compute each reference query's log-probability. Drawing inspiration from the evaluation metrics of TruthfulQA-MC [10, 29], the metrics used to assess the truthfulness of the model-generated queries include MC1 (the percentage of all data where the best query log-probability is greater than all bad queries log-probability), MC2 (normalized total probability assigned to the set of good queries), and MC3 (the percentage of all good queries where each good query log-probability is greater than all bad queries log-probability).

Models and Baselines. We employed two types of backbone LLMs, Qwen1.5 7B chat [3] and LLaMA2 7B chat [48], and utilized four LLM-based query generation approaches, including (1) **Base**: using the backbone LLMs to directly generate queries in a zero-shot manner; (2) **PQGR** [12]: prompting the LLM with 8 in-context examples to generate queries, which achieves more suitable queries compared to the Base approach; (3) **Inpars** [5]: includes not only good queries in the in-context examples but also bad queries to enable the model to generate better queries through comparison; (4) **AQG** [25]: employ LoRA [17] to fine-tuning the LLM using real-world user-input queries and context data to enhance the model's query generation capability. The implementation details of these LLM-based query generation approaches are in Appendix A.5. Our approach, **LargePiG**, is model-agnostic and can be applied to different LLM-based query-generation methods, reducing the relevance and factuality hallucinations associated with model-generated queries. The implementation details of LargePiG are provided in Appendix A.6. For baseline models, we compared LargePiG with recent closely related work aimed at reducing hallucinations in LLMs: **DoLa** [10], which enhances factuality in LLMs by decoding through contrasting layers, and Contrastive Decoding (**CD**) [27], which improves factuality in LLMs' generations by leveraging the contrasts between LLMs of different sizes, selecting tokens that maximize their log-likelihood difference. For Qwen1.5 7B chat, we chose Qwen1.5 1.8B chat [3] as the contrast model for CD. Since there is no smaller-sized model for LLaMA2 7B chat, we could not perform CD experiments on this model. *DoLa, CD, and LargePiG are all training-free decoding methods for reducing hallucinations in LLM generation, making them fair for comparison.*

4.2 Results

Main result. As shown in Table 1, LargePiG has demonstrated improvements across two datasets, various backbone methods, and different metrics, validating LargePiG's ability to enhance the truthfulness of LLM-based query generation methods. The effectiveness observed across datasets in different languages further corroborates the analysis presented in Section 3.4. Moreover, our method has surpassed CD and DoLa, which even exhibited negative gains on some datasets. The primary reason is that query generation primarily relies on the factual knowledge in the inputs, requiring less generated factual knowledge from the model, whereas DoLa and CD stimulate the model's knowledge by contrasting shallow layers' logits with deep layers' logits or contrasting large LLM's logits with small LLM's logits, which may lead to the generation of facts that do not align with the context. In the following analysis experiments, we will further discuss the respective advantages of CD, DoLa and LargePiG, and analyze in detail from the perspectives of relevance hallucinations and factuality hallucinations how LargePiG can improve the truthfulness of LLM generation. The experiments of LargePiG on multimodal datasets can be found in the appendix A.7, which also shows improvements over the backbone model, demonstrating the broad applicability of LargePiG.

Table 1: Performance comparisons between LargePiG and the baselines. The boldface represents the best performance. '†' means improvements are significant (paired t-test at p-value < 0.05).

Model	Qwen1.5 7B Chat						LLaMA2 7B Chat					
	TruthfulVQG			TruthfulDQG			TruthfulVQG			TruthfulDQG		
	MC1	MC2	MC3	MC1	MC2	MC3	MC1	MC2	MC3	MC1	MC2	MC3
Base	40.35	66.97	37.70	27.34	85.77	39.83	52.94	75.12	46.01	33.72	**71.61**	34.29
+ CD	35.79	63.43	36.49	24.25	85.60	37.99	–	–	–	–	–	–
+ DoLa	37.97	64.73	35.68	23.52	85.05	37.09	52.79	75.25	46.10	35.09	69.97	33.19
+ LargePiG	**41.49**†	**68.12**†	**38.92**†	**29.91**†	**89.33**†	**42.18**†	**54.56**†	**76.15**†	**47.20**†	**37.23**†	70.95	**36.93**†
PQGR	43.61	70.08	41.26	25.86	77.23	36.86	52.22	74.21	45.60	32.28	65.74	31.41
+ CD	41.71	66.10	40.69	23.84	77.90	35.58	–	–	–	–	–	–
+ DoLa	40.13	66.50	38.24	23.79	76.51	35.67	51.83	73.69	44.54	31.92	64.41	31.52
+ LargePiG	**45.52**†	**70.79**†	**42.54**†	**27.12**†	**79.20**†	**38.35**†	**52.87**†	**74.87**†	**46.27**†	**34.66**†	**68.34**†	**34.21**†
InPars	44.35	70.77	41.56	26.09	78.82	37.37	52.53	74.53	45.85	30.66	64.43	30.32
+ CD	43.91	68.90	39.82	24.06	77.20	35.69	–	–	–	–	–	–
+ DoLa	40.35	66.90	38.48	24.48	77.57	36.96	51.59	74.33	44.86	29.87	63.97	29.52
+ LargePiG	**46.26**†	**71.51**†	**42.82**†	**27.34**†	**81.17**†	**38.53**†	**53.03**†	74.74	**46.20**†	**33.70**†	**67.30**†	**33.36**†
AQG	40.50	67.26	37.85	27.41	85.86	39.93	54.00	75.92	46.87	34.82	**71.62**	34.42
+ CD	36.79	63.36	33.44	24.23	83.56	37.96	–	–	–	–	–	–
+ DoLa	37.99	64.65	35.62	25.59	85.28	39.21	52.79	75.25	46.10	33.02	70.96	33.17
+ LargePiG	**41.56**†	**68.13**†	**39.06**†	**29.99**†	**89.58**†	**42.35**†	**54.84**†	**76.73**†	**47.76**†	**37.09**†	71.04	**36.82**†

Table 2: Experiment results on FACTOR.

