



Welcome to Elastic Bangalore User Group!

Som

Who Am I?



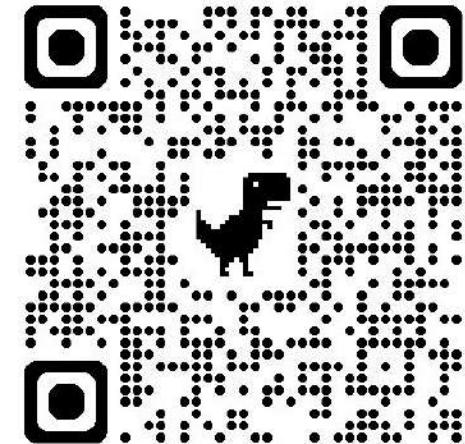
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Elasticsearch Logstash Kibana



Let's Make this **Interactive**?

Make a promise()

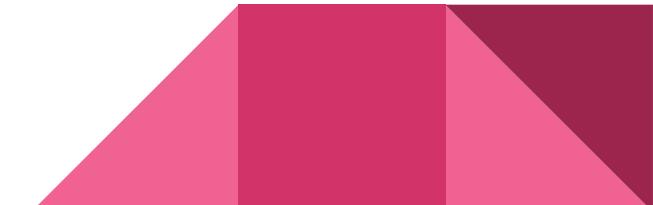


Let's understand Who is Here?



Let's understand Who is Here?

- AI Engineers or Backend Developers?
(anyone working with Vectors?)
- SREs or DevOps or FinOps engineers here?
- Any students or learners exploring AI for the first time?



Why Am here?

From Float32 to BBQ: Practical Vector Search
Optimization

Quick Activity - Guess the Image/Person/Movie?

(If you know, don't say it, just raise your hand)

Babu Bhaiya!

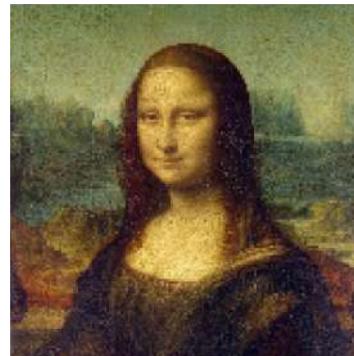


1 billion vectors @ 1024 dimensions

64 nodes



16 nodes



8 nodes



= 32× RAM savings
(vs. float32)

2 nodes



float32

int8

int4

bit

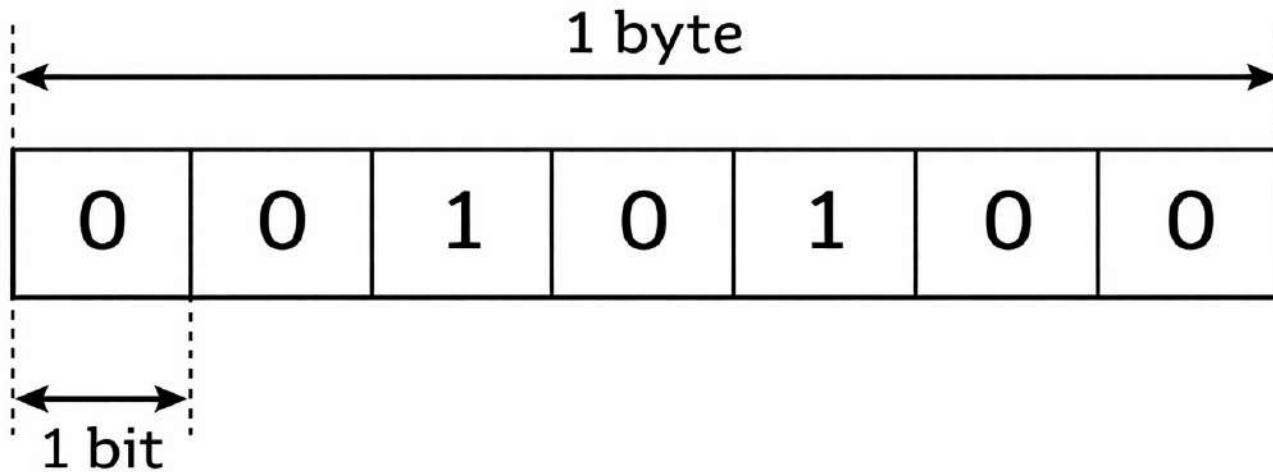
BBQ

What's the Problem?

