EAReranker: Efficient Embedding Adequacy Assessment for Retrieval Augmented Generation

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Abstract

With the increasing adoption of Retrieval-Augmented Generation (RAG) systems for knowledge-intensive tasks, ensuring the adequacy of retrieved documents has become critically important for generation quality. Traditional reranking approaches face three significant challenges: substantial computational overhead that scales with document length, dependency on plain text that limits application in sensitive scenarios, and insufficient assessment of document value beyond simple relevance metrics. We propose EAReranker, an efficient embedding-based adequacy assessment framework that evaluates document utility for RAG systems without requiring access to original text content. The framework quantifies document adequacy through a comprehensive scoring methodology considering verifiability, coverage, completeness and structural aspects, providing interpretable adequacy classifications for downstream applications. EAReranker employs a Decoder-Only Transformer architecture that introduces embedding dimension expansion method and bin-aware weighted loss, designed specifically to predict adequacy directly from embedding vectors. Our comprehensive evaluation across four public benchmarks demonstrates that EAReranker achieves competitive performance with state-of-the-art plaintext rerankers while maintaining constant memory usage ($\sim$550MB) regardless of input length and processing 2-3x faster than traditional approaches. The semantic bin adequacy prediction accuracy of 92.85% LACC@10 and 86.12% LACC@25 demonstrates its capability to effectively filter out inadequate documents that could potentially mislead or adversely impact RAG system performance, thereby ensuring only high-utility information serves as generation context. These results establish EAReranker as an efficient and practical solution for enhancing RAG system performance through improved context selection while addressing the computational and privacy challenges of existing methods. The source code of EAReranker is available in https://github.com/zjzdy/EAReranker.

1 Introduction

Retrieval-Augmented Generation (RAG) [1] has emerged as a pivotal paradigm for enhancing Large Language Models (LLMs) in knowledge-intensive applications. By incorporating external knowledge as context, RAG systems mitigate hallucinations and enhance response accuracy. As these systems evolve, ensuring retrieved knowledge is not merely **relevant** but genuinely **adequate** in comprehensively and accurately addressing query requirements has become increasingly critical.

The canonical RAG workflow consists of retrieval and reranking stages [2, 3, 4, 5, 6]. While contemporary reranking methods effectively capture semantic relationships through cross-attention

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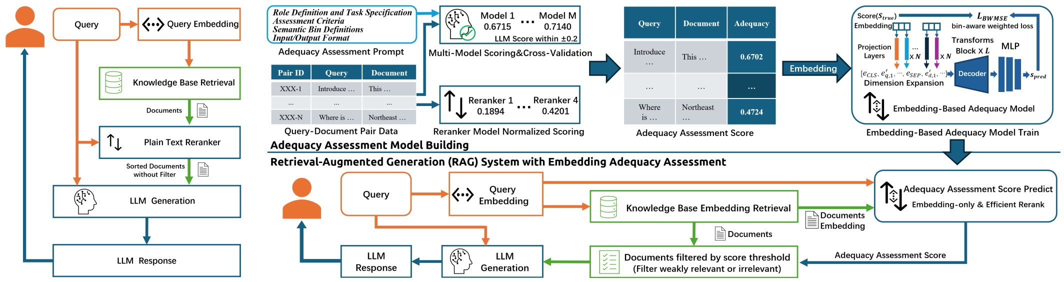

(a) Traditional plantext-based Reranker RAG

(b) Overall Workflow of EAReranker: Embedding-based Document Adequacy Assessment for RAG

Figure 1: Traditional Reranker RAG vs EAReranker RAG.

mechanisms [7] or pre-trained language models [8], their direct dependency on original text introduces significant limitations.

These limitations manifest in three primary challenges. First, **substantial and unstable computational overhead** arises as computational requirements scale with text length, creating deployment barriers in resource-constrained environments and performance instability with variable document lengths. Second, **dependency on plain text** restricts deployment in scenarios where content exposure raises intellectual property or data governance concerns, impeding wider RAG adoption. Finally, a more fundamental constraint lies in the **lack of refined content value assessment**. Traditional reranking primarily evaluates "relevance," whereas effective RAG systems require assessment of "adequacy," which represents the substantive value and reliability of content in addressing the query yet remains challenging to quantify.

To address these limitations comprehensively, we propose EAReranker, an efficient embedding-based adequacy assessment model that predicts document adequacy solely from embedding vectors without accessing original text. Operating entirely in vector space, EAReranker leverages the semantic understanding capabilities of pre-trained embedding models to perform sophisticated adequacy assessment and reranking.

