CS572 Assignment 4 Report

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1 Introduction

In this assignment, we are looking to improve a Dense Retriever Model.

2 Hybrid Retrieval Approach

Our approach to Hybrid Retrieval is inspired by the work of Priyanka Mandikal and Raymond Mooney, particularly their paper titled "Sparse Meets Dense: A Hybrid Approach to Enhance Scientific Document Retrieval." We sought to integrate the strengths of both sparse and dense retrieval models to enhance the accuracy and relevance of scientific document retrieval.

In the context of our work, the dense retrieval model provides a nuanced and context-aware representation of documents and queries. This model captures intricate relationships and semantic nuances in the text, allowing for a more precise understanding of the information contained within scientific documents. On the other hand, the sparse retrieval model captures broader statistical patterns and features, contributing valuable insights into the overall content and structure of the documents.

Our Hybrid Retrieval approach, as represented by the equation 2.1 $\mathrm{S}_{\mathrm{hybrid}}(D, Q)$, combines these two models using a parameter λ. This parameter controls the balance between the dense and sparse components, allowing us to fine-tune the emphasis placed on each model during the retrieval process.

$$\mathrm{S}_{\mathrm{hybrid}}(D, Q) = \lambda \cdot \mathrm{Sim}\left(\mathrm{z}_{\mathrm{dense}}(D), \mathrm{z}_{\mathrm{dense}}(Q)\right) + (1 - \lambda) \cdot \mathrm{Sim}\left(\mathrm{z}_{\mathrm{sparse}}(D), \mathrm{z}_{\mathrm{sparse}}(Q)\right) \tag{1}$$

where λ is a parameter, $\mathrm{z}_{\mathrm{dense}}(D)$ and $\mathrm{z}_{\mathrm{dense}}(Q)$ are dense representations of document D and query Q respectively, and $\mathrm{z}_{\mathrm{sparse}}(D)$ and $\mathrm{z}_{\mathrm{sparse}}(Q)$ are sparse representations of document D and query Q respectively.

3 Experiments and Parameter Tuning

During our experiments, we initialized $\lambda = 1$ to see how much the value of λ converges away from 1. However, we found that our final trained λ converged to a slightly lower value, specifically $\lambda = 0.9926$.

In another experiment where we initialized $\lambda = 0.5$ to see the effect of an even balance in the start, we observed a decrease in performance, and a final trained $\lambda = 0.4947$. This decrease was attributed to a lack of emphasis on the dense retriever, highlighting the importance of balancing the contributions of both models in the hybrid approach.

Finally, we conducted a run with a fixed lambda value of $\lambda = 0.8$ based on insights from prior research. However, this performed worse. This performance loss could be attributed to the differences in Sparse Retrieval method as they employed vector-space retrieval using bag of words.

4 Results

Table 1: Summary of Experimental Results (Attention used on all)

Model	**Recall@5**	**Recall@20**
Base	0.776	0.914
Base, Hybrid, Init Lambda = 1	0.784	0.940
Base, Hybrid, Init Lambda = 0.5	0.776	0.914
Base, Hybrid, Fixed Lambda = 0.8	0.767	0.940