Why are we talking about it now?

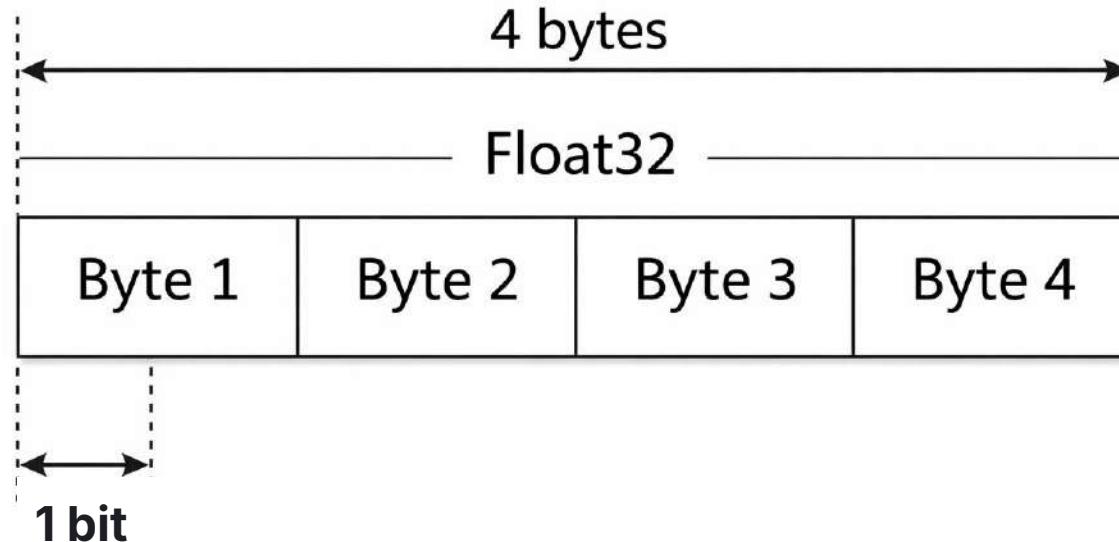
Let's do some Math

Q1: How many **Bits** are 1-byte?



Q2: How many Bits are 1-float32 vector?

Q3: How many Bytes are 1-float32 vector?



Q4: How many Bytes does a float32 Image (100×100 pixels) need?

Let's see in Practice!
(notebook)

What's the Problem now?

Did we find it?

Vector Traversal!

Numbers you should know

Latency Numbers Everyone Should Know

Operation	Time in ns	Time in ms (1ms = 1,000,000 ns)
L1 cache reference	1	
Branch misprediction	3	
L2 cache reference	4	
Mutex lock/unlock	17	
Main memory reference	100	
Compress 1 kB with Zippy	2,000	0.002
Read 1 MB sequentially from memory	10,000	0.010
Send 2 kB over 10 Gbps network	1,600	0.0016
SSD 4kB Random Read	20,000	0.020
Read 1 MB sequentially from SSD	1,000,000	1

Vector from memory

Vector from disk

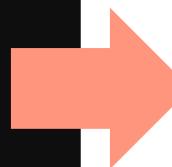
Lovingly borrowed from:

<https://static.googleusercontent.com/media/sre.google/en//static/pdf/rule-of-thumb-latency-numbers-letter.pdf>



Your data is more than just vectors

```
{  
  STRING  
  FLOAT  
  DENSE_VECTOR  
  GEO_POINT  
  DATE  
  NESTED OBJECT  
    {  
      "name": "Bar Cecil",  
      "star_rating": 4.8,  
      "description": "The best restaurant and bar in Palm Springs, CA..",  
      "description_embedding": [0.2, 0.12, 0.5, 0.22, 0.97, 0.32, 0.74, 0.49,...]  
      "location": {  
        "lat": 41.12, "lon": -71.34  
      },  
      "@timestamp": "2024-12-22T00:00:26.464Z",  
      "owners_and_operators": [  
        {  
          "first": "John",  
          "last": "Smith",  
          "position": "bar tender"  
        },  
        {  
          "first": "Alice",  
          "last": "White",  
          "position": "head chef"  
        }  
      ]  
    }  
}
```