Our contributions include: **(1) An embedding-oriented adequacy assessment architecture:** EAReranker employs a Decoder-Only Transformer with **embedding dimension expansion** techniques and a **bin-aware weighted loss function**, eliminating dependence on plain text while effectively utilizing embedded knowledge. **(2) A principled adequacy assessment methodology:** We introduce a multi-dimensional semantic binning approach that quantifies document utility into discrete interpretable levels, validated through multiple LLMs to ensure consistent assessment quality. **(3) Empirical validation of efficiency and effectiveness:** Comprehensive experiments demonstrate that EAReranker achieves comparable performance to plaintext models while significantly reducing computational requirements and maintaining consistent efficiency regardless of document length.

2 Related Work

2.1 Language Embedding Models

Text embedding methods represent a fundamental technology in modern natural language processing, mapping textual data into continuous vector spaces where semantic relationships can be captured through geometric proximity. The evolution of these techniques has significantly enhanced the capabilities of information retrieval and ranking systems.

Embedding approaches have advanced from context-independent word representations to sophisticated contextual models. Early techniques like Word2Vec [9] and GloVe [10] established foundational vector space modeling principles, while Transformer-based architectures including BERT [11] and RoBERTa [12] later introduced dynamic contextual understanding. The development of sentence-level embedding frameworks such as Sentence-BERT [13] further refined semantic representation by optimizing vector spaces specifically for similarity assessment.

Recent architectural innovations have substantially expanded embedding capabilities. Models based on XLM-RoBERTa [14], such as bge-m3 [15] and jina-embeddings-v3 [16], demonstrate robust multilingual and multi-domain processing abilities. Advanced architectures including Qwen2-based [17] KaLM-embedding [18] and Gemma2-based [19] bge-multilingual-gemma2 [15] leverage increased parameter scales to achieve enhanced semantic modeling and extended context support [20].

The demonstrated capability of modern embeddings to effectively encode semantic content suggests that embedding vectors alone can sufficiently represent semantic adequacy information. Our EAReranker framework builds upon this foundation, conducting document adequacy evaluation exclusively within the embedding space while maintaining semantic fidelity.

2.2 Language Reranking Models

Document reranking serves as a critical component in RAG for refining initially retrieved candidates [2, 3, 4, 5]. Traditional approaches utilized lexical heuristics such as BM25 [21] and TF-IDF [22], which offer computational efficiency but exhibit limited semantic understanding.

Neural reranking models have introduced sophisticated semantic modeling through various architectural paradigms. Encoder-based approaches, exemplified by bge-reranker-v2-m3 [15] and jina-reranker-v2-base-multilingual [23], process query-document pairs using token-level cross-attention mechanisms. Decoder-Only architectures, including bge-reranker-v2-gemma [15] and lb-reranker [8], leverage autoregressive modeling over combined sequences to capture complex dependencies.

An alternative approach involves directly prompting large language models for ranking tasks, as demonstrated by RankGPT [6] and UPR [24]. While this method offers flexibility, it requires substantial computational resources and full text access.

Current reranking approaches face two significant limitations. First, they require direct access to query and document text, resulting in computational costs that scale with input length. Second, they primarily focus on relevance assessment rather than comprehensive adequacy evaluation for RAG.

Our proposed EAReranker addresses these limitations by operating solely on embedding vectors, enabling efficient computation and privacy preservation while maintaining competitive performance. This approach represents a significant advancement in developing practical and scalable solutions for document adequacy assessment in RAG.

3 Embedding Adequacy Assessment Framework

3.1 Framework Overview

Figure 1 contrasts traditional reranker-based RAG systems with our proposed EAReranker approach. While conventional rerankers perform detailed query-document interaction requiring computational resources proportional to text length, EAReranker operates exclusively on fixed-dimension embedding vectors, enabling efficient adequacy assessment without accessing original text content. This design strategically addresses three critical limitations of existing approaches: **(1) Computational invariance:** Processing fixed-dimension embeddings decouples runtime and memory requirements. **(2) Avoidance of dependence on original text:** By operating solely on embeddings, our method mitigates issues arising from direct text exposure or handling. **(3)Adequacy-centric evaluation:** The model learns to assess multi-dimensional adequacy factors rather than relying solely on relevance.

