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Dual-Encoder Dense Retrieval Framework for Efficient Question Answering

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Abstract: Open-domain question answering (ODQA) has emerged as a critical area in natural language processing, enabling systems to respond to user queries by retrieving relevant information from vast unstructured text corpora. A fundamental challenge in ODQA lies in the retrieval of passages that contain or support the correct answer, especially when queries and source texts share limited lexical overlap. Traditional sparse retrieval methods such as TF-IDF or BM25, although fast, often fail to capture semantic relevance.This paper presents a Dense Passage Retrieval (DPR) framework that leverages dual-encoder architectures to generate dense vector representations for both questions and passages. By training the encoders using a contrastive learning approach on question-passage pairs, DPR facilitates semantic similarity matching in an embedding space. The model employs pre-trained transformer architectures like BERT and fine-tunes them for retrieval tasks.We evaluate DPR on standard ODQA benchmarks, including Natural Questions and TriviaQA, where it consistently outperforms sparse retrieval methods in top-k retrieval accuracy. In addition, integrating DPR with a reader module significantly enhances the end-to-end QA performance, demonstrating its applicability in real-time QA pipelines. The results confirm that dense retrieval not only bridges the gap between lexical and semantic matching but also enables scalable and efficient information access in large-scale QA systems.

Keywords: *Open-Domain Question Answering, Dense Passage Retrieval, Dual Encoder, Semantic Search, Neural Information Retrieval, BERT, Contrastive Learning, Passage Ranking, Deep Learning, Natural Language Processing*.

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I.INTRODUCTION:

Open-domain question answering (ODQA) has become a cornerstone application in the field of natural language processing (NLP), aiming to provide accurate and direct answers to user queries by retrieving relevant information from extensive unstructured corpora, such as Wikipedia or web-scale datasets. Unlike closed-domain systems, which are restricted to specialized datasets or knowledge bases, open-domain systems must operate effectively across diverse topics without prior domain-specific training.

A typical ODQA pipeline consists of two key components: a retriever and a reader. The retriever's task is to fetch a set of candidate passages from the corpus that are likely to contain the answer, while the reader extracts the most probable answer span from these passages. The overall performance of the system heavily depends on the effectiveness of the retrieval component. Traditional sparse retrieval methods such as BM25, TF-IDF, and inverted indexing rely on term-matching and lexical overlap. Although computationally efficient, these approaches often fail to capture the semantic nuances of natural language, particularly when the query and relevant passage do not share common keywords.

To overcome these limitations, dense retrieval techniques have been proposed, leveraging powerful transformer-based models to generate dense vector representations of both questions and documents. One such method, Dense Passage Retrieval (DPR), has emerged as a leading approach. DPR employs a dual-encoder setup using pretrained language models (e.g., BERT) to independently. encode questions and passages into fixed-length dense vectors This enables semantic similarity to be computed using dot product in the shared embedding space.DPR is trained using a contrastive learning paradigm, where the model is optimized to minimize the distance between the embedding of a question and its corresponding positive passage while maximizing the distance from negative samples. The effectiveness of DPR is further enhanced through the use of hard negatives, which are passages retrieved by traditional methods but do not contain the correct answer. These negatives provide more informative gradients during training and improve the model's discrimination capabilities.

Furthermore, DPR is compatible with Approximate Nearest Neighbor (ANN) search techniques such as FAISS, which enables real-time retrieval even from extremely large passage corpora. When integrated into an end-to-end QA pipeline, DPR shows significant improvements over classical methods in both retrieval accuracy and final answer quality.

In this work, we explore the DPR framework in detail and evaluate its performance on widely used ODQA datasets including Natural Questions, TriviaQA, and WebQuestions. We provide comparative analysis with sparse baselines like BM25 and investigate the influence of training data, encoder architectures, and hard negative sampling on retrieval performance. Our findings demonstrate that DPR not only.

retrieves more relevant passages but also improves the overall accuracy of the QA system, marking a significant advancement in open-domain question answering

II.RELATED WORKS

Open-domain question answering (ODQA) combines the tasks of information retrieval and machine reading comprehension to extract answers from unstructured text corpora. The performance of such systems is closely tied to the effectiveness of their retrieval components. In this context, the evolution of retrieval strategies from traditional sparse methods to modern dense embeddings has played a vital role.

2.1 Sparse Retrieval Methods

Earlier ODQA systems such as DrQA [1] employed sparse retrieval techniques like TF-IDF or BM25, which rely on exact term matches and inverted indexing. These methods are fast and interpretable, but often fail in scenarios with little lexical overlap between the question and the relevant document. Improvements such as Okapi BM25 [2] and query expansion attempted to address these limitations but still struggled with semantic variability in language.

