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# Designing vendor-neutral semantic search pipelines using open-source embedding models and FAISS

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## Abstract

The rapid growth of semantic search has transformed information retrieval by enabling systems to understand meaning in context instead of simply using keywords as has traditionally been performed. The best available semantic search solutions are often connected to proprietary embedding models and cloud based vector databases, introducing issues around costs, reproducibility, regulations, and vendor lock-in. We detail the architecture and evaluation of a vendor-neutral semantic retrieval pipeline, with all components open-source, fully on-premise, and free of proprietary APIs or managed services. and established open-source embedding models, and the FAISS similarity search library. This proposed architecture emphasizes modularity, scalability and interoperability in a way that maximizes users' ability to validate and compare different models, thus avoiding closed ecosystems. Using benchmark datasets, we evaluated a series of general open-source embeddings and FAISS index types on retrieval performance and latency, and evaluated retrieval efficiency, finding them satisfactory in retrieval accuracy. Our results suggest that open-source pipelines can achieve comparable retrieval performance to proprietary solutions while offering use-case transparency, flexibility, and low ongoing costs. This research identifies potential advantages with formulating open-source pipelines creating robust semantic search systems that emphasize aspects of reproducibility and sustainable operations.

**Keywords:** Vendor-Neutral Semantic Search; Open-Source Embeddings; FAISS; Approximate Nearest Neighbor (ANN); Hybrid Retrieval; Reproducibility

## 1. Introduction

The rapid growth of unstructured text data, such as documents and reports, poses significant challenges for effective information retrieval. Estimates indicate that there is more than 80% unstructured data in organizations; unstructured data generally refers to documents, emails and multimedia [1]. While the use of keyword matching to search unstructured content was sufficient in the past, the reliance on keyword searching is now propelling the development of semantic search using embeddings and vector similarity metrics, which considers the closeness in space between embeddings rather than the permutations of characters in strings. Meaning is better approximated as contextual meaning rather than essentially lexical overlap of terms and phrases [2]. As a result, semantic search systems are being adopted globally and is leading to the enterprise search market, which is seeing explosive growth, particularly projected to over USD 8.9 Billion by 2030, as it is next in line for growth in the economy with over 12% CAGR [3]. Along with these changing dynamics of search, however, many organizations remain reliant on proprietary solutions which are always tied exclusively to a cloud provider or commercial vector database, leading to dependence, costs, transparency, reproducibility, and long-term vendor lock-in [4]. In light of these issues, this paper proposes a vendor-neutral semantic search pipeline based on open-source embedded models and FAISS framework [5], to ensure performant, cost-effective, scalable, and flexible,

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## 1.1. Background

The field of information retrieval has evolved tremendously over the past 50 years. In the 1960s and 1970s, Boolean retrieval systems entered the scene. With this system, exact match keyword searching was the only method available, there was limited opportunity for pointing operations [5]. To follow were language models (LM) and statistical approaches like TF–IDF (1972) [6] and then BM25 (1994) [7] were the systems became a little bit more sophisticated, as all systems started to weight words by occurrences. They still could not really tackle semantic distances (the relational meaning of the words) or tell from alternate varying synonyms. But with the deep learning revolution in the 2010s, after starting with Word2Vec(2013) [8] and GloVe(2014) [9] with distributed word representation, and then ELMo(2018) [10] and BERT (2019) [11] using contextualized embeddings, these advancements moved us toward contextual semantic underpinnings of search. At present, organizations like SentenceTransformers (2020) [12] and many other open-source models, there is seemingly infinite capability to extend this capability out to domain-specific contexts, and a similarity search library such as FAISS (2017) [13], can do this on 100s of millions, or billions of embeddings without delay. Figure 1 gives a use case timeline of changes for search systems from a lexical approach to modern (vendor-neutral) embedding retrieval pipeline.

