Optimizing Information Retrieval: A Comparative Analysis of Query Expansion and Ranking Strategies

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Abstract

This paper presents a systematic investigation of advanced query optimization techniques for a Lucene-based information retrieval system, evaluated on the Text REtrieval Conference (TREC) dataset. Beginning with an Okapi BM25 baseline (Mean Average Precision (MAP) 0.2652, Precision at 20 (P@20) 0.4220), we explored multiple enhancement strategies including text preprocessing, field boosting, alternative similarity models (Divergence from Randomness (DFR)), and query expansion through Pseudo-Relevance Feedback (PRF). While aggressive symbol removal and heuristic field boosting proved detrimental, PRF parameter tuning yielded measurable improvements. Our primary contribution is a novel query diversification approach using Reciprocal Rank Fusion (RRF) [4] that combines five distinct query formulations—each independently expanded via PRF—with weighted fusion and negative term filtering. This multi-query strategy achieved our best performance (MAP 0.3676, P@20 0.5360), representing a 38.6% improvement over the baseline, demonstrating that query ambiguity can be effectively addressed through diverse query decomposition and robust score aggregation.

CCS Concepts

• **Information systems → Retrieval models and ranking**; **Query reformulation**; *Information retrieval.*

Keywords

information retrieval, query expansion, pseudo-relevance feedback, reciprocal rank fusion, BM25, query diversification

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1 Introduction

Information retrieval (IR) systems must bridge the semantic gap between user queries and document collections—a challenge that intensifies when queries are ambiguous or underspecified. This paper presents a systematic investigation of optimization strategies for a Lucene-based search engine [1] evaluated on the Text REtrieval Conference (TREC) ad-hoc retrieval task. We focus on two complementary metrics: Mean Average Precision (MAP), which measures ranking quality across all recall levels, and Precision at 20 (P@20), which assesses the relevance concentration in top-ranked results.

Starting from a robust Okapi BM25 [5] baseline (MAP 0.2652, P@20 0.4220), we conducted controlled experiments across multiple dimensions: index-time text preprocessing, query-time expansion via Pseudo-Relevance Feedback (PRF), heuristic field weighting, and alternative probabilistic models. While several intuitive approaches failed to improve performance, we identified a critical insight: query formulation ambiguity, typically viewed as a limitation, can be exploited as a strength when different query representations are systematically combined.

Our primary contribution is a query diversification framework based on Reciprocal Rank Fusion (RRF) [4] that generates five distinct query variants from each TREC topic, expands each independently via PRF, and aggregates results through weighted rank-based fusion. This approach achieved MAP 0.3676 and P@20 0.5360, representing 38.6% and 27.0% improvements over the baseline—substantial gains in the context of TREC evaluations. Our results demonstrate that embracing query ambiguity through systematic decomposition and evidence aggregation produces more robust rankings than attempting to construct a single "optimal" query formulation.

2 Methodology

2.1 System Architecture

Our search engine is implemented in Java using Apache Lucene 9.9.3 [1]. The indexing pipeline processes four TREC collections: LA Times (131,896 docs), FBIS (130,471 docs), Financial Times (210,158 docs), and Federal Register (55,630 docs). Document parsing extracts structured fields (`headline`, `title`, `author`, `section`) and body text, aggregating all content into a unified `content` field to maximize term coverage. Term positions and frequencies are stored to support phrase queries and relevance feedback.

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2.2 Baseline Configuration

We established a rigorous baseline using the Okapi BM25 probabilistic retrieval model [5] with standard parameters:

$$\mathrm{BM25}(d,q) = \sum_{t \in q} \mathrm{IDF}(t) \cdot \frac{f(t,d) \cdot (k_1 + 1)}{f(t,d) + k_1 \cdot (1 - b + b \cdot \frac{|d|}{\mathrm{avgdl}})} \tag{1}$$

where q is the query, d is a document, t is a query term, $\mathrm{IDF}(t)$ is the inverse document frequency of term t, $f(t,d)$ is the term frequency of t in document d, $|d|$ is the document length (in words), avgdl is the average document length in the collection, $k_1 = 1.2$ controls term frequency saturation (higher values give more weight to term frequency), and $b = 0.75$ governs document length normalization (higher values increase the penalty for longer documents). Text analysis employs Lucene's `EnglishAnalyzer`, implementing tokenization, case normalization, stopword removal (standard English stopword list), and Porter stemming. This baseline configuration achieved MAP 0.3453 and P@5 0.6640 on the TREC topics.

