Building AI-powered data-driven applications using pgvector, LangChain and LLMs

Lab 1 hour No cost Intermediate

Rate Lab

This lab may incorporate AI tools to support your learning.

Previous Next

This hands-on lab will show you how you can add vertex AI features to your own applications with just a few lines of code using pgvector, LangChain and LLMs on Google Cloud. This lab help you to understand, how you can add vertex AI features to your own applications with just a few lines of code using pgvector, LangChain and LLMs on Google Cloud.

In this lab, we will build together a sample Python application that will be able to understand and respond to human language queries about the relational data stored in your PostgreSQL database. In fact, we will further push the creative limits of the application by teaching it to generate new content based on our existing dataset.

Scenario

This lab uses an e-commerce company that runs an online marketplace for buying and

Dataset:

- The dataset for this notebook has been sampled and created from a larger public retail dataset available at Kaggle. The sampled dataset used in this notebook has only about 800 toy products, while the public dataset has over 370,000 products in different categories.

The goals are:

- (Usecase 1) For buyers: Build a new AI-powered hybrid search, where users can describe their needs in simple English text, along with regular filters (like price, etc.)
- (Usecase 2) For sellers: Add a new AI-powered content generation feature, where sellers will get auto-generated item description suggestions for new products that they want to add to the platform.

Objective

- How to use the pgvector extension extension to store and search vector embeddings in PostgreSQL

by large language models. LangChain makes it easier to develop and deploy applications against any LLM model in a vendor-agnostic manner.

- How to use the powerful features in Google models made available through Vertex AI.

What you will do

1. Download the dataset and load it into a PostgreSQL table called `products`. This table has 4 fields: `product_id` `product_name` `description` `list_price`

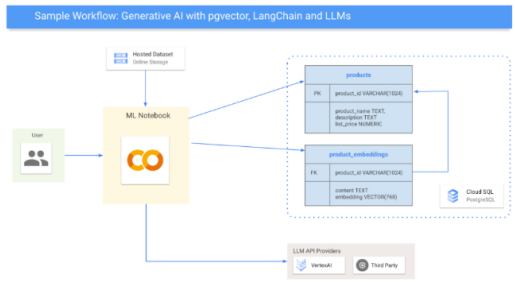
table has 4 fields: `product_id`, `product_name`, `description`, `list_price`.

2. Split the long `description` field values into smaller chunks and generate vector embeddings for each chunk. The vector embeddings are then stored in another PostgreSQL table called `product_embeddings` using the `pgvector` extension. The `product_embeddings` table has a foreign key referencing the products table.

3. For a given user query, generate its vector embeddings and use `pgvector` vector similarity search operators to find the closest matching products after applying the relevant SQL filters.

quality context using an LLM model .

5. Finally, pass the context to an LLM prompt to answer the user query. The LLM model will return a well-formatted natural sounding English result back to the user.



Let's dive in!

Setup and requirements

Before you click the Start Lab button

Read these instructions. Labs are timed and you cannot pause them. The timer, which starts when you click **Start Lab**, shows how long Google Cloud resources will be made available to you.

This Qwiklabs hands-on lab lets you do the lab activities yourself in a real cloud environment, not in a simulation or demo environment. It does so by giving you new, temporary credentials that you use to sign in and access Google Cloud for the duration of the lab.

What you need

To complete this lab, you need:

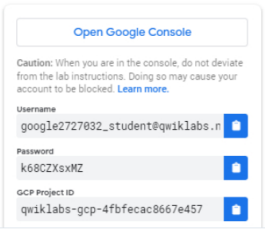
- Access to a standard internet browser (Chrome browser recommended).

Note: If you already have your own personal Google Cloud account or project, do not use it for this lab.

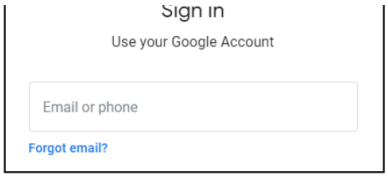
Note: If you are using a Pixelbook, open an Incognito window to run this lab.

How to start your lab and sign in to the Google Cloud Console

1. Click the **Start Lab** button. If you need to pay for the lab, a pop-up opens for you to select your payment method. On the left is a panel populated with the temporary credentials that you must use for this lab.