Model	LLaMA-7B		LLaMA-13B	
	News	Wiki	News	Wiki
Base	58.3	58.6	61.1	62.6
+ CD [26]	-	-	62.3	64.4
+ DoLa [10]	62.0	62.2	62.5	66.2
+ LargePiG	**71.0**	60.4	**72.1**	63.1
+ DoLa + LargePiG	63.4	**64.7**	65.3	**68.8**

Table 3: Relevance win rate comparison between Qwen1.5-7B-Chat with LargePiG and without LargePiG on TruthfulVQG.

Model	LargePiG Win	Original Model Win	Tie
Base	827	70	103
PQGR	749	181	70
InPars	805	141	54
AQG	831	73	96

4.3 Analysis

LargePiG's ability to reduce factuality hallucinations. To specifically validate LargePiG's capability to address factual hallucinations, we selected the News and Wiki categories of FACTOR dataset [33], which assesses LLMs' factuality in long-paragraph settings by completion task. The News' ground-truth answers are based on facts from news content, which LLMs may not have sufficiently learned during training; the Wiki contains general facts well-learned during pre-training, allowing LLMs to respond based on pre-trained knowledge and also to learn from the context. To ensure a fair comparison with DoLa, we chose LLaMA-7B and LLaMA-13B as the backbone LLMs following DoLa's setting.

The experimental results shown in Table 2 demonstrate that on the News dataset, LargePiG successfully enhanced the copy ability of Base models to address hallucinations, thereby significantly outperforming other methods that solely rely on the model's intrinsic pre-trained knowledge and original context understanding capabilities. Given the feature of the Wiki dataset, although the results for LargePiG on Wiki do not surpass other methods that stimulate the model's own pre-trained knowledge, they still exceed the base model, validating the contribution of LargePiG's copy ability to resolving hallucinations. Moreover, LargePiG can be combined with state-of-the-art methods that are based on the model's pre-trained knowledge, achieving advancements beyond the current state of the art (i.e., +DoLa + LargePiG > +DoLa). This suggests that LargePiG's copy ability can be synergistically integrated with the model's inherent pre-trained knowledge.

LargePiG's ability to reduce relevance hallucinations. To independently verify LargePiG's capability to resolve relevance hallucinations, we generated queries using different models and

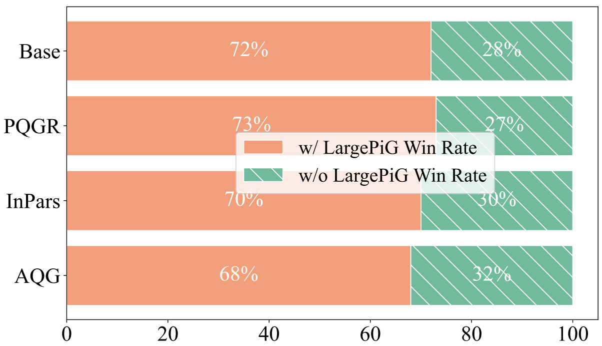


Figure 3: Semantic similarity win rate of Qwen1.5-7B-Chat with LargePiG vs without LargePiG on TruthfulVQG.

then encoded them and the corresponding context using the current state-of-the-art text representation model BGE [53] to calculate their cosine semantic similarity. The pairwise comparisons of cosine similarity are presented on Figure 3, demonstrating that LargePiG notably outperforms the baseline models. This indicates that LargePiG effectively reduces the relevance hallucinations of query generation. In addition, we used GPT-4o (from OpenAI) to assess LargePiG's ability to reduce relevance hallucinations. Considering time and API cost factors, we sampled 1000 data points from TruthfulVQG for evaluation. The experiments in Table 3, judged by GPT-4o, further confirm that LargePiG can mitigate relevance hallucinations.

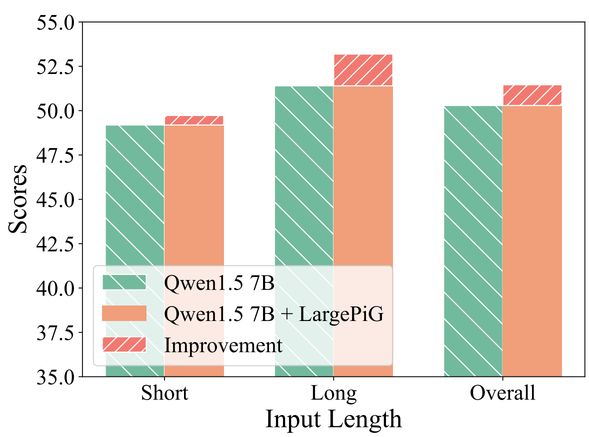


Figure 4: Comparison of the Copying Ability between Qwen1.5-7B-Chat and Qwen1.5-7B-Chat with LargePiG on the SQuAD dataset.

