SIEVE: Effective Filtered Vector Search with Collection of Indexes

Zhaoheng Li*
UIUC
zl20@illinois.edu

Silu Huang
Bytedance Inc.
silu.huang@bytedance.com

Wei Ding
Bytedance Inc.
wei.ding@bytedance.com

Yongjoo Park
UIUC
yongjoo@illinois.edu

Jianjun Chen
Bytedance Inc.
jianjun.chen@bytedance.com

ABSTRACT

Real-world tasks such as recommending videos tagged *kids* can be reduced to finding *similar* vectors associated with *hard* predicates. This task, *filtered vector search*, is challenging as prior state-of-the-art graph-based (unfiltered) similarity search techniques degenerate when hard constraints are considered: effective graph-based filtered similarity search relies on sufficient connectivity for reaching similar items within a few hops. To consider predicates, recent works propose modifying graph traversal to visit only items that satisfy predicates. However, they fail to offer the just-a-few-hops property for a wide range of predicates: they must restrict predicates significantly or lose efficiency if only few items satisfy predicates.

We propose an opposite approach: instead of constraining traversal, we build many indexes each serving different predicate forms. For effective construction, we devise a three-dimensional analytical model capturing relationships among index size, search time, and recall, with which we follow a workload-aware approach to pack as many useful indexes as possible into a collection. At query time, the analytical model is employed yet again to discern the one that offers the fastest search at a given recall. We show superior performance and support on datasets with varying selectivities and forms: our approach achieves up to 8.06× speedup while having as low as 1% build time versus other indexes, with less than 2.15× memory of a standard HNSW graph and modest knowledge of past workloads.

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The source code, data, and/or other artifacts have been made available at https://github.com/BillyZhaohengLi/SIEVE-vldb25.

1 INTRODUCTION

Finding *semantically similar* items satisfying *hard constraints* is a common task. Moms may search for videos (semantic) tagged "safe-for-kids" (hard). Online shoppers may search for costumes (semantic) with a specific price range (hard) [74]. This task is called *filtered vector search*: we query similar *vectors*—encoding semantics—associated with *hard* predicates. The problem has been increasingly studied [15, 16, 21, 23, 31, 39, 44, 48, 51, 61, 66, 74] as quality vector embeddings become available via modern ML models [35, 36, 43].

Some works tackle filtered vector search by *constraining* graph-based approximate nearest neighbor (ANN) indexes for *unfiltered vector search* [17, 27, 33]: FilteredVamana interleaves graph traversal and filter evaluations; ACORN [44] induces query-time subgraphs by visiting only predicate-passing nodes. These works outperform naïve methods like *pre-filtering*, which uses a (slow) linear scan for similarity computations. Graph-based methods navigate items via edges to reach targets with a few hops. Effective filtered vector search aims to serve queries with *compact* graphs; if the property—*small world*—is lost, graph traversal will lose efficiency.

Unfortunately, **existing graph-based methods fail to offer the small-world property for low-selectivity predicates,** thus delivering poorer performance. Moreover, we cannot simply use pre-filtering as a linear scan is still too costly unless the selectivity is *too low*. This selectivity band is called the "unhappy middle" [23]. FilteredVamana aims to mitigate this by linking attribute-sharing vectors into local, dense, per-filter subgraphs, but requires restricting filter forms [21]. ACORN [44] supports general predicates at a cost: its induced subgraph can provably lose the small-world property if it becomes too sparse [4, 29, 33]. We conjecture that a single graph is insufficient for handling *all* predicates, whose support may overlap with one another in a complex way. We may need multiple graphs, each specialized for different predicate sets.

Our Goal. We aim to offer *compact* graphs for nearly all filtered queries with varying selectivities or forms by building an *index collection.* A collection is more expressive than one index. By leveraging *filter stability* in real-world filtered vector search workloads [39, 53], we can tailor indexes to observed workloads to maximize expected search quality. Each index can serve multiple predicates: a graph, e.g., built for `stars=1-3`, can also serve `stars=1` if it is *dense enough* for the sub-predicate. An index collection requires more memory than one index; yet, indexes are relatively small versus raw data, i.e., high-dimensional vectors. In our experiments, hundreds of (small) additional indexes took only as much memory as one dataset-wide index, while they boost performance significantly versus relying on one index. Our proposed index collection can succeed if it offers high-quality filtered search to nearly all queries, each with a compact graph, while being memory-efficient.

Challenge. Building an effective index collection is challenging due to conflicting goals. For construction, graphs can trade recall

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*Work done during internship at Bytedance.

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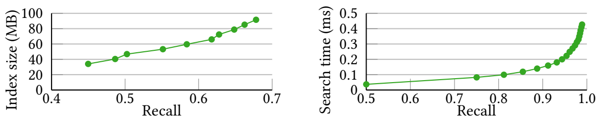
Table 1: Comparison between SIEVE (ours) and other indexing methods for filtered vector search.

Approach	Query Selectivity high	Query Selectivity medium	Query Selectivity low	Complex Filters	Potential Weaknesses
Partition-Based [23, 39]	×	✓	✓	×	Restrictive filter format
Data Attr.-aware Graphs [21, 61, 66]	✓	✓	×	×	Requires limiting data attribute cardinality (<200)
Intra-Search Filtering [44]	✓	✓	×	✓	Potentially excessive TTI (up to 219× of regular HNSW)
Exhaustive Indexing [31, 74]	✓	✓	✓	×	High memory cost, restrictive filter format
Index Collection (Ours, SIEVE)	✓	✓	✓	✓	Needs bounded extra memory and past workload (up to 2.15× of HNSW)



(a) Mem. vs. recall, 100K random vecs. (b) Time vs. recall, 100k random vecs.

Figure 1: ANN vector search trade-offs: (Left) indexes can be built with varying recall/memory trade-offs. (Right) indexes can be *over-searched* to trade slower search for higher recall.

for smaller size (Fig 1a), allowing more indexes and coverage. Yet, graphs must be dense enough for high recall. Likewise, for querying, we can trade search speed for higher recall (Fig 1b). This relationship must be quantified to find which index to use for a given query. These unique properties distinguishes our task from existing problems [49, 52]. For example, materialized view selection targets *exact* querying, whereas ANN is *approximate* with speed/recall trade-offs.

Our Approach. Our framework, called SIEVE (Set of Indexes for Efficient Vector Exploration), builds an index collection tailored to an observed query workload to maximize expected throughput with a memory budget and specified recall. Every candidate index is assigned *benefit*—its marginal performance gain when added to a collection, and memory *cost*, with which we build a collection. This approach isn't new; what's new are (1) how to estimate the benefit/cost and (2) how to serve queries with the index collection.

First, we design an analytical, predicate form-agnostic benefit/cost model capturing three-dimensional relationships among index size, search time, and recall, allowing us to find the minimal (i.e., most sparse) graph satisfying a specific recall. Since each index is smaller, more indexes are allowed within a memory budget, thus accelerating search for more predicates. Our model is based on empirical observations and existing small-world network theories [4].

Second, query serving dynamically chooses the fastest-searching index given a specific recall. This query-time selection is needed since our indexes may overlap: a query may be servable by multiple indexes. For optimal selection, we again employ our model to determine (1) which index to use, and (2) its search parameterization.

Difference from Existing Work. SIEVE significantly differs from existing vector search works (Table 1). Versus works in MV selection [2, 70], partitioning [53, 68] and query rewriting [19, 20] for exact queries, SIEVE's optimizations notably considers recall, and performs theory-driven index tuning (§4.2) and dynamic, recall-aware serving (§5.2) for desired memory/speed/recall tradeoffs.

Contributions. We propose SIEVE, an indexing framework for filtered vector search (§3) with the following contributions:

- **Index Selection:** We introduce a three-dimensional cost model for evaluating the search speed, recall, and memory cost of vector search strategies, which we use to jointly perform index selection and parameterization under bounded memory. (§4)
- **Query Serving:** We utilize our derived cost model to derive a dynamic search strategy that selects the most efficient serving method and parameterization at any target recall. (§5)
- **Effective Filtered Vector Search**: We show via experimentation that SIEVE achieves up to 8.06× speedup over existing indexes with <2.15× memory of a standard HNSW and modest past workload knowledge on diverse query filter formats. (§7)

2 MOTIVATION

SIEVE builds on HNSW[33], a performant unfiltered vector index[12, 73]. We describe HNSW (§2.1), how works have (ineffectively) extended it to filtered search (§2.2), and our ideas for building and using an HNSW index collection for effective filtered search (§2.3).

2.1 HNSW Graph

HNSW is a graph-based vector index [33] which combines the idea of *small-world graphs* [4] and skip-lists [65] to create a multi-layer graph structure for effective similarity search on vector datasets.

HNSW Graph Structure. An HNSW graph consists of multiple layered small-world graphs [4]. The topmost (entry) layer contains the fewest vectors and features long edge lengths, facilitating long-range vector space travel; the bottom (base) layer contains all vetors and features short edge lengths, representing local neighborhoods. HNSW graphs are built by incrementally inserting vectors: each vector is linked to a number of neighbors in each layer, controlled by a construction parameter M, which acts as an outdegree limit and ensures vectors connect to other similar vectors in each layer.

HNSW Search. Given a query vector, graph layers are traversed from top to bottom, using long high-layer links to go to neighborhoods with similar data vectors, then using short low-layer links to find top-k choices. Alg. 1 presents the per-layer search algorithm.

2.2 Existing Filtering Methods Underperform

While the original HNSW graph proposal did not consider performing filtered vector search, a number of HNSW-based filtered search methods have been proposed, which this section will overview.

Post-Search Filtering. For filtered top-k queries with selectivity sel, the graph can be over-searched for top-k/sel vectors. Non-matching results are dropped expecting that k of top-k/sel results remain: if not, another top-$2k/sel$ search is performed, and so on.

Algorithm 1: HNSW_SEARCH_LAYER

```
1  Input: query vector q, enter points ep, exploration factor ef, layer l_c
2  Output: ef closest vectors to q
3  Initialize visited set V, candidate set C, top-ef set W to ep;
4  while |C| > 0 do
5      c ← extract nearest vector in C to q
6      f ← furthest vector in W to q
7      if dist(c, q) > dist(f, q): break
8      nbrs ← neighborhood(c) at layer l_c //ACORN filters here
9      for each e ∈ nbrs do
10         if e ∈ V: continue
11         V ← V ∪ e
12         f ← furthest vector from W to q
13         if dist(e, q) < dist(f, q) or |W| < ef: then
14             C ← C ∪ e
15             W ← W ∪ e //hnswlib filters here
16             If |W| > ef: remove furthest vector from W to q
17 Return W.
```

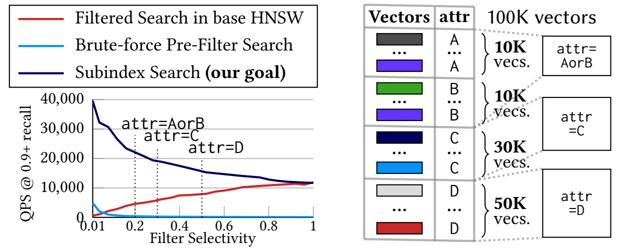
Result-Set-Filtering. hnswlib [40] evaluates the query filter during HNSW search before adding candidates into the top-k result set (line 13, Alg. 1). While this improves over post-search filtering by returning k satisfying results in one pass, each candidate still has a $(1-sel)$ chance to be rejected from the top-k set by the filter. Hence, while recall is negligibly impacted, search time scales inversely with selectivity (Fig 2a), effectively still underperforming when sel is low but with many points for pre-filter search (e.g., large datasets [8]). [1]

Other Filter Application Methods. ACORN [44] applies filtering at neighbor expansion (line 6, Alg. 1), effectively searching in an induced subgraph of satisfying vectors in the HNSW graph. However, as subgraph induction is equivalent to edge and node removal, the subgraph can lose small-world properties, notably connectivity [67], required for effective search if it is too sparse [41]; searching as is with Alg. 1 can result in early stops and low recall. Hence, ACORN modifies both HNSW construction and search, notably expanding into 2-hop neighbors to avoid subgraph sparsity. However, ACORN can still underperform when even the 2-hop subgraph is sparse. As we will show via experimentation (§7.2), result-set filtering sometimes outperforms ACORN and vice versa. SIEVE uses result-set-filtering in its HNSW indexes as it is applicable without specialized graph construction, which may incur excessive time-to-index (TTI, §7.3) and limit discussion to result-set-filtering in the following sections. However, SIEVE can also use ACORN's filtering instead given minor adjustments.