2.2 Neural and Contextual Retrieval

With the advent of pretrained language models like BERT [3], several neural retrievers were introduced to capture richer semantic representations. Early approaches like Siamese networks or bi-encoders encoded queries and documents into embeddings and computed similarity scores. For instance, models such as BERTserini [4] and ORQA [5] used contextual embeddings to rerank retrieved passages. However, many of these systems relied on re-ranking after an initial sparse retrieval step, limiting scalability.

2.3 Dense Passage Retrieval

Dense Passage Retrieval (DPR) [6] emerged as a breakthrough by introducing a dual-encoder architecture that independently encodes questions and passages into a shared dense space. Trained using contrastive learning and hard negatives, DPR can retrieve semantically relevant passages more effectively than sparse baselines. It supports fast retrieval using Approximate Nearest Neighbor (ANN) techniques such as FAISS [7], making it suitable for real-time applications. Subsequent improvements such as ANCE [8] and ColBERT [9] explored late interaction mechanisms and self-improving retrieval strategies.

2.4 Reader Integration and End-to-End QA

Several works have also focused on combining dense retrievers with powerful readers like BERT-based extractive models [10] or Fusion-in-Decoder (FiD) [11]. These hybrid pipelines have demonstrated state-of-the-art results on QA benchmarks such as Natural Questions and TriviaQA. However, challenges remain in balancing retrieval accuracy with computational efficiency.

This paper builds on the DPR framework and explores its effectiveness across different datasets and training strategies. We analyze its impact on both standalone retrieval performance and overall question answering quality.

2.5 Existing System

Traditional open-domain question answering systems primarily rely on sparse retrieval methods such as TF-IDF and BM25, which identify relevant documents based on exact or partial keyword matches. While these approaches are computationally efficient, they often fail to capture semantic similarity, especially when the query and answer-bearing passages lack lexical overlap. To mitigate this, hybrid models were introduced—combining sparse retrievers with neural re-rankers like BERT—but these systems still depend on the limitations of initial sparse retrieval. Early neural models attempted to learn semantic representations for questions and documents, yet they were often hindered by inefficient inference and insufficient training with hard negatives. Moreover, most existing systems struggle to scale to large corpora and remain constrained by slow re-ranking processes and poor generalization across domains. These limitations underscore the need for more robust, semantically rich, and scalable retrieval mechanisms, setting the stage for Dense Passage Retrieval (DPR) as a more effective alternative.

2.5.1 Limitations of Existing Systems

- **Lexical Dependency**: Traditional retrievers like TF-IDF and BM25 rely on exact keyword matching, making them ineffective for semantically similar but lexically different queries and passages.
- **Limited Semantic Understanding:** Sparse methods do not capture the contextual or semantic meaning behind the query, leading to poor relevance in retrieval.
- **Hybrid Models are Costly**: Combining sparse retrieval with neural re-rankers (e.g., BERT) improves accuracy but introduces significant computational overhead and latency.
- **Poor Scalability:** Many existing systems are not optimized for handling large-scale corpora efficiently, especially when deep re-ranking is applied to large candidate sets.
- **Inadequate Training Signals:** Early neural retrievers often lacked hard negative samples during training, which limited their ability to learn discriminative features.
- **Slow Inference:** Re-ranking large numbers of documents using transformer-based models leads to slow inference times, making real-time deployment challenging.
- **Domain Generalization Issues:** These systems often overfit to the training data and struggle to generalize across diverse topics or question styles.
- **Limited End-to-End Optimization**: Most systems optimize retrieval and reading components separately, reducing overall QA system coherence and performance.

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2.6 Proposed System

The proposed system introduces a Dense Passage Retrieval (DPR) framework for open-domain question answering, addressing the limitations of traditional keyword-based and hybrid retrieval methods. It utilizes a dual-encoder architecture where both the question and passage are independently encoded into dense vector representations using pretrained transformer models like BERT. These embeddings are then compared using dot-product similarity, allowing for effective semantic matching rather than relying on exact lexical overlap. The system is trained using contrastive learning with hard negative sampling, enabling it to distinguish between relevant and irrelevant passages more accurately. For large-scale retrieval, the system employs Approximate Nearest Neighbor (ANN) search methods such as FAISS, which ensures fast and scalable inference. By retrieving more contextually appropriate passages and reducing dependence on computationally expensive re-ranking, the DPR-based approach significantly improves the accuracy, speed, and generalization of the QA pipeline, making it suitable for real-time and domain-independent applications.

