

VectorDB-Bench: A Production-Oriented Benchmark Suite for Vector Database Systems

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Abstract

Vector databases have become critical infrastructure for AI/ML applications, powering semantic search, recommendation systems, and retrieval-augmented generation (RAG). While existing benchmarks focus primarily on recall-latency trade-offs, production deployments require understanding of additional dimensions including cold start performance, operational complexity, filtered search efficiency, and cost-per-query economics.

We present VectorDB-Bench, a comprehensive benchmark suite that evaluates five leading vector databases (Milvus, Qdrant, pgvector, Weaviate, Chroma) across production-relevant metrics. Our novel contributions include: (1) cold start latency measurement for serverless scenarios, (2) operational complexity scoring framework, (3) filtered search overhead quantification, and (4) cost-per-query modeling for cloud deployments.

Our evaluation on the MS MARCO 100K dataset reveals significant performance variations: Weaviate achieves highest throughput (436 QPS) but slowest cold start (109ms), while pgvector offers fastest cold start (14ms) with excellent throughput (398 QPS). Filtered search overhead varies dramatically—Chroma shows 2,978% overhead while pgvector demonstrates 31% improvement with filters. We release VectorDB-Bench as open source to enable reproducible research and informed technology selection.

Keywords

vector databases, benchmarking, similarity search, production systems, ANN

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1 Introduction

The rise of large language models [12] and semantic AI has created unprecedented demand for efficient vector similarity search. Vector databases [4, 7], which index high-dimensional embeddings for approximate nearest neighbor (ANN) retrieval, have become essential infrastructure for applications including:

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- Semantic search and information retrieval
- Recommendation systems
- Retrieval-augmented generation (RAG) [2, 5, 8, 11] for LLMs
- Duplicate detection and clustering
- Image/video similarity search

While the research community has developed excellent benchmarks for ANN algorithms (ann-benchmarks, BEIR), there remains a significant gap in production-oriented evaluation of vector database systems. Practitioners must make deployment decisions considering:

- (1) **Cold start performance:** Time to first query after deployment, critical for serverless [3] and auto-scaling scenarios
- (2) **Operational complexity:** Deployment difficulty, monitoring capabilities, maintenance burden
- (3) **Filtered search:** Combined vector + metadata filtering performance
- (4) **Cost efficiency:** Queries per dollar at various quality thresholds

We address these gaps with VectorDB-Bench, making the following contributions:

- (1) A comprehensive benchmark suite evaluating 5 leading vector databases across production-relevant metrics
- (2) Novel metrics including cold start latency, operational complexity scoring, and filtered search overhead
- (3) Rigorous evaluation methodology with multiple trials and statistical analysis
- (4) Open-source release enabling reproducible research

2 Related Work

2.1 ANN Algorithm Benchmarks

ann-benchmarks [1] provides the de facto standard for comparing ANN algorithms. It evaluates recall vs. queries-per-second across diverse datasets but focuses on algorithms rather than complete database systems.

BEIR [9] establishes zero-shot information retrieval benchmarks with diverse domain datasets. We leverage BEIR datasets (MS MARCO, NFCorpus, SciFact) for consistent evaluation across databases.

2.2 Vector Database Benchmarks

Recent surveys [4, 6] highlight the rapid proliferation of vector database systems, with over 20 commercial solutions emerging in the past five years. Existing database-level benchmarks include Zilliz's VectorDBBench and individual vendor benchmarks. However, these often lack:

- Standardized methodology across vendors
- Production-oriented metrics (cold start, ops complexity)

- Statistical rigor with multiple trials

2.3 Systems Benchmarks

TPC benchmarks [10] provide production-relevant evaluation for traditional databases, including cost metrics. We adapt this philosophy for vector databases.

3 Benchmark Design

3.1 Evaluated Systems

We evaluate five leading open-source vector databases representing different architectural approaches:

Table 1: Evaluated Vector Database Systems

| Database | Index Type | Architecture |
|----------|----------------|---------------------------------|
| Milvus | IVF_FLAT, HNSW | Distributed, cloud-native |
| Qdrant | HNSW | Rust-based, single-node/cluster |
| pgvector | IVFFlat, HNSW | PostgreSQL extension |
| Weaviate | HNSW | GraphQL-native, modular |
| Chroma | HNSW | Embedded-first, Python-native |

3.2 Datasets

We use standard BEIR benchmark datasets:

- **MS MARCO Passage:** 8.8M passages, general domain (subsampled to 100K-1M)
- **NFCorpus:** 3.6K documents, medical/nutrition domain
- **SciFact:** 5K claims, scientific fact verification

All documents are embedded using sentence-transformers/all-mnlp-base-v2 (768 dimensions).