2.3 SIEVE's Intuition for Faster Search

Existing HNSW-based filtering methods underperform on "unhappy-middle" selectivities. SIEVE aims to mitigate this by workload-driven fitting of a HNSW (sub)index collection over data subsets in which these queries can be effectively served from their matching points being dense in the subindexes. As mentioned in §1, building and using HNSW graphs involves speed/recall/memory trade-offs (Fig 1); hence, SIEVE should decide both *which* and *how* to build and use the index collection; this section describes our intuitions.

[1] In particular, hnswlib, ACORN (and our work) all implement filtering via a commonly-used bitmap-based filtering method that in principle handles arbitrary predicates: it assigns IDs to inserted vectors, then computes a binary ID→{0,1} mapping from IDs of vectors that pass the filter w.r.t. scalar attributes (e.g., via an external RDBMS, §6).



(a) QPS vs. sel. on 100K-vector dataset **(b) Example Candidate Subindexes**

Figure 2: SIEVE aims to build subindexes with high relative speedup and applicability to many queries (e.g., `attr=AorB`)

Three-Dimensional Modeling. Without loss of generality, SIEVE treats recall and memory as constraints and optimizes for speed, as users often have ① bounded memory for indexing [32, 53, 54] and ② target recalls (e.g., SLOs [49, 52]). This differs from MV Selection for (exact) querying which is typically only memory-constrained; SIEVE's intuition is that with theory-driven modeling, the recall dimension can be *reduced* by reasoning *how* an index should be built (explained shortly) for different target recalls. Then, SIEVE can use established methods to choose *which* indexes to build with bounded memory to maximize serving speed. Finally, for serving, SIEVE can determine with similar modeling *which* and *how* to use built indexes for fastest search under a possibly new target recall.

How to Build Indexes? Each subindex's memory size scales linearly with the (1) indexed vector count and (2) density-controlling construction parameter M (§2.1). M can be tuned for different memory/recall tradeoffs: higher M increases both memory size and recall (from increased density) and vice versa (Fig 3a). A target recall effectively dictates the *lowest M value* each index can be built with;[2] Intuitively, smaller indexes need lower M values to reach the same target recall (e.g., Fig 2's `attr=C` requires lower M to serve queries at average x recall vs. `attr=D`, Fig 3b), which we describe in §4.2.

What Indexes to Build? SIEVE aims to build subindexes that efficiently serve (observed) queries with which alternative methods (e.g., brute-force KNN) are inefficient (i.e., *marginal benefits*). Suppose we have the base HNSW index in Fig 2b: While building subindex (`attr=D`) benefits its respective filtered query, `attr=D` has high selectivity (50%) that the base index serves it *fast enough* via result-set-filtering. In comparison, subindex (`attr=AorB`) is high marginal benefit: It serves (`attr=AorB`) significantly faster than the base index (Fig 2). Subindexes can also serve non-exact matching filtered queries: For example, (`attr=AorB`) can also serve (`attr=A`) effectively, which has high-enough (50%) selectivity in the subindex. This expands utility of subindexes like (`attr=AorB`) from applicability to other filters. We describe SIEVE's index selection in §4.3.

How to Serve Queries? SIEVE decides between indexed search or brute-force KNN when serving queries with a built index collection. A key parameter controlling HNSW indexes' search speed/recall tradeoff is the search exploration factor sef (Alg. 1): higher sef (*over-searching* the graph) trades lower speed for higher recall (Fig 3c). SIEVE will need to tune sef if the serving target recall is

[2] SIEVE optimizes for average recall as to the best of our knowledge, there exists no method that guarantees *absolute*, per-query recall, as query hardness can vary [62].

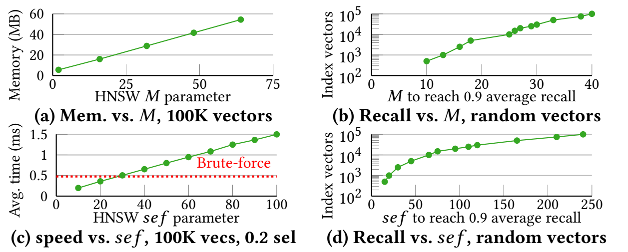


Figure 3: M and sef respectively increase the memory size and search time (Left), but smaller graphs require smaller M and sef values to reach the same recall (Right).

higher than that assumed at construction; Similar to M, SIEVE aims to use the *lowest* sef for indexed searches, and smaller subindexes also require smaller sef for the same target (Fig 3d). Then, given the best found index and sef, SIEVE evaluates whether falling back to brute-force KNN is faster (e.g., $sef > 30$, Fig 3c), which also always has perfect recall. We describe SIEVE's serving strategy in §5.2.

3 SIEVE FRAMEWORK OVERVIEW

SIEVE (Fig 4) effectively serves filtered vector queries by building and using an index collection. §3.1 describes SIEVE's index construction; §3.2 describes how SIEVE serves filtered vector queries.

3.1 SIEVE Construction

During construction, SIEVE aims to build a collection of the most beneficial HNSW subindexes given a memory budget and target recall based on the data distribution and a historical query workload.

Inputs. SIEVE takes as input (1) an attributed vector dataset—a set of vectors and their scalar attributes, (2) a historical query workload—a set of query filters with probability/frequency counts, (3) a target recall, and (4) a memory budget. Unlike some specialized indexes (e.g., CAPS [23], HQANN [66]), SIEVE does not restrict attribute or filter forms, only requiring filters to be evaluable on attributes, e.g., `A in attr` evaluates to `True` for `attr={A,B}`. (§4.1)

Cost Modeling. SIEVE models candidate indexes' memory size and serving speed given their construction with sufficient density/M to serve queries at the target recall (§2.3). It then accordingly sets up the candidates' unit (marginal) benefits for optimization. (§4.2)

Optimization. SIEVE selects the subindexes to build under the memory budget with greedy submodular optimization, prioritizing high-unit marginal benefit and/or high (re)use-probability subindexes in a manner akin to *Materialized View Selection* [5, 50, 70]. (§4.3)

Indexing. SIEVE builds the chosen subindexes over the dataset. SIEVE always includes the *base index* over the entire vector dataset in the collection, which acts as a fallback for queries that any other subindex in the collection cannot effectively handle. This design choice allows SIEVE to handle arbitrary (un-)filtered queries (§7).

3.2 Serving Queries with SIEVE

For serving, SIEVE aims to choose the optimal search method for filtered queries based on the subindexes in the built collection and (a potentially different from construction-time) target recall.

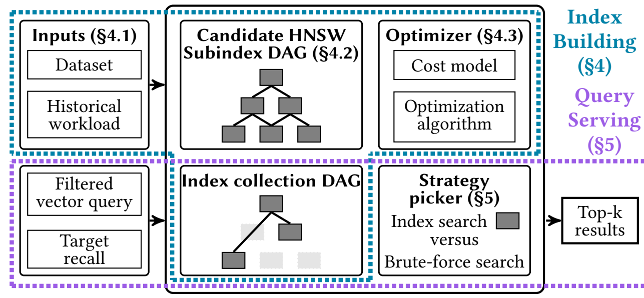


Figure 4: SIEVE framework. SIEVE fits an index collection from an observed historical workload, then serves queries strategically with the collection and other metrics.

Identifying the Optimal Indexed Search. The first, straightforward approach SIEVE uses for serving a query is with a built subindex. SIEVE finds the best subindex/sef combination for serving the query at target recall—following intuition in §2.3, preferably a small subindex in which the query is dense, using low sef. (§5.1)

Choosing Search Method. SIEVE chooses between serving the query with the best-found subindex/sef combination (with result-set-filtering if needed) or brute-force KNN. SIEVE estimates serving speed of both methods with its cost model, then chooses the faster one, analogous to *MV-aware query rewriting* [1, 57, 69]. (§5.2)

4 INDEX COLLECTION CONSTRUCTION

This section covers how SIEVE builds its index collection. We describe preliminaries in §4.1, SIEVE's cost model and optimization problem (SIEVE-Opt) in §4.2, and solution to SIEVE-Opt in §4.3.

4.1 Preliminary and Definitions

Definition 4.1. An **Attributed Dataset** is a set of n vectors $\mathcal{V} = \{v_1, ..., v_n\}$ and a set of n attribute sets $\mathcal{A} = \{a_1, ..., a_n\}$, where each a_i is an attribute value set associated with each vector $v_i \in \mathbb{R}^d$.

Fig 5 depicts an example where each a_i is a set of strings.

Definition 4.2. An **Filtered Query Workload** is pair of sets of m vectors and m filters $\mathcal{M} = \{w_1, ..., w_m\}$ and $\mathcal{F} = \{f_1, ..., f_m\}$, where f_i is the filter of query vector $w_j \in \mathbb{R}^d$ and each $f_i : \mathcal{A} \rightarrow \{0, 1\}$ is a function that maps attribute values $a_j \in \mathcal{A}$ to a binary indicator.

Each query filter f_i can be evaluated on the attributes a_j of each vector u_j: a_j *satisfies* f_i if $f_i(a_j) = 1$. For example, in Fig 5, $f_1 =$ (`A in attrs`) (shortened to `A` for brevity) evaluates to 1 on $a_1 =$ `{A,E}`, while $f_2 =$ (`D`∧`E`) evaluates to 1 on $a_2 =$ `{D,E}`.[3] We define the *cardinality* of each filter f_i as the number of dataset rows that satisfy the filter, i.e., $card(f_i) = |\{a_j \in \mathcal{A} | f_i(a_j) = 1\}|$.

Definition 4.3. A **Filtered Vector Search Problem** takes an attributed dataset $(\mathcal{V}, \mathcal{A})$, a filtered query workload $(\mathcal{M}, \mathcal{F})$, and a similarity metric $\mathcal{S}$. The output is a $|\mathcal{M}| \times k$ matrix $\mathcal{R}$ of top-k results, where each row $R_i = \{v_{i_1}, ..., v_{i_k}\}$ is the top-k closest vectors in $\mathcal{V}$ based on $\mathcal{S}$ that satisfy filter f_i, i.e., $f_i(a_{i_l}) = 1, \forall 1 \leq l \leq k$.

[3] SIEVE defines attributes, filters, and evaluations following the RDBMS model [46], where attributes are column values that filters can be applied on, e.g., `gender=female && price<20` is a filter evaluable on attributes `gender` and `price` from two different columns. We express attributes nevertheless as sets for simplicity in this paper.

Table 2: Table of Symbols

Symbols	Definition
$\{\mathcal{V}, \mathcal{A}\}$	Attributed vector dataset of N vectors
$\mathcal{H} = \{(h_1, c_1)...\}$	Set of weighted observed historical query filters
B	SIEVE indexing memory budget
$card(f) \to [0, N]$	Cardinality of filter f in the dataset
M_∞	M of the root index I_∞ representing build-time target recall
$\mathcal{M}_\downarrow(I_h) \to \mathbb{Z}^+$	Subindex M downscaling function
$C(I_h, f) \to \mathbb{R}^+$	Indexed search cost for query with filter f in subindex I_h
$C_{bf}(f) \to \mathbb{R}^+$	Brute-force search cost for query with filter f over dataset
$S(I_h) \to \mathbb{R}^+$	In-memory size of subindex I_h
I_∞	Root index constructed over entire dataset
γ	Brute-force scaling constant
$cor(w, f, h)$	Query correlation of w given filter f and subindex I_h
$\mathcal{I} := \{I_{h_1}, ..., I_{h_i}\}$	Index collection of i subindexes
$C(\mathcal{I}, f) \to \mathbb{R}^+$	Cost of best possible search for query filter f given $\mathcal{I}$
sef_∞	sef of the root index I_∞ representing serving-time target recall
$\mathcal{S}_\downarrow(I_h) \to \mathbb{Z}^+$	Subindex sef downscaling function

A solution $\mathcal{R}$'s quality is commonly evaluated via ① *recall*=$\frac{|\mathcal{R}\cap\mathcal{R}^*|}{m\cdot k}$ where $\mathcal{R}^*$ is the actual top-k, and ② *latency*=$\frac{t}{m}$ or *Queries-per-second* (QPS, $\frac{m}{t}$), where t is the total search time. Effective filtered search can be achieved by serving queries with *(sub)indexes* (§2.3):

Definition 4.4. A **Subindex** I_{f_i} is an index constructed over a subset of data points that satisfy filter f_i, i.e., $\mathcal{V}_{f_i} := \{v_j | f_i(a_j) = 1\}$.

