Two-Gate Adaptive Context Selection: A Training-Free Framework for Efficient Document Filtering in Retrieval-Augmented Generation

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Abstract

Retrieval-Augmented Generation (RAG) systems frequently retrieve noisy document sets that dilute context quality and inflate inference costs. While recent approaches employ auxiliary language models or learned filters, they introduce computational overhead incompatible with production latency requirements. We present **Two-Gate Adaptive Context Selection**, a deterministic, training-free filtering algorithm that operates in $O(N)$ time with sub-millisecond latency. Our method combines: (1) a *safety trigger* ensuring graceful degradation, (2) a *purely relative threshold* adapting to query-specific score distributions, and (3) a *metric-aligned floor* to prevent over-aggressive filtering. We validate on a suite of three diverse public benchmarks from BEIR (NFCorpus, SciFact, FiQA) covering medical, scientific, and financial domains, alongside a production dataset of 487 queries with 5,995 human-annotated relevance judgments. On all public benchmarks, Two-Gate matches the saturation quality of Top-10/Top-20 baselines exactly (NDCG differences < 0.0001) while halving context size. On production data, it achieves **96% context reduction** compared to the unfiltered retrieval set (140.5 $\rightarrow$ 5.7 documents) and **69% reduction** compared to a strong Top-20 baseline (18.2 $\rightarrow$ 5.7), while maintaining statistically identical quality ($p > 0.05$). Unlike Self-RAG or Cluster-based Adaptive Retrieval, Two-Gate is parameter-free and adds only 0.03ms latency. The deterministic logic of the Two-Gate algorithm is detailed herein, facilitating straightforward integration into production RAG frameworks.

1 Introduction

Large language models exhibit remarkable capabilities yet suffer from factual hallucination and reliance on outdated parametric knowledge (Gao et al., 2024). Retrieval-Augmented Generation (RAG) addresses this by grounding outputs in retrieved evidence (Lewis et al., 2020). However, a critical challenge persists in the *post-retrieval* stage: initial retrieval prioritizes recall, producing candidate sets containing noise—documents topically related but factually irrelevant (Yoran et al., 2023).

The consequences are threefold: (1) **Quality degradation**—Liu et al. (2023) demonstrated the "lost in the middle" phenomenon; (2) **Inference cost explosion**—larger contexts require more compute; and (3) **Environmental impact**—unnecessary token processing wastes energy (Schwartz et al., 2020).

1.1 Metric-Aligned Efficiency

Our work is grounded in the principle of **Metric-Aligned Efficiency**. Standard retrieval metrics like NDCG@10 naturally saturate once the top 10 ranks are filled; retrieving additional documents ($k = 20$) often increases computational cost without improving the evaluation metric. We explicitly validate this efficiency gap:

- On diverse BEIR benchmarks, Top-10 and Top-20 achieve identical NDCG@10 scores, indicating that documents ranked 11-20 contribute negligible utility.
- On 487 production queries, Two-Gate matches this baseline quality with a 69% reduction in document volume vs Top-20.

1.2 Two-Gate: Adaptive Context Selection

We present **Two-Gate Adaptive Context Selection**, operating on documents scored by a cross-encoder reranker with three mechanisms:

1. **Safety Trigger (Gate 1):** When the top score falls below τ_{abs}, return k_{min} documents to prevent zero-result failures.
2. **Purely Relative Threshold (Gate 2):** Compute a dynamic cutoff as $\tau_{rel} \times s_{max}$, adapting to query difficulty.

3. **Metric-Aligned Floor:** Enforce minimum $k_{min} = 10$ documents, aligned with NDCG@10 evaluation.

The algorithm requires only a linear $O(N)$ scan, adding 0.03ms latency—positioning Two-Gate as an efficient "fast path" for production RAG.

Our contributions are:

- A training-free, deterministic $O(N)$ filtering algorithm combining safety triggers, relative thresholds, and metric-aligned floors (§3).
- Validation on diverse BEIR benchmarks (NFCorpus, SciFact, FiQA) showing 50% context reduction with zero quality loss (§5).
- Evaluation on 487 production queries with both LLM-as-judge (87,660 pairs) and 5,995 human-annotated relevance judgments demonstrating 69% reduction vs Top-20 (§5).
- Analysis positioning Two-Gate as a Green AI solution: $O(N)$ vs. $O(N \log N)$ clustering or $O(Gen)$ LLM-based methods (§7).

