Building Stateless Serverless Vector DBs via Block-based Data Partitioning

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Retrieval-Augmented Generation (RAG) and other AI/ML workloads rely on vector databases (DBs) for efficient analysis of unstructured data. However, cluster (or *serverful*) vector DB architectures, such as Milvus, lack the elasticity to handle high workload fluctuations, sparsity, and burstiness. Serverless vector DBs—*i.e.*, vector DBs built on top of cloud functions—have emerged as a promising alternative architecture, but they are still in their infancy.

This paper presents the first experimental study comparing data partitioning strategies in vector DBs built atop stateless Function-as-a-Service (FaaS). Through extensive benchmarks, we reveal key limitations of clustering-based data partitioning when applied to dynamic datasets (*e.g.*, complexity, load balancing). We then evaluate a block-based alternative that addresses such limitations (*e.g.*, up to 5.8× faster data partitioning, up to 63% lower costs, similar querying times). Moreover, our results show that a stateless serverless vector DB using block-based data partitioning achieves competitive performance with Milvus in several aspects (*e.g.*, up to 65.6× faster data partitioning, similar recall), while reducing costs for sparse workloads (up to 99%). Our empirical insights aim to guide the design of next-generation serverless vector DBs.

CCS Concepts: • **Information systems → Data management systems**; **Search engine architectures and scalability**; • **Computer systems organization → Cloud computing**.

Additional Key Words and Phrases: Vector Databases, Serverless Functions, Data Partitioning, Indexing

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1 Introduction

The exponential growth of unstructured data has created a pressing need to leverage AI and machine learning (ML) techniques to unlock its potential. Modern AI workloads, such as those using Retrieval-Augmented Generation (RAG) models, rely heavily on generating *vector embeddings* [14] from unstructured data (*e.g.*, text, images, and audio) to enable efficient and meaningful analysis. These embeddings convert complex, high-dimensional data into lower-dimensional vectors that preserve

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semantic relationships, facilitating advanced tasks like natural language processing [27], image recognition [17], and recommendation systems [38]. Consequently, the ability to manage vector embeddings is key for extracting value from unstructured data in AI/ML applications.

The need for managing vector embeddings has led to the rising popularity of *vector databases* (vector DBs) [15, 28, 35, 36]. Vector DBs are specialized systems designed to store and retrieve high-dimensional vectors efficiently [31]. They enable fast and accurate similarity search, making them essential for AI and ML applications. In this sense, Pinecone [28], Weaviate [36], and Milvus [15, 35] are, among others, examples of popular vector DBs used at scale in production analytics pipelines.

1.1 Motivation

Despite the specialization of their search and indexing algorithms, most distributed vector DBs rely on a traditional cluster or *serverful*[1] *architecture* [25, 31]. This requires that administrators carefully manage the resources of the vector DB deployment. Under fluctuating or sparse query workloads, this architecture can result in periods of over-provisioning—leading to higher cost—and under-provisioning—causing saturation. Likewise, adapting such an architecture to handle high workload burstiness is challenging.

In response to such architectural limitations, there is an emerging trend for porting vector DBs to the *serverless paradigm*. In the industry, the main objective seems to be simplifying the provisioning of vector DBs and offering them "as-a-service"—and, in some cases, applying a pay-per-query model. Instantiations of this trend include Weaviate Serverless Cloud [36], Upstash [34], and Amazon OpenSearch Service as a Vector DB [1], to name a few.

However, the true realization of a serverless vector DB architecture goes far beyond simplified provisioning: it lies in distributing the vector DB engine across *cloud functions*. Function-as-a-Service (FaaS) providers, such as AWS Lambda [2], Azure Functions [5], or Google Cloud Functions [12], deliver a powerful substrate for executing embarrassingly parallel workloads. Crucially, such a design has the potential to overcome the elasticity and burstiness challenges that serverful vector DB architectures typically face.

Serverless vector DBs must distribute tasks across parallel cloud functions that are normally executed on compute nodes in serverful vector DBs. These tasks include: i) *data ingestion*, which consists in adding new vector embeddings to the system; ii) *data partitioning*, which involves distributing a collection of vector embeddings into smaller pieces (*e.g.*, data objects in AWS S3); iii) *data indexing*, which generates indexes for efficient vector lookups within dataset partitions; and iv) *querying*, which performs similarity searches on vectors across dataset partitions. While promising, building a serverless vector DB presents unique challenges from a design perspective compared to serverful vector DBs (see Section 3).

1.2 Challenge: Stateless FaaS & Dynamic Data

The concept of a serverless vector DB is still in its early stages. Vexless [32] stands out as the pioneering work, demonstrating the potential of using cloud functions to parallelize vector search workloads. However, the design space for serverless vector DBs remains largely unexplored, particularly when considering the challenges introduced by *stateless FaaS platforms* and *dynamic datasets*:

Stateless FaaS: A key dimension in this space is the nature of the FaaS platform itself. The most popular FaaS offerings—such as AWS Lambda [2], Azure Functions [5], and Google Cloud Functions [12]—are inherently *stateless*. This means that functions cannot retain state across invocations and cannot directly communicate with one another. In contrast, Vexless is built on

[1] We use the term *serverful* for architectures built for a traditional cluster of servers.

Azure Durable Functions [4], a stateful FaaS platform that supports direct message passing and persistent workflows. This model is hard to compare or port to stateless FaaS environments. While statelessness imposes certain limitations, it also offers a highly elastic and cost-efficient execution model for embarrassingly parallel workloads that we aim to explore.

Dynamic Datasets: Another critical dimension is data management, particularly in the context of dynamic datasets that evolve over time. A practical serverless vector DB must support efficient ingestion, partitioning, indexing, and querying of data that grows continuously. In this paper, we evaluate the trade-offs of clustering-based (*e.g.*, K-means) data partitioning strategies used in the state of the art [32] when applied to a stateless FaaS setting.

1.3 Contributions

This work aims to empirically explore the feasibility of building serverless vector DBs[2] atop stateless FaaS platforms from two angles: *data partitioning* and *comparison with serverful vector DBs*. First, a core contribution of this paper is to identify the key limitations of clustering-based data partitioning for dynamic datasets and evaluate a block-based data partitioning alternative. Second, we empirically show that block-based data partitioning in serverless vector DBs enables competitive system designs compared to a serverful one. In summary, our contributions in this paper are:

- We present an overview of serverless vector DBs, highlighting their key components and design trade-offs. Given their recent emergence, this work is the first to offer a timely overview of this new family of systems (see Section 3).
- We identify the main limitations of using a clustering-based data partitioning scheme for serverless vector DBs, as it is the approach used in the state of the art [32] (see Section 4).
- We provide an experimental comparison of clustering-based data partitioning with a simple, yet practical, block-based data partitioning scheme for serverless vector DBs (see Section 6).
- We show through experimentation that a serverless vector DB using block-based data partitioning is competitive with a serverful vector DB (Milvus) in terms of indexing time, query latency, recall, and economic cost (see Section 7).

We have built a serverless vector DB prototype on AWS Lambda. Our experiments show that a block-based data partitioning outperforms a clustering-based scheme in terms of partitioning performance (3.5× to 5.8×) and cost (56% to 63%), while querying times vary from 29.9% faster to 31.2% slower based on the configuration. Also, we find that techniques proposed to enhance clustering-based partitioning [32], such as balancing data partitions and vector redundancy, may not offer clear benefits overall. Finally, when comparing our prototype with Milvus, we achieve better partitioning time (9.2× to 65.6×), similar query recall, and an acceptable overhead in querying in exchange of cost reduction (66% to 99%).

The rest of the paper is as follows. We provide key background in Section 2. We present a timely overview of serverless vector DBs in Section 3. In Section 4, we analyze the data partitioning trade-offs in serverless vector DBs and, after introducing our experimental framework (see Section 5), we show an empirical evaluation of clustering-based data partitioning versus block-based data partitioning (Section 6). In Section 7, we compare our block-based serverless vector DB implementation against Milvus. We revisit the related work in Section 8 and conclude the paper in Section 9.

2 Background

In this section, we provide the necessary background to understand the remainder of the paper: FaaS and vector DBs.

[2] The term "serverless vector DB" in this work refers to systems built on stateless FaaS.

2.1 Function-as-a-Service (FaaS)

The *serverless computing paradigm* is a cloud execution model where developers build and deploy applications without managing the underlying infrastructure [30]. Instead, cloud providers dynamically handle provisioning, scaling, and maintenance. This enhances agility, reduces operational complexity, and optimizes resource utilization by charging only for actual code execution.

