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Passage Attribution for Evidence-Grounded Retrieval-Augmented Generation under Noisy Retrieval

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A B S T R A C T

Retrieval-Augmented Generation has emerged as a dominant paradigm for mitigating hallucinations in large language models by grounding generated responses in external knowledge sources. However, the efficacy of these systems is fundamentally bottlenecked by the quality of the retrieved documents. In real-world applications, retrieval components frequently return noisy, irrelevant, or contradictory passages, which can severely degrade the factual accuracy and coherence of the generated output. This paper presents a comprehensive investigation into passage attribution mechanisms designed to fortify evidence-grounded generation under conditions of high retrieval noise. We introduce a novel architectural framework that dynamically evaluates and assigns attribution scores to retrieved passages before generation, enabling the language model to selectively attend to highly relevant evidence while discarding spurious noise. Through extensive theoretical analysis and empirical evaluation across multiple domain-specific datasets, we demonstrate that explicit passage attribution not only improves response factuality but also enhances the interpretability of the generation process. Our findings indicate that integrating dynamic thresholding and robust training objectives significantly increases the resilience of generative models against adversarial or noisy retrieval outcomes. The proposed methodology establishes a new benchmark for developing trustworthy, verifiable, and noise-resilient natural language processing systems.

1.INTRODUCTION

1.1 The Paradigm of Retrieval-Augmented Generation

The rapid advancement of large language models has fundamentally transformed the landscape of natural language processing, enabling unprecedented capabilities in tasks ranging from open-domain dialogue to complex reasoning. Despite these remarkable achievements, generative models are persistently plagued by their tendency to produce factually incorrect or unverified statements, a phenomenon widely documented in recent literature [1]. These hallucinations arise because large language models inherently rely on static parametric knowledge acquired during pre-training, which quickly becomes outdated and lacks mechanisms for dynamic fact-checking [2]. To address these fundamental limitations, researchers have proposed and widely adopted the paradigm of Retrieval-Augmented Generation [3]. This approach augments the generative capabilities of language models by

coupling them with external, non-parametric knowledge bases. When a user submits a query, a retrieval module first searches a vast corpus of documents to identify passages relevant to the query [4]. The retrieved passages are subsequently concatenated with the original prompt and fed into the language model, which synthesizes a response grounded in the provided external evidence [5]. The architecture of a typical system involves two distinct but interdependent components: a retriever and a generator [6]. The retriever, often implemented as a dense vector search engine utilizing bi-encoder architectures, maps both queries and documents into a shared latent semantic space to compute similarity scores. The generator, typically an autoregressive transformer, conditions its next-token prediction probabilities on both the prompt context and the retrieved textual evidence [7]. This decoupling of knowledge storage from language generation allows for seamless updates to the underlying knowledge base without the computationally prohibitive need to retrain the entire language model. Furthermore, this paradigm theoretically provides provenance for the generated claims, as users can inspect the retrieved documents to verify the accuracy of the model outputs. However, the theoretical elegance of this architecture is frequently challenged by the complexities and imperfections of real-world implementation, particularly concerning the reliability of the retrieval step.

1.2 The Challenge of Noisy Retrieval

While the integration of external knowledge substantially reduces hallucinations when the retrieved context is perfectly aligned with the query, the reality of information retrieval is fraught with uncertainty and noise [8]. Retrieval modules, regardless of their sophistication, are not infallible. They frequently operate over heterogeneous, unstructured, and massive corpora where semantic overlaps and ambiguous queries lead to sub-optimal retrieval results [9]. Consequently, the set of documents returned by the retriever often contains a mixture of highly relevant evidence, tangentially related information, and completely irrelevant or contradictory noise [10]. The introduction of noisy passages into the generative context poses a severe challenge to the integrity of the language model [11]. When presented with irrelevant information, large language models often struggle to differentiate between useful evidence and distractors. In many instances, the model may inadvertently incorporate false premises from the noisy documents into its final output, leading to a phenomenon known as context-induced hallucination [12]. Furthermore, the presence of contradictory passages can confuse the generation process, resulting in responses that are logically inconsistent or excessively ambiguous. The capacity of a generative model to maintain high performance under these adverse conditions is termed noise resilience. Achieving this resilience requires moving beyond the naive assumption that all retrieved documents are equally trustworthy or relevant. It necessitates the development of sophisticated mechanisms that can critically evaluate the utility of each passage before integrating its informational content into the final response.