LargePiG's ability to copy. To validate whether LargePiG has a stronger copy ability compared to the original LLM decoder, we tested the performance of LLM with and without the addition of LargePiG on tasks that require copying from the inputs. Following the setting of Jelassi et al. [18] for validating LLMs' copy capability, we selected the SQuAD question-answering dataset [37], which provides text paragraphs along with several questions pertaining to the text and features various inputs lengths. We conducted experiments on Qwen1.5-7B-Chat, reported the F_1 score, and classified questions into short and long categories based on whether their length exceeded 200 words. The results on Figure 4 show that LargePiG significantly improved the F_1 score on Qwen1.5-7B-Chat, with more pronounced improvements for scenarios with long inputs, indicating that LargePiG indeed enhances the copy ability of LLMs.

Table 4: Decoding latency (ms/token).

	Baseline	DoLa	LargePiG
Base / AQG	95.9 (×1.00)	99.9 (×1.04)	101.8 (×1.06)
InPars	135.1 (×1.00)	142.4 (×1.05)	139.8 (×1.03)
PQGR	142.0 (×1.00)	148.3 (×1.04)	149.1 (×1.05)

Efficiency analysis. We use NVIDIA V100-32G GPUs and 52-core Intel(R) Xeon(R) Gold 6230R CPUs at 2.10GHz machine to analyze the efficiency of original decoding (baseline), DoLa, and LargePiG when applied across different query generation models. The decoding time of LargePiG in LLaMA2-7B models increases by a maximum of 6% compared to the baseline and is on par with the decoding time of DoLa, as shown in Table 4. The results demonstrate that LargePiG can enhance the truthfulness of query generation with negligible additional time consumption, proving the practical applicability of LargePiG.

5 Conclusions

LLM-based query generation significantly improves query quality and user experience in information retrieval systems, but it also introduces hallucination challenges, hindering its application in emerging use cases such as "related search". To address these, we propose LargePiG, a training-free method transforming an LLM into a Pointer-Generator. LargePiG separates content and form in LLM-generated queries, using input knowledge for fact generation and LLM capabilities for syntactic structure. It combines self-attention weights for pointer attention distribution, LLM original output as vocabulary distribution, and high-layer vocabulary distribution for copy probability. Our empirical evaluations on the proposed TruthfulVQG and TruthfulDQG datasets confirm LargePiG's effectiveness in reducing hallucination on query generation tasks.

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References

[1] Alessandro Achille, Giovanni Paolini, Glen Mbeng, and Stefano Soatto. 2021. The information complexity of learning tasks, their structure and their distance. Information and Inference: A Journal of the IMA 10, 1 (2021), 51–72.

[2] Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebron, and Sumit Sanghai. 2023. GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing. 4895–4901.

[3] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen Technical Report. arXiv preprint arXiv:2309.16609 (2023).

[4] Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, et al. 2016. Ms marco: A human generated machine reading comprehension dataset. arXiv preprint arXiv:1611.09268 (2016).

[5] Luiz Bonifacio, Hugo Abonizio, Marzieh Fadaee, and Rodrigo Nogueira. 2022. Inpars: Unsupervised dataset generation for information retrieval. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval. 2387–2392.

[6] Zheng Cai, Maosong Cao, Haojiong Chen, Kai Chen, Keyu Chen, Xin Chen, Xun Chen, Zehui Chen, Zhi Chen, Pei Chu, et al. 2024. Internlm2 technical report. arXiv preprint arXiv:2403.17297 (2024).

[7] Haw-Shiuan Chang, Zonghai Yao, Alolika Gon, Hong Yu, and Andrew Mccallum. 2023. Revisiting the Architectures like Pointer Networks to Efficiently Improve the Next Word Distribution, Summarization Factuality, and Beyond. In Findings of the Association for Computational Linguistics: ACL 2023. 12707–12730.

[8] Xiang Chen, Chenxi Wang, Yida Xue, Ningyu Zhang, Xiaoyan Yang, Qiang Li, Yue Shen, Jinjie Gu, and Huajun Chen. 2024. Unified Hallucination Detection for Multimodal Large Language Models. arXiv preprint arXiv:2402.03190 (2024).

[9] I-Chun Chern, Steffi Chern, Shiqi Chen, Weizhe Yuan, Kehua Feng, Chunting Zhou, Junxian He, Graham Neubig, Pengfei Liu, et al. 2023. FacTool: Factuality Detection in Generative AI–A Tool Augmented Framework for Multi-Task and Multi-Domain Scenarios. arXiv preprint arXiv:2307.13528 (2023).

[10] Yung-Sung Chuang, Yujia Xie, Hongyin Luo, Yoon Kim, James R Glass, and Pengcheng He. 2023. DoLa: Decoding by Contrasting Layers Improves Factuality in Large Language Models. In The Twelfth International Conference on Learning Representations.

[11] Damai Dai, Li Dong, Yaru Hao, Zhifang Sui, Baobao Chang, and Furu Wei. 2022. Knowledge Neurons in Pretrained Transformers. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 8493–8502.

[12] Zhuyun Dai, Vincent Y Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith Hall, and Ming-Wei Chang. 2022. Promptagator: Few-shot Dense Retrieval From 8 Examples. In The Eleventh International Conference on Learning Representations.

[13] Siqi Fan, Xin Jiang, Xiang Li, Xuying Meng, Peng Han, Shuo Shang, Aixin Sun, Yequan Wang, and Zhongyuan Wang. 2024. Not all Layers of LLMs are Necessary during Inference. arXiv preprint arXiv:2403.02181 (2024).

[14] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. 2023. Retrieval-augmented generation for large language models: A survey. arXiv preprint arXiv:2312.10997 (2023).

