05

Text Embeddings for Classification and Search

In this module, you learn to ...

01 Use PaLM API to generate text embeddings

02 Create a classification model using text embeddings

03 Store embeddings in Vertex AI Vector Search to enable semantic search on datasets

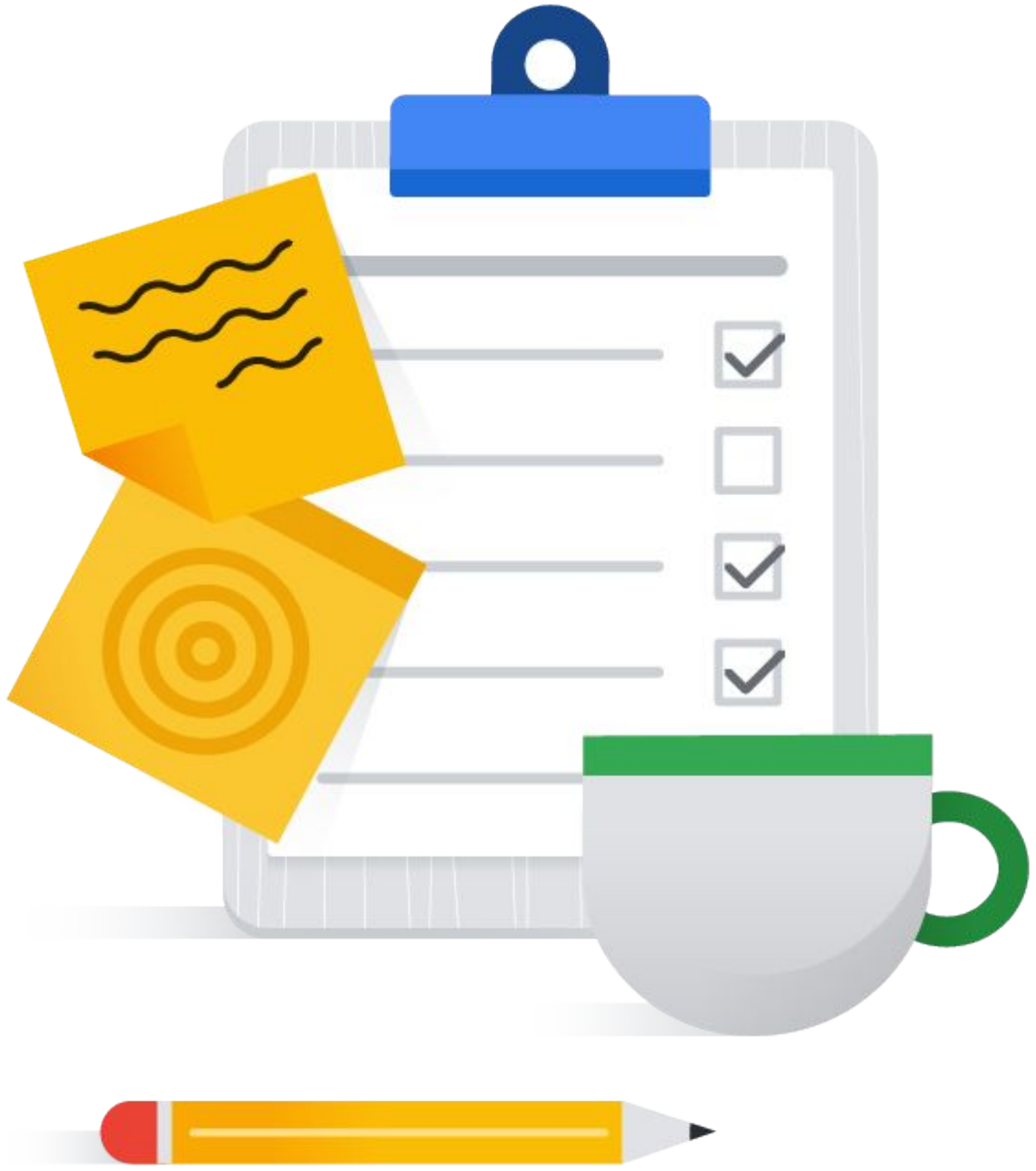
Topics

01 Text Embeddings

02 Classification using Text Embeddings

03 Search using Text Embeddings

04 Multimodal Embeddings



Text embeddings are generated using ML models

Models are trained on a huge corpus of data

- The models find the similarities in words
- Text is converted to vectors

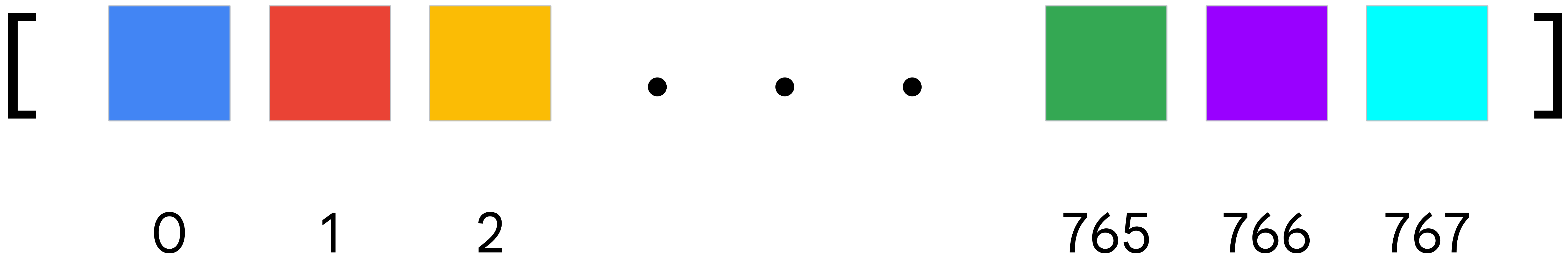
Models that generate text embeddings include:

- Word2Vec
- Bert
- GPT
- PaLM
- others...

Text embeddings for natural language processing tasks

- Text Classification
- Semantic Search
- Q & A
- Translation

An Embedding vector is an array of numbers that captures the semantic meaning of the words they represent



Create embeddings using PaLM Text Embedding Model

```
import vertexai
from vertexai.language_models import TextEmbeddingModel

embedding_model = TextEmbeddingModel.from_pretrained("textembedding-gecko@002")

embeddings = embedding_model.get_embeddings(["Python"])

vector = embeddings[0].values
print(f"Length = {len(vector)}")
print(vector)
```

Generate embeddings with `get_embeddings` function

```
import vertexai
from vertexai.language_models import TextEmbeddingModel

embedding_model = TextEmbeddingModel.from_pretrained("textembedding-gecko@002")

embeddings = embedding_model.get_embeddings(["Python"])

vector = embeddings[0].values
print(f"Length = {len(vector)}")
print(vector)
```

In PaLM, the embedding is a 768 dimension numeric vector

```
import vertexai
from vertexai.language_models import TextEmbeddingModel

embedding_model = TextEmbeddingModel.from_pretrained("textembedding-gecko@002")

embeddings = embedding_model.get_embeddings(["Python"])

vector = embeddings[0].values
print(f"Length = {len(vector)}")
print(vector)
```

```
Length = 768
[0.004732407163828611, -0.006129439201869965, 0.009944838471710682, 0.007499585855947752]
```

You can generate multiple embeddings at the same time

```
embeddings = embedding_model.get_embeddings(["Python", "Java",
                                             "BASIC", "COBOL",
                                             "JavaScript", "Lisp"])

for embedding in embeddings:
  vector = embedding.values
  print(vector)
```

```
[0.004647018387913704, -0.005934776272624731, 0.009972385130822659, 0.007659510243684053]
[0.011879554018378258, -0.01254566665738821, 0.02245570532977581, 0.055603329092264175]
[0.03372093290090561, -0.013127876445651054, 0.006259562913328409, 0.030314505100250244]
[-0.004371516406536102, -0.011225558817386627, -0.004736965987831354, 0.006307495757937431]
[-0.011748245917260647, 0.01277634222060442, 0.04550836980342865,0.01685352623462677]
[0.0040577128529548645, -0.011785312555730343, 0.005976524204015732, 0.04450475424528122]
```

