# Vector search

George Panchuk
HSE AI Fall 2025

github.com/joein/vector-search-course

# George Panchuk

**ML Team Lead @ Qdrant 2022 - ...**
qdrant-client and fastembed maintainer

**HSE MLDS (AI) Alumni 2023**

**Thesis supervisor 2023 - ...**

**@jmzzomg**

**github.com/joein**

# Course structure

**10 lectures, optional seminars (on demand)**

**Formulae:**

*0.8 * HW + 0.2 * (Bonus HW || vector search talk)*

**HW:**

*0.1 * HW1 + 0.2 * HW2 + 0.2 * HW3 + 0.1 * HW4 + 0.2 * HW5 + 0.1 * HW6*

**Late submission multiplier:**

*≤ 1 week late: 0.75*
*> 1 week late: 0.5*

**HW1**: Brute-force search (13.11, 23.11)
**HW2**: ANN Search (26.11, 7.12)
**HW3**: Vector search engines (3.12, 14.12)
**HW4**: Payload filters (4.12, 14.12)
**HW5**: Sparse models, late interaction models (10.12, 18.12)
**HW6**: Hybrid search (11.12, 18.12)
**Bonus HW**: Solve an embedding-based game (1.12, 20.12)

**Course assistant:**
**Arsenii Korol**

**@senyafeelsgood**

# How to submit a task?

- Create a private repository at GitHub.com
- Invite GitHub.com/joein and GitHub.com/senyafeelsgood to become a contributor
- Each hw should be done in its own branch, e.g. hw-1
- Once a task is ready for review:
  - Create a pull request to main
  - Request a review from both of us*
  - Once a PR is approved by 1 of us - merge
- If the task was sent 5 days before the first deadline, you can receive comments to address in order to improve the final mark**

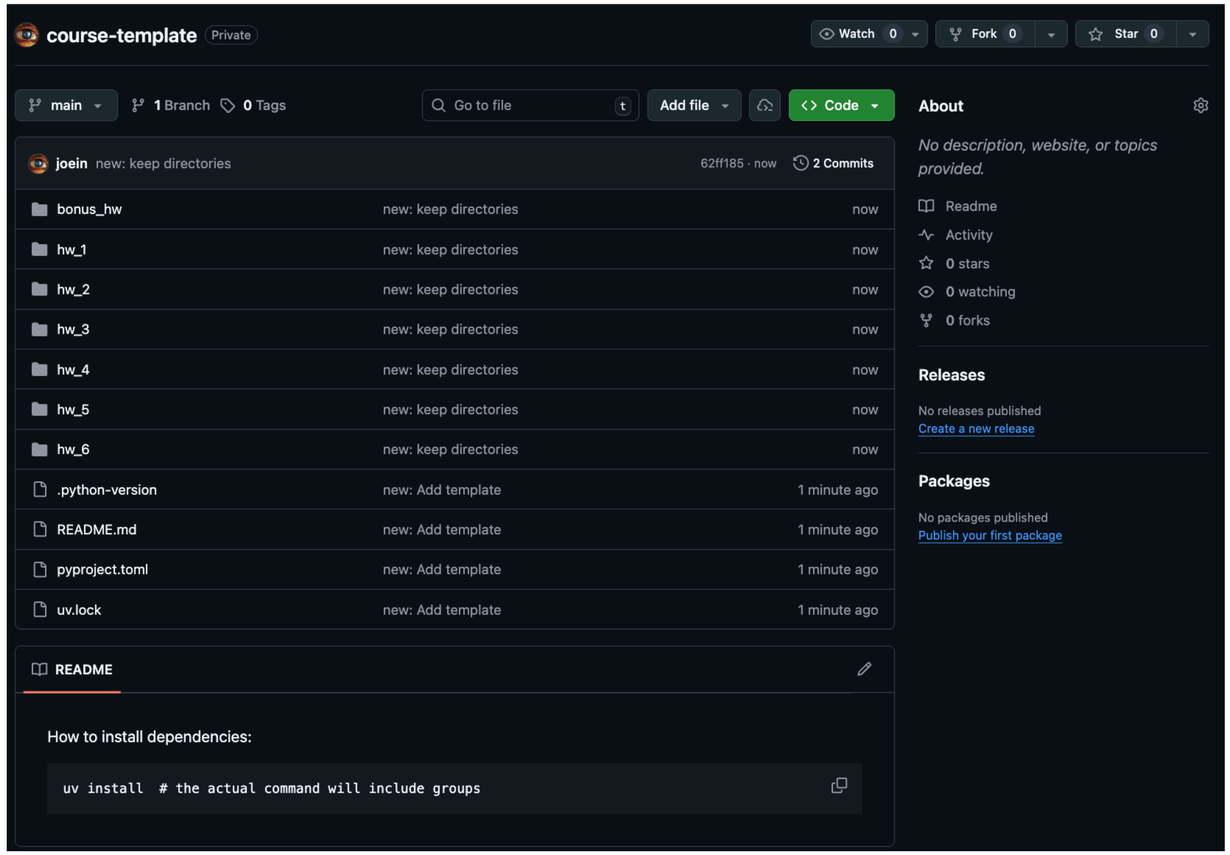
* Counted as a date of submission

** Time to address the comments is max(2 days, deadline date), comments can be received only 1 time per hw

# Task requirements

- Complete the task
- Have a clean repository
- Write clean well-structured code (pre-commit hooks, ruff, type hints, etc)
- Python version: 3.10+
- Package manager: uv
- Each hw has to have a dependency group, common dependencies can be put without a group
- Readme with installation instructions

Repository structure:



# What this course is about?

## What this course is about

- Applications of vector search in different scenarios and modalities
- Various vector search algorithms, their advantages and disadvantages
- Understanding, building and evaluating retrieval pipelines (including multistep ones)
- Optimizations for real world use cases
- Vector search beyond just k-nn

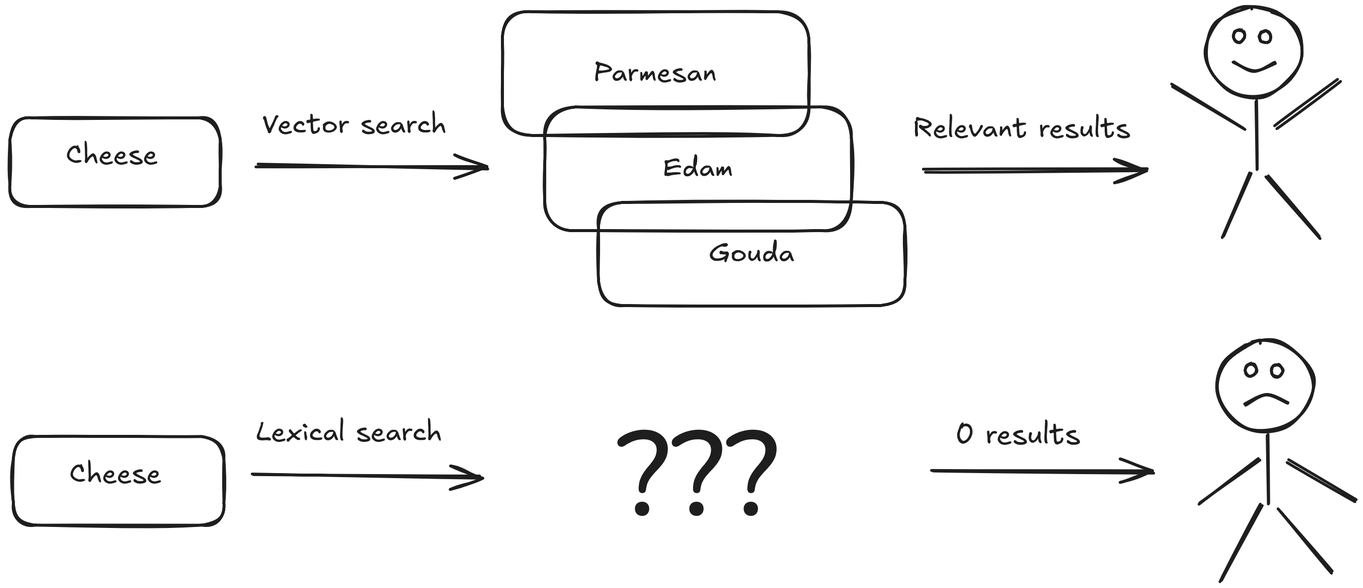
## What this course is not about

- Training your own models
- Deep dive into LLMs
- Building e2e platforms
- Covering unrelated topics (e.g. image generation)
- Memorizing math formulas of proofs

