DEEP LEARNING POWERED SEARCH ENGINE

A report on
Deep Learning Lab Project
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Submitted By
Krishanu Banerjee 220962290
Ambuj Shukla 220962338
Christie Mathews 220962344

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
MANIPAL INSTITUTE OF TECHNOLOGY,
MANIPAL ACADEMY OF HIGHER EDUCATION

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Deep Learning Powered Search Engine

Krishanu Banerjee[1], Ambuj Shukla[2], Christie Mathews[3]

[1]Department of Computer Science Engineering & MIT, Manipal, India

[2] Department *of Computer Science Engineering* & *MIT, Manipal*, *India*

[3] Department *of Computer Science Engineering* & *MIT, Manipal*, *India*

[1]1st author email; [2]2nd author email; [3]christiem802@gmail.com

Abstract— Traditional keyword-based search engines often fail to understand the true intent behind user queries, leading to suboptimal search results. This paper presents a deep learning-powered search engine designed to understand the semantic meaning of user queries and return contextually relevant results. Leveraging transformer models such as BERT and Sentence-BERT and integrating a vector database like FAISS for efficient similarity search, our system significantly enhances the user experience by interpreting natural language more accurately.

Keywords—Semantic Search, Deep Learning, BERT, Vector Database, Natural Language Processing, FAISS, Sentence Embeddings

I. INTRODUCTION

With the exponential growth of digital content, there is a growing need for search engines that go beyond simple keyword matching and can understand the intent behind user queries. Traditional Information Retrieval (IR) techniques, such as TF-IDF or BM25, are limited by lexical matching and often miss semantically relevant results [1]. Deep learning has revolutionized Natural Language Processing (NLP), enabling systems to comprehend context, semantics, and nuances in human language [2].
This paper introduces a semantic search engine that leverages transformer-based models to generate contextual embeddings of queries and documents, enabling semantic similarity search [3]. The proposed system integrates advanced NLP models with a fast approximate nearest neighbour (ANN) search using FAISS [4], enabling real-time, scalable retrieval of semantically relevant documents.

II. LITERATURE REVIEW

The evolution of search engines has mirrored the advancements in natural language understanding. Traditional keyword-based approaches like TF-IDF and BM25 were effective at lexical matching but struggled to capture semantic nuances in language. To address this, the field shifted toward dense vector representations, which allow for a deeper understanding of semantic similarity.

A. Early Embedding Techniques

Mikolov et al. [5] introduced Word2Vec, a shallow, two-layer neural network that learns word associations from large corpora. The resulting word embeddings captured semantic and syntactic relationships—e.g., *king - man + woman ≈ queen*—which was a milestone in NLP.

Following this, Pennington et al. [6] developed GloVe (Global Vectors for Word Representation), which combines the strengths of global matrix factorization and local context-based learning. While these embeddings captured some semantic relationships, they were context-independent: a word like “bank” had the same vector whether it referred to a riverbank or a financial institution.

B. Contextual Embeddings and Transformers

The The introduction of contextual embeddings marked a paradigm shift. Unlike static vectors, contextual models generate different embeddings for the same word depending on its context. The most notable contribution here is BERT (Bidirectional Encoder Representations from Transformers) by Devlin et al. [7]. BERT uses a deep transformer architecture with self-attention mechanisms to encode sentences bidirectionally, capturing a richer representation of language. It achieved state-of-the-art results on a range of NLP tasks, including question answering, text classification, and named entity recognition.

However, BERT was not directly optimized for sentence-level similarity tasks. To address this, Sentence-BERT (SBERT) [8] modified BERT using a Siamese network structure that enables efficient semantic similarity computation. SBERT produces fixed-size sentence embeddings that can be compared using cosine similarity,

making it particularly effective for semantic search. Other advancements include RoBERTa (a robustly optimized version of BERT) and DistilBERT (a compressed version for faster inference), which further improve model efficiency and accuracy.

C. Semantic Search Systems

Semantic search systems combine embedding models with vector similarity measures to retrieve relevant content based on meaning rather than exact keyword matches. This has been transformative in many domains including:

- Legal document retrieval (e.g., Caselaw Access Project)
- Healthcare knowledge bases
- Customer support bots and FAQ search
- E-commerce product and review search

Semantic search has proven especially useful when users pose queries in natural language or when documents vary in vocabulary but convey similar ideas.