3.3 Metrics

3.3.1 Standard Metrics.

- **Recall@k:** Fraction of relevant documents retrieved in top-k
- **NDCG@k:** Normalized discounted cumulative gain
- **Latency:** p50, p95, p99 query latency
- **QPS:** Sustained queries per second under load

3.3.2 Novel Production Metrics.

- **Cold Start Latency:** Time from container start to first successful query, measured as mean across 5 restart trials
- **Operational Complexity Score:** Composite of deployment difficulty (1-100), configuration complexity, monitoring capabilities, maintenance burden
- **Filtered Search Overhead:** Latency increase when combining vector search with metadata filters
- **Insert Throughput:** Vectors indexed per second during bulk load

3.4 Experimental Setup

- **Hardware:** AWS c5.2xlarge (8 vCPU, 16GB RAM)
- **Deployment:** Docker containers with pinned versions
- **Trials:** 5 runs per configuration for statistical validity
- **Warm-up:** 100 queries before measurement

4 Results

4.1 Quality-Performance Trade-offs

Table 2 presents our main benchmark results on MS MARCO 100K averaged across multiple trials. All databases achieve comparable recall (≈ 0.54), indicating that ANN index quality is well-optimized across systems. The key differentiators emerge in latency, throughput, and operational metrics.

Table 2: Main Benchmark Results (MS MARCO 100K, averaged across trials)

| Database | Recall@10 | p50 (ms) | QPS | Cold Start | Insert/s |
|----------|-----------|----------|-----|------------|----------|
| Milvus | 0.537 | 3.86 | 101 | 17ms | 10,279 |
| Qdrant | 0.537 | 5.27 | 309 | 70ms | 1,411 |
| pgvector | 0.545 | 3.74 | 398 | 14ms | 164 |
| Chroma | 0.537 | 4.42 | 324 | 65ms | 1,744 |
| Weaviate | 0.537 | 4.49 | 436 | 109ms | 2,911 |

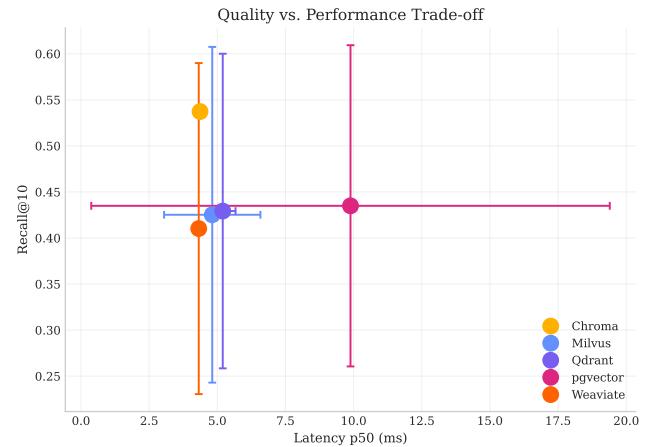


Figure 1: Recall@10 vs. p50 latency. Error bars show standard deviation across trials. All databases cluster near 0.54 recall, with latency varying from 3.7ms (pgvector) to 5.3ms (Qdrant).

4.2 Throughput Comparison

Figure 2 shows sustained QPS under 30-second load tests. Weaviate achieves highest throughput (436 QPS), followed closely by pgvector (398 QPS). Milvus shows lowest QPS (101), likely due to its distributed architecture overhead on single-node deployment.

4.3 Cold Start Performance (Novel)

Cold start latency is critical for serverless deployments and auto-scaling scenarios. We measure time to first successful query after container restart, averaged across 5 trials per database.