# What is vector search?

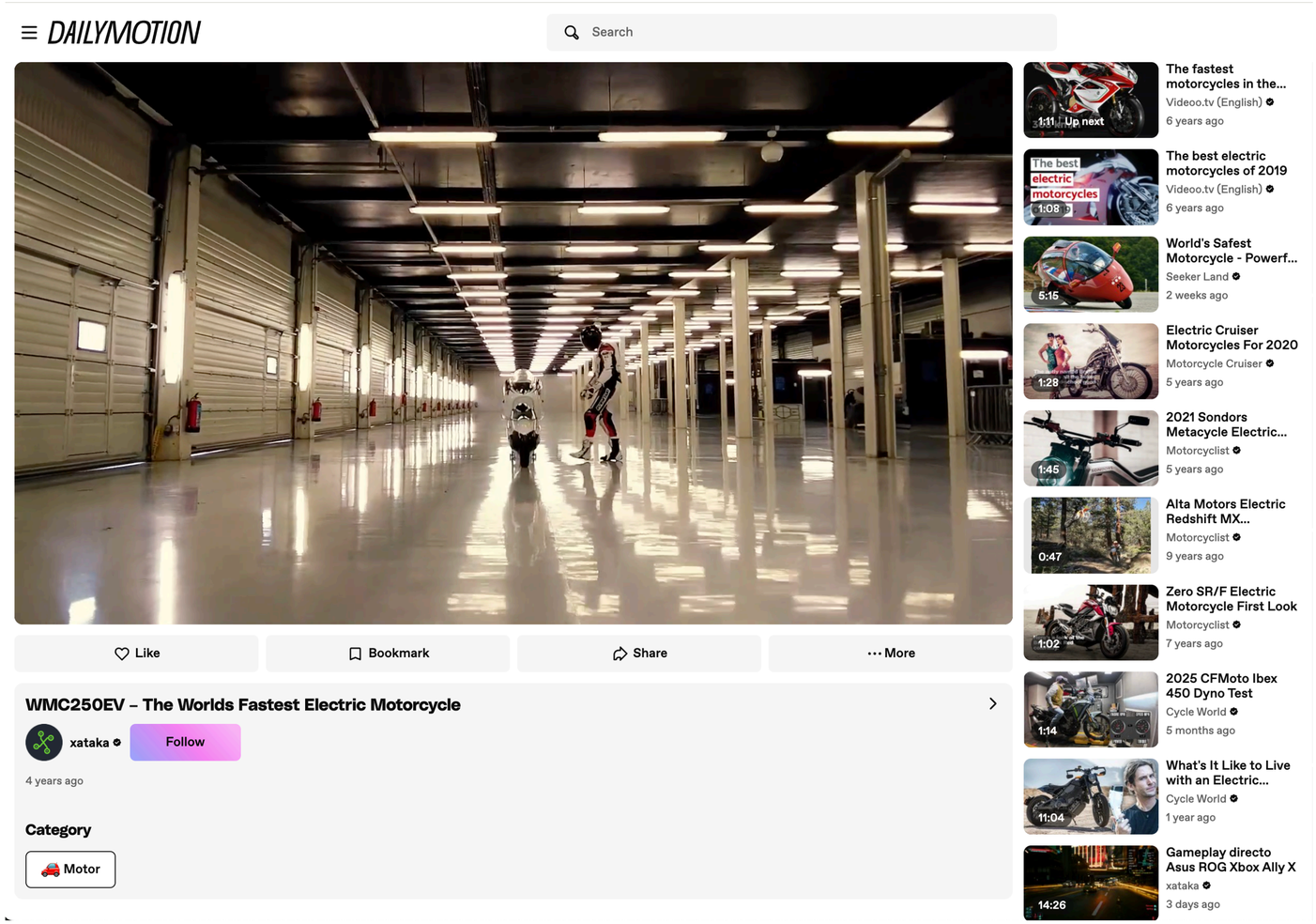
Vector search - is a type of search which captures *semantic meanings* of objects

- Does not require an exact match
- Multimodal (text, audio, video, etc.)
- Unlocks or simplifies advanced search scenarios (e.g. exploratory search)



# Examples

- Video recommendation
- Image search
- Music recommendation
- RAG
- ...
- Your ideas?



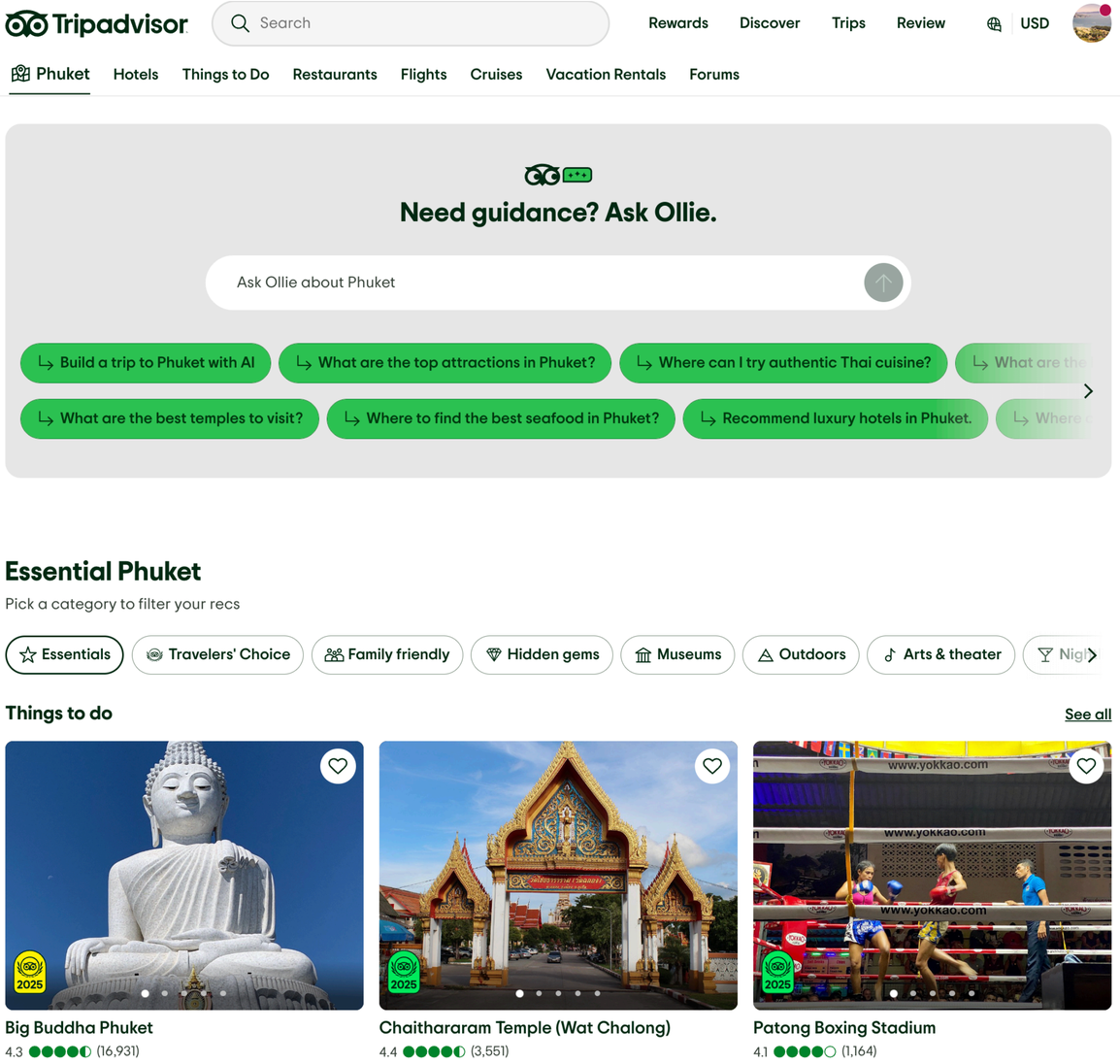
# Examples

*''When you're dealing with over a billion plus user-generated, multi-modal pieces of content from hundreds of millions of monthly active users across 21 countries, 11M businesses and all the complex user interactions that come with it, you need a way to bring it all together.*

*Now, we can represent everything from hotel preferences to restaurant choices to user behavior in a unified way.''*