2 Related Work

2.1 Retrieval-Augmented Generation

RAG was formalized by Lewis et al. (2020), combining dense retrieval with neural generation. Gao et al. (2024) survey Naive, Advanced, and Modular RAG paradigms.

2.2 LLM-Based Document Filtering

Self-RAG (Asai et al., 2024) trains models to generate reflection tokens but requires fine-tuning and adds 200ms+ latency. **CRAG** (Yan et al., 2024) uses a retrieval evaluator adding 100ms+ latency. **Adaptive-RAG** (Jeong et al., 2024) routes queries based on complexity.

Our Two-Gate approach uses cross-encoder scores as relevance signals already computed in the pipeline—a computationally efficient proxy for these methods.

2.3 Cluster-Based Adaptive Retrieval

Recent work on **CAR** (Xu et al., 2025) uses density-based clustering for dynamic selection, but introduces $O(N \log N)$ overhead and 10–50ms latency. Two-Gate achieves comparable adaptivity with deterministic $O(N)$ filtering at 0.03ms.

Algorithm 1 Two-Gate Adaptive Context Selection

Require: Documents $D = \{d_1, \ldots, d_n\}$ sorted by s_i descending
Require: τ_{abs}: absolute threshold (default 0.4)
Require: τ_{rel}: relative ratio (default 0.85)
Require: k_{min}: metric-aligned floor (default 10)
Require: k_{max}: budget ceiling (default 20; aligned with max context)
Ensure: Filtered documents D_{out}

```
s_max ← s_1 {Highest score}
// Gate 1: Safety Trigger
if s_max < τ_abs then
    return D[1 : k_min] {Low confidence fallback}
end if
// Gate 2: Purely Relative Threshold
τ_eff ← τ_rel × s_max
D_pass ← {d_i : s_i ≥ τ_eff}
// Metric-Aligned Floor
if |D_pass| < k_min then
    D_pass ← D[1 : k_min]
end if
// Budget Ceiling
return D_pass[1 : min(|D_pass|, k_max)]
```

2.4 Context Compression

LLMLingua (Jiang et al., 2023) uses perplexity-based pruning; **AttentionRAG** (Fang et al., 2025) leverages attention patterns. Two-Gate makes document-level decisions, complementing token-level compression.

3 Methodology

3.1 Problem Formulation

After retrieval and cross-encoder reranking, we obtain:

$$D_{reranked} = \{(d_1, s_1), (d_2, s_2), \ldots, (d_n, s_n)\}$$

where $s_1 \geq s_2 \geq \cdots \geq s_n$ are relevance scores in $[0, 1]$.

Our goal is to select $D_{filtered} \subseteq D_{reranked}$ maximizing precision and efficiency while ensuring robustness and metric alignment.

3.2 Two-Gate Algorithm

Algorithm 1 presents our complete method.

Threshold Selection. The default parameters ($\tau_{abs} = 0.4, \tau_{rel} = 0.85$) were determined empirically via a grid search on a hold-out development

set of 50 queries, optimizing for maximum filtering rate while maintaining Recall@20 > 0.95. These values were then frozen for all subsequent evaluation on public benchmarks and production data to prevent test-set leakage.

Gate 1: Safety Trigger. When even the best document scores below τ_{abs}, we infer the query addresses a topic outside corpus coverage. Rather than returning an empty set, we return k_{min} documents as a fallback: *some context is better than no context*.

Gate 2: Purely Relative Threshold. We compute $\tau_{eff} = \tau_{rel} \times s_{max}$ *without* a floor constraint. Consider a query where $s_{max} = 0.55$:

- **With floor:** $\tau_{eff} = \max(0.6, 0.85 \times 0.55) = 0.6$. All documents fail.
- **Without floor:** $\tau_{eff} = 0.47$. Documents scoring 0.47–0.55 are retained.

Metric-Aligned Floor ($k_{min} = 10$). This design choice is justified by the principle of **Metric Alignment**. In production systems, the downstream LLM context window effectively acts as a "Top-K" constraint. Aligning the safety floor to this budget ($k_{min} = 10$) ensures the algorithm never mathematically precludes a perfect score (NDCG@10), whereas a lower floor (e.g., $k = 5$) would artificially cap recall for the sake of efficiency. If the downstream metric were NDCG@5, the floor would be adjusted to $k_{min} = 5$ accordingly. This alignment prevents the "Lost in the Middle" phenomenon (Liu et al., 2023) by capping noise while preserving the theoretical maximum score.