A critical distinction underlying our work is that between *relevance* and *adequacy*. Traditional retrieval systems prioritize relevance—measuring topical alignment between queries and documents through lexical or semantic similarity. However, for RAG systems performing complex generation tasks, relevance alone is insufficient. Adequacy measures a document's *functional utility* in enabling the generation model to produce complete, accurate, and well-structured responses. For instance, a document containing only the query keywords may achieve high relevance scores but provide minimal generation value, while a comprehensive, well-structured explanation may score lower on similarity metrics yet offer substantially higher utility for answer generation. Our adequacy framework evaluates documents across four complementary dimensions to capture this multi-faceted utility.

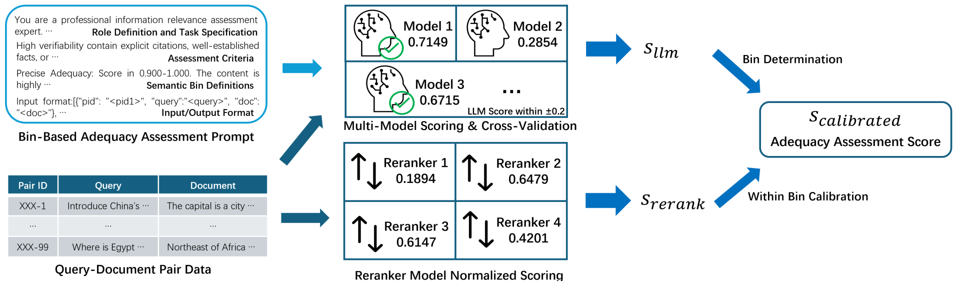

Figure 2: Pipeline of Adequacy Assessment Annotation.

3.2 Problem Formal Characterization

Traditional document reranking is typically defined as learning a function $f(q, d)$ that evaluates the relevance between the original query text q and document text d, and ranks documents accordingly. We redefine this task as learning a model $\mathcal{M}$ that predicts a scalar score $s' \in [0, 1]$ reflecting the "adequacy" of document d for query q, using only their embedding vectors $\mathbf{e}_q \in \mathbb{R}^d$ and $\mathbf{e}_d \in \mathbb{R}^d$ generated by pre-trained embedding models:

$$f(q, d) \to s \quad \text{(Traditional)} \quad \Rightarrow \quad \mathcal{M}(\mathbf{e}_q, \mathbf{e}_d) \to s' \quad \text{(Ours)}, \tag{1}$$

where documents $\{d_i\}$ are then reranked based on these predicted adequacy scores s'_i.

More precisely, given a query embedding $\mathbf{e}_q$ and a collection of document embeddings $\{\mathbf{e}_{d_i}\}_{i=1}^N$ obtained during the initial retrieval phase, we aim to train a model $\mathcal{M}(\mathbf{e}_q, \mathbf{e}_{d_i}) \to s'_i$ that approximates the true adequacy score s_i with high fidelity. The final document ranking is determined by sorting the documents in descending order of their predicted adequacy scores, such that:

$$s'_{i_1} \geq s'_{i_2} \geq ... \geq s'_{i_N}, \tag{2}$$

where $(i_1, i_2, ..., i_N)$ represents the indices of the documents after ranking. A critical property of our framework is score interpretability—documents with similar predicted scores should demonstrate comparable utility across query-document pairs, enabling meaningful threshold-based filtering.

To effectively assess adequacy from embeddings, our model must exhibit four essential capabilities: extraction of fine-grained semantic information from fixed-dimension vectors; exclusive operation on embeddings without requiring original text; evaluation across multiple adequacy dimensions beyond simple relevance; and computational efficiency invariant to document length. These requirements guide our architectural design and implementation strategies detailed in subsequent sections, with Section 4 presenting our annotation methodology and Section 5 describing our model architecture.

4 Adequacy Assessment Annotation

This section establishes a formal framework for evaluating document adequacy in RAG systems, transcending traditional relevance metrics to capture the multidimensional utility of retrieved content as generation context. We introduce a rigorous methodology for quantifying document adequacy through interpretable value classification, providing both theoretical foundations and high-quality labeled datasets for training our proposed EAReranker model. As illustrated in Figure 2, our annotation pipeline integrates semantic bin-based standards, multi-model evaluation, and cross-model validation to ensure consistency across diverse query-document domains.