2.3 Experimental Design

Experiment 1: Pseudo-Relevance Feedback. We explored PRF parameter space: number of feedback documents $K \in \{2, 5\}$, number of expansion terms $M \in \{10, 20\}$, and whether expansion terms receive explicit boosts. Terms were selected by Term Frequency-Inverse Document Frequency (TF-IDF) scores computed across feedback documents.

Experiment 2: Heuristic Field Boosting. Based on the assumption that `title` and `headline` fields are more descriptive than body text, we applied index-time boosts: $\texttt{title}^{5.0}$ and $\texttt{headline}^{3.0}$.

Experiment 3: Query Diversification via RRF. Our primary contribution employs query decomposition and rank fusion. For each TREC topic, we generate five query variants: (1) Title only, (2) Description only, (3) Title+Description, (4) Description+Positive Narrative, (5) Full topic. Each variant undergoes independent PRF expansion ($K = 5$ documents, $M = 20$ terms) and retrieval. Results are fused using weighted Reciprocal Rank Fusion:

$$\mathrm{RRF}_{\mathrm{score}}(d) = \sum_{q=1}^{5} \frac{w_q}{k + \mathrm{rank}_q(d)} \tag{2}$$

where d is a document, q indexes the five query variants ($q = 1$ to 5), $\mathrm{rank}_q(d)$ is the position (rank) of document d in the ranked list produced by query variant q (rank 1 is best), $k = 60$ is a smoothing constant that reduces the influence of documents ranked very low (standard RRF parameter), and w_q are empirically tuned weights encoding the reliability of each query type: Title ($w_1 = 1.3$, most precise), Description ($w_2 = 0.9$, broader context), Title+Description ($w_3 = 1.1$, balanced), Description+Narrative ($w_4 = 0.8$, includes usage context), and Full topic ($w_5 = 1.0$, all fields). We augment this with negative term filtering (penalizing documents matching negated narrative terms such as "NOT relevant if...") and required term enforcement (ensuring essential query terms appear in retrieved documents).

Experiment 4: Alternative Similarity Model. Once we had our final system in place, to squeeze everything out of the search system built, we trialed a series of different similarity scoring models. This led to us finding that Divergence from Randomness (DFR) was the optimal model. DFR is a probabilistic model that uses a series of components, with the basic model, first normalization (after effect), and second normalization (normalization) to generate a similarity score. We found that using the geometric approximation, Laplace's law of succession, and H2 normalization yields the highest result in MAP given the rest of the searching methods are the same.

3 Results

The performance of each experimental run was evaluated using the `trec_eval` tool. Table 1 summarizes the results across the key metrics.

Table 1: Comparative Performance of Optimization Strategies

Run Configuration	MAP	P@20	nDCG@20
Baseline (BM25)	0.2652	0.4220	0.4659
Exp 1: PRF (Terms=20, Freq=50)	0.1719	0.4500	0.5085
Exp 2: PRF w/ Boosting	0.3388	0.4900	0.5650
Exp 3: RRF	0.2640	0.4420	0.4943
Exp 4a: Final System (BM25)	0.3604	0.5280	0.5945
Exp 4b: Final System (DFR)	**0.3676**	**0.5360**	**0.6003**

The RRF-based approach (Exp 5) achieved the best performance across all metrics, with a 4.4% improvement in MAP, 3.6% in P@5, and 4.6% in P@20 over the baseline. This represents a substantial gain in retrieval effectiveness.

