How I used PostgreSQL® to find pictures of me at a party

By Tibs (they / he)

Slides and source code at
https://github.com/aiven-labs/pgvector-find-faces-talk

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

Broad structure

Introduction and vague background

Not an explanation of ML

Finding pictures of me

Why PostgreSQL®.

Part the first: Introduction and vague background

I'm an AI skeptic

I lived through the last AI boom in the 1980s, and the subsequent AI winter of the 1990s

But we did get expert systems, knowledge based systems, etc. - they just dropped the name "AI"

My colleagues have been convincing me

- Quick prototypes of boring code
- Rewrite this paragraph a different way
- And now, finding my face

Also, recently, a demo I saw on multi-modal comparisons - comparing text, audio, image and video.

Part the second: not an explanation of ML

Photo by Markus Winkler on Unsplash

Not an introduction to vectors and embeddings

ML people talk about vectors and embeddings and vector embeddings.

"Embedding" means representing something in a computer.

So a "vector embedding" is

- a vector that represents something,
- stored in a computer.

Not enough about vectors

Broadly, we can describe the characteristics of things with numbers.

For instance, we can describe colours with RGB values.

A 3d graph showing a vector

Image from JCC Math.Phys 191: The vector class, CC BY-SA 3.0

We can do mathematics with vectors

We can compare their

- length
- direction

and we can do maths between vectors - but look elsewhere for that

Calculating the vectors

By hand for relatively simple cases

(for instance, in early text analysis)

but with ML, we can

- *train* a machine learning system
- to *"recognise"* that a thing belongs to particular categories.

This is wonderful - and sometimes leads to surprising results

Part the third: Finding pictures of me

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

Our aim

Find which files contain my face, using SQL like the following:

```
SELECT filename FROM pictures
  ORDER BY embedding <-> [0.38162553310394287, ..., 0.20030969381332397]
  LIMIT 10;
```

Stage 1. Find faces and store their embeddings

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

It's not perfect!

May not find all the faces

When analysing a group photo, it also found these two faces:

768 floating point numbers

Each embedding is an array of 768 floating point numbers.

```
0.38162553310394287, ..., 0.20030969381332397
```

Stage 2. Look for photos with my face in them

[0.681, ...]

SELECT ...

AIVEN2752.jpg
AIVEN2839.jpg
AIVEN2838.jpg

Using my slack image as the reference face

Set up the environment

We're going to be using

- opencv-python to find faces
- imgbeddings to calculate embeddings from an image
- the `haarcascade_frontalface_default.xml` file from the OpenCV GitHub repository, which defines the pre-trained Haar Cascade model

My example programs also use click and psycopg2-binary

Enable pgvector

Enable the pgvector extension:

```
CREATE EXTENSION vector;
```

This only works if the `pgvector` extension is installed.

It may already be available, as in Aiven for PostgreSQL®

Create our database table

```
CREATE TABLE pictures (face text PRIMARY KEY, filename text, embedding vector(768));
```

`face` is the string we use to identify this particular face

`filename` is the name of the file we found the face in

`embedding` is the vector itself

Program 1. Find faces and store their embeddings

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

Find faces and store their embeddings

`find_faces_store_embeddings.py`

```
Usage: find_faces_store_embeddings.py [OPTIONS] IMAGE_FILES...

Options:
-p, --pg-uri TEXT  the URI for the PostgreSQL service, defaulting to
                    $PG_SERVICE_URI if that is set
--help             Show this message and exit.
```

Find faces and store their embeddings (1)

```
def main(image_files: tuple[str], pg_uri: str):
    haar_cascade = load_algorithm()
    ibed = imgbeddings()

    for image_file in image_files:
        with psycopg2.connect(pg_uri) as conn:
            orig_image = cv2.imread(picture_file, 0)
            gray_image = cv2.cvtColor(orig_image, cv2.COLOR_RGB2BGR)
            faces = find_faces(gray_image, haar_cascade)

            write_faces_to_pg(faces, orig_image, picture_file, conn, ibed)
```

cv2 is the OpenCV package

Find faces and store their embeddings (2)

```
def load_algorithm():
    algorithm = "haarcascade_frontalface_default.xml"
    haar_cascade = cv2.CascadeClassifier(algorithm)
    if haar_cascade.empty():
        raise GiveUp(f'Error reading algorithm file {algorithm} - no algorithm found')
    return haar_cascade
```

Find faces and store their embeddings (3)

```
# Read the image in, and convert it to greyscale
orig_image = cv2.imread(picture_file, 0)
gray_image = cv2.cvtColor(orig_image, cv2.COLOR_RGB2BGR)
```

Find faces and store their embeddings (4)

```
def find_faces(gray_image, haar_cascade):
    return haar_cascade.detectMultiScale(
        gray_image,
        scaleFactor=1.05,
        minNeighbors=2,
        minSize=(250, 250),
        #minSize=(100, 100),
    )
```