Embeddings can be created from any block of text

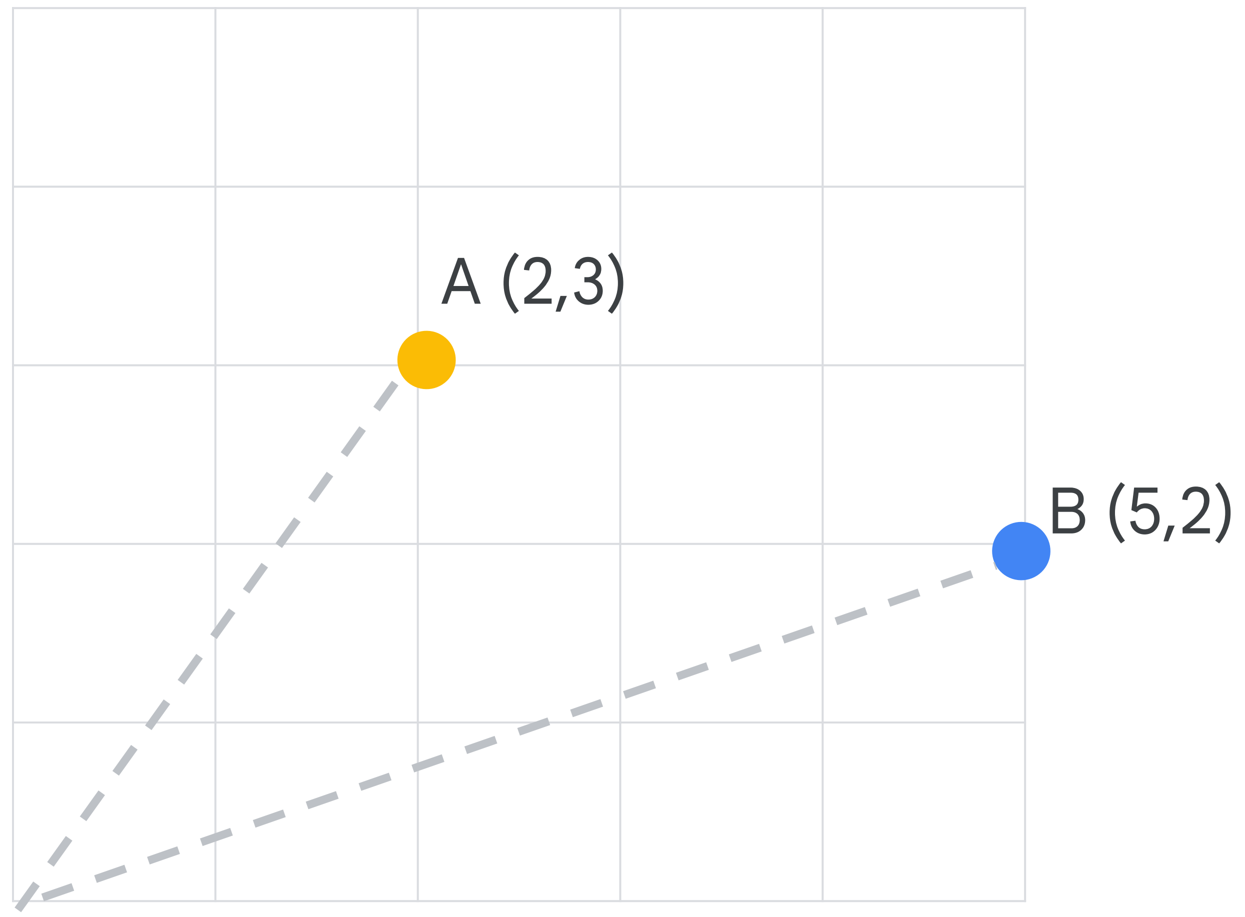
```
embeddings = embedding_model.get_embeddings(["""Text embedding is an important NLP
      technique that converts textual data into numerical vectors that can be processed
      by machine learning algorithms, especially large models. These vector
      representations are designed to capture the semantic meaning and context
      of the words they represent."""])


for embedding in embeddings:
  vector = embedding.values
  print(vector)
```

```
[-0.011677264235913754, -0.04742889106273651, -0.05371042340993881, 0.006055985111743212,
-0.01956809125840664]
```

Once you have vectors, how do you use them?

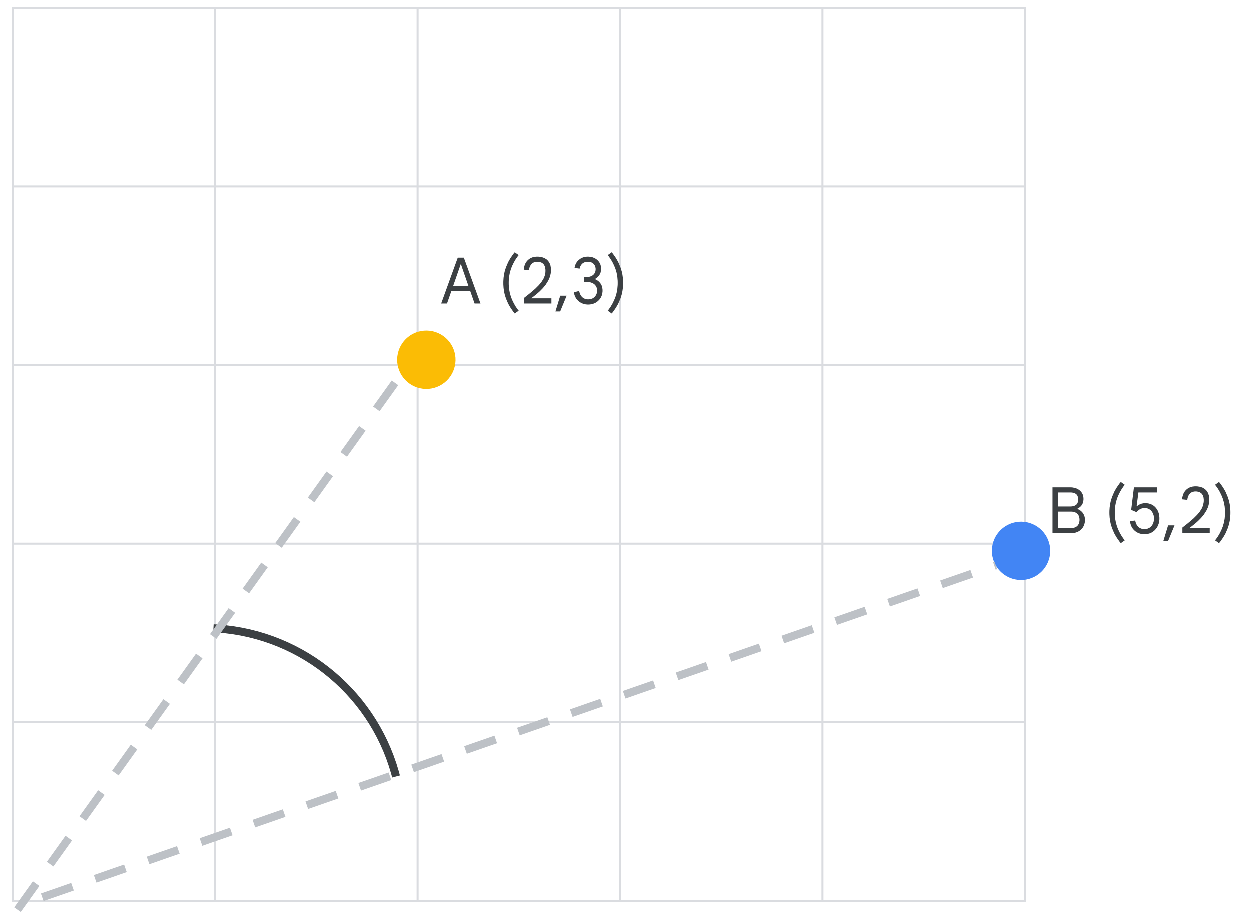
You are typically interested in finding the nearest neighbors to a vector to find semantically similar documents (or images, videos, etc.)

For example, with two-dimensional vectors, you can see our two most similar vectors.



Cosine similarity

- Similarity based on the angle between two vectors
  - Returns a value between -1.0 and 1.0
  - 1.0 means the vectors are the same
  - -1.0 means they are the opposite of each other
- Unaffected by the magnitude of the vectors
  - High similarity even from text of different lengths



Cosine distance

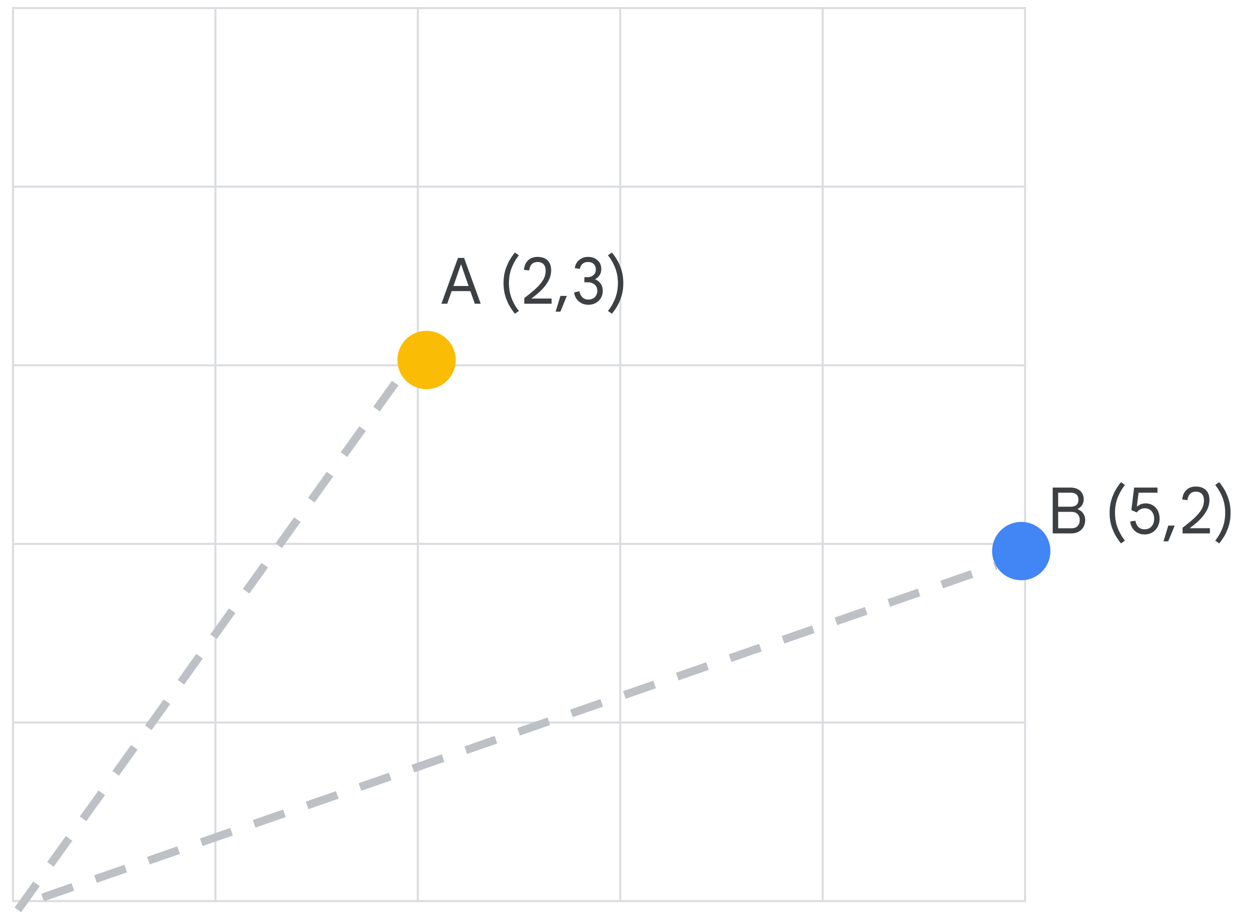
= 1 -cosine similarity
= 1- cos(Θ)

$$\cos\theta = \frac{a \cdot b}{||a||\ ||b||}$$

||a|| denotes the magnitude or norm of a vector.