4.1 Semantic Bin-Based Adequacy Scoring

Adequacy assessment represents a fundamental advancement beyond conventional relevance evaluation. While relevance primarily quantifies semantic proximity between queries and documents, adequacy measures the substantive utility of documents as generation context. This distinction is critical: relevance indicates topical alignment, whereas adequacy evaluates whether a document provides reliable information that comprehensively addresses query requirements.

Table 1: Semantic Binning Scheme for Adequacy Scoring.

Semantic Bin	Score Range	Verifiability	Need Coverage	Evidence Completeness	Structure Suitability	Description
Precise Adequacy	$[0.90, 1.00]$	High	High	High	High	Optimal context
High Adequacy	$[0.75, 0.90)$	High	High	High	Medium	High-quality context
Middle Adequacy	$[0.50, 0.75)$	Medium	Medium	Medium	Medium	Usable context with supplementation
Marginal Relevance	$[0.25, 0.50)$	Low	Low	Low	Low	Marginally usable context
Weak Relevance	$[0.10, 0.25)$	Very Low	Low	Very Low	-	Negligible value context
Irrelevance	$[0.00, 0.10)$	-	Very Low	-	-	Unusable context

We formalize adequacy assessment through four complementary dimensions: **(1) Verifiability**: Quantifies information reliability and factual foundation. High verifiability documents present explicitly cited or well-established facts, while low verifiability documents contain predominantly unsubstantiated claims. **(2) Need Coverage**: Evaluates comprehensive addressing of query requirements. High coverage documents provide complete responses to information needs, whereas low coverage documents may contain superficially relevant terminology without addressing query intent. **(3) Evidence Completeness**: Assesses logical coherence and supporting evidence. Documents with high completeness present well-structured arguments with sufficient substantiation, while those with low completeness exhibit logical discontinuities or insufficient support. **(4) Structure Suitability**: Measures alignment between document presentation and required content format. High suitability documents present information in readily utilizable formats, while low suitability documents require significant transformation.

We discretize the adequacy spectrum into six distinct bins spanning [0,1], as detailed in Table 1. Documents in the **Precise Adequacy** bin ([0.90, 1.00]) represent optimal context with high performance across all dimensions. **High Adequacy** documents ([0.75, 0.90)) contain all required information with minimal redundancy. **Middle Adequacy** documents ([0.50, 0.75)) address main issues but require supplementation. **Marginal Relevance** documents ([0.25, 0.50)) cover only peripheral aspects of the query. **Weak Relevance** documents ([0.10, 0.25)) provide minimal substantive information. **Irrelevance** documents ([0.00, 0.10)) have no discernible relationship to query requirements.

This structured binning provides clear operational thresholds for RAG systems. Documents scoring above 0.75 can be directly incorporated, while those below 0.25 should generally be excluded to prevent hallucination or inaccuracy in generated content. The granular discrimination between bins enables automated optimization of context selection, significantly enhancing generation quality.

4.2 Multi-Model Semantic Bin Scoring

Constructing high-quality training data necessitates a robust annotation methodology. We employ a multi-model scoring framework that leverages diverse large language models under a principled cross-validation scheme to ensure reliable and consistent scoring across heterogeneous query-document pairs. Our framework employs a cross-validation architecture that aggregates assessments from multiple LLMs with distinct architectures and training paradigms. This approach mitigates individual model biases and captures diverse evaluation perspectives, enhancing annotation reliability particularly for ambiguous cases.

Effective LLM-based scoring relies on carefully engineered prompts encompassing: (1) Professional role definition with explicit evaluation criteria, (2) Four-dimensional adequacy framework articulation, (3) Precise semantic bin definitions with boundary cases, and (4) Structured input/output formats. We incorporate exemplar cases demonstrating assessment criteria across diverse scenarios, enhancing model understanding of nuanced adequacy distinctions.

The scoring process follows Algorithm 1, which implements a hierarchical validation mechanism to identify consistent model assessments. The algorithm's innovation lies in its combinatorial approach, systematically evaluating all possible combinations of four model scores to find consistent subsets. Specifically, it begins with four LLM scores and checks consistency (tolerance 0.2); if unsuccessful, additional models are consulted and all four-score combinations are evaluated to find self-consistent subsets. This approach offers several advantages: **flexibility in finding reliable assessments** without requiring all models to agree, **computational efficiency** through progressive validation, and **effective handling of outlier scores** by identifying alternative combinations that provide consistent assessments.

Algorithm 1: Multi-Model Semantic Bin Scoring.