Find faces and store their embeddings (5)

```
def write_faces_to_pg(faces, orig_image, picture_file, conn, ibed):
    file_path = Path(picture_file)
    file_base = file_path.stem
    file_posix = file_path.as_posix()

    for x, y, w, h in faces:
        # Convert to a Pillow image since that's what imgbeddings wants
        cropped_image = Image.fromarray(orig_image[y: y + h, x: x + w])
        embedding = ibed.to_embeddings(cropped_image)[0]
        face_key = f'{file_base}-{x}-{y}-{w}-{h}'

        write_to_pg(conn, face_key, file_posix, embedding)
```

Find faces and store their embeddings (6)

And here's where we actually write to PostgreSQL

```
def write_to_pg(conn, face_key, file_name, embedding):
    with conn.cursor() as cur:
        cur.execute('INSERT INTO pictures (face_key, filename, embedding)'
                    ' VALUES (%s,%s,%s)'
                    ' ON CONFLICT (face_key) DO UPDATE'
                    '   SET filename = EXCLUDED.filename,'
                    '       embedding = EXCLUDED.embedding'
                    ';',
                    (face_key, file_name, embedding.tolist())
                    )
```

Find faces and store their embeddings (7)

`ON CONFLICT` is interesting:

```
ON CONFLICT (face_key) DO UPDATE
   SET filename = EXCLUDED.filename,
       embedding = EXCLUDED.embedding;
```

Program 2. Find "nearby" faces

Find "nearby" faces

`find_nearby_faces.py`

```
Usage: find_nearby_faces.py [OPTIONS] FACE_FILE

Options:
-n, --number-matches INTEGER
-p, --pg-uri TEXT             the URI for the PostgreSQL service, defaulting
                                to $PG_SERVICE_URI if that is set
--help                        Show this message and exit.
```

Find "nearby" faces (1)

```python
def main(face_file: tuple[str], number_matches: int, pg_uri: str):
    haar_cascade = load_algorithm()
    ibed = imgbeddings()

    # Calculate the embedding for the face file - we assume only one face
    embedding = calc_reference_embedding(face_file, haar_cascade, ibed)

    # Convert to something that will work in SQL
    vector_str = ", ".join(str(x) for x in embedding.tolist())
    vector_str = f'[{vector_str}]'

    ask_pg_and_report(pg_uri, vector_str, number_matches)
```

Find "nearby" faces (2)

```
def calc_reference_embedding(face_file, haar_cascade, ibed):
    orig_image = cv2.imread(face_file, 0)
    gray_image = cv2.cvtColor(orig_image, cv2.COLOR_RGB2BGR)
    faces = find_faces(gray_image, haar_cascade)

    # We hope there's only one face!
    cropped_images = []
    for x, y, w, h in faces:
        cropped_images.append(orig_image[y : y + h, x : x + w])

    face = Image.fromarray(cropped_images[0])
    return ibed.to_embeddings(face)[0]
```

Find "nearby" faces (3)

In fact, in the real code it doesn't say:

```
# We hope there's only one face!
```

I couldn't resist an actual check:

```
if len(faces) == 0:
    raise GiveUp(f"Didn't find any faces in {face_file}")
elif len(faces) > 1:
    raise GiveUp(f"Found more than one face in {face_file}")
```

Find "nearby" faces (4)

Our embedding needs turning into something that SQL will understand:

```
vector_str = ", ".join(str(x) for x in embedding.tolist())
vector_str = f'[{vector_str}]'
```

Find "nearby" faces (5)

```
def ask_pg_and_report(pg_uri, vector_str, number_matches):
    with psycopg2.connect(pg_uri) as conn:
        with conn.cursor() as cur:
            cur.execute(
                "SELECT filename FROM pictures ORDER BY embedding <-> %s LIMIT %s;",
                (vector_str, number_matches)
            )
            rows = cur.fetchall()
        print(f'Number of results: {len(rows)}')
        for index, row in enumerate(rows):
            print(f'  {index}: {row[0]}')
```

But how good is it?

779 files, 5006 faces

- 21 minutes to calculate and store the embeddings
- 3 seconds to find the 10 nearest faces

Wednesday at Crab Week

There were 779 photos, and 5006 faces.

Going through them manually, I found 25 that had my face visible,

- some were in a crowd or obscured,
- three were of my back (!)
- two were with a false moustache

Results the program found

And here are the first 10 matches from the program (9 are me)

```
AIVEN2752.jpg -- just me
AIVEN2839.jpg -- just me
AIVEN2838.jpg -- just me
AIVEN2806.jpg -- me in front of audience
AIVEN2808.jpg -- just me, from side
AIVEN2750.jpg -- me plus another
AIVEN2751.jpg -- me plus others
AIVEN2748.jpg -- me plus others
AIVEN2681.jpg -- me in group sitting
AIVEN3104.jpg -- not me, beard and glasses
```

The first: AIVEN2752

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

Me in a group

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

Thursday at Crab Week

There were 574 photos and 3486 faces.

