QUANTIZATION IN ANN SEARCH

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Quantization Methods Tested

Two phases

1. Rotational quantization and int8 with metadata.
2. Matryoshka embeddings with binary quantization and reranking.

Rotational quantization and metadata

Summary

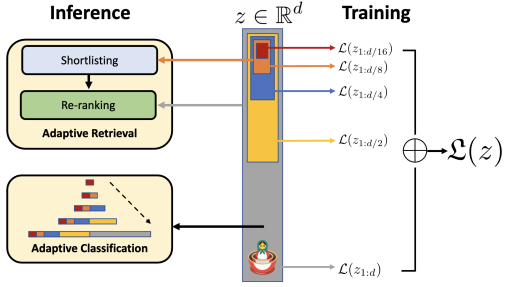
- Rotation does not seem to help much.
- Adding metadata to int8 (decoded distance) improves significantly.

	SIFT 1M		Wikipedia	
Quantization	TH10	TH100	TH10	TH100
1-bit	13.9	17.2	54.4	51.5
1-bit w/ rot	15.0	19.3	57.4	52.3
8-bit	73.7	92.1	69.3	86.3
8-bit w/ rot	70.4	92.8	70.1	86.4
8-bit SQ	**98.2**	**98.9**	99.1	**99.5**
8-bit SQ w/ rot	96.5	97.8	**99.4**	99.4

Matryoshka embeddings

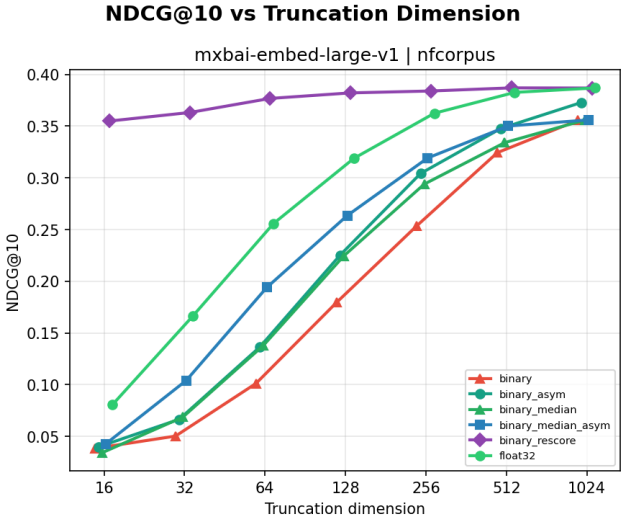
Matryoshka embeddings allows compression along two axis.

Dim	fp32	int8	binary
1024	1×	4×	32×
512	2×	8×	64×
256	4×	16×	128×
128	8×	32×	256×
64	16×	64×	512×



Nice property: $\langle x, q \rangle = \langle x_{1:d}, q_{1:d} \rangle + \langle x_{d:n}, q_{d:n} \rangle$

Matryoshka embeddings



Matryoshka embeddings

Asymmetric scoring only quantize documents:

$$\langle q,\, \hat{d} \rangle = \langle q,\, d \rangle + \underbrace{\langle q,\, \varepsilon_d \rangle}_{\text{one error term}}$$

Symmetric scoring quantizes both:

$$\langle \hat{q},\, \hat{d} \rangle = \langle q, d \rangle + \underbrace{\langle q, \varepsilon_d \rangle + \langle \varepsilon_q, d \rangle + \langle \varepsilon_q, \varepsilon_d \rangle}_{\text{three error terms}}$$

Less error with no extra storage.

Median binarization:

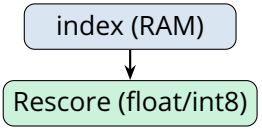
$$\hat{d}_i = \operatorname{sign}(d_i - \mu_i)$$

where $\mu_i = \operatorname{median}_j(d_i^{(j)})$.

