Attribute Filtering in Approximate Nearest Neighbor Search: An In-depth Experimental Study (Appendix)

CCS Concepts

• **Information systems → Retrieval efficiency**.

Keywords

Approximate Nearest Neighbor, Filtering, Survey

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1 Appendix 1: Complexity

In some cases, complexity analysis is prohibitive [1], as no algorithm can guarantee sub-linear query efficiency in the worst case. Nevertheless, we can still analyze the additional time and memory overhead introduced by filtering techniques, relative to the underlying ANN search algorithm. In this section, we focus on graph-based methods, including Filtered-DiskANN, AIRSHIP, NHQ, SeRF, ACORN, β-WST, iRangeGraph, and UNIFY.

Table 1 presents our complexity analysis, where Γ denotes the selectivity of a query. To avoid the intricacies of detailed complexity discussions for each base index, we adopt the following notations, where the indexing complexity is represented as n^α, typically with $1 < \alpha < 2$, and the query complexity as n^λ, where $0 < \lambda < 1$. The index size for graph-based methods is denoted as Mn, where M is a hyperparameter that controls the degree of each vertex. For all HNSW-based algorithms, the base indexing complexity is $n\log(n)$, and the query complexity is $\log(n)$ [2].

For any algorithm that adjusts the pruning strategy, the impact on indexing complexity is typically minimal. Consequently, the indexing complexity remains n^α for methods such as AIRSHIP, VG in Filtered-DiskANN, NHQ, SeRF, and UNIFY. However, in the case of SVG within Filtered-DiskANN — which merges multiple subgraphs into a single graph — the indexing time increases to Ln^α, where L denotes the total number of attribute values.

Filtered-DiskANN offers two indexing strategies. The Filtered Vamana Graph retains the original indexing complexity, introducing no significant overhead. In contrast, the Stitched Vamana Graph builds a separate subgraph for each categorical attribute value, resulting in an overall indexing complexity of $O(Ln^\alpha)$, where L is the number of distinct categorical values. Despite this, its memory complexity remains Mn, constrained by the maximum degree parameter M.

Table 1: Complexity of Graph-based FANN Algorithms

Algorithm	Index Time Complexity	Query Time Complexity	Memory Complexity
FDiskANN-VG	n^α	$(\Gamma n)^\lambda$	Mn
FDiskANN-SVG	Ln^α	$(\Gamma n)^\lambda$	Mn
NHQ	n^α	n^λ	Mn
SeRF	$nM^2\log(n)$	$(\Gamma n)^\lambda$	$Mn\log(n)$
DSG	$nM^2\log(n)$	$(\Gamma n)^\lambda$	$Mn\log(n)$
ACORN	$n\log(n)$	$\log(\Gamma n)$	Mn
β-WST	$n^d\log(n)$	$(\Gamma n)^\lambda$	$Mn\log(n)$
iRangeGraph	$n^d\log(n)$	$(\Gamma n)^\lambda$	$Mn\log(n)$
UNIFY	$n\log(n)$	pre-:Γn joint-:$\log(\Gamma n)$ post-:$\log(n)$	$L'MSn$

NHQ and ACORN do not significantly change the way they construct index, so their indexing complexity, query time complexity, and memory complexity stay unchanged.

For SeRF, determining the upper bound timestamp incurs no additional cost in any aspect. However, to perform arbitrary range queries like $r_k = [od(l_k), od(u_k + 1)]$, SeRF searches for the top K neighbors($\log(n)$ time complexity) for each vector ($O(n)$) at any $od(l_k)$ that $od(l_k) < od(u_k + 1)$(takes about $O(n)$). This leads to a worst-case time cost of $O(n^2\log(n))$ and a memory cost of $O(Mn^2)$. Fortunately, the average index time cost is $O(M^2n\log(n))$ and the memory footprint is $O(Mn\log(n))$.

2 Appendix 2: Experiment Settings

Algorithm Settings.

In this study, we have gathered the latest algorithms for both range and label-based FANN to evaluate their performance. Our primary focus is on analyzing the advantages and disadvantages of their filtering architectures, which is why most traditional ANN systems are excluded from our experiments. Below, we list all the algorithms considered in our analysis.

Overall configuration. To make the experiment comparable, we use the same setting as much as possible for all algorithms. We use $M = 40$ and $ef\_construction = 1000$ for all graph-based algorithms. For IVFPQ methods, we take $ncentroids = 4\sqrt{N}$ and $partition\_M = d/2$. But both Milvus-IVFPQ and Faiss-IVFPQ failed at 1% and 0.1% selectivity in SIFT and Spacev, so in these cases, we take $partition\_M = d$ to ensure they can fetch 90% recall.

Faiss. Faiss uses `is_member()` to check whether or not a vector's attribute matches our restriction. To define `is_member()` for all vectors and all queries, it is necessary to compare query restrictions

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with all attributes. However, it is inefficient and unnecessary to compare each item. Specifically, `is_member()` is used only when ANN index scans on the vector, which is unnecessary to check others. So we exclude the computation time for building `is_member()` for each query, but only take ANN search time into our consideration. To accelerate its computing efficiency, we enable AVX2 to accelerate L2 distance computation. In Faiss HNSW, we further static the total number of overall distance computations, instead of the original number of bottom layer computations.

Besides, we implement the brute force computation for range Filtering ANN search. Instead of using `is_member()`, we check whether its attribute fits the query range.

In our experiment, we use brute-force search to generate the ground truth. Faiss-HNSW and Faiss-IVFPQ are used as baselines for comparison with the filtering ANN algorithms.

ACORN. ACORN is designed based on Faiss library, but it designs a highly efficient `is_member()` function, which simply stores true or false for each item. Like Faiss, we enable AVX2 acceleration, and exclude the computation overhead of `is_member()`. We use it for both label and range queries since it supports arbitrary FANN query tasks. ACORN uses $M\gamma$ to present its $ef\_construction$, so we take $\gamma = ef\_construction/M = 25$.

Milvus. We use Milvus 2.5.9 Standalone version in our experiments, with Milvus_HNSW and Milvus_IVFPQ representing Milvus Filtering ANN. The default partition size is set to 64. Since Milvus is a highly integrated ANN system, it is not possible to directly obtain Comparisons Per Query (CPQ) for HNSW queries. As a result, we report Query Per Second (QPS) as the performance metric.

Filtered DiskANN. We include the Filtered Vamana Graph (VG) and Stitched Vamana Graph (SVG) in our experiments, using $\alpha = 1.2$ as recommended.

NHQ. We include NHQ_nsw and NHQ_kgraph in our experiments, as these two methods demonstrate the best performance in their respective papers and align closely with the core ideas of this work. Note that NHQ_kgraph relies on more than 9 hyperparameters, including L, $iter$, S, R, $RANGE$, PL, B, kg_M, and L_search, making it quite complex. For consistency, I set $RANGE = M$, $PL = efconstruction$, and $Lsearch = efsearch$, while the remaining parameters are $L = 100$, $iter = 12$, $S = 10$, $R = 300$, $B = 0.4$, $kg\_M = 1$.

SeRF. SeRF uses M differently; it stores pruned neighbors as segmented neighbors, meaning it's not necessary to set M as large as in other methods. Therefore, we assign $M = 8$ for SeRF as recommended, while both ef_max and $efconstruction$ are set to 1000. For all algorithms, constructing graph index will sacrifice the accuracy. This paper does not guarantee the accuracy of building index in parallel, but it is unfair to compare them in different indexing parallelization, so we enable the same index scale for them. Besides, we enable SSE acceleration for L2 distance computation.

DSG DSG operates similarly to SeRF and shares the same hyperparameters, so we set M and ef_max to the same values as those used for SeRF. Similar to SeRF, we enable parallel index building and SSE distance computation acceleration.

β-WST β-WST offers several methods for constructing a BST and querying on them. In this paper, we focus on the super-optimized post-filtering (WST_opt) and Vamana tree (WST_vamana) methods, as they demonstrate competitive performance. Additionally, these methods use the $split\_factor$ to control the splitting scale and the $shift\_factor$ to manage the overlap size. We set $split\_factor = 2$ to align the scale with that of $iRangeGraph$, and $shift\_factor = 0.5$ as recommended.

iRangeGraph. iRangeGraph uses the fewest hyperparameters, requiring only M, $ef\_construction$ for index construction. Therefore, we set these to the same values as the global ones. We enable SSE acceleration for iRangeGraph.

UNIFY. UNIFY requires B to set the number of slots inside the index; we set it to 8 as recommended. We enable combined filtering method for unify, setting $low\_threshold = 5\%$ and $high\_threshold = 50\%$, which means if the selectivity of a query is lower than 5%, we use skip table to find results; if it is between 5% and 10%, we use hybrid filtering (the core algorithm of UNIFY) to perform ANN search; if the selectivity is larger than 50%, we use post filtering to find the results. To estimate hybrid filtering performance on low and high selectivity, we also enable UNIFY-hybrid to search for any selectivity using joint-filtering, and UNIFY-CBO to search using pre-/joint-/filtering.

3 Appendix 3: Algorithm Performance on Different Selectivity Ranging From 1% to 100%

We evaluate the performance of the algorithms across a wide range of selectivity levels, from 1% to 100%, to comprehensively assess their behavior. The average number of Comparisons Per Query (CPQ) is used as one of the primary performance metrics. This metric effectively reflects the quality of graph-based Filtering ANN indices, as all algorithms are designed to minimize computational overhead. Importantly, CPQ abstracts away implementation-specific factors such as the exact distance computation or filtering techniques. Therefore, a lower CPQ indicates better performance.