Input: Query-document pair (q, d), LLM models $\mathcal{M} = \{M_1, ..., M_m\}$
Output: LLM adequacy score s_{llm}

$\mathcal{S} \leftarrow \{\text{Score}(M_i, q, d) \mid i \in \{1, 2, 3, 4\}\}$; `/* Initialize with first 4 scores */`
$\mu \leftarrow \text{Mean}(\mathcal{S})$;
if $\max_{s \in \mathcal{S}} |s - \mu| \leq 0.2$ **then**
  return μ;
for $i \leftarrow 5$ **to** m **do**
  $\mathcal{S} \leftarrow \mathcal{S} \cup \{\text{Score}(M_i, q, d)\}$;
  foreach $\mathcal{S}_{subset} \in$ *Combinations*$(\mathcal{S}, 4)$ **do**
    $\mu_{subset} \leftarrow \text{Mean}(\mathcal{S}_{subset})$;
    if $\max_{s \in \mathcal{S}_{subset}} |s - \mu_{subset}| \leq 0.2$ **then**
      return μ_{subset};
return $\text{Mean}(\mathcal{S})$;

4.3 Within-Bin Score Calibration Methodology

While multi-model validation provides reliable bin assignments, we observed that LLMs tend to produce clustered scores within each bin, limiting intra-bin differentiation. To enhance score granularity while preserving semantic boundaries, we developed a within-bin calibration methodology that incorporates auxiliary ranking signals from diverse reranking models.

The calibration process begins with normalization of reranker scores across the dataset:

$$s_{R_j}^{norm} = \frac{s_{R_j} - \min(s_{R_j})}{\max(s_{R_j}) - \min(s_{R_j})}. \tag{3}$$

These normalized scores are aggregated to produce a composite reranking signal:

$$s_{rerank} = \langle s_{R_j}^{norm} \rangle_{j=1}^{|\mathcal{R}|}. \tag{4}$$

For documents with LLM-assigned scores s_{llm} within bin $[l_i, h_i]$, the calibration formula applies:

$$s_{calibrated} = 0.5 \times ((s_{llm} - l_i)/(h_i - l_i) + s_{rerank}) \times (h_i - l_i) + l_i. \tag{5}$$

This calibration methodology preserves semantic bin boundaries while enhancing intra-bin differentiation, transforming discrete score clusters into continuous distributions and maintaining semantic consistency with original assessments.

Through this comprehensive annotation framework, we construct large-scale training datasets with high-quality adequacy scores. The methodology's ability to produce consistent, fine-grained adequacy annotations while preserving semantic interpretability represents a significant advancement in automated document assessment for RAG.

5 Embedding-Based Adequacy Assessment Model

We propose EAReranker, an efficient embedding-based model for document adequacy assessment that operates exclusively in the vector space, as illustrated in Figure 3. The model leverages a specialized Decoder-Only Transformer architecture to evaluate adequacy using only query and document embedding, eliminating the need for access to original text while maintaining competitive performance with traditional text-based approaches. The architecture consists of two primary components:

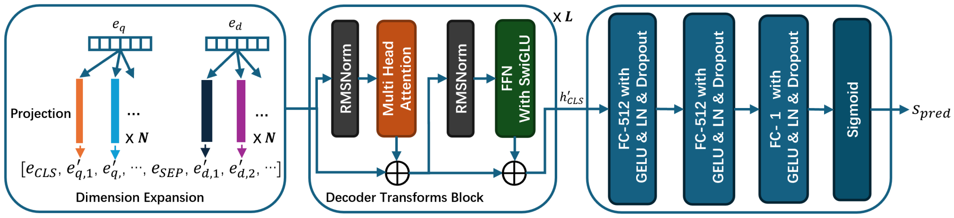

Figure 3: Overall of Adequacy Assessment Model.

Embedding Dimension Expansion: To enable rich semantic feature extraction from fixed-dimensional embeddings, we transform single embedding vectors into sequential representations through independent projection layers. Given query embedding $\mathbf{e}_q$ and document embedding $\mathbf{e}_d$, the expansion is performed as:

$$\mathbf{e}'_{q,i} = L_{q,i}(\mathbf{e}_q) = \mathbf{W}_{q,i}\mathbf{e}_q + \mathbf{b}_{q,i}, \quad \mathbf{e}'_{d,i} = L_{d,i}(\mathbf{e}_d) = \mathbf{W}_{d,i}\mathbf{e}_d + \mathbf{b}_{d,i}, \tag{6}$$

where each projection layer $L_{q,i}$ and $L_{d,i}$ is initialized independently to capture distinct semantic aspects. The expanded sequence combines these transformed embeddings with trainable special tokens embedding vectors $\mathbf{e}_{CLS}$ and $\mathbf{e}_{SEP}$: $[\mathbf{e}_{CLS}, \mathbf{e}'_{q,1}, \ldots, \mathbf{e}'_{q,N}, \mathbf{e}_{SEP}, \mathbf{e}'_{d,1}, \ldots, \mathbf{e}'_{d,N}]$.