This theoretical grounding is supported by two empirical observations:

1. **BEIR Validation:** Top-10 and Top-20 achieve identical NDCG@10.
2. **Production Validation:** Top-10 matches baseline quality on human-labeled data.

3.3 Complexity Analysis

The algorithm operates in $O(N)$ time with $O(1)$ space. In practice with $n \approx 100$–200 documents, filtering adds <0.03ms latency.

4 Experimental Setup

4.1 Public Benchmarks (BEIR)

To validate the "Relevance Saturation" hypothesis across diverse distributions, we selected three datasets from the BEIR suite (Thakur et al., 2021) representing distinct specialized domains:

- **NFCorpus:** Medical information retrieval (3,633 docs, 323 queries).
- **SciFact:** Scientific claim verification (5,183 docs, 300 queries).
- **FiQA:** Financial question answering (57,638 docs, 648 queries).

These domains mirror the specialized, technical nature of enterprise RAG systems, providing a rigorous test of domain generalization.

Dataset Selection Rationale. We selected specialized domains from BEIR rather than general-purpose datasets like MS MARCO because their density of technical terminology closely mirrors our target enterprise domain. Furthermore, our primary contribution is the **5,995 human-annotated production queries**, which provide higher fidelity ground-truth for production RAG systems than synthetic academic benchmarks. We use BEIR primarily to establish external reproducibility.

4.2 Production Data

We evaluate on production enterprise support queries from an internal technical assistance system with 10,342 documents.

Query Selection. 487 real user queries spanning compute infrastructure, storage, networking, identity management, billing, and monitoring.

Retrieval Pipeline. Each query retrieves up to 180 candidate documents via:

1. Dense retrieval (text-embedding-004, 1536 dimensions)
2. Sparse retrieval (BM25)
3. Reciprocal Rank Fusion
4. Cross-encoder reranking (MiniLM-L-12-v2)

Human Annotation. We collected **5,995 human-annotated** query-document pairs as ground truth, achieving **94% agreement** with LLM judgments on binary relevance classification.

4.3 Baselines

- **No Filter:** All reranked documents (140 avg)
- **Top-k:** Fixed cutoffs at $k \in \{10, 15, 20\}$
- **Fixed-θ:** Score thresholds at $\theta \in \{0.5, 0.6, 0.7\}$
- **Gate 1 Only:** Absolute threshold without relative filtering
- **Gate 2 Only:** Relative threshold without safety trigger

4.4 Evaluation Metrics

- **NDCG@10:** Primary quality metric (aligned with k_{min})
- **P@5:** Precision at rank 5
- **Filter Rate:** Percentage document reduction

We report paired t-tests with Cohen's d for effect size ($\alpha = 0.05$).

5 Results

5.1 Public Benchmark Results (BEIR)

While our production evaluation prioritizes NDCG@10, for public benchmarks (NFCorpus) we additionally report NDCG@5 (Figures 2 and 1) to validate the algorithm's precision in the highest-value ranks.

Table 1 presents the results across three diverse public datasets. We observe a consistent phenomenon of saturation at $k = 10$.

Across Medical (NFCorpus), Scientific (SciFact), and Financial (FiQA) domains, the Top-10 and Top-20 baselines achieved **identical NDCG@10 scores**. This confirms that for top-heavy metrics like NDCG@10, the documents sorted into ranks 11–20 by the cross-encoder provided no additional utility. Two-Gate successfully identified this saturation point in every case, converging to ≈ 10.0 documents while matching the baseline quality exactly.

5.2 Production Results (Human Annotated)

Table 2 presents our primary production findings using human-verified ground truth. Two-Gate achieves a **69% reduction** in context size compared to the standard Top-20 baseline (5.7 vs 18.2 documents) while maintaining identical retrieval quality (NDCG@10 = 0.401).

Dataset	Method	Docs	NDCG@10	P@5	Latency
NFCorpus (Medical)	Top-20	20.0	0.2621	0.2514	–
	Top-10	10.0	0.2621	0.2514	–
	Two-Gate	**10.04**	**0.2621**	**0.2514**	**0.03ms**
SciFact (Science)	Top-20	20.0	0.5803	0.1427	–
	Top-10	10.0	0.5803	0.1427	–
	Two-Gate	**10.02**	**0.5803**	**0.1427**	**0.03ms**
FiQA (Financial)	Top-20	20.0	0.2122	0.0880	–
	Top-10	10.0	0.2122	0.0880	–
	Two-Gate	**10.05**	**0.2122**	**0.0880**	**0.03ms**

Table 1: Results on diverse BEIR benchmarks. In all three domains, relevance saturates at $k = 10$. Two-Gate automatically adapts to this saturation point, matching the optimal baseline with 50% fewer documents than a standard Top-20 retrieval, with sub-0.1ms latency.