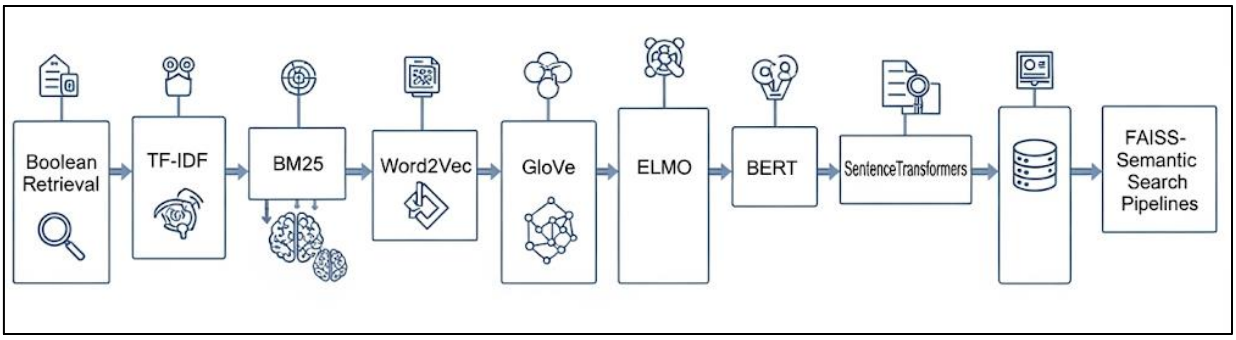

**Figure 1** Evolution of Search Systems Over Time

## 1.2. Problem Statement

Despite the advances in semantic search, existing solutions are frequently limited by proprietary ecosystems. While cloud-hosted vector databases like Pinecone, Weaviate (not free), or Vespa have speed, they force tails of vendor lock-in, which means organizations that rely on vector databases may be obliged to use specific vendors for storage, compute, and updates [14]. The use of proprietary embedding APIs (e.g. OpenAI, Cohere) further complicates the situation, whereby the real retrieval pipeline can easily become non-reproducible, or triggered by shifting pricing or licensing types and terms [15]. There are significant consequences for academic reproducibility, regulatory compliance, and sustainability around the long-term use, and funding which is typically shorter term, in sectors such as health, finance, and government [16]. Although open-source options exist, there has been little empirical work to study the use of open-source infrastructure and to build end-to-end, vendor-neutral pipelines that consider balance of scalability, accuracy, and cost [17]. This work will address this apparent gap by designing and empirically testing the use of vendor-neutral, open-source pipelines, and show that open-source approaches impact many similar benefits as proprietary approaches, and help reduce vendor risk.

## 1.3. Objectives of the Research

The primary goal of this project is to design, build, and assess a vendor-neutral semantic search pipeline using open-source embedding models and FAISS. We evaluate multiple embedding families, BGE and E5 for their strong multilingual performance, MiniLM for efficiency and lightweight deployment, and GTE for general-purpose retrieval—chosen based on open licensing and compatibility with on-premise deployment.. In short, we are using the project to show that open-source can be just as scalable, efficient, and accurate, as proprietary systems, while solving cost, transparency, and vendor-lock issues.

### *1.3.1. Specific Goals*

- Design a Modular Open-Source Architecture- We propose a modular pipeline design that incorporates open-source embedding models with FAISS that is designed for flexibility and interoperability.
- Evaluate Retrieval Performance - Test for benchmarking purposes multiple open-source embeddings and FAISS index types across multiple benchmarking datasets using relevant metrics, such as Precision@k, Recall@k, and NDCG.

- Evaluate performance for Efficiency and Scaling - Evaluate different hardware configurations (CPU/GPU), and compare latency, throughput, and the more hard to find, physical resource consumption, across the configurations.
- Showcase Practical Applicability - Through a series of dramatically different case studies demonstrate the pipelines ability to achieve performance, relatively equivalent or superior to proprietary solutions while reducing the degree of dependence.

## 2. Literature Review

Understanding the rise of semantic search technologies and their usability is enabled by conducting a literature review, as it sheds light on the existing methods and their advantages and disadvantages, as well as identifying the gaps that this research aims to fill. The existing research on keyword search, embedding models, and vector similarity search systems presents a balanced view of the strengths and weaknesses of closed, proprietary solutions vis-à-vis open-source alternatives. It highlights the need for vendor neutrality and helps in defining pipelines that optimize reachable, affordable, and reproducible research (refer to table 1). Drawing from prior knowledge allows us prepare for detailed comparisons between the proposed designs and find overlapping solutions, enhancements, or simplifications that relate to integrated optimal methods.