Vector databases provide other distance metrics as well

- L2 Euclidean distance
- L1 Manhattan distance
- Dot product distance

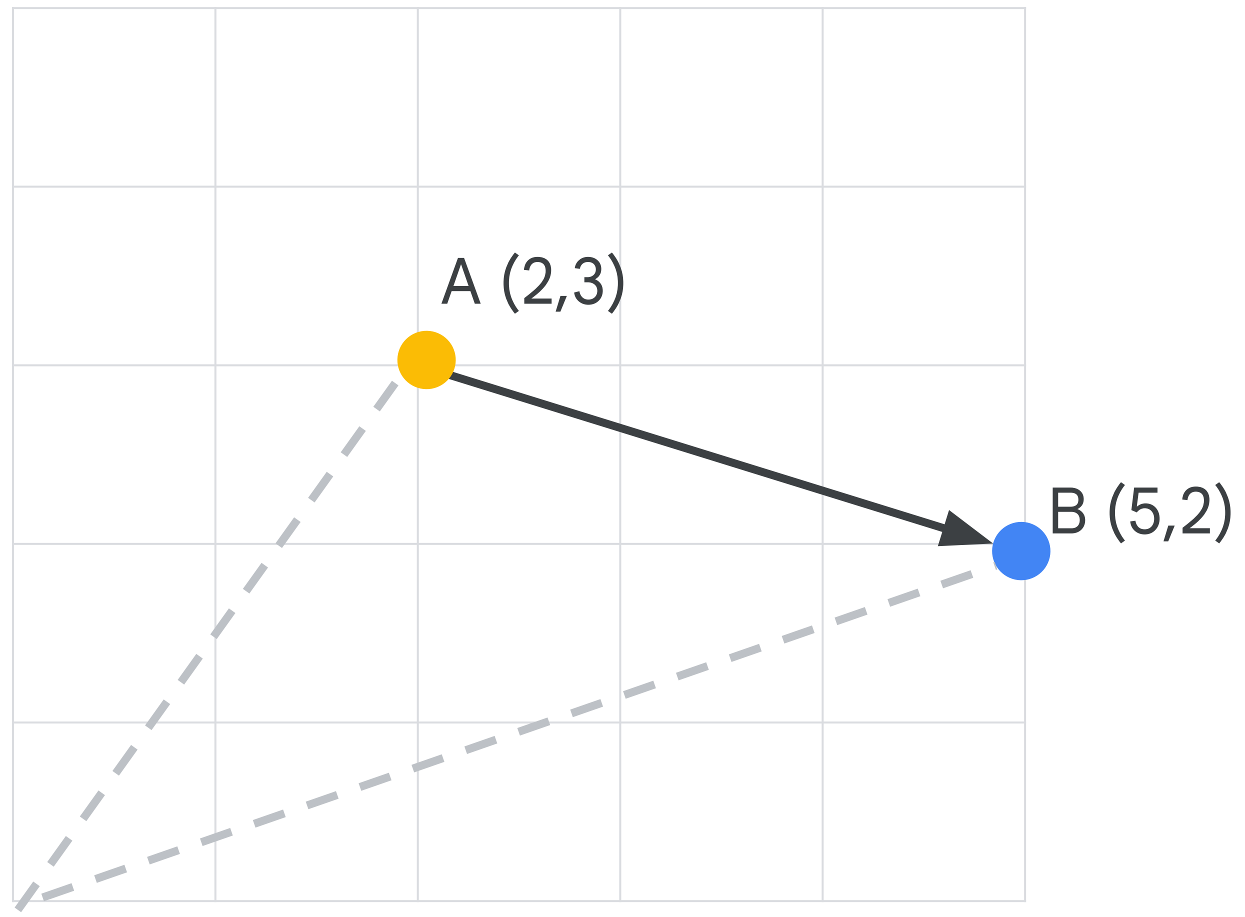


L2 Euclidean Distance

- The distance between between two points in a vector space
- Square root of the sum of squared differences between corresponding coordinates of two vectors

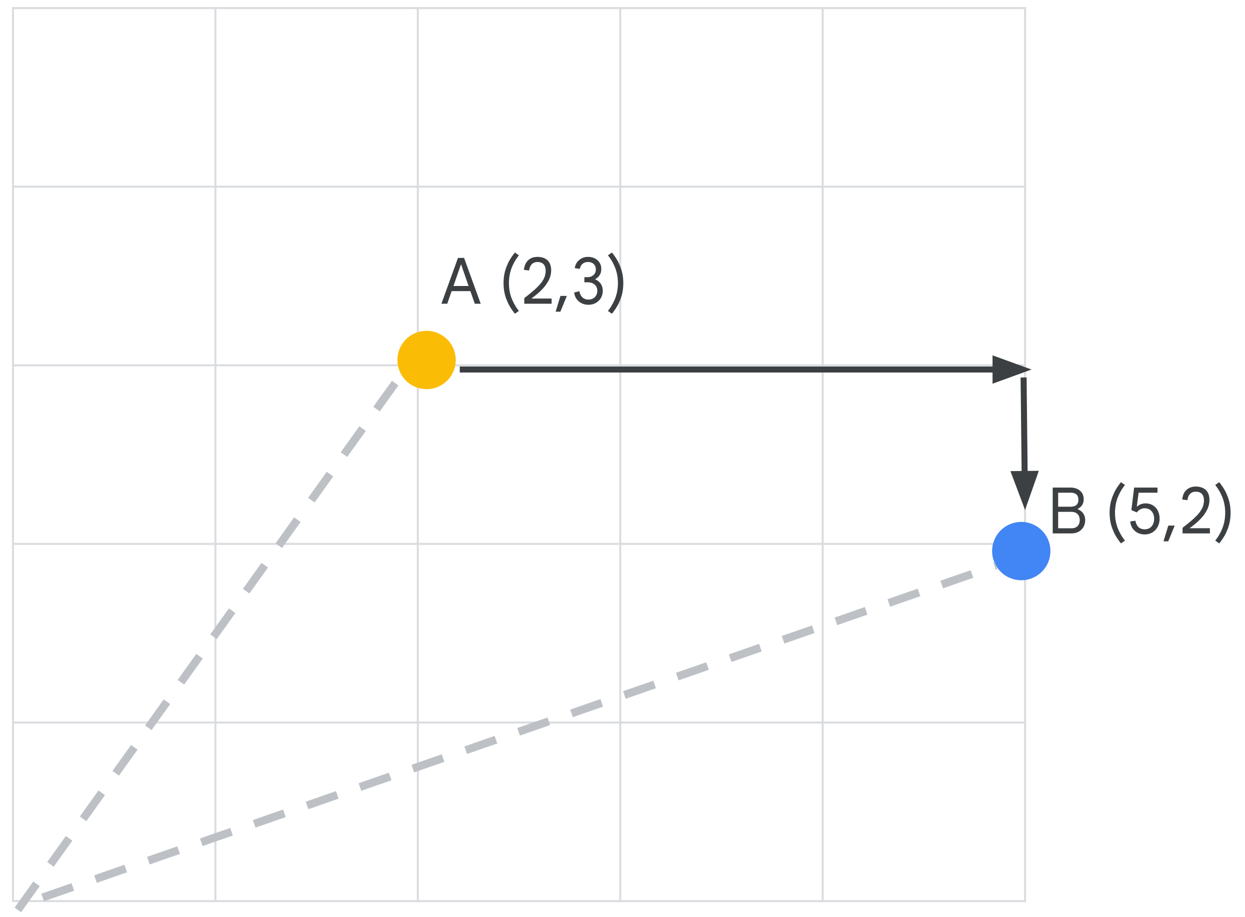
Euclidean (L2)

$$\sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$



L1 Manhattan Distance

- Sum of the absolute distances between corresponding coordinates of two vectors
- Less sensitive to outliers compared to Euclidean
- Faster to calculate than Euclidean



Manhattan (L1)