Going through them manually, I found 7 that had my face visible

- although in 4 of them I had dark glasses

Results the program found

And here are the first 10 matches from the program (3 are me)

```
AIVEN3933.jpg  -- me in audience looking down, slightly sideways
AIVEN3697.jpg  -- me in group
AIVEN3670.jpg  -- not me, but sort of understandable - beard & glasses
AIVEN3760.jpg  -- not me, but sort of understandable - beard & glasses
AIVEN3671.jpg  -- not me, but sort of understandable - beard & glasses
AIVEN3739.jpg  -- me in group as in the tutorial
AIVEN3673.jpg  -- not me, but sort of understandable - beard & glasses
AIVEN3999.jpg  -- not me, but sort of understandable - beard & glasses
AIVEN4316.jpg  -- not me, but sort of understandable - beard & (dark) glasses
AIVEN3679.jpg  -- not me, but sort of understandable - beard & glasses
```

The first: AIVEN3933

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

As in the tutorial: AIVEN3739 (cropped)

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a

So was this a success, so far?

Definitely yes.

I learnt a lot.

I got not awful (!) results with really very low effort.

I know what to do for the next set of investigations

What I'd do next

Improve `find_faces_store_embeddings.py`:

- Add a switch to allow setting the "face detecting" parameters
- Make a different table for each set of parameters
- Add a switch for "generate reference face"

Improve `find_nearby_faces.py`

- Add a switch to specify which face (from the db) to look for
- Add a switch to specify which table to search

Part the fourth: Why PostgreSQL?

Why is PostgreSQL a surprising choice?

We expect Python to be a good fit for exploring ML

But PostgreSQL isn't a dedicated vector database

So why PostgreSQL?

and/or

Images from https://pixabay.com/, by OpenClipart-Vectors

It's significantly better than nothing

(faint praise indeed)

There comes a point when you need to store your embeddings in some sort of database

PostgreSQL is a *good* place to start

We already have it

Quite often, we're already running PostgreSQL

It can SQL all the things

This can be *really useful*:

Find me things like <this order>, that are in stock

Find the pictures of me taken in Portugal, between <these dates>

Find things that match <these qualities>, and choose the one most like <this other thing>

PostgreSQL optimisation techniques work

You can use all the techniques you normally use in PG to optimise the query

and can do ANALYZE on the query, too

Indexing

Speeds up the *use* of embeddings.

- IVFFlat - exact nearest neighbours, slower
- HNSW - approximate nearest neighbours, faster

HNSW was just added in pgvector 0.5.0

A recurring pattern

We should recognise this pattern:

> Work in PostgreSQL until it's not suitable,
>
> and *then* move to something else

When not to use PG?

When it can't cope

When it doesn't actually do what you want

When vectors are too big

The pgvector Reference section says:

> Each vector takes `4 * dimensions + 8` bytes of storage. Each element is a single precision floating-point number (like the `real` type in Postgres), and all elements must be finite (no `NaN`, `Infinity` or `-Infinity`).
>
> Vectors can have up to 16,000 dimensions.

When vectors are too big to index

According to the pgvector FAQ

> You can't currently **index** a vector if it has more than 2,000 dimensions

When there are too many vectors

According to the pgvector FAQ

> A non-partitioned table has a limit of 32 TB by default in Postgres. A partitioned table can have thousands of partitions of that size.

When you need more speed

pgvector is ultimately limited by being based on a relational database that is not, itself, optimised for this task.

Remember to profile!

When you need a missing distance function

Although this can change...

When the queries aren't SQL

Relational databases and SQL aren't always the best solution.

For instance, OpenSearch also has vector support.

Other tools

Is pgvector the only PostgreSQL solution?

Neon provides pg_embedding, which uses an HNSW index

There's an article by them comparing its performance with pgvector HNSW

A quick and not very rigorous search

There are lots of vector databases! Here are some open source solutions:

- Weaviate https://weaviate.io/
- Milvus https://milvus.io/
- Qdrant https://qdrant.tech/
- Vespa https://vespa.ai/
- Chroma https://www.trychroma.com/

And some more

- OpenSearch has vector database functionality
- SingleStore vector db https://www.singlestore.com/built-in-vector-database/
- Relevance AI vector db https://relevanceai.com/vector-db
- The FAISS library https://faiss.ai/

And see lists like https://byby.dev/vector-databases

The future is bright (judging from history)

Vectors are the new JSON in PostgreSQL by Jonathan Katz

Things will get better and faster and support larger vectors over the next few years.

(I'm also minded of large blob support - TOAST is always an issue, but they work on it)

Acknowledgements

Postgres, PostgreSQL and the Slonik Logo are trademarks or registered trademarks of the PostgreSQL Community Association of Canada, and used with their permission

- ML Typewriter image from https://unsplash.com/, by Markus Winkler
- Penknife and Hammer images from https://pixabay.com/, by OpenClipart-Vectors
- Vector graph from JCC Math.Phys 191: The vector class, CC BY-SA 3.0

My colleague Francesco Tisiot for the original tutorial, and much good advice

Fin

Get a free trial of Aiven services at
https://go.aiven.io/pyconuk-signup

Also, we're hiring! See https://aiven.io/careers

Written in reStructuredText, converted to PDF using rst2pdf

Slides and accompanying material at
https://github.com/aiven-labs/pgvector-find-faces-talk

tony.ibbs@aiven.io / https://aiven.io/tibs / @much_of_a