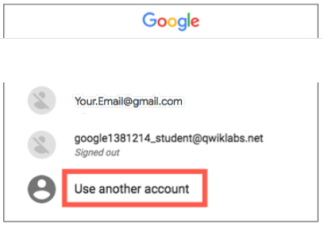


2. Copy the username, and then click **Open Google Console**. The lab spins up resources, and then opens another tab that shows the **Sign in** page.



Tip: Open the tabs in separate windows, side-by-side.

If you see the **Choose an account** page, click **Use Another Account**.



3. In the **Sign in** page, paste the username that you copied from the Connection Details panel. Then copy and paste the password.

Important: You must use the credentials from the Connection Details panel. Do not use your Qwiklabs credentials. If you have your own Google Cloud account, do not use it for this lab (avoids incurring charges).

4. Click through the subsequent pages:

- Accept the terms and conditions.
- Do not add recovery options or two-factor authentication (because this is a temporary account).
- Do not sign up for free trials.

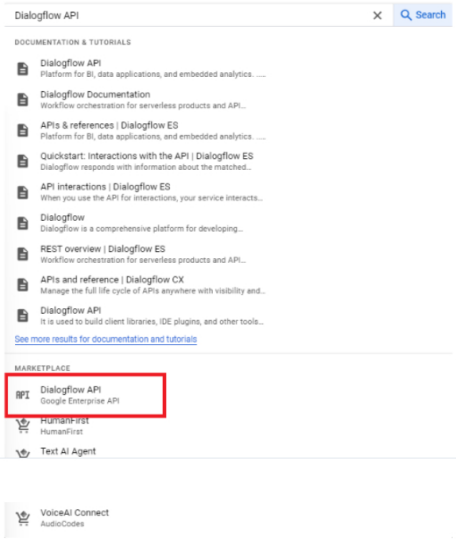
Note: You can view the menu with a list of Google Cloud Products and Services by clicking the **Navigation menu** at the top-left.

Task 1. Enable APIs

In this task, you need to enable the Dialogflow API.

To enable the Dialogflow API, follow these steps:

1. Type **Dialogflow API** into the top search bar of the Google Cloud console, choose the selected result as shown below, and continue.



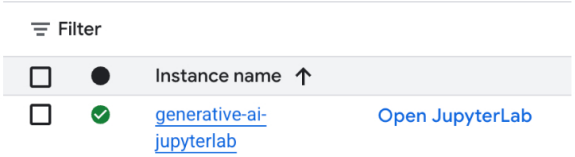
2. Click the **Enable** button.

Task 2. Open Python notebook and install packages

1. In your Google Cloud project, navigate to **Vertex AI Workbench**. In the top search bar of the Google Cloud console, enter **Vertex AI Workbench**, and click on the first result.

2. Click on **Instances** and then click on **Open JupyterLab**.

The JupyterLab will run in a new tab.



3. On the **Launcher**, under **Notebook**, click on **Python 3** to open a new python notebook.

4. In the first cell, enter the following command to install the latest version of Google

button at the top.

```
# Install dependencies.
!pip install asyncio==3.4.3 asyncpg==0.27.0 cloud-sql-
python-connector["asyncpg"]==1.2.3
!pip install numpy==1.26.4 pandas
!pip install pgvector==0.1.8
!pip install langchain langchain_google_vertexai
transformers
!pip install -U langchain-google-vertexai langchain-
community
!pip install google-cloud-aiplatform
!pip install shapely
!pip install google-cloud-
aiplatform[langchain,reasoningengine]
!pip install langchain-text-splitters
!pip install pydantic>=2.0
```

Output:

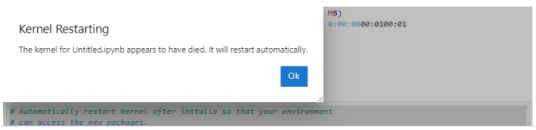
```
les>=0.2.1->google-auth<3.0dev,>=1.25.0->google-api-core[grpc]!=2.0.*,!=2.1.*,!=2.2.*,!=2.3.*,!=2.4.*,!=2.5.*,!=
2.6.*,!=2.7.*,<3.0.0dev,>=1.32.0->google-cloud-aiplatform==1.26.0) (0.5.0)
Downloading google_cloud_aiplatform-1.26.0-py2.py3-none-any.whl (2.6 MB)
     Successfully uninstalled google-cloud-aiplatform-1.36.0
Successfully installed google-cloud-aiplatform-1.26.0
```

5. To use the newly installed packages in this Jupyter runtime, it is recommended to restart the runtime. Restart the kernel by running the below code snippet or clicking the refresh button at the top, followed by clicking **Restart** button.

```
# Automatically restart kernel after installation so that
your environment can access the new packages.
import IPython

app = IPython.Application.instance()
app.kernel.do_shutdown(True)
```

Output:



```
{'status': 'ok', 'restart': True}
```

Click **OK** to move to the next step.