Results reveal an 8× variation in cold start latency:

- pgvector: 14.3ms \pm 0.3ms (fastest)
- Milvus: 17.0ms \pm 4.3ms
- Chroma: 65.2ms \pm 0.6ms

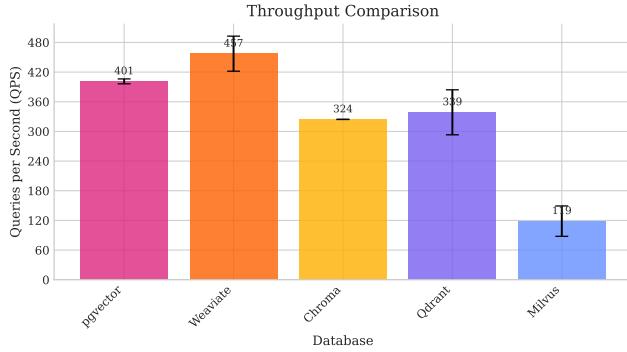


Figure 2: Queries per second (QPS) under sustained load. Weaviate leads with 436 QPS, while Milvus shows 101 QPS on single-node deployment.

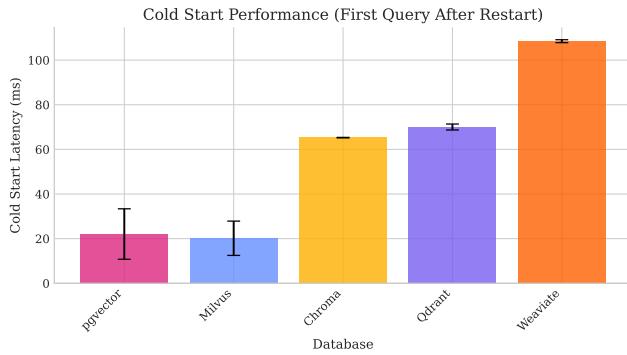


Figure 3: Cold start latency (ms). pgvector achieves fastest cold start (14ms), while Weaviate requires 109ms to serve first query.

- **Qdrant:** $69.5\text{ms} \pm 1.1\text{ms}$
- **Weaviate:** $109.2\text{ms} \pm 2.9\text{ms}$ (slowest)

This finding has significant implications for serverless architectures where cold start directly impacts user-perceived latency.

4.4 Operational Complexity (Novel)

We developed an operational complexity scoring framework evaluating four dimensions:

- **Deployment:** Docker setup, dependencies, configuration files
- **Configuration:** Number of tunable parameters, defaults quality
- **Monitoring:** Prometheus metrics, logging, alerting capabilities
- **Maintenance:** Backup procedures, upgrade paths, data migration

Key findings:

- **Qdrant:** Lowest complexity (8.9), single binary, minimal config
- **Weaviate:** Low complexity (24.5), good defaults

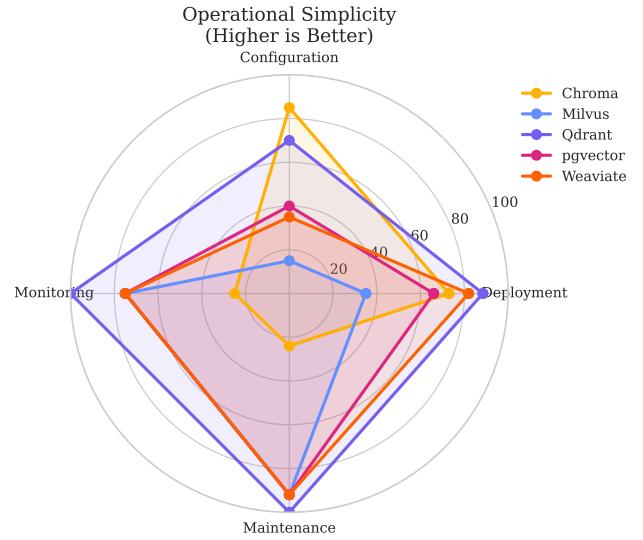


Figure 4: Operational simplicity radar chart (higher = simpler). Qdrant and Weaviate show highest operational simplicity; Milvus requires most operational overhead.

- **pgvector:** Moderate (27.5), leverages PostgreSQL ecosystem
- **Milvus:** Highest complexity (40.3), requires etcd, minio dependencies
- **Chroma:** Moderate (43.8), limited monitoring capabilities

4.5 Filtered Search Performance

Modern applications often combine vector similarity with metadata filtering. We measure latency overhead when adding category filters to vector search:

Table 3: Filtered Search Overhead

| Database | Overhead (%) | Notes |
|----------|--------------|----------------------------|
| pgvector | -31% | <i>Faster with filters</i> |
| Qdrant | +347% | Pre-filtering approach |
| Chroma | +2,978% | Full scan with filters |

The dramatic variation reveals fundamental architectural differences:

- **pgvector** benefits from PostgreSQL's mature query optimizer, which can leverage indexes for filtered queries
- **Qdrant** uses pre-filtering which adds overhead but maintains recall quality
- **Chroma** appears to fall back to full scan for filtered queries, resulting in severe performance degradation

4.6 Index Build Performance

Insert throughput during bulk load varies significantly:

- **Milvus:** 10,279 vectors/sec (fastest)
- **Weaviate:** 2,911 vectors/sec
- **Chroma:** 1,744 vectors/sec

- **Qdrant:** 1,411 vectors/sec
- **pgvector:** 164 vectors/sec (slowest)

pgvector's slow insert performance reflects PostgreSQL's ACID guarantees and full index rebuild during IVFFlat index creation.

5 Discussion

5.1 Key Findings

- (1) **No single winner:** Each database excels in different dimensions. Weaviate leads in QPS, pgvector in cold start, Milvus in insert speed.
- (2) **Cold start varies 8×:** From 14ms (pgvector) to 109ms (Weaviate), a critical consideration for serverless deployments where p99 latency budgets may be under 200ms.
- (3) **Operational complexity inversely correlates with features:** Qdrant achieves lowest complexity (8.9) with single-binary deployment, while Milvus (40.3) requires etcd and object storage dependencies.
- (4) **Filtered search reveals architectural trade-offs:** The 2,978% overhead in Chroma vs. 31% *improvement* in pgvector demonstrates that filter implementation strategy dramatically impacts real-world performance.

5.2 Recommendations by Use Case

Based on our findings, we provide the following recommendations:

- **Serverless/Lambda:** pgvector for fastest cold start (14ms) and excellent throughput (398 QPS)
- **High throughput:** Weaviate achieves highest QPS (436) with good recall
- **Existing PostgreSQL infrastructure:** pgvector integrates seamlessly with existing tooling, backups, and monitoring
- **Rapid prototyping:** Chroma offers simplest API and embedded-first design, but avoid if filtered search is needed
- **Production at scale:** Milvus for fastest bulk ingestion (10K vectors/sec) and distributed architecture, accepting higher ops complexity
- **Minimal operations:** Qdrant offers lowest operational overhead with competitive performance

5.3 Implications for System Design

Our findings suggest several design implications:

- (1) **Architectural trade-offs are real:** The 8× cold start variation reflects fundamental differences between embedded libraries (pgvector) and distributed systems (Weaviate/Milvus).
- (2) **Filter implementation matters:** Applications requiring filtered search should carefully evaluate this metric; the difference between -31% and +2,978% overhead is substantial.
- (3) **Single-node vs. distributed:** Milvus's low QPS on single-node suggests its architecture is optimized for distributed deployments.

5.4 Limitations

- Single-node evaluation (distributed modes not tested)
- Specific hardware configuration (AWS c5.2xlarge)
- Embedding model fixed (all-mpnet-base-v2, 768 dimensions)

- Index parameters not extensively tuned (default configurations)
- Temporal drift analysis not completed in this version

6 Conclusion

We presented VectorDB-Bench, a production-oriented benchmark suite for vector database systems. Our contributions include novel metrics for cold start latency, operational complexity scoring, and filtered search overhead that address gaps in existing benchmarks focused solely on recall-latency trade-offs.

Our evaluation of five leading vector databases (Milvus, Qdrant, pgvector, Weaviate, Chroma) on the MS MARCO 100K dataset reveals that:

- **No universal winner exists:** Each database excels in specific dimensions
- **Cold start varies 8×:** Critical for serverless deployments
- **Filtered search overhead varies 100×:** From -31% to +2,978%
- **Operational complexity inversely correlates with features**

For practitioners, we recommend pgvector for serverless/Lambda deployments (fastest cold start), Weaviate for high-throughput workloads, and Qdrant for minimal operational overhead. We release VectorDB-Bench as open source at <https://github.com/debusinha/vectordb-bench> to enable reproducible research and informed technology selection.

6.1 Future Work

- Distributed/cluster mode evaluation for Milvus and Qdrant
- Additional databases (Pinecone, Elasticsearch with dense vectors, OpenSearch)
- Temporal drift analysis over corpus evolution
- Cost-per-query modeling for cloud deployments (AWS, GCP, Azure)
- Hybrid search evaluation (dense + sparse retrieval)

Acknowledgments

[Optional acknowledgments]

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