Transformer Processing: The expanded sequence is processed through L stacked Decoder layers with Multi-Head Self-Attention and Feed-Forward Networks. The [CLS] token output is passed through a three-layer MLP head to predict the final adequacy score.

The model is trained using a bin-aware weighted loss function that emphasizes accurate prediction near semantic bin boundaries:

$$\mathcal{L}_{BWMSE}(S_{true}, S_{pred}) = \frac{1}{N}\sum_{i=1}^{N} w_i \cdot (s_{true,i} - s_{pred,i})^2, \tag{7}$$

where weights w_i are computed based on prediction deviation from bin boundaries.

This architecture effectively addresses the key challenges of embedding-based adequacy assessment while maintaining high computational efficiency and privacy preservation.

6 Experiments

We present a comprehensive evaluation of EAReranker's effectiveness in embedding-based adequacy assessment and reranking. Our experiments assess the model's ranking performance across public benchmarks, adequacy classification accuracy, and computational efficiency, demonstrating its ability to achieve competitive results while operating exclusively on embedding vectors.

6.1 Experimental Settings

Our evaluation utilized a dataset comprising 1 million query-document pairs, partitioned into training (80%) and testing (20%) sets. Vector representations were generated using established embedding models: bge-m3 (1024-dimensional)[15], jina-embeddings-v3 (jina-v3, 1024-dimensional) [16], gte-multilingual-base (gte-base, 768-dimensional) [18], and KaLM-embedding-multilingual-mini-instruct-v1.5 (KaLM, 896-dimensional) [20]. We deliberately excluded higher-dimensional models like NV-Embed-v2 (4096-dimensional) [25] to focus on commonly dimensions in RAG.

The evaluation framework compares EAReranker against multiple baselines: traditional lexical models (BM25 [21]), embedding cosine similarity methods, and plaintext-based reranking models including gte-multilingual-reranker-base [18], bge-reranker-v2-m3 [15], jina-reranker-v2-base-multilingual [23], and lb-reranker-v1.0 [8].

EAReranker employs a stacked Transformer architecture with 4 layers and an embedding dimension expansion factor of 4, balancing representational capacity with computational efficiency. Training utilized the AdamW optimizer (batch size 256, learning rate 1e-5) for 50 epochs with early stopping.

Table 2: Comparative Case Study: Traditional Retrieval Scores Versus Adequacy Assessment.

Query	Document	bge-m3	gte-base	bge-r2	gte-rb	Adequacy
Introduce China's capital.	Beijing City (Beijing), abbreviated as Jing, historically known as Yanjing and Beiping ...	0.7305	0.7983	2.4641	0.3608	0.9261
Introduce China's capital.	The capital is a nation's most important political center. Throughout Chinese history ...	0.6684	0.7723	2.4453	0.9229	0.8749
Introduce China's capital.	Beijing is the capital of the People's Republic of China, categorized as a super first-tier city.	0.6717	0.7634	0.7334	0.2303	0.5763
Introduce China's capital.	Beijing is the capital	0.7858	0.8427	2.4805	0.3511	0.3102
Introduce China's capital.	Introduce China's capital	1.0000	1.0000	10.1562	3.2539	0.1740
The formula for multiplying two numbers to 10.	1*5=5; 2*5=10; 3*5=15; 4*5=20 ...	0.6137	0.6300	0.1333	0.3533	0.8137
Where is Egypt located in Africa? A. Northeast B. Southwest	A	0.3278	0.5939	-4.7656	0.6436	0.1523
What is China's capital city?	Beijing	0.6024	0.7688	2.8633	0.6348	0.1893
What is China's capital city?	The railway runs east to west	0.3977	0.4263	-10.7734	-0.4365	0.0324

6.2 Metrics

Our evaluation framework incorporates both ranking effectiveness and classification accuracy metrics:

Ranking Metrics: Normalized Discounted Cumulative Gain (NDCG@10) evaluates ranking quality considering both relevance and position. Mean Reciprocal Rank (MRR) quantifies the position of the first relevant document.