For example, the subindex I_A only indexes the first three rows in Fig 5. The *base index* indexing all rows can be expressed as $\mathcal{I}_\infty$, where ∞ is a 'dummy filter' that always evaluates to 1. Given a subindex I_{f_i}, it ① can be used to evaluate a filtered query (w_j, f_j) with serving cost $C(I_{f_i}, w_j, f_j) \to \mathbb{R}+$, and ② has a (in-memory) size $S(I_{f_i}) \to \mathbb{R}+$, for which we perform cost modeling in §4.2.

Definition 4.5. A **Historical Query Workload** is a query filter tally $\mathcal{H} = \{(h_1, c_1), ..., (h_l, c_l)\}$ where filter h_i has occurred c_i times.

Fig 5 depicts a workload with 6 unique filters. SIEVE assumes *filter stability* [39, 53] for anticipated future workloads: the future workload's filter distributions $\mathcal{F}$ follow those observed in $\mathcal{H}$. SIEVE's definitions only require all query filters to be evaluable on all dataset attributes, hence can inherently handle arbitrarily complex predicates and attributes. However, the specific predicate and attribute forms may affect SIEVE's optimization quality (§6) and other nuances such as adaptability to workload shifts (§7.7.2).

4.2 SIEVE-Opt: Problem Setup

This section defines SIEVE's problem: candidate subindexes for construction and their benefits/costs (i.e., index speed/size when serving queries at target recall), then formalizes SIEVE-Opt.

Candidate Subindex DAG. There are exponentially many possible subindexes for an attributed dataset. Besides the base index, SIEVE limits its problem space by only considering subindexes corresponding to filters in $\mathcal{H}$. For example, in Fig 5, I_A is a candidate while I_B is not. The YFCC dataset, with 100K queries, produces 24K candidates [8]. For optimization, SIEVE organizes candidates in a directed acyclic graph (DAG) where edges represent subsumption (e.g., $(I_{\mathsf{A}\vee\mathsf{B}}, I_\mathsf{A})$ in Fig 5),[4] which enables computing of subindex unit marginal benefits (described in §4.3).

[4] SIEVE currently defines and evaluates subsumption logically following established theoretical work [22]. However, other definitions can potentially also be used (§6).

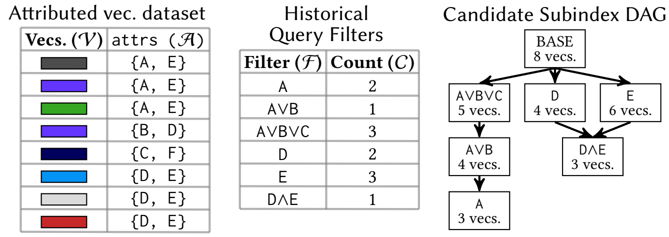


Figure 5: Example attributed vector dataset, historical workload, and SIEVE's corresponding candidate subindex DAG.

Defining Target Recall. Without loss of generality, SIEVE takes in a base M_∞ value for calibrating the query serving target recall, defined as the average recall of searching in the base index I_∞ built with $M = M_\infty$ and $sef = k$, where k is the number of results to return and the lower bound of sef (i.e., no over-searching).

Indexing Parameters at Target Recall. SIEVE aims to build subindexes with sufficient parameters to serve queries at target recall (§2.3). Either M (for construction) or sef (for serving) can be tuned to achieve this; however, for construction, SIEVE assumes that all subindexes will use a uniform minimum $sef = k$ and tunes only M: this is because $sef = k$ is the lowest-recall and fastest search parameterization; if SIEVE's subindexes (with sufficient M) serves queries at target recall with $sef = k$, SIEVE's index collection can too; hence, SIEVE can then evaluate subindexes based on highest potential speedups. Versus M_∞ used for I_∞, candidate subindexes $S(I_h)$ are evaluated and built with downscaled M (Fig 3b):

Definition 4.6. The *Subindex M downscaling function* $\mathcal{M}_\downarrow$ takes in a subindex I_h, and returns the M value required to build I_h with to achieve at least the same average query serving recall as the base index I_∞ built with M_∞: $\mathcal{M}_\downarrow(I_h) := \frac{M_\infty log(card(h))}{log(N)}$.

SIEVE's intuition for $\mathcal{M}_\downarrow$ is that HNSW graph layers (§2.1) are based on Delaunay graphs [14], which requires suitable node degrees ($\Theta(logN)$) for effective search. Hence, each subindex I_h's M should match its size's logarithm: $\mathcal{M}_\downarrow(I_h) \propto log(card(h))$. For example, if I_∞ in Fig 5 is built with $M_\infty = 32$, subindex I_D would be built with $M_\mathsf{D} = \frac{32log(4)}{log(8)} \approx 21$. SIEVE will evaluate the memory size (explained shortly) of each candidate subindex I_h assuming construction with $M = \mathcal{M}_\downarrow(I_h)$ and $sef = k(= 1$, for discussion).

Subindex Memory Size. Each subindex I_h has a memory size proportional to indexed points $card(h)$ and M: $S(I_h) = M \cdot card(h)$ (Fig 1a). For example, I_D indexing 4 points built with $\mathcal{M}_\downarrow(I_h) = 21$ has size 84. Notably, due to M's effect on memory, SIEVE's M downscaling ($\mathcal{M}_\downarrow$) saves memory for smaller subindexes, enabling more subindexes to be built under the same memory constraint versus a naive method that builds all subindexes with a uniform M_∞ (§7.6).

Subindex Search Cost. SIEVE defines subindexes' search costs as their serving latency:

Definition 4.7. The *Indexed Search Cost Function* (with result-set-filtering, §2.2) C takes a subindex I_h, sef, and a filtered query (w, f), and returns the expected latency of using I_h with sef to serve (w, f): $C(I_h, sef, w, f) := log(card(h)) \cdot sef \cdot (\frac{card(h)}{card(f)})^{cor(w,f,h)}$.

Table 3: SIEVE's Cost Model for Filtered HNSW Search

Operation	Cost
Brute-force search	$C_{bf}(f) = \gamma card(f)$
Indexed Search	$C(I_h, sef, w, f) = log(card(h)) \cdot sef \cdot (\frac{card(h)}{card(f)})^{cor(w,f,h)}$ if h subsumes f else ∞
Index Size	$S(I_h) = M \cdot card(h) = \frac{M_\infty log(card(h))}{log(N)} card(h)$

SIEVE bases C on that HNSW's search time scales logarithmically [33] with graph size and linearly with sef [33], and there is $\frac{card(h)}{card(f)}$ probability that a data vector similar to the query vector w passes the filter with result-set-filtering (§2.2), scaled by *query correlation*—$cor(w, f, h)$—ratio of average distance from w to points that satisfy f in I_h versus non-satisfying points [44].[5] Positive correlation ($cor(w, f, h) < 1$) improves query performance, mitigating low selectivity's effects as satisfying vectors are reached faster. Conversely, negative correlation ($cor(w, f, h) > 1$) amplifies low selectivity's impact and increases query cost. SIEVE assumes constant correlation across all subindexes and filters, i.e., $cor(w, f, h) == c$, and for discussion, set $c = 1$ and simplify $C(I_h, sef, w, f)$ as $C(I_h, f)$ (as sef is also assumed to be fixed at 1) in this section. For example, in Fig 5, serving a query with filter A with $I_{A\vee B}$ incurs $\frac{4log(4)}{3}$ cost. SIEVE constrains for simplicity that a subindex I_h can only serve a query with filter f if h subsumes f; otherwise, $C(I_h, f) = \infty$. [6]

Brute-force Search Cost. Any query (w, f) can be served via brute-force KNN, performing distance computations between w and all vectors in $\{\mathcal{V}, \mathcal{A}\}$ that satisfy f, i.e., $\mathcal{V}_f := \{v_i | f(a_i) = 1\}$. This trivially incurs cost $C_{bf}(f) = card(f)$ linear to the cardinality.

Aligning Search Costs. The alignment between indexed and brute-force search costs is influenced by factors such as distance function implementation [11] and index memory access patterns [18]. Hence, SIEVE scales the brute-force search cost C_{bf} with a constant $\gamma \in \mathbb{R}+$ for alignment: SIEVE compares C with $\gamma \cdot C_{bf}$ when evaluating indexed versus brute-force search. For illustration purposes, however, we assume $\gamma = 1$. The aligned costs allow us to define the cost of the *best serving method* for a query (w, f) given an index collection $\mathcal{I}$:

Definition 4.8. The collection query serving cost function C takes in a subindex collection $\mathcal{I} := I_{h_1}, ..., I_{h_x}$ and a filtered vector query (w, f), and returns the cost of the *best possible serving strategy* given $\mathcal{I}$: $C(\mathcal{I}, f) := min(C_{bf}(f), min(\{C(I_h, f) | I_h \in \mathcal{I}\})$.

$C(\mathcal{I}, f)$ represents the lower cost of ① brute-force KNN and ② searching with the smallest subindex subsuming (w, f) in $\mathcal{I}$: if $\mathcal{I}$ is the entire DAG in §4.2, $C(\mathcal{I}, \mathsf{A}) = log(3)$ as it is best served by its corresponding subindex I_{A}, while $C(\mathcal{I}, \mathsf{F}) = 1$, as its best indexed search (with I_∞) costs $8log(8) \div 1 \approx 16.6$, more than brute-force KNN (1). With the collection serving cost $C(\mathcal{I}, f)$ and index size $S(I_h)$, SIEVE's optimization problem, SIEVE-Opt, can be defined:

Problem 1. SIEVE-Opt

Input: *(1) Attributed Vector Dataset* $\{\mathcal{V}, \mathcal{A}\}$
(2) Historical Workload Distribution $\mathcal{H} = \{(h_i, c_i)\}$
(3) M_∞ *representing target recall*
(4) memory budget for subindex collection B

Output: *(1) A subindex collection to construct* $\mathcal{I} := \{I_{h_{i_1}}, ..., I_{h_{i_x}}\}$

Objective function: *Minimize collection query serving cost over historical workload* $C(\mathcal{I}, \mathcal{H}) = \sum_{i=1}^{|\mathcal{H}|} c_i \cdot C(\mathcal{I}, h_i)$.

Constraints:
Base index must exist: $I_\infty \in \mathcal{I}$
Total subindex size is less than the memory budget $\sum_{l=1}^{x} S(I_{h_{i_l}}) \le B$

[5] M also potentially affects latency; however, there is no definite analytical nor empirical trend [33, 45] (§7.6), hence we omit it for simplicity.

[6] We study unconstrained cases, e.g., for multi-subindex search, in our tech report [71].

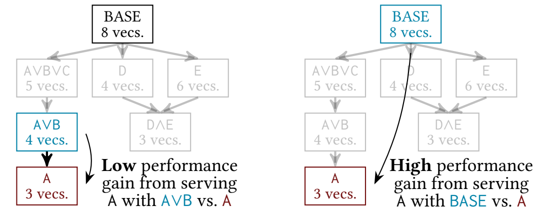


Figure 6: *Diminishing returns*: building A when A∨B exists brings lower marginal benefits versus when A∨B doesn't exist.

