

# **Bringing vectors to POSTGRES**

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# Agenda



- 2 What is vector search and why is it used?
- 3 Generating and querying embeddings
- 4

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- New index types: IVFFlat and HNSW
- Future of vectors, AI and Postgres



# pgvector

Open-source Postgres extension for vector similarity search



# Language Support

- Go: pgvector-go
- Python: pgvector-python
- Rust: pgvector-rust
- C: pgvector-c
- JavaScript, TypeScript: pgvector-node
- PHP: pgvector-php



### What is vector (similarity) search?

Vector similarity search is a technique used to find the most similar vectors to a given vector (usually a query vector).

This query is typically performed by calculating distances in vector space, and various **metrics** (such as **Euclidean distance, cosine similarity**) can be used to measure the similarity between the query vector and other vectors.



# What is vector (similarity) search?



Image source: https://www.elastic.co/what-is/vector-search



What is vector (similarity) search?

# queen

king - man + woman



warsaw

#### paris - france + poland





# What is vector search useful for?

#### Al applications: working with high-dimensional data

- Recommendation engines
- Image search
- Natural language processing (NLP)
- Content-based filtering
- Similarity-based AI tasks
- Prediction solutions



# What is vector? X = [1, 3, 5]





#### What is vector?



Image source: https://media5.datahacker.rs/2020/03/Picture36-1-768x712.jpg



#### **Vector Data Type**



#### Each vector takes 4 \* dimensions + 8 bytes of storage

Vectors can have up to 16,000 dimensions.



- <-> Euclidean distance
- <#> negative inner product
- <=> cosine distance
- + element-wise addition
  - element-wise subtraction
- \* element-wise multiplication



- cosine\_distance
- inner\_product
- I2\_distance (Euclidean distance)
- I1\_distance
- vector\_dims (number of dimensions)
- vector\_norm



# Sample app code

https://github.com/gulcin/pgvector\_blog





# postgres=# Create extension vector; CREATE EXTENSION

# CREATE TABLE documents ( id int PRIMARY KEY, title text NOT NULL, content TEXT NOT NULL



);

# -- Create document\_embeddings table CREATE TABLE document\_embeddings ( id int PRIMARY KEY, embedding vector(1536) NOT NULL );

CREATE INDEX document\_embeddings\_embedding\_idx ON document\_embeddings USING hnsw (embedding
vector\_l2\_ops);



— Insert documents into documents table INSERT INTO documents VALUES ('1', 'pgvector', 'pgvector is a PostgreSQL extension that provides support for vector similarity search and nearest neighbor search in SQL.'); INSERT INTO documents VALUES ('2', 'pg\_similarity', 'pg\_similarity is a PostgreSQL extension that provides similarity and distance operators for vector columns.'); INSERT INTO documents VALUES ('3', 'pg\_trgm', 'pg\_trgm is a PostgreSQL extension that provides functions and operators for determining the similarity of alphanumeric text based on trigram matching.'); INSERT INTO documents VALUES ('4', 'pg\_prewarm', 'pg\_prewarm is a PostgreSQL extension that provides functions for prewarming relation data into the PostgreSQL buffer cache.');



# What are embeddings and how do we generate them?





Image source: https://cdn.openai.com/new-and-improved-embedding-model/draft-20221214a/vectors-1.svg



# Python code to preprocess and embed documents
import openai
import psycopg2

```
# Load OpenAI API key
openai.api key = "sk-..." #YOUR OWN API KEY
```

# Pick the embedding model
model\_id = "text-embedding-ada-002"

```
# Connect to PostgreSQL database
conn = psycopg2.connect(database="postgres", user="gulcin.jelinek", host="localhost", port="5432")
```

```
# Fetch documents from the database
cur = conn.cursor()
cur.execute("SELECT id, content FROM documents")
documents = cur.fetchall()
```

```
# Process and store embeddings in the database
for doc_id, doc_content in documents:
    embedding = openai.Embedding.create(input=doc_content, model=model_id)['data'][0]['embedding']
    cur.execute("INSERT INTO document_embeddings (id, embedding) VALUES (%s, %s);", (doc_id,
embedding))
    conn.commit()
```

```
# Commit and close the database connection
conn.commit()
```



# **Querying Embeddings**





```
# Python code to preprocess and embed documents
import psycopg2
```

```
# Connect to PostgreSQL database
```

conn = psycopg2.connect(database="postgres", user="gulcin.jelinek", host="localhost", port="5432")

```
cur = conn.cursor()
# Fetch extensions that are similar to prvector based on their descriptions
query = """
WITH pgv AS (
    SELECT embedding
      FROM document_embeddings JOIN documents USING (id)
     WHERE title = 'pgvector'
SELECT title, content
  FROM document_embeddings
 JOIN documents USING (id)
 WHERE embedding <-> (SELECT embedding FROM pgv) < 0.5;"""
cur.execute(query)
# Fetch results
results = cur.fetchall()
# Print results in a nice format
for doc_title, doc_content in results:
    print(f"Document title: {doc_title}")
    print(f"Document text: {doc_content}")
    print()
```



#### **Results**

> python3 query.py Document title: pgvector Document text: pgvector is a PostgreSQL extension that provides support for vector similarity search and nearest neighbor search in SQL.

Document title: pg\_similarity Document text: pg\_similarity is a PostgreSQL extension that provides similarity and distance operators for vector columns.

















# Indexing

- pgvector performs "exact nearest neighbor search" by default
- Add index to use "approximate nearest neighbor search"
- Supported index types:
  - IVFFlat
  - HNSW (added with 0.5.0)





# IVFFLAT

- Divides vectors into lists
- Faster build times
- Uses less memory
- Lower query performance (speed-recall tradeoff)
- Create index after the table has some data

# **HNSW**

- Creates a **multilayer graph**
- Slower build times
- Uses more memory
- Better query performance
- Index can be created without any data in the table (no training step)





pgvector 0.5.1 HNSW m=16, ef\_construction=200 4XL: 16-core CPU, 64GB RAM pgvector 0.6.0 HNSW m=16, ef\_construction=200 4XL: 16-core CPU, 64GB RAM

Image source: https://supabase.com/blog/pgvector-fast-builds



# **Future of vectors and Postgres**

- pgvector 0.7.0 (unreleased)
  - Add halfvec and sparsevec type
  - Support for **bit vectors** to HNSW
  - Add hamming\_distance function and jaccard\_distance function
  - Add quantize\_binary function and subvector function
  - Updated comparison operators to support vectors with different dimensions

#### pgvector 0.6.0 (29 Jan 2024)

- Support for **parallel index builds** for HNSW
- Improved performance of HNSW
- Reduced memory usage and reduced WAL generation for HNSW index builds





# Děkuji! Thank you!

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