[15] Mitko Gospodinov, Sean MacAvaney, and Craig Macdonald. 2023. Doc2query–: When less is more. In European Conference on Information Retrieval. Springer, 414–422.

[16] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 770–778.

[17] Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-Rank Adaptation of Large Language Models. In International Conference on Learning Representations. https://openreview.net/forum?id=nZeVKeeFYf9

[18] Samy Jelassi, David Brandfonbrener, Sham M Kakade, and Eran Malach. 2024. Repeat after me: Transformers are better than state space models at copying. arXiv preprint arXiv:2402.01032 (2024).

[19] Xin Jia, Wenjie Zhou, Xu Sun, and Yunfang Wu. 2021. Eqg-race: Examination-type question generation. In Proceedings of the AAAI conference on artificial intelligence, Vol. 35. 13143–13151.

[20] Che Jiang, Biqing Qi, Xiangyu Hong, Dayuan Fu, Yang Cheng, Fandong Meng, Mo Yu, Bowen Zhou, and Jie Zhou. 2024. On Large Language Models' Hallucination with Regard to Known Facts. arXiv preprint arXiv:2403.20009 (2024).

[21] Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2019. Billion-scale similarity search with GPUs. IEEE Transactions on Big Data 7, 3 (2019), 535–547.

[22] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling laws for neural language models. arXiv preprint arXiv:2001.08361 (2020).

[23] Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations. 66–71.

[24] Chunyuan Li, Cliff Wong, Sheng Zhang, Naoto Usuyama, Haotian Liu, Jianwei Yang, Tristan Naumann, Hoifung Poon, and Jianfeng Gao. 2024. Llava-med: Training a large language-and-vision assistant for biomedicine in one day. Advances in Neural Information Processing Systems 36 (2024).

[25] Xingxuan Li, Ruochen Zhao, Yew Ken Chia, Bosheng Ding, Shafiq Joty, Soujanya Poria, and Lidong Bing. 2023. Chain-of-knowledge: Grounding large language models via dynamic knowledge adapting over heterogeneous sources. In The Twelfth International Conference on Learning Representations.

[26] Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. 2022. Contrastive decoding: Open-ended text generation as optimization. arXiv preprint arXiv:2210.15097 (2022).

[27] Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. 2023. Contrastive Decoding: Open-ended Text Generation as Optimization. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, Toronto, Canada, 12286–12312. https://doi.org/10.18653/v1/2023.acl-long.687

[28] Yuanzhi Li, Sébastien Bubeck, Ronen Eldan, Allie Del Giorno, Suriya Gunasekar, and Yin Tat Lee. 2023. Textbooks are all you need ii: phi-1.5 technical report. arXiv preprint arXiv:2309.05463 (2023).

[29] Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. TruthfulQA: Measuring How Models Mimic Human Falsehoods. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 3214–3252.

[30] Fuxiao Liu, Tianrui Guan, Zongxia Li, Lichang Chen, Yaser Yacoob, Dinesh Manocha, and Tianyi Zhou. 2023. Hallusionbench: You see what you think? or you think what you see? an image-context reasoning benchmark challenging for gpt-4v (ision), llava-1.5, and other multi-modality models. arXiv preprint arXiv:2310.14566 (2023).

[31] Ang Lv, Kaiyi Zhang, Yuhan Chen, Yulong Wang, Lifeng Liu, Ji-Rong Wen, Jian Xie, and Rui Yan. 2024. Interpreting Key Mechanisms of Factual Recall in Transformer-Based Language Models. arXiv preprint arXiv:2403.19521 (2024).

[32] ML Menéndez, JA Pardo, L Pardo, and MC Pardo. 1997. The jensen-shannon divergence. Journal of the Franklin Institute 334, 2 (1997), 307–318.

[33] Dor Muhlgay, Ori Ram, Inbal Magar, Yoav Levine, Nir Ratner, Yonatan Belinkov, Omri Abend, Kevin Leyton-Brown, Amnon Shashua, and Yoav Shoham. 2023. Generating benchmarks for factuality evaluation of language models. arXiv preprint arXiv:2307.06908 (2023).

[34] Rodrigo Nogueira, Wei Yang, Jimmy Lin, and Kyunghyun Cho. 2019. Document expansion by query prediction. arXiv preprint arXiv:1904.08375 (2019).

[35] Zhiyuan Peng, Xuyang Wu, and Yi Fang. 2023. Soft prompt tuning for augmenting dense retrieval with large language models. arXiv preprint arXiv:2307.08303 (2023).

[36] Zhiyuan Peng, Xuyang Wu, Qifan Wang, Sravanthi Rajanala, and Yi Fang. 2024. Q-PEFT: Query-dependent Parameter Efficient Fine-tuning for Text Reranking with Large Language Models. arXiv preprint arXiv:2404.04522 (2024).

[37] Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know What You Don't Know: Unanswerable Questions for SQuAD. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Iryna Gurevych and Yusuke Miyao (Eds.). Melbourne, Australia, 784–789. https://doi.org/10.18653/v1/P18-2124

[38] Jon Saad-Falcon, Omar Khattab, Keshav Santhanam, Radu Florian, Martin Franz, Salim Roukos, Avirup Sil, Md Sultan, and Christopher Potts. 2023. UDAPDR: Unsupervised Domain Adaptation via LLM Prompting and Distillation of Rerankers. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing. 11265–11279.