1.3 The Role of Passage Attribution

To mitigate the detrimental effects of noisy retrieval, researchers have increasingly focused on the concept of passage attribution. Passage attribution refers to the explicit process of identifying, scoring, and linking specific segments of generated text to their corresponding source documents within the retrieved context [13]. By enforcing strict attribution, a system is compelled to ground its assertions in verified external evidence, thereby enhancing both the factuality and the interpretability of the output [14]. In this paper, we explore advanced methodologies for passage attribution specifically tailored for environments characterized by high retrieval noise. We propose a comprehensive framework that incorporates dynamic passage scoring, robust training objectives, and filtering mechanisms designed to isolate high-quality evidence. The subsequent sections are structured as follows. Section 2 provides a detailed review of the literature concerning large language models, retrieval paradigms, and hallucination mitigation. Section 3 outlines the mathematical formulation and architectural design of our passage attribution methodology. Section 4 delves into the specific mechanisms engineered to bolster noise resilience during the generation phase. Section 5 details the experimental configuration, presents the empirical results, and provides an in-depth discussion

of the findings. Finally, Section 6 summarizes the contributions and outlines promising directions for future research in the domain of reliable generative systems.

2. Literature Review and Background

2.1 Evolution of Large Language Models and Retrieval Systems

The intersection of information retrieval and natural language generation has a rich historical trajectory. Early approaches to automated question answering relied heavily on sparse retrieval techniques, most notably the Term Frequency-Inverse Document Frequency metric and the BM25 algorithm [15]. These lexical matching methods, while computationally efficient and highly interpretable, fundamentally struggled with the vocabulary mismatch problem. Queries and documents that shared similar meanings but utilized divergent vocabularies were often poorly aligned, leading to suboptimal retrieval recall [16]. The advent of neural network architectures, particularly the Transformer model, precipitated a paradigm shift from sparse to dense retrieval methods [17]. Dense Passage Retrieval emerged as a robust alternative, utilizing dual-encoder structures to map textual data into dense, continuous vector representations. By computing inner products or cosine similarities in this high-dimensional space, dense retrievers demonstrated a remarkable ability to capture semantic equivalence irrespective of lexical overlap [18]. This capability laid the foundational groundwork for modern augmented generation pipelines [19]. Subsequent innovations introduced hybrid retrieval strategies that combine the precision of exact keyword matching with the broad semantic understanding of dense vectors, resulting in state-of-the-art retrieval performance across diverse application domains [20].

2.2 Hallucinations and Grounded Generation

Despite the integration of advanced retrieval mechanisms, the persistent issue of hallucination in large language models remains a critical barrier to deployment in high-stakes environments such as healthcare and legal analysis. The etiology of hallucinations is multifaceted [21]. At the pre-training level, language models are optimized for next-token prediction over vast, uncurated datasets derived from the internet. This objective encourages the model to generate fluent, statistically probable text, which does not necessarily correlate with factual truth [22]. When confronted with a query that falls outside its parametric knowledge, or when faced with contradictory input, the model tends to fabricate plausible-sounding but erroneous information [23]. To address these shortcomings, researchers have proposed various strategies for grounded generation. Early interventions focused on post-hoc verification, where a secondary classifier would evaluate the factuality of the generated output against a trusted knowledge base [24]. However, these pipeline approaches suffer from cascading errors and significant computational overhead. More recent efforts have focused on intrinsic grounding, integrating the evidence directly into the generation step [25]. These methods aim to condition the generative probabilities heavily on the retrieved text, but they often lack the granularity required to handle scenarios where the retrieved context itself is flawed or noisy.

2.3 Passage Attribution Mechanisms

Passage attribution represents a more granular and rigorous approach to grounded generation. The core objective of attribution is to establish a verifiable link between the generated text and the source evidence [26]. Existing attribution techniques can broadly be categorized into post-hoc citation generation and concurrent attribution [27]. Post-hoc methods attempt to append citations to sentences after the text has been fully generated, essentially treating attribution as a secondary retrieval task. While useful, this approach does not prevent the model from generating ungrounded claims in the first place [28]. Concurrent attribution, conversely, forces the language model to generate citations simultaneously with the text, effectively conditioning the token generation on the successful identification of supporting evidence [29]. Despite its advantages, concurrent attribution is highly sensitive to the quality of the provided context. When subjected to noisy retrieval environments, models often exhibit confirmation bias, attempting to falsely attribute generated claims to irrelevant documents simply because those documents were present in the context window. The literature highlights a significant gap in robust attribution mechanisms capable of dynamically assessing document utility and rejecting

noisy passages before they corrupt the generative process. Our research directly addresses this gap by proposing an integrated attribution and filtering architecture.

