FAISS: Similarity Search Library by Facebook AI

Agenda

1. Introduction: similarity search
2. Deep dive: FAISS
3. Beyond similarity search: vectorization

Introduction: What is Similarity Search?

Traditional seaching in databases

- Structured tables with fixed symbolic representation
- Searching involves finding out the entries that matches the description

Similarity seach

- Find similar entries of input multi-media / text / profile
- Returns a list of entries that are nearest to the given query

Introduction: Use-Cases of Similarity Search

- Google's image search
- Facebook's news feed
- RAG: retrival augmented generation

Introduction: How to Do Similarity Search

1. Vectorization: convert both query and stored data entries into **high-dimensional vectors**
2. Find the closest entires to the query by simply calculating the **Euclidean distance**

Introduction: Challenges of Similarity Search

1. Number of entires is super large: multiple billions
2. Latency is critical for user experience
3. How close / relevant are the returned results?

Therefore, 3 metrics of interest:

Speed, **memory usage** and **accuracy**

Deep Dive: FAISS (Facebook AI Similarity Search)

Open-source library that supports quickly search for multimedia documents.

Key ideas:

- **Quantization**: memory usage and accuracy
- **GPU acceleration**: speed

Deep Dive: Quantization

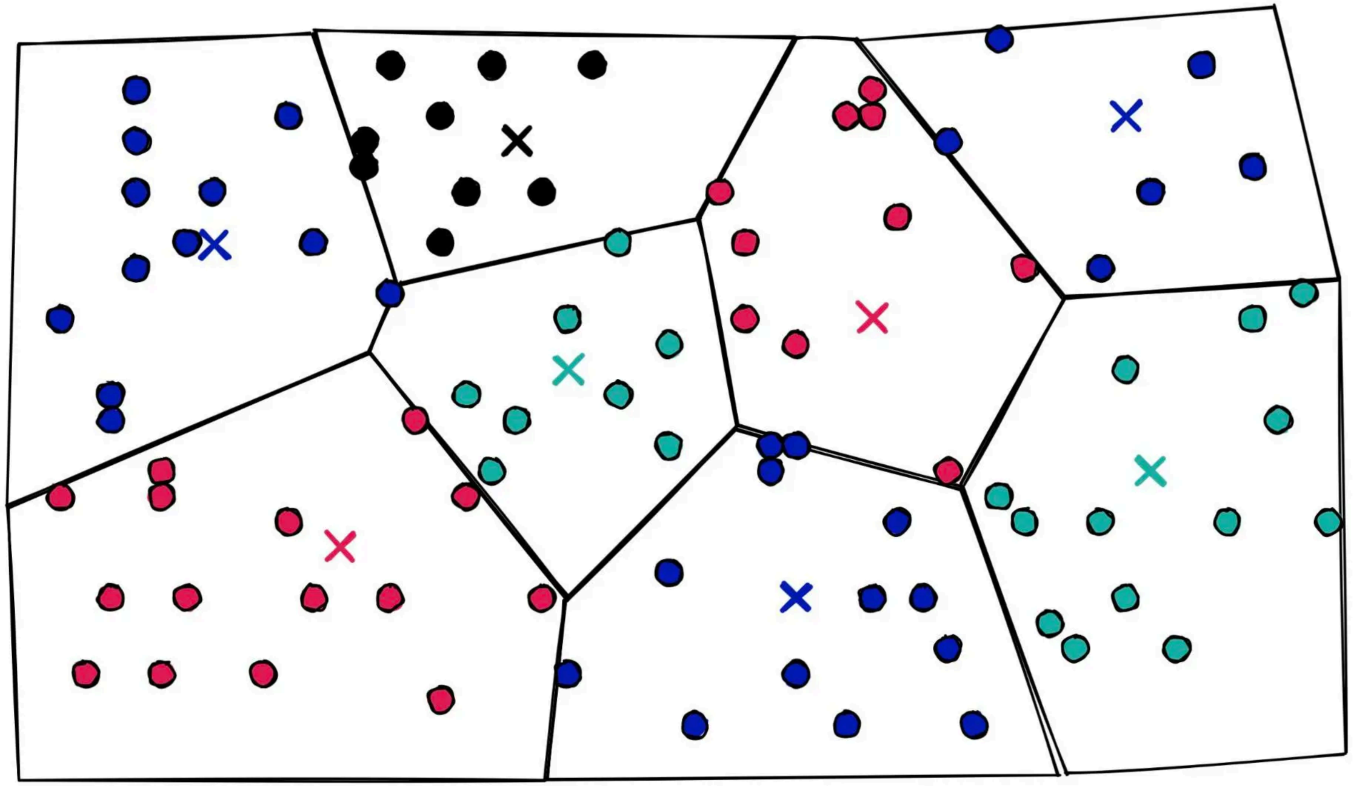
IVFADC

2-levels of indexing

- Coarser quantization: **IVF (inverted file)**
  - Groups the database entries into sub-domains.
  - Non-exhaustive search: sacrifice accuracy for speed and memory usage.
- Finer quantization: **ADC (asymmetric distance computation)**
  - "Asymmetric": database vectors are compressed while query vectors are not.