Presence of the Base Index. SIEVE enforces that I_∞ must exist for handling arbitrary (e.g., unseen) filtered queries. Worst case, SIEVE can serve queries with the better of I_∞ or brute-force KNN, which lower-bounds SIEVE's serving performance (§7.1).

4.3 SIEVE-Opt: Solution

This section presents our solution to SIEVE-Opt, whose formulation naturally gives rise to a greedy solution for subindex selection [3].

Marginal Benefits. Adding a new index I_h into $\mathcal{I}$ decreases the collection query serving cost by its marginal benefit w.r.t. $\mathcal{H}$: $C(\mathcal{I}, \mathcal{H}) - C(\mathcal{I} \cup \{I_h\}, \mathcal{H}) \ge 0 \, \forall \mathcal{I}, \mathcal{H}, I_h$. For example, in Fig 6, if $\mathcal{I} = \{I_{A\vee B}, I_\infty\}$, $\mathcal{H} = \{(\mathsf{A}, 1)\}$ (left), adding I_{A} into $\mathcal{I}$ brings $\frac{4log(4)}{3} - log(3) \approx 0.75$ marginal benefit. This is less (4.45) than adding I_{A} into a collection $\mathcal{I} = \{I_\infty\}$ with only a base index (right)—there is *diminishing returns* with adding I_{A} when $I_{A\vee B}$ exists. This property is generalizable:

$$\underbrace{C(\mathcal{I} \cup \{I_h\}, \mathcal{H}) - C(\mathcal{I}, \mathcal{H})}_{\text{large marginal benefit}} \le \underbrace{C(\mathcal{J} \cup \{I_h\}, \mathcal{H}) - C(\mathcal{J}, \mathcal{H})}_{\text{small marginal benefit}} \forall \mathcal{I} \subseteq \mathcal{J}$$

That is, the query serving cost $C(\mathcal{I}, \mathcal{H})$ is a *supermodular set function* w.r.t $\mathcal{I}$ [58], and SIEVE-Opt is a *supermodular minimization problem* with the knapsack memory constraint B [10]. This problem class gives rise to an empirically effective greedy algorithm—GreedyRatio [3, 37]:[7] It starts with $\mathcal{I} = \{I_\infty\}$, then iteratively adds the highest marginal benefit/index size ratio subindex (*unit marginal benefit* $\frac{C(\mathcal{I} \cup \{I_h\}, \mathcal{H}) - C(\mathcal{I}, \mathcal{H})}{S(I_h)}$) until reaching the constraint.

Example (Fig 7). Using Fig 5's problem setting, $M_\infty = 10$ for I_∞ and $\sum_{I_h \in \mathcal{I}} S(I_h) < 165 = B$, GreedyRatio proceeds as follows:

(1) **Step 1:** I_{A} is selected (top right). Its unit benefit is high (0.253): serving A with I_{A} is much better than via brute-force search, and I_{A} is space efficient, requiring only $\mathcal{M}_\downarrow(I_{\mathsf{A}}) = \frac{10 log_{10}(3)}{log_{10}(10)} = 5$.
(2) **Step 2:** I_{D} is selected (bottom left). Its unit benefit is high (0.217): serving D with I_{D} is much better than via the root index I_∞.

[7] While theoretically bounded solutions exist [55], their high overhead (e.g., $O(|\mathcal{H}|^5)$ computations) makes them impractical [37].

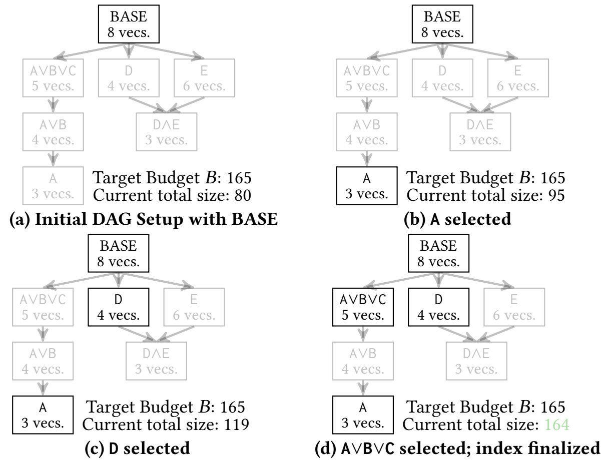


Figure 7: Solving SIEVE-Opt for inputs in Fig 5 by iteratively adding subindexes with the highest unit marginal benefit.

(3) **Step 3:** $I_{\text{A}\vee\text{B}\vee\text{C}}$ is selected (bottom right). While its unit marginal benefit (0.209) is decreased by the already constructed I_{A}, it still has high marginal benefits for serving both A∨B∨C and A∨B.

No index can be further added to $\mathcal{I}$ without exceeding B, hence, $\mathcal{I} = \{I_\infty, I_{\text{A}}, I_{\text{A}\vee\text{B}\vee\text{C}}, I_{\text{D}}\}$ is the index collection that SIEVE constructs.

Analysis. GreedyRatio has time complexity $O(E + |\mathcal{H}|log(|\mathcal{H}|))$ where E is the candidate subindex DAG's edge count (Fig 5), using a priority queue for sorting unit marginal benefits and after adding each subindex, updating its parents' and children's benefits. Optimization time is negligible versus SIEVE's construction time: For example, on the YFCC dataset [8] with 6,006 candidates to optimize over, SIEVE solves SIEVE-Opt in (only) 18ms, versus the 136 seconds for building the index collection post-optimization (§7.3).

5 QUERY SERVING

This section describes SIEVE's dynamic query serving strategy with the built index collection and a (potentially different from construction-time) target recall. SIEVE first finds the optimal subindex for an incoming query (§5.1), then determines the optimal search method—parameterized index search or brute-force KNN (§5.2).

5.1 Identifying the Optimal Subindex

This section describes how SIEVE efficiently finds optimal subindexes for query serving. SIEVE's cost model (§4.2) dictates that a query (w, f) is best served with the smallest subindex I_h (i.e., minimum $card(h)$) in $\mathcal{I}$ where the subindex filter h subsumes the query filter f, following uniform query correlation assumptions in §4.2.

Index Collection DAG. Like the candidate DAG in §4.1, SIEVE builds a DAG, specifically, a *Hasse diagram [64]*, over the index collection: given two subindexes $I_h, I_q \in \mathcal{I}$, a directed edge (I_h, I_q) exists only if h subsumes q, and there is no other $I_u \in \mathcal{I}$ such that h subsumes u, and u subsumes q. Fig 8 (center) depicts the DAG built on the index collection from solving SIEVE-Opt in Fig 7.

DAG Traversal. For a filtered query (w, f), the Index Collection DAG can be efficiently traversed via BFS starting from the root I_∞ to find the best subindex I_h: at each step, if the current subindex I_q's filter does not subsume f, none of its descendants can either. In other words, for any descendant I_p of I_q in the DAG, p cannot subsume f, allowing the entire subgraph rooted at I_q to be pruned from the search. For example, in Fig 8, the subindex $I_{\text{A}\vee\text{B}\vee\text{C}}$ does not subsume the query filter D∧(C∨E), hence its child I_{A} can be skipped, efficiently leading to the best subindex I_{D} to be found. In practice, for the YFCC workload with 100K filtered queries and an index collection with 658 subindexes, finding the optimal subindex for all queries took (only) 297 ms, which is a low percentage of the total search time (e.g., minimum 20.76 seconds, Fig 9).

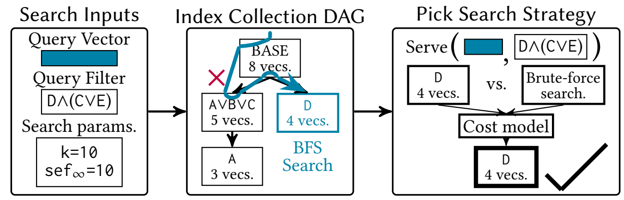


Figure 8: Choosing an optimal search strategy for a query with the constructed index collection from Fig 7. SIEVE finds the best applicable subindex, then chooses indexed or brute-force search based on estimated search costs.

Remark. SIEVE currently evaluates subsumptions for traversing the Hasse diagram logically (e.g., A is subsumed by A∨B). However, in cases where logical subsumption is rare (e.g., complex filter and attribute space, UQV dataset, §7.1), other subsumption definitions such as bitvector-based subsumption can be used in its place (§6).

5.2 Determining Optimal Search Strategy

This section outlines how SIEVE determines the serving method based on the best-found subindex. It first determines the search parameter (sef) required for the (new) target recall, then chooses between indexed search with the found sef or brute-force KNN.

Search Parameterization. Like $\mathcal{M}_\infty$ (§4.2), Users provide a *global* sef_∞ to SIEVE (potentially different from the assumed build-time $sef = k$) for each query representing the serving-time target recall, defined as the expected recall of (over-)searching the base index I_∞ with sef_∞. Following §2.3, SIEVE aims to serve queries with sef values to match the target recall; hence, versus sef_∞, lower sef (increments) can be used when serving queries with subindexes:

Definition 5.1. The *Subindex sef downscaling function $\mathcal{S}_\downarrow$* takes in a subindex I_h, and returns the sef value required to search I_h with to achieve at least the same average query serving recall as searching the base index I_∞ with sef_∞: $\mathcal{S}_\downarrow(I_h) := max(k, \frac{sef_\infty log(card(h))}{log(N)})$, where k is the neighbors to query (and minimum value of sef, §4.2) and assuming I_h was built with proportional $M = \mathcal{M}_\downarrow(I_h)$.

SIEVE's intuition for $\mathcal{S}_\downarrow$ is that each HNSW search visits $O(logn)$ points [33] in its hierarchical structure (§2.1): to maintain recall, the proportion between sef—the dynamic closest neighbors list size—and $logn$ must be maintained, i.e., lists must cover a consistent proportion of the visited $logn$ points, hence $\mathcal{S}_\downarrow(I_h) \propto log(card(h))$. For example, if $sef_\infty = 50$ is specified for the base index in Fig 8 as the serving-time recall, the same recall can be achieved with

$\mathcal{S}_{\downarrow}(I_{\mathsf{D}}) = \frac{50\times log(4)}{log(8)} = 33$ when searching in the subindex I_{D}. As HNSW's search time scales linearly with sef [33] (Fig 3c), SIEVE's sef downscaling saves search time versus a static strategy that uses uniform sef_{∞} for indexed searches while maintaining recall (§5.2).

Indexed vs. Brute-force Search. Given a query (w, f), its best subindex I_h in §5.1, and downscaled $sef_h = \mathcal{S}_{\downarrow}(I_h)$, SIEVE chooses between serving the query with indexed or brute-force KNN with its cost model from §4.2: it chooses the lower-cost method out indexed search ($C(I_h, sef_h, f)$) and brute-force search ($\gamma C_{bf}(f)$). For example, in Fig 8, assuming $k = 1$, serving D∧(C∨E) with I_{D} at $sef_{\infty} = 1$ has a lower cost $max(1, \frac{1log(4)}{log(8)}) \times \frac{4log(4)}{3} \approx 1.84$ vs. brute-force KNN (3), but at $sef_{\infty} = 3$, brute-force KNN is faster as the indexed search cost becomes $max(1, \frac{3log(4)}{log(8)}) \times \frac{4log(4)}{3} \approx 3.670 \geq 3$.

6 DISCUSSION

Size of Optimization Space. One potential problem for SIEVE is an exploding optimization space when the historical workload contains many distinct filter templates. To address this, SIEVE currently prunes small-cardinality candidates with no marginal benefit over brute-force KNN prior to solving SIEVE-Opt in §4.2; if still insufficient, SIEVE can also only use top-k-common filters as candidates, which would often sufficiently approximate the full problem due to filter commonality [53]. Large optimization spaces may also affect SIEVE during workload shifts, which we study in §7.7.2.

Availability of Filter Cardinalities. SIEVE assumes availability of accurate filter cardinality info ($card(h)$). This is because many recent vector search frameworks [39, 42, 44, 60, 63] separately manage scalar attributes using methods such as inverted indexes, B-trees, or partitioning. For search, filters will first be applied on scalars to compute a *bitmap* of passing vectors' IDs (implying cardinality via nonzero count), which is then passed to the vector index.