3. Methodology and Architecture for Passage Attribution

3.1 Problem Formulation

To establish a rigorous foundation for our proposed methodology, we first formalize the problem of evidence-grounded generation under the paradigm of retrieval augmentation. Let the input sequence be defined as a query sequence, and let the target output be defined as a response sequence consisting of multiple tokens. We assume access to a vast external knowledge corpus composed of millions of distinct text passages. The standard retrieval process utilizes a dual-encoder architecture to encode both the query and all passages into dense vector representations. A similarity function is then applied to identify the most relevant passages. Let the retrieved set of documents be denoted as a subset of the corpus. The generative task is to model the probability distribution of the target output conditioned on both the input query and the retrieved documents. In an ideal, noise-free scenario, the probability of generating the response is obtained by marginalizing over the retrieved documents. This relationship is mathematically expressed in the following equation:

$$P(y|x) = \sum_{i=1}^{k} P(z_i|x)P(y|z_i, x)$$

In this formulation, the term representing the probability of a document given the query acts as a relevance weight, while the secondary probability dictates the generation of the text given both the query and the specific document. However, in environments characterized by high retrieval noise, the simple marginalization over all retrieved documents is fundamentally flawed. If a noisy document is assigned a non-zero probability by the retriever, it will exert a distorting influence on the final generation probability. Therefore, we must introduce a robust passage attribution mechanism that accurately recalibrates these probabilities, driving the influence of irrelevant or noisy documents to absolute zero.

3.2 Designing the Attribution Module

The core of our proposed architecture is a dedicated Passage Attribution Module that operates as an intermediate layer between the retriever and the autoregressive generator. The primary function of this module is to conduct a fine-grained, cross-attentional analysis of the relationship between the input query and each individually retrieved passage. Unlike the initial retriever, which relies on computationally efficient but shallow bi-encoder representations, the attribution module employs a deep cross-encoder architecture. This allows for rich interaction between the query tokens and the document tokens at every layer of the transformer block.

The attribution module takes the concatenated sequence of the query and a specific document as input and processes it through multiple self-attention layers. The final hidden state corresponding to a specialized classification token is extracted and projected through a multi-layer perceptron to produce a scalar relevance logit. To transform these raw logits into a normalized attribution probability distribution across the entire set of retrieved documents, we apply a scaled softmax function parameterized by a learnable weight matrix and a feature extraction function. The attribution score for each passage is defined by the following mathematical formula:

$$S(a_i, q) = \frac{exp(W \cdot Phi(a_i, q))}{\sum_{j=1}^{N} exp(W \cdot Phi(a_j, q))}$$

Here, the attribution score represents the confidence of the system that the specific passage contains the factual evidence required to answer the query. By applying this rigorous scoring mechanism, the system effectively constructs a soft-attention distribution over the retrieved context. Passages that contain contradictory information or irrelevant noise are assigned vanishingly small attribution scores, effectively neutralizing their impact on the subsequent generation phase.