3.1 Experiments for range filtering ANN search

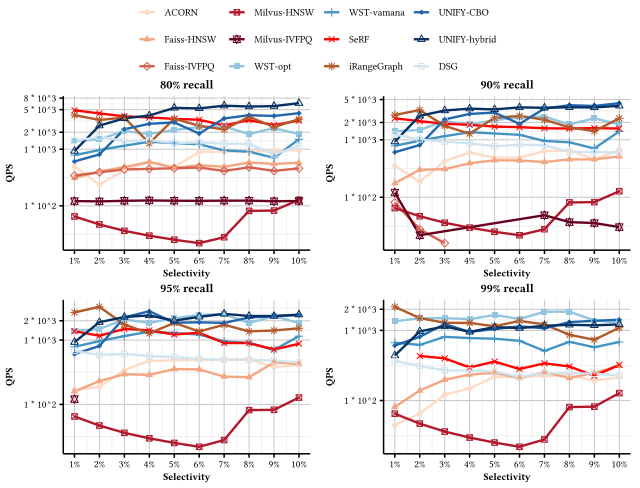


Figure 1: QPS for range query with selectivity from 1% to 10% in SIFT

Figure 1 presents the QPS results for range ANN search with selectivity levels from 1% to 10%, while Figure 2 extends the analysis

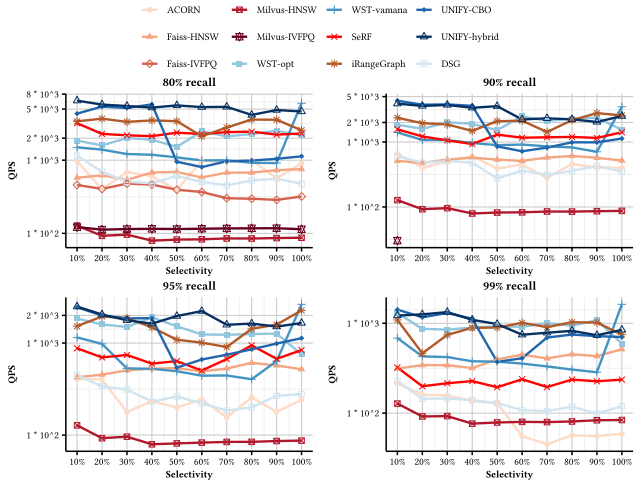


Figure 2: QPS for range query with selectivity from 10% to 100% in SIFT

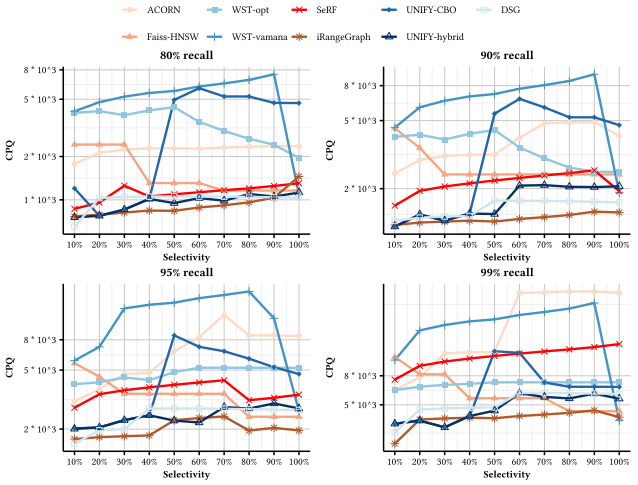


Figure 4: CPQ for range query with selectivity from 10% to 100% in SIFT

to selectivity levels from 10% to 100%. Overall, most algorithms exhibit a consistent performance trend across both QPS and CPQ metrics—namely, higher QPS generally corresponds to lower CPQ, indicating more efficient computation.

In Figure 1, UNIFY-hybrid, WST-opt, and iRangeGraph demonstrate the best performance, with UNIFY-hybrid slightly outperforming the others. In contrast, as shown in Figure 2, WST-vamana achieves the highest QPS at higher selectivity levels, benefiting from the elimination of multi-subgraph searches. Meanwhile, WST-CBO shows a decline in performance when selectivity exceeds 50%, due to the overhead introduced by its post-filtering strategy.

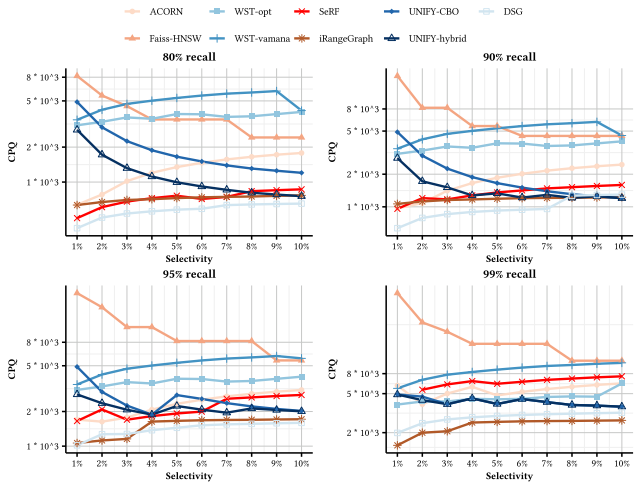


Figure 3: CPQ for range query with selectivity from 1% to 10% in SIFT

Figure 3 and Figure 4 show similar but stable performance reports. iRangeGraph achieved the best performance instead of UNIFY, mainly because of the different implementation in terms of code details.

One difference is that DSG achieved significantly better performance than QPS showed. This is mainly because of the extra cost of edge selection. Even though SeRF has the same strategy as DSG, it has fewer edges, making it more efficient. Similar case apply to ACORN, which searches two-hop neighbors to find suitable edges, making it significantly inefficient at 1% selectivity, but its CPQ is still low and comparable.

3.2 Experiments for label filtering ANN search

We conduct our experiment on the selectivity from 1% to 100% to estimate their performance. Figure 5, 6, 7 and 8 shows our experiment on those methods.

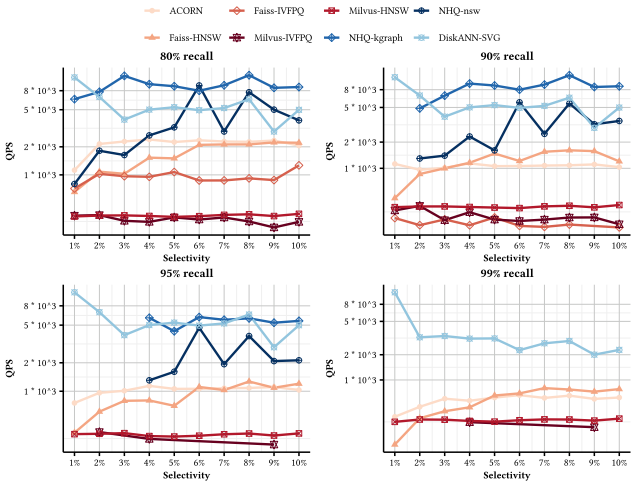


Figure 5: QPS for label query with selectivity from 10% to 100% in SIFT1M

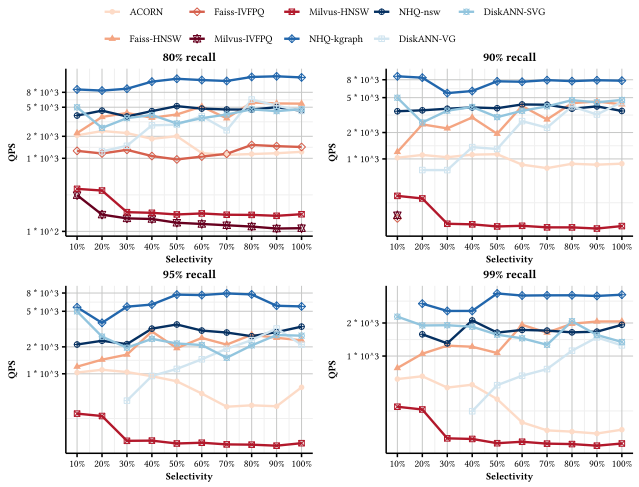


Figure 6: QPS for label query with selectivity from 10% to 100% in SIFT1M

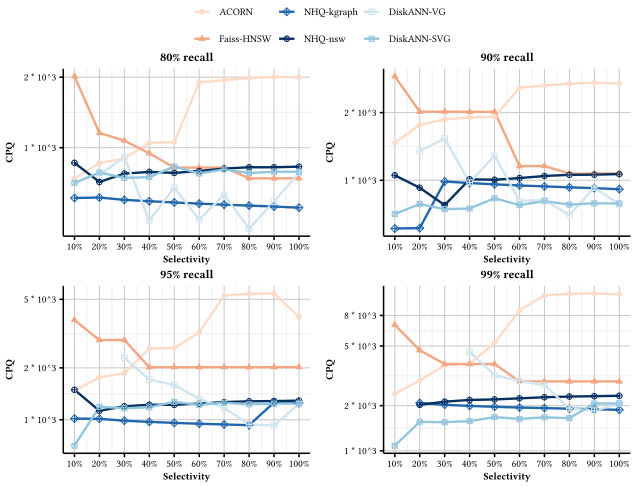


Figure 8: CPQ for label query with selectivity from 10% to 100% in SIFT1M

NHQ-kgraph shows the best performance across all selectivity. While Faiss-IVFPQ achieved better QPS at 1% selectivity, showing IVF-based method outstanding tolerance to low selectivity.