Filter Evaluation Costs. While reported as part of total query serving time in experiments (§7), SIEVE omits modeling of filter evaluation costs from optimization (§4). This is because SIEVE currently follows the aforementioned bitmap-based filtering: for each query, SIEVE computes the bitmap before choosing the serving strategy (i.e., brute-force KNN or indexed search), hence its computation cost is orthogonal to SIEVE's optimizations. Moreover, we find that bitmap computation time is negligible in our experiments; for example, on the UQV dataset, evaluating the complex, up to 10-attribute disjunction filters for 10K queries took (only) 16ms—0.2% of total query serving time at 0.95 recall (Fig 9).

Complex Predicate and Attribute Spaces. While SIEVE conceptually supports arbitrary predicates and attributes, a current limitation is that complex spaces (e.g., 200K attributes with up to 10-attribute disjunction filters of UQV, Table 4) with few subsumption relations (2 random predicates rarely subsuming each other, §7.7.2) can reduce subindex serving opportunities (for non-exact matching query and subindex filters) and performance (§5.1). Potential mitigations are to use looser ① bitmap subsumption checks, where filter B subsumes A if all attributed vectors satisfying A also satisfy B even if logically otherwise, and ② expanded problem space with sub-predicates, such as considering A and B to also be valid candidates when A∧B is observed. Both methods increase chance of subsumptions between built subindexes and query filters while potentially increasing optimization time via costlier subsumption checks [9] and larger problem space, respectively; a cost-based mechanism for choosing when to use them (e.g., Calcite's [7] rule-based usage of logical checks for simple inequalities) can be valuable future work.

Workload Shifts. We design SIEVE for production workloads with query filter stability [25, 39, 53, 54] where future queries can be predicted from past filters. Regardless, if filter distribution shifts from $\mathcal{H}$ to a new $\mathcal{H}'$, SIEVE can be incrementally updated by re-solving SIEVE-Opt over $\mathcal{H}'$ to find a new collection $\mathcal{I}'$, building new indexes in $\mathcal{I}'-\mathcal{I}$, then deleteing indexes in $\mathcal{I}-\mathcal{I}'$ (§7.7). Notably, the base index I_{∞}, which forms a significant part of SIEVE's build time and memory size, does not need updating. Furthermore, SIEVE is robust to moderate shifts (§7.5), and even for complete shifts (serving queries from unrelated $\mathcal{H}'$ when fit on $\mathcal{H}$), SIEVE's performance will be lower bounded by SIEVE-NoExtraBudget (§7.7.2).

Multi-Subindex Search. SIEVE currently only considers serving queries with a single subindex that subsumes the query filter for indexed search (§4.2). One potential alternative is to use multiple subindexes, e.g., re-ranking results from subindexes I_p and I_q to answer $p \vee q$. This can be useful for queries that SIEVE otherwise finds no good serving strategy (e.g., those with 'unhappy middle' selectivities, but the best subindex found is the base index $\mathcal{I}_{\infty}$); However, finding optimal subindex sets for multi-index search is computationally hard. We evaluate the feasibility and potential gains of multi-subindex search in detail in our technical report [71].

7 EXPERIMENTS

This section studies SIEVE's performance on various filtered vector search workloads. We describe our experiment setup in §7.1, study end-to-end query serving (§7.2), index building (§7.3), effect of memory budget (§7.4) and historical workload (§7.5) on index quality, our dynamic index building and serving parameterization (§7.6), and SIEVE's adapting to cold starts and workload shifts (§7.7).

7.1 Experiment Setup

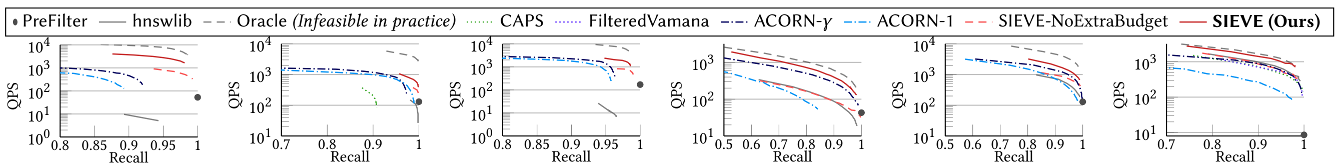
Datasets (Table 4). ① **YFCC-10M [8]**: Dataset comes with queries with filters of form A or A∧B. ② **Paper [61]**: we generate data attributes where each vector has the $i^{th}/20$ attribute with $1/i$ probability as in NHQ [61] and Milvus [60]. Conjunctive AND query filters are generated following a zipf distribution [53] as described in HQI [39]. ③ **UQV [59]**: we generate data/query filters following methodology of the Paper dataset, with $1 \leq i \leq 200K$ and disjunctive OR filters. ④ **GIST [6]**: we generate 2 normally-distributed numerical attributes X and Y for each vector, and zipf-distributed disjunctive range filters. ⑤ **SIFT [56]**: we generate data/query filters following methodology of the GIST dataset with conjunctive range filters. ⑥ **MSONG [34]** : we generate query filters uniformly of form a_i for 80% of queries; the remaining 20% are unfiltered.

Methods. We evaluate SIEVE against these existing methods:

(1) ACORN-γ **[44]:** We use M=32, M_{β}=64, and $\gamma = max(80, 1/\texttt{min. filter selectivity})$. For each dataset, we sweep selectivity threshold for brute-force KNN fallback from 0.0005 to 0.05.
(2) ACORN-1 **[44]:** Ablated ACORN-γ with $\gamma = 1$ and $M_{\beta} = 32$.

Table 4: Summary of Datasets for Evaluation.

Dataset	# Vectors	Dim	Data Type	# Queries	# Attrs.	Predicates	Pred. Type	# Unique Preds.	Avg. Selectivity
YFCC-10M [24]	10000000	192	Images	100000	200000	$\bigwedge_{i=1}^{k} A_i$ `in attr`, $1 \leq i \leq 2$	attr. match+AND	23930	0.018
Paper [61]	2029997	200	Text	10000	20	$\bigwedge_{i=1}^{k} A_i$ `in attr`, $2 \leq i \leq 5$	attr. match+AND	2500	0.019
UQV [59]	1000000	256	Video	10000	200000	$\bigcup_{i=1}^{k} A_i$ `in attr`, $3 \leq i \leq 10$	attr. match+OR	2500	0.037
GIST [6]	1000000	960	Scenes	1000	2	$x_i < X < x_j \vee y_i < y < y_j$	range filter+OR	200	0.097
Sift [56]	1000000	128	Image	10000	2	$x_i < X < x_j \wedge y_i < y < y_j$	range filter+AND	200	0.196
Msong [34]	992272	420	Audio	200	20	`A in attr`, `No filter`	attr. match	20	0.616



(a) YFCC-10M (b) Paper (c) UQV (d) GIST (e) SIFT (f) MSONG

Figure 9: SIEVE's Recall@10-QPS curves vs. baselines on various datasets. SIEVE achieves up to 8.06× QPS increase at 0.9 recall@10 vs. the next best non-Oracle **method (**ACORN-γ**).**

(3) hnswlib **[42]:** We use the better of $M = \{16, 32\}$ and $efc = 40$.
(4) SIEVE-**NoExtraBudget:** Ablated SIEVE with $B = S(I_\infty)$ that only builds a base index. Equivalent to hnswlib that falls back to brute-force KNN based on SIEVE's serving strategy (§5.2).
(5) PreFilter**:** We first use the predicate filter, then perform brute-force KNN with hnswlib's SIMD-enabled distance function.
(6) Oracle**:** Exhaustive indexing method which ACORN-γ aims to mimic [44]; it builds a subindex for every observed filter. Oracle is expected to outperform SIEVE but incur higher TTI and memory cost; we present it as a bound for SIEVE's performance.
(7) FilteredVamana **[21]** only supports filters of form `A in attr` (or no filter); we compare against it on MSONG only. We build in-memory using DiskANNPy's recommended parameters [13].
(8) CAPS **[23]** only supports conjunctive attribute matching on under 256 data attributes; we compare against it on Paper/MSONG only. We sweep cluster count from 10-1000 on each dataset.

For SIEVE, we use hnswlib [42] for our index collection. For each dataset, we sweep $M_\infty = \{16, 32\}$ and $efc = 40$ for the base index, with downscaled M and same efc for subindexes (§4.2). Budget B is set to **3**× hnswlib's index size on the same dataset. The brute-force scaling constant γ is empirically chosen where $\gamma \cdot c_{bf}(f) = c(I_h, f)$ when $card(f) = card(h) = 1000$, i.e., brute-force KNN and perfect-selectivity indexed search cost the same for a 1K-cardinality filtered query with $sef = k$ (§4.2). The query correlation factor $q(w, f, h)$ is set to 0.5 (i.e., average positive correlation, §4.2) for all w, f, h.

Index Fitting. We use the first 25% query slice (unless otherwise stated, e.g., in §7.5 and §7.7) as the observed workload $\mathcal{H}$, then serve all queries (including the fitting slice) with the built index, following methodology in prior workload-aware indexing works [39].

Measurement. For Oracle, hnswlib, SIEVE-NoExtraBudget, we generate QPS-recall@10 curves with $sef \in [10, 110]$ in steps of 10. For SIEVE, we use $sef_\infty \in [10, 110]$ for the base index and downscale sef for subindexes (§5.2). For ACORN-γ, ACORN-1, we vary $sef \in [10, 510]$ in steps of 50. For CAPS, we vary $np \in [3K, 30K]$ in steps of 3K. For FilteredVamana, we vary $L \in [10, 510]$ in steps of 50.

Environment. Experiments are run on an Ubuntu server with 2 AMD EPYC 7552 48-core Processors and 1TB RAM. We store datasets on local disk, build indexes in-memory with 96 threads, and run queries with 1 thread in Neurips'23 BigANN challenge's environment [24] reporting best-of-5 QPS. Our Github repository [72] contains our SIEVE implementation and experiment scripts.

7.2 High and Generalized Search Performance

This section studies SIEVE's overall filtered vector search performance vs. existing baselines: we run each method on applicable datasets and compare their generated QPS-recall@10 curves.

Fig 9 reports results. SIEVE is the best-performing non-Oracle approach on all 6 datasets, achieving up to 8.06× speedup (YFCC) at 0.9 recall versus ACORN-γ. Notably, SIEVE also achieves higher recalls (>0.99 in SIEVE vs. peaking at ~0.95 in ACORN-γ) on low-selectivity datasets (YFCC, Paper, UQV): while ACORN-γ's induced subgraphs degenerate for selective queries (§2.2), SIEVE actually builds the (sub)indexes in which filters are dense for effective search.

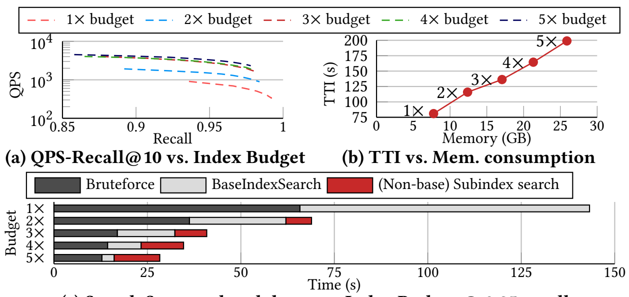
Bounded Performance. SIEVE-NoExtraBudget bounds SIEVE's performance (§5.2) when the best subindex SIEVE finds for any query is the base index I_∞ (e.g., workload shifts, §7.7.2), and can only choose between searching with I_∞ or brute-force KNN. While SIEVE significantly outperforms SIEVE-NoExtraBudget (4.01× QPS on YFCC at 0.95 recall), the latter is still effective in its own right, outperforming ACORN-γ on 2/6 datasets (YFCC, MSONG).

High Generalizability. SIEVE's filter and attribute format-agnostic formulation (§4.1) allows it to handle (1) any number of data attributes and (2) a wide range of predicate forms—conjunctions (YFCC, Paper), disjunctions (UQV), and range filters (GIST, SIFT), unlike FilteredVamana and CAPS, which struggle with large data attribute sets, disjunctions, and range queries. In addition, SIEVE still outperforms CAPS on Paper (10.61× QPS @ 0.9 recall) and both CAPS and FilteredVamana on MSONG (2.29× QPS @ 0.9 recall).