Task 3. Create a Cloud SQL Instance and PostgreSQL database.

1. Run the following code in the next cell, for declaring values prior to creating CloudSQL instance.

```
import os
import pandas as pd
import vertexai
```

```
from IPython.display import display, Markdown

from langchain_google_vertexai import VertexAIEmbeddings
import vertexai

project_id = "GCP Project ID"
database_password = "cymbal@123!"
region =  "Lab GCP Region"
instance_name = "retail-ins"
database_name = "retail"
database_user = "retail-admin"

# Initialize Vertex AI SDK
vertexai.init(project=project_id, location=region)
```

2. Run the following code in the next notebook cell for creating a Cloud SQL instance and PostgreSQL database.

```
#@markdown Create and setup a Cloud SQL PostgreSQL
instance, if not done already.
database_version = !gcloud sql instances describe
{instance_name} --format="value(databaseVersion)"
```

```
else:
  print("Creating new Cloud SQL instance...")
  !gcloud sql instances create {instance_name} --database-
version=POSTGRES_15 \
  --region={region} --cpu=1 --memory=4GB --root-password=
{database_password}

# Create the database, if it does not exist.
out = !gcloud sql databases list --instance={instance_name}
--filter="NAME:{database_name}" --format="value(NAME)"
if ''.join(out) == database_name:
  print("Database %s already exists, skipping creation." %
database_name)
else:
  !gcloud sql databases create {database_name} --instance=
{instance_name}

# Create the database user for accessing the database.
!gcloud sql users create {database_user} \
--instance={instance_name} \
--password={database_password}
```

Output:

```
Creating new Cloud SQL instance...
Creating Cloud SQL instance for POSTGRES_15...done.
Created [https://sqladmin.googleapis.com/sql/v1beta4/projects/qwiklabs-gcp-04-63807e05b641/instances/ins-001].
NAME     DATABASE_VERSION  LOCATION       TIER              PRIMARY_ADDRESS  PRIVATE_ADDRESS  STATUS
ins-001  POSTGRES_15       us-central1-b  db-custom-1-4096  34.42.33.53      -                RUNNABLE
Creating Cloud SQL database...done.
Created database [retail].
instance: ins-001
name: retail
project: qwiklabs-gcp-04-63807e05b641
Creating Cloud SQL user...done.
Created user [retail-admin].
```

3. Run the following code in the next notebook cell to verify that you are able to connect to the database.

```
# @markdown Verify that you are able to connect to the
database. Executing this block should print the current
PostgreSQL server version.

import asyncio
import asyncpg
from google.cloud.sql.connector import Connector
```

```
    # get current running event loop to be used with
Connector
    loop = asyncio.get_running_loop()
    # initialize Connector object as async context manager
    async with Connector(loop=loop) as connector:
        # create connection to Cloud SQL database
        conn: asyncpg.Connection = await
connector.connect_async(
            f"{project_id}:{region}:{instance_name}",  #
Cloud SQL instance connection name
            "asyncpg",
            user=f"{database_user}",
            password=f"{database_password}",
            db=f"{database_name}"
            # ... additional database driver args
        )

        # query Cloud SQL database
        results = await conn.fetch("SELECT version()")
        print(results[0]["version"])

        # close asyncpg connection
        await conn.close()
```

```
await main()  # type: ignore
```

Output:

```
PostgreSQL 15.4 on x86_64-pc-linux-gnu, compiled by Debian clang version 12.0.1, 64-bit
```

Task 4. Download and load the dataset in PostgreSQL

In this task, let's load the dataset from a web URL and store it in a pandas dataframe. Later save the Pandas dataframe in a PostgreSQL table.