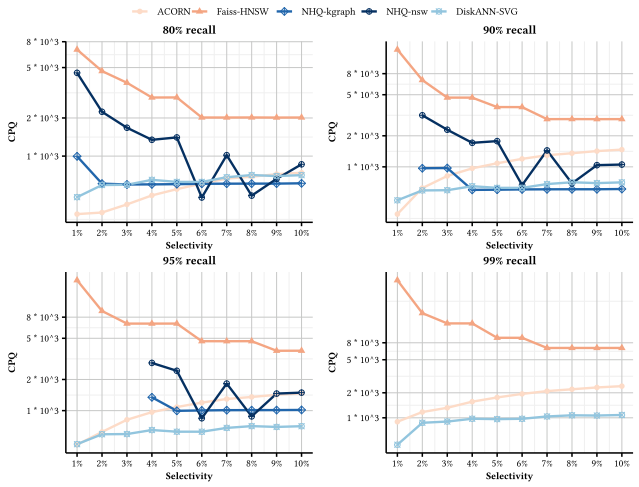


Figure 7: CPQ for label query with selectivity from 1% to 10% in SIFT1M

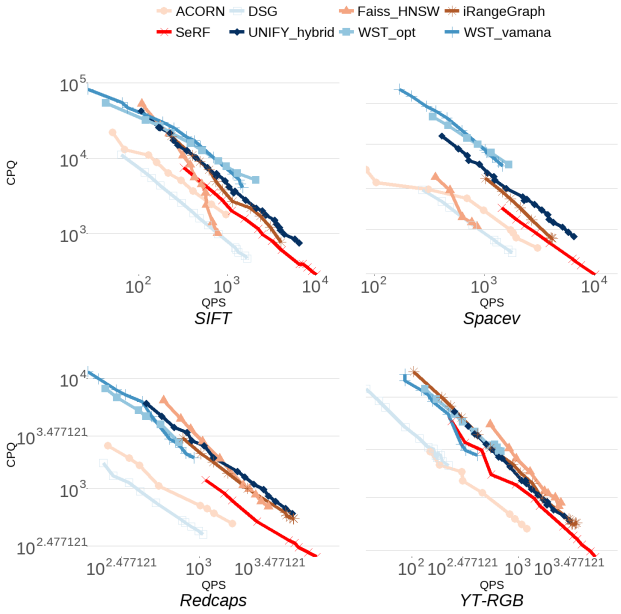


Figure 9: CPQ vs QPS at 80% recall and 10% selectivity

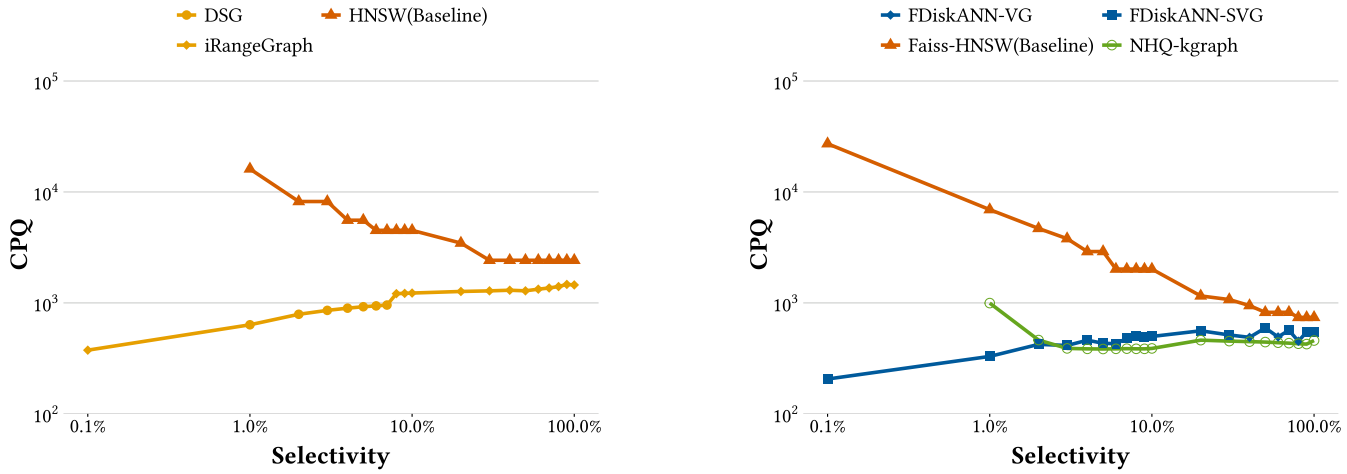
4 Appendix 4: CPQ vs. QPS

Figure 9 shows the relationship between CPQ and QPS in different configurations(for example, different ef_search value). All algorithms show a negative power relationship. All algorithms are parallel to each other, indicating that CPQ directly reflects the performance of QPS. Note that comparing CPQ-QPS between different algorithms is invalid, since they are not guaranteed to get the same recall at the same QPS. Besides, CPQ provides more stable metrics on all graph-based experiments.

Even if QPS and CPQ are closely connected in certain selectivity, they are not guaranteed to be comparable across algorithms and selectivity levels.

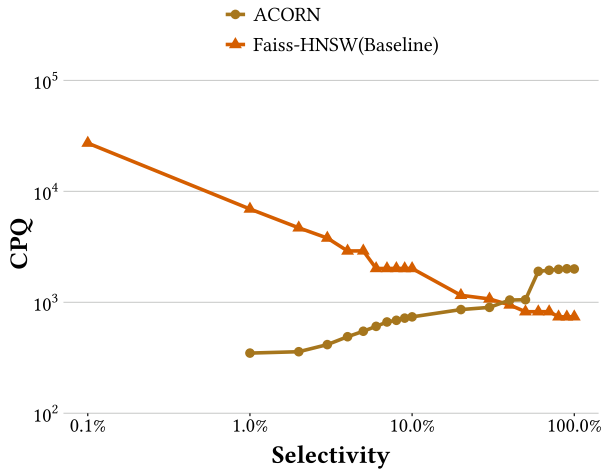
5 Appendix 5: Comparison

Figure 10 shows the comparison of baseline (Faiss-HNSW) and the best performance in range filtering (RF), label filtering (LF), multi-cardinality label filtering (MCLF), and arbitrary filtering (AF), and the comparison among pre-/post-/joint-filtering methods. For all filtering ANN methods, the greater the selectivity, the closer the

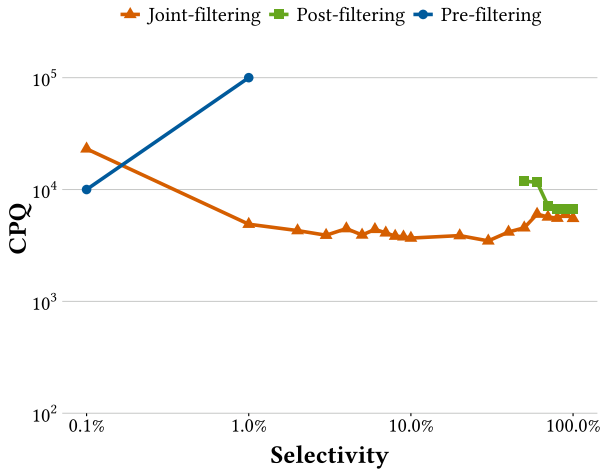


(a) Baseline vs. RF at 80% recall in SIFT10M

(b) Baseline vs. LF vs. MCLF at 80% recall in SIFT1M



(c) Baseline vs. AF at 80% recall in SIFT1M



(d) Pre-/Post/-Joint filtering at 99% recall in SIFT10M

Figure 10: Baseline comparison for different filtering ANN scenarios with selectivity from 10% to 100% in SIFT. The lower CPQ the better

performance will be. For range and label filtering cases, the filtering ANN algorithms show significantly better performance than the baseline.

In figure 10a, what is out of our expectation is that DSG performs well with selectivity at 1%~10%. To analyse its reason, we consider 9. For the same ef_search, DSG got lower QPS and CPQ than other methods(DSG's line is significantly parallel but lower than other methods). This indicates that even though DSG constructs a large index, fewer edges are legal for a search range. In other words, the edges are strictly classified, making the search task perform well at low selectivity. However, DSG failed to achieve competitive performance with extremely small and large selectivity, mainly due to the low quality of its connection.

In Figure 10b, we split Filtered DiskANN methods and NHQ methods apart, because they focus on different filtering scenarios. NHQ failed in 0.1% recall, because its heuristic distance estimation method failed when its connection is no longer guaranteed by graph index. DiskANN Stitched shows outstanding performance throughout all selectivities, showing the effective improvement in constructing subgraphs for all labels.

However, arbitrary filtering performance is still limited, especially when the selectivity exceeds 50%. This is mainly because ACORN's pruning method drops RNG connectivity and scalability, making searching less efficient when most one-hop edges can be used.

In Figure 10d, all methods are based on UNIFY. Pre-filtering is a linear scan, post-filtering is a search on the UNIFY complete index and then filtering out matched candidates, while joint-filtering is the UNIFY filtering algorithm. In SIFT10M, pre-filtering works only when selectivity is extremely small(less than 0.5%, but this value varies when dataset scale changes). While post-filtering becomes relatively effective when selectivity exceeds 70%, this differs from

Table 2: CPQ (%) change from original entry point strategy in SIFT10M

Algorithm	Selectivity			
	1%	10%	50%	100%
UNIFY	**default**	**default**	**default**	**default**
UNIFY-middle	-0.14%	0.10%	1.09%	2.21%
UNIFY-left	-0.14%	0.10%	1.09%	2.21%
UNIFY-right	-0.14%	0.10%	1.09%	2.21%
SeRF	**default**	**default**	**default**	**default**
SeRF-left	0.00%	0.00%	0.00%	0.00%
SeRF-right	0.00%	0.00%	0.00%	0.00%
DSG	**default**	**default**	**default**	**default**
DSG-left	0.00%	0.00%	0.00%	0.00%
DSG-right	0.00%	0.00%	0.00%	0.00%

the recommended thresholds in UNIFY (10% and 50%). In conclusion, joint filtering performs best overall. Pre-filtering is only ideal at extremely low selectivity.

6 Appendix 6: entry point experiments

Inspired by SeRF and DSG, which overlook the hierarchical structure and perform search directly on the bottom layer, we investigate the role of hierarchy in the context of filtering ANN. In this section, we adjust UNIFY to select entry points directly from the bottom layer, aiming to analyze the impact of hierarchical design in filtering scenarios. Specifically, we seek to verify two aspects: (1) the influence of hierarchical traversal from top entry points down to the bottom layer, and (2) the effect of selecting different entry points within the bottom layer itself.