Adequacy Assessment Metrics: ACC25 measures the proportion of samples where the absolute error between predicted and true scores is within 0.25, directly reflecting bin classification accuracy. LACC@25 and LACC@10 evaluate binary classification accuracy at thresholds of 0.25 and 0.10 respectively, indicating the model's ability to distinguish relevant from irrelevant documents. These metrics are particularly significant for RAG systems that require effective filtering mechanisms to prevent noise contamination.

6.3 Dataset

We curated a comprehensive adequacy assessment dataset by augmenting the `bge-m3-data` [15] comprising diverse query-document pairs with additional samples sourced from multiple heterogeneous collections [26, 27, 28, 29, 30, 31, 32, 33, 34, 35]. This aggregated dataset spans a wide spectrum of domains and query intents, encompassing fact verification, specialized knowledge retrieval, etc.

To ensure annotation quality, we adopted a multi-model scoring framework employing seven LLMs [36, 37, 38, 39, 17, 40, 41] with diverse architectures and training regimes. Each query-document pair was scored multiple times, with cross-validation and iterative selection to reduce model-specific bias and improve consistency, particularly for ambiguous boundary samples.

Table 2 contrasts traditional retrieval scores with our bin-based adequacy assessment across representative examples. Here, bge-r2 and gte-rb denote reranking scores from bge-reranker-v2-m3 [15] and gte-multilingual-reranker-base [18], respectively; bge-m3 and gte-base represent cosine similarity scores. The comparison illustrates how traditional methods often conflate lexical or semantic similarity with true informational value. For instance, exact query repetition achieves maximal similarity scores but receives low adequacy ratings, reflecting its lack of substantive content. Conversely, documents offering structured, detailed information receive high adequacy despite lower similarity scores, highlighting traditional models' inability to fully capture content utility for generation tasks.

6.4 Performance Experiments

Ranking Effectiveness. Evaluation across four public benchmarks (FEVER [30], NFCorpus [28], DuRetrieval [42], and T2Ranking [43]) reveals consistent performance patterns, as shown in Table 3. Traditional lexical methods demonstrate the weakest performance, with embedding similarity methods showing significant improvements in NDCG and MRR. Plaintext-based reranking models achieve superior performance. However, EAReranker maintains competitive results within 0.54%-1.30% of the best plaintext model. This performance is particularly noteworthy given that EAReranker

Table 3: Ranking Performance on Public Benchmarks (%).

Type	Model	FEVER		NFCorpus		DuRetrieval		T2Ranking	
		NDCG@10	MRR	NDCG@10	MRR	NDCG@10	MRR	NDCG@10	MRR
Lexical	BM25	48.09	32.97	32.08	43.96	19.47	21.03	46.34	35.89
Embedding Similarity	Cosine (gte-base)	92.11	94.19	36.66	56.60	87.54	93.38	84.71	92.60
	Cosine (bge-m3)	81.37	85.64	31.41	52.17	83.96	90.77	81.37	90.30
	Cosine (jina-v3)	89.05	91.28	36.44	55.30	83.17	89.72	83.16	91.53
	Cosine (KaLM)	86.54	89.65	25.92	39.31	80.23	86.49	79.78	87.61
Plaintext Rerankers	gte-reranker-base	94.83	96.12	38.79	59.25	89.37	94.81	87.06	94.37
	bge-reranker-v2-m3	95.26	96.78	39.41	60.83	90.16	95.24	87.85	95.41
	jina-reranker-v2	93.74	95.82	38.04	58.96	88.65	93.94	86.34	93.85
	lb-reranker-v1.0	95.11	96.44	39.28	60.71	89.82	94.76	87.52	94.93
Embedding Reranker	EAReranker (gte-base)	94.36	95.87	38.14	58.93	88.96	94.23	86.47	93.91
	EAReranker (bge-m3)	94.72	96.21	38.76	59.32	89.57	94.82	87.11	94.68
	EAReranker (jina-v3)	94.51	96.08	38.51	59.14	89.23	94.56	86.89	94.32
	EAReranker (KaLM)	93.84	95.43	37.65	58.46	88.54	93.95	86.12	93.57

Table 4: EAReranker Adequacy Performance(%).

Embedding	ACC25	LACC@25	LACC@10
gte-base	81.98	84.17	91.32
bge-m3	84.28	86.12	92.85
jina-v3	83.52	85.42	92.27
KaLM	83.09	85.06	91.98

Table 5: Ablation Performance on bge-m3 (%).