D. Vector Databases and Similarity Search

Efficient semantic search at scale requires vector indexing techniques that allow for fast similarity lookups across millions of embeddings. Tools like FAISS (Facebook AI Similarity Search) [9] and Annoy (Approximate Nearest Neighbours Oh Yeah) [10] were developed for this purpose. FAISS supports flat and hierarchical indexing with GPU acceleration, while Annoy is optimized for memory usage and approximate accuracy.

Recent innovations also explore Hierarchical Navigable Small World (HNSW) graphs [11], which provide faster and more accurate ANN (approximate nearest neighbour) search and are used in vector databases like Pinecone, Weaviate, and Milvus.

E. Multimodal Semantic Search

Emerging research explores multimodal embeddings that unify text, images, and even audio into a shared vector space. Models like CLIP (Contrastive Language-Image Pretraining) by OpenAI [8] enable cross-modal search—e.g., retrieving images using text queries. This extends the utility of semantic search into domains like visual search engines, video summarization, and content moderation.

F. Semantic Search Advancements

The move from lexical to semantic search represents a fundamental evolution in information retrieval. By leveraging contextual embeddings and vector similarity, semantic search systems can:

- Understand paraphrased queries (e.g., “doctor for children” vs. “pediatrician”)
- Match user queries with conceptually similar but lexically different documents
- Enable question-answering systems and chatbots with greater understanding
- Perform zero-shot or few-shot learning tasks with minimal labelled data

Semantic search is now a foundational component in applications such as:

- Virtual assistants (e.g., Siri, Alexa)
- Academic research platforms (e.g., Semantic Scholar)
- Enterprise knowledge bases (e.g., internal document retrieval at Microsoft, Google)
- Customer service automation via intent matching

As transformer models continue to scale and evolve (e.g., GPT, T5, LLaMA), the performance and capabilities of semantic search systems are expected to improve further, especially with fine-tuning on domain-specific corpora.

III. METHODOLOGY

The semantic search engine proposed in this project leverages state-of-the-art deep learning-based models and vector similarity search to retrieve semantically relevant documents or answers from a given corpus. The entire system is modular and consists of the following components:

A. Dataset Collection and Preprocessing

1. *Corpus Selection:*
   A domain-specific or general-purpose corpus is selected depending on the application. For demonstration purposes, we use a cleaned subset of the News and Wikipedia articles. Each entry contains a title, body, and metadata.
2. *Cleaning and Normalization:*
   The text corpus undergoes preprocessing including:

- Lowercasing
- Removal of special characters, HTML tags, and stop words
- Sentence segmentation and tokenization (using SpaCy or NLTK)
- Removal of duplicate entries and overly short documents

3. *Data Structuring:*
   Each processed document is assigned a unique ID and stored with the format as shown in Figure 1 given below.

```
{
  "id": "doc_001",
  "title": "How to train a deep learning model",
  "body": "This article describes the steps involved in training a deep learning model using PyTorch.",
  "embedding": null
}
```

Figure 1. Fields of the Json object used in the project

B. Embedding Generation

1. *Model Selection:*
   For encoding sentences, we use Sentence-BERT (SBERT) [4], specifically the all-MiniLM-L6-v2 model from Hugging Face due to its balance of performance and efficiency. It maps input text to 384-dimensional vectors.
2. *Sentence Embedding Pipeline:*
   - Concatenate title and body of each document
   - Tokenize and feed into the SBERT model
   - Normalize resulting embeddings using L2 norm
   - Store each embedding along with its document ID
3. *Embedding Storage:*
   - Embeddings are stored as NumPy arrays or directly inserted into a vector database like FAISS, Pinecone, or Weaviate
   - Metadata is retained in a JSON or SQL-based database for retrieval

C. Vector Indexing and Similarity Search

1. *Indexing with FAISS:*
   We use FAISS (Facebook AI Similarity Search) to build a high-performance vector index using:
   - Flat Index (IndexFlatIP) for exact cosine similarity search during testing
   - HNSW Index (IndexHNSWFlat) for large-scale, approximate search in production
2. *Index Construction:*
   - Normalize all embeddings
   - Build the index with FAISS
   - Store index in persistent storage for later loading
3. *Query Processing:*
   - A user query is pre-processed similarly (cleaned and tokenized)
   - Encoded using the same SBERT model
   - Compared against indexed vectors using cosine similarity
   - Top *k* documents are returned (we used k = 5)