[39] Devendra Sachan, Mike Lewis, Mandar Joshi, Armen Aghajanyan, Wen-tau Yih, Joelle Pineau, and Luke Zettlemoyer. 2022. Improving Passage Retrieval with Zero-Shot Question Generation. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing. 3781–3797.

[40] Tal Schuster, Adam Fisch, Jai Gupta, Mostafa Dehghani, Dara Bahri, Vinh Tran, Yi Tay, and Donald Metzler. 2022. Confident adaptive language modeling. Advances in Neural Information Processing Systems 35 (2022), 17456–17472.

[41] Abigail See, Peter Liu, and Christopher Manning. 2017. Get To The Point: Summarization with Pointer-Generator Networks. In Association for Computational Linguistics. https://arxiv.org/abs/1704.04368

[42] Noam Shazeer. 2019. Fast transformer decoding: One write-head is all you need. arXiv preprint arXiv:1911.02150 (2019).

[43] Zhongxiang Sun, Zihua Si, Xiaoxue Zang, Dewei Leng, Yanan Niu, Yang Song, Xiao Zhang, and Jun Xu. 2023. KuaiSAR: A Unified Search And Recommendation Dataset. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (Birmingham, United Kingdom) (CIKM '23). Association for Computing Machinery, New York, NY, USA, 5407–5411. https://doi.org/10.1145/3583780.3615123

[44] Zhongxiang Sun, Zihua Si, Xiaoxue Zang, Kai Zheng, Yang Song, Xiao Zhang, and Jun Xu. 2024. Large Language Models Enhanced Collaborative Filtering. In Proceedings of the 33rd ACM International Conference on Information and Knowledge Management (Boise, ID, USA) (CIKM '24). Association for Computing Machinery, New York, NY, USA, 2178–2188. https://doi.org/10.1145/3627673.3679558

[45] Zhongxiang Sun, Zihua Si, Xiao Zhang, Xiaoxue Zang, Yang Song, Hongteng Xu, and Jun Xu. 2024. To Search or to Recommend: Predicting Open-App Motivation with Neural Hawkes Process. In Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval (Washington DC, USA) (SIGIR '24). Association for Computing Machinery, New York, NY, USA, 1018–1028. https://doi.org/10.1145/3626772.3657732

[46] Zhongxiang Sun, Xiaoxue Zang, Kai Zheng, Yang Song, Jun Xu, Xiao Zhang, Weijie Yu, and Han Li. 2024. ReDeEP: Detecting Hallucination in Retrieval-Augmented Generation via Mechanistic Interpretability. arXiv preprint arXiv:2410.11414 (2024).

[47] Surat Teerapittayanon, Bradley McDanel, and Hsiang-Tsung Kung. 2016. Branchynet: Fast inference via early exiting from deep neural networks. In 2016 23rd international conference on pattern recognition (ICPR). IEEE, 2464–2469.

[48] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. arXiv preprint arXiv:2307.09288 (2023).

[49] Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. Advances in neural information processing systems 28 (2015).

[50] Siyuan Wang, Zhongyu Wei, Zhihao Fan, Yang Liu, and Xuanjing Huang. 2019. A multi-agent communication framework for question-worthy phrase extraction and question generation. In Proceedings of the AAAI conference on artificial intelligence, Vol. 33. 7168–7175.

[51] Yujing Wang, Yingyan Hou, Haonan Wang, Ziming Miao, Shibin Wu, Qi Chen, Yuqing Xia, Chengmin Chi, Guoshuai Zhao, Zheng Liu, et al. 2022. A neural corpus indexer for document retrieval. Advances in Neural Information Processing Systems 35 (2022), 25600–25614.

[52] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent Abilities of Large Language Models. Transactions on Machine Learning Research (2022).

[53] Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighof. 2023. C-pack: Packaged resources to advance general chinese embedding. arXiv preprint arXiv:2309.07597 (2023).

[54] Zhilin Yang, Zihang Dai, Ruslan Salakhutdinov, and William W Cohen. 2018. Breaking the Softmax Bottleneck: A High-Rank RNN Language Model. In International Conference on Learning Representations.

[55] Chunting Zhou, Pengfei Liu, Puxin Xu, Srinivasan Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. 2024. Lima: Less is more for alignment. Advances in Neural Information Processing Systems 36 (2024).

A Appendix / supplemental material

A.1 Experimental Verification of Hallucination Classification

Our hallucination classification for generated query is grounded in real-world observations, aiming to help readers better understand the distinct types of hallucinations present in query generation. This categorization is intended to offer valuable insights for future research in this domain. To further validate our classification, we conducted an analysis experiment using the TruthfulVQG dataset (Detailed in Section 4.1). In this experiment, we encoded both the generated queries and corresponding video content using BGE [53] and computed the cosine similarity to obtain a **Semantic Similarity score**. The results demonstrate that factual hallucinations can occur independently, even in the absence of relevance hallucinations, highlighting the need to decouple these two types of hallucinations for more precise handling.

The experimental results in Table 5 confirm that factual hallucinations can persist even with high semantic similarity scores. This finding underscores the importance of treating relevance and factual hallucinations separately to improve query generation and retrieval quality.