We define three different methods for selecting entry points from a sorted vector list V, given a range query q_k. Let the matched subset of V_k be located within the indices $[l, r]$, such that the size of the range is $|V_k| = r - l + 1$. The three methods of choosing entry points are:

$$EP = \begin{cases} \{v_{l+i\times|V_r|/ep}\} & \text{Middle} \\ \{v_{l+i}\} & \text{Left} \\ \{v_{l+|V_r|-i}\} & \text{Right} \end{cases} \quad (1)$$

Table 2 presents our entry point selection experiments, where UNIFY (short for UNIFY-hybrid) is evaluated under different conditions. The results demonstrate a significant performance impact when avoiding heretical entry points at high selectivity. Notably, as selectivity decreases to 10%, UNIFY actually benefits from omitting heretical entry points.

On the other hand, as long as the entry point lies within the queried subset, the method of selecting entry points from the bottom layer has minimal impact. Both UNIFY, SeRF, and DSG's -left and -right entry points exhibit negligible performance differences.

7 Appendix 7: Search Parameters

Unlike traditional ANN, filtering ANN must handle varied selectivity, leading to searches over subsets of different sizes. As a result, the search parameter varies with selectivity, an aspect that has not been thoroughly discussed in previous studies.

In this appendix, I introduce the search parameters that achieved the best performance for each algorithm. For IVF-based methods, we provide *nprobe*; for graph-based methods, we provide ef_search. For algorithms that do not use ef_search, we specify L_search for NHQ-kgraph and Filtered DiskANN, and $Beam\_size$ for β-WST.

Table 3 shows the part of the hyperparameters that reached our best results. Milvus and Faiss methods show unstable parameter choice, where the higher selectivity, the lower value they choose. This case applies to ACORN and DiskANN.

Besides, the larger the dataset, the larger the parameter value. Besides, Youtube-RGB shows the hardest case since all algorithms have to apply the large parameter to achieve the recall.

SeRF and DSG show stable hyperparameter choice, which is a strong advantage. However, iRangeGraph and WST-opt have to assign larger hyperparameters to larger selectivity, which is opposed to Milvus and Faiss, because they have to search on a larger subindex.

UNIFY has to assign ef_search and AL to search, making its hyperparameter more unstable.

8 Appendix 8: M in SeRF

Figure 11 shows that hyper-parameter M in SeRF has limited influence, while larger M even get worse at low selectivity.

Figure 12 shows that the low recall at SIFT is not related to the stitching operation, but only related to the natural quality of Vamana Graph, which can not guarantee the quality of each subgraph, so the stitched index is of low quality too.

9 Appendix 9: Thread number to SeRF and DSG

Figure 13 shows that thread number show little effect to their performance.

10 Appendix 10: QPS at Different Recall Target

In this section, we report the QPS at 95% and 99% recall targets. Figures 16 and 17 present the QPS for range queries at 95% and 99% recall, respectively. Figures 18 and 19 illustrate the label query performance under the same recall settings. Figures 20 and 21 show the results for arbitrary queries. All methods perform similarly at the 90% recall level, but several insights emerge at higher recall targets.

1. Brute-force scan shows stable performance at high recall. As all methods require larger scan ranges to achieve higher recall, brute-force scan methods exhibit stable performance. This is evident from UNIFY-CBO at 0.1% selectivity. As the requirement of recall level increases, scan-based methods tend to perform better in low-selectivity settings. **2. Quantization-based methods struggle at high recall.** Due to limited precision, IVFPQ and Milvus-IVFPQ fail to maintain high recall for relatively lower-dimension datasets. On high-dimensional datasets such as YouTube-RGB (1024 dimensions), quantization-based methods can achieve 99% recall by retaining more information during retrieval, but this comes at the cost of efficiency, with throughput dropping to 2–3 QPS, which is negligible in practice. **3. Query hardness impacts performance at 99% recall.** According to our analysis, datasets such as SpaceV and

Table 3: Search parameters for range filtering ANN algorithm

Algorithm	Selectivity															
	SIFT				Spacev				Redcaps				Youtube-RGB			
	0.1%	1%	10%	50%	0.1%	1%	10%	50%	0.1%	1%	10%	50%	0.1%	1%	10%	50%
Milvus-IVFPQ	100	1	30	20	300	150	80	50	80	20	20	20	30	20	20	20
Milvus-HNSW	18	60	10	10	12	150	40	80	40	60	40	40	200	200	60	300
IVFPQ	300	150	80	50	800	300	150	150	200	50	20	20	80	50	20	20
HNSW	-	300	80	30	-	400	100	40	-	300	60	18	-	1000	300	200
ACORN	-	100	60	80	-	100	100	150	-	80	18	40	-	300	60	300
SeRF	-	150	80	35	-	400	400	300	-	100	40	40	-	-	-	300
DSG	-	40	80	80	-	150	150	150	-	18	15	20	-	40	60	60
WST-vamana	12	20	12	15	18	1000	40	40	15	10	10	10	12	20	600	800
WST-opt	12	20	20	40	10	20	18	20	15	18	10	15	20	40	200	300
UNIFY	-	-	20	20	-	-	18	40	-	-	10	40	-	-	40	40
UNIFY-hybrid	9	18	20	20	10	12	18	40	8	10	10	10	10	20	40	60
iRangeGraph	15	20	40	80	40	20	60	60	10	12	10	18	12	60	150	200

Table 4: Search parameters for label filtering ANN algorithm

Algorithm	Selectivity															
	SIFT				Spacev				Redcaps				Youtube-RGB			
	0.1%	1%	10%	50%	0.1%	1%	10%	50%	0.1%	1%	10%	50%	0.1%	1%	10%	50%
Milvus-IVFPQ	150	150	30	20	200	300	200	150	50	20	30	20	20	20	20	10
Milvus-HNSW	1000	20	40	20	18	15	40	40	18	12	12	10	10	200	150	100
IVFPQ	300	300	80	50	800	300	150	100	200	50	20	20	100	50	20	20
HNSW	-	300	80	40	-	500	80	40	-	300	40	18	-	1000	300	200
ACORN	-	80	40	60	-	400	100	150	-	60	18	40	-	1000	60	300
DiskANN	-	-	-	150	-	-	-	1000	-	-	-	100	-	-	-	-
DiskANN-Stitched	300	-	-	-	20	40	60	40	20	20	20	20	20	1200	1400	1000
NHQ-kgraph	-	100	100	100	-	-	100	100	-	-	100	100	-	-	100	100
NHQ-nsw	-	-	-	100	-	-	1400	200	-	-	-	60	-	-	1200	1200

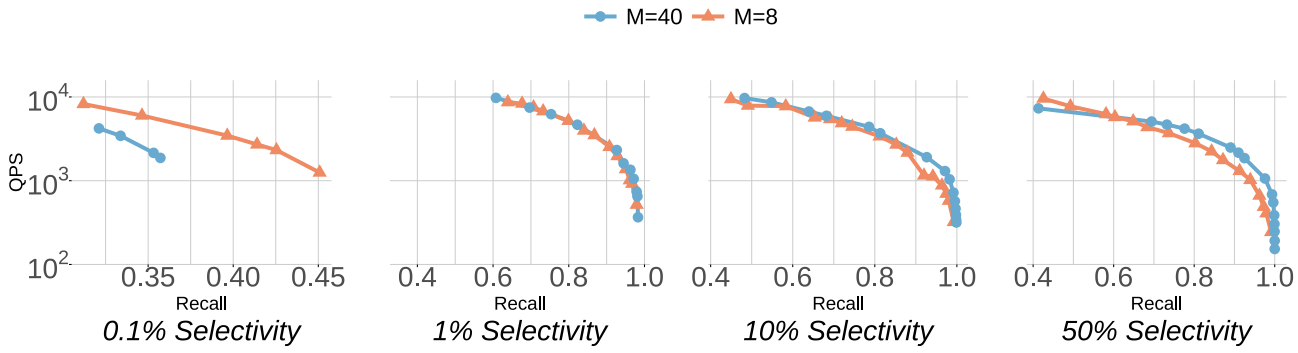


Figure 11: SeRF recall/qps in Redcaps with different M

YouTube-RGB present higher query hardness compared to the other two. This increased difficulty causes several methods to fall short of achieving 99% recall.

11 Appendix 11: DiskANN analysis

In the SIFT dataset, DiskANN-Stitched fails to achieve 90% recall at 50% selectivity, which contrasts with its performance on other selectivity levels and datasets. To better understand this anomaly,

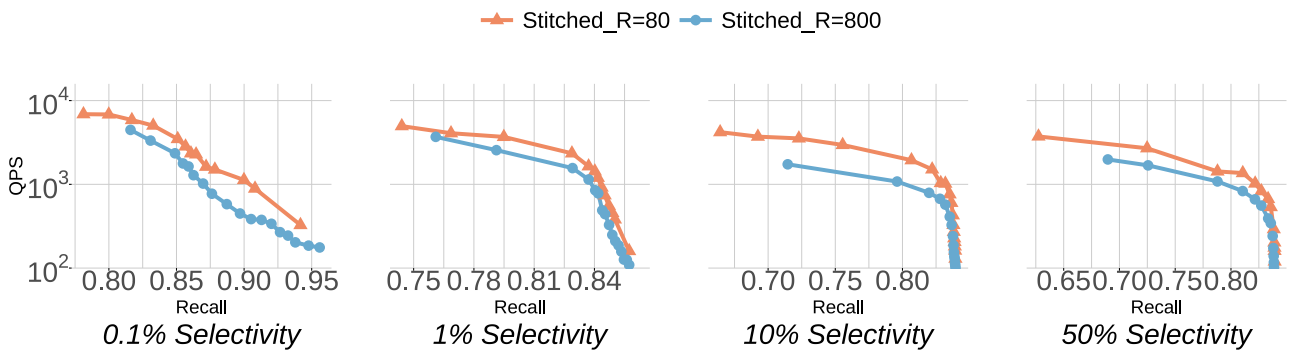


Figure 12: Filtered DiskANN Stitched recall/QPS in SIFT with different Stitched_R