*Rahul Todkar - VP, head of data and AI @ Tripadvisor*

*https://qdrant.tech/blog/case-study-tripadvisor/*



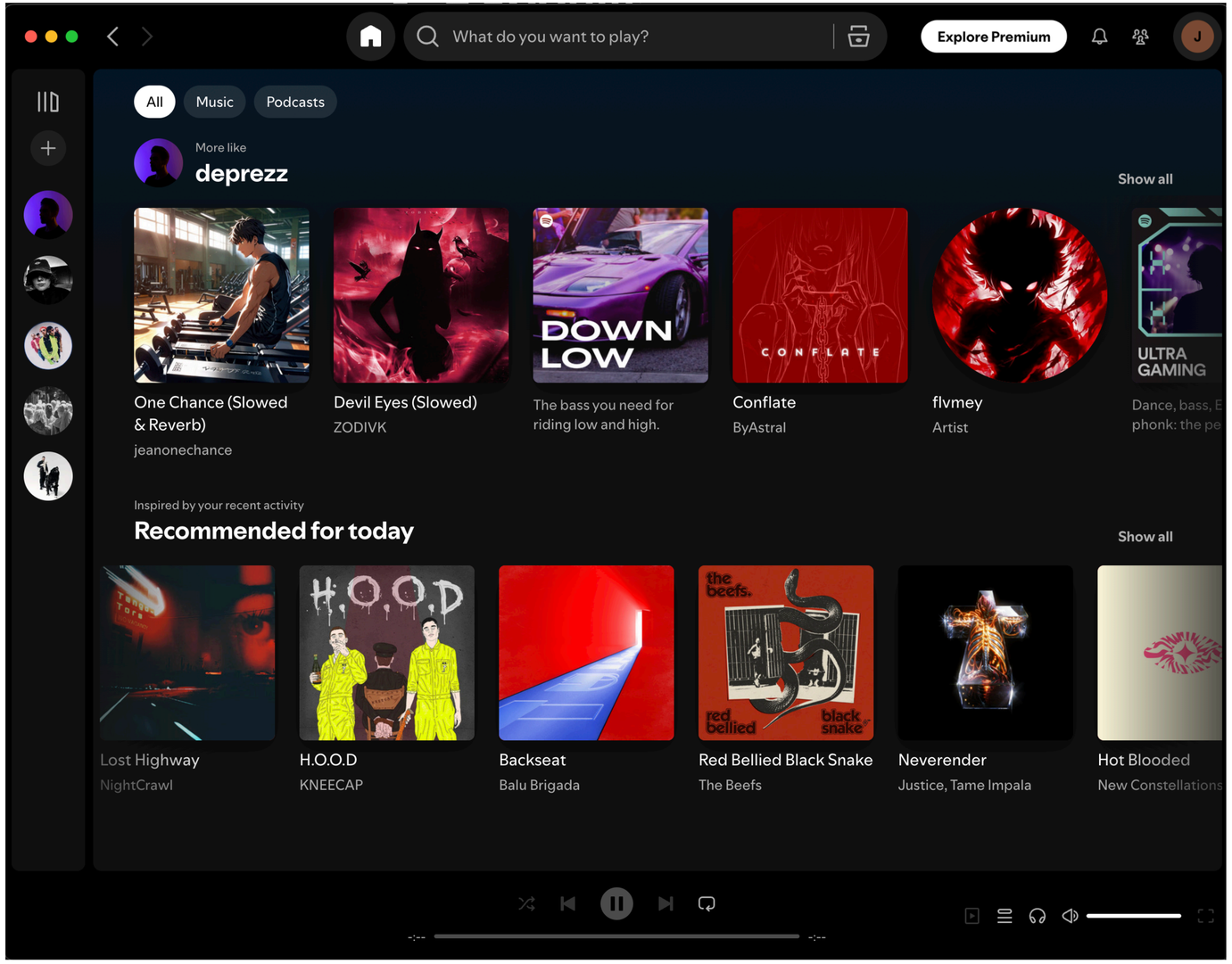
# Examples

*"For the past decade, Spotify has used approximate nearest-neighbor search technology to power our personalization, recommendation, and search systems.*

*These technologies allow engineers and researchers to build systems that recommend similar items (like similar tracks, artists, or albums) without needing to run slow and expensive machine learning algorithms in real time."*

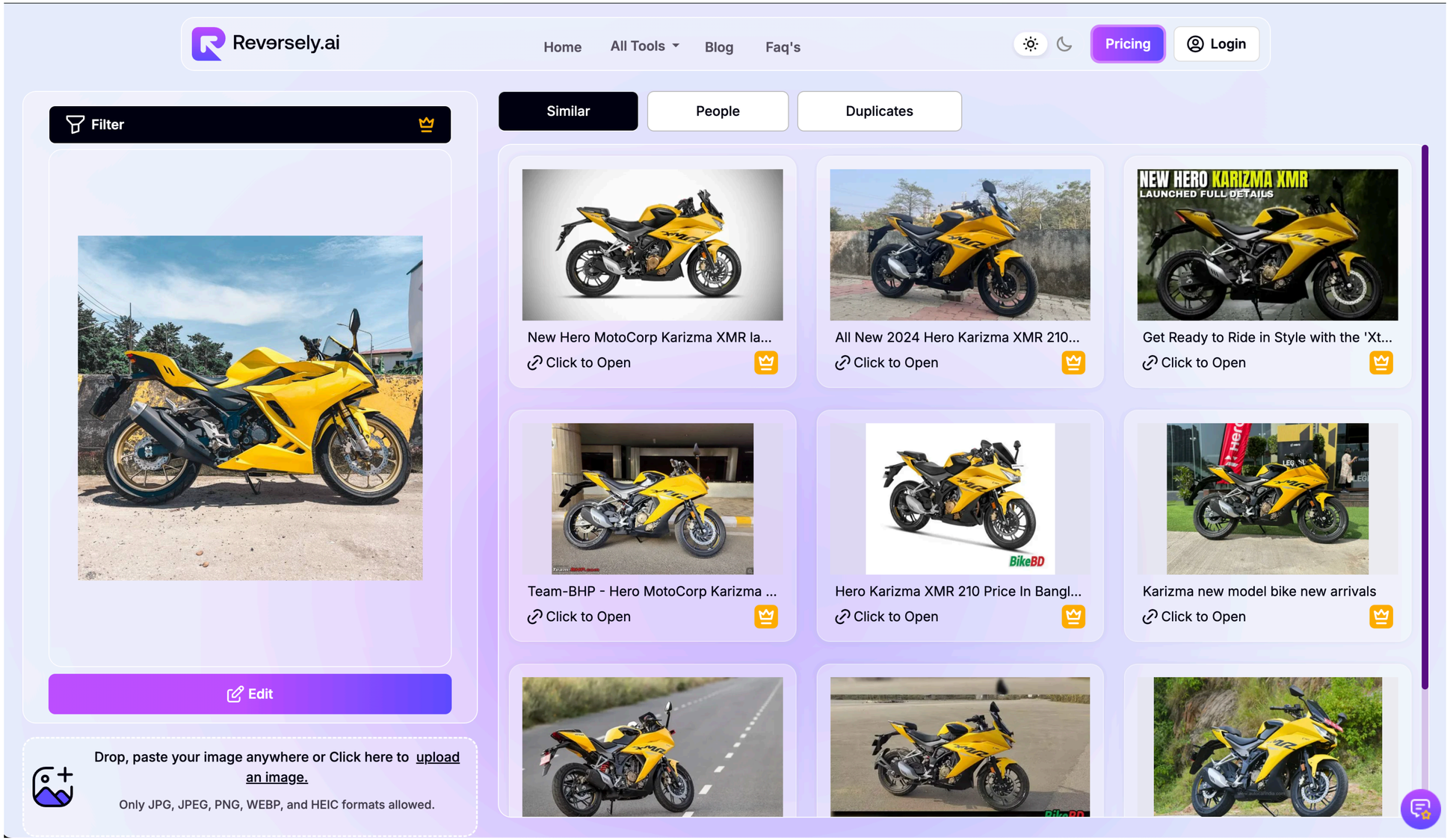
*Peter Sobot - Staff ML Engineer @ Spotify*

https://engineering.atspotify.com/2023/10/introducing-voyager-spotifys-new-nearest-neighbor-search-library



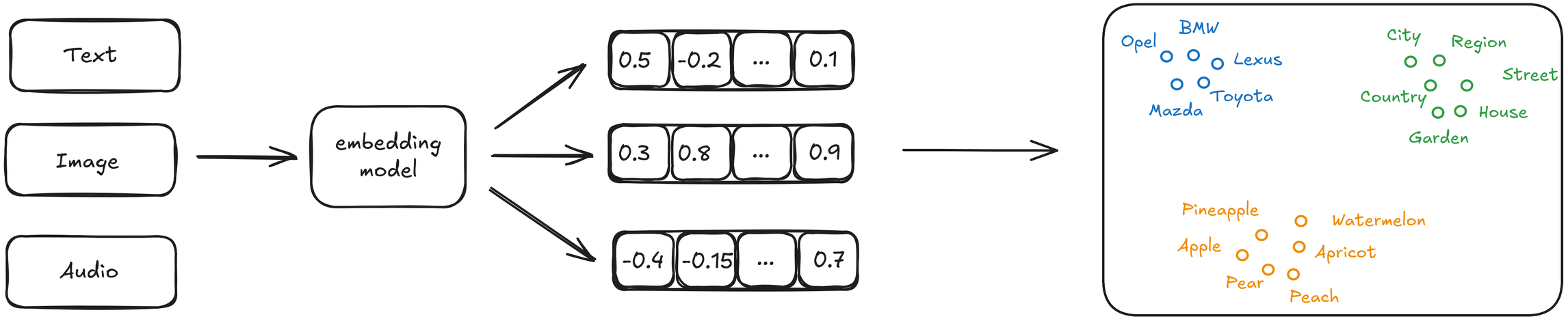
# Examples

I have no proof that it uses vector search, but it definitely does something that could be done with vector search.



# What are embeddings?

*Embeddings* are numerical representations of the semantic of the input data.