Deep Dive: Quantization

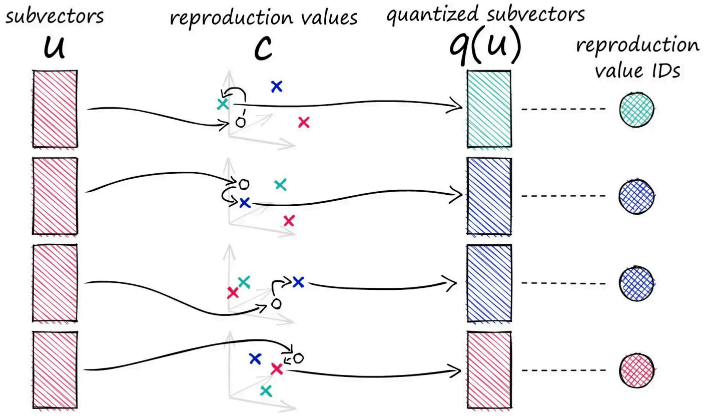
Illustration of IVF



Deep Dive: Quantization

ADC: PQ (product quantization)

- Evenly dissect vector into N sub-vectors
- Quantize each sub-vector into 1-byte reproduction value ID
- Concatenate N-byte results and store them



Deep Dive: GPU Acceleration

Batching

Euclidean distance calculation: X are the query vectors, Y are the stored database entries.

$$\|x_j - y_i\|_2^2 = \|x_j\|^2 + \|y_i\|^2 - 2\langle x_j, y_i \rangle.$$

- 1st term: not needed before k-selection
- 2nd term: can be pre-calculated
- 3rd term: matrix multiplication

Batching ideas:

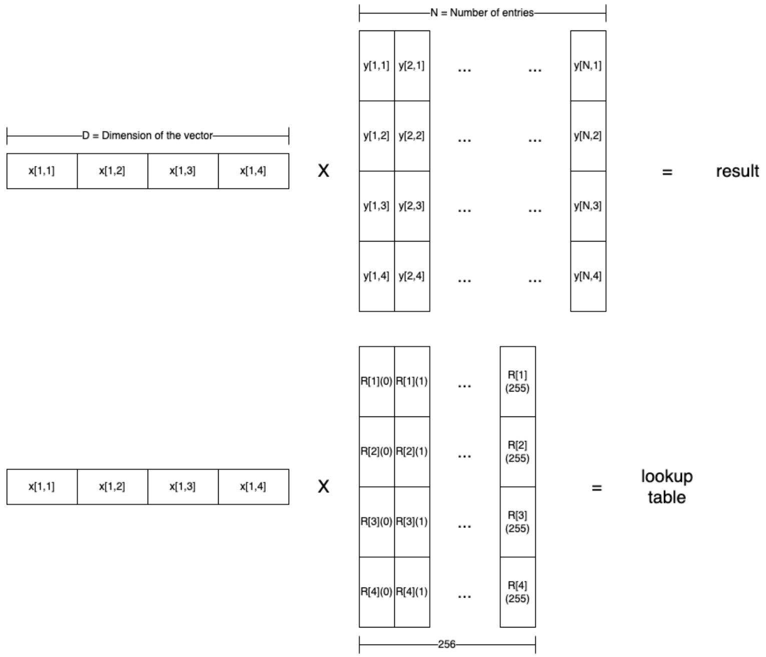
1. Batching over the queries
2. Tiling the Euclidean distance calculation