A.2 Implementation Details of Words Information

In the experiments concerning word information, we conducted tests using the TruthfulVQG and TruthfulDQG benchmarks constructed in this paper. For English in the TruthfulDQG benchmark, we used Spacy [2] for tokenization and part-of-speech tagging, while for TruthfulVQG (Chinese corpus), we employed Jieba [3] and Hanlp [4]. Factual knowledge words include organizations, personal names, locations, and dates. Function words include auxiliary verbs, prepositions, determiners, conjunctions, and coordinating conjunctions. Subsequently, on both datasets, we removed an equal number of factual knowledge words and function words and then utilized BGE embeddings [53] to align and compare the cosine similarity between the modified sentences and the original sentences. The results are shown below:

- In the TruthfulDQG benchmark, removing factual knowledge words resulted in a similarity score of 0.7741, while removing function words led to a higher similarity score of 0.9296.
- In the TruthfulVQG benchmark, the removal of factual knowledge words produced a similarity score of 0.7415, compared to 0.9477 when function words were eliminated.

The results show that on both datasets, removing factual knowledge words causes a greater decrease in semantic similarity scores with the original sentence compared to function words. These findings confirm that factual knowledge words contribute more significantly to the sentence's informational content than function words, highlighting the complexity of predicting factual knowledge words. Verifying that the pattern found in [10, 40], rooted in the linguistic properties of human language, is a principle that holds true across multiple languages, even though initial studies focused on English scenarios.

Why Can LLM Identify Factual Knowledge Words and Function Words?

Considering that LLMs can only directly learn to predict the next word in the natural language training corpus, they may not have an intuitive concept of what constitutes factual knowledge words and function words. Therefore, we conducted an intrinsic frequency analysis of factual knowledge and function words on the TruthfulDQG benchmark. The statistical results are shown below:

- Number of different words in function words: 228
- Number of different words in factual knowledge words: 3263
- Total number of words in function words: 33849
- Total number of words in factual knowledge words: 6026
- Average occurrence of function words: 148.46

[2] https://spacy.io
[3] https://github.com/fxsjy/jieba
[4] https://www.hanlp.com

Table 5: Semantic similarity scores across query types, highlighting that factual hallucinations can occur despite high similarity with relevant content.

Type	Max Semantic Similarity	Min Semantic Similarity	Average Semantic Similarity
Facticity hallucination queries	0.8492	0.3792	0.6479
Facticity truth queries	0.8607	0.2647	0.6482
Random similarity	N/A	N/A	0.2709

- Average occurrence of factual knowledge words: 1.85

These results show that function words appear much more frequently than factual knowledge words, particularly evident from their average occurrences. It is evident that due to the substantially larger training data of function words compared to factual knowledge words, LLMs can predict function words at shallower layers while predicting factual knowledge words need deeper layers.

Another Perspective on the Effectiveness of Copy Probability in LargePiG.

Besides the pattern we mentioned above, Jiang et al. [20] observes that in hallucinated cases, the output token's information rarely shows abrupt increases and maintains consistent superiority in high layers of the LLMs. This corresponds to cases in LargePiG where there is a higher copy probability, thus enabling the reduction of hallucinations by copying factual knowledge words from the source document. This further demonstrates the capability of the copy probability in LargePiG to address the issue of hallucinations.

A.3 Details about Dataset Collection

The TruthfulVQG dataset is collected from a real short video platform used by over one billion users. The TruthfulDQG dataset is adapted from the MS-MARCO dataset [4]. The data processing for TruthfulVQG is more complex than TruthfulDQG's. Thus, we will use TruthfulVQG as an example to illustrate the process.

Data Collection:

The raw data was collected from Search Click Data and Post-Watch Search Data, and the final processed public data does not include any user search information, only video content, and LLM-generated queries.

- **Collected Data Source:**
  - **Search Click Data (30,000 samples):** We collect 30,000 samples of users' clicked videos after searching the corresponding queries with data flowing from query to video.
  - **Post-Watch Search Data (10,000 samples):** We collect 10,000 samples of users' searched queries after watching the corresponding videos, which is a smaller subset compared to click data, with data flowing from video to query.
- **Criteria for Inclusion:**
  - **Search Click Data:** Include only data with positions greater than one and less than twenty to mitigate position bias of the top results and low relevance of farther results.
  - **Post-Watch Search Data:** Include only data with total count numbers greater than five to ensure relevance to previously viewed videos.

Components of Video Content:

- **Title:** Accurate representation of video content.
- **Video Dialogue Text (ASR):** Prone to noise but contain detailed information about the video.
- **Video Text Information (OCR):** More reliable than ASR and contains more information than Title.

Data Preprocessing: Remove examples lacking textual features, containing sensitive words, or background music that affect ASR results.

Next, we will use LLMs to generate multiple queries for data annotation of all videos. To enable the LLMs have the ability to generate high-quality queries, we first fine-tuned these LLMs. Then, we combined them with the original LLMs to generate queries.

Model Fine-Tuning:

- **Models Used:**
  - **Qwen1.5 7B Chat** [3] and **InternLM 7B Chat** [6] [5]: Among the strongest for Chinese language capabilities.
- **Purpose:**
  - Employing multiple LLMs ensures diversity in generated queries, reducing the risk of repetitive queries that single model sampling might produce.

Data Utilization and Query Generation

- Sort data by video quality scores and select the top 10,000 samples for query generation (Generation is time-intensive, approximately 40 hours per week. Hence, only the top entries are used).
- Approximately 20+ queries are generated per video using the following prompt.

Query Generation Prompt:

```
instruction: Based on the video's title, dialog text, and
  ↪ text information within the video, generate a
  ↪ relevant and engaging search query. This query
  ↪ should accurately reflect the video content,
  ↪ adhere to factual information, and stimulate user
  ↪ interest to drive clicks. Ensure the query is
  ↪ concise and contains key information points.
input: Title: {Title content}
       Dialog text: {Dialog text content}
       Text information: {Text information content}
       Query:
output: {Query content}
```

This prompt is also used in our experiments to generate queries [6].