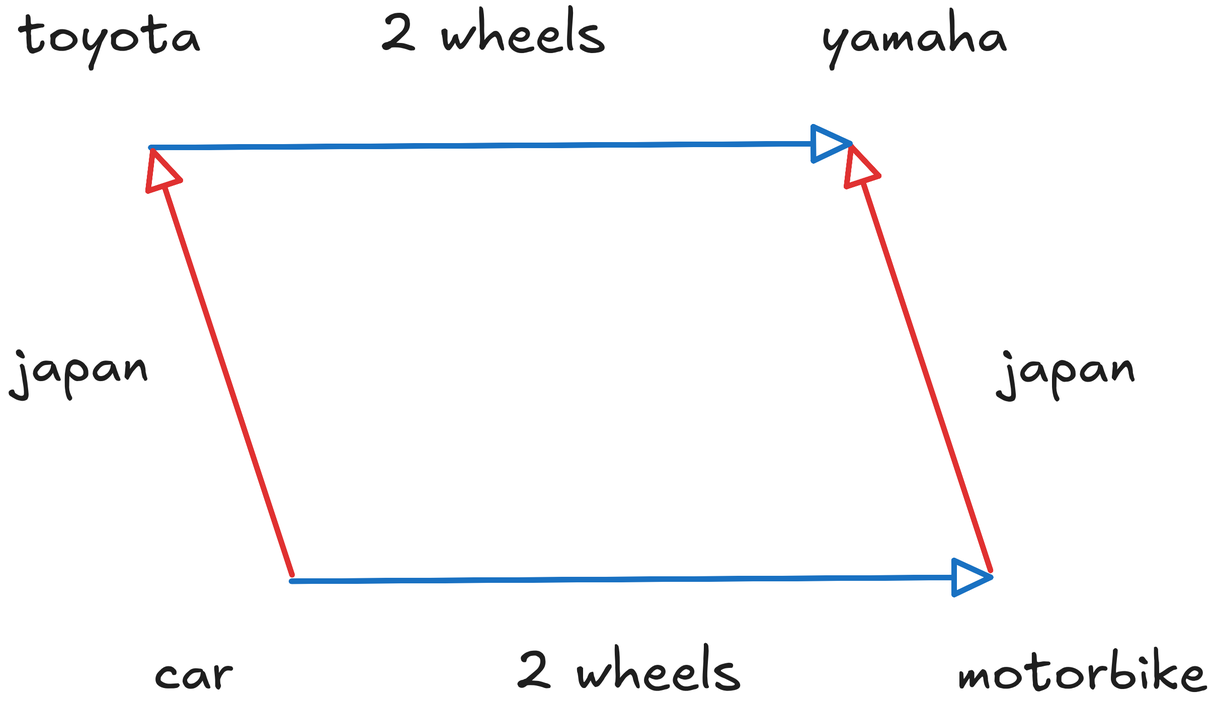


# How to get embeddings?

## Word2vec

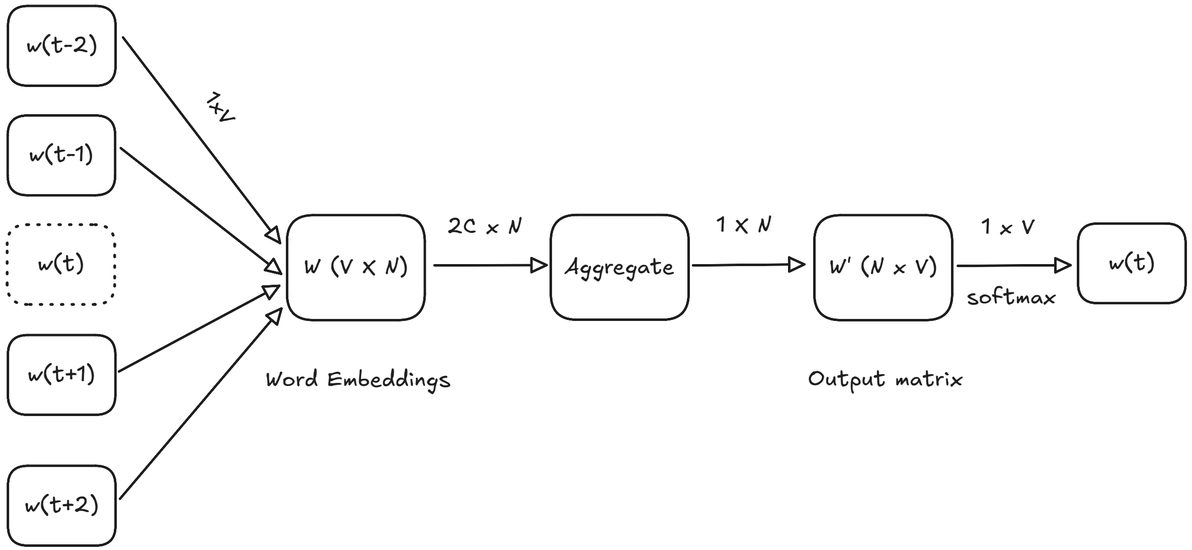
*Word2Vec* is a method to represent words as vectors in a continuous vector space so that similar words have similar vectors.

- Captures semantic meaning
- Fast inference -> just a dictionary lookup O(1) time.
- Context-independent
- No builtin out-of-vocabulary and typos handling
- Limited to textual data
- Requires preprocessing

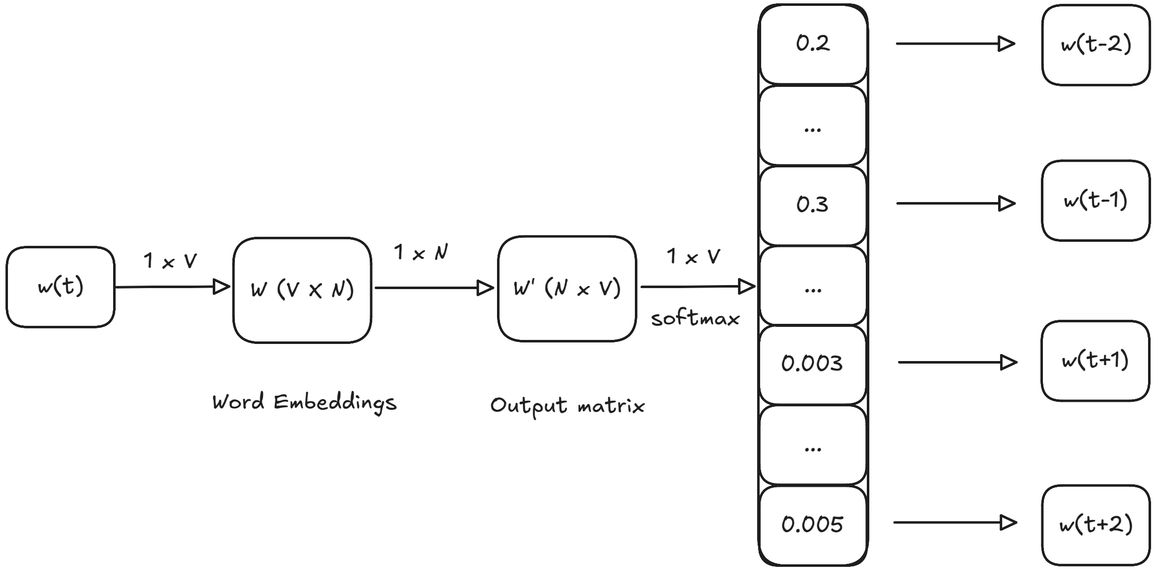


# Word2vec

## CBOW




## Skip-gram



# fastText

- Operates over n-grams
- Understands words morphology
- Better at handling out-of-vocabulary and typos
- Limited to textual data
- Does not require stemming or lemmatisation