Elasticsearch Platform

INVERTED INDICES

HNSW

OPTIMIZED BKD TREES

COLUMNAR INDICES

Vector Retrieval+Storing Techniques

HNSW (RAM-Resident)

BBQ (disk-resident vectors + RAM metadata)

If you're using HNSW, the graph must also be in memory. To estimate the required bytes, use the following formula below. The default value for the HNSW `m` parameter is `16`.

$$\begin{aligned} \text{estimated bytes} &= \text{num_vectors} \times 4 \times m \\ &= \text{num_vectors} \times 4 \times 16 \end{aligned}$$

The following is an example of an estimate with the HNSW indexed `element_type: float` with no quantization, `m` set to `16`, and `1,000,000` vectors of `1024` dimensions:

$$\begin{aligned} \text{estimated bytes} &= (1,000,000 \times 4 \times 16) + (1,000,000 \times 4 \times 1024) \\ &= 64,000,000 + 4,096,000,000 \\ &= 4,160,000,000 \\ &= 3.87GB \end{aligned}$$

If you're using DiskBBQ, a fraction of the clusters and centroids need to be in memory. When doing this estimation, it makes more sense to include both the index structure and the quantized vectors together as the structures are dependent. To estimate the total bytes, first compute the number of clusters, then compute the cost of the centroids plus the cost of the quantized vectors within the clusters to get the total estimated bytes. The default value for the number of `vectors_per_cluster` is `384`.

$$\text{num_clusters} = \frac{\text{num_vectors}}{\text{vectors_per_cluster}} = \frac{\text{num_vectors}}{384}$$

$$\begin{aligned} \text{estimated centroid bytes} &= \text{num_clusters} \times \text{num_dimensions} \times 4 \\ &\quad + \text{num_clusters} \times (\text{num_dimensions} + 14) \end{aligned}$$

$$\text{estimated quantized vector bytes} = \text{num_vectors} \times ((\text{num_dimensions}/8 + 14 + 2) \times 2)$$

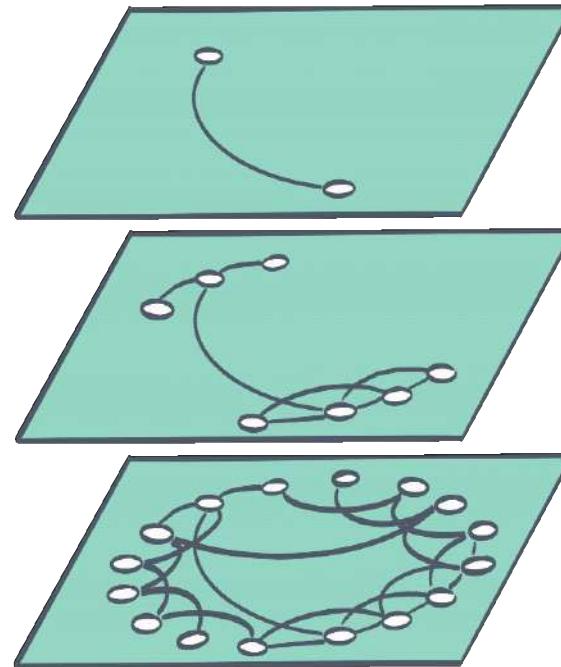
Note that the required RAM is for the filesystem cache, which is separate from the Java heap.

Now, what's the problem this quantization solves?

We're trying to solve the RAM problem (For NOW)!