1. Run the following code in the next notebook cell for loading the dataset from a web URL and storing it in a pandas dataframe.

```
# Load dataset from a web URL and store it in a pandas
dataframe.

import pandas as pd
import os

DATASET_URL =
"https://github.com/GoogleCloudPlatform/python-docs-
samples/raw/main/cloud-
sql/postgres/pgvector/data/retail_toy_dataset.csv"
df = pd.read_csv(DATASET_URL)
df = df.loc[:, ["product_id", "product_name",
"description", "list_price"]]
df = df.dropna()
df.head(10)
```

Output:

	product_id	product_name	description	list_price
0	7e8697b5b7cdb5a40daf54caf1435cd5	Koplow Games Set of 2 D12 12-Sided Rock, Paper...	Rock, paper, scissors is a great way to resolv...	3.56
1	7de8b315b3cb91f3680eb5b88a20dcee	12"-20" Schwinn Training Wheels	Turn any small bicycle into an instrument for ...	28.17
2	fb9535c103d7d717f0414b2b111cfaaa	Bicycle Pinochle Jumbo Index Playing Cards - 1...	Purchase includes 1 blue deck and 1 red deck...	6.49
4	dec7bd1f983887650715c6fafaa5b593	Step2 Naturally Playful Welcome Home Playhouse...	Children can play and explore in the Step2 Nat...	600.00
5	74a695e3675efc2aad11ed73c46db29b	Slip N Slide Triple Racer with Slide Boogies	Triple Racer Slip and Slide with Boogie Boards...	37.21
6	3eae5293b56c25f63b47cb8a89fb4813	Hydro Tools Digital Pool/Spa Thermometer	The solar-powered Swimline Floating Digital Th...	15.92
7	ed85bf829a36c67042503ffd9b6ab475	Full Bucket Swing With Coated Chain Toddler Sw...	Safe Kids&Children Full Bucket Swing With Coa...	102.26
8	55820fa53f0583cb637d5cb2b051d78c	Banzai Water Park Splash Zone	Dive into fun in your own backyard with the B...	397.82
9	0e26a9e92e4036bfaa68eb2040a8ec97	Polaris 39-310 5-Liter Zippered Super Bag for ...	Keep your pool water sparkling clean all seaso...	39.47

2. Save the pandas dataframe in a PostgreSQL table.

```
# Save the Pandas dataframe in a PostgreSQL table.

import asyncio
import asyncpg
from google.cloud.sql.connector import Connector
```

```
async def main():
    loop = asyncio.get_running_loop()
    async with Connector(loop=loop) as connector:
```

```
connector.connect_async(
            f"{project_id}:{region}:{instance_name}",  #
Cloud SQL instance connection name
            "asyncpg",
            user=f"{database_user}",
            password=f"{database_password}",
            db=f"{database_name}",
        )

        await conn.execute("DROP TABLE IF EXISTS products
CASCADE")
        # Create the `products` table.
        await conn.execute(
            """CREATE TABLE products(
                                product_id VARCHAR(1024)
PRIMARY KEY,
                                product_name TEXT,
                                description TEXT,
                                list_price NUMERIC)"""
        )

        # Copy the dataframe to the `products` table.
        tuples = list(df.itertuples(index=False))
        await conn.copy_records_to_table(
```

```
        )
        await conn.close()


# Run the SQL commands now.
await main()  # type: ignore
```

Task 5. Generate vector embeddings using a Text Embedding model

1. Split long product description text into smaller chunks

    - The product descriptions can be much longer than what can fit into a single API request for generating the vector embedding.

```
5,012 input tokens for a single API request.
```

    - Use the `RecursiveCharacterTextSplitter` from the LangChain library to split the description into smaller chunks of 500 characters each.

Run the following code in the next notebook cell.

```
from langchain_text_splitters import
RecursiveCharacterTextSplitter
from langchain.schema import Document

from langchain.text_splitter import
RecursiveCharacterTextSplitter

text_splitter = RecursiveCharacterTextSplitter(
    separators=[".", "\n"],
    chunk_size=500,
    chunk_overlap=0,
    length_function=len,
)

max_documents = 47  # Reduced limit to further control API
```

```
# Create Document objects with product_id as metadata
for index, row in df.iterrows():
    product_id = row["product_id"]
    desc = row["description"]
    documents.append(Document(page_content=desc, metadata=
{"product_id": product_id}))

# Use the text splitter on a subset of documents (e.g., 40-
50)
chunked = []
docs =
text_splitter.split_documents(documents[40:max_documents])

# Collect split content along with product_id
for doc in docs:
    chunked.append({"product_id":
doc.metadata["product_id"], "content": doc.page_content})
```

