Embeddings and vector stores

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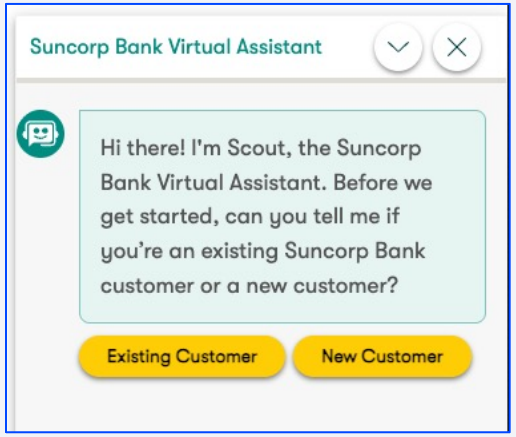
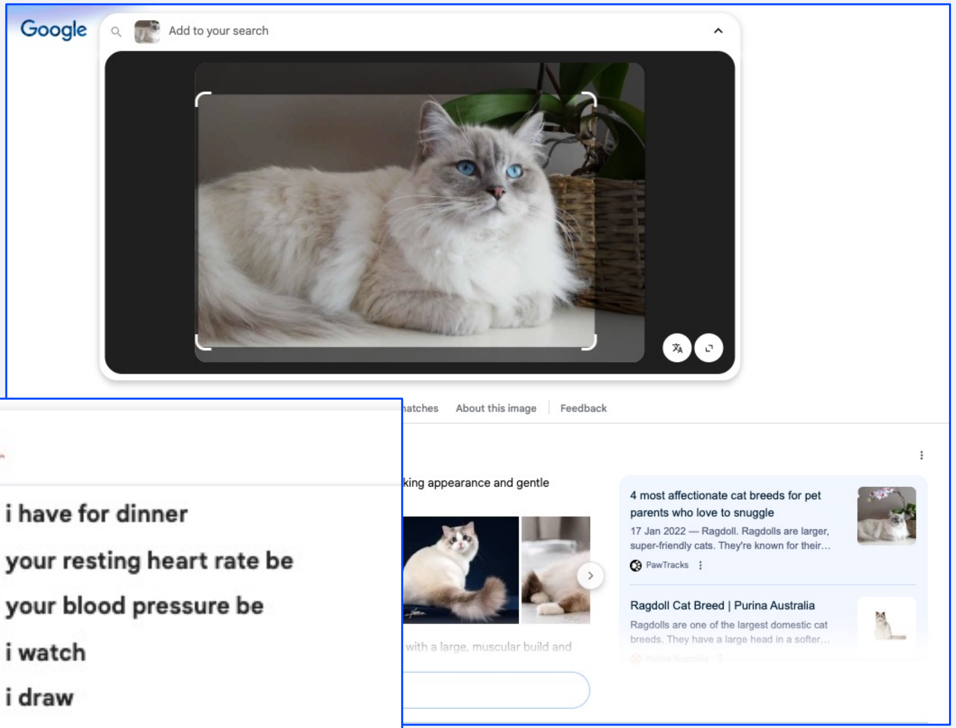
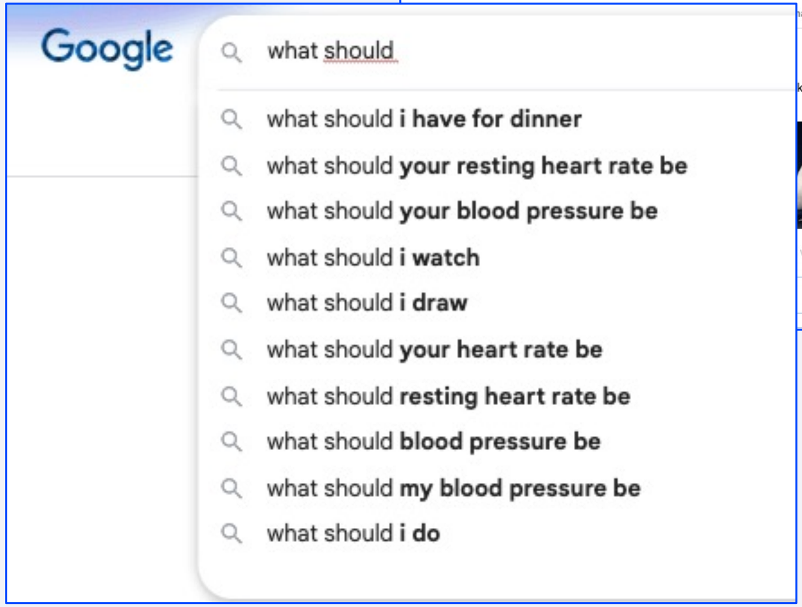
- Embeddings
- Types of embeddings and uses

Embeddings

Semantic search
Recommendation engines
RAG
Image similarity and MANY MORE







Multimodal embeddings

- **Modalities:** different types of data (text, images, audio, video, medical scans, diagrams, etc.)