Handles Diverse Selectivities. We additionally study SIEVE's per-query selectivity band performance in our technical report [71].

Table 5: SIEVE's TTI (seconds) and memory consumption (GB) vs. baselines. Numbers from indexing configurations used to generate QPS-recall@10 curves in Fig 9. N/A indicates a method not applicable to that dataset.

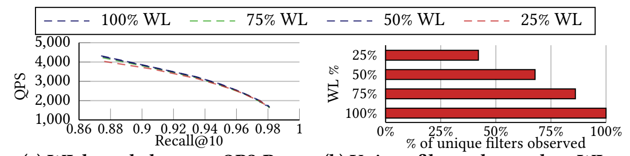
Index	hnswlib		Oracle		CAPS		FilteredVamana		ACORN-γ		ACORN-1		**SIEVE (Ours)**	
Dataset	TTI	Mem.	TTI	Mem.	TTI	Mem.	TTI	Mem.	TTI	Mem.	TTI	Mem.	TTI	Mem.
YFCC	80.968	7.759	479.849	84.275	N/A	N/A	N/A	N/A	17782.532	11.445	116.378	6.266	136.132	17.066
Paper	30.435	2.874	1811.820	76.014	8.893	4.419	N/A	N/A	2529.372	3.485	25.061	2.570	59.581	5.260
UQV	10.140	1.797	1588.513	68.573	N/A	N/A	N/A	N/A	1179.420	2.090	13.565	1.635	19.312	3.194
GIST	74.828	4.317	1477.429	14.204	N/A	N/A	N/A	N/A	5791.505	4.479	50.247	4.104	208.393	5.552
SIFT	10.335	0.943	539.409	19.520	N/A	N/A	N/A	N/A	265.534	1.142	10.133	0.965	25.377	2.241
MSONG	24.467	2.068	427.15	9.226	22.501	3.383	323.639	2.384	638.60	2.222	27.707	2.017	63.857	3.271



(a) QPS-Recall@10 vs. Index Budget (b) TTI vs. Mem. consumption

(c) Search Strategy breakdown vs. Index Budget @ 0.95 recall

Figure 10: SIEVE's budget vs. QPS-recall; and search breakdowns (YFCC)**. It prioritizes high-benefit subindexes (§4.2).**



(a) WL knowledge % vs. QPS-Rec. (b) Unique filters observed vs. WL %

Figure 11: SIEVE's QPS-recall vs. workload knowledge (YFCC)**. After seeing only 42% of unique filters in a 25% workload slice, it achieves ~96% QPS of a collection fit on the full workload.**

7.3 Low Construction Overhead

This section studies SIEVE's construction overhead. We fix B as 3× hnswlib's index size on the same dataset (§7.1), and compare SIEVE's TTI and memory consumption vs. existing methods.

Table 5 reports results. SIEVE adheres to its memory budget w.r.t. hnswlib: Notably, while the budget is 3× hnswlib's index size, SIEVE's actual memory consumption including datasets is $< 3\times$, being as low as 1.29× on GIST as the high-dimensional (960) vectors contribute significantly to memory size (3.84GB). The TTI increase is also $< 3\times$ (1.68× on YFCC to 2.78× on GIST), as subindexes's build time scales superlinearly with vector count [33], hence larger indexes (e.g., base index) take more indexing time per vector. Versus ACORN-γ, while SIEVE uses more memory (up to 1.96×, SIFT), its TTI is a fraction of ACORN-γ's (0.8% on YFCC to 9.5% on SIFT) as it avoids ACORN-γ's specialized graph building (§2.2). This makes SIEVE desirable when TTI is the main constraint instead of memory (e.g. on-disk indexing). Versus Oracle, which has potentially prohibitive size (84.2GB, YFCC), SIEVE performs competitively (Fig 9) using as little as 3.0% and 4.6% of Oracle's TTI and memory (UQV).

7.4 Efficient Usage of Memory Budget

This section studies SIEVE's performance vs. its indexing budget B, which we vary from 1× size of hnswlib (equivalent to SIEVE-NoExtraBudget) to 5× and report the QPS-Recall@10 curves, resource consumption, and search strategy breakdowns on YFCC.

Fig 10 reports results. SIEVE's QPS-Recall@10 trade-off expectedly improves with more budget. However, contrasting the linear increase in TTI and memory, the improvement diminishes for each 1× budget increase—the serving time decrease for 100K queries at 0.95 recall from 1× to 2× is 2.63×, but only 1.22× from 4× to 5×. This is because SIEVE prioritizes building high-benefit subindexes (§4.3, also verified in our tech report [71]), which is reflected in its search strategy breakdown in Fig 10c: the first budget increase from 1× to 2× focuses on building subindexes for queries with highest gains from being served by a subindex versus brute-force or base index search, decreasing the spent time of the 2 methods by 25.5s and 51.6s, respectively. Further budget increases yield smaller reductions in brute-force (<19.3s) or base index search (<10.4s) time.

7.5 Effective Fitting from Historical Workload

This section studies the impact of discrepancies between the historical workload $\mathcal{H}$ used to build SIEVE and the actual workload. We vary the query slice size we use as the historical workload for SIEVE from 25% (our default for other experiments) to 100% on YFCC, and report the QPS-recall@10 of each fitted index collection.

Fig 11 reports results. SIEVE fit with 25% workload performs comparably (96% QPS at 0.9 recall) versus theoretically optimized SIEVE fit with 100% workload despite (1) the 25% slice only containing 42% of unique filter templates and (2) the two fits being significantly different—170/711 indexes in SIEVE (25% WL) are absent in SIEVE (100% WL) and 141/682 vice versa, showcasing SIEVE's robustness to moderate workload shifts (we study larger shifts in §7.7.2). At intermediate values, while each 25% slice increases SIEVE's choices from seeing more unique filters, performance increase is negligible.

7.6 Dynamic Construction & Serving

This section studies the effectiveness of SIEVE's dynamic, recall-aware index construction (§4.2) and serving parameterization (§5.2). We compare SIEVE's QPS-recall@10 curves with ablated versions of SIEVE—using static $M = M_\infty$ for all subindexes and/or static $sef = sef_\infty$ for all searches—on UQV and Paper with $M_\infty = \{32, 64\}$.

We report the results in Fig 12. At high (0.985) recall, SIEVE achieves up to 1.60× QPS increase versus SIEVE with no optimization and up to 1.09× QPS increase with only one of dynamic

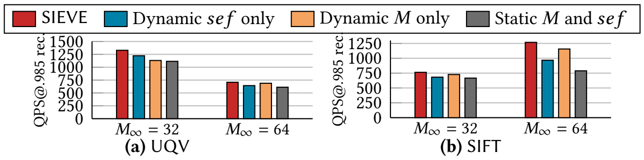


Figure 12: SIEVE's recall-aware index construction and serving parameterization achieves up to 1.60× QPS increase at high recalls (~0.985) vs. static, non-recall-aware ablations.

Table 6: SIEVE's recall-aware index tuning allows for building more indexes under the same memory constraint.

Dataset ($M_\infty = 32$)	UQV		SIFT	
Dynamic index (M) tuning	**Yes**	No	**Yes**	No
# Indexed vectors	**2286197**	2005930	**2298746**	2074841
# Subindexes	**200**	169	**22**	16

Table 7: SIEVE's recall-aware search parameterization increases search efficiency at high (0.985) recalls.

Dataset ($M_\infty = 32$)	UQV		SIFT	
Dynamic search (sef) parameterization	**Yes**	No	Yes	No
Avg. HNSW distance computations	**5917**	6111	**6448**	6665
Avg. brute-force distance computations	**1136**	1195	**583**	629

subindex construction (M) or query serving (sef) (UQV, $M_\infty = 64$). Interestingly, while the $M_\infty = 64$ setting is more performant than $M_\infty = 32$ on SIFT, the opposite holds for UQV; we hypothesize that this is due to intrinsic hardness difference of the datasets, i.e., $M_\infty = 32$ suffices for the base index in UQV,[8] and further increasing M_∞ results in increased latency with negligible recall gains.

More Indexes Under Same Memory Constraint. SIEVE's recall-aware subindex construction downscales the M parameter of smaller indexes in the collection (§4.2): this decreases the memory consumption of these small indexes (Fig 3b), which results in more built indexes under the same memory constraint (Table 6).

Fewer Distance Computations. SIEVE's dynamic search parameterization downscales sef when searching with smaller indexes (§5.2). This increases smaller indexes's search efficiency from incurring fewer distance computations (Fig 3c), and reduces searches SIEVE falls back to serving via brute-force KNN on (Table 7).

7.7 Handling Cold Starts and Workload Shifts

This section studies SIEVE's robustness to cold starting with no historical workload (§7.7.1) and sudden workload shifts (§7.7.2).

7.7.1 SIEVE can Effectively Cold Start. We choose the YFCC dataset, temporally slice the 100K queries into 20 5K workload slices, then sequentially serve slices to SIEVE initialized with no historical workload (i.e., $\mathcal{H} = \emptyset$) and an index collection with only the base index $\mathcal{I}_\infty$. Each slice H', after serving, is added to the historical workload (i.e., $\mathcal{H} \leftarrow \mathcal{H} \cup H'$) and SIEVE's index collection is incrementally updated following procedures described in §6. We study per-slice query performance and SIEVE's update time between slices.

[8] Recall that M_∞ is user-specified (§4.2).

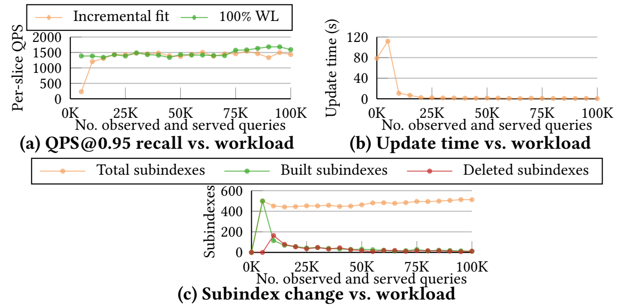


Figure 13: Cold starting with SIEVE on YFCC: SIEVE can be initialized with only the base index, then incrementally updated during serving; SIEVE's performance quickly approaches an optimal fit after it observes and serves 3 5K workload slices.

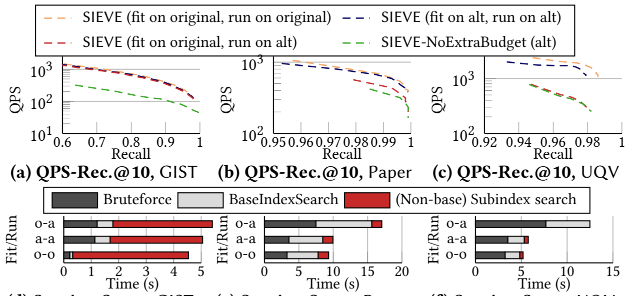
We report results in Fig 13. As observed in Fig 13a, while SIEVE's per-slice QPS is lower than the theoretically optimized SIEVE (100% WL) (§7.5) on the first 2 slices—SIEVE only has the base index for the 1^{st} and a suboptimal index collection fit to the first 5K queries for the 2^{nd}, SIEVE effectively cold starts as it observes more slices, reaching 97% QPS of 100% WL by the 3^{rd} slice. This is also seen in SIEVE's update time (Fig 13b) and built/deleted subindexes per update (Fig 13c): while SIEVE's first update takes significant time (111s)—it uses all budget to build 499 subindexes fit to the first slice, subsequent updates become increasingly faster due to SIEVE's observed workload $\mathcal{H}$ quickly approaching the true workload distribution: it builds and deletes fewer subindexes per update, with update time becoming sub-second after the 15^{th} slice.