The most prominent form of serverless computing is *Function-as-a-Service* (FaaS) [2, 5], which allows developers to write modular functions triggered by specific events, such as HTTP requests, database updates, or message queues. FaaS follows an *event-driven programming model*, where each invocation is ephemeral, stateless, and performs a single task. This allows fine-grained, *pay-per-use* billing, based on the number and duration of invocations, typically measured in milliseconds. Unlike traditional server-based pricing models that incur costs for idle resources, FaaS promotes automatic scaling and efficient utilization. Developers can focus entirely on business logic, which is key for improving developer productivity and democratizes access to cloud platforms.

Importantly, most FaaS services are stateless. This statelessness has limitations, such as cold start latency (*i.e.*, start-up delay after a period of inactivity) [20, 23], lack of persistent state, and barriers to inter-function communication [7]. Note that Microsoft offers stateful FaaS extensions like Azure Durable Functions [4] and Durable Entities, enabling persistent state and workflow orchestration. However, these solutions are still niche and tightly coupled to a specific vendor, limiting the generalizability of the applications that use them. Building a serverless vector DB on top of a stateless FaaS introduces unique challenges that we explore in this paper.

2.2 Vector DBs

Typical database operations consists of two main phases: (i) *Data ingestion and storage*, which uses different schemas and generates indexes for fast retrieval; (ii) *Querying*, where the database performs efficient lookups on the stored data. The architecture of vector DBs is similar to general-purpose ones. However, vector DBs store and index high-dimensional vectors, using nearest neighbor search with similarity metrics (*e.g.*, cosine similarity, dot product, or Euclidean distance). Due to the high computational cost of exact nearest neighbor search, vector DBs employ approximate nearest neighbor (ANN) algorithms with specialized index structures (*e.g.*, HNSW, IVF, PQ) to balance recall and latency [37].

When the collection of stored vector embeddings grows, vector DBs face two main scalability-related challenges: (i) the index(es) must often be recomputed when the stored data changes, and (ii) as the number of vectors grows, searching becomes slow. For this reason, in recent years, a new generation of vector DBs have emerged to address these challenges via a distributed architecture and parallel data management. In a distributed vector DB, the different tasks are performed by individual services that can be scaled independently. Moreover, a vector dataset is split into chunks, so vector DB tasks can be executed in parallel. Interestingly, this architecture shift introduces a new dimension to the vector DB operation that is the primary focus of this paper: *data partitioning*.

One instance of distributed vector DB is Milvus [15, 35]. It scales each process independently as services, with nodes (servers or VMs) assigned to specific roles: Data, Index, or Query. Data nodes are responsible for ingestion, partitioning, and storage management. Index nodes create indexes for data chunks, while Query nodes load these indexes and data into memory to respond to queries. Additionally, specialized nodes such as Query Coordinators and Data Coordinators aggregate results and manage data flows, including load balancing. Although services are scaled independently, the stateful nature of this cluster architecture can be rigid and difficult to adapt to rapid workload changes. It also requires an administrator to carefully right-size the deployment. Solving such elasticity and provisioning issues is a key goal of serverless vector DBs.

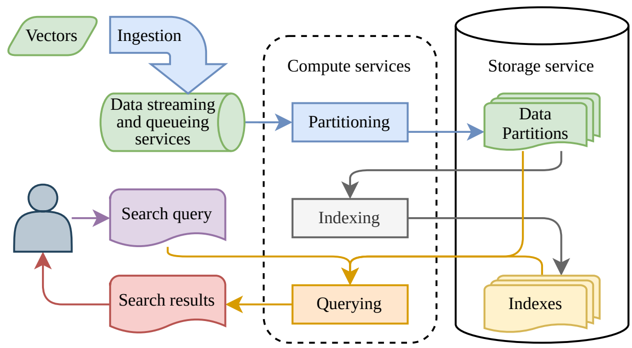


Fig. 1. Key processes of a serverless vector DB.

3 Serverless Vector DBs: An Overview

Building a vector DB on top of a FaaS service is an emerging trend. In this section, we contribute a general description of the architecture and design trade-offs of this new family of systems.

3.1 Architecture

A serverless vector DB retains the core components of a serverful vector DB but leverages serverless compute services for elasticity and cost efficiency (see Fig. 1). A serverless vector DB consists of two service types: *data services* for ingestion and storage, and *compute services* for partitioning, indexing, and querying. The *data ingestion component* handles vector inserts, supporting both batch and streaming data [13] through event brokers (*e.g.*, Kafka [18], AWS Kinesis) or event-driven pipelines (*e.g.*, AWS Lambda with S3 triggers). After ingestion, vectors undergo *partitioning and preprocessing* (*e.g.*, K-means clustering) before being stored in object storage (*e.g.*, AWS S3) for long-term retention.

Data partition *indexing* is a crucial process performed by index generator functions, which transform vector partitions into efficient approximate nearest neighbor (ANN) search structures. Common indexing techniques include tree-based (KD-Tree), graph-based (HNSW), and quantization-based (IVF-PQ) approaches, enabling fast vector retrieval. These indexes, along with the raw vector data, are stored in scalable object storage systems, ensuring durability and high availability. Since indexing workloads are intermittent, FaaS services are well-suited for dynamically executing index generation without maintaining persistent compute resources.

Query execution in a serverless vector DB is distributed and parallelized across multiple partitions. Typically, a *query coordinator* orchestrates the execution of serverless functions responsible for retrieving candidate vectors from different partitions. These functions compute similarity scores (*e.g.*, cosine similarity, Euclidean distance) and return partial results that are then aggregated using a *reduce function*. Given the stateless nature of cloud functions, query coordination mechanisms (*e.g.*, Step Functions) are essential for synchronizing results. The final ranked vectors are returned to the user and functions terminate their execution.

By combining cloud functions with scalable storage, a serverless vector DB eliminates the need for persistent infrastructure while maintaining high-performance search capabilities. Compared to serverful architectures, this approach automatically scales with workload demands, optimizes cost through pay-as-you-go billing, and reduces operational overhead. This makes serverless vector databases a compelling choice for applications requiring efficient and scalable similarity search, such as recommendation systems, image retrieval, and AI-powered analytics.

Table 1. Comparison of Vector DB architectures.

Dimension	Milvus [15, 35]	Vexless [32]	This work
Architecture	Serverful	*Stateful* Serverless (Azure Durable Functions)	*Stateless* Serverless (AWS Lambda)
Communication	Distributed coordination with gRPC	Stateful functions with message passing	Object storage-based communication
Elasticity	Horizontal node scaling	Automatic function scaling	Automatic function scaling
Operation	Node management and maintenance	Automatic function provisioning	Automatic function provisioning
Billing	Node/hour based	Pay per function invocation	Pay per function invocation
Data Ingestion	Data nodes (streaming-based)	Not supported (static datasets)	Supported (as data objects)
Data Partitioning	Shard-based (dynamic sharding with load balancing)	Clustering-based (balanced K-means with redundancy)	Block-based (fixed-size parallel blocks)
Data Indexing	Per shard segment on Index nodes (multi-algorithm)	Per cluster on cloud functions* (HNSW)	Per block on cloud functions (IVF)
Querying	Query nodes (similarity/multi-vector search) Interactive or batch	Cloud functions on partition subsets (similarity search) Interactive	Cloud functions on all partitions (similarity search) Batch

*Vexless actually performs indexing in a centralized VM, but as we show in Section 6 this phase can be parallelized.

3.2 Vector DB Design: Serverful vs Serverless

Next, we discuss the architectural differences between a popular serverful vector DB (Milvus) and existing serverless counterparts (Vexless, this paper). In Table 1, the systems compared represent different architectural approaches to vector DB management.

Milvus is a popular example of a serverful vector DB architecture designed to manage vector embeddings as a service. One of the primary advantages of its design is its ability to scale both horizontally and vertically, allowing the addition of more resources per node to handle increasing workloads. This makes it particularly well-suited for handling continuous query workloads with moderate fluctuations, as it provides fast interactive queries. In a typical deployment, Milvus uses event streaming systems (*e.g.*, Kafka, Pulsar) to achieve high-performance data ingestion. The low latency and high performance of service nodes are key advantages of the serverful architecture over serverless counterparts, making it an attractive option for applications that require low-latency guarantees on vector search.

However, a serverful vector DB deployment may be cumbersome to manage under high workload fluctuations and burstiness. This is because this architecture introduces additional complexity and operational burden to adapt the service to the workload needs. Furthermore, workload sparsity can lead to low cost-effectiveness for a serverful vector DB, as resources can be underutilized during periods of low activity. In such scenarios, serverless vector DBs have emerged as an interesting alternative, building on top of FaaS offerings (*e.g.*, Azure Functions). By automatically provisioning cloud functions and billing them on a per-execution basis, serverless vector DBs can minimize operational overhead and reduce cost. As a result, serverful and serverless vector DB architectures provide trade-offs that make them ideal for different scenarios, thus requiring careful consideration of the specific use case at hand.