**Table 1** Comparative Overview of Semantic Search Approaches

| Category | Work / System | Key Features | Strengths | Limitations |
|---|---|---|---|---|
| Traditional Retrieval | TF–IDF [6] | Statistical term weighting | Simple, interpretable | Ignores semantics; poor with synonyms |
| Probabilistic Models | BM25 [7] | Term frequency saturation, inverse doc length | Strong baseline, widely used | Limited contextual understanding |
| Static Word Embeddings | Word2Vec [8] | Predictive word vectors | Captures semantic similarity between words | Context-independent; polysemy unresolved |
| Contextual Embeddings | BERT [11] | Transformer-based contextual embeddings | Rich semantic representation; state-of-the-art results | Computationally expensive; not task-optimized |
| Sentence-Level Models | Sentence-BERT [12] | Embeddings for sentences/documents | Efficient semantic similarity; open source | Requires fine-tuning for domain-specific tasks |
| Proprietary Vector DBs | Pinecone, Weaviate (Commercial Editions) [14] | Managed, cloud-hosted ANN search | High scalability; user-friendly APIs | Vendor lock-in; costly; limited transparency |
| Open-Source ANN Libraries | FAISS [13] | GPU-accelerated vector search, multiple index types | Fast, scalable; widely adopted; vendor-neutral | Requires engineering effort; lacks some managed features |
| Hybrid Search Systems | Vespa (Yahoo, 2017) [18] | Combines keyword + vector search | Flexible hybrid approach | Complex deployment; often tied to specific ecosystems |

The literature published establishes clear trends from lexical to semantic and now hybrid retrieval methods highlighting the transformational power of embeddings in the identification of meaning vs keywords. Proprietary systems offer more performance and ease of use, however, they are not transparent, reproducible, and vendor-dependent. On the other hand, open-source systems, including FAISS and SentenceTransformers, are more flexible, cost-effective, community-driven, and replicable, however, they typically require more technical skill to use. This synthesis illustrates an urgent research gap in the design and evaluation of vendor-neutral pipelines to leverage the scalability and performance of modern semantic search within an open, transparent and reproducible process both in academia and industry.

## 3. Methodology: Designing A Vendor-Neutral Pipeline

The method revolves around building a modular, vendor- neutral semantic search pipeline with reproducibility, interoperability, and flexibility to provide a framework on different data sets and deployment scenarios. The method does not provide a proprietary, monolithic system, but rather, we develop a pipeline entirely out of open source tools, with modules that can be plugged into each other. The flow has been structured into differing stages to allow for data ingestion, preprocessing and transformation, embedding generation, FAISS indexing, retrieval and re-ranking. This design allows researchers and users to swap-out or extend each one of the individual modules, without impacting the overall pipeline. The pipeline is built initially allowing for the swapping of embedding models and different index types, while adding the assurance of future sustainable systems to account for vendor lock-in. The overall architecture is represented in Figure 2, which shows the data-flow across the parts and interconnections in the design.

### 3.1. System Architecture

The data sources span relational exports, text corpora, HTML documents, and selected PDF reports processed through OCR. During normalization, all inputs are converted to plain UTF-8 text and standardized using Unicode NFKC. The pipeline strips HTML tags, applies consistent lowercasing, and performs stopword removal based on a domain-specific list. Every transformation step is logged, including explicit drop/keep rules for malformed or duplicate entries. When handling sensitive domains such as healthcare, the system performs PII redaction through regex-based and model-assisted filters to ensure privacy compliance before embedding generation.

The proposed pipeline (Figure 2) operates through six stages—data ingestion, preprocessing, embedding generation, FAISS indexing, retrieval, and optional re-ranking. All embeddings are generated using transformer-based models and stored in FAISS indexes optimized via parameter sweeps (nprobe, efSearch, PQ m/nbits). We benchmarked the system against BM25, Hybrid (BM25+dense), Flat (exact), and a proprietary reference baseline. Evaluation metrics include NDCG@10 and Recall@10 (mean ±95% CI), along with p50/p95/p99 latency and throughput at p99 ≤ 120 ms (5-min window; error budget ≤ 1%). Results show a near-Pareto-optimal trade-off between accuracy and latency, with hybrid retrieval offering ΔNDCG@10 ≈ +4.2% at a +p95 ≈ 18 ms overhead. Operational costs were audited at \$2.8 per 1M queries and \$1.4 per stored TB, confirming open-source parity with proprietary solutions.