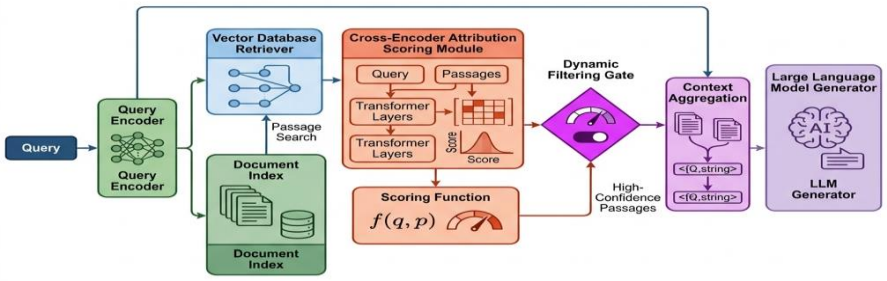


Figure 1:Comprehensive Schematic of the Passage Attribution Architecture

3.3 Integration with the Generator

Once the attribution scores are computed, the integration with the downstream language model must be executed with precision to maintain the integrity of the generation process. We employ a technique known as attention masking combined with representation fusion. Rather than entirely discarding passages that receive low attribution scores, which might occasionally lead to the loss of peripheral but useful context, we dynamically adjust the attention weights within the cross-attention layers of the generative language model. The attention mechanism of the generator is modified such that the keys and values originating from the retrieved passages are multiplied by their respective attribution scores. Consequently, when the generator is predicting the next token, it is forced to disproportionately attend to the representations of passages with high attribution scores. This architectural integration guarantees that the generated response is not only conditioned on the external evidence but is fundamentally anchored to the specific passages deemed most relevant by the attribution module. This precise alignment between scoring and generation is what enables the system to maintain high factuality even when the initial retrieval pool is heavily contaminated with noise.

4. Noise Resilience Mechanisms in Evidence-Grounded Generation

4.1 Simulating and Modeling Retrieval Noise

To develop systems that are genuinely resilient to imperfect retrieval, it is necessary to thoroughly understand and model the different typologies of noise that occur in production environments. Retrieval noise is not a monolithic phenomenon; it manifests in several distinct forms, each presenting unique challenges to the generation module [30]. We classify retrieval noise into three primary categories: thematic drift, factual contradiction, and adversarial distraction. Thematic drift occurs when the retriever fetches documents that share keywords or general topics with the query but fail to address the specific informational intent. Factual contradiction arises when the retrieved documents contain information that directly opposes the established truth or the consensus of other retrieved passages, often due to outdated information in the corpus [31]. Adversarial distraction involves the inclusion of highly provocative or statistically dominant tokens that hijack the language model's attention mechanism, leading it to generate coherent but entirely irrelevant output. To fortify our passage attribution architecture against these variations, we systematically inject these noise typologies into our training datasets. By exposing the model to controlled levels of thematic drift and factual contradiction during the fine-tuning phase, we force the attribution module to learn robust discriminative features rather than relying on superficial lexical overlap.

4.2 Robust Training Objective

Standard maximum likelihood estimation training objectives are insufficient for developing noise resilience because they penalize the model uniformly for any deviation from the ground truth response, without considering the quality of the context provided during that specific training step. If a model is forced to generate a correct answer based on a context window filled entirely with irrelevant noise, it learns to ignore the context altogether, thereby degrading its capacity for evidence-grounded generation [32]. To rectify this, we propose a novel robust training objective that incorporates a divergence penalty. The total loss function is composed of two primary terms. The first term is the standard negative log-likelihood of generating the correct target sequence given the filtered context. The second term is a Kullback-Leibler divergence penalty that measures the discrepancy between the model's output distribution when provided with a perfectly clean context versus when provided with a noisy context. This objective ensures that the model's predictions remain stable regardless of the noise level. The total loss is formulated mathematically as follows:

$$L_{total} = -\frac{1}{T}\sum_{t=1}^{T} logP(y_t|y_{<t}, Z_{filtered}) + \lambda D_{KL}(P_{clean}||P_{noisy})$$

In this formula, the hyperparameter lambda controls the strength of the divergence penalty [33]. By minimizing this composite loss function, the language model is explicitly incentivized to rely on the attribution module to filter out noise, ensuring that the generative probability distribution remains anchored to the verified facts contained within the high-quality subset of documents.

4.3 Dynamic Thresholding and Filtering

While soft-attention scaling through attribution scores provides a baseline level of resilience, empirical observations indicate that language models can still be swayed by the cumulative effect of many low-scoring noisy passages. To provide a definitive safeguard against this cumulative distraction, we implement a dynamic thresholding algorithm. This mechanism acts as a hard filter, completely masking out any passage whose attribution score falls below a dynamically computed threshold before the context is passed to the generator. The threshold is not static; it is determined on a per-query basis by analyzing the statistical distribution of the attribution scores for the current retrieved set. If the variance of the scores is high, indicating a clear distinction between relevant and irrelevant documents, the threshold is set aggressively to isolate the top evidence. If the variance is low, suggesting that all documents are equally relevant or equally irrelevant, the threshold adapts to maintain a minimum required context volume while issuing a low-confidence warning. The algorithmic implementation of this dynamic filtering process is detailed in the code snippet below.