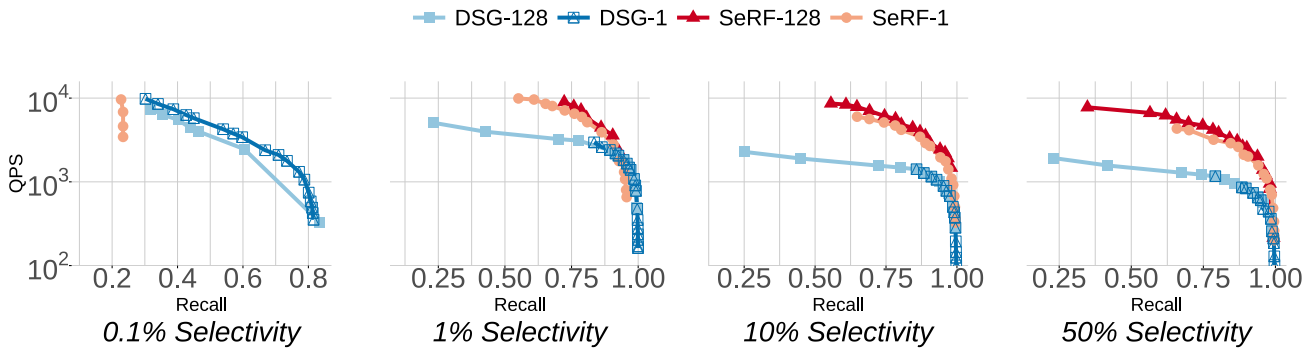


Figure 13: SeRF and DSG recall/QPS in redcaps with different thread number

Table 5: Index information of DiskANN-VG and DiskANN-SVG

Algorithm	Dataset	Max Degree	Average Degree
DiskANN-VG	SIFT	40	40.00
DiskANN-SVG	SIFT	40	35.65

we provide detailed index statistics and recall/QPS plots to support the analysis.

Figure 22 presents the recall versus QPS for DiskANN-VG and DiskANN-SVG on SIFT10M under different selectivity settings. Notably, DiskANN-SVG exceeds 90% recall only at 0.1% selectivity, while at higher selectivities it reaches at most approximately 85% recall.

Table 5 reports the maximum and average degrees of DiskANN-VG and DiskANN-SVG. DiskANN-VG demonstrates a higher average degree, contributing to its stable performance on SIFT. In contrast, the sparser graph of DiskANN-SVG limits its ability to maintain high recall at high selectivity.

12 Appendix 12: Performance With Different K

To gain further insights across different target K values, we conduct additional experiments with $K = 100$. Since Milvus-HNSW requires $ef\_search > 100$ for this setting, we apply a consistent configuration across all compared methods. Figures 23, 24, and 25 show the QPS results for range filtering, label filtering, and arbitrary filtering, respectively.

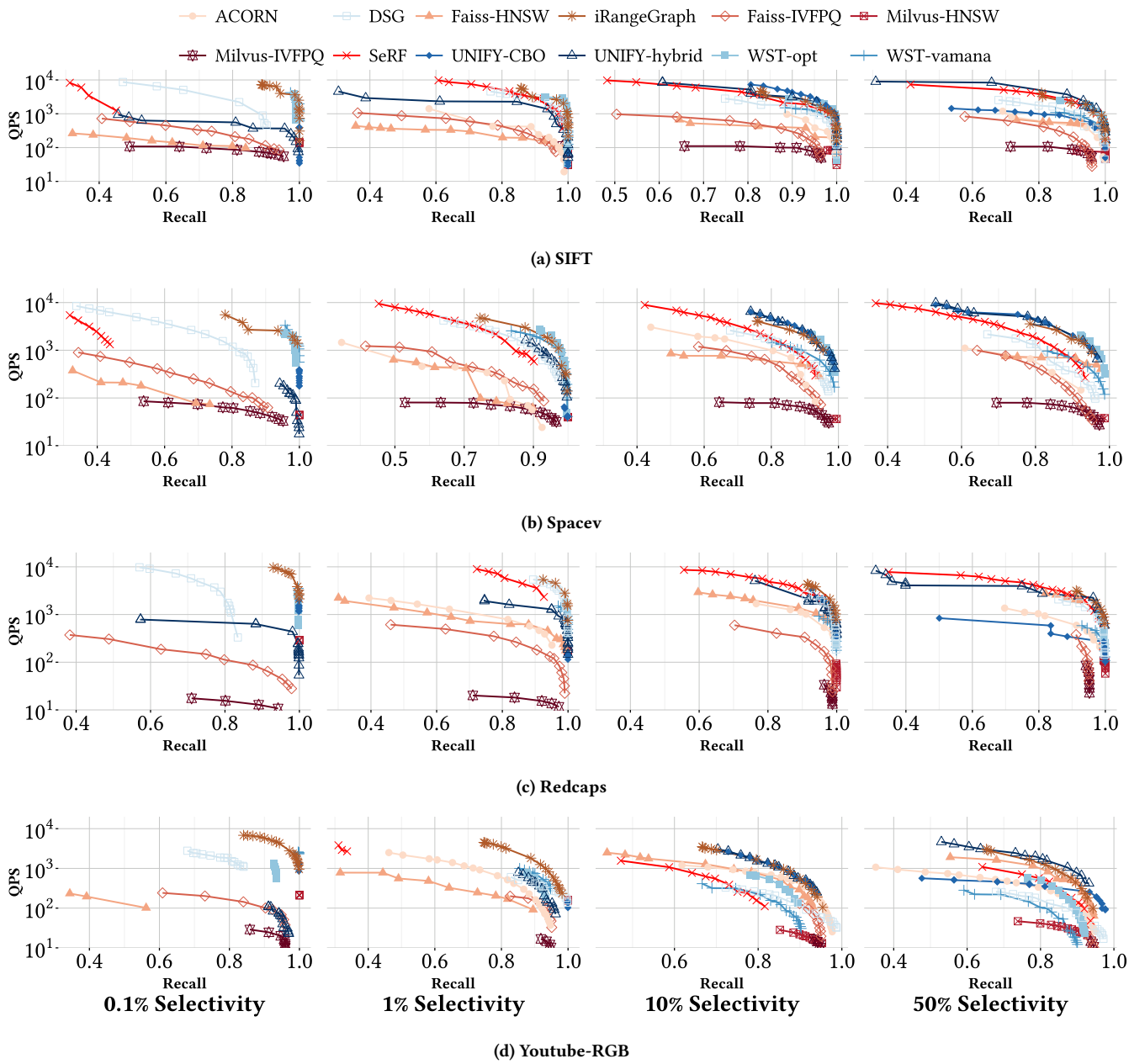
1. Higher K demands higher index quality. Compared to the $K = 10$ setting, DiskANN-SVG fails in most cases, as it cannot retrieve over 100 results reliably. Meanwhile, other methods also exhibit reduced QPS relative to their $K = 10$ performance due to adjustments in search hyperparameters.

2. Scan-based methods show stable performance. Consistent with the results at $K = 10$ and 99% recall, scan-based methods achieve near-100% recall and maintain stable QPS, as they search over a fixed-size dataset regardless of query difficulty.

References

[1] Piotr Indyk and Haike Xu. 2023. Worst-case performance of popular approximate nearest neighbor search implementations: Guarantees and limitations. *Advances in Neural Information Processing Systems* 36 (2023), 66239–66256.

[2] 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.



(a) SIFT

(b) Spacev

(c) Redcaps

(d) Youtube-RGB

Figure 14: Recall/QPS for range filtering ANN algorithms.

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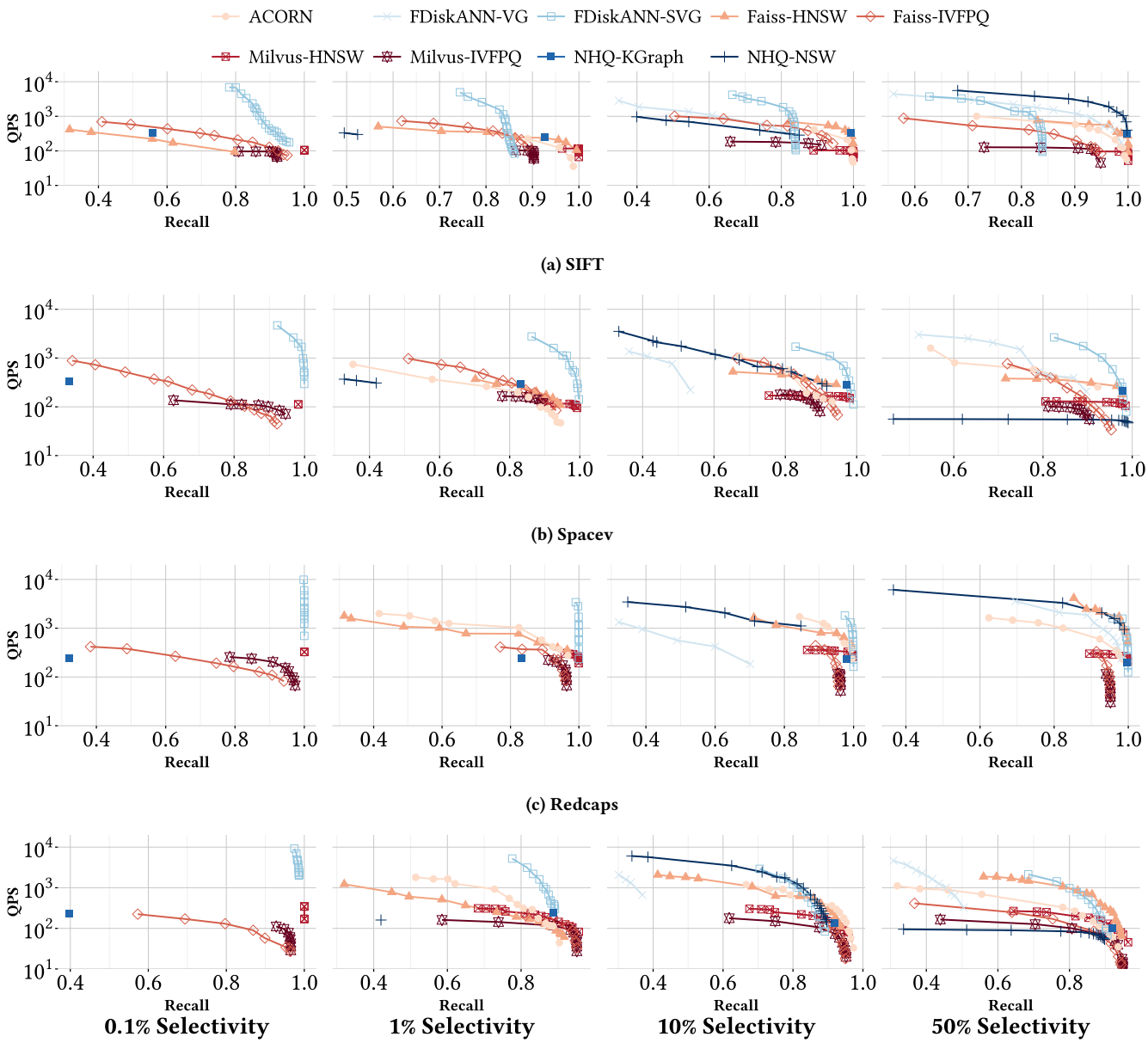