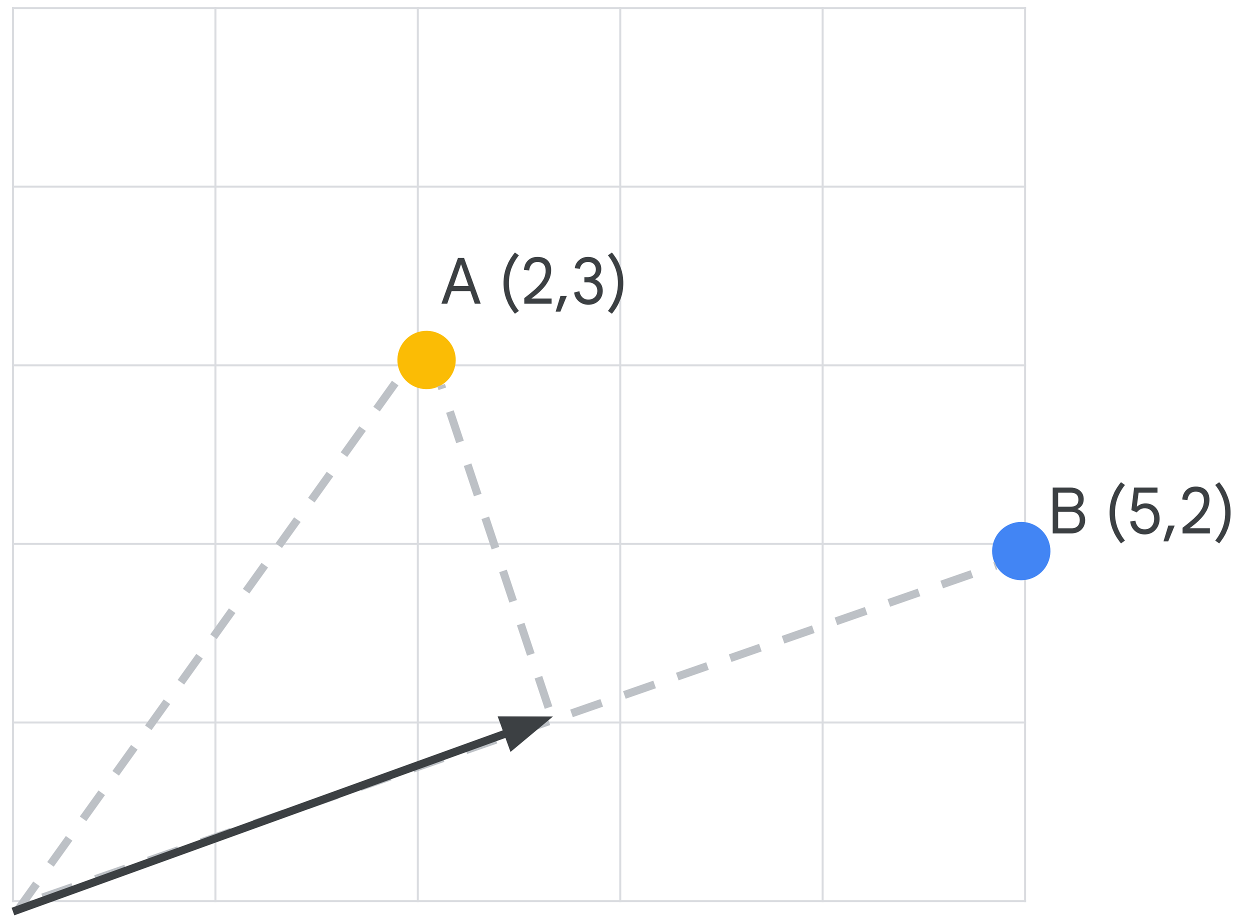
$$\sum_{i=1}^{n} |x_i - y_i|$$

Dot Product Distance

- Calculated by multiplying the components of the two vectors and adding the products together
- Length of one vector projected onto the other
- A higher dot product indicates that the vectors are more similar in direction
- The default when using Vertex AI Vector Search

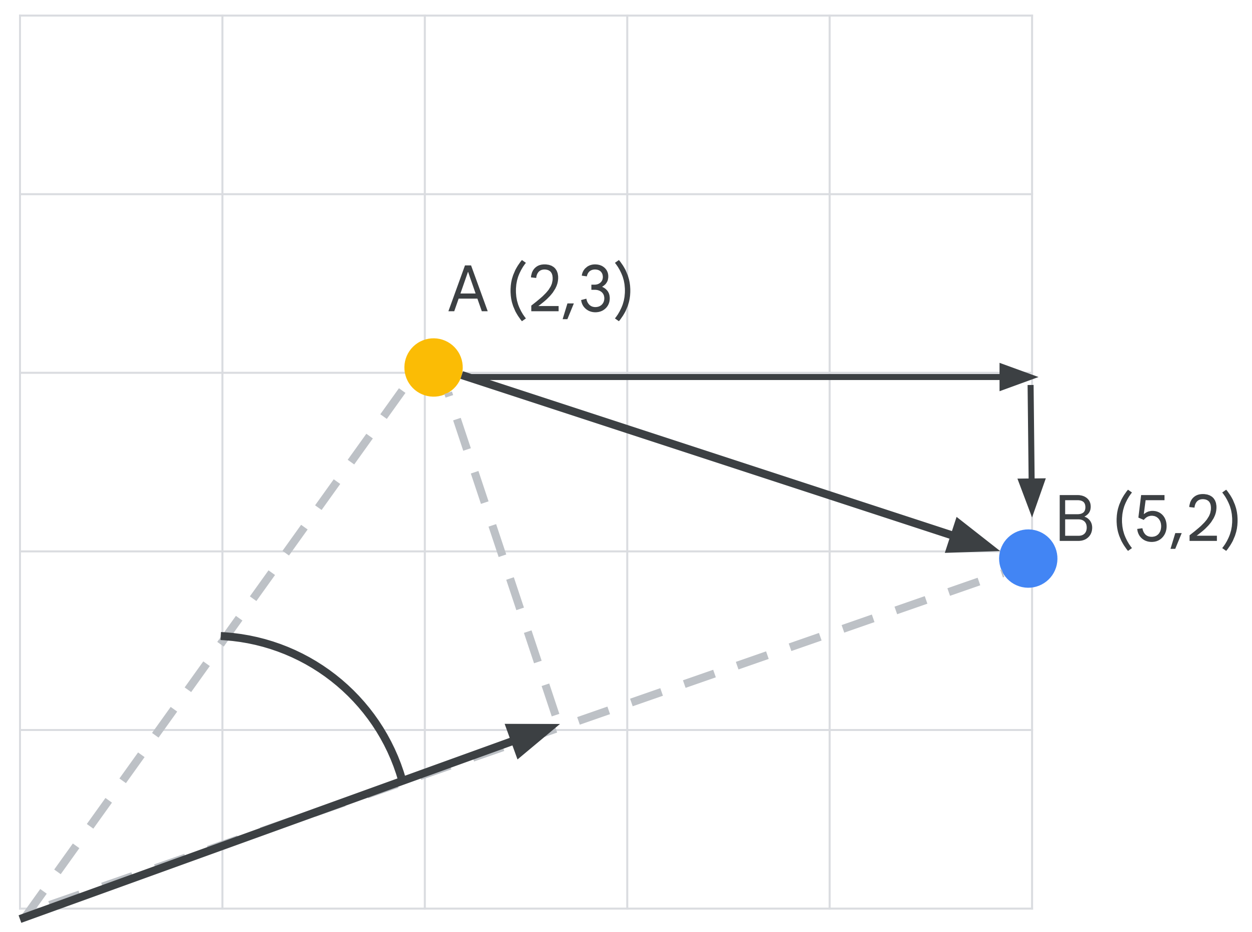
Dot product distance

=-(dot product)
=-(||a|| ||b||*cos(Θ))



Which do you choose?

- If using Vertex AI Vector Search, try Dot Product Distance (*the default*)
- Understand the embeddings of your space
- Experiment to see which gives you the proper results
- Experiment with and without Unit L2 Normalization



Calculating how similar text embeddings are using cosine similarity

```
from sklearn.metrics.pairwise import cosine_similarity

emb_1 = embedding_model.get_embeddings(['Python is a great programming language..'])
emb_2 = embedding_model.get_embeddings(['JavaScript is my favorite great programming.'])
emb_3 = embedding_model.get_embeddings(['The dog chased that car.'])

print(cosine_similarity([emb_1[0].values],[emb_2[0].values]))
print(cosine_similarity([emb_2[0].values],[emb_3[0].values]))
print(cosine_similarity([emb_1[0].values],[emb_3[0].values]))
```

```
[[0.67716792]]
[[0.45840928]]
[[0.47702179]]
```

Visualize vectors in a 2 dimensional space

```
in_1 = "Missing flamingo discovered at swimming pool"
in_2 = "Sea otter spotted on surfboard by beach"
in_3 = "Baby panda enjoys boat ride"
in_4 = "Breakfast themed food truck beloved by all!"
in_5 = "New curry restaurant aims to please!"
in_6 = "Python developers are wonderful people"
in_7 = "TypeScript, C++ or Java? All are great!"
input_text_lst_news = [in_1, in_2, in_3, in_4, in_5, in_6, in_7]

embeddings = []
for input_text in input_text_lst_news:
    emb = embedding_model.get_embeddings(
        [input_text])[0].values
    embeddings.append(emb)
```

Which sentences are most similar to one another?

Principal Component Analysis (PCA)

- Finds the elements in the array with the maximum variance (the principal components)
  - Uses them to reduce the number of dimensions in the vector
- In the example below, the vectors from the prior slide are reduced to 2 dimensions