Deep Dive: GPU Acceleration

PQ (product quantization) lookup table

Use lookup table to replace expensive matrix multiplication

- Before: DxN MACs
- After: Dx256 MACs + NxB lookup add

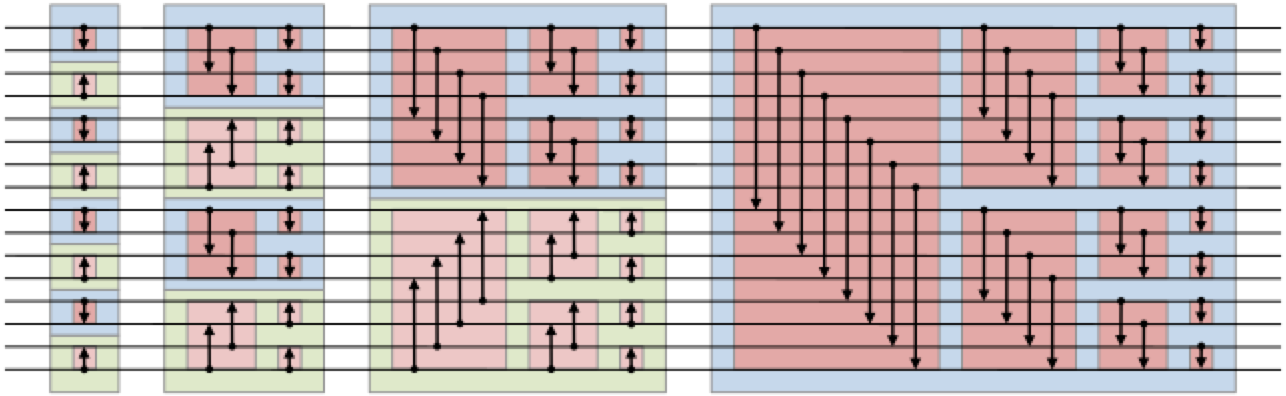


Deep Dive: GPU Acceleration

Fast k-selection

Bitonic sorting algorithm

- Can be easily parallelized
- Can be done completely using GPU registers



Deep Dive: GPU Acceleration

WarpSelect

FAISS's implementation using CUDA

- Single pass over data: memory bound problem
- No cross-warp synchronization: minimize data exchange, maximize parallelism
- Can deal with total number not equal to 2^N

Deep Dive: GPU Acceleration

Multi-GPU parallelism

Replication: replicate the same algorithm and target data across multiple GPUs, to parallelize different queries

Sharding: distribute target data across multiple GPUs and join the partial results in a single GPU

Deep Dive: Summary

1. CUDA implementation of k-selection algorithm
    i. Parallelization
    ii. In register compute
    iii. Optimized memory access
2. Quantizations are used to trade-off speed against accuracy

Beyond similarity search: vectorization

How to vectorize image?

- Train the model with image classification task
- Remove the last fully connected layer, and use output embedding

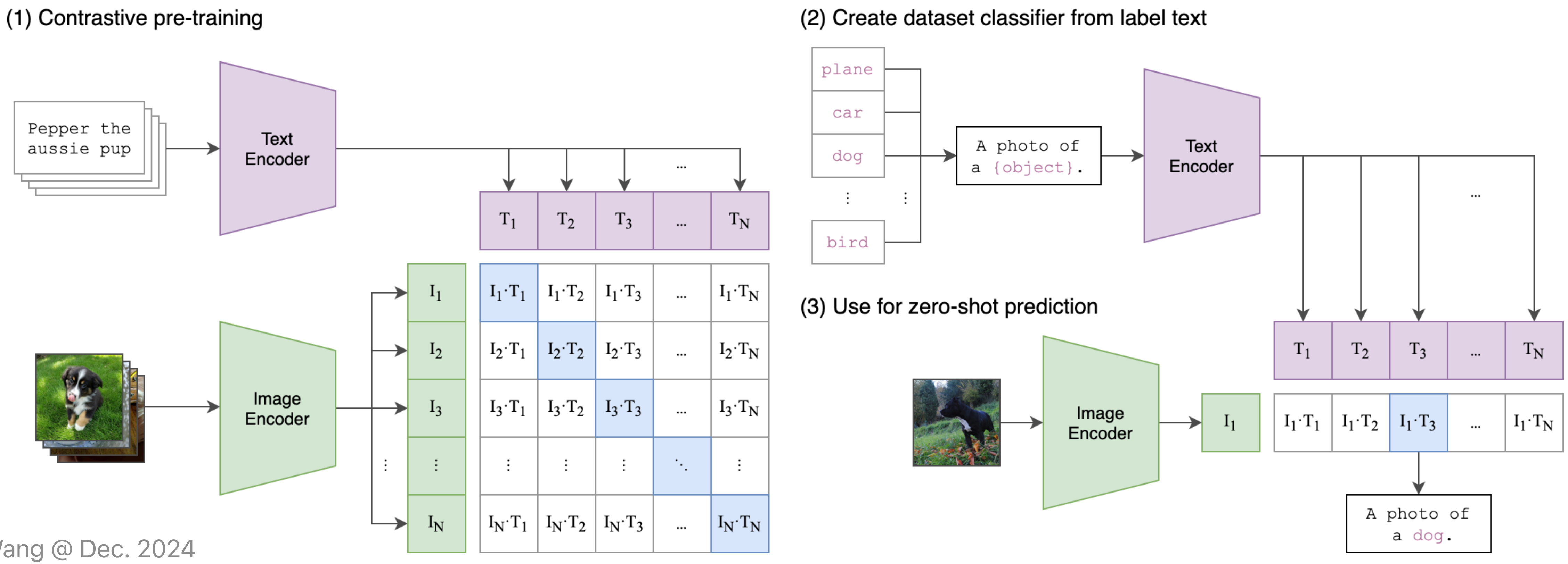
From CNN to ViT (vision transformer)

Beyond similarity search: multimodality

CLIP (Contrastive Language-Image Pre-training)

Mapping both text and image to the same vector space

- OpenCLIP (open-source implementation of OpenAI's CLIP)



QnA