2. Generate vector embedding for each chunk by calling an Embedding Generation service

   In this lab, the Vertex AI text embedding model is used to generate vector

   Run the following code in the next notebook cell.

```
from langchain_google_vertexai import VertexAIEmbeddings
from google.cloud import aiplatform
import time

embeddings_service = VertexAIEmbeddings(model_name="text-
embedding-005")

# Helper function to retry failed API requests with
exponential backoff.
def retry_with_backoff(func, *args, retry_delay=10,
backoff_factor=2.5, **kwargs):  # Increased delay and
backoff factor
    max_attempts = 10
    retries = 0
    for i in range(max_attempts):
        try:
            return func(*args, **kwargs)
        except Exception as e:
            print(f"error: {e}")
            retries += 1
seconds...")
            time.sleep(wait)

# Reduced batch size for API calls to manage quota limits
batch_size = 3
for i in range(0, len(chunked), batch_size):
    request = [x["content"] for x in chunked[i : i +
batch_size]]
    response =
retry_with_backoff(embeddings_service.embed_documents,
request)
    # Store the retrieved vector embeddings for each chunk
back.
    for x, e in zip(chunked[i : i + batch_size], response):
        x["embedding"] = e

# Store the generated embeddings in a pandas dataframe.
product_embeddings = pd.DataFrame(chunked)
product_embeddings.head()
```

Note: The following code snippet may run for a few minutes.

	product_id	content	embedding
0	7e8697b5b7cdb5a40daf54caf1435cd5	Rock, paper, scissors is a great way to resolv...	[-0.01565113663673401, -0.022118045017123222, ...
1	7e8697b5b7cdb5a40daf54caf1435cd5	games, creating your own game, and friends and...	[-0.016362388549613, -0.052170153707265854, 0....
2	7de8b315b3cb91f3680eb5b88a20dcee	Turn any small bicycle into an instrument for ...	[-0.029525158926844597, -0.023656629025936127,...
3	7de8b315b3cb91f3680eb5b88a20dcee	teel brackets stand up to heavy use. Customiza...	[0.0014654349070042372, -0.027971144765615463,...
4	7de8b315b3cb91f3680eb5b88a20dcee	es.com. Follow ride Schwinn on: Twitter. Faceb...	[-0.014323981478810 31, -0.015937959775328636, ...

Task 6. Use pgvector to store the generated embeddings within PostgreSQL

The `pgvector` extension introduces a new vector data type. The new vector data type allows you to directly save a vector embedding (represented as a NumPy array) through

1. Run the following code snippet to store the generated vector embeddings in a PostgreSQL table.

```
# Store the generated vector embeddings in a PostgreSQL
table.
# This code may run for a few minutes.

import asyncio
import asyncpg
from google.cloud.sql.connector import Connector
import numpy as np
from pgvector.asyncpg import register_vector
```

```
async def main():
    loop = asyncio.get_running_loop()
    async with Connector(loop=loop) as connector:
        # Create connection to Cloud SQL database.
        conn: asyncpg.Connection = await
connector.connect_async(
            f"{project_id}:{region}:{instance_name}",  #
Cloud SQL instance connection name
```

```
            password=f"{database_password}",
            db=f"{database_name}",
        )

        await conn.execute("CREATE EXTENSION IF NOT EXISTS
vector")
        await register_vector(conn)

        await conn.execute("DROP TABLE IF EXISTS
product_embeddings")
        # Create the `product_embeddings` table to store
vector embeddings.
        await conn.execute(
            """CREATE TABLE product_embeddings(
                                product_id VARCHAR(1024)
NOT NULL REFERENCES products(product_id),
                                content TEXT,
                                embedding vector(768))"""
        )

        # Store all the generated embeddings back into the
database.
        for index, row in product_embeddings.iterrows():
            await conn.execute(
```

```
                row["product_id"],
                row["content"],
                np.array(row["embedding"]),
            )

        await conn.close()


# Run the SQL commands now.
await main()  # type: ignore
```