Configuration	ACC25	LACC@10
Complete model	84.28	92.85
w/o Dimension Expansion	80.58 (-3.70)	89.62 (-3.23)
w/o Bin-Aware Loss	81.61 (-2.67)	90.65 (-2.20)
w/o Score Calibration	82.95 (-1.33)	91.98 (-0.87)

Table 6: Inference Computational Efficiency Comparison.

Model (Max Length)	VRAM(MB)	Inference Time(s)
gte-reranker-base (8K)	1209-2225	0.1697-0.3506
bge-reranker-v2-m3 (8K)	2176-2527	0.1312-0.5468
jina-reranker-v2 (1K)	547-603	0.1846-0.2128
lb-reranker-v1.0 (128K)	967-8441	0.3479-5.9219
EAReranker (gte-base)	544	0.1111
EAReranker (bge-m3)	550	0.1128
EAReranker (jina-v3)	550	0.1127
EAReranker (KaLM)	547	0.1124

processes only fixed-dimensional embedding vectors rather than full text. Additional experimental information is provided in Appendix B.

Adequacy Assessment Capability. Table 4 presents the model's performance on adequacy classification metrics. EAReranker achieves 84.28% ACC25 using bge-m3 embeddings, with LACC@10, reaching 92.85% and LACC@25 achieving 86.12%. These results demonstrate effective discrimination between adequacy levels, particularly in identifying irrelevant or marginal documents that should be filtered from RAG contexts.

Computational Efficiency. Table 6 compares the computational efficiency of EAReranker with traditional reranking models. EAReranker demonstrates significant advantages in resource utilization, maintaining consistent memory usage (∼550MB) regardless of input length, while traditional models exhibit substantial variation (up to 8441MB for lb-reranker-v1.0).

In terms of inference speed, EAReranker processes queries in 0.11s-0.13s, consistently faster than traditional models, especially for longer documents. Unlike traditional approaches with fixed maximum sequence lengths, EAReranker's processing capability depends only on the underlying embedding model's input capacity, providing greater flexibility for varied document lengths.

Component Contribution Analysis. Ablation studies confirm the importance of EAReranker's architectural components, as shown in Table 5. Removing the embedding dimension expansion strategy results in significant performance degradation (3.70% in ACC25, 3.23% in LACC@10), demonstrating its essential role in extracting fine-grained semantic features from compressed embeddings. Similarly, the bin-aware weighted loss proves crucial for learning precise adequacy boundaries, with its removal causing notable performance reduction (2.67% in ACC25, 2.20% in LACC@10). Our score calibration methodology also contributes 1.33% improvement in ACC25, confirming its effectiveness in enhancing within-bin score granularity.

The experimental results collectively validate EAReranker's effectiveness as an embedding-based adequacy assessment model for RAG systems. The model maintains competitive ranking performance while operating exclusively on embedding vectors, effectively distinguishes between documents, and significantly reduces computational requirements compared to traditional approaches.

7 Conclusion

This paper introduces a novel framework for document adequacy assessment in RAG systems, shifting from traditional relevance-centric metrics to a comprehensive multi-dimensional evaluation framework that encompasses *verifiability*, *need coverage*, *evidence completeness*, and *structure suitability*. Through our semantic binning methodology and multi-model scoring approach, we provide a quantification of retrieved documents' intrinsic utility as generative context.

Our proposed EAReranker operates exclusively on embedding vectors without accessing original text, achieving comparable ranking performance to state-of-the-art plaintext models while significantly reducing computational overhead. This demonstrates the viability of embedding-based methods for efficient and plaintext-preserving RAG deployments in resource-constrained environments.

Despite promising empirical results, several challenges remain. The current semantic bin segmentation and integration of adequacy dimensions rely on empirically-informed heuristic criteria that require further theoretical research and discussion. Additionally, our reliance on multi-model LLM annotations introduces potential biases that warrant systematic investigation through more robust validation methodologies. Future research directions include refining calibration techniques for enhanced scoring granularity, and adapting the framework for domain-specific applications to improve generation factuality. Exploring alternative embedding expansion mechanisms and model architectures may yield further efficiency gains and performance improvements.

In conclusion, this work establishes fundamental theoretical and practical contributions toward embedding-based adequacy assessment, advancing the development of semantically nuanced, computationally efficient, and trustworthy retrieval-augmented generation systems.

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