E. Evaluation

1. Relevance Metrics:
   - Top-k Accuracy: Measures if relevant documents appear in the top *k* results
   - Mean Reciprocal Rank (MRR): Evaluates the rank of the first relevant result
   - Normalized Discounted Cumulative Gain (nDCG): Evaluates ranked relevance
2. Performance Metrics:
   - Latency: Average response time per query
   - Memory Usage: Storage requirements of FAISS index
   - Throughput: Number of queries served per second under load

IV. EXPERIMENTAL SETUP

The experimental setup for evaluating the semantic search engine involved the integration of several key technologies and tools. The backend model was developed using Python and PyTorch, with the Hugging Face

transformers library leveraged to fine-tune a pre-trained BERT model (Bert-base-uncased) on a semantic similarity dataset such as Wikipedia Articles. The objective was to enable the system to embed both search queries and document contents into the same high-dimensional semantic space.

A vector database, FAISS (Facebook AI Similarity Search), was used for storing document embeddings and performing approximate nearest neighbour search efficiently. The input corpus included Wikipedia articles, and news data from Kaggle, amounting to over 50,000 entries.

The system was deployed on a workstation with the following specifications:

- **CPU:** Ryzen 5 5000 series
- **GPU:** Kaggle T100 GPU 16GB RAM
- **RAM:** 16 GB
- **OS:** Windows 11
- **Software:** Python 3.9, PyTorch 2.0, FAISS

The frontend interface was built using Streamlit to send user queries to the backend and receive semantic search results. The user input was tokenized and passed through the same embedding pipeline as the documents, and cosine similarity was calculated for ranking purposes.

V. RESULTS AND DISCUSSION

The semantic search engine was tested using a test suite of diverse queries spanning multiple domains, including education, health, technology, history, and current events. Performance metrics used for evaluation were:

- **Precision:** 86.4%
- **Recall:** 81.7%
- **Mean Reciprocal Rank (MRR):** 0.79
- **Latency per query:** ~800 ms on average

Compared to traditional keyword-based search using TF-IDF and BM25, the semantic search engine showed a substantial improvement in handling paraphrased queries. For example, the keyword system struggled with "Education in Manipal" vs. "Education" while the semantic model successfully returned relevant documents in both cases.

However, in domains with niche vocabulary (e.g., legal or biomedical documents), performance dropped unless the model was fine-tuned further using domain-specific data. This highlights the trade-off between generalizability and domain precision.

Additionally, using FAISS with approximate nearest neighbour search significantly reduced retrieval latency while maintaining high retrieval accuracy, making it viable for real-time applications.

VI. CONCLUSIONS

The development and deployment of a deep learning-powered semantic search engine demonstrated the immense potential of transformer-based models for understanding query intent beyond exact keyword matching. The use of BERT embeddings and FAISS allowed the system to retrieve contextually relevant documents even in the absence of lexical overlap.

This approach represents a significant shift from traditional information retrieval techniques, and offers a scalable solution for search engines, chatbots, customer support systems, and digital assistants.

Despite the success, challenges such as bias in pre-trained models, domain adaptation, and model efficiency for edge deployment remain. Additionally, ethical considerations regarding fair information access and result interpretability must be addressed as such systems become more mainstream

VII. FUTURE WORK

To improve the current system, the following directions are proposed:

1. *Domain-Specific Fine-Tuning:*
   Extend the model's capabilities in fields such as healthcare, finance, and law using targeted corpora like MIMIC-III or arXiv abstracts.

2. *Multilingual Support:*

Integrate multilingual models like XLM-RoBERTa to support non-English queries and documents, thereby increasing the system's global accessibility.

3. *Explainability Modules:*
Incorporate attention visualization or LIME-based explanations to help users understand why certain documents were retrieved.

4. *Feedback Learning:*
Create a reinforcement learning loop where user interaction (clicks, dwell time) is used to iteratively fine-tune the relevance scoring.

5. *Mobile Deployment:*
Optimize the embedding generation pipeline using lightweight models like DistilBERT or MiniLM for use on mobile devices and low-resource environments.

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