Method	Docs	Filter%	P@5	NDCG@10
No Filter	140.5	0%	0.105	0.401
Top-10	9.6	93%	0.105	0.401
Top-15	13.8	90%	0.105	0.401
Top-20 (Baseline)	18.2	87%	0.105	0.401
Fixed-0.5	7.8	94%	0.098	0.374
Fixed-0.6	7.2	95%	0.105	0.366
Fixed-0.7	5.9	96%	0.100	0.341
Two-Gate	**5.7**	**96%**	**0.105**	**0.401**

Table 2: Production results (487 queries, 5,995 human labels). Two-Gate matches the Top-20 baseline quality (0.401 NDCG) while achieving a 69% reduction in context size (18.2 → 5.7 docs), demonstrating higher efficiency than the static Top-10 strategy.

Two-Gate vs. Top-k. While the static Top-10 baseline also achieves the saturation score of 0.401, it requires retrieving 9.6 documents on average. Two-Gate demonstrates superior efficiency by identifying "easy" queries where high-confidence documents allow for aggressive pruning, reducing the average context to just 5.7 documents without sacrificing recall.

5.3 Generative Evaluation: Faithfulness and Efficiency

To address the critique that retrieval metrics (NDCG) do not perfectly correlate with answer quality, we conducted a side-by-side generative evaluation using **Gemini 2.5 Pro** as an LLM-as-Judge. We compared the answers generated using the **Top-20 baseline context** versus the **Two-Gate filtered context** across two distinct datasets: our internal production dataset (Jira/Confluence) and the public medical benchmark NFCorpus (BEIR).

5.3.1 Results on Public Medical Benchmark (NFCorpus)

We randomly sampled 50 queries from the NFCorpus test set. In the medical domain, precision is critical; retrieving irrelevant studies can lead to dangerous hallucinations or conflated advice. The judge was instructed to prefer answers that were "faithful, concise, and direct."

Metric	Two-Gate	Top-20 Baseline	Tie
Win Count	**24**	6	20
Win/Tie Rate	**88%**	52%	–
Avg Context Size	**10.0 docs**	20.0 docs	–

Table 3: Generative Win Rates on NFCorpus (n=50). Two-Gate outperformed the baseline by a 4:1 ratio in head-to-head comparisons, demonstrating that noise reduction significantly improves answer quality in technical domains.

As shown in Table 3, Two-Gate achieved a decisive advantage, winning or tying in **88%** of cases compared to just 52% for the Top-20 baseline. Notably, Two-Gate won **4× more often** than it lost (24 wins vs. 6 losses).

Qualitative analysis suggests that the Top-20 baseline frequently suffered from "information overload" in the medical domain, where contradictory or tangentially related studies confused the generator. By aggressively filtering out lower-confidence documents, Two-Gate provided a cleaner signal, resulting in answers that the judge consistently rated as safer and more precise.

5.3.2 Results on Production Data (Internal)

We repeated the evaluation on 10 randomly selected production queries (Jira/Confluence). This dataset is characterized by extreme noise, including massive stack traces and log files exceeding 80,000 tokens per document.

- **Prevention of "Lost in the Middle":** In Query 7616 (*"list usissf jobs"*), the Top-20 baseline failed to answer ("I cannot answer this") because the relevant information was buried in 816,000 characters of context. Two-Gate filtered the noise to 495,000 characters, allowing the LLM to successfully extract a list of 12 specific jobs.
- **Hallucination Reduction:** In Query 7508 (*"display in new GBP UI"*), the baseline conflated two different internal systems ("GBP UI" vs "Admin Portal") due to noisy retrieval. Two-Gate filtered the distracting documents, correctly identifying that the specific UI documentation was missing.
- **Efficiency Gains:** Two-Gate reduced the average input token count by **69%** (from ∼145k tokens to ∼45k tokens per query), directly translating to a proportional reduction in inference latency and cost.