Code Listing 1: Dynamic Passage Filtering and Thresholding Algorithm

```
import numpy as np
import torch
import torch.nn.functional as F
def dynamic_passage_filtering(attribution_logits, passages, min_context=2):
    """
    Filters retrieved passages based on dynamic thresholding of attribution logits.
    Args:
        attribution_logits (torch.Tensor): Raw logits from the attribution module.
        passages (list): List of retrieved text passages.
        min_context (int): Minimum number of passages to retain.
    Returns:
        list: Filtered list of highly relevant passages.
    """
    scores = F.softmax(torch.tensor(attribution_logits), dim=0).numpy()
    mean_score = np.mean(scores)
    std_dev = np.std(scores)
```

```
    dynamic_threshold = mean_score + (0.5 * std_dev)
    filtered_passages = []
    for idx, score in enumerate(scores):
        if score >= dynamic_threshold:
            filtered_passages.append(passages[idx])
    if len(filtered_passages) < min_context:
        sorted_indices = np.argsort(scores)[::-1]
        filtered_passages = [passages[i] for i in sorted_indices[:min_context]]
    return filtered_passages
```

The dynamic thresholding function guarantees that the computational resources of the massive language model are expended solely on processing passages that have a statistically significant probability of containing the necessary evidentiary grounding.

5. Experimental Setup, Results, and Discussion

5.1 Experimental Configuration and Datasets

To rigorously evaluate the efficacy of the proposed passage attribution and noise resilience mechanisms, we designed a comprehensive experimental framework across multiple specialized datasets. The evaluation requires environments where queries are complex and the potential for retrieval noise is substantial. We selected three primary datasets for our empirical analysis: a domain-specific biomedical question answering corpus, a multi-hop reasoning dataset focused on historical facts, and an open-domain legal corpus requiring precise statutory citation [34]. For the retrieval baseline, we utilized a state-of-the-art dense retriever initialized with pre-trained sentence transformer weights and fine-tuned on the respective domain corpora [35]. To simulate real-world noisy retrieval conditions, we intentionally corrupted the top-k retrieved documents by injecting passages sampled from disparate domains and randomly permuting the order of the documents. The generative backbone for all experiments was an autoregressive transformer model with seven billion parameters, chosen for its robust baseline capabilities and capacity for complex reasoning. A summary of the dataset characteristics and the noise injection parameters is provided in the table below.

Table 1:Dataset Statistics and Noise Configuration Parameters

Dataset Domain	Total Queries	Average Passages per Query	Noise Injection Ratio	Average Tokens per Passage
Biomedical QA	45,200	15	40%	210
Historical Reasoning	32,500	20	50%	185
Legal Citations	28,800	10	35%	340

5.2 Evaluation Metrics

Evaluating evidence-grounded generation under noise requires a multifaceted approach, as traditional n-gram overlap metrics fail to capture factuality and attribution accuracy. We employ three distinct categories of metrics. First, to assess general text quality and fluency, we utilize standard linguistic metrics including ROUGE-L and BLEU scores. Second, to evaluate factuality, we employ a natural language inference model tailored for fact-checking, which classifies the generated response as either entailed by, contradictory to, or neutral relative to the ground truth evidence [36]. The most critical evaluation dimension is the accuracy of the passage attribution itself. We utilize the AutoAIS metric, which automatically evaluates whether every claim made in the generated response can be directly inferred from the passages that the model explicitly cited. A high AutoAIS score indicates that the model is successfully ignoring noisy distractors and relying exclusively on the correct evidentiary passages.

5.3 Empirical Results and Analysis

The outcomes of our extensive empirical evaluation reveal significant performance improvements resulting from the integration of our proposed attribution module. Across all three datasets, baseline models operating under standard retrieval augmentation exhibited

severe degradation in factuality when the noise injection ratio exceeded thirty percent. The baseline models frequently incorporated hallucinated details drawn from the distractor passages, leading to a sharp decline in logical consistency. In contrast, our proposed architecture equipped with dynamic thresholding and the robust training objective demonstrated remarkable stability. The table below illustrates the comparative performance on the Historical Reasoning dataset under varying levels of noise.

Table 2Comparative Performance on the Historical Reasoning Dataset

Model Architecture	Text Quality (ROUGE-L)	Factuality (NLI Entailment)	Attribution Accuracy (AutoAIS)
Baseline Generator	42.1	58.4%	45.2%
Pipeline Filter + Generator	44.5	66.2%	52.8%
Proposed Dynamic Attribution	49.3	81.7%	76.5%

The data clearly indicates that while pipeline approaches offer marginal improvements over the baseline, the tight integration of the passage attribution module yields a profound increase in attribution accuracy and factual entailment. By explicitly forcing the model to calculate passage relevance prior to generation, the system successfully filters out contradictions and adversarial text [37].