When focusing on serverless vector DBs, there are fundamental differences between Vexless and this work. Vexless leverages a *stateful FaaS platform* (Azure Durable Functions) for keeping data in memory and enabling direct function re-invocation, thus avoiding cold starts. These properties allow Vexless to maintain *low query times in interactive mode*, as previously loaded data can be reused across queries without repeated access to external storage. However, Azure Durable

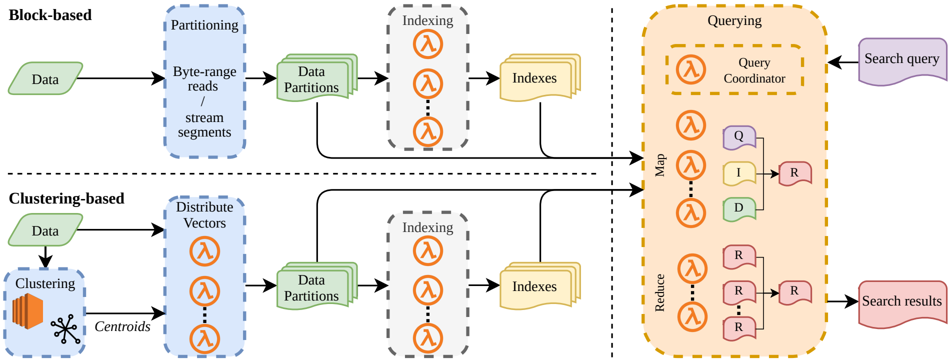


Fig. 2. Life cycle of a serverless vector DB comparing block-based and clustering-based data partitioning. Querying is similar architecture-wise in both cases. Still, while the block-based scheme must query on all partitions, clustering-based partitioning allows the query coordinator to filter data based on the distance between the query vector and a partition's centroid.

Functions represents a niche FaaS model that is not widely adopted across cloud providers. In contrast, our work explores *stateless FaaS platforms*—such as AWS Lambda, Azure Functions, and Google Cloud Functions—which represent the mainstream model today. Stateless FaaS functions are ephemeral and cannot retain state between invocations, which means that each query must fetch data from external storage (*e.g.*, object stores), introducing additional latency that can impact interactive performance. While this model imposes certain trade-offs, our experiments show that we can amortize statelessness costs via *query batching* (see Section 5). Importantly, the fundamental differences between stateful and stateless FaaS platforms make it difficult to directly compare serverless vector DBs built on top of different platforms. As such, this work evaluates exclusively stateless FaaS as a widely available foundation for serverless vector DBs.

Crucially, the design of Vexless cannot handle continuous data ingestion as it assumes static datasets. Vexless performs a clustering-based data partitioning and indexing approach that must be executed in advance, limiting its ability to handle dynamic datasets. In contrast, we propose a block-based data partitioning approach that enables continuous data ingestion to the system, providing greater flexibility and scalability. In the next section, we analyze in depth the trade-offs of data partitioning between Vexless and this work.

4 Trade-offs in Data Partitioning

We have overviewed the architecture of serverless vector DBs. Next, we focus on a critical aspect when distributing a vector DB engine across stateless cloud functions: *data partitioning*. Concretely, we compare the state-of-the-art clustering-based data partitioning [32] with our block-based data partitioning scheme (see Fig. 2) regarding three dimensions relevant in a serverless scenario: i) *partitioning complexity*, ii) *load balancing*, and iii) *query performance*.

4.1 Clustering-based Data Partitioning

Partitioning complexity: This partitioning method creates clusters of nearby vectors aiming to accelerate queries by filtering out unrelated data partitions. To this end, it uses a three-step indexing pipeline. First, an unsupervised clustering algorithm, such as K-means, is implemented to cluster nearby vectors. It is important to note that clustering algorithms like K-means, hierarchical, or spectral clustering are *computationally complex* and require the *entire dataset* to operate. In practice, while distributed versions of K-means have been investigated [11], it seems inefficient to implement it on top of cloud functions. For this reason, we found that resorting to a virtual machine for executing the clustering algorithm is a feasible alternative. Once the clustering algorithm completes, the dataset is partitioned and distributed among multiple cloud functions, along with the centroids, to classify the vectors to their clusters/partitions. Finally, multiple parallel cloud functions index the dataset partitions containing nearby vectors.

Load balancing: Clustering algorithms like K-means can lead to unbalanced dataset partitions, where some clusters may contain significantly more vectors than others. To address this issue, balanced versions of K-means have been developed, which ensure equal partitioning of datasets across clusters. As pointed out in Vexless [32], producing balanced data partitions is crucial in a serverless setting to avoid straggler cloud functions. Stragglers can delay query responses due to uneven data distribution. However, the balanced version of K-means incurs a higher computational cost compared to the standard algorithm, making it impractical for large datasets [8, 22] under a continuous ingestion workload.

Query performance: This method groups vectors based on their closeness, enabling users to discard partitions with vectors far from the query input. Upon receiving a query, a clustering-based data partitioning system identifies the centroids closest to the query vector. Based on a *data discard* parameter, only the closest centroids are returned. The similarity search is then performed exclusively on data partition indexes associated with these nearby centroids. However, querying fewer centroids reduces *query recall*, as it increases the likelihood of missing the actual closest vectors. Users must understand the trade-off between data filtering and query recall, which can be challenging since many applications require high recall (*e.g.*, $> 90\%$). To address this, Vexless [32] incorporates a data redundancy mechanism that replicates vectors near partition boundaries into adjacent partitions. In Section 6, we evaluate the behavior of vector redundancy for clustering-based partitioning.

4.2 Block-based Data Partitioning

Partitioning complexity: In a block-based scheme, the complexity of data partitioning is significantly reduced by not requiring a view of the entire dataset. This approach creates equal-sized data partitions, which simplifies the process and ensures uniform distribution of data. Additionally, the ability to partition these chunks in parallel improves scalability, as multiple chunks can be processed simultaneously without dependencies on other parts of the dataset.

Load balancing: By creating equal-sized chunks, the scheme ensures that each cloud function handles a uniform amount of data, thus preventing straggler functions. Moreover, the ability to partition chunks in parallel allows multiple cloud functions to operate simultaneously, maximizing resource utilization.

Query performance: A block-based data partitioning scheme does not consider vector relationships, requiring all partitions to be queried for similarity searches. This results in fast and simple partitioning and indexing phases, avoiding the complexity of analyzing vector relationships. However, the querying phase becomes more computationally expensive, as it must query all partitions without discarding initially dissimilar vectors. Consequently, all vectors are downloaded and queried across indexes, increasing computational requirements and potentially lengthening query times. This trade-off highlights the balance between efficient indexing and comprehensive querying for accurate results.

5 Experimental Methodology

In this section, we provide details on our serverless vector DB implementation, as well as the experimentation setup and methodology.

5.1 Prototype Implementation

We have developed a serverless vector DB prototype that leverages cloud functions (AWS Lambda) to parallelize the execution of vector DB compute services [6]. Our prototype orchestrates the invocation of stateless cloud functions and transfers data through object storage. The implementation uses Lithops [29], a serverless framework for running cloud functions in parallel in map-reduce fashion. Lithops simplifies Python cloud function development and allows seamless execution on multiple FaaS services, Kubernetes clusters, or VMs. Our prototype is highly configurable with many parameters such as the number of partitions, cloud functions for each phase, index parameters, etc. A complete list is available in the prototype repository and documentation.

Partitioning workflow. The main goal of our prototype is to evaluate different data partitioning schemes in serverless vector DBs. Irrespective of the scheme, the data partitioning process reads a dataset from object storage and stores back N partitions. To generate indexes, the data partitions are distributed across a set of functions using a Lithops `map` operation. Each function creates the corresponding index (or indexes) using Faiss [10] and uploads it to object storage. We use an Inverted File (IVF) configuration of $k = 512$ and multi-probe at 32. After extensive testing, this proved to give the best results overall for the datasets explored in this evaluation.

Query workflow. When querying the data, our prototype acts as a query coordinator and uses two Lithops `maps` to perform a map-reduce operation. Due to the statelessness of cloud functions, queries are processed in *batches*, with each Lithops operation (a set of cloud functions) handling a full batch. The `map` phase distributes the data partitions among parallel functions, each of which runs all queries on the corresponding index (or indexes) and generates partial similarity responses. If a function processes multiple partitions, it combines the partial results before passing them to the `reduce` phase. The `reduce` phase aggregates the map responses and produces the overall top-k similarity results. Finally, our prototype collects the results and computes their accuracy. This process enables efficient and scalable similarity search, leveraging the power of distributed computing and object storage.