4 Discussion

4.1 Failed Optimization Attempts

Experiment 1 (Symbol Removal) degraded MAP by 0.0012, indicating that Lucene's `EnglishAnalyzer` already handles noise effectively. Aggressive regex-based cleaning appears to remove punctuation that contextualizes term boundaries, particularly in newswire text containing acronyms and structured formatting.

Experiment 3 (Field Boosting) catastrophically failed, dropping MAP to 0.3192 (−7.6% relative). Analysis reveals that in this heterogeneous news collection, `title` and `headline` fields are often generic or editorial rather than content-descriptive. Over-weighting short fields amplified false matches where tangential terms appeared in titles.

4.2 PRF Trade-offs

PRF implementation (Exp 1: Terms=20, Freq=50) significantly degraded MAP by 35.2% (0.1719 vs 0.2652 baseline) despite improvements in P@20 (+0.0280) and nDCG@20 (+0.0426). Adding term boosting (Exp 2) reversed this decline dramatically: MAP increased to 0.3388 (+97.1% over Exp 1, +27.7% over baseline) while P@20 reached 0.4900 and nDCG@20 0.5650. This demonstrates that unboosted PRF expansion caused severe "query drift"—expansion terms without proper weighting diluted relevance signals—while boosting restored ranking quality by emphasizing the most discriminative feedback terms.

4.3 Success of Query Diversification

RRF (Exp 3 and 4b) achieved the strongest performance through three synergistic mechanisms:

Complementary Evidence Aggregation. Different query formulations retrieve partially overlapping but distinct relevant sets. Title-only queries maximize precision but sacrifice recall; description queries broaden coverage but introduce noise. By treating these as independent retrieval runs, RRF leverages the strengths of each while mitigating individual weaknesses.

Rank-Based Score Normalization. Raw BM25 scores from queries of different lengths are incomparable. A 3-term title query produces different score distributions than a 20-term full-topic query. RRF elegantly sidesteps this by operating on document ranks rather than scores [4], making fusion robust to query-specific calibration issues.

Independent PRF Expansion. Each query variant undergoes separate PRF, capturing variant-specific expansion vocabularies. Title PRF emphasizes precise synonyms; description PRF captures broader semantic fields. Fusion aggregates these diverse expansions into a richer representation than single-query PRF.

The weighted fusion scheme encodes domain knowledge: title queries ($w = 1.3$) proved most reliable, while narrative-based queries ($w = 0.8$) contributed useful but noisier signals. Negative term filtering and required term penalties further refined rankings by encoding explicit relevance constraints beyond what probabilistic models capture.

4.4 Critical Analysis

When approaching trying to increase scores, along with using existing methods such as PRF or RRF to improve precision, certain task-specific methods were tried. Many queries contain a '

5 Conclusion

This work demonstrates that effective query optimization often requires challenging conventional assumptions. While standard techniques (aggressive text cleaning, heuristic field boosting, alternative similarity models) failed to improve upon the BM25 baseline, and basic PRF tuning yielded only modest gains, our query diversification approach produced substantial improvements.

Our key insight: rather than seeking a single "optimal" query formulation, we embraced query ambiguity as a source of diverse evidence. TREC topics contain multiple signals (precise title, elaborative description, usage narrative), each of which retrieves partially unique relevant documents. Our RRF-based framework systematically exploits this by: (1) decomposing topics into five query variants, (2) independently expanding each via PRF to capture variant-specific vocabularies, and (3) fusing results through weighted rank aggregation.

The resulting system achieved MAP 0.3676 and P@20 0.5360-38.6% and 27.0% relative improvements over a strong BM25 baseline. These gains, substantial in the context of TREC evaluations, validate our hypothesis that complementary query formulations, when properly aggregated, yield more robust rankings than any single formulation.

Future directions include: (1) learning query-specific fusion weights rather than using fixed weights, (2) neural query reformulation to generate more diverse variants, and (3) integrating semantic embeddings to capture synonymy beyond term-based expansion. The core principle—transforming query ambiguity from limitation to advantage—offers a generalizable strategy for information retrieval systems facing underspecified or ambiguous queries.

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