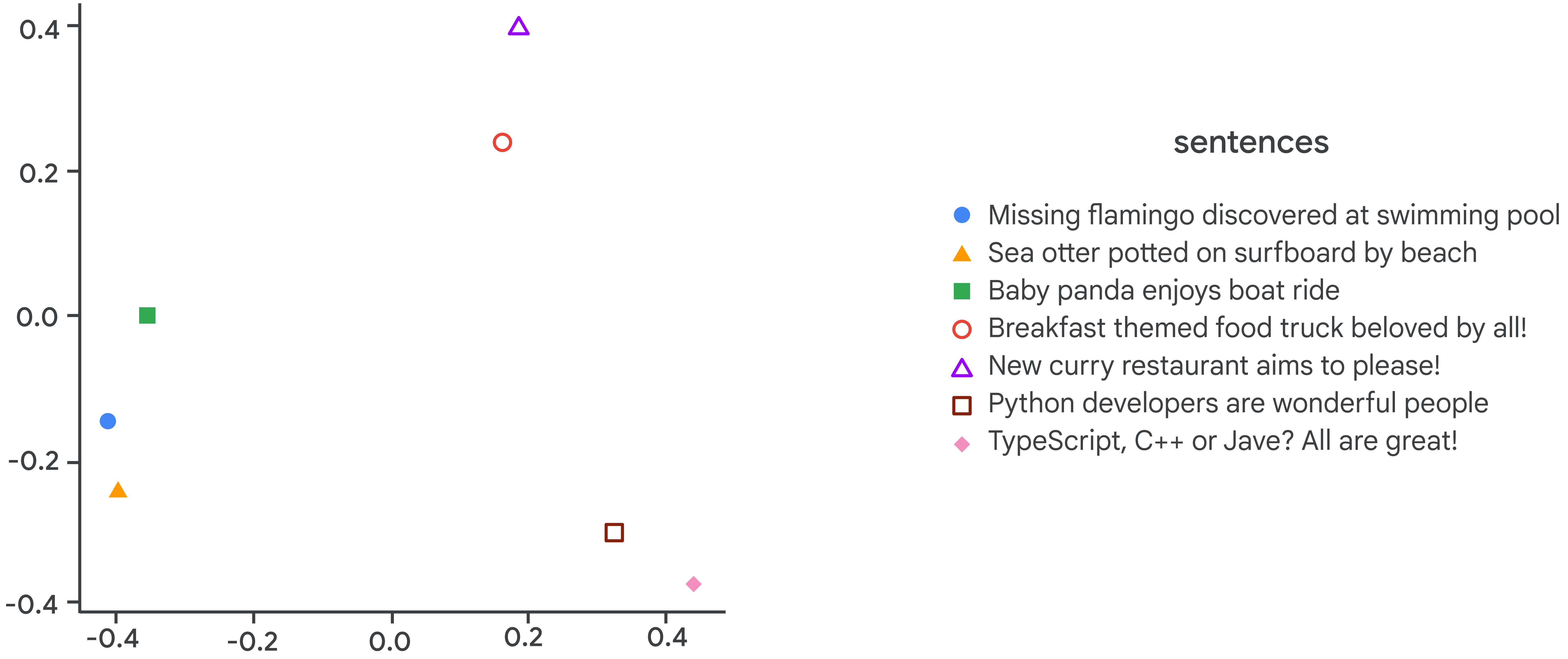
```
from sklearn.decomposition import PCA

# Perform PCA for 2D visualization
PCA_model = PCA(n_components = 2)
PCA_model.fit(embeddings_array)
new_values = PCA_model.transform(embeddings_array)

print("Shape: " + str(new_values.shape))
print(new_values)
```

```
Shape: (7, 2)
[[-0.40980753  -0.10084478]
 [-0.39561909  -0.18401444]
 [-0.29958523   0.07514691]
 [ 0.16077688   0.32879395]
 [ 0.1893873    0.48556638]
 [ 0.31516547  -0.23624716]
 [ 0.4396822   -0.36840086]]
```

Use Seaborn to create a plot of the embeddings

```
import seaborn as sns
import pandas as pd

data = pd.DataFrame({ 'x':new_values[:,0],
                      'y':new_values[:,1],
                      'sentences': input_text_lst_news})

# Create a visualization
sns.relplot(data, x='x', y='y',
    kind='scatter', hue='sentences'
)
```

Does the plot accurately reflect the similarity of the text?



If you prefer, you can use LangChain to create embeddings

```
from langchain.embeddings import VertexAIEmbeddings

input_array = [
        "Missing flamingo discovered at swimming pool",
        "Sea otter spotted on surfboard by beach",
        "Baby panda enjoys boat ride",
        "Breakfast themed food truck beloved by all!",
        "Hello World!",
        "New curry restaurant aims to please!",
        "Python developers are wonderful people",
        "TypeScript, C++ or Java? All are great!"
    ]

embedding_langchain_model=VertexAIEmbeddings()
embeddings = embedding_langchain_model.embed_documents(input_array)
```

Rate limiting when generating embeddings

There is a limit to the number of requests you can make to the PaLM embeddings API

- At the time of this writing the limit is 100 requests per minute
- There is also a limit on documents per request
- Each input document has a token limit
- Documents beyond the token limit are automatically truncated

This is a similar problem as you had when covering MapReduce

If you are generating a large number of embeddings, you will need to add rate limiting logic

Rate limiting function

```
from typing import List
import time

def rate_limit(max_per_minute):
    period = 60 / max_per_minute
    print("Waiting")
    while True:
        before = time.time()
        yield
        after = time.time()
        elapsed = after - before
        sleep_time = max(0, period - elapsed)
        if sleep_time > 0:
            print(".", end="")
            time.sleep(sleep_time)
```

Create a derived class that uses the rate limiting function

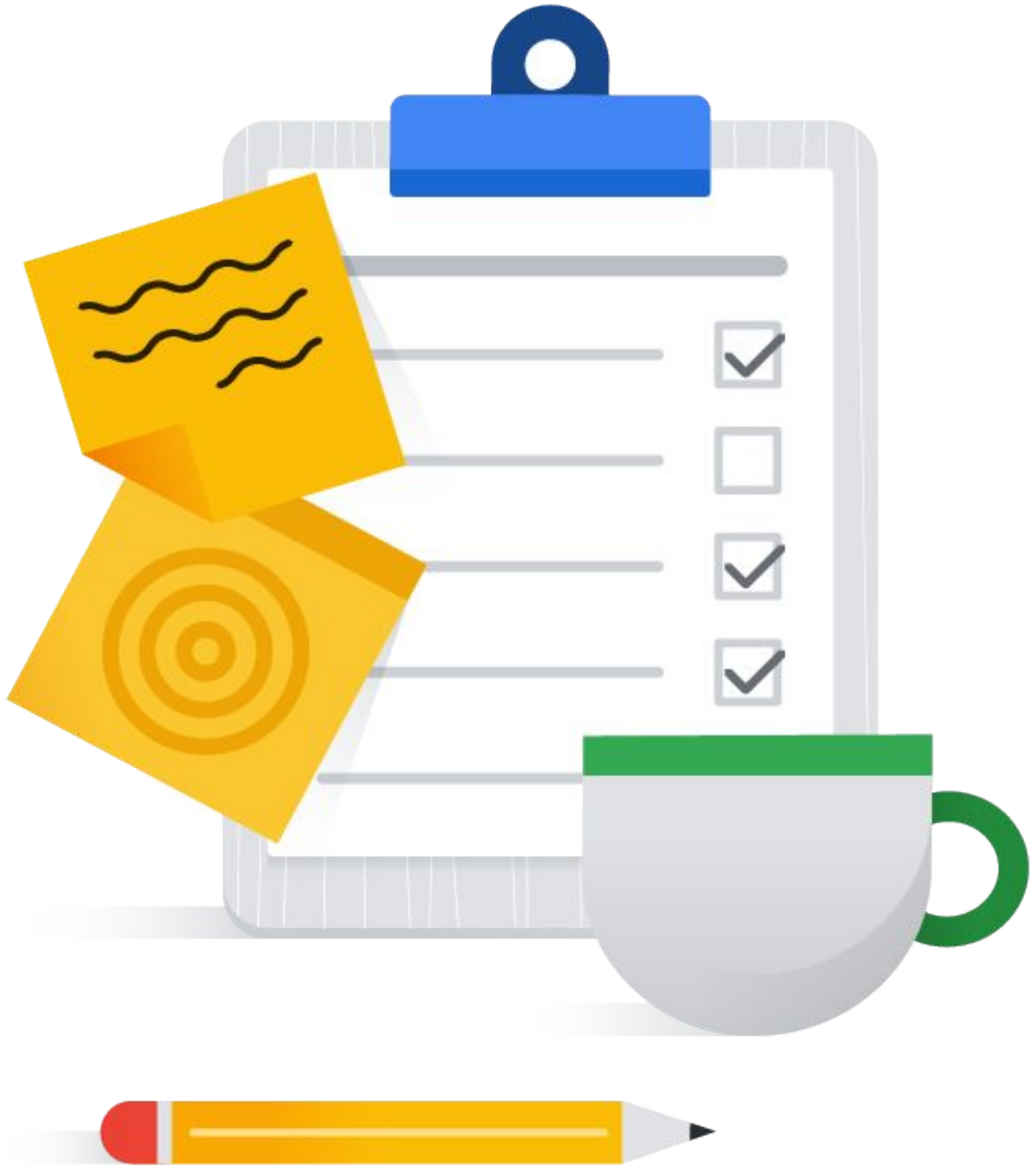
```
class CustomVertexAIEmbeddings(VertexAIEmbeddings, BaseModel):
    requests_per_minute: int
    num_instances_per_batch: int

    def embed_documents(self, texts: List[str]):
        limiter = rate_limit(self.requests_per_minute)
        results = []
        docs = list(texts)

        while docs:
            head, docs = (docs[: self.num_instances_per_batch],
                docs[self.num_instances_per_batch :])
            chunk = self.client.get_embeddings(head)
            results.extend(chunk)
            next(limiter)

        return [r.values for r in results]
```

Need to send documents in batches

Use custom rate limiting class to generate embeddings

```
# Embedding
EMBEDDING_QPM = 100
EMBEDDING_NUM_BATCH = 5

embedding_langchain_model = CustomVertexAIEmbeddings(
    requests_per_minute=EMBEDDING_QPM,
    num_instances_per_batch=EMBEDDING_NUM_BATCH,
)

embeddings = embedding_langchain_model.embed_documents(input_array)
```

Topics



Product catalog data with a product name and description

Name	Description
Cymbal 806451 Belt for Washer	The is a genuine replacement part. The model number and name for the following item is ...
Cymbal 774 White Electric Washer/Dryer	Electric Laundry Center with 2.5 cu. ft. Washer 5.9 cu. Ft. Dryer, 8 Wash Cycles, Clean Lint ...
Cymbal Dryer LP Gas Conversion Kit OEM	Genuine OEM Cymbal Dryer LP Gas Conversion Kit W10073228 Replacement number: kq33 ...
Cymbal Part Number 4388947: HANDLE	This is a genuine replacement part. The model number and name for the following item is ...
Cymbal 297318010 Defrost Timer	This is a genuine replacement part. The model number and name for the following item is ...
Cymbal DA97-0859A Assembly Ice Maker	This is an authorized aftermarket product. Fits with various Cymbal brand products ...