[5] We replace InternLM 7B Chat with LLaMA2 7B Chat on TruthDQG.
[6] As the TruthfulVQG is a Chinese Dataset, we translate the prompt from Chinese using ChatGPT-4.

A.4 Details about Dataset Annotation.

During the data annotation section, we first performed further cleaning and filtering of the data. We utilized a combination of LLM and manual annotation to label TruthfulDQG and TruthfulVQG. This hybrid approach of LLM and manual annotations has been employed in numerous works on hallucination benchmark annotation [8, 30].

A.4.1 Phase One: Filter Dataset. Remove sensitive words and perform heuristic query quality filtering based on repetitiveness and length scores.

A.4.2 Phase Two: Relevance Assessment. This phase focuses on detecting relevance hallucination by measuring the relevance of generated queries to the video content.

Similarity Calculations

(1) **Embedding-Based Similarity:** Utilizes BAAI BGE Embedding [53] and cosine similarity to compute similarity scores between text embeddings.
(2) **Word-Based Similarity:** Employs Jieba for text segmentation and calculates similarity using the Jaccard similarity [7].

Weighting Method Adjusts relevance scoring based on the ASR noise level:

$$\text{ASR Score} = 0.6 \times \cos(\text{ASR}, \text{OCR}) + 0.4 \times \cos(\text{ASR}, \text{Title})$$

$$\text{Query Scoring} = \begin{cases} 0.34 \times (\text{Query}, \text{Title}) + \\ \quad 0.33 \times (\text{Query}, \text{ASR}) + \\ \quad 0.33 \times (\text{Query}, \text{OCR}), & \text{if ASR Score} > 0.5 \\ 0.4 \times (\text{Query}, \text{Title}) + \\ \quad 0.2 \times (\text{Query}, \text{ASR}) + \\ \quad 0.4 \times (\text{Query}, \text{OCR}), & \text{if ASR Score} > 0.3 \\ 0.5 \times (\text{Query}, \text{Title}) + \\ \quad 0.1 \times (\text{Query}, \text{ASR}) + \\ \quad 0.4 \times (\text{Query}, \text{OCR}), & \text{otherwise} \end{cases}$$

A.4.3 Phase Three: Factuality Assessment. Detecting the factuality hallucination of the generated queries by using LLM-based fact-checking methods–Self-Check (4-shot CoT) and FacTool [9].

Self-Check (4-shot CoT). We implement Self-Check (4-shot CoT) using the larger and more powerful LLM Qwen1.5-72B-Chat [3] to detect queries' factuality hallucination.

Advanced Fact-Checking. For indeterminate cases after Self-Check, we use advanced fact-checking tools FacTool [9] with Qwen1.5 72B Chat [3] and Serper [8] to further check queries' factuality based on external data sources from Google Search. The prompt is shown below [9]:

```
You are an excellent assistant.
You will receive a piece of text. Your task is to identify any factual errors within this text.
When judging the factuality of the given text, you may refer to provided evidences if necessary.
These evidences could be helpful. Some evidences might contradict each other. You must be
careful when using evidences to assess the factuality of the given text.
The response should be a dictionary containing three keys - "reasoning", "factuality",
"error", and "correction", corresponding to the reasoning, whether the given text is
true (Boolean value - True or False), the factual error present in the text, and the
corrected text.
Below is the given text
[text]: {query}
Below is the provided evidence
[evidences]: {evidence}
You should respond only in the format described below. Do not return any other content.
Start your response with '{{'.
[response format]:
{{
  "reasoning": "Why is the given text factual or not? Be careful when you claim
  something is not factual. When you claim something is not factual, you must provide
  multiple pieces of evidence to support your decision.",
  "error": "If the text is factual, then None; otherwise, describe the error.",
  "correction": "If there is an error, then the corrected text.",
  "factuality": "If the given text is factual, then True; otherwise, False."
}}
```

Finally, the completed data format is shown in Table 6, and the statistics of TruthfulVQG and TruthfulDQG are shown in Table 7.

Human Assessment. To further ensure the relevance and factual accuracy of the query, we request three annotators with graduate-level qualifications to manually evaluate the "good queries" to confirm factuality and relevance to the context, ensuring they are both engaging and appropriate.

A.5 Implementation Details of LLM-based Query Generation Approaches

The prompts used on TruthfulDQG for different LLM-based query generation approaches are shown below (The prompts used on TruthfulVQG are just different in the instruction, which has been demonstrated on Appendix A.3):

Base / AQG:

```
Given the following document, generate a concise, factual and relevant query that a user might type into a search engine to find this information.
Document: {Document contents}.
Related Query:
```

PQGR:

[7]https://scikit-learn.org/stable/modules/generated/sklearn.metrics.jaccard_score.html
[8]The website of Serper is https://serper.dev/.
[9]As the TruthfulVQG is a Chinese Dataset, we translate the prompt from Chinese using ChatGPT-4.

Table 6: Description of data fields in TruthfulVQG and TruthfulDQG.

	Video / Document Content	Best query	Good Queries	Bad Queries
Data Type	string	string	[string]	[string]
Description	Description of the video / document content	Best query (factual and most relevent)	Array of good queries	Array of bad queries

Table 7: Statistics of TruthfulVQG and TruthfulDQG. # denotes the average number.