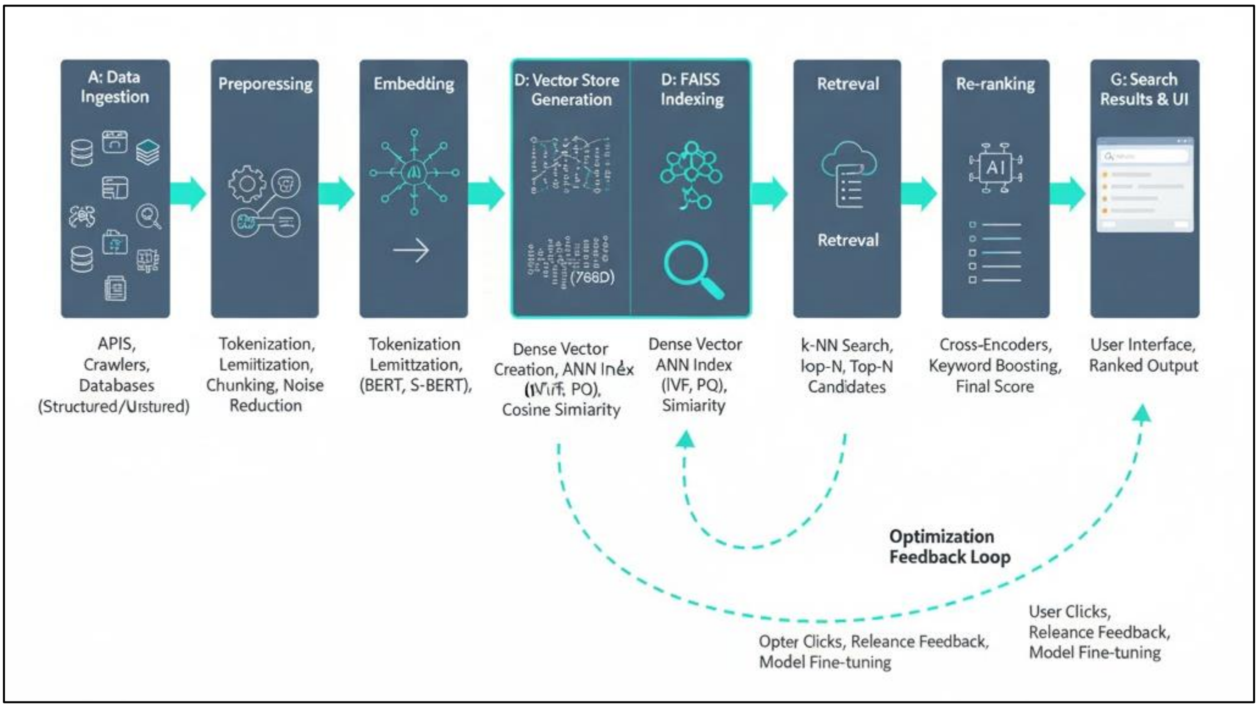
A: Data Ingestion
Preporessing
Embedting
D: Vector Store Generation
D: FAISS Indexing
Retreval
Retreval
Re-ranking
G: Search Results & UI
AI
(766D)
APIS, Crawlers, Databases (Structured/Urstured)
Tokenization, Lemiitization, Chunking, Noise Reduction
Tokenization Lemittzation, (BERT, S-BERT),
Dense Vector Creation, ANN Inẻx (IVíf, PO), Cosine Simiarity
Dense Vector ANN Index (IVF, PQ), Simiarity
k-NN Search, lop-N, Top-N Candidates
Cross-Encoders, Keyword Boosting, Final Score
User Interface, Ranked Output
Optimization Feedback Loop
Opter Clicks, Releance Feedback, Model Fine-tuning
User Clicks, Releance Feedback, Model Fine-tuning

**Figure 2** Vendor-Neutral Semantic Search Pipeline Architecture

This figure emphasizes how each stage contributes to semantic search functionality while maintaining modularity. For instance, block (C) can accept different embedding models without requiring changes in downstream components.