Generate the embeddings

```
descriptions = products_df['description'].values.tolist()
response = encode_text_to_embedding_batched(descriptions, api_calls_per_minute=20)
```

Original dataset with embeddings for each description

```
print(f'Original text: \n{products_df["description"][0]}\nEmbedding vector:')
print(response[1][0])
```

```
Original text:
CYMBAL NAILTECH Formula #3 Protection for Dry, Brittle Nails, 47oz
Embedding vector:
[ 7.15385750e-03 -4.29799780e-02  1.26909539e-02  4.06474955e-02
  3.32920589e-02 -3.13577242e-02  1.17542723e-03  4.91597764e-02
 -3.15157063e-02  2.28883326e-02 -1.06803495e-02 -2.03404780e-02
 -8.10595509e-03  5.78571521e-02 -2.30540130e-02  2.81607080e-03
 -3.40594761e-02  1.62891373e-02  5.20878360e-02 -2.91049127e-02
 -3.44198048e-02  1.58195440e-02  4.27926099e-03 -2.42937859e-02
 -4.03086506e-02 -1.00072347e-01  3.45601961e-02  3.35591137e-02
 -9.63283181e-02  1.69923436e-02  2.54319627e-02 -1.66077930e-02
  7.08263554e-03 -4.55290545e-03  5.14889322e-02 -2.29180660e-02
 -3.43148340e-03  3.82181592e-02  1.08421817e-02  3.67002264e-02
  5.52216880e-02  7.56995240e-03 -8.73890519e-03 -1.41722541e-02
 -4.04832661e-02 -3.24015990e-02 -7.56350011e-02  2.39020046e-02
...
```

K Means is a clustering algorithm

- Specify the number of clusters (classes) you want
- Run the fit() function over the embeddings

```
from sklearn.cluster import KMeans

embeddings = response[1]
kmeans = KMeans(n_clusters=5, n_init="auto").fit(embeddings)
```

Use the `predict()` method

Original embeddings passed to predict which returns one of the 5 clusters (0 to 4)

```
predictions = kmeans.predict(embeddings)
kmeans.labels_[:20]
```

```
array([4, 3, 4, 4, 4, 4, 4, 0, 4, 4, 4, 4, 0, 4, 4, 4, 4, 4, 4, 4], dtype=int32)
```

Assign classification names to the cluster indices

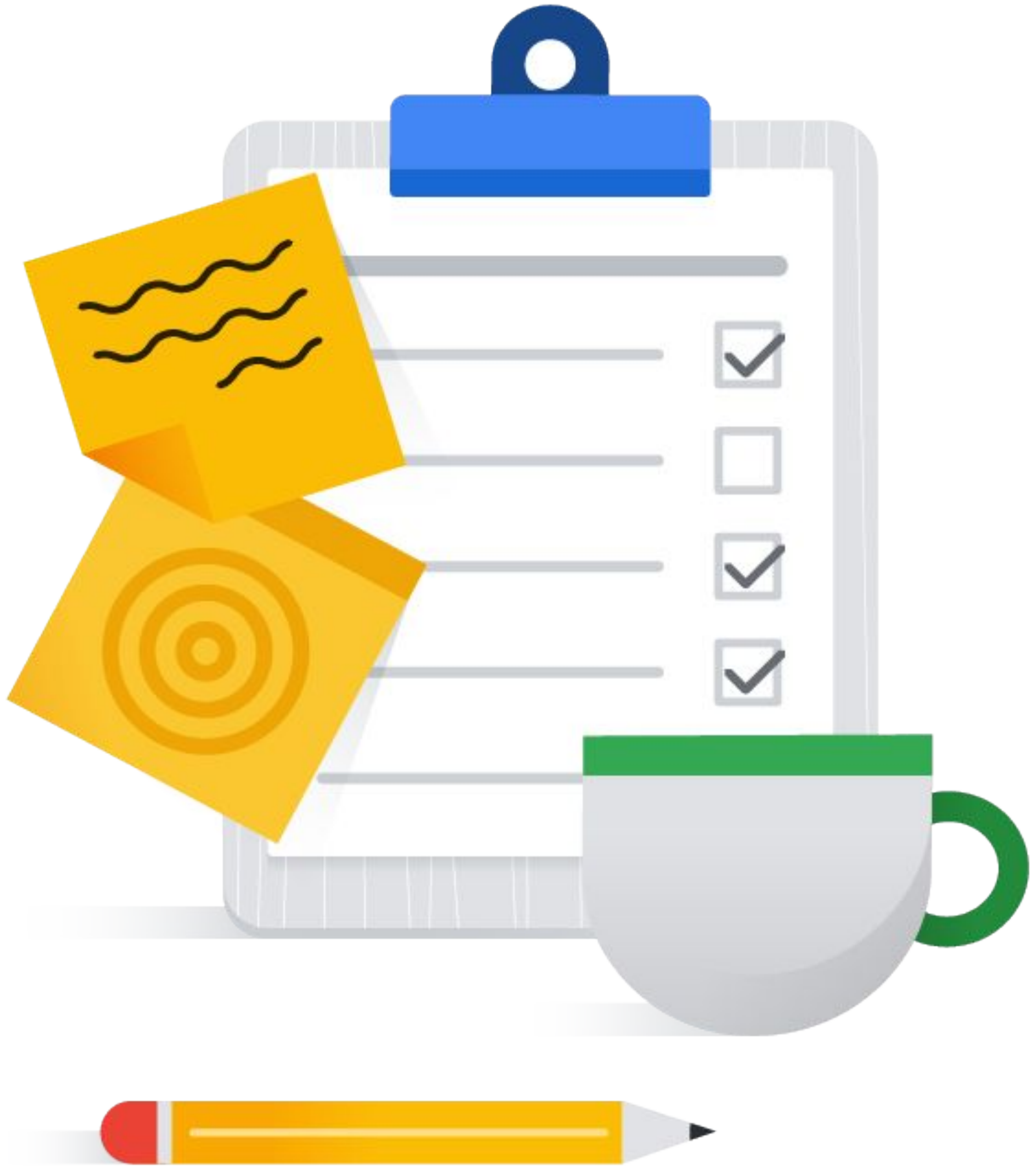
```
product_category_list = [‘instrument', 'all_beauty', 'software', 'appliance',
'pantry']
```

Classify products based on their description

```
new_embeddings = model.get_embeddings(['Debian Linux 11',
                                        'Yamaha Baby Grand Piano'])

new_embeddings_nd = np.squeeze(np.stack([embedding.values for embedding in
new_embeddings if embedding is not None]))
new_predictions = kmeans.predict(new_embeddings_nd)
print(new_predictions)

new_predictions_clusters = [cluster_map[x] for x in new_predictions]
print(new_predictions_clusters)
```

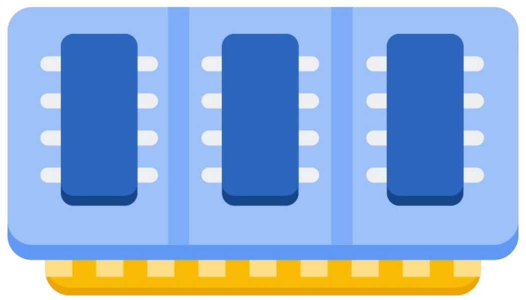
```
[2 0]
['software', 'instrument']
```

