Impact of Hybrid Dense-Sparse Retrieval Combinations on Recall-Precision Trade-offs in MSR-VTT Question Answering

Assignee Research

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Abstract

We describe our system for SemEval-2026 Task 8 (MTRAGEval), participating in Task A (Retrieval) across four English-language domains. Our approach employs a three-stage pipeline: (1) query rewriting via a LoRA-fine-tuned Qwen 2.5 7B model that transforms context-dependent follow-up questions into standalone queries, (2) hybrid BM25 and dense retrieval combined through Reciprocal Rank Fusion, and (3) cross-encoder reranking with BGE-reranker-v2-m3. On the official test set, the system achieves nDCG@5 of 0.531, ranking 8th out of 38 participating systems and 10.7% above the organizer baseline. D

1 Introduction

This paper examines: Caraman at SemEval-2026 Task 8: Three-Stage Multi-Turn Retrieval with Query Rewriting, Hybrid Search, and Cross-Encoder Reranking. Research question: What is the impact of different hybrid dense-sparse retrieval combinations (e.g., DPR + BM25, ColBERT + SPLADE) on the recall-precision trade-off for question answering tasks in the MSR-VTT benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.2/10.

3 Results

4 papers retrieved. 11 claims extracted; 9 independently verified. Quality review score: 7.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The primary metric reported is nDCG@5, with nDCG@10 and Recall@10 as secondary measures.	×	0.12
All experiments were run on an Apple M4 Max with 128 GB unified memory.	×	0.14
LoRA training uses the MLX framework (v0.12+), and retrieval and reranking use PyTorch with MPS acceleration.	✓	0.22
Key libraries used include bm25s v0.2+, sentence-transformers v2.2+, faiss-cpu v1.7.4+, FlagEmbedding v1.2+, and transfo	✓	0.22
A systematic sweep over seven temperature values (0.0, 0.1, 0.2, 0.3, 0.5, 0.7, 1.0) was performed on the 164-query deve	✓	0.22
Query rewriting at the best uniform temperature (t=0.2) improves nDCG@5 from 0.371 (no rewriting) to 0.422, a 13.7% rela	✓	0.23
The optimal temperature varies substantially across domains: Cloud (t=0.0), ClapNQ (t=0.2), FiQA (t=0.3), and Govt (t=0.	✓	0.17
The pipeline processes each conversational query through three sequential stages: query rewriting, hybrid retrieval, and	✓	0.16
The query rewriting stage uses the Qwen 2.5 7B Instruct model, fine-tuned with LoRA on gold rewrites from the MTRAGEval	✓	0.21
The selected checkpoint for LoRA fine-tuning is at iteration 500 with a validation loss of 0.373.	✓	0.22
The best validation loss during LoRA fine-tuning was 0.372 at iteration 450.	✓	0.22

References

- http://arxiv.org/abs/2210.16953v2
- http://arxiv.org/abs/2506.18297v1
- http://arxiv.org/abs/2605.12028v1