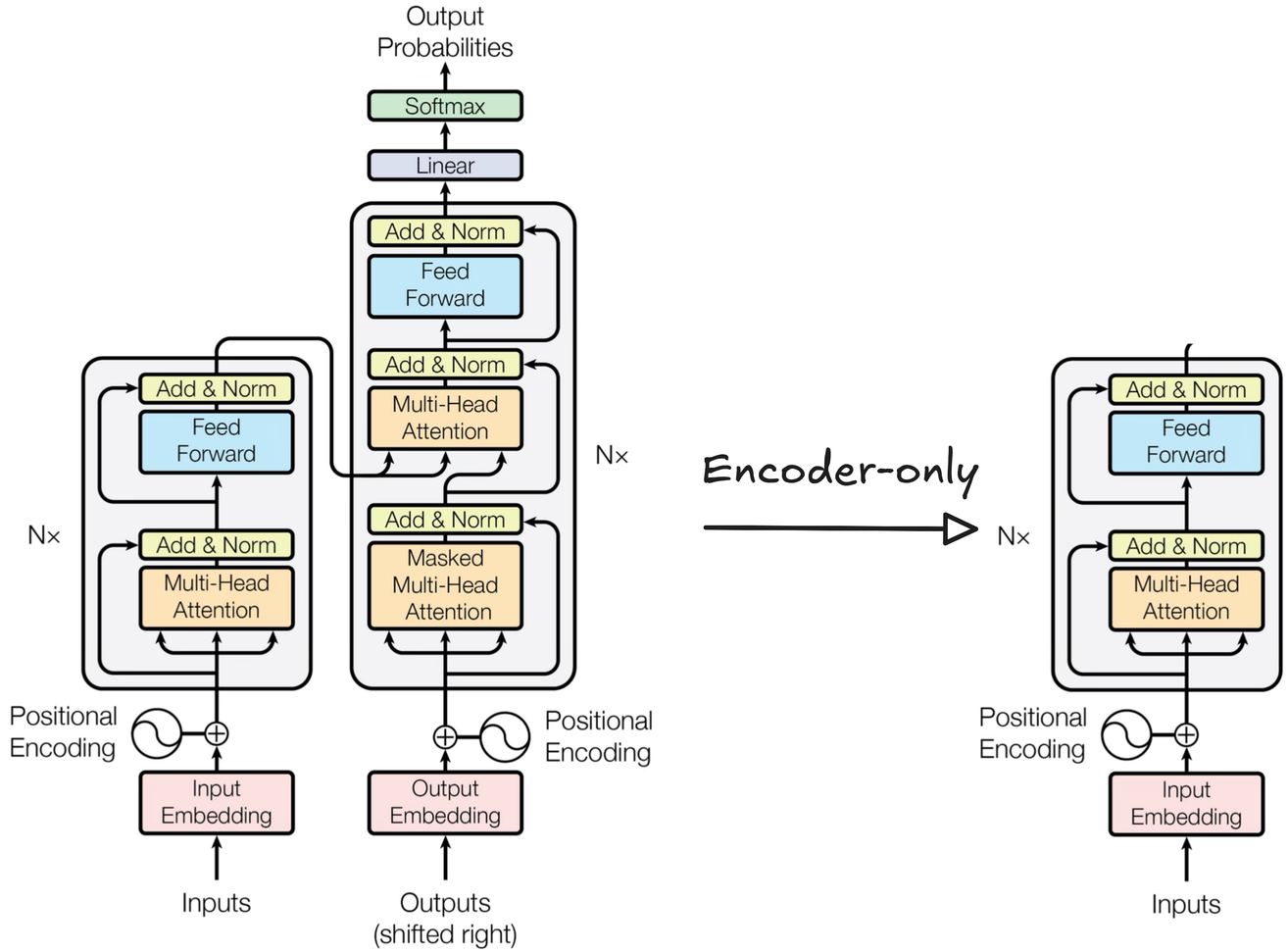
I am using fastText

3 grams <fa fas ast stT tTe Tex ext xt>

4 grams <fas fast astT stTe Text ext>

# Attention, transformers, etc.

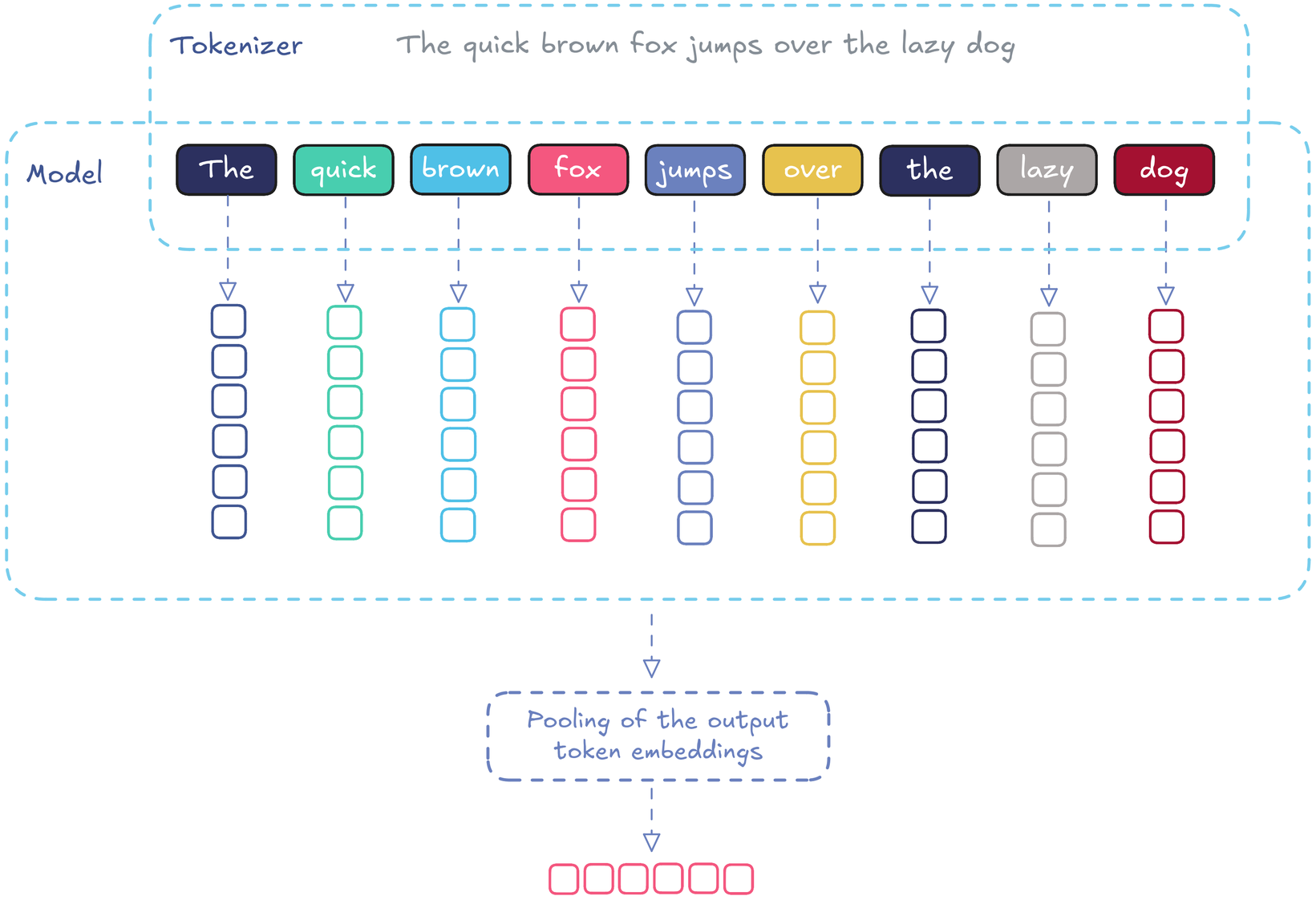
- Context aware
- Better at sentence-level semantics
- Easier extended to multimodal capabilities (CLIP)
- More semantically aligned -> better recall




https://arxiv.org/pdf/1706.03762

# Transformer embeddings

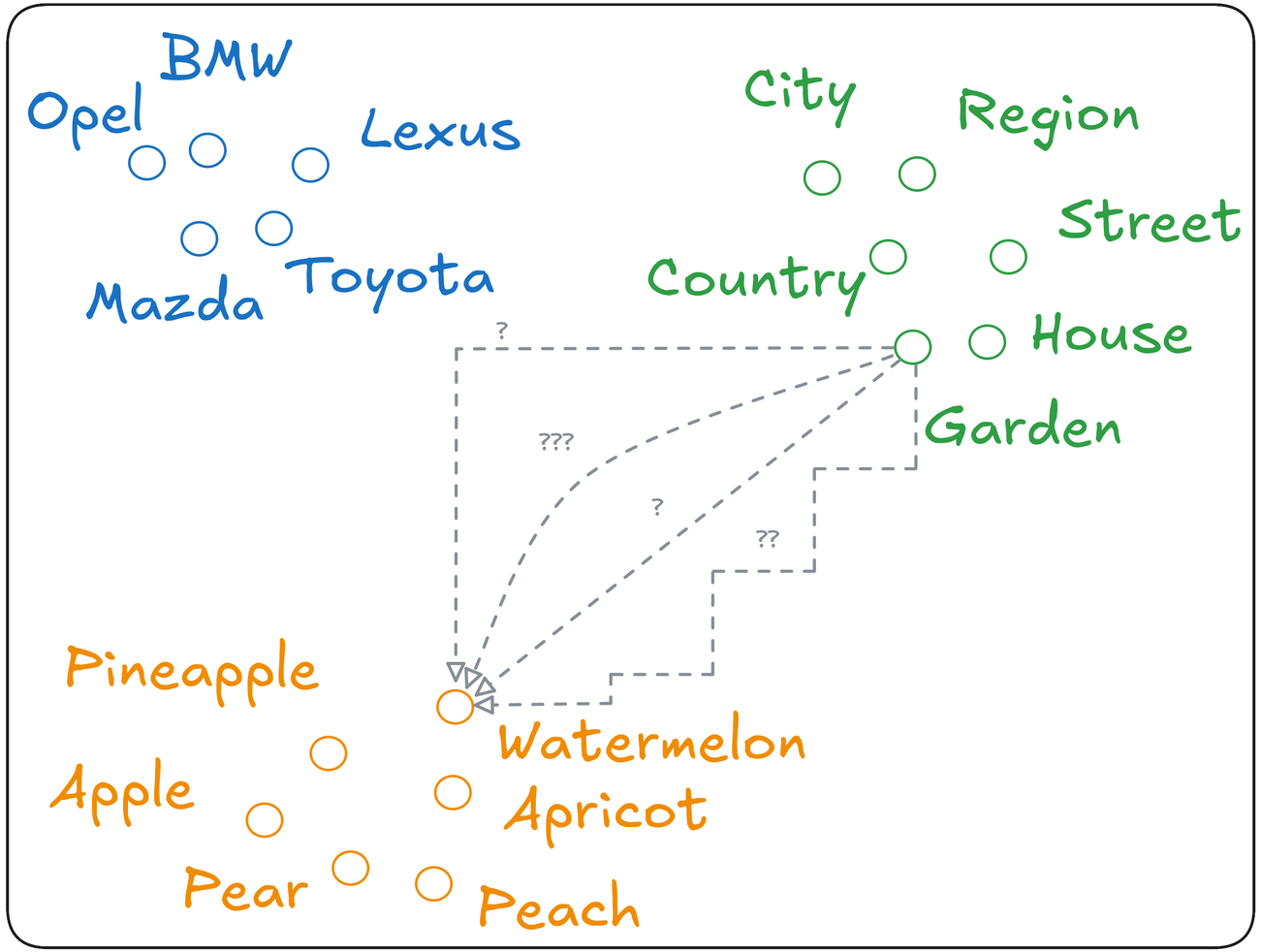
- Split input into tokens
- Compute embedding per token
- Pool or take [CLS] embedding



# How do we compare?

## Distance metrics

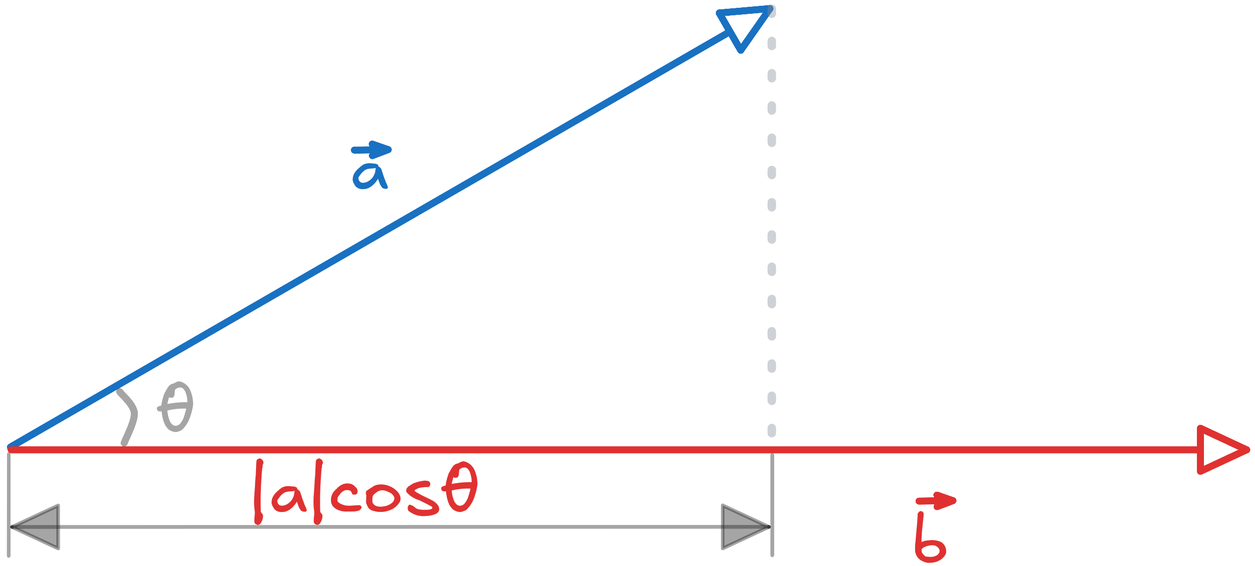
- Dot product
- Cosine
- Euclidean
- Manhattan
- Custom