Block-based approach. Data partitioning is applied directly on the indexing functions. Since this approach simply splits the data into chunks, the functions read the dataset from object storage with byte-range requests to get a specific partition. Indexing is then applied to each partition. For querying, the full batch of queries is sent to all parallel functions and applied to all N partitions.

Clustering-based approach. This partitioning approach requires three additional steps: (1) dataset clustering, (2) vector distribution with redundancy, and (3) partition filtering in querying.

First, clustering is executed on a VM and produces a set of N clusters $c_1, c_2, \ldots, c_N$ with centroids $C_1, C_2, \ldots, C_N$, and a label for each vector in the database that assigns it to a cluster. The baseline clustering algorithm is the Faiss K-means implementation. We also explore the balanced version [19] proposed in Vexless [32]. Using a VM for computing the clustering is the strategy also followed in Vexless and it is a favorable configuration, as it is faster and more practical than implementing this phase in a distributed approach on top of cloud functions.

After clustering, we must distribute the vectors to their corresponding partition. While Vexless does this on the same VM where clustering happens, we parallelize this step with a Lithops `map` operation on cloud functions to speed up the process. Each function reads a part of the input dataset from storage using byte ranges (like the blocks implementation) and applies the distribution logic layout in Algorithm 1. This logic includes vector redundancy, which adds boundary vectors to multiple partitions to improve search accuracy. We develop our own redundancy logic for vector redundancy because Vexless does not offer specific guidelines or code for this purpose. Our solution

Algorithm 1 Vector distribution for clustering-based partitioning.

Input: Database D of m vectors in $\mathbb{R}^n$. Clusters $c_1, c_2, \ldots, c_N$ with centroids $C_1, C_2, \ldots, C_N$, and labels for each vector in D. Percentage of redundancy threshold r.
Initialize: For each cluster c_i, initialize indexing partition I_i.
for all vector v in D **do**
  $c_h \leftarrow$ label from clustering assignment of v.
  Add v to I_h.
  for $i = 1, k$ where $i \neq h$ **do**
    if $d(v, C_i) \leq (1 + r) d(v, C_h)$ **then**
      Add v to I_i.
    end if
  end for
end for

is based on a redundancy percentage[3] r that acts as threshold on how close a second centroid must be compared to the closest for that vector to also be included in the second partition. Initially, vectors are added to the partition that K-means assigns them to.[4] Then the vector is added to other partitions if the distance to their centroid is lower than to the first one extended by r. For instance, if the clustering assigns a vector v to a cluster c_h with its centroid C_h at distance $d(v, C_h) = 1$, with $r = 5\%$ we will add v to any partition whose centroid C_i is at $d(v, C_i) \leq 1.05$.

To optimize queries, we employ a data partition filtering technique that selectively discards partitions. We can configure the system to search only on N_{search} partitions, given as a number or as a percentage of the total number of partitions N. During query coordination, we rank partitions based on the proximity of their centroid to the query vector and select the top N_{search} for searching. This process generates a mapping that determines which partitions to search for each vector in the query batch, which is then sent to the query functions for execution. Querying is aware of vector redundancy and checks for potential duplicates. Although all functions are typically spawned for each batch, the search computation is reduced by $100 - N_{\text{search}}\%$, resulting in improved efficiency.

5.2 Setup

Deployment. All experiments are run on Amazon Web Services (AWS) using a combination of AWS Lambda, EC2, and S3. In the case of our serverless prototype, the coordination runs on a `c7i.xlarge` EC2 instance. All data is stored in S3, including the datasets and the intermediate results of the processes. AWS Lambda functions are configured with 10 GiB of memory for indexing and 8 GiB for querying, which gives them 6 and 4 vCPUs, respectively, according to service documentation.[5] The indexing process is parallelized on 16 functions for all configurations, splitting partitions evenly among them. Querying uses 4 functions (or 8 in Fig. 11) in the map phase (also splitting partitions evenly) and a single one for the reduce phase. The block-based approach does not need any additional resources. For the clustering-based approach, K-means clustering runs on a `c7i.12xlarge` instance, which also acts as coordinator in these executions. Vector distribution uses 16 parallel functions (10 GiB). Datasets must be stored in an S3 bucket, while query files must be uploaded to the client EC2 instance.

The architecture of Milvus makes it impossible to run on cloud functions without considerable modifications. FaaS cannot be used to host a serverful technology due to its statelessness and a single

[3] As opposed to Vexless, which uses an arbitrary distance value.
[4] This is the closest centroid for the baseline K-means, but it could be another one in the balanced version of the algorithm.
[5] Functions have one vCPU per 1769 MiB and scale both resources proportionally [3].

function cannot fit a Milvus deployment capable of handling our selected datasets. Therefore, we deploy Milvus on `c7i.4xlarge` and `c7i.8xlarge` VMs.[6] This setup matches the CPU and memory resources of our serverless vector DB prototype, ensuring a fair and comparable evaluation. Milvus is set to use the same IVF configuration for indexing as our prototype. These experiments also use a `c7i.xlarge` instance as a client running the `vectordbbench` tool [40], developed by the same team as Milvus (Zilliztech). Specifically, we use a custom docker container image that includes the `vectordbbench` tool, all its requirements, and both the datasets and query vectors in the specific format.

Methodology. Datasets containing collections of vectors are initially stored in object storage as a single object each. All processes of a vector DB are evaluated on different number of partitions $N = \{16, 32, 64, 128\}$, and use equivalent resources in all systems, either with cloud functions or VMs. Data ingestion, partitioning, and indexing are reported aggregated as "data partitioning time" because it is the most significant part and the focus of our evaluation. All times reported include the corresponding cloud function invocation latency. Ingestion is always from object storage and equivalent for all systems. Indexing is an independent, stateless process that only depends on the size of the partitions, not the partitioning scheme. We did not find significant variation between the evaluated approaches. Reported results are averaged across ≥ 5 executions, and whiskers in plots denote standard deviation (σ).

We evaluate search accuracy using the recall metric, which measures the proximity of the response to the true neighbors of the query vector, with 100% recall indicating a perfect score. To calculate recall, we first identify the true neighbors of all query vectors using a Flat Index on the entire dataset and store them in object storage. During evaluation, each query execution is compared to these pre-computed true results to assess accuracy. For querying evaluation, we utilize a batch of 1000 queries extracted from the original query file accompanying each dataset, with each query requesting the top-10 nearest vectors.

We calculate cost based on the processing time of the experiments and the resources being utilized at each moment. We use current AWS pricing as of March 2025. For the serverless implementation, cost is the sum of the running time of all cloud functions plus invocation fees. We account the cost of VMs as the fraction corresponding to the seconds they are actively used in the experiments. Later, we also show the cost of having a serverful system running for longer periods of time, even if idle, as in a real scenario.

Datasets. We use three publicly available datasets that are commonly employed to evaluate the quality of approximate nearest neighbors search algorithms in vector DBs: (i) DEEP [39], which we use in subsets of 100k, 1M, 10M, and 100M embeddings of the Deep1B with 96 dimensions normalized with L2 distance extracted from the last fully-connected layer of a GoogLeNet [33] model trained with the ImageNet [9] dataset; (ii) SIFT [21], which consists of 10M embeddings with 128 dimensions, the Scale Invariant Feature Transform (SIFT) transforms the image data into a large number of features (scale invariant coordinates) that densely cover the image features; and (iii) GIST [24], which consists of 1M embeddings with 960 dimensions, a gist represents an image scene as a low-dimensional vector.

6 Clustering vs Block-based Data Partitioning

In the first experimental section, we aim to answer the following questions regarding data partitioning in serverless vector DBs:

[6]Experiments with larger VMs for Milvus (*e.g.*, `c7i.24xlarge` to match serverless indexing resources) suggest it underutilizes resources during indexing.

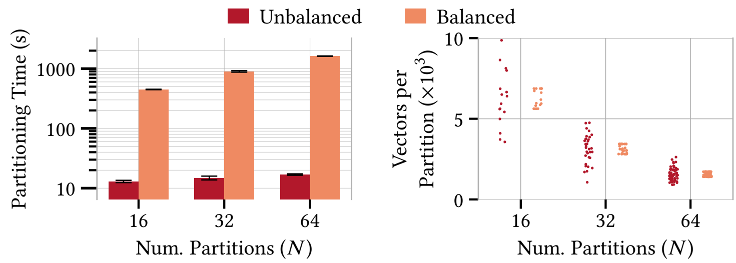


Fig. 3. Partitioning time and vector dispersion across partitions for the two K-means versions on DEEP100k dataset.