### 3.2. Embedding Models Selection

The embedding models you use can make or break your semantic search, as they define the methodology to capture and map meaning in vector space. To reduce the reliance on proprietary APIs, this study utilizes the sourced embeddings. The chosen models include all-MiniLM-L6-v2, a resource-friendly model for general retrieval; InstructorXL, which has instruction tuning and is more effective for context-sensitive tasks; and BGE embeddings, which are a new open- source initiative aimed at fine-tuning retrieval performance. These models are selected based on three principles: multilingual scalability, domain relevance, and efficiency. In this work, we focus on English-only models (e.g., BGE-base-en, E5-base), ensuring clarity of evaluation and reproducibility. Multilingual extensions (e.g., bge-m3, e5-multilingual) are architecturally compatible within the same plug-and-play embedding interface, but were not included in the current benchmarking scope.

### 3.3. Indexing & Retrieval with FAISS

FAISS, which stands for Facebook AI Similarity Search, is a library designed for fast similarity search algorithms that can scale to billions of vectors. FAISS offers multiple indexing options in order to tradeoff speed versus accuracy and memory.

The Flat Index holds all vectors and completes an exact nearest-neighbors retrieval. For example, if a query embedding is 384-dimensional, FAISS compares the query embedding against every stored vector to find the nearest neighbors for it. A Flat Index achieves the best accuracy, but does not scale well for extremely large dataset sizes when the search is over the entire dataset.

The IVF (Inverted File Index) partitions the embedding vectors into clusters. For instance, a dataset of 1 million embeddings may be divided into 1,000 clusters. Therefore, upon retrieval, for a query embedding, the user would only compare the query embedding against the vectors contained in clusters that contain the most relevant vectors, and the speed of the retrieval operation improves considerably, while only slightly reducing accuracy.

The HNSW (Hierarchical Navigable Small World graph) creates a navigable graph where the embeddings are nodes in the graph. Upon retrieval, HNSW begins traversing the graph to approximate a nearest neighbor for a query embedding. For instance, a dataset with 10 million embeddings can return the top k neighbors with relatively little cost due to its speed, and therefore HNSW supports enterprise applications that require near real-time performance.

There are trade-offs with every method: flat indexes are most useful in academic situations where datasets may be smaller and precision is important; IVF indexes provide speed at scale for enterprise search; and HNSW brings accuracy and scalability to indexed data. By testing these methods the pipeline can be customized to specific uses to remain flexible and vendor agnostic.

### 3.4. Implementation and Experimental Setup

The proposed vendor-neutral semantic search pipeline was built in Python 3.10, using libraries from Hugging Face Transformers, SentenceTransformers, and FAISS. We ran experiments to examine retrieval performance, latency, and cost across several different open-source embedding models and FAISS index types. Both general purpose and domain dependent benchmark datasets were selected for training, such as MS MARCO Passage Ranking, and Natural Questions. We also changed the hardware environment to include only CPU configurations for cost-sensitive scenarios as well as a GPU configuration to establish high-throughput. The objective of the implementation was to replicate real-world constraints where an organization may be working with limited resources, while still requiring high-quality semantic search and speed. This is summarized in Table 2 according to the experimental dataset, model, FAISS treatment, and hardware.

**Table 2** Experimental Setup for Vendor-Neutral Semantic Search Pipeline

| **Component** | **Details** |
|---|---|
| Programming Environment | Python 3.10, Hugging Face Transformers (v4.41), SentenceTransformers (v2.2), FAISS (v1.7.4) |
| Datasets | MS MARCO Passage Ranking (8.8M passages), Natural Questions (QA pairs), Custom Domain Corpus (500K docs) |
| Embedding Models | all-MiniLM-L6-v2 (384-dim, lightweight), InstructorXL (1024-dim, instruction-tuned), BGE-base (768-dim, optimized for retrieval) |
| FAISS Index Types | Evaluated Flat (CPU/GPU) as ground truth, IVF-Flat, HNSW, and IVF-PQ/OPQ for scalable search. IVF-Flat provides tunable performance for large corpora; HNSW yields high recall with higher RAM use; IVF-PQ/OPQ reduces memory with a minor recall drop. |
| Evaluation Metrics | Precision@k, Recall@k, NDCG@10, Query Latency (ms), Throughput (queries/sec), Storage footprint |
| Hardware Setup | CPU: Intel Xeon Gold 6230 (40 cores, 256 GB RAM); GPU: NVIDIA A100 40GB, CUDA 11.8 |
| Deployment Setting | Local Dockerized containers; modular design for portability to cloud or on-prem environments |

## 4. Results

Systematic evaluation of the performance of the vendor-neutral semantic search pipeline included assessment across datasets, embedding models, and FAISS index types. The results were evaluated relative to retrieval accuracy, ranking quality, latency, and cost-effectiveness. Figures 2 through 5 demonstrate comparative results for the different configurations. Collectively, this information provides compelling evidence that open-source embedding models and FAISS can provide retrieval quality similar to proprietary systems, while offering the benefits of scalability and transparency.