# Dot product

$$\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^{n} a_i b_i = |\mathbf{a}||\mathbf{b}| cos\theta$$

- Depends on both magnitude and direction
- $\mathbf{a} \cdot \mathbf{b} = 0 \rightarrow$ Vectors are orthogonal (no similarity)
- $\mathbf{a} \cdot \mathbf{b} > 0 \rightarrow$ vectors point in the same direction
- $\mathbf{a} \cdot \mathbf{b} < 0 \rightarrow$ vectors point in the opposite directions
- Scaling a vector increases the dot product proportionally to its magnitude
- If embeddings have different norms, a vector with larger magnitude can appear more “similar” just because it’s longer even if directions differ



# Cosine

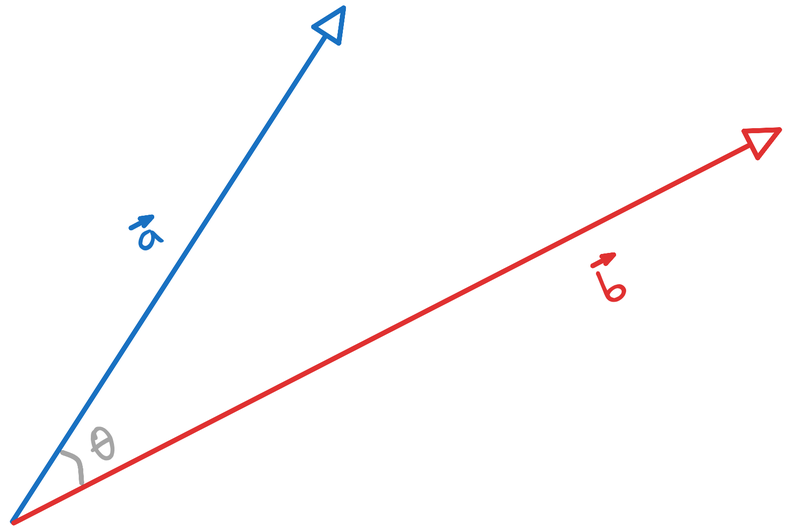
- Depends only on direction
- Normalising vectors makes cosine similarity equivalent to the dot product
- Robust to differences in vector norms, so longer embeddings don't bias similarity
- Usually scaled to [0; 1]
- The most popular choice

$$sim(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{|\mathbf{a}||\mathbf{b}|}$$

$$cos\theta \in [-1; 1]$$

$$scaled\_cos\theta = \frac{cos\theta + 1}{2}$$

$$scaled\_cos\theta \in [0; 1]$$



# Euclidean and Manhattan

$$d(\mathbf{a}, \mathbf{b}) = \sqrt{\sum_i (a_i - b_i)^2}$$

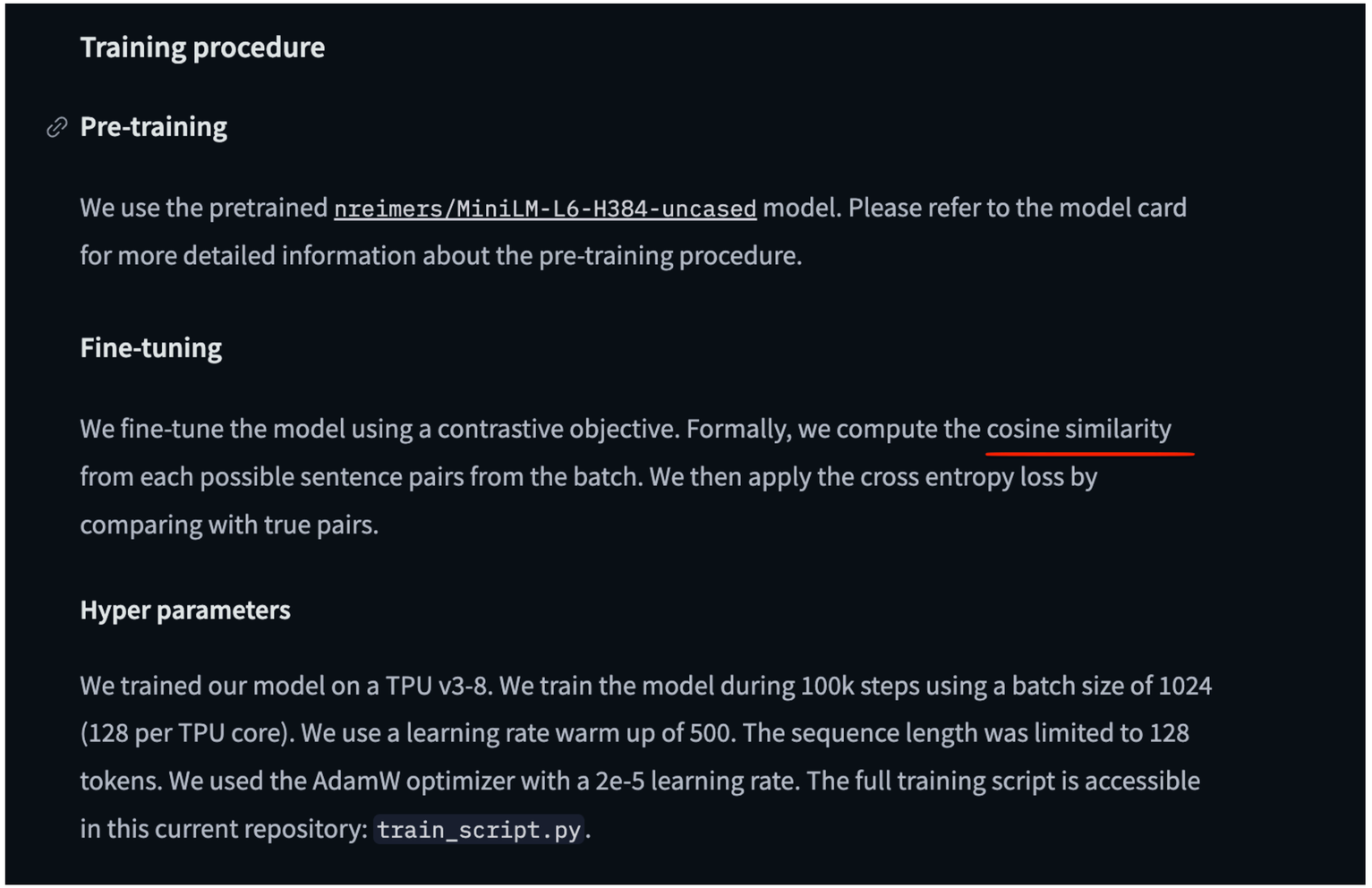
- Measures the “straight-line” distance between vectors
- Sensitive to both magnitude and direction
- $d(\mathbf{a}, \mathbf{b}) = 0 \rightarrow$ vectors are identical

$$d(\mathbf{a}, \mathbf{b}) = \sum_i |a_i - b_i|$$

- Sensitive to both magnitude and direction
- $d(\mathbf{a}, \mathbf{b}) = 0 \rightarrow$ vectors are identical
- More robust to outliers in some cases

# How to choose the correct metric?

- Benchmark on your data
- Choose whatever written in a model card or the distance it was trained with



**Training procedure**

**Pre-training**

We use the pretrained `nreimers/MiniLM-L6-H384-uncased` model. Please refer to the model card for more detailed information about the pre-training procedure.

**Fine-tuning**

We fine-tune the model using a contrastive objective. Formally, we compute the cosine similarity from each possible sentence pairs from the batch. We then apply the cross entropy loss by comparing with true pairs.