Topics

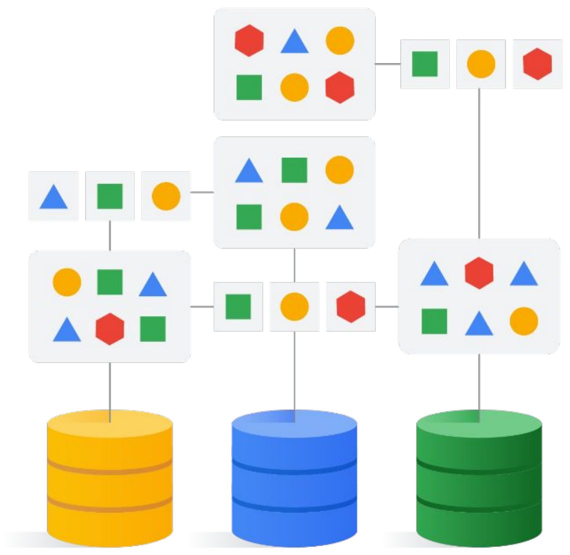


Stored embeddings don’t have to be recomputed

Memory

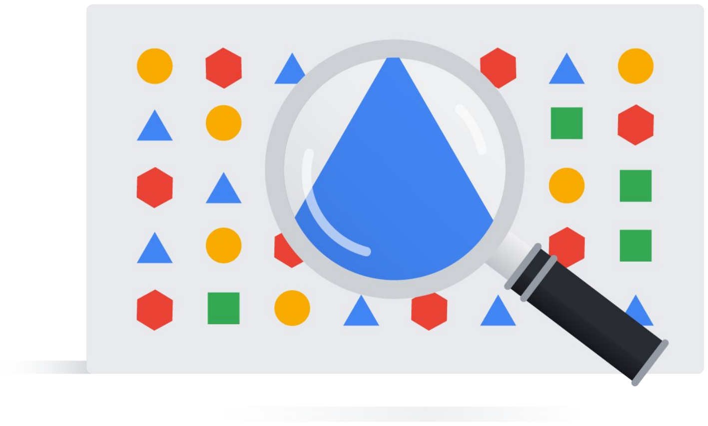


Relational DBs



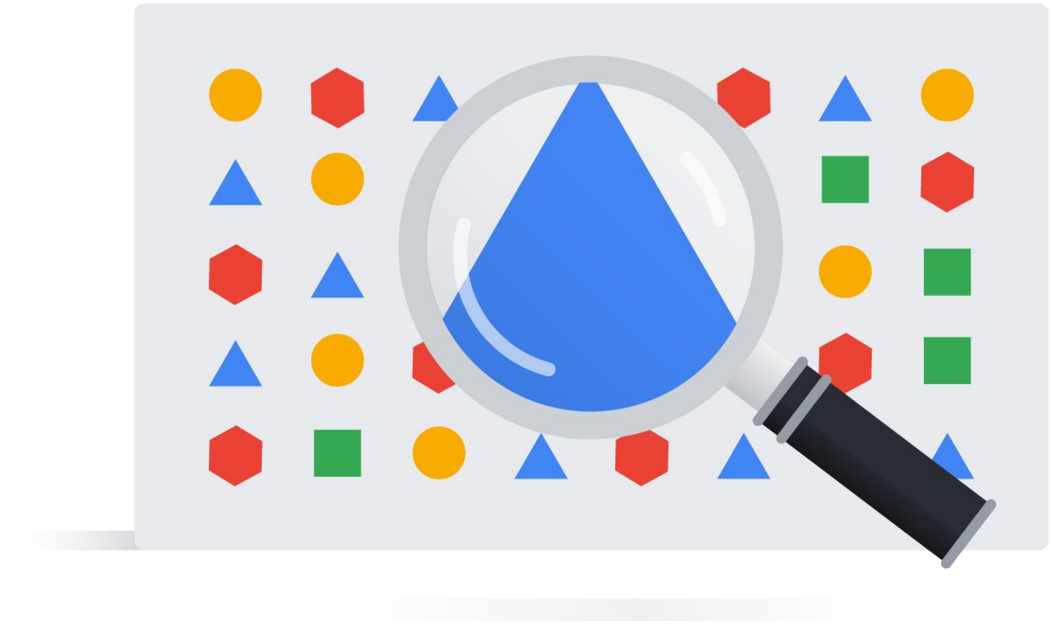
Files

Vector DBs



Steps to using Google Vector Search

- Create an index
- Create an index endpoint
- Deploy the index
- Query the index



Creating an Index

- `contents_delta_uri` parameter represents a Cloud Storage bucket that contains your index file(s)
- The dimensions parameter is set to 768 because that is the size of a PaLM text embedding
- `approximate_neighbors_count` parameter is the default number of results to return from a query

```
BUCKET_URI = gs://your-storage-bucket-index-files

my_index = aiplatform.MatchingEngineIndex.create_tree_ah_index(
    display_name = “my-great-index",
    contents_delta_uri = BUCKET_URI,
    dimensions = 768,
    approximate_neighbors_count = 10,
)
```

Index files are JSON files containing embedding vectors

- The first few rows of an index file includes the `id`, the `name` and the `embedding` of the product
- The index file needs to be prepared prior to creating the index
- Later you can update the index using new file(s)


```
{"id":"11863","name":"wacoal women's embrace lace chemise - 814191"
,"embedding":[0.024530868977308273,-0.040793128311634064,...,-0.029402086511254311]}
{"id":"19536","name":"original penguin men's pro-bro mock sweater"
,"embedding":[0.015607465989887714,0.0183266568928957,...-0.035911291837692261]}
{"id":"18090","name":"soffe men's classic cotton pocket short"
,"embedding":[0.026446744799613953,0.021272433921694756,...-0.0416882187128067]}
```

Creating a Public Index Endpoint

- An index endpoint makes the indexes available to a query
- Endpoints can be shared by multiple indexes
- To use a public endpoint, set the publicEndpointEnabled field to True

```
my_index_endpoint = aiplatform.MatchingEngineIndexEndpoint.create(
    display_name = “my-great-endpoint",
    public_endpoint_enabled = True
    project = “your-project-id”
    Region = “us-central1”
)
```

Creating a Private Index Endpoint

- A private index endpoint is peered to a network that you specify
- The endpoint would only be available to instances within your network
- Set the public_endpoint_enabled parameter for False (the default), and specify your network

```
my_index_endpoint = aiplatform.MatchingEngineIndexEndpoint.create(
    display_name = “my-great-endpoint",
    public_endpoint_enabled = False
    network = your-vpc-name
    project = “your-project-id”
    Region = “us-central1”
)
```

Deploying the index

- Once the index endpoint is created, you can deploy one or more indexes to it

```
my_index_endpoint.deploy_index(
    index = my-great-index,
    deployed_index_id = DEPLOYED_INDEX_ID
)
```

A query uses a nearest neighbor search

Finds the vectors that most closely match the embedding of the user's query

Steps:

- Create an embedding from the user input
- Use the `find_neighbors` function to query the index
- Retrieve the responses from the query

Query response contains the object that was indexed and the distance from the user's query

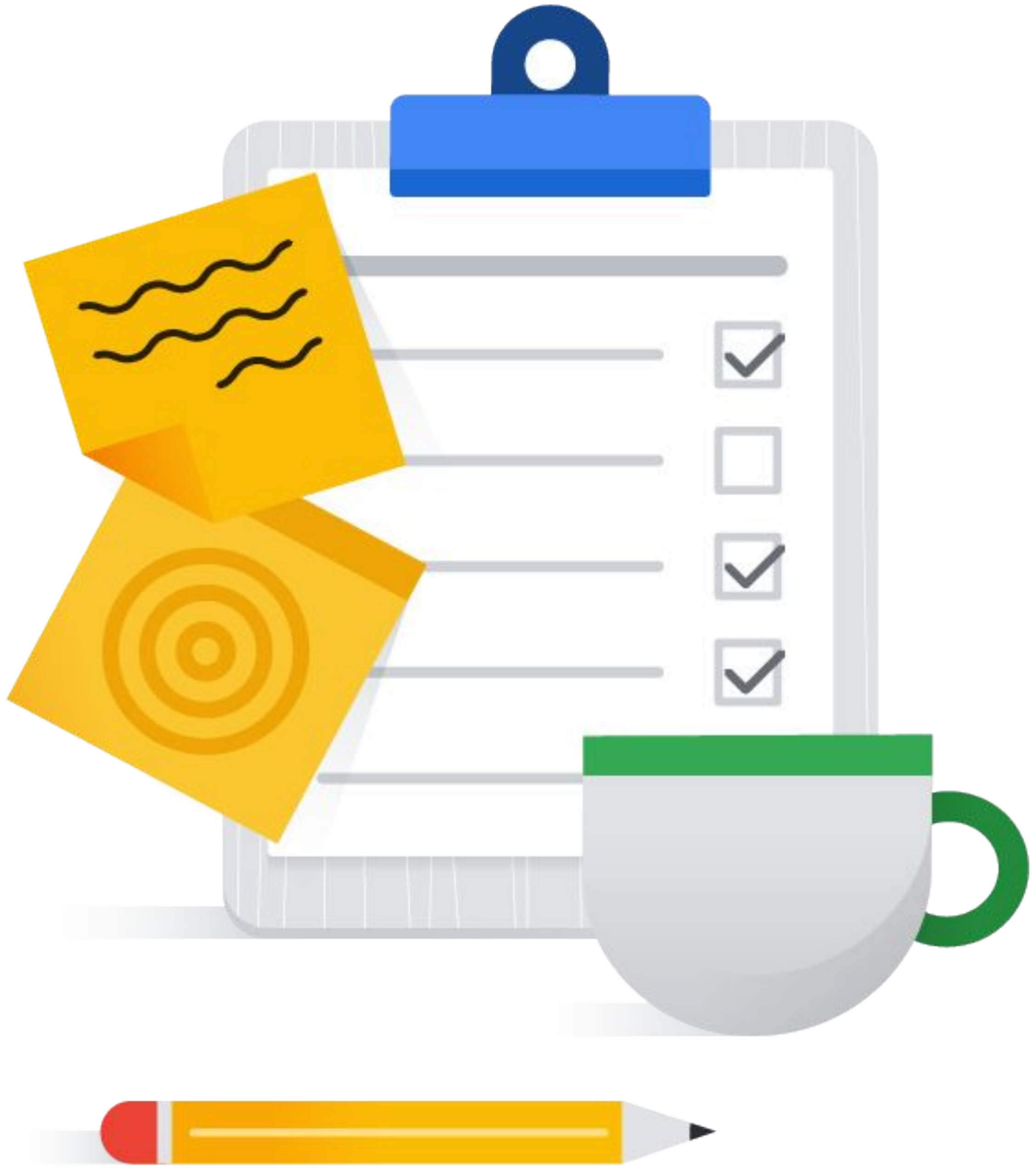
Query example

```
embedding_model = TextEmbeddingModel.from_pretrained("textembedding-gecko@001")

input_query = "I am looking for a women's bathing suit for the swim team"
embedding = embedding_model.get_embeddings([input_query])
embedding_vector = embedding[0].values

response = my_index_endpoint.find_neighbors(
    deployed_index_id = DEPLOYED_INDEX_ID,
    queries = [embedding_vector],
    num_neighbors = 10
)

for idx, neighbor in enumerate(response[0]):
    print(f"{neighbor.distance:.2f} {product_names[neighbor.id]}")
```

Query response

```
0.76 cymbal women’s team collection swimsuit
0.75 cymbal women’s team collection power swimsuit
0.74 cymbal women’s breaststroke 4 hope journey splice two piece swimsuit
0.74 cymbal sport women’s solid diamondback workout bikini swim suit
0.74 cymbal women’s rapid extra life lycra energy performance swimsuit
0.73 cymbal women’s mighty cobra extra life lycra fly performance swimsuit
0.73 cymbal aqua sphere women’s swimwear
0.72 cymbal women’s aquatic endurance piped sheath dress swimsuit
0.72 cymbal women’s power sprint fly endurance swimsuit
0.71 cymbal women’s solid reversible extreme back endurance swimsuit
```

Topics



Multimodal embeddings

Embeddings

Embeddings can be created from:

- Text
- Images
- Audio
- Video

Use cases

Uses cases for multimodal embeddings include:

- Image search from natural language
- Personalization or ad targeting
- Trust and safety such as copyright detection
- Recommendations

Multimodal Embeddings for text and images

"An Australian Shepherd herding sheep."