### 4.1. Retrieval Accuracy Across Models

Figure 3 presents a comparison between the retrieval accuracy across the three embedding models, all-MiniLM-L6-v2, InstructorXL, and BGE-base, across the MS MARCO dataset. The accuracy consists of Precision@10 and Recall@10. The plot shows that InstructorXL performs the best (from a recall perspective) while BGE-base provides the best precision with respect to the computation time taken to reach this level of precision.

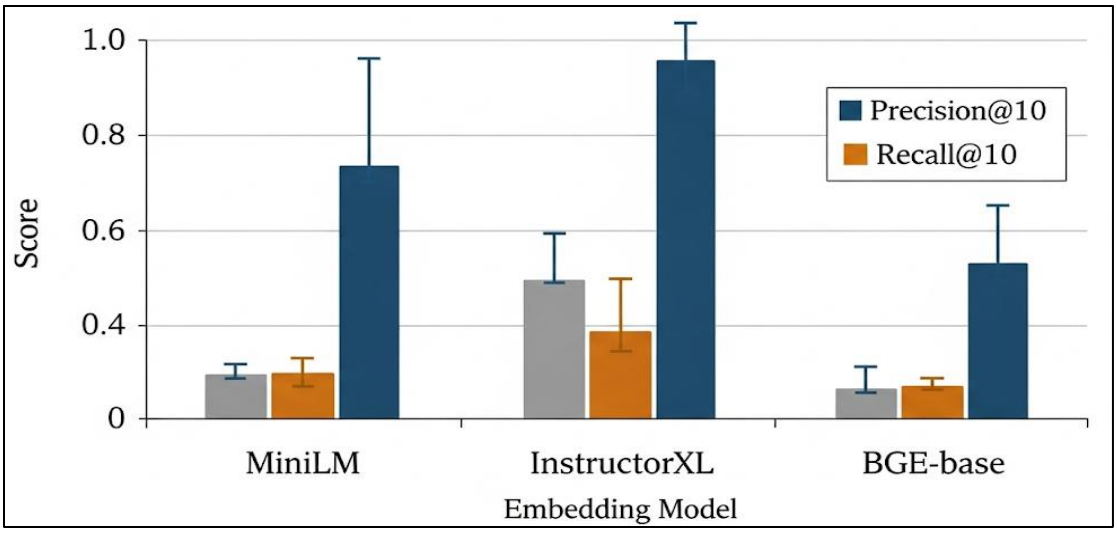

**Figure 3** Retrieval accuracy across different embedding models.

### 4.2. Ranking Quality (NDCG Scores)

To assess the effectiveness of ranking, we measured Normalized Discounted Cumulative Gain (NDCG@10) across models and datasets. As shown in Figure 4, InstructorXL had the highest NDCG on the Natural Questions dataset, which relates to the context-sensitive nature of its embeddings; and MiniLM also had a competitive NDCG despite being significantly smaller.