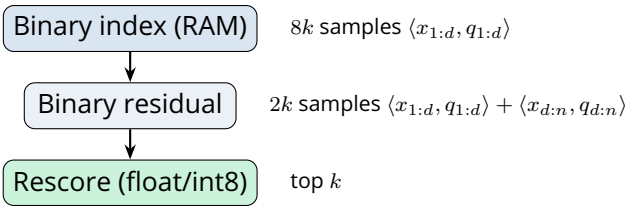
Centering at the median ensures each bit is balanced.

Matryoshka embeddings

Standard rescore:



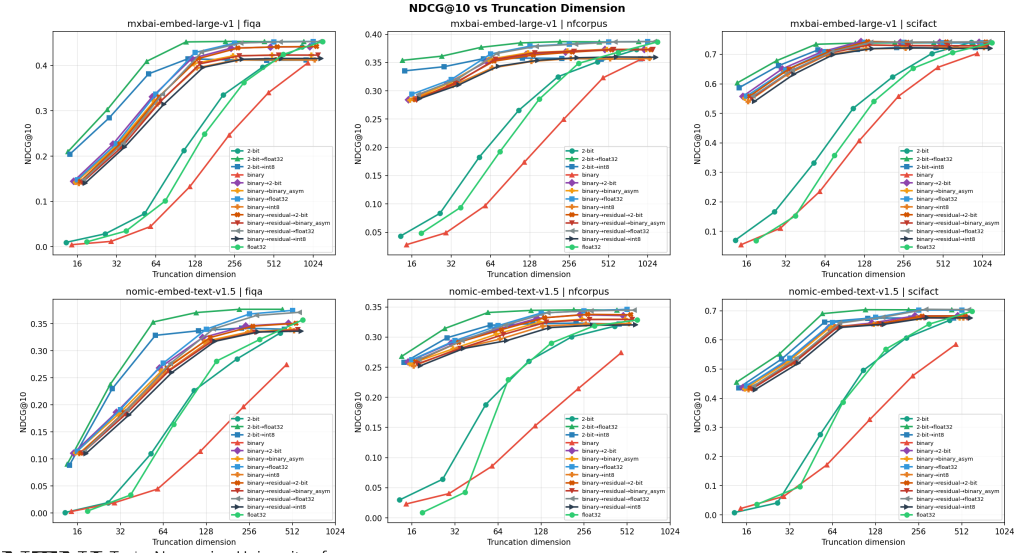
Residual rescore:



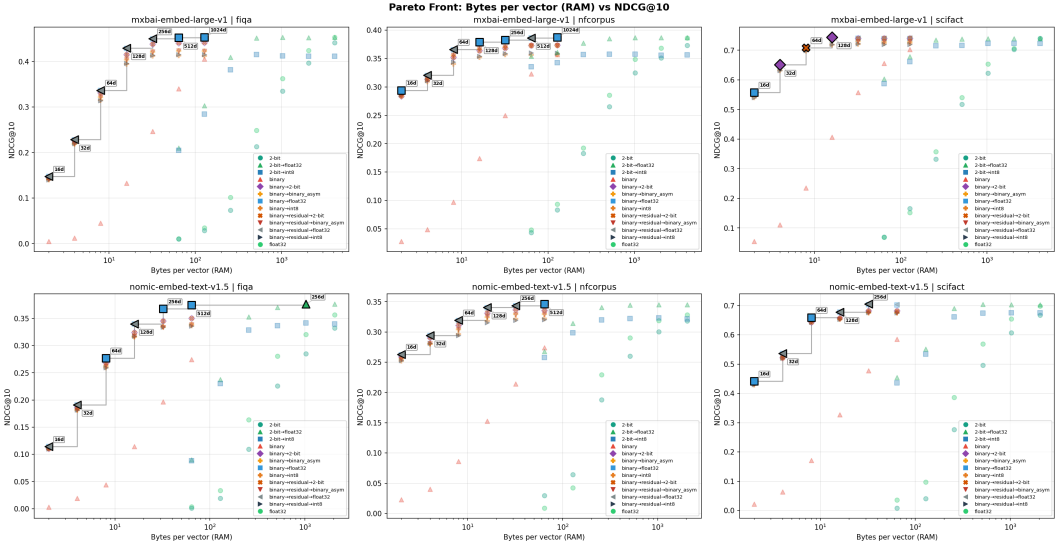
Final rescore is always asymmetric:

$$\text{score} = \langle q_{\text{float}},\ \hat{d}_{\text{quant}} \rangle$$

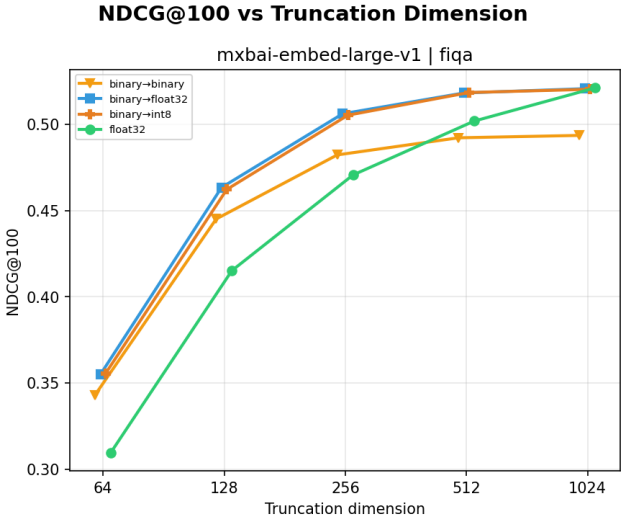
Matryoshka embeddings



Matryoshka embeddings



Matryoshka embeddings: vespa cloud



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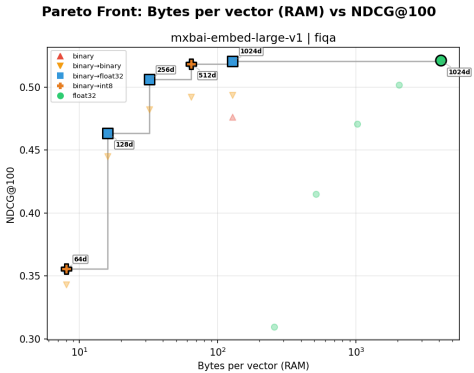

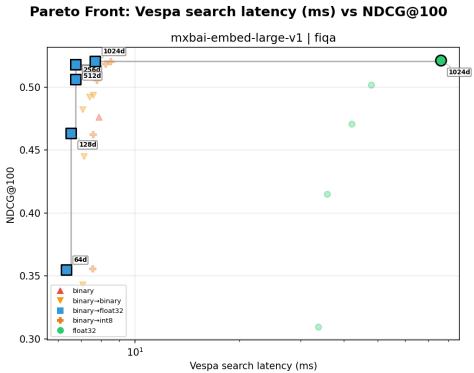

Matryoshka embeddings: vespa cloud

Binary→float32 is great!

Method	Trunc. Dim.	Compr.	Retain. (NDCG@100)	Lat. (ms)
float32†⋆	1024	1×	100.0%	75.9
binary→float32†⋆	1024	32×	99.9%	7.7
binary→float32⋆	512	64×	99.4%	6.8
binary→float32†⋆	256	128×	97.1%	6.7
binary→float32†⋆	128	256×	88.9%	6.5
binary→float32⋆	64	512×	68.1%	6.3

† Pareto-optimal (memory) ⋆ Pareto-optimal (latency)

Matryoshka embeddings: vespa cloud

Method	Trunc. Dim.	Compr.	Retain. (NDCG@10)	Lat. (ms)
float32	1024	1×	100.0%	75.9
binary→float32*	1024	32×	100.0%	7.7
binary→float32*	512	64×	99.9%	6.8
binary→float32†*	256	128×	99.2%	6.7
binary→float32†*	128	256×	94.8%	6.5
binary→float32*	64	512×	74.3%	6.3