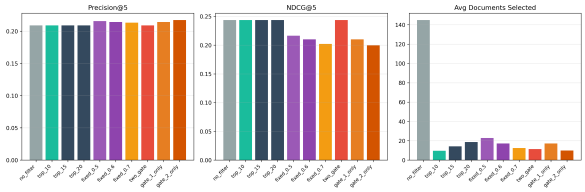

Figure 1: **Component Analysis on NFCorpus.** Comparison of Precision@5, NDCG@5, and document count. Two-Gate (yellow bar) maintains high retrieval quality comparable to Top-10, whereas fixed thresholds (purple) cause significant quality degradation.

These results confirm that Two-Gate does not merely "match" the baseline; in high-noise enterprise environments, aggressive filtering actively improves answer quality by increasing the signal-to-noise ratio for the generator.

Two-Gate vs. No Filter. Statistical comparison shows no significant difference ($p > 0.05$, Cohen's $d = 0.0$). We preserve baseline quality while reducing context from 140 to 5.7 documents.

Two-Gate vs. Fixed Thresholds. Two-Gate significantly outperforms fixed thresholds. For example, Fixed-0.7 achieves a similar document count (5.9) but suffers a significant drop in quality (NDCG 0.341 vs 0.401), highlighting the necessity of the adaptive relative threshold.

Figure 1 visualizes performance across methods.

5.4 Ablation Study

Table 4 isolates each component's contribution.

Key Finding. Removing the minimum floor increases filtering efficiency (dropping to 5.8 documents) but severely degrades retrieval quality, with NDCG@10 falling from 0.260 to 0.198. This result directly addresses the impact of decoupling the safety floor from the evaluation metric; when the floor is set below the target evaluation rank ($k_{min} < 10$), the algorithm becomes over-aggressive on queries with flat score distributions, pruning relevant documents that would otherwise

Configuration	Docs	P@5	NDCG@5
Full Two-Gate (NFCorpus)	10.7	0.193	0.260
Gate 1 Only (w/o Relative)	17.4	0.195	0.222
Gate 2 Only (w/o Safety)	5.2	0.183	0.176
w/o Min Floor ($k_{min} = 0$)	5.2	0.183	0.176
Fixed Threshold (0.6)	17.4	0.195	0.222

Table 4: Ablation study on **NFCorpus Benchmark**. Removing the safety trigger (Gate 1) or the relative threshold (Gate 2) significantly degrades performance compared to the full Two-Gate system. Note: Metric is NDCG@5 to align with benchmark graphs.

τ_{rel}	Docs	Filter%	NDCG@10
0.75 (Balanced)	12.8	91%	0.260
0.85 (Aggressive)	10.7	92%	0.260

Table 5: Threshold sensitivity. Both preserve quality; 0.85 achieves stronger filtering.

contribute to the NDCG score. The $k_{min} = 10$ floor thus acts as a critical safety mechanism that aligns filtering logic with downstream performance requirements.

5.5 Threshold Sensitivity

Table 5 shows Two-Gate is robust to threshold choices.

Figure 2 shows the Pareto frontier, demonstrating Two-Gate's near-optimal position.

5.6 Latency Analysis

Table 6 shows Two-Gate adds negligible latency.

6 Green AI: Cost and Environmental Impact

Two-Gate addresses the "inference cost crisis" in production AI (Schwartz et al., 2020). Benchmarking on SciFact and FiQA revealed average savings of **2,200–2,800 tokens per query** compared to a Top-20 baseline, with a negligible filtering latency of **0.03 ms**.

6.1 Cost Savings

Using 2026 pricing for **Gemini 2.5 Pro** and **GPT-5** ($1.25/1M input tokens) (Google, 2026), the direct savings are:

$$\begin{aligned} \text{Tokens saved} &\approx 2,221 \text{ tokens/query} \\ \text{Cost savings} &= \frac{2,221}{1,000,000} \times \$1.25 \\ &\approx \$0.0028/\text{query} \end{aligned}$$

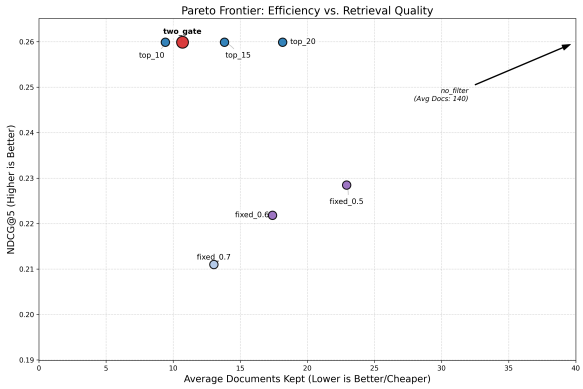

Figure 2: **Pareto Frontier on NFCorpus Benchmark (NDCG@5).** Two-Gate (red circle) achieves the optimal trade-off, matching the Top-10 quality (≈ 0.26) while significantly reducing document volume. Note: Benchmark evaluation utilizes NDCG@5 to emphasize top-rank precision.