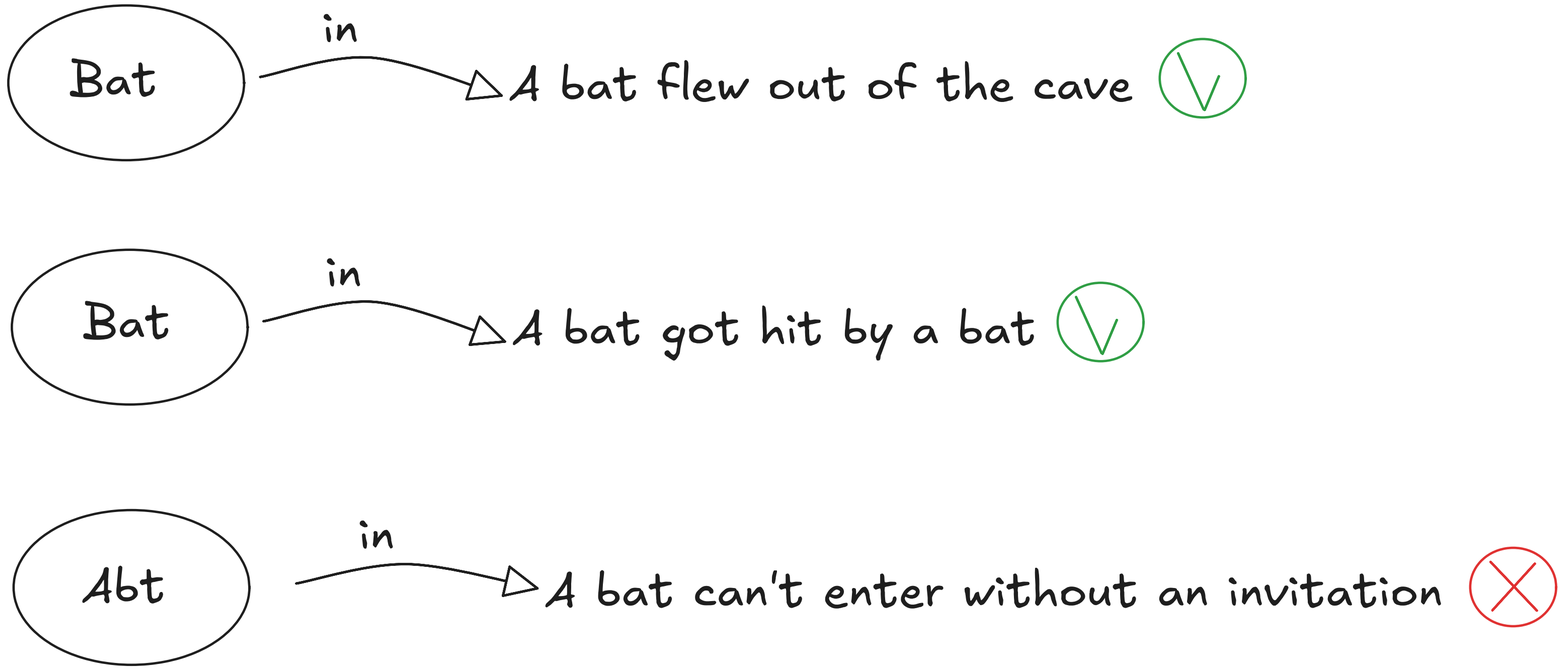
**Hyper parameters**

We trained our model on a TPU v3-8. We train the model during 100k steps using a batch size of 1024 (128 per TPU core). We use a learning rate warm up of 500. The sequence length was limited to 128 tokens. We used the AdamW optimizer with a 2e-5 learning rate. The full training script is accessible in this current repository: `train_script.py`.

# Lexical search

## Exact keyword match

- Retrieves documents containing exact query terms
- Fast for small datasets
- Easy to implement and interpret
- Works well for rare or unique keywords
- No term weighting
- Cannot handle partial matches or typos
- No semantic understanding



# Bm25

$$BM25(q,d) = \sum_{t \in q} log[\frac{N}{df(t)}] \cdot \frac{(k_1 + 1) \cdot tf(t,d)}{k_1 \cdot [(1-b) + b \cdot \frac{dl(d)}{dl_{avg}}] + tf(t,d)}$$

- Retrieves documents containing exact query terms
- Cheap and fast
- Strong baseline
- Can be extended with synonyms
- Takes into account frequency of term in document and in the dataset
- Cannot handle typos out-of-the-box
- No semantic understanding

$k_1$ - term frequency saturation; Typical range: [1.2; 2.0]

$b$ - length normalisation. $b \in [0; 1]$; Typical value 0.75

$dl(d)$ - document length

$dl_{avg}$ - average document length in the corpus

$N$ - number of documents in the corpus

$df(t)$ - the number of documents containing the term

$tf(t,d)$ - term frequency

# Vector search vs lexical search

## Algorithms result comparison

Neither of the algorithms works perfect.
Sometimes Bm25 is better, sometimes - semantic.

Examples based on a e-commerce dataset WANDS.

| Query | Bm25 | Semantic |
|---|---|---|
| Cybersport desk | Desk | Gaming desk |
| Plates for ice cream | “Eat” plates on wood wall decor | Alicyn 8.5 ” melamine dessert plate |
| Kitchen table with a thick board | Craft kitchen acacia work cutting board | Industrial solid wood dining table |
| Wooden bedside table | 30” bedside table lamp | Portable bedside end table |
| Computer chair | Vibrant computer task chair | Office chair |
| 64.2 inch console table | Cervantez 64.2 “ console table | 69.5 “ console table |

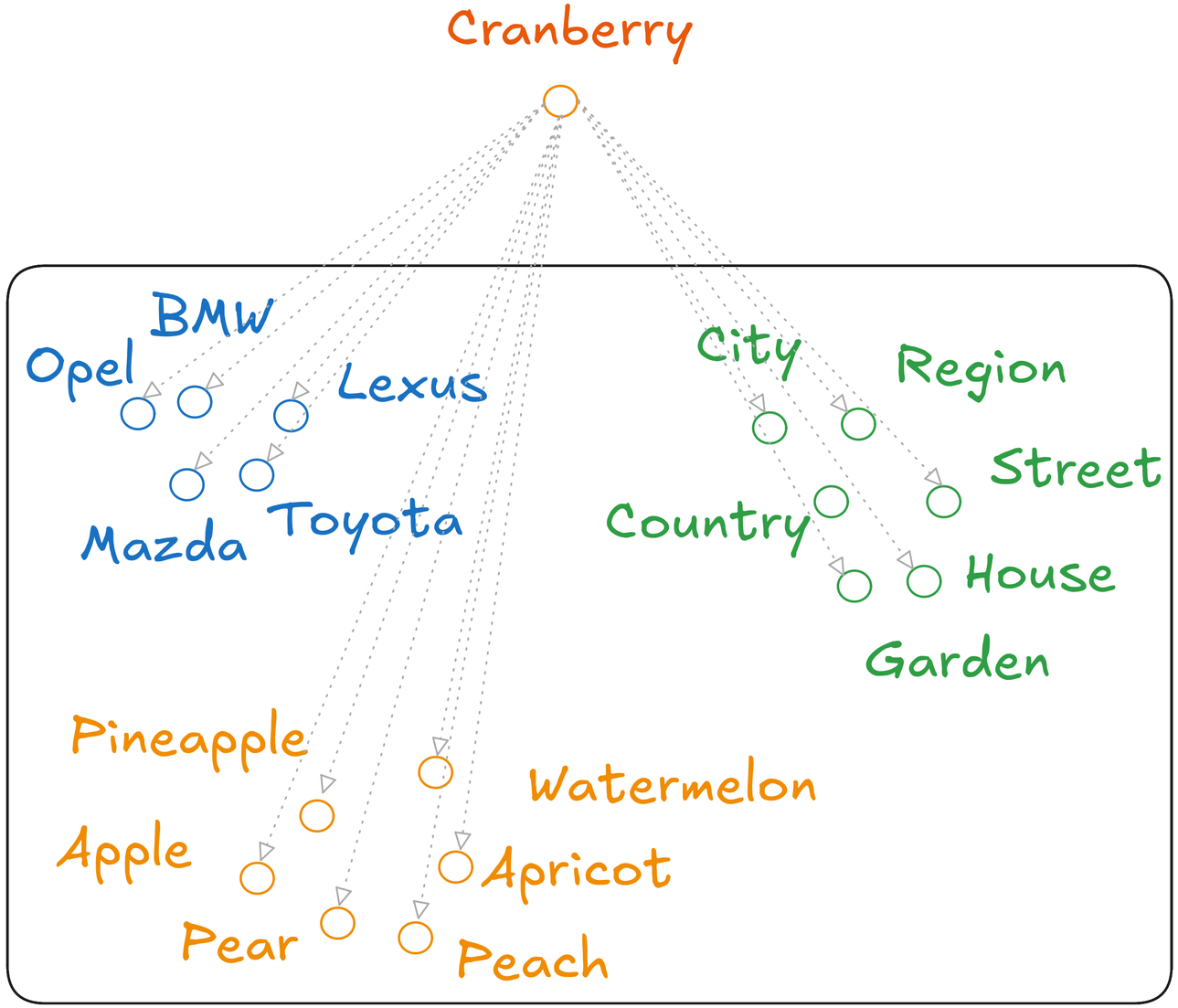
# Vector search vs lexical search

## Pros and cons

| | Lexical search | Vector search |
|---|---|---|
| **Matching type** | Matches exact keywords in the text | Matches meaning or intent |
| **Handling synonyms** | Requires expansion | Naturally capture synonyms |
| **Handling typos / variations** | Fails unless fuzzy search is implemented | Often robust to typos / variations, depends embeddings |
| **Explainability** | High, formula is straightforward | Hard to interpret |
| **Number and dates** | Supports if formatting is well defined | Might struggle even if with a defined formatting |
| **Speed and implementation** | Fast for low-frequency terms, slower for high-frequency | Fast (might be significantly slower if embedding generation is included) |
| **Memory usage** | Low-to-moderate | High |

# Brute force approach

- Compares query vector to all the vectors in a collection
- Computes exact similarity
- Guarantees 100% vector recall
- $O(N \cdot D)$ complexity
- Stores only vectors, no index overhead
- Performs well on small datasets (20-100k vectors), slow and costly for large



# Brute force

## Code snippet example

```python
import numpy as np
import time

# Generate random vectors
N, D = 50_000, 512  # 50k vectors, 512 dimensions
data = np.random.randn(N, D).astype(np.float32)
query = np.random.randn(D).astype(np.float32)

# Normalize for cosine similarity
data /= np.linalg.norm(data, axis=1, keepdims=True)
query /= np.linalg.norm(query)

# Benchmark brute-force search
start = time.perf_counter()
scores = data @ query  # dot product = cosine similarity
top_k = np.argpartition(-scores, 5)[:5]  # top 5 nearest neighbors
elapsed = time.perf_counter() - start

print(f"Top-5 indices: {top_k}")
print(f"Search time: {elapsed*1000:.2f} ms")
```