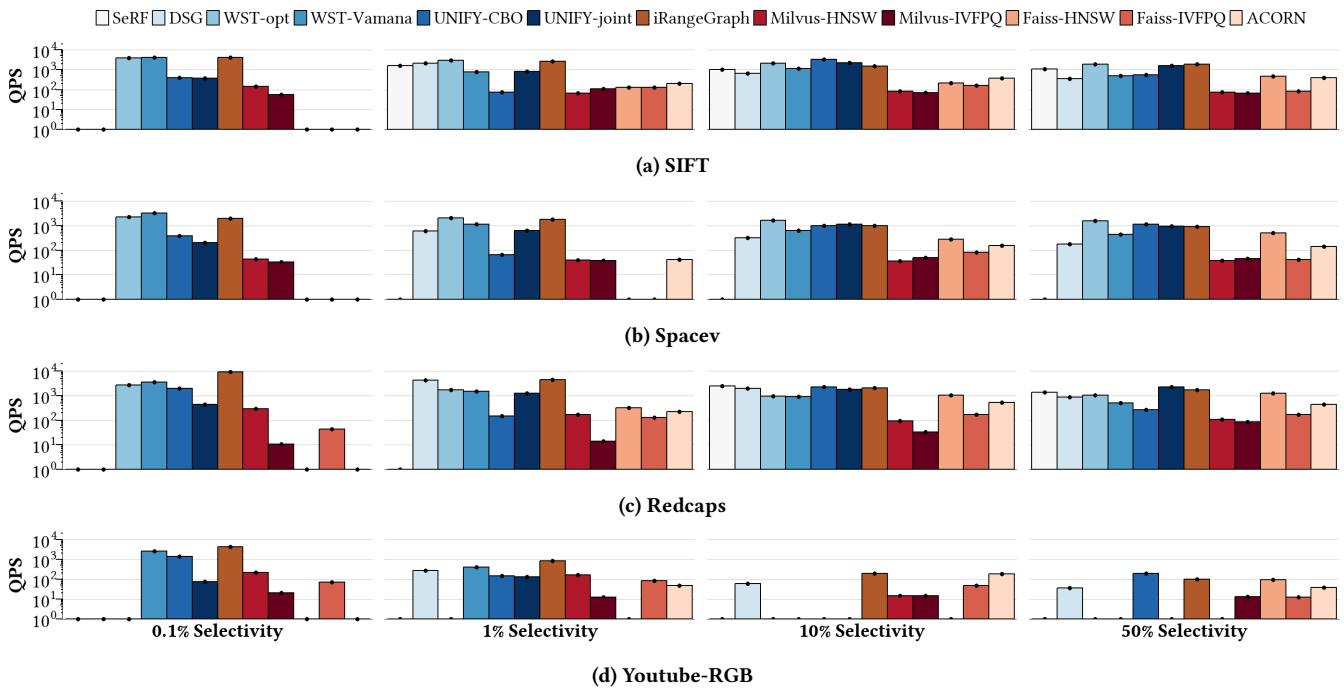
(a) SIFT

(b) Spacev

(c) Redcaps

(d) Youtube-RGB

Figure 15: Recall/QPS for label filtering ANN algorithms.



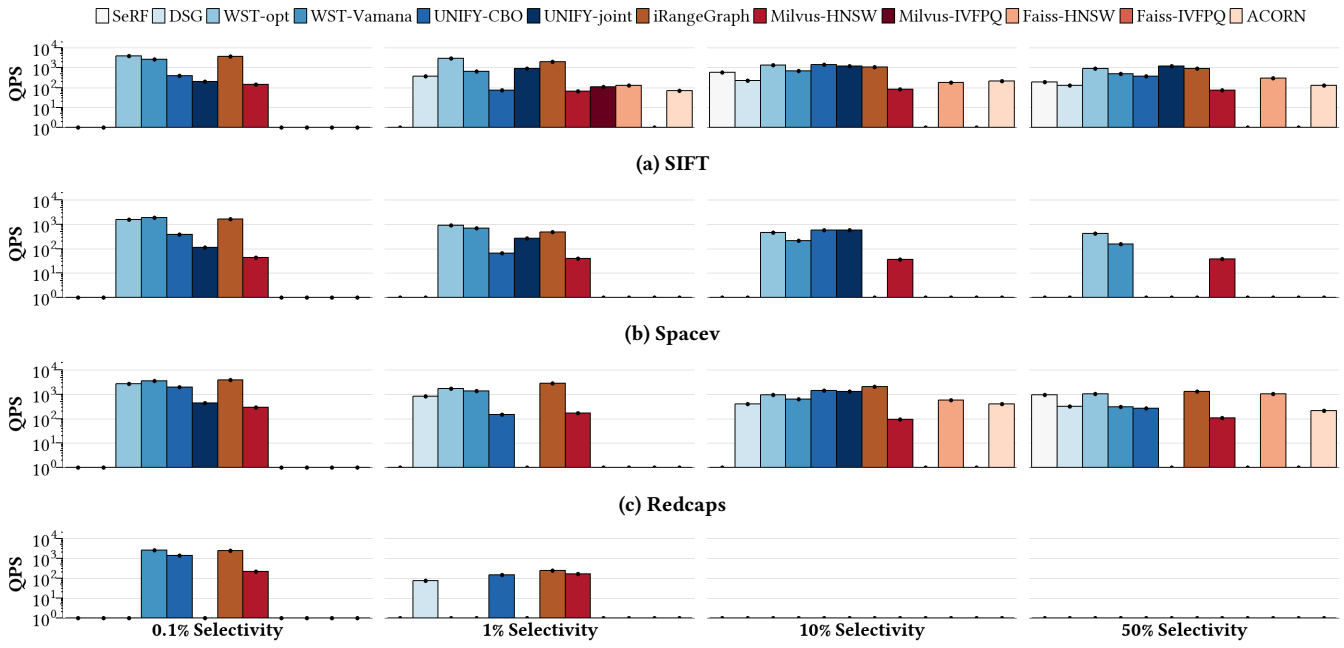
(a) SIFT

(b) Spacev

(c) Redcaps

(d) Youtube-RGB

Figure 16: QPS for range Filtering ANN algorithms at 95% recall@10.



(a) SIFT

(b) Spacev

(c) Redcaps

(d) Youtube-RGB

Figure 17: QPS for range Filtering ANN algorithms at 99% recall@10.

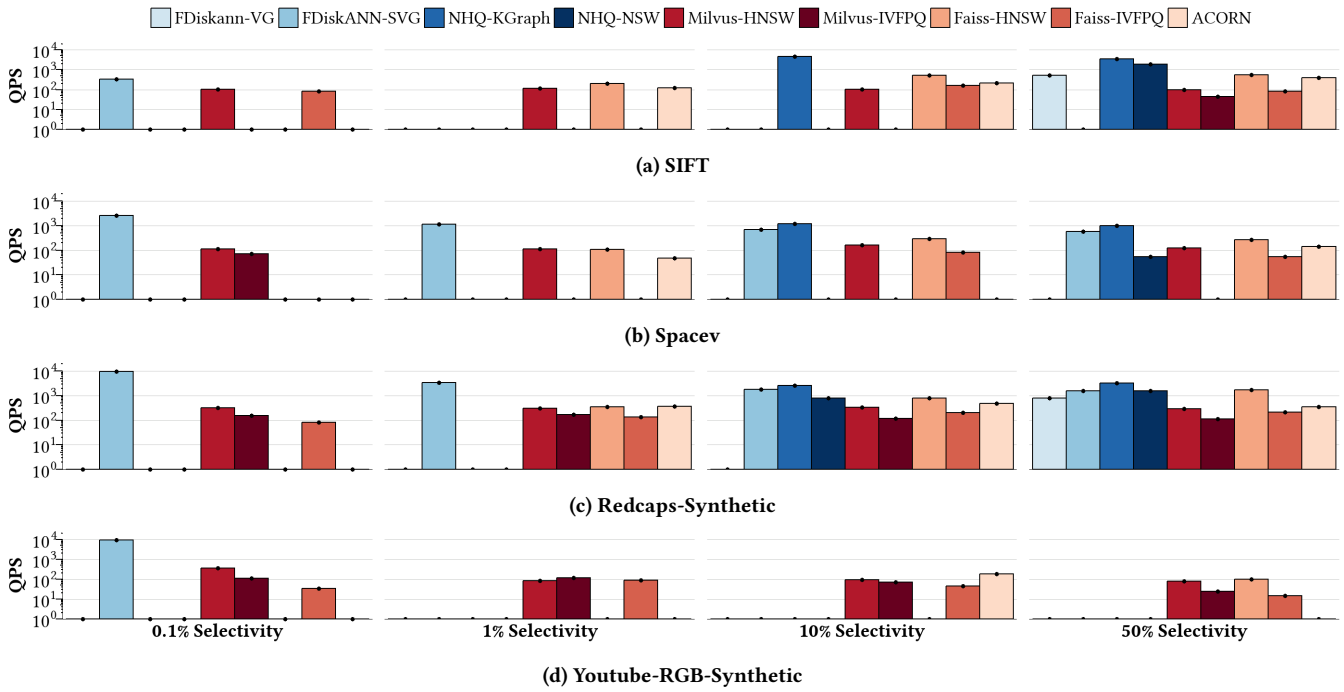


Figure 18: QPS for label Filtering ANN algorithms at 95% recall@10.