7.7.2 SIEVE can Adapt to Complete Workload Shifts. We choose the GIST, Paper and UQV datasets, on which we generate alternative workloads with different filter templates[9] that follow similar distribution characteristics (i.e., average selectivity, §7.1). We study the performance of serving the alternative workload on SIEVE fit on the alternative workload versus SIEVE fit on the original workload (i.e., to simulate a workload shift), and time for re-fitting SIEVE's index collection from the original to the alternative workload.

We report results in Fig 14. As expected, serving a workload with SIEVE that significantly differs from the workload that SIEVE was fit on expectedly causes degradation, achieving only 92%, 71% and 49% QPS of an index collection fit with the corresponding workload on GIST, Paper and UQV, respectively (Fig 14a, Fig 14b, Fig 14c).

Quantifying Degradation. While query filter templates in the original and alternative workloads almost completely differ for all datasets—the optimal index collections of the workloads share only 1 subindex on Paper and 0 on GIST and UQV (Fig 14g), the degradation degree depends on the filter space complexity (§6): two random filters on GIST are most likely to have a subsumption relation, followed by UQV, then Paper, as GIST only has 2 range-filtered attributes versus Paper and UQV's 20 and 200K for attribute matching. Hence, SIEVE still finds significant opportunities for query serving with subindexes despite the workload shift on GIST (Fig 14d) to achieve 2.77× speedup versus SIEVE-NoExtraBudget, finds fewer on Paper (Fig 14e) with 1.35× speedup, and almost none on UQV

[9] We accomplish this via setting alternative seeds for randomized generation.



(a) **QPS-Rec.@10,** GIST (b) **QPS-Rec.@10,** Paper (c) **QPS-Rec.@10,** UQV

(d) **Serving Strat.,** GIST (e) **Serving Strat.,** Paper (f) **Serving Strat.,** UQV

Dataset	Update time (s) (% of init. time)	Subindex # change	New subindexes size (GB) (% of original size)
GIST	149.325 (66.7%)	15→14 (-15, +14)	1.264 (22.7%)
Paper	47.648 (79.9%)	76→90 (-75, +89)	2.298 (43.6%)
UQV	15.110 (78.2%)	200→163 (-200, +163)	1.397 (43.7%)

(g) Updating SIEVE**'s fitted index from original to alternative workload**

Figure 14: SIEVE **can degrade when serving a new workload (top); yet, it may still find optimization opportunities (middle).** SIEVE **can be accordingly re-fit, which is faster than the initial build as the base index is unchanged (bottom).**

(Fig 14f) and degrades to only 1.03× speedup. Degradation can also occur if the predicates are sparse by complexity (e.g., `A<5 && B in attr && C like \w+`). Hence, a current limitation of SIEVE (and other general workload-driven methods [39, 53, 54]) is that large predicate spaces (e.g., UQV) are inherently more difficult for SIEVE's optimization w.r.t. workload shifts. However, SIEVE can be updated upon detecting such degradation/shifts either incrementally as in §7.7.1 or completely refitting to the new workload—notably, even if no subindexes are kept on refit (Fig 14g), refitting is still faster than complete rebuild as the base index does not need updating (§6).

7.8 Experimentation Summary

We claim the following w.r.t. SIEVE's experimental evaluations:

(1) *Effective and generalizable search:* SIEVE handles arbitrary data attribute and query filter formats, achieving up to 8.06× higher QPS at 0.9 recall@10 versus the next best alternative on low and high selectivity query workloads alike (§7.2).
(2) *Low construction overhead:* SIEVE operates within its memory budget, requiring only up to 2.15× memory of hnswlib and just 1% of time-to-index (TTI) versus ACORN-γ [44] (§7.3).
(3) *Effective usage of memory budget:* SIEVE achieves large performance gains even with small budget (e.g., 2× of hnswlib) as its modeling effectively prioritizes high-benefit subindexes (§7.4).
(4) *Effective fitting from historical workload:* SIEVE's construction requires only modest knowledge of the workload distribution—an index collection fit from a 25% workload slice performs within 96% of a collection fit on the true distribution (§7.5).
(5) *Effective recall-aware construction and serving:* SIEVE's recall-aware index (M) tuning and dynamic serving (sef) achieves up to 1.19× higher QPS at 0.985 recall versus ablated, recall-agnostic SIEVE versions with static parameterization (§7.6).
(6) *Handling cold starts and workload shifts*: We show that SIEVE can handle cold start scenarios with no workload knowledge and complete workload shifts via incremental refitting (§7.7).

8 RELATED WORK

Filtered Vector Search. There exists many filtered vector search indexes [15, 16, 21, 23, 31, 39, 44, 48, 61, 66, 74]. FilteredVamana and StitchedVamana [21] are Vamana-based [27] indexes for single-attribute filters. CAPS [23] and HQI [39] partition data to maximize query-time partition skipping; the latter is also workload-aware. However, CAPS only handles low-cardinality conjunctions, while HQI targets batched query serving. NHQ [61] and HQANN [66] jointly indexing vectors and attributes but only support soft filters. SeRF [74] and IVF2 [31] are specialized indexes for 1-attribute range queries [10] and YFCC,[11] respectively. ACORN [44] supports arbitrary predicates via subgraph traversal. SIEVE supports arbitrary predicates like ACORN, but achieves higher QPS/recall with a faster-to-build, workload-aware index collection (§7.3). Versus SeRF, which also conceptually builds multiple subindexes, SIEVE focuses on its cost modeling for subindex selection in a potentially large, multi-attribute space (§4.2); SeRF focuses orthogonally on compressing its subindexes that are otherwise naively and exhaustively built over a single attribute. SIEVE still outperforms other specialized methods (e.g., CAPS) supporting limited predicates (§7.2).

Vector Search Plan Selection. Cost-based query plan selection has been studied in vector indexing systems [60, 63]. Milvus [60] uses a cost model to choose between partitioned and pre-filter search. AnalyticDB-V [63] additionally considers query selectivity. In comparison, SIEVE dynamically picks the best strategy *considering recall*, unlike these systems (and ACORN's resorting to brute-force KNN at low selectivity [44]) treating indexes as already tuned to serve with sufficient recall, and uses recall-agnostic models at serving time. SIEVE's strategy *bounds* its performance: it will always be faster than the best of brute-force/indexed search at any recall (§7.2).

Materialized View Selection. There is extensive work on selecting MVs for speeding up (exact) queries [26, 28, 30, 32, 38, 47], which typically assume access to historical info for predicting the future workload [39, 53, 54]. One common issue is the large candidate MV optimization space; BigSubs [28] mitigates this via randomized approximation, while SparkCruise [47] reduces the problem space according to subsumptions. While SIEVE shares similarities with these works such as fitting from historical workload (§4.1) and using greedy approximation (§4.3), it orthogonally incorporates recall (§4.2), a key and unique dimension present in vector indexing for filtered search but lacking in MV selection for (exact) queries.

9 CONCLUSION

We present SIEVE, an indexing framework enabling efficient filtered vector search via an index collection. SIEVE uses a three-dimensional cost model for memory size, search speed, and recall to determine benefits and costs of candidate indexes at a target recall to build the index collection with bounded memory via workload-driven optimization. For query serving, SIEVE finds the fastest search strategy—a parameterized index search or brute-force KNN, at a potentially new target recall. SIEVE achieves up to 8.06× QPS gain over existing indexing methods at 0.9 recall on various datasets while requiring as little as 1% TTI versus other specialized indexes.

[10] Hence, we omit SeRF from our experiments as it is not applicable.
[11] IVF2 was tuned specifically for YFCC, handling only filtered queries of form `a (AND b) in attr`. We omit it from experimentation due to its lack of generality.

REFERENCES

[1] [n.d.]. Query Rewrite With A Nested Materialized View. https://patents.google.com/patent/US20090228432A1/en.

[2] Sanjay Agrawal, Surajit Chaudhuri, and Vivek R Narasayya. 2000. Automated selection of materialized views and indexes in SQL databases. In *VLDB*, Vol. 2000. 496–505.

[3] Georgios Amanatidis, Federico Fusco, Philip Lazos, Stefano Leonardi, Alberto Marchetti-Spaccamela, and Rebecca Reiffenhäuser. 2021. Submodular maximization subject to a knapsack constraint: Combinatorial algorithms with near-optimal adaptive complexity. In *International Conference on Machine Learning*. PMLR, 231–242.

[4] Luıs A Nunes Amaral, Antonio Scala, Marc Barthelemy, and H Eugene Stanley. 2000. Classes of small-world networks. *Proceedings of the national academy of sciences* 97, 21 (2000), 11149–11152.

[5] Kamel Aouiche, Pierre-Emmanuel Jouve, and Jérôme Darmont. 2006. Clustering-based materialized view selection in data warehouses. In *East European conference on advances in databases and information systems*. Springer, 81–95.

[6] Antonio Torralba Aude Oliva. [n.d.]. Modeling the shape of the scene: a holistic representation of the spatial envelope. http://people.csail.mit.edu/torralba/code/spatialenvelope/.

[7] Edmon Begoli, Jesús Camacho-Rodríguez, Julian Hyde, Michael J Mior, and Daniel Lemire. 2018. Apache calcite: A foundational framework for optimized query processing over heterogeneous data sources. In *Proceedings of the 2018 International Conference on Management of Data*. 221–230.

[8] big-ann benchmarks. 2024. YFCC10M - Neurips23 BigANN Challenge Filter Track. https://github.com/harsha-simhadri/big-ann-benchmarks/blob/main/benchmark/datasets.py.

[9] Samy Chambi, Daniel Lemire, Owen Kaser, and Robert Godin. 2016. Better bitmap performance with roaring bitmaps. *Software: practice and experience* 46, 5 (2016), 709–719.

[10] Chandra Chekuri. [n.d.]. Combinatorial Optimization. https://courses.grainger.illinois.edu/cs586/sp2022/main.pdf.

[11] CloudFlare. [n.d.]. Computing Euclidean distance on 144 dimensions. https://blog.cloudflare.com/computing-euclidean-distance-on-144-dimensions/.

[12] cmuparlay. 2024. Benchmarking nearest neighbors.

[13] DiskANN. [n.d.]. DiskAnnPy - API. https://microsoft.github.io/DiskANN/docs/python/latest/diskannpy.html.

[14] David P Dobkin, Steven J Friedman, and Kenneth J Supowit. 1990. Delaunay graphs are almost as good as complete graphs. *Discrete & Computational Geometry* 5 (1990), 399–407.

[15] Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. 2024. The faiss library. *arXiv preprint arXiv:2401.08281* (2024).

[16] Joshua Engels, Ben Landrum, Shangdi Yu, Laxman Dhulipala, and Julian Shun. [n.d.]. Approximate Nearest Neighbor Search with Window Filters. In *Forty-first International Conference on Machine Learning*.

[17] Cong Fu, Chao Xiang, Changxu Wang, and Deng Cai. 2017. Fast approximate nearest neighbor search with the navigating spreading-out graph. *arXiv preprint arXiv:1707.00143* (2017).

[18] Jianyang Gao and Cheng Long. 2023. High-dimensional approximate nearest neighbor search: with reliable and efficient distance comparison operations. *Proceedings of the ACM on Management of Data* 1, 2 (2023), 1–27.

[19] Parke Godfrey, Jarek Gryz, Andrzej Hoppe, Wenbin Ma, and Calisto Zuzarte. 2009. Query rewrites with views for XML in DB2. In *2009 IEEE 25th International Conference on Data Engineering*. IEEE, 1339–1350.

[20] Jonathan Goldstein and Per-Åke Larson. 2001. Optimizing queries using materialized views: a practical, scalable solution. *SIGMOD Rec.* 30, 2 (May 2001), 331–342. https://doi.org/10.1145/376284.375706

[21] Siddharth Gollapudi, Neel Karia, Varun Sivashankar, Ravishankar Krishnaswamy, Nikit Begwani, Swapnil Raz, Yiyong Lin, Yin Zhang, Neelam Mahapatro, Premkumar Srinivasan, et al. 2023. Filtered-diskann: Graph algorithms for approximate nearest neighbor search with filters. In *Proceedings of the ACM Web Conference 2023*. 3406–3416.

[22] Georg Gottlob. 1987. Subsumption and implication. *Inform. Process. Lett.* 24, 2 (1987), 109–111.

