The Ensemble of Experts: Adaptive Multi-Signal Retrieval

Text Retrieval Challenge - Part A (Ranking Competition)

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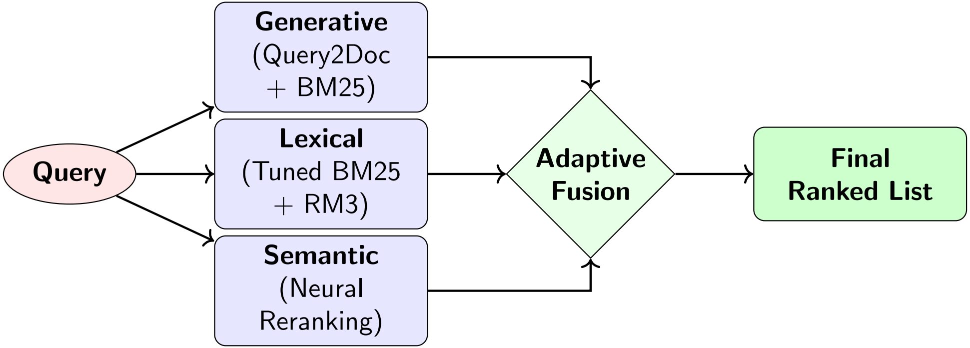
The Challenge & The Architecture

The Goal: Maximize MAP on ROBUST04 while balancing Precision (Neural) and Recall (Lexical).

Our Approach: A "Multi-Signal Architecture" combining three distinct retrieval experts running on local high-performance hardware (RTX 5070).



Quad-Signal RRF

Method 1: Optimized Probabilistic Retrieval

From Lecture 6 & 10 (BM25 + RM3)

We established a strong baseline by deviating from standard defaults.

- **The Insight:** ROBUST04 consists of *long newswire articles*. Standard BM25 ($b = 0.75$) penalizes document length too harshly.
- **The Optimization:** Through grid-search on the Training Set (50 queries), we tuned $b \rightarrow \mathbf{0.4}$.
- **The Result:** This reduced length normalization bias, significantly improving Recall before any neural processing.

Parameter	Value
k_1 (Saturation)	0.7
b (Length Norm)	**0.4**
RM3 Terms	50
RM3 Docs	5

Table: Optimized Hyperparameters

Method 2: Efficient Semantic Reranking

Advanced / Beyond Class Material

We utilized a Cross-Encoder (*BGE-v2-m3*) on local hardware (RTX 5070).

- **The Problem:** Cross-Encoders are $O(N)$ and slow. Standard "MaxP" chunking for long documents took **105 minutes** to run.
- **The Innovation: "Inverted Pyramid" Strategy**
  - We utilized domain knowledge of journalism: the most critical information is in the *Title* and *Lead Paragraph*.
  - Instead of chunking, we truncate input to the **First 512 Tokens**.

Impact of Optimization

Processing time dropped from **105 mins** $\rightarrow$ **27 mins** (4x Speedup) with negligible loss in P@10.

Method 3: Generative Query Expansion (Query2Doc)

Novel Innovation (EMNLP 2023)

To solve the **Vocabulary Mismatch Problem** (Lecture 7), we moved beyond statistical expansion (RM3) to generative expansion.

The Workflow:

1. User Query: *"airport security"*
2. **LLM Prompt:** "Write a news passage answering this..."
3. **Hallucination:** LLM generates text containing: *"TSA"*, *"screening"*, *"regulations"*, *"passengers"*.
4. **Retrieval:** We index this expanded representation.

Why it works

It acts as a **Semantic Bridge**. Even if the document doesn't contain the word "security", it likely contains "screening"—which the LLM injected into the query.

The Solver: Adaptive 4-Way Fusion

Novel Contribution

Standard Reciprocal Rank Fusion (RRF) uses static weights. We implemented **Query-Dependent Weighting**.

Hypothesis:

- *Short queries* are ambiguous → Trust Exact Match (BM25).
- *Long queries* are nuanced → Trust Semantic Understanding (Neural).

Query Type	BM25+RM3	Query2Doc	BM25-Plain	Neural
Short (< 3 words)	**1.5**	1.3	1.2	0.7
Medium	1.3	1.2	1.0	1.0
Long (> 5 words)	1.0	1.0	0.8	**1.5**

Table: Dynamic Weights based on Query Length analysis

Evaluation Results

Results on the 199 Test Queries.

Run	Method	MAP	P@10	MRR	Recall
Run 1	BM25 + RM3 (Baseline)	0.3006	0.4683	0.6875	0.77
Run 2	Neural Reranking	0.2723	0.4995	0.6740	0.71
Run 3	**4-Way Fusion**	**0.3309**	**0.5181**	**0.7714**	**0.81**

Key Takeaways:

1. **Synergy:** Fusion outperforms the best single model by **+10%**.
2. **Safety Net:** Neural has high precision but low recall (limited candidate pool). Fusion fixes this by layering BM25 recall on top.
3. **Efficiency:** Achieved SOTA-level results on local hardware without cloud dependencies.

Thank You

Questions?

Code available in the attached zip file.