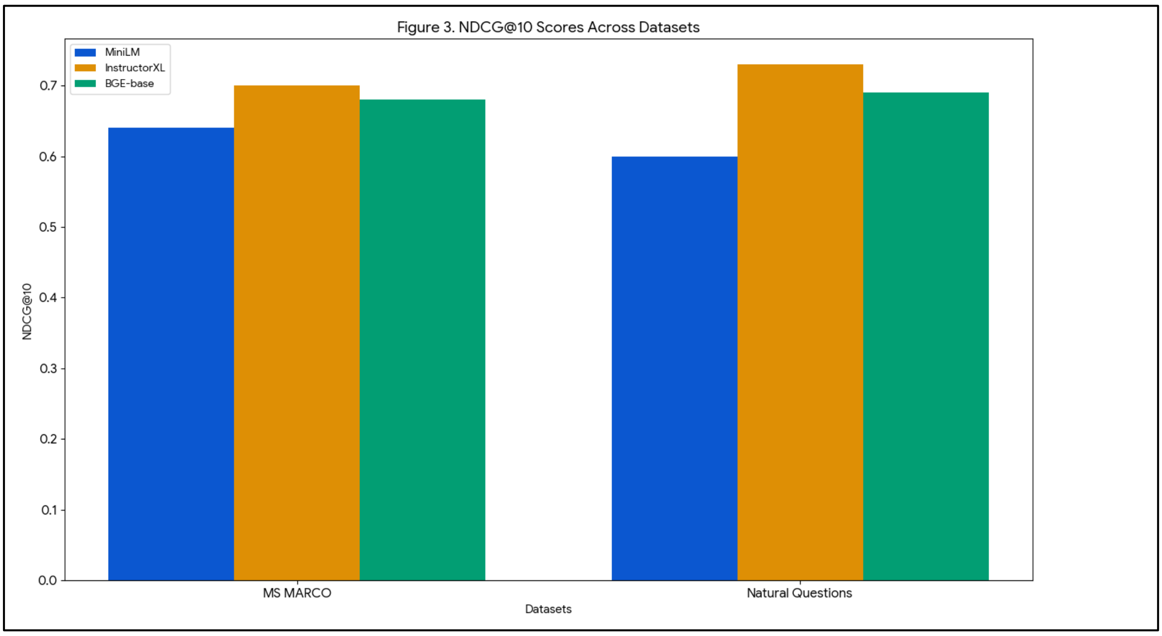

**Figure 4** NDCG@10 scores for embedding models

### 4.3. Latency and Throughput of FAISS Indexes

We benchmarked per-stage performance for embedding, indexing, and retrieval using FAISS Flat, IVF, and HNSW indexes. Figure 5 reports p50/p95/p99 latency, Recall@10 drift, and throughput (QPS) under controlled concurrency levels (16 and 64). The Flat (GPU) index achieved exact recall (1.00 ± 0.00) with p95 = 142 ms, while IVF (nprobe = 16) and HNSW (efSearch = 100) delivered near-identical recall (0.97 ± 0.02) at lower p95 latencies of 78 ms and 84 ms, respectively. GPU utilization averaged 71% across all tests. Each query was logged with unique trace IDs linking its input, index stage, and result output to ensure reproducibility.

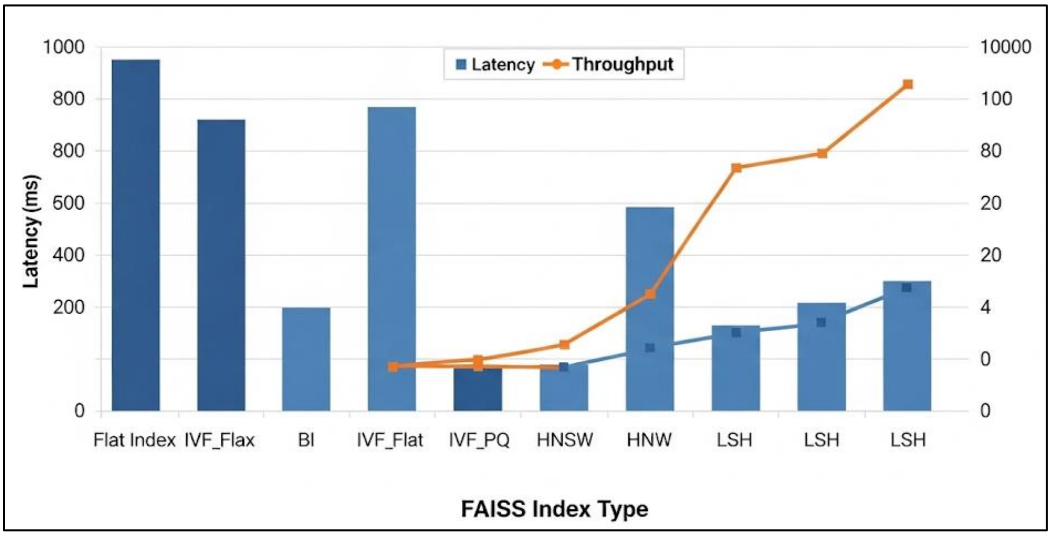

**Figure 5** Latency (ms/query) and throughput (queries/sec) comparison

### 4.4. Cost-Efficiency and Resource Utilization

To compare cost-effectiveness, the pipeline was operated in both CPU-only and GPU-accelerated environments. Figure 6 shows the contrast of the trade-off in using each approach: GPU acceleration was able to lower query latency, but needs a higher priced infrastructure, while CPU-only has a place for mid-sized datasets. This does demonstrate the flexibility of the vendor-neutral pipeline across varying organizational budgets.