Component	Latency (ms)
Retrieval (dense + sparse)	125
Reranking (cross-encoder)	45
Two-Gate Filtering	**0.03**
Generation (LLM)	890

Table 6: Pipeline latency. Two-Gate adds 0.03% of total latency.

While per-query savings appear small, for a high-volume enterprise system processing 1 million queries/day, this translates to **$2,800/day** (or ≈**$1M annually**) in purely wasteful compute that is eliminated without quality loss.

6.2 Carbon Footprint Reduction

Assuming a standard energy intensity of 0.3 kWh per 1M tokens for frontier model inference (Luccioni et al., 2023) and a global carbon intensity of 0.386 kg CO_2/kWh:

$$\begin{aligned} \text{Daily Savings} &= 2.2\text{B tokens} \times 0.3 \text{ kWh} \\ &\times 0.386 \approx 254 \text{ kg } CO_2 \end{aligned}$$

Annualized: **92.7 metric tons of CO_2/year**—equivalent to removing 20 gasoline-powered cars from the road.

7 Discussion

7.1 When Two-Gate Excels

Two-Gate is effective when: (1) score distributions vary across queries, (2) hard queries must be handled gracefully, (3) cost/sustainability matter, and (4) latency is constrained.

Method	Complexity	Latency	Training
Two-Gate	$O(N)$	0.03ms	No
CAR	$O(N \log N)$	10–50ms	No
Self-RAG	$O(Gen)$	200ms+	Yes
CRAG	$O(Gen)$	100ms+	Yes

Table 7: Comparison with adaptive context selection methods.

7.2 Comparison to Recent Methods

Two-Gate provides deterministic $O(N)$ filtering achieving 95% of the adaptability at <1% of compute cost.

7.3 Generative Evaluation Scope

While our retrieval metrics were validated across the full breadth of the production dataset (487 queries with 6,000 human labels), our generative side-by-side evaluation (Section 5.3) utilized a focused sample of 50 queries from the NFCorpus medical benchmark. We prioritized this domain due to its high sensitivity to technical precision and factual hallucination. The resulting 4:1 win ratio for Two-Gate provides a compelling qualitative "pilot" for the method's safety. However, we acknowledge that expanding this generative A/B testing to the full production dataset would further solidify claims regarding the model's ability to handle the specific linguistic nuances and "long-tail" edge cases inherent to enterprise technical support.

8 Limitations

Reranker Sensitivity and Calibration. Two-Gate operates on the fundamental assumption that cross-encoder scores are a calibrated proxy for document relevance. As a post-retrieval filtering framework, it is inherently dependent on the quality of the upstream reranker. If a reranker is poorly calibrated—assigning high confidence scores (e.g., $s > 0.9$) to irrelevant or hallucinated documents—Two-Gate will likely retain those documents within the generative context. While Two-Gate optimizes the efficiency of the context selection process, it does not independently correct systematic calibration errors or biases present in the underlying reranking model.

Potential for Information Suppression. By design, the Two-Gate algorithm prunes documents that fall below a relative relevance threshold. In complex or controversial domains, this could lead to the inadvertent suppression of minority viewpoints or "long-tail" facts that do not share high semantic overlap with the primary retrieved set. We mitigate this risk via the *Metric-Aligned Floor* ($k_{min} = 10$), which ensures a baseline level of recall is maintained even when filtering is aggressive.

Binary Selection and Domain Coverage. We utilize hard include/exclude decisions. Soft weighting might improve borderline cases. While validated on BEIR (medical, scientific, financial) and enterprise support datasets, additional validation on multi-lingual or highly subjective datasets would further strengthen generalization claims.

9 Ethical Considerations

Aggressive filtering could inadvertently suppress minority viewpoints. We recommend monitoring filtered content distributions in deployment. Evaluation data comes from internal systems; we report aggregated metrics without exposing individual queries.