Task 7. Finding similar toy products using pgvector cosine search operator

1. Run the following code in the next notebook cell to search for similar toy products

```
# @markdown Enter a short description of the toy to search
for within a specified price range:
toy = "playing card games"  # @param {type:"string"}
min_price = 25  # @param {type:"integer"}
max_price = 100  # @param {type:"integer"}

# Quick input validations.
assert toy, "⚠️ Please input a valid input search text"

from langchain_google_vertexai import VertexAIEmbeddings
from google.cloud import aiplatform

aiplatform.init(project=f"{project_id}", location=f"
{region}")

embeddings_service = VertexAIEmbeddings(model_name="text-
embedding-005")
qe = embeddings_service.embed_query(toy)
from pgvector.asyncpg import register_vector
import asyncio
import asyncpg
from google.cloud.sql.connector import Connector
```

```
async def main():
    loop = asyncio.get_running_loop()
    async with Connector(loop=loop) as connector:
        # Create connection to Cloud SQL database.
        conn: asyncpg.Connection = await
connector.connect_async(
            f"{project_id}:{region}:{instance_name}",  #
Cloud SQL instance connection name
            "asyncpg",
            user=f"{database_user}",
```

```
            password=f"{database_password}",
            db=f"{database_name}",
        )

        await register_vector(conn)
        similarity_threshold = 0.1
        num_matches = 50

        # Find similar products to the query using the
cosine similarity search
        # Over all vector embeddings. This new feature is
provided by `pgvector`.
        results = await conn.fetch(
```

```
                            SELECT product_id, 1 -
(embedding <=> $1) AS similarity
                            FROM product_embeddings
                            WHERE 1 - (embedding <=> $1) >
$2
                            ORDER BY similarity DESC
                            LIMIT $3
                            )
                            SELECT product_name,
list_price, description FROM products
                            WHERE product_id IN (SELECT
product_id FROM vector_matches)
                            AND list_price >= $4 AND
list_price <= $5
                            """,
            qe,
            similarity_threshold,
            num_matches,
            min_price,
            max_price,
        )

        if len(results) == 0:
            raise Exception("Did not find any results.
```

```
        for r in results:
            # Collect the description for all the matched
similar toy products.
            matches.append(
                {
                    "product_name": r["product_name"],
                    "description": r["description"],
                    "list_price": round(r["list_price"],
2),
                }
            )

        await conn.close()


# Run the SQL commands now.
await main()  # type: ignore

# Show the results for similar products that matched the
user query.
matches = pd.DataFrame(matches)
matches.head(5)
```

	product_name	description	list_price
0	Purple Mini Poker Chips Plastic 7/8in Bulk App...	Purple Mini Poker Chips Plastic 7/8in Bulk App...	27.78
1	Arkham Horror Living Card Game: The Dream-Eate...	There is a hidden realm outside the world of ...	25.82
2	Zelda Uno Card Game Special Legend Rule Exclus...	Bonus Zelda Rules Exclusive Card Game Zelda Un...	29.58

Task 8. LLMs and LangChain

We have extracted the semantic knowledge of the dataset and made it searchable through pgvector and PostgreSQL. This task further shows how you can use this semantic knowledge to answer complex natural language queries using LLMs.

Building an AI-curated contextual hybrid search

Combine natural language query text with regular relational filters to create a powerful

Example: A grandparent wants to use the **AI-powered search interface** to find an educational toy for their grandkid that fits within their budget.

1. Generate the vector embedding for the user query

```
# @markdown Enter the user search query in a simple English
```

```
# @markdown Enter the user search query in a simple English
text. The price filters are shown separately here for demo
purposes. These filters may represent additional input from
your frontend application.
# Please fill in these values.
user_query = "Do you have a beach toy set that teaches
numbers and letters to kids?"  # @param {type:"string"}
min_price = 20  # @param {type:"integer"}
max_price = 100  # @param {type:"integer"}

# Quick input validations.
assert user_query, "⚠️ Please input a valid input search
text"
```

```
qe = embeddings_service.embed_query(user_query)
```