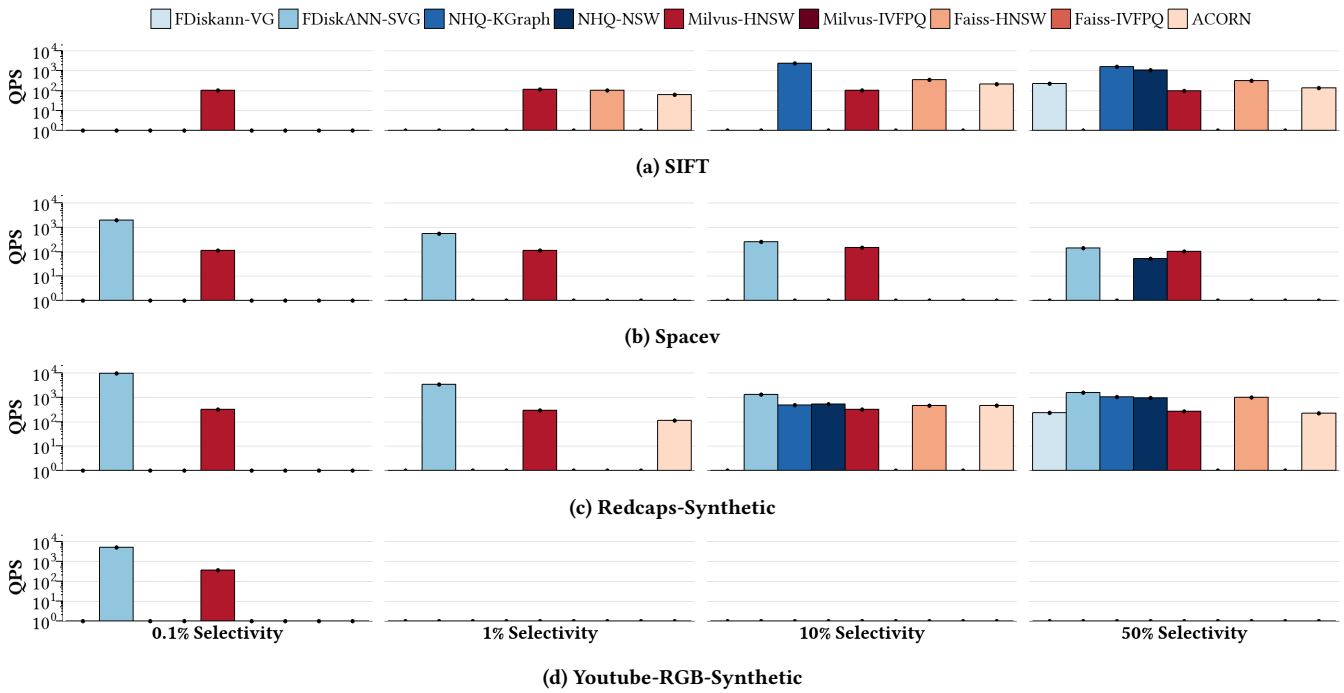


Figure 19: QPS for label Filtering ANN algorithms at 99% recall@10.

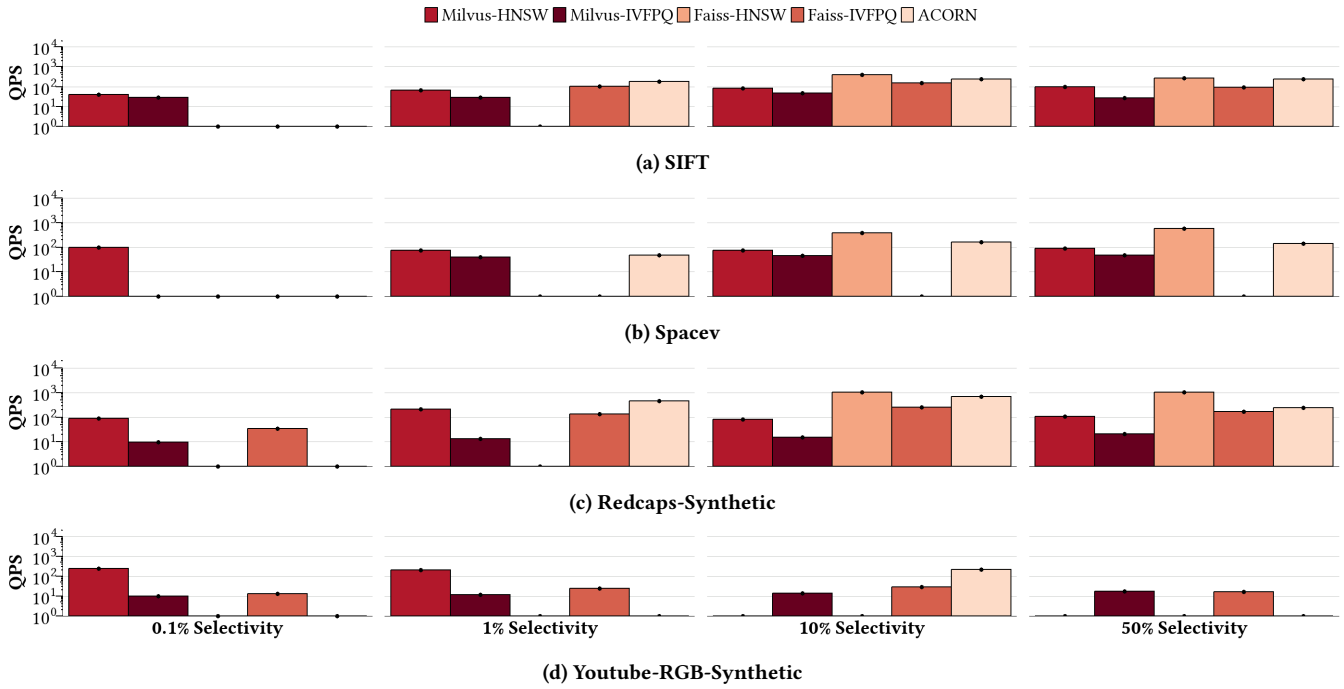


Figure 20: QPS for arbitrary Filtering ANN algorithms at 95% recall@10.

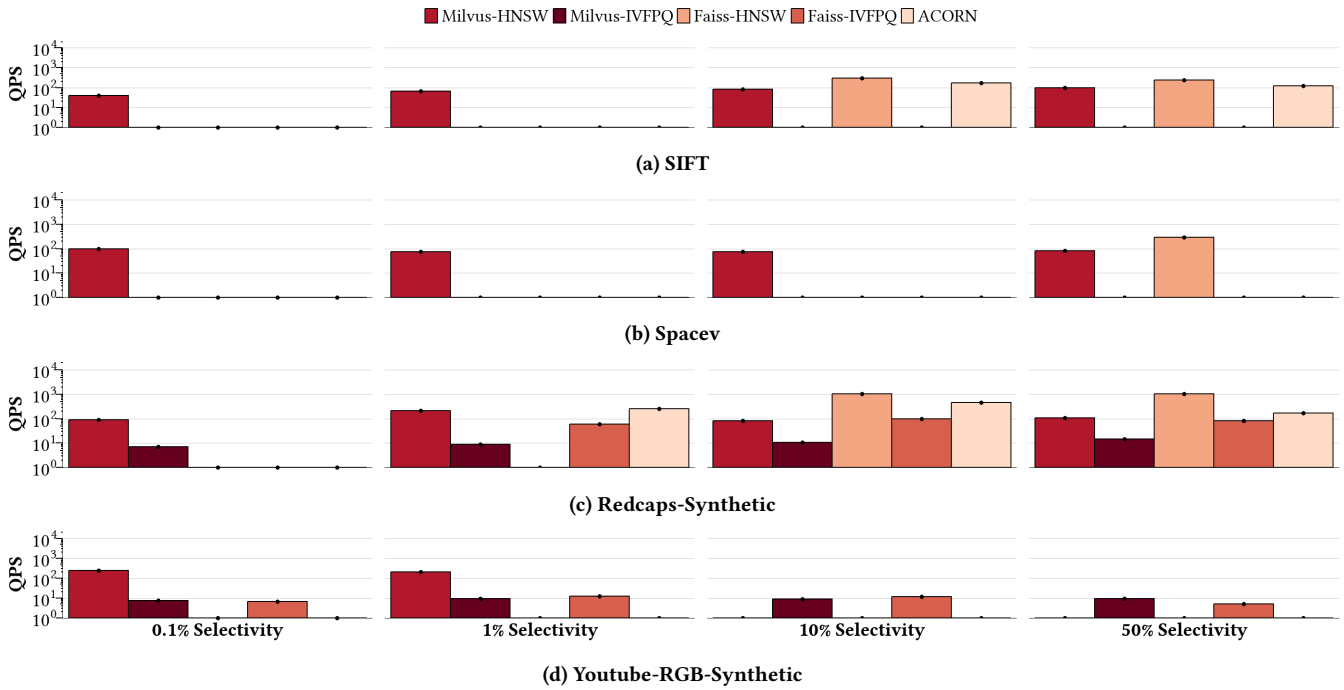


Figure 21: QPS for arbitrary Filtering ANN algorithms at 99% recall@10.

