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# Scalable Billion-point Approximate Nearest Neighbor Search Using SmartSSDs

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# Background and Motivation

SmartANNS Design

Results

Conclusion





### **Background of ANNS**







#### Approximate Nearest Neighbor Search (ANNS)





#### Traversal Path:









### **Background of ANNS**

Retrieval-Augmented Generation







### **Traditional Computing Architecture for ANNS**







### **CSD-empowered NDP Architecture**



#### Large Storage Capacity

**Performance scalability** 

### Mitigate Host Resource Contention





### **CSD-empowered NDP Architecture**

#### Large Storage Capacity



### Using SmartSSDs to handle large-scale ANNS is promising ...



**Performance scalability** 

### Mitigate Host Resource Contention





### **CSD-based ANNS Solution**

- Offline Index Construction
  - Split dataset
  - Construct graph for each partition
- ✤ Online Search
  - Traverse all the graph indices
  - Merge all intermediate results
  - Return top-k result

**Significant Computation** 

Limited Resource

CSDANN [TC'22], SmartSSD-based ANNS







### **Opportunities of Hierarchical Indexing**

- Offline Index Construction
  - Partition dataset using clustering
  - Construct graph for each shard
- Online Search
  - Prune irrelevant shards
  - Traverse closest graph of shards
  - Merge and return top-k result

Less computing overhead











#### **3.** Differences between queries







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Lack of communication channels

**Hierarchical indices in host and SmartSSDs** 



Load imbalance across SmartSSDs

Task scheduling based on the optimized data layout



**Differences between queries** 

Learning-based shard pruning algorithm





### **Hierarchical indices**

#### **Construction Step**

- Hierarchical Balanced Clustering
- Construct HNSW graph indices

For SmartSSDs

Store graph indices in SmartSSDs

For Host CPU

- Extract centroids for each shard
- Build shard-SmartSSD mapping table

"Host CPU + SmartSSDs" cooperation







### **Shard Pruning**

#### Gradient Boosting Decision Trees (GBDT)

A strong predictive model combing multiple decision trees
Training Stage

Iteratively predicting the mean, computing residuals, and fitting weak decision trees to these negative gradients

**Inference Stage** 

Assimilating weighted contributions of all individual weak models

#### **Input Features**

- The query vector
- Solution Distance between the query and the top-k nearest shards  $(D_k)$  / distance between the query and the top-1 nearest shard  $(D_1)$
- The total number of all shards

#### Training Setup

Training size	One million	
Learning rate	0.05	
Iteration	500	

Lightweight and high performance





#### Data Access Pattern of Hierarchical Indices

#### **Observation 1**

A large portion of shards are accessed by different queries over a period of time, implying a good data locality

#### **Observation 2**

The access distribution of different shards are highly skewed



- 1. Exploiting the data locality among queries
  - 2. Placing hot shards on different SmartSSDs





**Optimized Data Layout** 

#### **Offering more flexibility for task scheduling**

- Iteratively placing shard with highest hotness to the SmartSSD with lowest cumulative hotness
- Replicating shards from one SmartSSD to another SmartSSD once







#### **Scheduling Steps**



end

end





#### **Scheduling Steps**



end

end





#### **Scheduling Steps**



CGCL

1 3 8

9

7

6

5

1

8

Duplicate

3

Duplicate

4

Duplicate

end



### Implementation

#### Vector Search Engine

- Separate interface for parallel reading
- Boolean array as the visited list
- Bitonic sort algorithm for lists updating
- Loop unrolling and pipelining
- Data and kernel pooling

#### More details: checkout our paper

- FPGA kernel details
- GBDT implementation (LAET SIGMOD'20)
- HNSW search process







### **SmartANNS System**

\* "host CPU + SmartSSDs" cooperative processing architecture







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### **Experimental Setup**

#### Hardware Platform

#### Server

CPU	2 * Intel Xeon Gold 5220 CPUs		
GPU	Nvidia Tesla V100 (32GB HBM)		
DRAM	128 GB DDR4		
OS	Ubuntu 20.04.4 LTS		

#### **Computational Storage Device**

Туре	Samsung SmartSSD		
FPGA	Xilinx Kintex UltraScale+KU15P		
DRAM 4 GB DDR4			
Flash	4 TB, 4 GB/s		

#### Datasets

Dataset	Dimension	Data Type	Base Size	Source
SIFT1B	128	Uint8	119 GB	Image
SPACEV1B	100	Int8	93 GB	Web Search
DEEP1B	96	Float32	358 GB	Image
Turing1B	100	Float32	373 GB	Web Search





### **Comparison with Baselines**

#### Under different dataset



8.5-10.7X higher QPS compared with the stateof-the-art SmartSSDbased ANNS—CSDANNS





### **Comparison with Baselines**

#### Under different accuracy



With SIFT1B dataset, SmartANNS achieves 5.6-9.8X higher QPS compared with CSDANNS





### **Comparison with Baselines**

#### Scalability



SmartANNS achieve nearlinear performance scalability with the increase of SmartSSDS





### **Comparison with SSD/GPU-based ANNS**



SmartANNS is more efficient than SSD-based solution and GPU-based solutions





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- SmartANNS Design
- Results

## Conclusion





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### SmartANNS:

A hardware/software co-design architecture using SmartSSDs to support the large-scale and scalable ANNS service

# Thanks & QA



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