2. Use `pgvector` to find similar products.

   - The new `pgvector` similarity search operators provide powerful semantics to combine the vector search operation with regular query filters in a single SQL query.
   - Using `pgvector`, you can now seamlessly integrate the power of relational databases with your vector search operations!

```
from pgvector.asyncpg import register_vector
import asyncio
import asyncpg
from google.cloud.sql.connector import Connector

matches = []


async def main():
    loop = asyncio.get_running_loop()
    async with Connector(loop=loop) as connector:
        # Create connection to Cloud SQL database.
        conn: asyncpg.Connection = await
```

```
Cloud SQL instance connection name
            "asyncpg",
            user=f"{database_user}",
            password=f"{database_password}",
            db=f"{database_name}",
        )

        await register_vector(conn)
        similarity_threshold = 0.5
        num_matches = 10

        # Find similar products to the query using cosine
similarity search
        # over all vector embeddings. This new feature is
provided by `pgvector`.
        results = await conn.fetch(
            """
                        WITH vector_matches AS (
                        SELECT product_id, 1 -
(embedding <=> $1) AS similarity
                        FROM product_embeddings
                        WHERE 1 - (embedding <=> $1) >
$2
                        ORDER BY similarity DESC
```

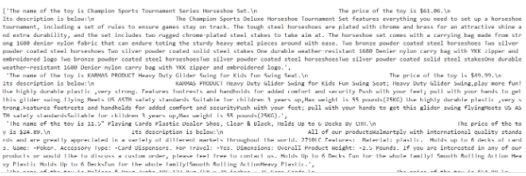
```
                        ),
                        SELECT product_name,
list_price, description FROM products
                        WHERE product_id IN (SELECT
product_id FROM vector_matches)
                        AND list_price >= $4 AND
list_price <= $5
                        """,
            qe,
            similarity_threshold,
            num_matches,
            min_price,
            max_price,
        )
        if len(results) == 0:
            raise Exception("Did not find any results.
Adjust the query parameters.")

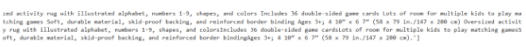
        for r in results:
            # Collect the description for all the matched
similar toy products.
            matches.append(
                f"""The name of the toy is
{r["product_name"]}.
                        The price of the toy is
                        its description is below:
                        {r["description"]}."""
            )
        await conn.close()
```

```
# Run the SQL commands now.
await main()  # type: ignore

# Show the results for similar products that matched the
user query.
matches
```

Output:





3. Use LangChain to summarize and generate a high-quality prompt to answer the user query

    - After finding the similar products and their descriptions using `pgvector`, the next step is to use them for generating a prompt input for the LLM model.
    - Since individual product descriptions can be very long, they may not fit within the specified input payload limit for an LLM model.
    - The `MapReduceChain` from LangChain framework is used to generate and combine short summaries of similarly matched products.
    - The combined summaries are then used to build a high-quality prompt for an input to the LLM model.

```
# Using LangChain for summarization and efficient context
building.

from langchain.docstore.document import Document
from langchain_google_vertexai import VertexAI
from langchain_core.prompts import PromptTemplate
from IPython.display import display, Markdown

llm = VertexAI(temperature=0.7)

map_prompt_template = """
            You will be given a detailed description of a
toy product.
            This description is enclosed in triple
backticks (```).
            Using this description only, extract the name
of the toy,
            the price of the toy and its features.

            ```{text}```
            SUMMARY:
            """
map_prompt = PromptTemplate(template=map_prompt_template,
input_variables=["text"])

combine_prompt_template = """
                You will be given a detailed description
question enclosed in
                double backticks(``).
                Select one toy that is most relevant to
answer the question.
                Using that selected toy description, answer
the following
                question in as much detail as possible.
                You should only use the information in the
description.
                Your answer should include the name of the
toy, the price of the toy
                and its features. Your answer should be
less than 200 words.
                Your answer should be in Markdown in a
numbered list format.


                Description:
                ```{text}```


                Question:
                ``{user_query}``

                """
```

```
combine_prompt = PromptTemplate(
    template=combine_prompt_template, input_variables=
["text", "user_query"]
)

docs = [Document(page_content=t) for t in matches]
chain = load_summarize_chain(
    llm, chain_type="map_reduce", map_prompt=map_prompt,
combine_prompt=combine_prompt
)
output = chain.invoke(
    {
        "input_documents": docs,
        "user_query": user_query,
    }
)


#display(Markdown(answer))
# Extract and display the output
answer = output.get('output_text', ' ')
display(Markdown(answer))
```

1. The Melissa & Doug Jumbo ABC-123 Rug is an oversized activity rug that includes an illustrated alphabet and numbers 1-9.
2. The rug is priced at $54.99.
3. It comes with 36 double-sided game cards and is made of soft, durable material with a skid-proof backing and reinforced border binding.
4. It is suitable for ages 3 and up.