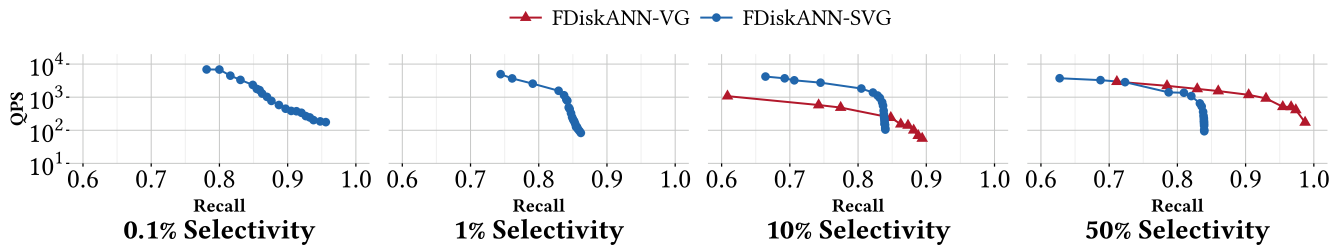


Figure 22: Recall/QPS in SIFT for DiskANN-VG and DiskANN-SVG

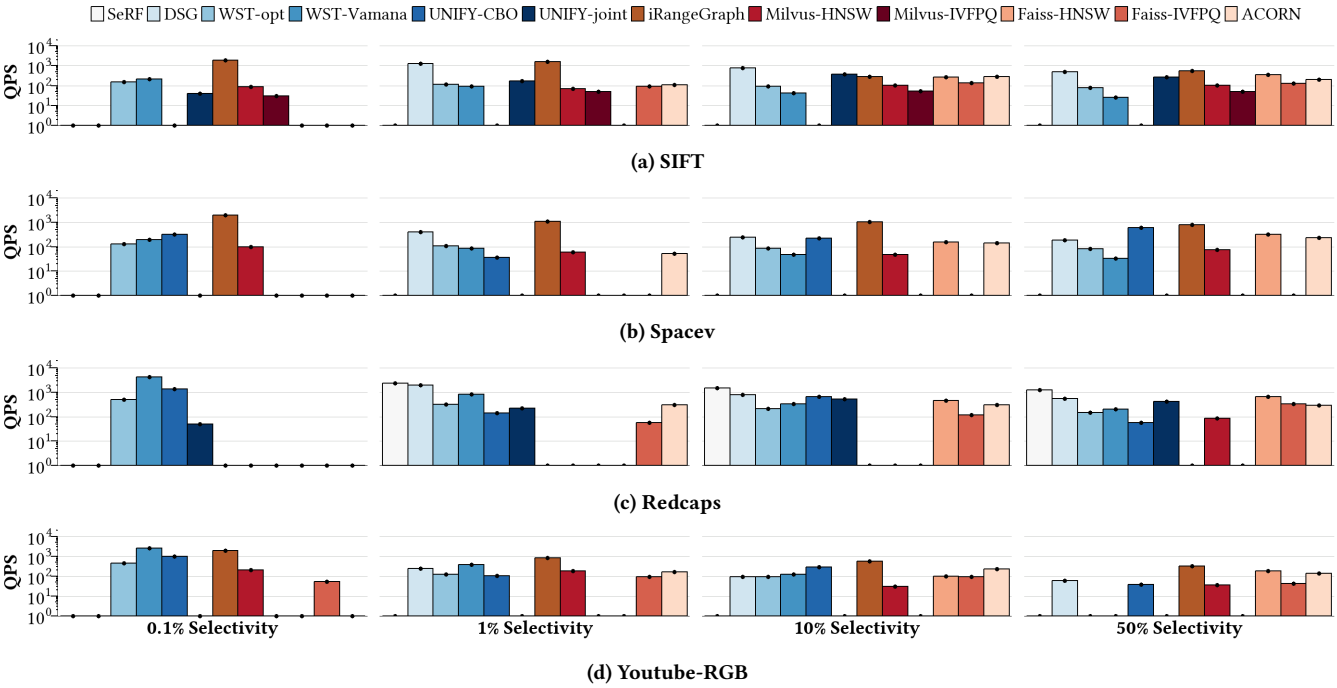


Figure 23: QPS for range Filtering ANN algorithms at 90% recall@100.

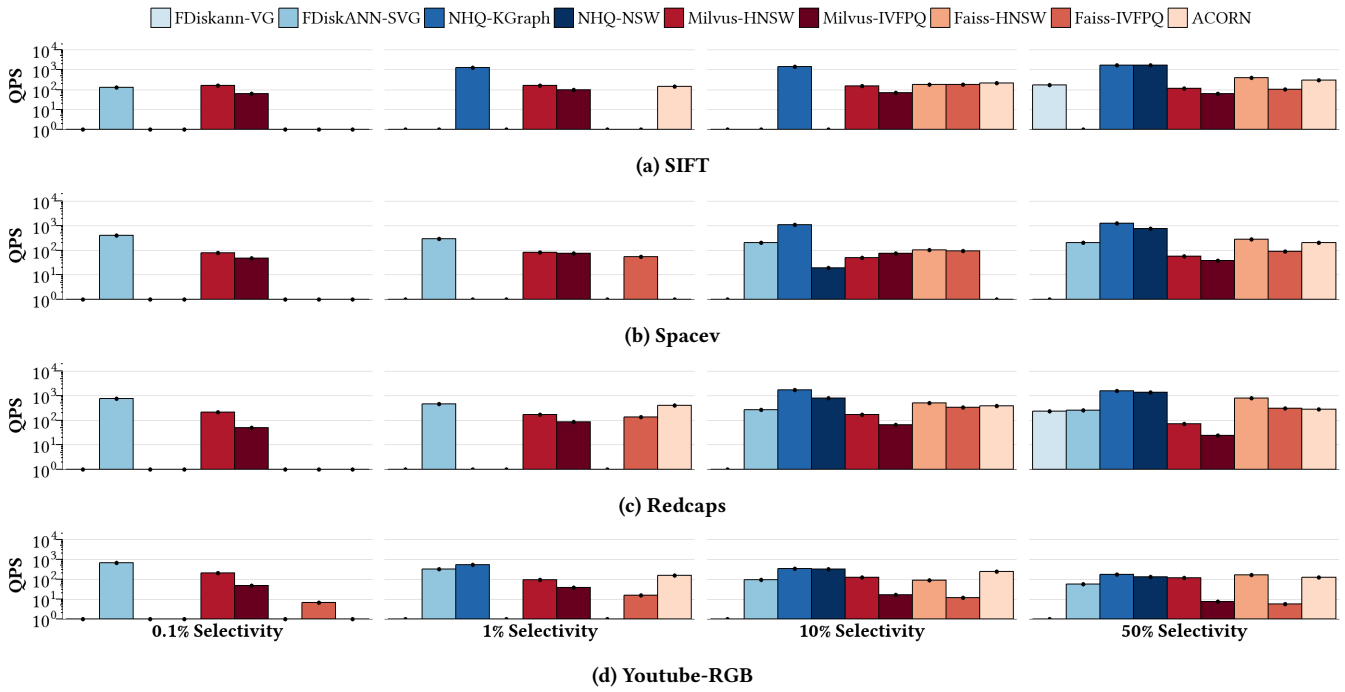


Figure 24: QPS for label Filtering ANN algorithms at 90% recall@100.

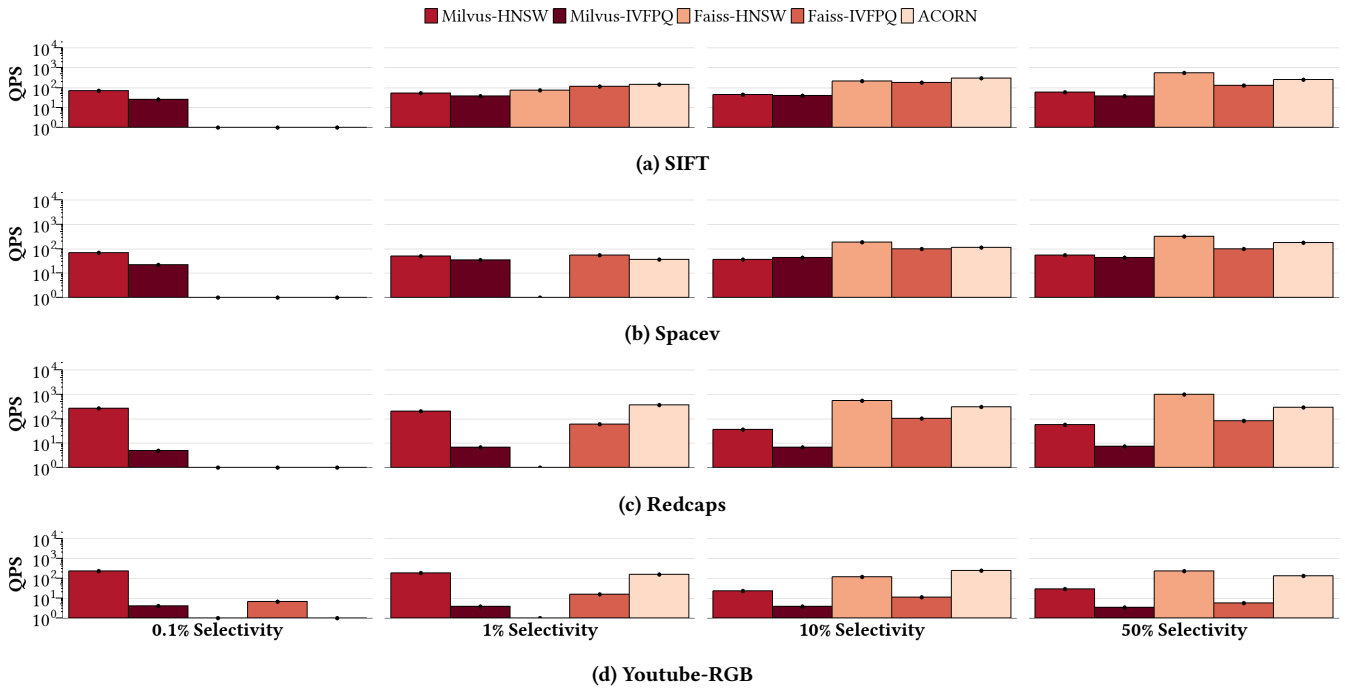


Figure 25: QPS for arbitrary Filtering ANN algorithms at 90% recall@100.