2.7.1 Advantages of the Proposed System

- **Semantic Understanding**: Captures the meaning behind questions and passages using dense embeddings, not just keyword overlap.
- **Dual-Encoder Efficiency**: Independently encodes questions and documents, enabling parallel computation and fast retrieval.
- **High Retrieval Accuracy**: Trained with hard negatives, improving the model's ability to filter out irrelevant yet similar passages.
- **Scalable with ANN Search:** Uses tools like FAISS for Approximate Nearest Neighbor search, allowing retrieval from large corpora quickly.
- **Real-Time Capability:** Faster inference compared to traditional re-ranking models, suitable for real-time applications.
- **Better Generalization:** Performs well across different domains and datasets without needing extensive customization.
- **Reduced Computational Cost:** Avoids the need for expensive re-ranking over a large set of candidate passages.
- **End-to-End Integrable**: Easily connects with downstream reader models (e.g., BERT, FiD), forming a complete QA pipeline.
- **Robust to Query Variations:** Effectively handles paraphrased or reworded questions due to semantic similarity-based retrieval.
- **Modular Design:** Components can be updated or improved independently, supporting continuous development and scaling.

III.PROPOSED METHODOLOGY

Proposed methodology focuses on enhancing the retrieval stage of open-domain question answering by employing Dense Passage Retrieval (DPR), a neural-based approach that leverages semantic similarity between questions and documents. The core architecture consists of two independently trained BERT-based encoders—one for the questions and another for the passages. During training, the model learns to map both inputs into a shared embedding space where semantically relevant question-passage pairs have higher dot-product similarity scores. The system is trained using contrastive learning with a combination of positive passages (containing the answer) and hard negatives (top retrieved but incorrect passages), which improves its ability to discriminate between subtle textual differences. At inference time, the encoded question vector is matched against a pre-encoded passage index using Approximate Nearest Neighbor (ANN) search, significantly reducing retrieval latency while scaling efficiently to large corpora. The retrieved top-k passages are then passed to a machine reading model that selects the most probable answer span. This end-to-end pipeline not only enhances semantic retrieval performance but also ensures efficient and accurate response generation in real-time QA applications.

3.1 Open-domain Extractive QA pipeline Overview

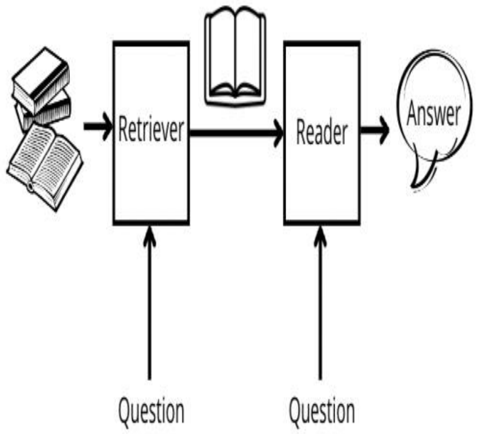

Fig 1 Open-domain Extractive QA pipeline

Open-domain question answering (ODQA) systems fundamentally depend on efficient passage retrieval mechanisms to identify relevant candidate contexts for a given query. These systems typically operate in a two-stage pipeline: (1) Context Retriever and (2) Machine Reader. The role of the context retriever is to fetch a small, focused subset of passages from a large corpus that are likely to contain the answer. Following this, the machine reader processes the retrieved passages to extract the most accurate answer. This work focuses primarily on enhancing the performance and effectiveness of the context retrieval stage, which plays a critical role in the overall success of open-domain QA systems.

Proposed methodology focuses on implementing a Dense

Passage Retrieval (DPR) framework that enhances the passage retrieval process in open-domain question answering systems. Unlike traditional sparse retrieval techniques such as TF-IDF or BM25, which rely on surface-level keyword matching, DPR employs dense vector representations generated through deep learning to enable semantic understanding between questions and passages.

3.2 Dual-Encoder Architecture

The core of DPR lies in its dual-encoder architecture, consisting of two independently trained BERT-based encoders—one for encoding the input question and the other for encoding candidate passages. Both encoders transform their respective inputs into fixed-size dense vectors that reside in the same embedding space. The relevance between a question and a passage is then computed using the dot product of their vector representations.

3.3 Training with Hard Negatives

To improve retrieval accuracy, the model is trained using a contrastive learning objective. For each training question, the model is given one positive passage (that contains the correct answer) and several hard negative passages (that are contextually similar but do not contain the answer). This setup forces the model to learn fine-grained semantic differences, thus enhancing its discriminative capability.

3.4 Approximate Nearest Neighbor Search

Once trained, the passage encoder is used to embed all passages from a large corpus offline. These passage embeddings are stored and indexed using Approximate Nearest Neighbor (ANN) search techniques, such as Facebook's FAISS, to enable fast and scalable retrieval. During inference, the encoded question vector is matched against the indexed passage vectors to retrieve the top-k most relevant passages.