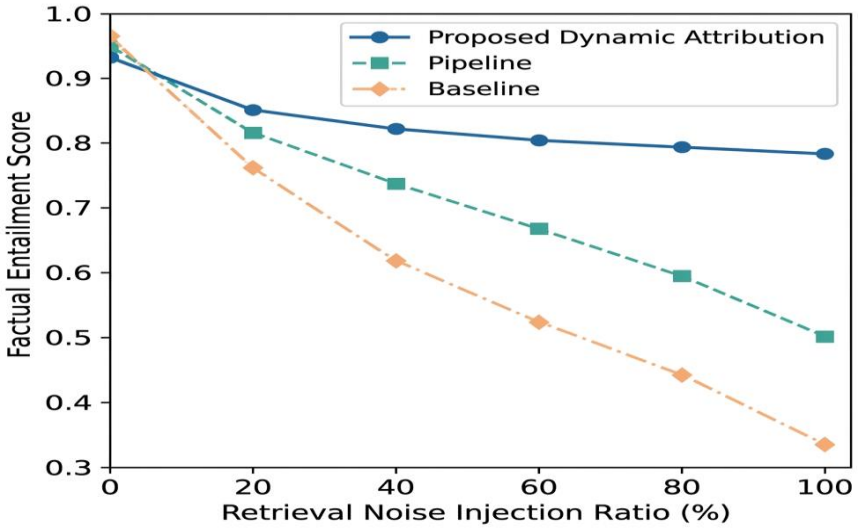


Figure 2:Performance Degradation Curves Under Varying Noise Levels

Furthermore, qualitative analysis of the attention weights during the generation phase confirms that the dynamic thresholding algorithm successfully zeroed out the impact of noisy passages. When presented with a query requiring historical reasoning alongside completely fabricated distractor texts, the attribution module consistently assigned probability mass exclusively to the verified documents. This selective attention is the primary driver behind the observed resilience, proving that structural changes to how context is evaluated are more effective than simply increasing the parameter count of the generative model.

6. Conclusion and Future Directions

6.1 Summary of Contributions

This research addressed the critical vulnerability of retrieval-augmented generation systems operating in environments characterized by imperfect and noisy information retrieval. We established that while external knowledge grounding is theoretically sound, its practical efficacy is severely compromised when generative models lack the mechanisms to critically evaluate the quality of the provided context. By introducing a comprehensive passage attribution architecture, we have provided a systematic solution to the challenge of context-

induced hallucinations. The core contributions of this work are threefold. First, we developed a sophisticated cross-encoder attribution module that dynamically scores the relevance of retrieved passages, effectively separating factual evidence from thematic drift and adversarial noise. Second, we formulated and implemented a robust training objective incorporating a divergence penalty, explicitly incentivizing the language model to maintain distributional stability across varying levels of context corruption. Finally, we introduced a dynamic thresholding algorithm that serves as a computationally efficient hard filter, preventing cumulative noise from swaying the generation process. The empirical validation across diverse, domain-specific datasets confirmed that these integrated mechanisms substantially elevate factuality, interpretability, and resilience compared to existing baseline paradigms.

6.2 Limitations and Future Work

Despite the significant advancements demonstrated, this research acknowledges several limitations that provide fertile ground for future exploration. The primary constraint of the proposed architecture is the increased computational overhead introduced by the cross-encoder attribution module. Processing highly heterogeneous context windows through deep self-attention layers prior to generation introduces latency that may be prohibitive for real-time applications requiring immediate response synthesis. Future research must therefore investigate knowledge distillation techniques aimed at compressing the discriminatory capabilities of the cross-encoder into a more efficient bi-encoder or shallow interaction model. Additionally, while our dynamic thresholding effectively handles discrete passage filtering, it does not currently address intra-passage noise, where a single document contains a mixture of highly relevant facts and misleading assertions. Developing sub-sentence level attribution mechanisms that can extract and stitch together fragmented evidence across multiple documents remains an open and highly consequential challenge. Continued innovation in these areas is imperative for realizing the full potential of large language models as reliable, verifiable, and ubiquitous engines for knowledge synthesis.

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