A golden retriever puppy playing with a blue ball

The goal of multimodal models: Create a **shared embedding space** where:

- Related things from **any modality** end up close together (e.g., photo of dog + word "dog" + barking sound clip).
- Unrelated things stay far apart.

A fluffy cat lying down with tail wrapped around

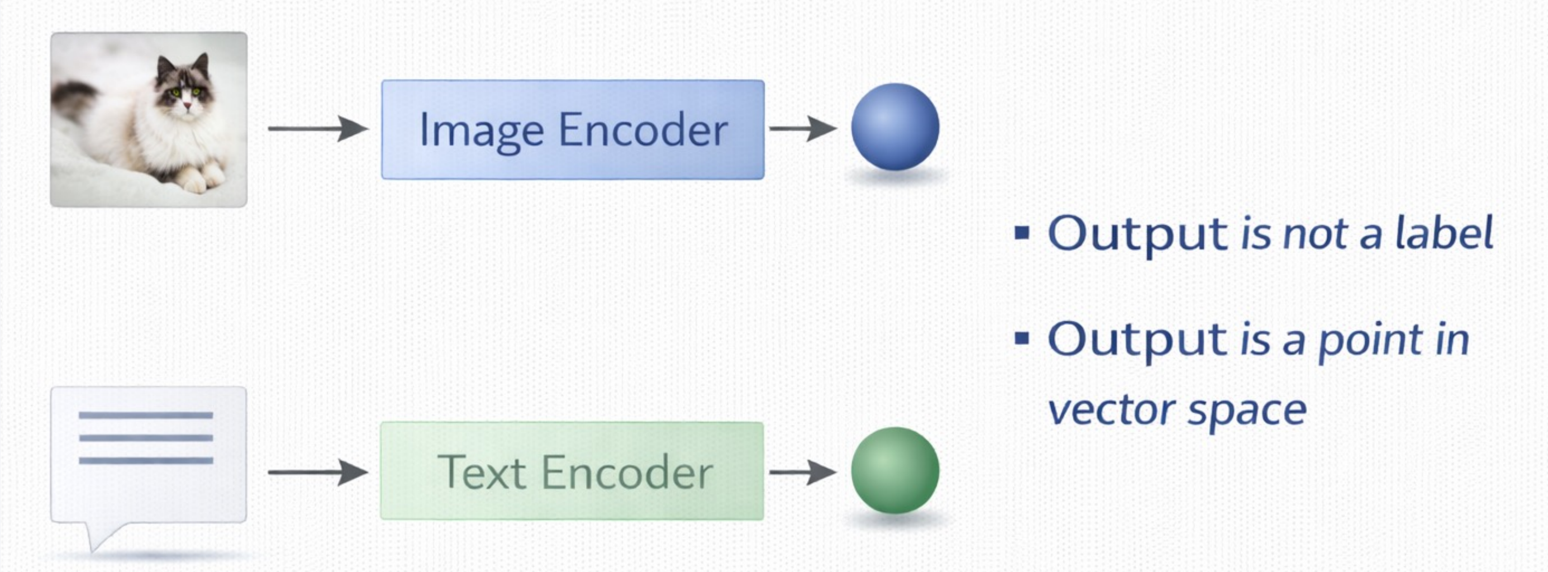
Contrastive learning:

technique that teaches models to

- identify similarities and differences in data
- by grouping similar examples (positive pairs) together in a vector space while
- pushing dissimilar ones (negative pairs) apart.

Multimodal embeddings: contrastive learning

- Learn embeddings by **pulling matching pairs together**
- **Pushing non-matching pairs apart**
- Distance in vector space is trained to reflect semantic correspondence.



Contrastive Learning

Intra-modality contrastive learning:
Learning structure within the same modality

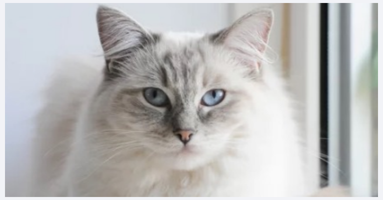
Positive pairs

- Represent the **same underlying concept**
- Should be **close** in embedding space