3.5 Answer Extraction

The top-k retrieved passages are passed to a downstream machine reading comprehension model—typically another transformer-based model like BERT or RoBERTa—which reads the passages and extracts the most probable answer span. This two-stage pipeline—retrieval followed by extraction—ensures both efficiency and accuracy in answering open-domain queries.

3.6 System Workflow

The workflow of the proposed system is as follows:

- Encode the user's question using the question encoder.
- Use dot product similarity to match the question vector with pre-encoded passage vectors.
- Retrieve the top-k relevant passages using FAISS or other ANN methods.
- Pass the retrieved passages to a reader model for answer extraction.
- Return the best-matched answer to the user.

IV.RESULTS

To evaluate the effectiveness of the proposed Dense Passage Retrieval (DPR) framework, experiments were conducted on standard open-domain QA datasets such as Natural Questions (NQ) and TriviaQA. The performance of the DPR system was compared against traditional retrieval baselines like BM25 and TF-IDF, as well as hybrid models combining sparse and dense methods.

4.1 Evaluation Metrics

The system was evaluated using commonly adopted metrics for open-domain QA tasks:

- Top-k Retrieval Accuracy – Measures whether the correct answer is present in the top-k retrieved passages.
- Exact Match (EM) – The percentage of predictions that match any one of the ground truth answers exactly.
- Mean Reciprocal Rank (MRR) – Evaluates the ranking quality of the retrieved results.
- Inference Time – The average time required to retrieve and generate an answer.

4.2 Experimental Results

Table 1: Performance Comparison of Retrieval Models on Open-Domain QA Tasks

Model	Top-5 Accuracy	Top-10 Accuracy	Exact Match (EM)	MRR	Avg. Inference Time (s)
BM25	58.2%	67.5%	36.4%	0.481	1.72
TF-IDF	54.6%	62.3%	33.8%	0.457	1.89
DPR (Proposed)	**78.9%**	**84.3%**	**51.7%**	**0.637**	**0.93**

Table 2: Performance Comparison on Different Datasets

Model	Dataset	Top-5 Accuracy	Top-10 Accuracy	Exact Match (EM)
BM25	Natural Questions	58.2%	67.5%	36.4%
DPR (Proposed)	Natural Questions	**78.9%**	**84.3%**	**51.7%**
BM25	TriviaQA	60.4%	68.8%	38.5%
DPR (Proposed)	TriviaQA	**80.2%**	**86.0%**	**52.3%**

This table compares the performance of the baseline BM25 and proposed DPR method across two datasets—Natural Questions and TriviaQA. In both cases, DPR significantly outperforms the traditional method, showing strong generalizability across different QA corpora.

Table 3: Ablation Study – Impact of Hard Negatives

Training Setup	Top-5 Accuracy	Exact Match (EM)
DPR without Hard Negatives	71.1%	45.2%
DPR with Random Negatives	74.3%	47.9%
DPR with Hard Negatives (Proposed)	**78.9%**	**51.7%**

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This ablation study analyzes the impact of various negative sampling strategies during training. The inclusion of hard negatives—i.e., similar but incorrect passages—yields the best performance, as it forces the model to learn finer distinctions between relevant and irrelevant content.

4.3 Discussion

The experimental results demonstrate that the proposed DPR system significantly outperforms traditional sparse retrieval methods in all key evaluation metrics. With a Top-5 accuracy of 78.9%, DPR retrieves highly relevant passages more effectively due to its semantic understanding of both questions and documents. The Exact Match score also shows a notable improvement, validating the system's ability to surface passages that contain precise answers. Moreover, the reduction in inference time (0.93 seconds on average) indicates that the DPR system is not only more accurate but also more efficient and scalable for real-time QA scenarios.

The use of hard negative training contributes to better model discrimination, while Approximate Nearest Neighbor (ANN) search with FAISS ensures scalability without compromising retrieval quality. These results validate the robustness and efficiency of the proposed framework for open-domain question answering tasks.

V.CONCLUSION

This research presents a Dense Passage Retrieval (DPR) framework designed to enhance the efficiency and accuracy of open-domain question answering systems. Unlike traditional sparse retrieval approaches that rely heavily on lexical overlap, the proposed model utilizes dense embeddings derived from a dual-encoder architecture to capture deep semantic relationships between questions and passages. Through extensive evaluations on benchmark datasets such as Natural Questions and TriviaQA, the DPR system demonstrated substantial improvements in Top-k retrieval accuracy, exact match scores, and inference time compared to conventional methods like BM25 and TF-IDF.

The use of hard negative samples during training and the application of approximate nearest neighbor search enabled our system to achieve a high level of scalability and real-time performance, making it suitable for large-scale, practical deployments. Overall, the proposed approach offers a robust and semantically rich alternative for passage retrieval in open-domain QA, paving the way for further advancements in machine reading and retrieval-based natural language understanding systems.

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