HNSW retrieval

- Graph based indices (like Vamana & HNSW) are fastest
- Logarithmic search scale
- Random access of single vectors



Linear scaling is for losers

Quantization 101

- Take continuous and make it discrete
- Lossy, but keeping the important stuff
- But, let's do it for vectors



float32

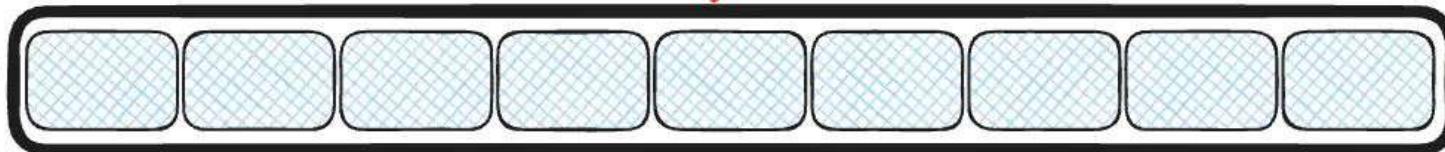
-1.0



1.0



-127



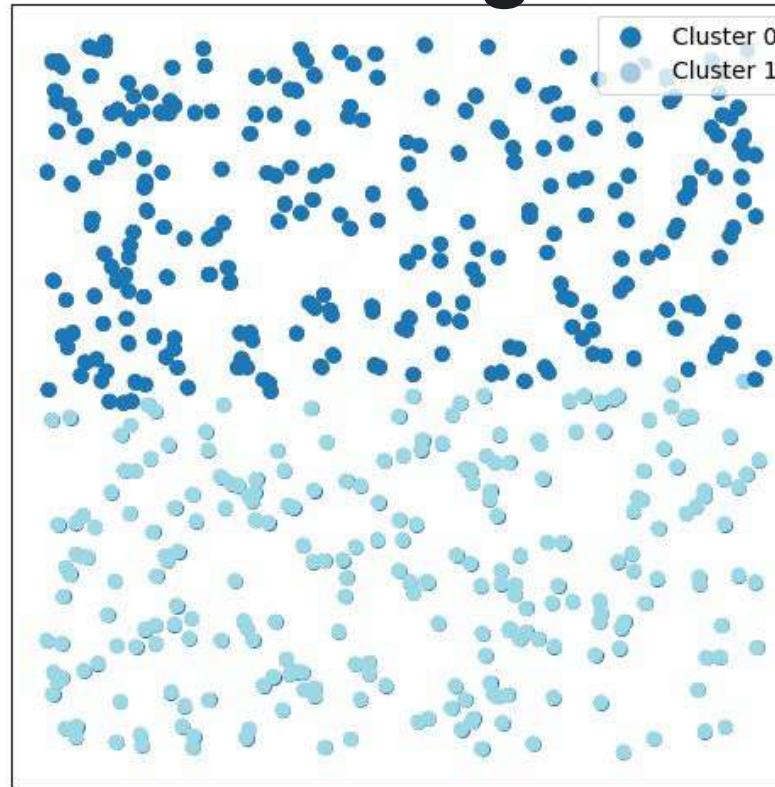
127

int8

**Now, we have a Second Problem!
How do we load this to RAM from
Disk?**

DiskBBQ to the Rescue!

Clusterize the vectors while Indexing!



Let's Connect the Dots!

- You have 100 million vectors
 - each with 1536 dimensions

What is the size per Vector?

100 Million Vectors, 1536 Dimensions

Memory Usage by Data Type



Note: Generated Image for cleaner representation

Now, it makes everything Possible !
And, Not Expensive !

Documentation References

Quantization (BBQ, Scalar Quantization)

- <https://www.elastic.co/search-labs/blog/better-binary-quantization-lucene-elasticsearch>
- <https://www.elastic.co/search-labs/blog/optimized-scalar-quantization-elasticsearch>
- <https://www.elastic.co/search-labs/blog/bit-vectors-elasticsearch-bbq-vs-pq>
- <https://www.elastic.co/docs/reference/elasticsearch/mapping-reference/bbq>

DiskBBQ

- <https://www.elastic.co/search-labs/blog/diskbbq-elasticsearch-introduction>
- <https://www.elastic.co/search-labs/blog/elasticsearch-latency-low-memory-diskbbq-hnswbbq-benchmark>

HNSW Graphs

- <https://www.elastic.co/search-labs/blog/hnsw-graph>
- <https://www.elastic.co/search-labs/blog/hnsw-graphs-speed-up-merging>

Related Benchmarks/Comparisons

- <https://www.elastic.co/search-labs/blog/elasticsearch-bbq-vs-opensearch-fais>