Negative pairs

- Represent **different concepts**
- Should be **far apart**

A fluffy Ragdoll cat lying down with tail wrapped around



Positive intra-modality

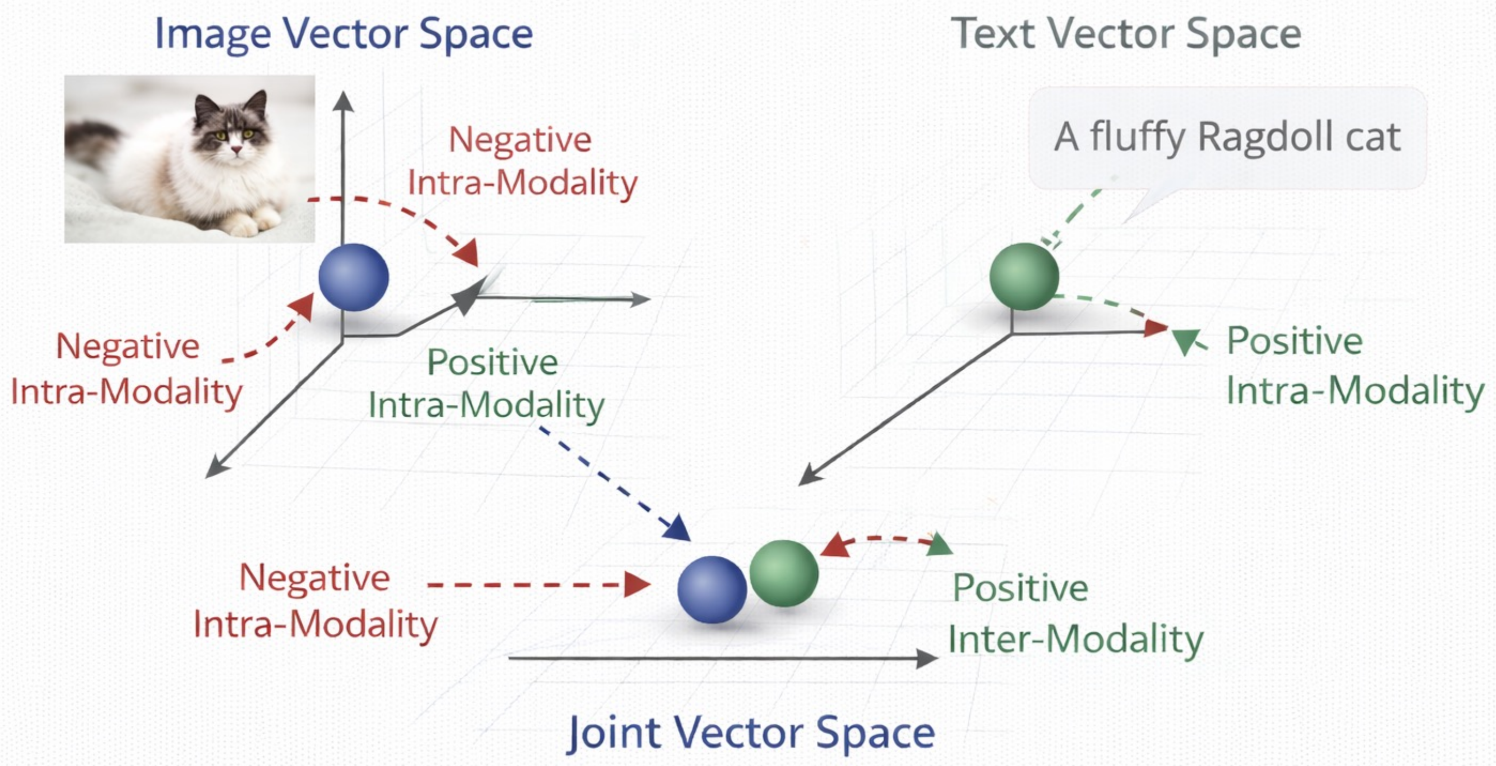
- Image ↔ image (same object, different views)
- Text ↔ text (paraphrases)

Negative intra-modality

- Image ↔ image (different objects)
- Text ↔ text (unrelated meanings)

Multimodal Vector Space

Combining image and text into a joint vector space



	Positive (pull together)	Negative (push apart)
Intra-modality	Same meaning, same modality	Different meaning, same modality
Inter-modality	Same meaning, different modalities	Different meaning, different modalities

Contrastive Learning

Measuring Quality

- There is **no universal “good embedding”** — quality is **task-dependent.**
- An embedding is **good** if **geometric relationships in vector space align with the task-relevant notion of similarity.**

- Same vocabulary
- Same inputs
- **Different geometry**

Because the **objective changes**

- There is no single “true” semantic space.

Cold

biomedical:
near "influenza", "rhinovirus", "hypothermia"

general:
near "hot", "winter", "cool"

News

legal:
near "judgment", "precedent", "litigation"

general:
near "box", "example", "situation"

How Embeddings Turn into Retrieval Metrics

A vector has **no meaning** until you:

- compare it to other vectors
- rank those comparisons
- use the ranking for something → nearest-neighbor search (retrieval)

Embeddings → Distance metric → Ranking → Metrics

- Precision
- Recall
- nDCG

Embeddings are not scored. Retrieval behaviour induced by embeddings is scored.

Did I return junk? → Precision
Did I miss good stuff? → Recall
Did I order the good stuff correctly? → nDCG