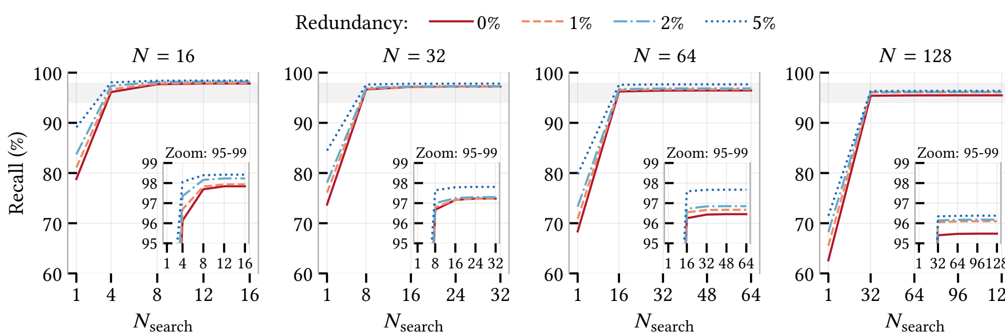


Fig. 4. Effect of redundancy (r) and N_{search} on recall depending on the total number of partitions (N).

(1) What is the cost of achieving balanced data partitions in the clustering-based approach? (Section 6.1)
(2) How do query recall and storage overhead trade off with vector redundancy in clustering-based partitioning? (Section 6.2)
(3) How do clustering-based and block-based partitioning compare in terms of data partitioning and indexing performance? (Section 6.3)
(4) What are the query performance differences between clustering-based and block-based data partitioning? (Section 6.4)
(5) Does clustering-based partitioning amortize partitioning costs via query filtering, compared to a block-based scheme? (Section 6.5)

6.1 The Cost of Balanced Data Partitions

As a representative of clustering-based data partitioning for serverless vector DBs, Vexless emphasizes the need for balanced data partitions to prevent straggler cloud functions. To this end, it proposes a balanced K-means algorithm that maintains near-equally-sized vector partitions. We analyze the cost of keeping balanced data partitions by deploying two clustering algorithms in our prototype: unbalanced K-means (Faiss default implementation) and balanced K-means [19]. The latter formulates the cluster assignment step as a Minimum Cost Flow linear network optimization problem.

First, we focus on the data partitioning and indexing cost for both K-means versions. Fig. 3 (right) shows the number of vectors per partition in both cases. Naturally, the balanced K-means exhibits

Table 2. Query performance comparison for the two K-means versions on DEEP100k dataset (single batch of 1000 queries).

Parameters		Balanced			Unbalanced		
N	N_{search}	Time (s)	$\pm\sigma$	Recall	Time (s)	$\pm\sigma$	Recall
16	1	7.103	0.924	71.30	7.491	1.791	70.68
16	4	6.716	0.031	92.55	6.742	0.026	92.97
16	8	6.712	0.026	95.01	6.789	0.048	95.37
16	12	6.771	0.026	95.49	6.779	0.066	95.64
16	16	6.761	0.048	95.52	6.825	0.077	95.65
32	1	7.095	0.874	63.54	7.118	0.923	65.59
32	8	6.766	0.049	94.35	6.750	0.031	94.75
32	16	6.772	0.036	95.64	6.823	0.036	95.90
32	24	6.856	0.027	95.81	6.860	0.062	96.05
32	32	6.934	0.048	95.82	7.128	0.343	96.05
64	1	7.127	0.904	60.54	6.708	0.029	60.43
64	16	6.815	0.065	96.44	7.247	0.888	96.34
64	32	7.699	0.993	97.03	8.315	0.976	96.97
64	48	8.811	0.480	97.12	9.371	1.706	97.03
64	64	9.061	0.425	97.13	10.287	2.169	97.06

a significantly lower dispersion of vectors per partition (*e.g.*, $\sigma = 0.541 \times 10^3$ for 16 partitions) compared to unbalanced K-means (*e.g.*, $\sigma = 1.778 \times 10^3$ for 16 partitions). However, Fig. 3 (left) also shows the differences in computational complexity related to partitioning and indexing the DEEP100k dataset for unbalanced ($O(nc)$) and balanced K-means ($O((n^3c + n^2c^2 + nc^3)\log(n + c))$) algorithms. Visibly, using the balanced version of K-means incurs from 35× up to 96× higher partitioning time, mostly due to the computation of centroids. We could not experiment with larger datasets using the balanced K-means version due to the growing clustering times.

One could think that higher partitioning and indexing cost may be linked to significant advantages in query performance. In Table 2, we observe that the balanced K-means algorithm outperforms the unbalanced version in terms of query time, with an average reduction of 2.6% across all experiments, and a maximum reduction of 13.5% for $N = 64$ and $N_{search} = 64$. In terms of recall, the balanced K-means algorithm achieves an average increase of 0.3% across all experiments, with a maximum increase of 0.8% for $N = 16$ and $N_{search} = 1$. The standard deviation of query times is also halved on average for the balanced K-means algorithm, indicating more consistent performance. However, such advantages seem modest compared to the cost related to data partitioning and indexing. This is especially true when considering large and/or dynamic datasets that require continuous indexing activity.

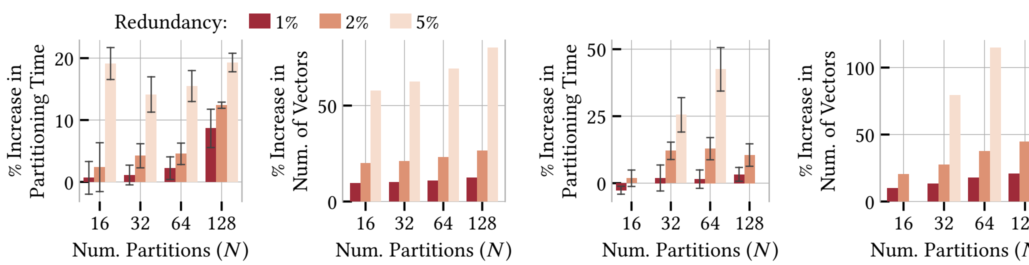
Conclusion. Balanced clustering algorithms are costly to compute and offer modest query gains, making them unsuitable for efficient dynamic dataset partitioning in serverless vector DBs.

6.2 The Effect of Vector Redundancy

Vexless contributes a vector redundancy mechanism to mitigate loss in query recall when filtering data partitions according to the input vector distance to centroids. Next, we provide an evaluation of the effect of incorporating vector redundancy. The vector redundancy implementation details can be found in Section 5.1.

Table 3. Impact of vector redundancy (r) on the vectors per data partition standard deviation (σ) for DEEP100k dataset.

K-means version	**Vector redundancy (r)**	**Standard deviation (σ)**		
		$N = 16$	$N = 32$	$N = 64$
Unbalanced	$r = 0\%$	1778	903	378
Balanced	$r = 0\%$	541	264	138
Balanced	$r = 5\%$	1491	1792	660



(a) DEEP10M dataset (b) GIST1M dataset

Fig. 5. Percentage of increase in partitioning time and stored vectors for different r values with respect to no redundancy.

Retaking the discussion on partition load balancing, Table 3 shows the impact of vector redundancy (r) on the dispersion of vectors per data partition (σ). Visibly, adding vector redundancy to the balanced K-means version re-introduces load imbalance across partitions. For example, in the DEEP dataset, setting $r = 5\%$ makes the dispersion of vectors per data partition (σ) to be up to 1.98× worse than the unbalanced K-means version ($N = 32$). This insight is important, as Vexless proposes using two techniques that seem to have conflicting outcomes. Note that given the previous results, the remainder of our analysis uses the unbalanced version of K-means.

Fig. 4 shows the recall of search queries based on the number of partitions available (N) and searched (N_{search}). Vector redundancy exhibits a 3% to 16% improvement in query recall compared to the baseline (*i.e.*, no redundancy) when searching in the closest data partition ($N_{search} = 1$). However, for $N_{search} = 1$, we also observe that query recall is relatively low (< 90%), which may not be precise enough for many applications. At the same time, the recall improvements of vector redundancy become less evident (< 2%) as N_{search} increases.

Interestingly, vector redundancy has additional cost in terms of data partitioning and indexing time, as well as storage overhead. Figs. 5a and 5b (left) show the relative increment in data partitioning and indexing time depending on the vector redundancy level for DEEP10M and GIST1M datasets. In case of DEEP, redundancy seems affordable up to $r = 2\%$ if $N \leq 64$ (< 5%). However, higher r or N configurations increase processing time between 9% to 19% on average. Storage overhead (right of Figs. 5a and 5b) also grows from 9% up to 80% depending on r and N. GIST, which has a higher dimensionality, suffers even more from this cost growth, reaching a 40% overhead in processing time and more than doubling stored vectors for $r = 5\%$ and $N = 64$.