† Pareto-optimal (memory) * Pareto-optimal (latency)

Matryoshka embeddings: vespa cloud

Method	Dim	Compr.	Retain. (NDCG@100)	Lat. (ms)
float32†⋆	1024	1×	100.0%	75.9
float32	512	2×	96.3%	48.0
float32	256	4×	90.3%	42.1
float32	128	8×	79.7%	35.7
float32	64	16×	59.4%	33.8
binary	1024	32×	91.4%	7.9
binary→binary	1024	32×	94.7%	7.6
binary→float32†⋆	1024	32×	99.9%	7.7
binary→int8	1024	32×	99.8%	8.5
binary→binary	512	64×	94.4%	7.4
binary→float32⋆	512	64×	99.4%	6.8
binary→int8†	512	64×	99.5%	8.2
binary→binary	256	128×	92.5%	7.1
binary→float32†⋆	256	128×	97.1%	6.7
binary→int8	256	128×	97.0%	7.8
binary→binary	128	256×	85.4%	7.1
binary→float32†⋆	128	256×	88.9%	6.5
binary→int8	128	256×	88.7%	7.6
binary→binary	64	512×	65.8%	7.1
binary→float32⋆	64	512×	68.1%	6.3
binary→int8†	64	512×	68.2%	7.6

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Compression Calculator

Find the optimal cost-accuracy trade-off for your vector search workload. Configure your setup and we'll compute the Pareto-optimal compression strategies.

1 Configure Your Workload

EMBEDDING MODEL
mxbai-embed-large-v1 (1024d)

NUMBER OF VECTORS
1,000,000

MAX EMBEDDING DIMENSION
1024

VESPA CLOUD PLAN
Commercial

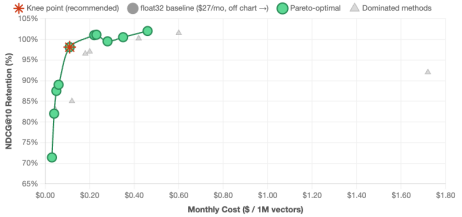
PRIORITY
Balanced (recommended)

Calculate Optimal Compression

Costs are based on Vespa Cloud pricing: RAM at $0.01/GB/hr (ANN index) and Disk at $0.0004/GB/hr (rescore vectors). RAM is 25x more expensive, making index format the dominant cost lever.

250x	$0.11	98.1%
COST REDUCTION	MONTHLY COST	QUALITY RETENTION
vs float32 baseline	per 1M vectors	NDCG@10 vs float32

Cost vs Accuracy Pareto Front — Live Simulation



Recommended Configurations — Top 5 Pareto-Optimal

#	PIPELINE	DIM	QUALITY RETENTION	COST / MO	SAVINGS	USE CASE

Compression Calculator

Find the optimal cost-accuracy trade-off for your vector search workload. Configure your setup and we'll compute the Pareto-optimal compression strategies.

250x
COST REDUCTION
vs float32 baseline

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NDCG@10 vs float32

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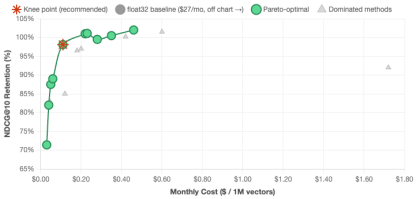

Recommended Configurations

Top 5 Pareto-Optimal

Summary

Conclusion

1. Huge potential memory savings! (w/ good embedder + resample)
2. Many tricks to regain accuracy. (asym, calibration, metadata, rotation?)

Things to investigate

1. Measure vector distribution $\rightarrow$ choose quantization scheme.
2. Make a feature for guiding customers without expensive experiments.