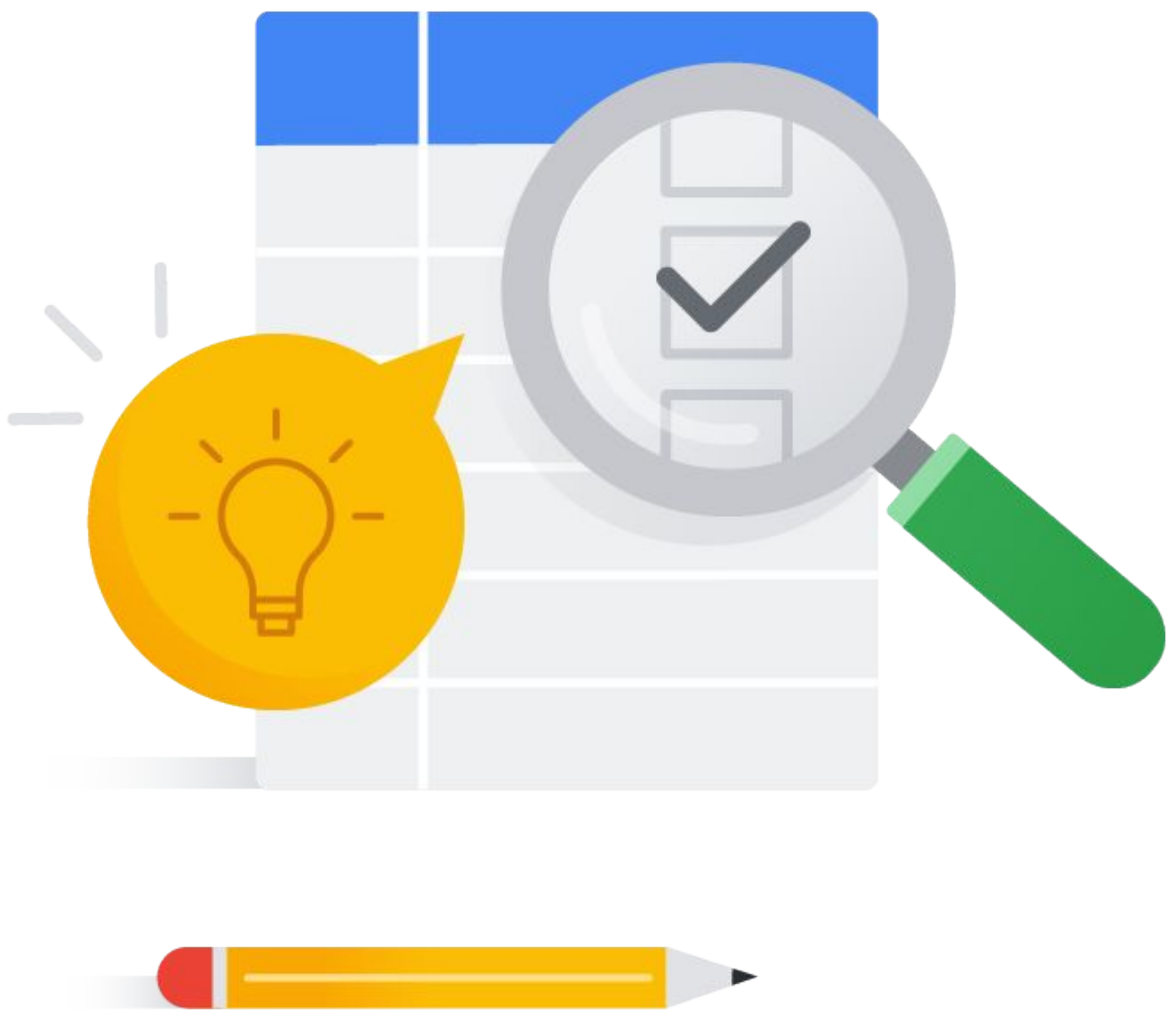
Multimodal embeddings example

```
from vertexai.vision_models import MultiModalEmbeddingModel, Image

image = Image.load_from_file("sheepdog.png")
embeddings_model = MultiModalEmbeddingModel.from_pretrained("multimodalembedding@001")

embeddings = embeddings_model.get_embeddings(
    image=image,
    contextual_text="An Australian Shepherd herding sheep."
)
print(len(embeddings.image_embedding))
print(len(embeddings.text_embedding))
print(embeddings.image_embedding)
print(embeddings.text_embedding)
```

```
1408
1408
[-0.00865975488, 0.0141715538, 0.023670394, 0.0476179533, -0.0237030219, -0.03225
[-0.00366886496, 0.0175162964, 0.00416901615, 0.00271574059, -0.0335324593, -0.01
```

Lab

45 min

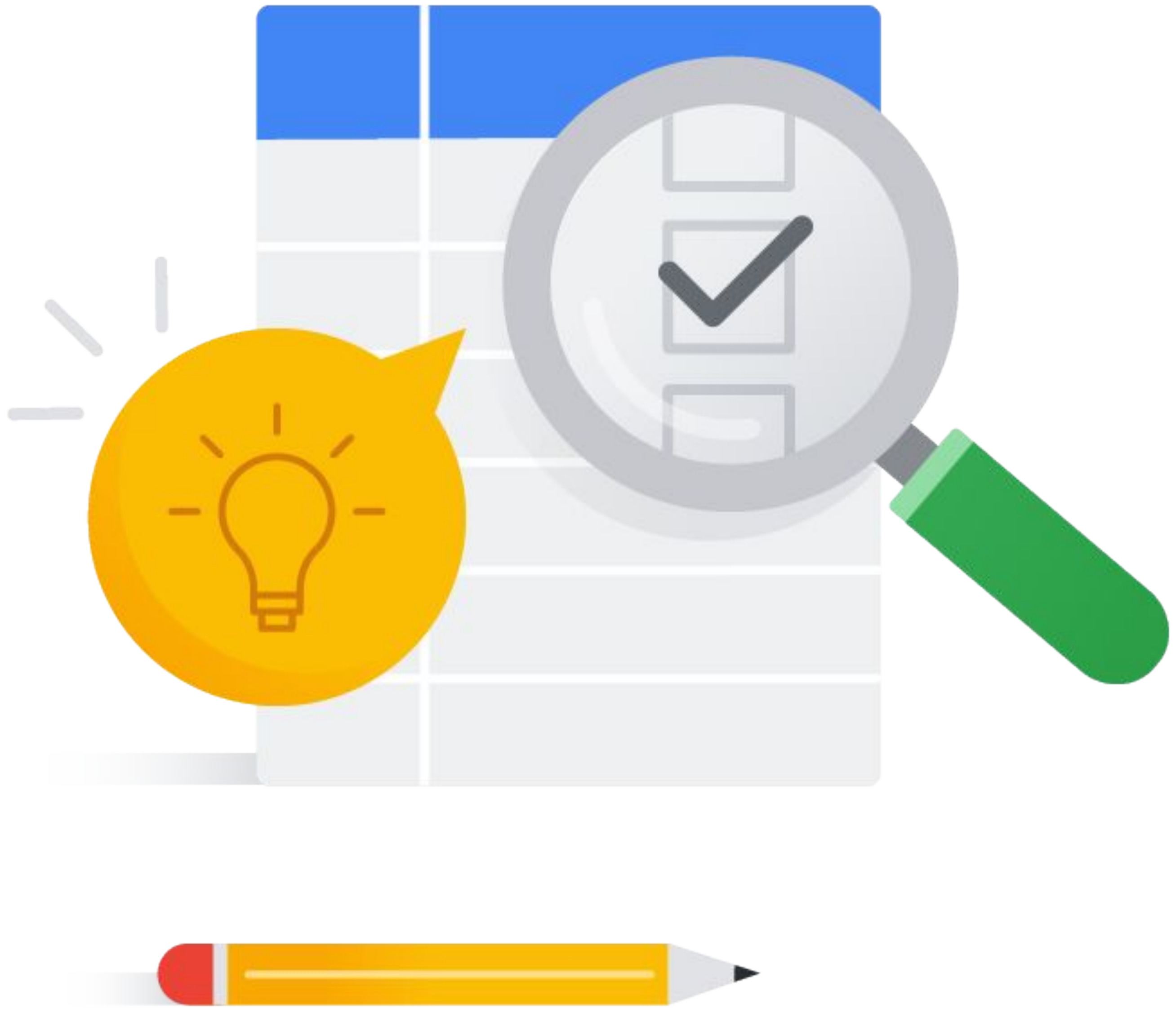


Lab: PaLM API to Cluster Products Based on Descriptions

Lab

45 min

Lab: Using Vertex AI Vector Search and Vertex AI Embeddings for Text for StackOverflow Questions



In this module, you learned to ...

01 Use PaLM API to generate text embeddings

02 Create a classification model using text embeddings

03 Store embeddings in Vertex AI Vector Search to enable semantic search on datasets

Questions and answers

Quiz question

What are potential use cases for text embedding? (Select all that apply)

A: Linear regression

B: Semantic Search

C: Text classification

D: Language translation

E. Fraud detection

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How are embedding vectors created?

A: They are a numeric hash of the words

B: They are encrypted values of each letter in the words

C: They are the unicode decimal values of the letters in the words

D: They use a ML algorithm that can capture the semantic meaning of the text and represent it as a multidimensional vector

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How could you store embeddings so they wouldn’t have to be recomputed?

A: In a file in Cloud Storage

B: In memory

C: In a relational database

D: In a vector database

E: All of the above

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Google Cloud