Scales linear with vector number and dimensionality:

- $50k, 512d \; - \; 3.56ms$
- $100k, 256d \; - 2.54ms$
- $100k, 512d \; - \; 7.20ms$
- $500k, 512d \; - \; 29.86ms$

# ANN

```python
import time
import numpy as np
from qdrant_client import QdrantClient, models

COLLECTION_NAME = 'brute-force-comparison'
DIM = 512
NUM_VECTORS = 500_000
cl = QdrantClient()
cl.create_collection(
  COLLECTION_NAME,
  vectors_config=models.VectorParams(size=DIM, distance=models.Distance.COSINE)
)

data = np.random.randn(NUM_VECTORS, DIM).astype(np.float32)
query = np.random.randn(DIM).astype(np.float32)

cl.upload_collection(COLLECTION_NAME, vectors=data)

start = time.perf_counter()
cl.query_points(COLLECTION_NAME, query=query, limit=5)
elapsed = time.perf_counter() - start

print(f"Search time: {elapsed*1000:.2f} ms")
```

Scales sub-linearly (usually logarithmically)

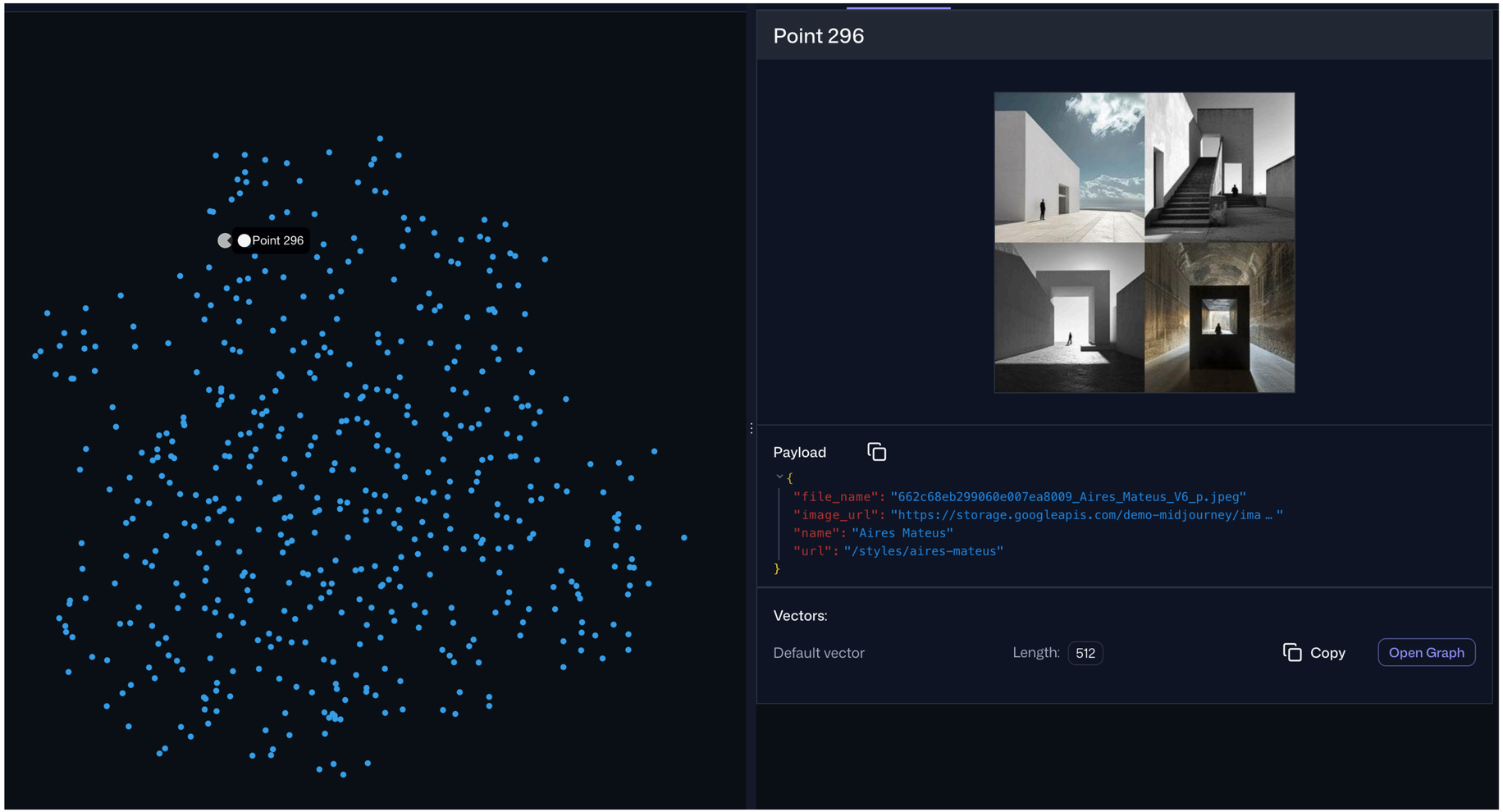
- $100k,\ 512d\ -\ 11.26ms$
- $500k,\ 512d\ -\ 12.2ms$
- $1kk,\ 512d\ -\ 17ms$

# Visualisation

It is important to know your data.

Points visualisation is one of the ways to understand the nature of the data.

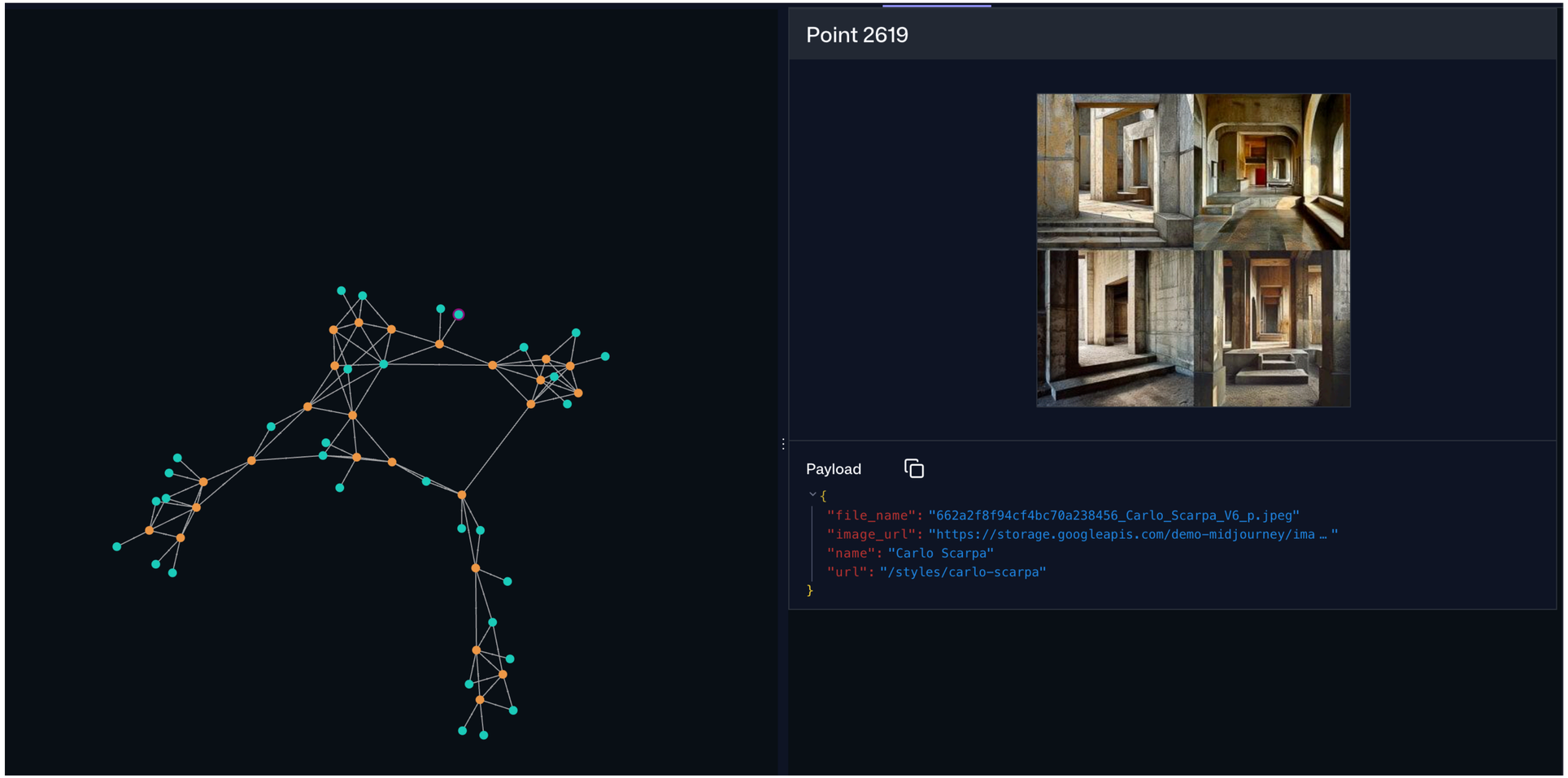
It can be done with various algorithms depending on your need. Such as PCA, T-SNE, U-Map, etc.



# Visualisation

## Graph exploration

Graph based visualisation let users explore the data and see nearest neighbours to the chosen points.



# Questions?