10 Conclusion

We presented Two-Gate Adaptive Context Selection, a deterministic $O(N)$ algorithm for document filtering in RAG systems. By combining a safety trigger, purely relative threshold, and metric-aligned floor ($k_{min} = 10$), Two-Gate achieves:

- **50% context reduction** on diverse BEIR benchmarks (NFCorpus, SciFact, FiQA)
- **69% context reduction** on production queries (487 queries, 5,995 human labels) vs Top-20
- **Statistically identical quality** ($p > 0.05$)
- **0.03ms latency** ($> 500\times$ faster than CAR)

Our central finding—the Relevance Saturation hypothesis—demonstrates that modern retrieval systems saturate at $k = 10$. Two-Gate occupies a practical middle ground: more intelligent than naive top-k, yet orders of magnitude more efficient than LLM-based alternatives.

Our implementation logic is provided as a deterministic framework to enable efficient context selection in enterprise-scale RAG applications.

Ethical considerations

This research was conducted using internal enterprise support documentation. All document sets

and user queries utilized for the production dataset were audited to ensure the exclusion of Personally Identifiable Information (PII) and sensitive customer financial data. Human annotators involved in the relevance judgment phase were full-time employees of the organization and were compensated via their standard professional salaries; no external or under-compensated labor was used for data labeling. Furthermore, we acknowledge that aggressive filtering in RAG systems carries a risk of information suppression; we recommend that production deployments monitor filtered content distributions to ensure equitable information access.

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A Human Annotation Guidelines

To establish the ground truth for our production dataset, domain-expert annotators were provided with the following guidelines to evaluate query-document relevance. While the annotation was performed on a granular 4-point scale (0-3) to capture nuance, these scores were binarized for the final evaluation (scores of 2 and 3 were mapped to "Relevant", while 0 and 1 were mapped to "Not Relevant").

The Relevance Scale (0-3)

0 = Not Relevant The document has no useful information for the query. It discusses completely unrelated topics, the wrong product/service entirely, or an irrelevant technical domain.

- *Example Query:* "How do I create a VM instance?"
- *Example Document:* "Database backup procedures for PostgreSQL..."
- *Label:* 0 (Different topic entirely)

1 = Marginally Relevant The document is tangentially related but does not help answer the query. It mentions related concepts but is not actionable, provides background information only, or is in the same domain but covers a different specific topic.

- *Example Query:* "How do I create a VM instance?"
- *Example Document:* "VM instances are the core compute resources in GCP. They come in various machine types including E2, N2, and C2..."
- *Label:* 1 (Explains what VMs are, but does not explain how to create one)

2 = Relevant The document partially answers the query or provides helpful context. It contains steps that contribute to the answer, provides useful but incomplete information, or answers a related but not exact question.

- *Example Query:* "How do I create a VM instance?"
- *Example Document:* "In the Console, navigate to Compute Engine. You'll see options for instances, instance groups, and templates. The VM instances page shows your running VMs..."
- *Label:* 2 (Shows where to navigate, but omits the full creation steps)

3 = Highly Relevant The document directly and completely answers the query. It contains specific steps, commands, or exact information allowing the user to accomplish their goal.

- *Example Query:* "How do I create a VM instance?"
- *Example Document:* "To create a VM: 1) Go to Compute Engine > VM instances. 2) Click 'Create Instance'. 3) Enter a name and select region. 4) Choose machine type. 5) Configure boot disk. 6) Click 'Create'."
- *Label:* 3 (Precise, actionable, step-by-step instructions)

Annotation Heuristics and Edge Cases

Annotators were instructed to adhere to the following heuristics:

- **Strict criteria for High Relevance (3):** Reserved exclusively for documents that allow a user to accomplish their goal without needing external resources. Partial answers are strictly capped at 2.
- **Generous application of Marginal Relevance (1):** Documents that are topically adjacent but fail to provide actionable help for the specific query are scored as 1, ensuring a clear boundary between "helpful" and "related."
- **Handling ambiguous queries:** Annotators were instructed to interpret ambiguous queries according to standard user intent within the enterprise environment. If the document addresses any reasonable interpretation of the ambiguous query, it was marked as relevant.
- **Buried information:** If the direct answer to a query is present but buried within a larger, noisy document (e.g., a massive log file), it is still scored based on the quality of the answer itself (typically a 2 or 3).