Conclusion. The benefits of vector redundancy are limited to searching very few partitions (*e.g.*, $N_{search} = 1$) and still result in low query recalls (< 90%) that may not meet the needs of many

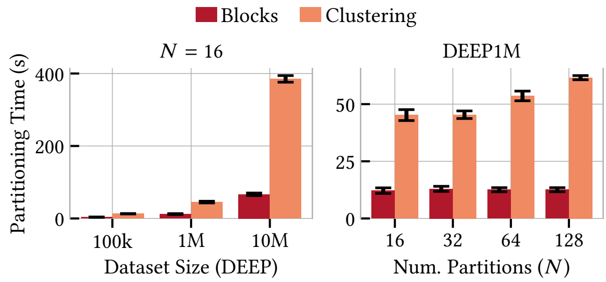


Fig. 6. Partitioning time comparison for different data volume and number of partitions (N).

Table 4. Partition size (in MiB) balance for a clustering-based approach when using the entire DEEP10M dataset (Full) or only the first 1000 vectors (1k).

Statistic	16 clusters		32 clusters		64 clusters	
	Full	1k	Full	1k	Full	1k
Min	90.00	61.00	52.00	1.30	27.00	1.00
Max	300.00	603.00	171.00	263.00	142.00	177.00
Mean	233.62	233.64	116.97	116.88	58.52	59.29
σ	51.94	87.18	28.49	61.87	21.19	39.22
CV	0.22	0.37	0.24	0.53	0.36	0.66

applications. Considering the load balancing, indexing, and storage costs, the general applicability of vector redundancy is unclear.

6.3 Clustering vs Blocks: Data Partitioning

Next, we compare the proposed block-based data partitioning with the clustering-based counterpart (unbalanced, no redundancy) in terms of data partitioning and indexing time (see Fig. 6). As described in Section 5.2, we use 16 cloud functions for indexing data partitions in both cases, whereas the clustering-based data partitioning uses an additional `c7i.12xlarge` VM for computing the centroids.

As expected, for a fixed dataset size (DEEP1M), the block-based partitioning is not sensitive to the number of partitions (see Fig. 6, right). The main reason is that block-based partitioning executes in an embarrassingly parallel fashion and can be performed with parallel byte-range reads from storage. On the other hand, the stateful nature of clustering-based data partitioning requires a complete view of the dataset and its complexity increases with the number of data partitions (*i.e.*, clusters).

However, the real limitation of clustering-based data partitioning is rendered when scaling the dataset size for the same amount of resources (Fig. 6, left). Visibly, increasing the dataset size from 100k to 1M and from 1M to 10M leads to data partitioning times 3.6× and 8.6× higher, respectively. The main reason is that the K-means clustering stage needs to load the full dataset in a single VM—not in parallel—and perform an increasingly expensive computation with dataset size. Conversely, for block-based data partitioning, partitioning time scales linearly with data volume for the same amount of resources. This is because each cloud function has more data to index in each block.

Lastly, we want to reinforce the observation that clustering-based partitioning is inherently unsuitable for dynamic data ingestion. Clustering algorithms operate on a static dataset to generate

Table 5. Query recall comparison of block-based (B) versus clustering-based (C) data partitioning (DEEP10M dataset).

	Num. Partitions (N)							
	16		**32**		**64**		**128**	
N_{search}	**B**	**C**	**B**	**C**	**B**	**C**	**B**	**C**
25%	99.24	96.13	99.26	96.67	99.44	96.25	99.30	95.40
50%		97.69		97.16		96.43		95.47
75%		97.84		97.23		96.45		95.48
100%		97.84		97.23		96.45		95.48

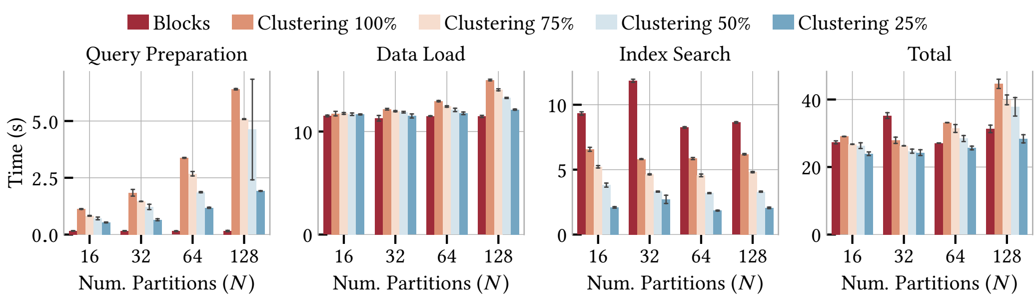


Fig. 7. Querying time comparison of block-based versus clustering-based data partitioning for different number of partitions (N) and N_{search} at 100%, 75%, 50%, and 25%. Besides the three phases shown, the total time includes function invocation overhead and the reduce operation, which vary minimally and, aggregated, add ≈6 s on average.

partitions. When new data arrives after the initial clustering, there are only two options: i) recompute the clustering to include the new data, or ii) continue using the existing partitioning. The former is computationally expensive, as it requires reprocessing the entire dataset and temporarily halting database operations. The latter leads to increasingly unbalanced partitions over time, degrading both performance and accuracy. Table 4 illustrates the latter issue using the DEEP10M dataset. We compare partition balance when clustering is computed on the full dataset versus only the first 1000 vectors. The results show that using a small subset for clustering significantly increases imbalance, raising the coefficient of variation by 1.7× to 2.2×. This negatively impacts query latency and recall. In contrast, block-based partitioning is well-suited for dynamic ingestion. New data can be incrementally added by splitting it into fixed-size blocks, without requiring global reorganization.

Conclusion. Block-based data partitioning is more efficient and scalable than clustering-based partitioning, especially as dataset size and number of partitions increase.

6.4 Clustering vs Blocks: Query Performance

In this section, we compare the implications of data partitioning on query performance: query recall (Table 5) and query times (Fig. 7).

Table 5 shows the query recall comparison between block-based and clustering-based data partitioning. We observe that the recall of the block-based scheme consistently outperforms clustering-based partitioning by 1.4% to 3.9% for different values of N and N_{search}. However, these query recall differences are not very significant, even for low values of N_{search}. This indicates that data filtering

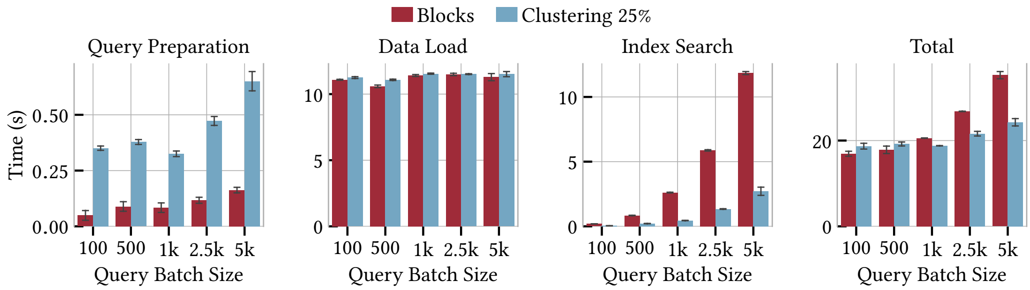


Fig. 8. Querying time comparison of block-based versus clustering-based (N_{search} = 25%) data partitioning for different query batch sizes, using the DEEP10M dataset with 32 partitions. Besides the three phases shown, the total time includes function invocation overhead and the reduction operation, which vary minimally and, aggregated, add ≈6 s on average.

in queries can be effectively leveraged while maintaining acceptable query recall. Interestingly, when $N = N_{\text{search}}$, the query recall of clustering-based data partitioning is slightly lower than the block-based scheme. This may be due to the interplay of vector distribution with IVF indexes in our prototype. To inspect this, we reproduced the experiment with HNSW indexes (as in Vexless) obtaining similar results (*i.e.*, block-based partitioning shows better recall than the clustering-based scheme by 0.09% to 3.25%).

Fig. 7 provides a breakdown of query latency in our prototype for both clustering-based and block-based data partitioning schemes. Interestingly, data partitioning has an impact on the query phases of a serverless vector DB.