Adding AI-powered creative content generation

Use knowledge from the existing dataset to generate new AI-powered content from an initial prompt.

Example: A third-party seller on the retail platform wants to use the **AI-powered content generation** to create a detailed description of their new bicycle product.

```
# @markdown Describe your a new product in just a few words:
# Please fill in these values.
creative_prompt = "A bicycle with brand name 'Roadstar bike' for
kids that comes with training wheels and helmet."  # @param
{type:"string"}
```

```
text"
```

1. Find an existing product description matching the initial prompt.
    - Leverage the `pgvector` similarity search operator to find an existing product description that closely matches the new product specified in the initial prompt.

```
from pgvector.asyncpg import register_vector
import asyncio
import asyncpg
from google.cloud.sql.connector import Connector

qe = embeddings_service.embed_query(creative_prompt)
qe_str = "[%s]" % (",".join([str(x) for x in qe]))
matches = []


async def main():
    loop = asyncio.get_running_loop()
    async with Connector(loop=loop) as connector:
```

```
connector.connect_async(
            f"{project_id}:{region}:{instance_name}",  #
Cloud SQL instance connection name
            "asyncpg",
            user=f"{database_user}",
            password=f"{database_password}",
            db=f"{database_name}",
        )

        await register_vector(conn)
        similarity_threshold = 0.5

        # Find similar products to the query using cosine
similarity search
        # over all vector embeddings. This new feature is
provided by `pgvector`.
        results = await conn.fetch(
            """
                        WITH vector_matches AS (
                        SELECT product_id, 1 -
(embedding <=> $1) AS similarity
                        FROM product_embeddings
                        WHERE 1 - (embedding <=> $2) >
$3
```

```
                            )
                            SELECT description FROM
products
                            WHERE product_id IN (SELECT
product_id FROM vector_matches)
                            """,
            qe,
            qe,
            similarity_threshold,
        )

        for r in results:
            matches.append(r["description"])

        await conn.close()


# Run the SQL commands now.
await main()  # type: ignore

# Show the matched product description.
matches
```

2. Use the existing matched product description as the prompt context to generate new creative output from the LLM.

```
from IPython.display import display, Markdown
from langchain_google_vertexai import VertexAI
from langchain_core.prompts import PromptTemplate
from langchain_core.runnables import RunnableSequence

template = """
            You are given descriptions about some similar
kind of toys in the context.
            This context is enclosed in triple backticks
(```).
            Combine these descriptions and adapt them to
match the specifications in
            the initial prompt. All the information from
the initial prompt must
            be included. You are allowed to be as creative
as possible,
            and describe the new toy in as much detail.

            Context:
            ```{context}```

            Initial Prompt:
            {creative_prompt}
            Answer:
        """

prompt = PromptTemplate(
    template=template, input_variables=["context",
"creative_prompt"]
)


# Define the LLM
llm = VertexAI(temperature=0.7)
# Example `matches` list

matches = [
    {"description": "This is a toy description 1."},
    {"description": "This is a toy description 2."},
    {},  # Missing `description`
    "Invalid item"  # Not a dictionary

# Construct the context by extracting valid descriptions
context = "\n".join(
    item["description"] for item in matches if
isinstance(item, dict) and "description" in item
)

# Use RunnableSequence for chaining
llm_chain = RunnableSequence(prompt | llm)
# Invoke the chain
answer = llm_chain.invoke({
    "context": context,
    "creative_prompt": creative_prompt,
})

# Display the answer in Markdown format
display(Markdown(answer))
```

Output:
```

with removable training wheels, making it easy for beginners to learn balance and coordination. Safety is paramount, so every Roadstar Bike includes a properly sized, comfortable helmet, ensuring your child is protected on every ride. The adjustable seat and handlebars allow the bike to grow with your child, providing years of fun and healthy outdoor activity. Get your little one started on a lifetime of cycling enjoyment with the Roadstar Bike!

Congratulations

Generative AI is a powerful paradigm shift in application development that lets you create novel applications to serve users in new ways - from answering patients' complex medical questions to helping enterprises analyze cyberattacks. In this lab, we showed you just two examples of powerful features that you can create by combining LLMs and databases.

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