Dataset	Data Count	# Good Queries	# Bad Queries	# Total Queries	Language
TruthfulVQG	4,148	3.82	4.75	8.56	Chinese
TruthfulDQG	2,718	4.04	4.00	8.05	English

```
Given the following document, generate a concise, factual
    ↪ and relevant query that a user might type into a
    ↪ search engine to find this information.
Example 1:
Document: {Document contents}.
Related Query: {The query relevant and factual to document
    ↪ contents}.
...
Example 9:
Document: {Document contents}.
Related Query:
```

InPars:

```
Given the following document, generate a concise, factual
    ↪ and relevant query that a user might type into a
    ↪ search engine to find this information.
Example 1:
Document: {Document contents}.
Related Query: {The query relevant and factual to document
    ↪ contents}.
Hallucination Query: {The query irrelevant and unfactual to
    ↪ document contents}.
...
Example 4:
Document: {Document contents}.
Related Query:
```

The size of the dataset for LoRA fine-tuning AQG is 10,000 pairs. The fine-tuning targets the q_proj and v_proj within the transformer layers. The learning rate is set to 5e-5, the per-device train batch size is 4, and the gradient accumulation steps are 4.

A.6 Implementation Details of LargePiG.

We run all the experiments on machines equipped with NVIDIA V100 GPUs and 52-core Intel(R) Xeon(R) Gold 6230R CPUs at 2.10GHz. We utilize the Huggingface Transformers package to conduct experiments. During the decoding of responses from the language models, we employ random sampling with a temperature of 0.8 and a maximum of 256 new tokens to generate responses. The rest of the parameters use the models' default settings. As for selecting the layer to calculate the pointer attention distribution, we used the last layer's attention weights by comparing them with other layers. As for selecting the words to calculate the pointer attention distribution, we recommend filtering the function words in the input using tools detailed in Appendix A.2. Considering that the Jensen-Shannon divergence is usually small in the high-dimensional space of vocabulary distribution, we scale the copy probability p_{cp} in LargePiG by a factor of α. To ensure that the scaled p_{cp} remains within a reasonable range, we clip its value to be less than 0.5, thus maintaining a balance between copy and generation. The value of α is selected from the set [100, 500, 1000]. The $O_{j\in\mathcal{J}}$ in Equation 8 is selected as $\max_{j\in\mathcal{J}}$, and $\mathcal{J}$ comprises the last 8 or 16 layers of the backbone LLMs, excluding the anchor layer which is the last layer (for increased efficiency, either even or odd numbered layers may be selected). We use two-fold validation to select the hyper-parameters. The LLaMA2-7B-Chat can be downloaded from https://huggingface.co/meta-llama/Llama-2-7b-chat-hf. The Qwen1.5-7B-Chat can be downloaded from https://huggingface.co/Qwen/Qwen1.5-7B-Chat. Due to the limited Chinese training corpus of LLaMA2-7B-Chat, we used Llama2-Chinese-7b-Chat on TruthfulVQG, which can be downloaded from https://huggingface.co/LinkSoul/Chinese-Llama-2-7b.

Table 8: Experimental results on multimodal data.

Model	MC1	MC2	MC3
LLaVA-7B	58.40	80.45	51.54
+ LargePiG	**59.80**	**81.74**	**52.94**
LLaVA-13B	57.20	79.18	50.74
+ LargePiG	**58.10**	**79.93**	**51.26**

A.7 Multimodal Experiments of LargePiG.

LargePiG is effective not only on large language models but can also be applied to Large Vision-Language Models (LVLM), further enhancing the truthfulness of query generation that integrates both vision and language modalities. We selected the recently popular large vision-language model LLaVA [24] as the backbone model. Detailed method descriptions about the implementation can be found in Appendix A.8. To validate LargePiG's ability to address hallucination issues in multimodal query generation tasks, we compiled a multimodal version of the TruthfulVQG dataset, named TruthfulVQG-M. Experimental results on LLaVA-7B/13B, shown in Table 8, indicate that the truthfulness of queries generated by LargePiG surpasses those produced by the original decoding method, confirming the effectiveness of LargePiG in multimodal tasks. We also observed that LLaVA-13B performs less effectively than LLaVA-7B, a potential reason being that in the video query generation task, due to the high noise level in video content, the more complex LLaVA-13B model might be more sensitive to noise. Furthermore, short videos contain some new content not present in the pre-training data, which could lead to easier overfitting to the training data in a zero-shot scenario, thus resulting in suboptimal performance compared to LLaVA-7B.

A.8 Details about LargePiG Applied to LLaVA

The architecture of LLaVA [24] is straightforward, comprising only a Vision Encoder, Projection, and Language Model, with training conducted in two stages: Stage 1: Pre-training for Feature Alignment, and Stage 2: Fine-tuning End-to-End. A key issue when applying LargePiG to LLaVA concerns how to map image tokens to text tokens, thus establishing an attention distribution based on the source content. Considering during the Feature Alignment stage, the primary task is aligning the image features $\mathbf{H}_v$ with the pre-trained LLM word embeddings, we propose mapping each image token to the closest text token in the embedding space when computing the Pointer Attention Distribution. In the implementation, we utilize the faiss vector database [21] to store text token embeddings and retrieve the corresponding tokens using image token embeddings, allowing for rapid retrieval of relevant tokens. Case studies reveal that this retrieval method can accurately reveal the main information in the images, although many noise tokens are also retrieved. Therefore, we apply rule-based filtering to remove tokens with low similarity to the text part and construct the attention distribution using the remaining tokens together with the text tokens.