The `preparation` phase sets up the job, which for clustering-based partitioning involves selecting the right partitions to query based on the input vectors, which adds overhead. The `search` phase executes vector search in the cloud functions for each data partition. The data filtering in the clustering-based approach has the largest impact here. The `data load` phase retrieves data partitions and the query batch file. This is constant in all cases because all partitions are required for any query batch. The times to invoke functions and execute the reduce operation are not differentiated in the plot, but contribute to the total time. These times are constant in all configurations. In this experiment, loading the data dominates the total time, resulting in similar performance for both approaches. Specifically, our prototype exhibits query times up to 16% faster using block-based compared to clustering-based partitioning. The results are best for clustering when using 32 partitions, where it improves block-based query times by 9.47%.

The advantages of clustering-based partitioning primarily impact index search time. Query performance improvements are visible only when this phase dominates querying times. To illustrate this, we evaluated query batches ranging from 100 to 5000 vectors. Fig. 8 shows that clustering increases preparation time with larger batches, while data loading remains stable. Although search time grows in both approaches due to higher workload, clustering benefits more from partition filtering, yielding an overall performance gain of 31.18% over block-based partitioning at 5k vectors. However, such large batches may be impractical in real-world scenarios.

Conclusion. The execution complexity in clustering-based partitioning prevents it to reduce query times in a serverless vector DB, even with query filtering, unless using large query batches.

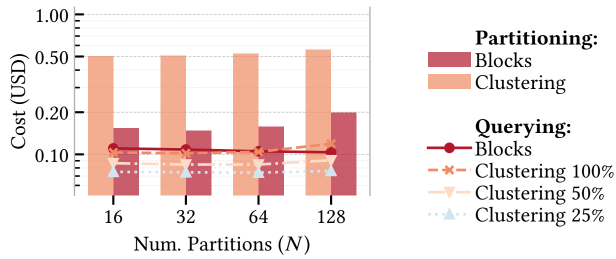


Fig. 9. Total indexing and querying costs of clustering-based and block-based data partitioning with 10 batches of 5000 queries (DEEP10M dataset).

6.5 Clustering vs Blocks: Cost Analysis

Next, we focus on understanding the partitioning and querying costs related to applying clustering-based and block-based data partitioning in a serverless vector DB. It is important to note that, due to using stateless FaaS, queries are executed in batches. Thus, query costs are calculated per batch (not individual queries).

In terms of data partitioning and indexing, Fig. 9 shows that the longer processing times of K-means clustering, plus the additional VM needed, incur a 2.82× to 3.44× increase in partitioning cost.[7] Note that we evaluate the partitioning and indexing of a static dataset. If we consider dynamic data, clustering-based partitioning cost would increase due to the re-processing of existing data.

Notably, our prototype reveals that query cost depends on the batch size. For batches of ≤ 1000 vectors, clustering-based data partitioning does not offset its own overhead, even with per-query data filtering. This aligns with previous results (Section 6.4). Fig. 9 shows the cost for batches of 5000 vectors, where the effect of partition filtering is most pronounced (1.6× improvement with 32 partitions and $N_{\text{search}} = 25\%$). Interestingly, the cost reduction from clustering becomes less significant compared to the block-based approach as the number of partitions increases. This observation highlights the trade-off between query cost, data filtering, and query latency in a serverless vector DB.

Conclusion. Clustering-based partitioning incurs significantly higher indexing cost than the block-based scheme. It offers no query cost benefits for small batches (≤ 1000 vectors), even with data filtering. For large batches, it can reduce search cost through partition filtering, but gains depend on batch size and configuration.

7 Milvus vs Block-based Serverless Vector DB

In this section, we compare our proposed serverless vector DB prototype ("SVDB" for short) with block-based data partitioning against a popular serverful vector DB system: Milvus. In particular, the following experiments aim to answer the following questions:

(1) How does vector indexing with SVDB compare to Milvus? (Section 7.1)
(2) How does querying with SVDB compare to Milvus? (Section 7.2)
(3) How does SVDB improve cost compared to Milvus? (Section 7.3)
(4) How does SVDB scale with data volume? (Section 7.4)

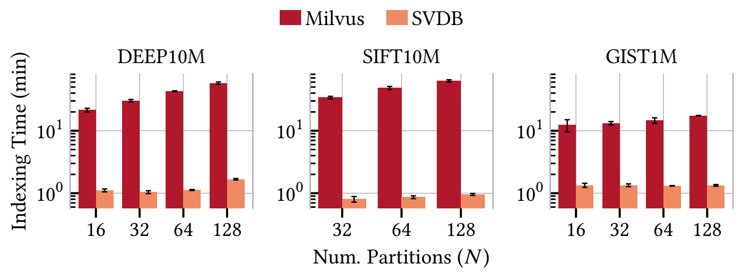


Fig. 10. Partitioning and indexing time for different datasets on Milvus and SVDB.

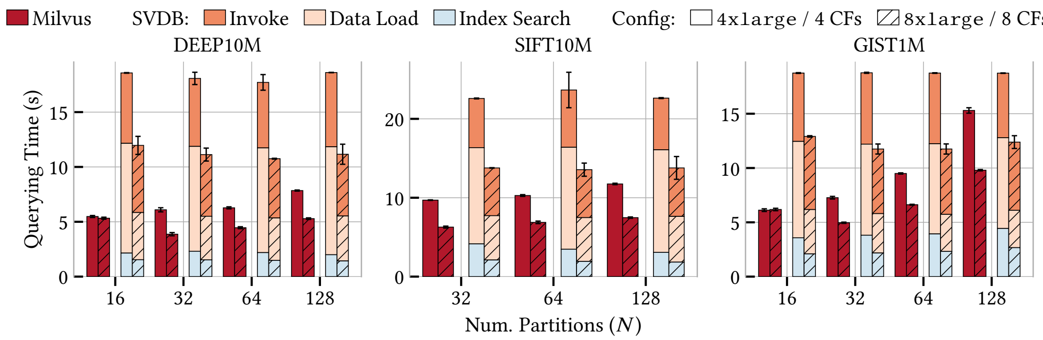


Fig. 11. Querying times for 3 datasets on Milvus and SVDB. The plot splits the time of SVDB into cloud function invocation overhead (Invoke), index downloading (Data Load), and query execution (Index Search). Milvus has the query node running with the data loaded.

7.1 Partitioning and Indexing Performance

Next, we compare the data partitioning/indexing performance in Milvus and SVDB. To this end, Fig. 10 shows the processing time of both systems for multiple datasets and partition numbers (N).

Visibly, SVDB indexes all three datasets 9.2× to 65.6× faster than Milvus. This is because SVDB fully exploits the parallelism of cloud functions. In contrast, Milvus does not parallelize the ingestion of a static dataset, resulting in under-utilization of available resources. Note that we experimented with deploying Milvus on different VM sizes (*e.g.*, `8xlarge`, `4xlarge`), but observed similar partitioning performance results. This may indicate some internal limitation in the indexing implementation of the system. Moreover, SVDB partitioning time is not sensitive to the number of partitions. Instead, Milvus processing time increases with the number of partitions.

Conclusion. SVDB achieves faster vector partitioning and indexing compared to Milvus for an equivalent amount of resources.

7.2 Query Performance

In this section, we evaluate the query performance of Milvus and SVDB in terms of querying time (Fig. 11) and recall (Table 6). As in the previous section, we evaluate query performance executing query batches (1000 vector queries/batch). For context, querying time reported for Milvus implies that the deployment is already set up and the data loaded into memory. However, reaching this state takes Milvus over 45 s which are not accounted in our results.

[7] Based on on-demand pricing; spot instance rates still lead to similar conclusions.

Table 6. Recall of top-10 similarity searches for a batch of 1000 queries in Milvus and SVDB.

Num. Partitions		16	32	64	128
DEEP	Milvus	99.27	99.43	99.38	99.28
	SVDB	99.24	99.26	99.44	99.30
SIFT	Milvus	-	99.80	99.70	99.60
	SVDB	-	99.37	99.41	99.50
GIST	Milvus	98.40	98.70	99.20	99.70
	SVDB	98.56	98.64	98.92	99.33

Table 7. Total cost of indexing and querying on Milvus and SVDB for the DEEP10M dataset across varying partition counts ($N = \{16, 32, 64, 128\}$, aggregated). Results for SIFT10M and GIST1M are similar. Q-Dense denotes 10 consecutive batches of 1000 queries; Q-Sparse-1 and Q-Sparse-24 spread the same batches over 1 hour and 24 hours, respectively.