[23] Gaurav Gupta, Jonah Yi, Benjamin Coleman, Chen Luo, Vihan Lakshman, and Anshumali Shrivastava. 2023. CAPS: A Practical Partition Index for Filtered Similarity Search. *arXiv preprint arXiv:2308.15014* (2023).

[24] harsha simhadri. 2024. Big ANN Benchmarks. https://github.com/harsha-simhadri/big-ann-benchmarks.

[25] Stratos Idreos, Martin L Kersten, Stefan Manegold, et al. 2007. Database Cracking.. In *CIDR*, Vol. 7. 68–78.

[26] Milena G Ivanova, Martin L Kersten, Niels J Nes, and Romulo AP Gonçalves. 2010. An architecture for recycling intermediates in a column-store. *ACM Transactions on Database Systems (TODS)* 35, 4 (2010), 1–43.

[27] Suhas Jayaram Subramanya, Fnu Devvrit, Harsha Vardhan Simhadri, Ravishankar Krishnawamy, and Rohan Kadekodi. 2019. Diskann: Fast accurate billion-point nearest neighbor search on a single node. *Advances in Neural Information Processing Systems* 32 (2019).

[28] Alekh Jindal, Konstantinos Karanasos, Sriram Rao, and Hiren Patel. 2018. Selecting subexpressions to materialize at datacenter scale. *Proceedings of the VLDB Endowment* 11, 7 (2018), 800–812.

[29] G Kashyap and G Ambika. 2019. Link deletion in directed complex networks. *Physica A: Statistical Mechanics and its Applications* 514 (2019), 631–643.

[30] Asterios Katsifodimos, Ioana Manolescu, and Vasilis Vassalos. 2012. Materialized view selection for XQuery workloads. In *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data* (Scottsdale, Arizona, USA) *(SIGMOD '12)*. Association for Computing Machinery, New York, NY, USA, 565–576. https://doi.org/10.1145/2213836.2213900

[31] Ben Landrum, Magdalen Dobson Manohar, Mazin Karjikar, and Laxman Dhulipala. 2025. IVF2 Index: Fusing Classic and Spatial Inverted Indices for Fast Filtered ANNS. In *The 1st Workshop on Vector Databases*. https://openreview.net/forum?id=kXw8E3xT7O

[32] Zhaoheng Li, Xinyu Pi, and Yongjoo Park. 2023. S/C: Speeding up Data Materialization with Bounded Memory. In *2023 IEEE 39th international conference on data engineering (ICDE)*. IEEE, 1981–1994.

[33] Yu A Malkov and Dmitry A Yashunin. 2018. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. *IEEE transactions on pattern analysis and machine intelligence* 42, 4 (2018), 824–836.

[34] Information Management and Preservation. 2024. Million Song Dataset Benchmarks. https://www.ifs.tuwien.ac.at/mir/msd/.

[35] Meta. [n.d.]. Llama Models. https://www.llama.com/.

[36] Microsoft. [n.d.]. Introducing Phi-3: Redefining what's possible with SLMs. https://azure.microsoft.com/en-us/blog/introducing-phi-3-redefining-whats-possible-with-slms/.

[37] Baharan Mirzasoleiman, Ashwinkumar Badanidiyuru, and Amin Karbasi. 2016. Fast constrained submodular maximization: Personalized data summarization. In *International Conference on Machine Learning*. PMLR, 1358–1367.

[38] Hoshi Mistry, Prasan Roy, S. Sudarshan, and Krithi Ramamritham. 2001. Materialized view selection and maintenance using multi-query optimization. In *Proceedings of the 2001 ACM SIGMOD International Conference on Management of Data* (Santa Barbara, California, USA) *(SIGMOD '01)*. Association for Computing Machinery, New York, NY, USA, 307–318. https://doi.org/10.1145/375663.375703

[39] Jason Mohoney, Anil Pacaci, Shihabur Rahman Chowdhury, Ali Mousavi, Ihab F Ilyas, Umar Farooq Minhas, Jeffrey Pound, and Theodoros Rekatsinas. 2023. High-throughput vector similarity search in knowledge graphs. *Proceedings of the ACM on Management of Data* 1, 2 (2023), 1–25.

[40] Bilegsaikhan Naidan, Leonid Boytsov, Yury Malkov, and David Novak. 2015. Non-metric space library manual. *arXiv preprint arXiv:1508.05470* (2015).

[41] Mark EJ Newman, Cristopher Moore, and Duncan J Watts. 2000. Mean-field solution of the small-world network model. *Physical Review Letters* 84, 14 (2000), 3201.

[42] nmslib. 2024. Hnswlib - fast approximate nearest neighbor search. https://github.com/nmslib/hnswlib.

[43] OpenAI. [n.d.]. OpenAI. https://openai.com/.

[44] Liana Patel, Peter Kraft, Carlos Guestrin, and Matei Zaharia. 2024. ACORN: Performant and Predicate-Agnostic Search Over Vector Embeddings and Structured Data. *Proc. ACM Manag. Data* 2, 3, Article 120 (May 2024), 27 pages. https://doi.org/10.1145/3654923

[45] Pinecone. [n.d.]. Hierarchical Navigable Small Worlds (HNSW). https://www.pinecone.io/learn/series/faiss/hnsw/.

[46] Karthikeyan Ramasamy, Prasad M Deshpande, Jeffrey F Naughton, and David Maier. 1998. Set-Valued Attributes in O/R DBMS: Implementation Options and Performance Implications. *R DBMS: Implementation options and performance implications, Madison: University of Wisconsin* (1998).

[47] Abhishek Roy, Alekh Jindal, Hiren Patel, Ashit Gosalia, Subru Krishnan, and Carlo Curino. 2019. Sparkcruise: Handsfree computation reuse in spark. *Proceedings of the VLDB Endowment* 12, 12 (2019), 1850–1853.

[48] Viktor Sanca and Anastasia Ailamaki. 2024. Efficient Data Access Paths for Mixed Vector-Relational Search. In *Proceedings of the 20th International Workshop on Data Management on New Hardware*. 1–9.

[49] Aneesh Sharma, Jerry Jiang, Praveen Bommannavar, Brian Larson, and Jimmy Lin. 2016. GraphJet: Real-time content recommendations at Twitter. *Proceedings of the VLDB Endowment* 9, 13 (2016), 1281–1292.

[50] Amit Shukla, Prasad Deshpande, Jeffrey F Naughton, et al. 1998. Materialized view selection for multidimensional datasets. In *VLDB*, Vol. 98. 488–499.

[51] Harsha Vardhan Simhadri, Martin Aumüller, Amir Ingber, Matthijs Douze, George Williams, Magdalen Dobson Manohar, Dmitry Baranchuk, Edo Liberty, Frank Liu, Ben Landrum, et al. 2024. Results of the Big ANN: NeurIPS'23 competition. *arXiv preprint arXiv:2409.17424* (2024).

[52] Justin JongSu Song, Wookey Lee, and Jafar Afshar. 2019. An effective high recall retrieval method. *Data & Knowledge Engineering* 123 (2019), 101603.

[53] Liwen Sun, Michael J Franklin, Sanjay Krishnan, and Reynold S Xin. 2014. Fine-grained partitioning for aggressive data skipping. In *Proceedings of the 2014 ACM SIGMOD international conference on Management of data*. 1115–1126.

[54] Liwen Sun, Michael J Franklin, Jiannan Wang, and Eugene Wu. 2016. Skipping-oriented partitioning for columnar layouts. *Proceedings of the VLDB Endowment* 10, 4 (2016), 421–432.

[55] Maxim Sviridenko. 2004. A note on maximizing a submodular set function subject to a knapsack constraint. *Operations Research Letters* 32, 1 (2004), 41–43.

[56] Texmex. 2024. Datasets for approximate nearest neighbor search. http://corpus-texmex.irisa.fr/.

[57] Dimitri Theodoratos and Wugang Xu. 2004. Constructing search spaces for materialized view selection. In *Proceedings of the 7th ACM international workshop on Data warehousing and OLAP*. 112–121.

[58] Donald M Topkis. 1998. *Supermodularity and complementarity*. Princeton university press.

[59] UQV. 2024. UQV. http://staff.itee.uq.edu.au/shenht/UQVIDEO/.

[60] Jianguo Wang, Xiaomeng Yi, Rentong Guo, Hai Jin, Peng Xu, Shengjun Li, Xiangyu Wang, Xiangzhou Guo, Chengming Li, Xiaohai Xu, et al. 2021. Milvus: A purpose-built vector data management system. In *Proceedings of the 2021 International Conference on Management of Data*. 2614–2627.

[61] Mengzhao Wang, Lingwei Lv, Xiaoliang Xu, Yuxiang Wang, Qiang Yue, and Jiongkang Ni. 2022. Navigable proximity graph-driven native hybrid queries with structured and unstructured constraints. *arXiv preprint arXiv:2203.13601* (2022).

[62] Zeyu Wang, Qitong Wang, Xiaoxing Cheng, Peng Wang, Themis Palpanas, and Wei Wang. 2024. Steiner-hardness: A query hardness measure for graph-based ann indexes. *Proceedings of the VLDB Endowment* 17, 13 (2024), 4668–4682.

[63] Chuangxian Wei, Bin Wu, Sheng Wang, Renjie Lou, Chaoqun Zhan, Feifei Li, and Yuanzhe Cai. 2020. AnalyticDB-V: a hybrid analytical engine towards query fusion for structured and unstructured data. *Proceedings of the VLDB Endowment* 13, 12 (2020), 3152–3165.

[64] Wikipedia. [n.d.]. Hasse Diagram - Wikipedia. https://en.wikipedia.org/wiki/Hasse_diagram.

[65] Wikipedia. 2024. Skip List Data Structure - Wikipedia. https://en.wikipedia.org/wiki/Skip_list.

[66] Wei Wu, Junlin He, Yu Qiao, Guoheng Fu, Li Liu, and Jin Yu. 2022. HQANN: Efficient and robust similarity search for hybrid queries with structured and unstructured constraints. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*. 4580–4584.

[67] Wentao Xiao, Yueyang Zhan, Rui Xi, Mengshu Hou, and Jianming Liao. 2024. Enhancing HNSW Index for Real-Time Updates: Addressing Unreachable Points and Performance Degradation. *arXiv preprint arXiv:2407.07871* (2024).

[68] Zongheng Yang, Badrish Chandramouli, Chi Wang, Johannes Gehrke, Yinan Li, Umar Farooq Minhas, Per-Åke Larson, Donald Kossmann, and Rajeev Acharya. 2020. Qd-tree: Learning Data Layouts for Big Data Analytics. In *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data* (Portland, OR, USA) *(SIGMOD '20)*. Association for Computing Machinery, New York, NY, USA, 193–208. https://doi.org/10.1145/3318464.3389770

[69] Zhengyu Yang, Danlin Jia, Stratis Ioannidis, Ningfang Mi, and Bo Sheng. 2018. Intermediate data caching optimization for multi-stage and parallel big data frameworks. In *2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*. IEEE, 277–284.

[70] Chuan Zhang, Xin Yao, and Jian Yang. 2001. An evolutionary approach to materialized views selection in a data warehouse environment. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 31, 3 (2001), 282–294.

[71] Li Zhaoheng, Huang Silu, Ding Wei, Park Yongjoo, and Chen Jianjun. [n.d.]. SIEVE Technical Report. https://arxiv.org/abs/2507.11907.

[72] Li Zhaoheng, Huang Silu, Ding Wei, Park Yongjoo, and Chen Jianjun. 2025. SIEVE - Github. https://github.com/BillyZhaohengLi/SIEVE-vldb25/.

[73] Zilliz. 2024. Faiss vs. HNSWlib: Choosing the Right Vector Search Tool for Your Application.

[74] Chaoji Zuo, Miao Qiao, Wenchao Zhou, Feifei Li, and Dong Deng. 2024. SeRF: Segment Graph for Range-Filtering Approximate Nearest Neighbor Search. *Proceedings of the ACM on Management of Data* 2, 1 (2024), 1–26.