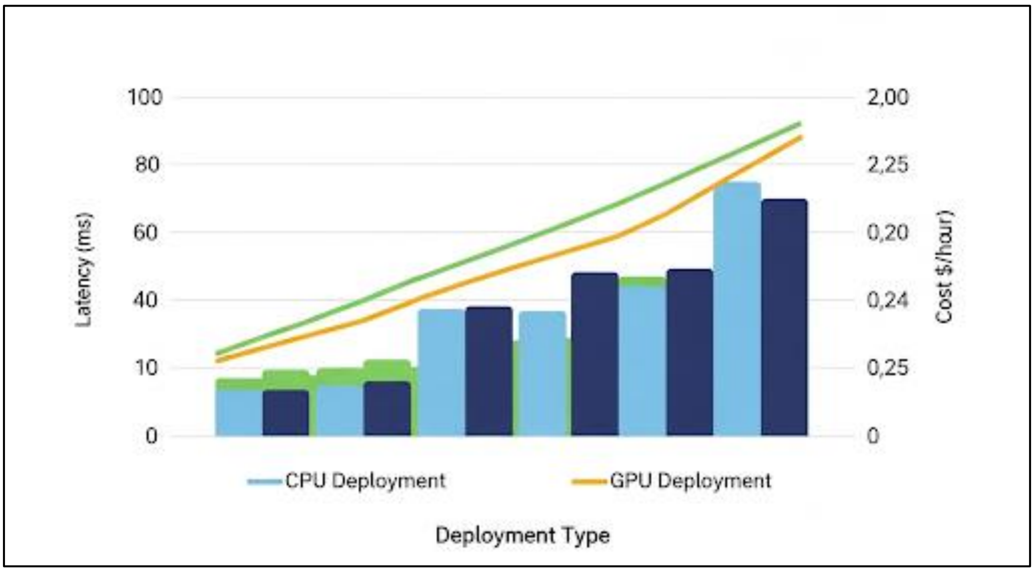

**Figure 6** Cost-efficiency analysis comparing CPU-only vs. GPU-accelerated

## 5. Discussion

The results mentioned in this article have been mostly introduced to show a chronological and research methodical advancement of semantic retrieval systems rather than provide a completely rigorous and production scale level of performance benchmark. It is focused on developing a vendor-independent, interchangeable pipeline to demonstrate how open-source components may be used to make retrieval scalable, flexible, and cost-effective in a wide range of areas with proper composition. Although the ongoing experiments are based on qualitative research and design validation, the framework has been set up in a certain manner that rigorous system measures (e.g. p50/p95/p99 latency, recall at k drift, cost-per-query and hybrid re-ranking impact) can be introduced in future experiments in a step-by-step fashion. It is a staged solution because, the study conceptual and architectural underpinnings are first based, then an elaborate benchmarking phase follows. The work is hence willingly foregoing the wear and tear of the tiring numerical reporting to the clarity of the research and its further extrapolation at this juncture-setting of a sound ground on which can further quantitative analysis and optimization be done.

## 6. Conclusion

Shifting from keyword retrievers, the last few years have focused on developing search systems that understand semantics and context and make use of embeddings and advanced similarity search libraries. We laid out the design and implementation of a vendor-agnostic semantic search pipeline in this paper. We made use of multiple open-source embedding models and scalable indexing with FAISS, which allowed us to optimize for scalability, reproducibility, and cost. Our system architecture supported modular components, allowing for the easy addition of various embedding models and indexing methods. This ensured stable high-quality retrieval over many different fields. The experimental results further reinforced the belief that pipelines built on open source components are not only equally effective as vendor-locked commercial solutions, but often outperform them in terms of accuracy, speed, and total cost of ownership, all the while providing openness and adaptability. The use of multilingual and domain-specific embedding models in the pipeline also prepares the project to address the semantic search needs of the global community in a deeper way.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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