	Indexing	**Q-Dense**	**Q-Sparse-1**	**Q-Sparse-24**
Milvus	\$10.71	\$0.07	\$1.43	\$34.39
SVDB	\$0.66	\$0.48	\$0.48	\$0.48

Fig. 11 compares the querying time in Milvus and SVDB for two equivalent resource configurations (*i.e.,* `4xlarge`/`8xlarge` VMs and 4/8 cloud functions). As expected, Milvus offers times 1.22× to 3.38× faster than SVDB. That is, Milvus is continuously running as a serverful service with the data loaded in memory, whereas SVDB requires to start the functions and load data on each query batch. We also observe that, in both systems, adding more resources reduces querying time. This implies that they are able to parallelize the execution of queries and fully utilize the underlying resources.

Inspecting the latency breakdown, the `index search` phase of querying in SVDB is faster than Milvus. However, querying also requires coordinating cloud functions, which is part of the `invoke` phase overhead. While part of this overhead is also present in Milvus for coordinating the queries, SVDB introduces additional function invocation latency. The `data load` phase is exclusive to SVDB. This overhead can be improved with stateful FaaS services, as proposed in Vexless [32]. Finally, Table 6 shows that query recall is equivalent in both systems,[8] ensuring accurate vector searches.

Conclusion. Querying time in SVDB is slower than Milvus due to the expected overhead in function invocation and data loading. Query recall is virtually the same in both systems.

7.3 Cost Analysis

Next, we focus on the economic cost of Milvus and SVDB. Table 7 shows that the indexing of the DEEP10M dataset is 16.2× cheaper in SVDB (\$0.66) compared to Milvus (\$10.71). A reason is that Milvus does not parallelize data indexing irrespective of the VM size. This induces longer processing time that translates into monetary cost.

Querying is more cost-effective on Milvus only if queries are executed as a dense workload (\$0.07 versus \$0.48 for running 10 batches of 1000 queries back to back). However, a serverful vector DB must always be running, leading to higher cost than a serverless solution for sparse workloads. For instance, if the 10 batches of queries are spread over an hour (Q-Sparse-1 in Table 7), Milvus costs

[8] Note that SIFT has higher dimensionality compared to DEEP and cannot be processed with 16 partitions, so the experiments start at 32 for this dataset.

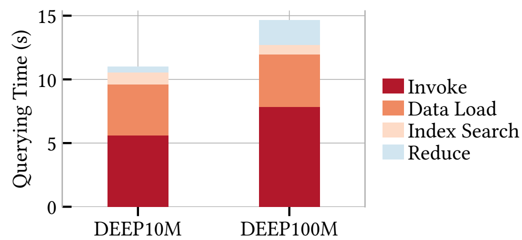


Fig. 12. Querying time breakdown for DEEP10M (32 partitions in 8 cloud functions) and DEEP100M (320 partitions in 80 cloud functions).

Table 8. Cost comparison for DEEP10M and DEEP100M for total partitioning and querying with 10 batches of 1000 queries.

Dataset Size	Partitioning Cost	Querying Cost
DEEP 10M	\$0.1477	\$0.0527
DEEP 100M	\$1.50	\$0.52

\$1.43, while SVDB remains at \$0.48. This cost difference increases with even sparser workloads. Also, the startup time for a Milvus deployment is much longer than for cloud functions ($\approx$ 45 seconds versus $\approx$ 2 seconds), making it impractical to start dynamically like SVDB, as it would severely impact query latency.

Conclusion. Compared to Milvus, SVDB enables faster indexing and on-demand query function allocation. This results in better cost-effectiveness, especially for sparse workloads.

7.4 Scalability

Finally, we aim to evaluate the scalability of SVDB, both in terms of data partitioning and as a system. To this end, we run both indexing and querying for two subsets of the DEEP1B dataset, containing 10M and 100M vectors. Accordingly, we also increase the amount of resources by 10× to process the latter. Specifically, we create 32 and 320 data partitions, indexed on 16 and 160 cloud functions, and use 8 and 80 functions for querying. Therefore, each partition is the same size in both configurations, and each function processes the same amount of data.

As expected, partitioning time is equal in both cases ($\approx$ 55 seconds) because it is an embarrassingly parallel process. Specifically, partitioning and indexing the DEEP100M dataset is about a second slower due to the overhead of invoking more functions. Fig. 12 presents a breakdown for the querying phase. The plot shows that loading the indexes and searching takes the same time in both cases, demonstrating the scalability of the task. As expected, the overhead of invoking and managing more functions is higher (40%) and reduce time for collecting the results also increases (4×). The latter aspect can be explained because Lithops by default uses a single reduce function [29]. This implementation limitation can be solved by using multiple reducers.

Table 8 compares execution costs. The data partitioning process incurs a 10× higher cost due to identical execution time but a tenfold increase in resource usage. Querying scales similarly, as only the invocation and reduction phases grow—both of which have minimal impact on overall cost.

Conclusion. Our serverless vector DB with block-based data partitioning can scale the resources to arbitrarily large dataset sizes.

8 Related Work

Vector DBs, such as Pinecone [28], Weaviate [36], and Milvus [15, 35], have gained significant attention in recent years due to the increasing demand for efficient and scalable similarity search in various applications [16], including natural language processing [27], image recognition [17], and recommendation systems [38]. Nevertheless, most distributed vector DBs rely on traditional serverful architectures, which can be limiting when handling sparse and bursty workloads. The emergence of serverless vector DBs is a relatively recent development, and as such, none of the recent surveys in the field have provided specific coverage of this new family of systems [25, 26, 30]. This paper aims to provide a timely and specific overview of the architecture of serverless vector DBs, including a systematic comparison with serverful counterparts.

The convergence of the serverless paradigm with vector DBs is the primary focus of this paper. Recently, the industry has seen the emergence of vector DB services marketed as "serverless," such as Weaviate Serverless Cloud [36], Amazon OpenSearch Service as a Vector DB [1], and Upstash [34]. However, these services primarily aim to automate the provisioning of vector DB deployments. While simplifying operational complexity, this model only partially realizes the potential of a serverless architecture. A truly serverless vector DB system involves distributing the vector DB engine across cloud functions, a concept that has only been explored in Vexless [32]: the first serverless vector DB of this kind to date.

To our knowledge, this paper is the first experimental analysis that evaluates in depth the design space of data management in serverless vector DBs, with especial emphasis on data partitioning. We believe that the observations from our analysis can help drive new generations of serverless vector DBs to achieve better performance, efficiency, and cost-effectiveness.

9 Discussion and Conclusions

Our experiments validate the hypothesis that clustering-based data partitioning is generally impractical in stateless serverless vector DBs. First, data partitioning and indexing is slower compared to our block-based scheme because it requires a clustering stage, which is stateful and cannot be efficiently parallelized. Furthermore, when revisiting the state-of-the-art method for performing clustering-based data partitioning in a serverless vector DB (Vexless [32]), we found interesting insights. For example, using a balanced K-means clustering for achieving balanced data partitions incurs partitioning times that are 35× to 96× higher than unbalanced K-means. We also found that vector redundancy—a technique to improve query recall when filtering data partitions—has limited benefits (and multiple costs) beyond querying very few data partitions, which generally leads to low recall. When executing query batches in a stateless FaaS system, clustering-based data partitioning introduces additional complexity that does not benefit from data filtering—neither in query time nor cost—unless large batches are used. Based on these observations, we conclude that block-based data partitioning is a more practical and effective way of managing large and dynamic datasets in serverless vector DBs.

As a natural next step of our analysis, we compared our serverless vector DB prototype with a popular serverful vector DB (Milvus). Our results show that our prototype achieves 9.2× to 65.6× faster data partitioning and indexing time than Milvus due to its ability to fully exploit the parallelism of cloud functions. While querying time in our serverless vector DB is slower than Milvus due to the expected overhead in function invocation and data loading, this has a direct translation into economic cost. To wit, our serverless vector DB also offers better cost-effectiveness, especially for sparse workloads, as it does not require a service continuously running like Milvus. Overall, we believe that a serverless vector DB with block-based data partitioning offers an interesting alternative to serverful vector DBs, especially when considering sparse/bursty workloads and reduced infrastructure/operational cost.

Conclusion. Serverless vector DBs are a promising architecture for managing sparse and bursty vector workloads while reducing operational cost. However, they are still in their infancy. In this paper, we provide a timely overview of this new family of systems. Additionally, we analyze a key aspect of their operation: data partitioning. Through extensive experiments, we demonstrate that the current state-of-the-art approach for data partitioning (clustering-based) has significant limitations. To address them, we propose a simple yet practical block-based data partitioning scheme. Our findings show that a serverless vector DB with block-based data partitioning is competitive compared to a serverful vector DB (Milvus) in various aspects (*e.g.*, indexing time, query recall). We hope that the insights from this work will help driving better performance and efficiency for the next generation of serverless vector DBs.

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