

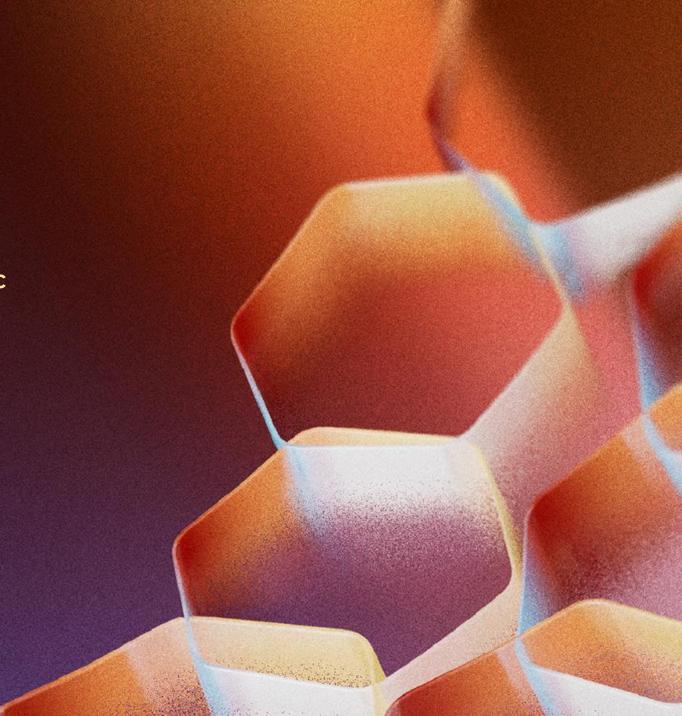
# **LAB360**

Build an Agentic App with GraphRAG, Semantic Kernel, and the new VS Code Extension for PostgreSQL

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Joshua Johnson

**Proctors:** 

Guy Bowerman Ismael Mejía Useche



## Agenda

- · Lab Overview
- PostgreSQL AI Core Concepts
- Part 0 Login to Azure
- Part 1 Setup your PostgreSQL Database
- · Part 2 Use Al-driven features in PostgreSQL
- Part 3 Build the Agentic App

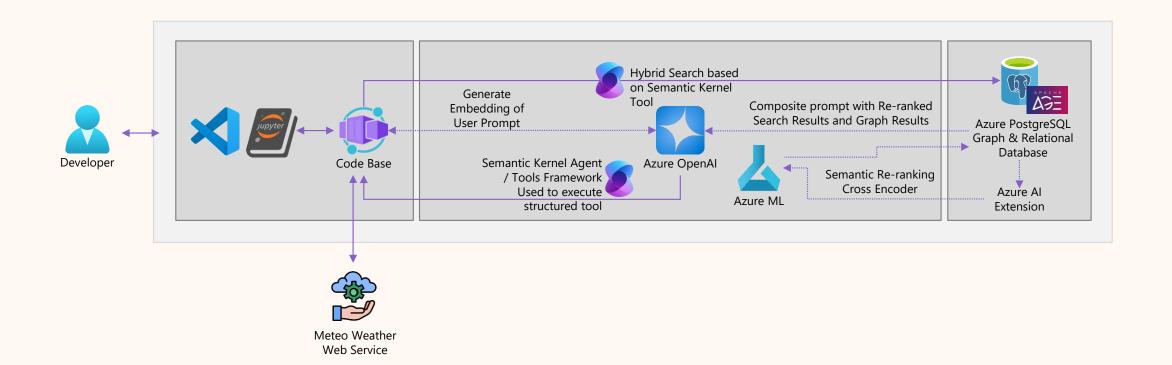
## **Lab Overview**

#### What you will learn:

- How to use the new VS Code PostgreSQL Extension
- Understand how to use Vector and Vector Indexes with PostgreSQL
- Learn about Agentic App architectures and coding patterns
- Hands-on building an Agentic App with PostgreSQL

# **Agentic App Architecture**

The App we are going to build today.



### Dataset for the Lab

- Caselaw Dataset for Washington State
- · Subset of 337 unique legal cases
- · Columns include: id, name, opinion, etc.
- Located at /Dataset/cases.csv

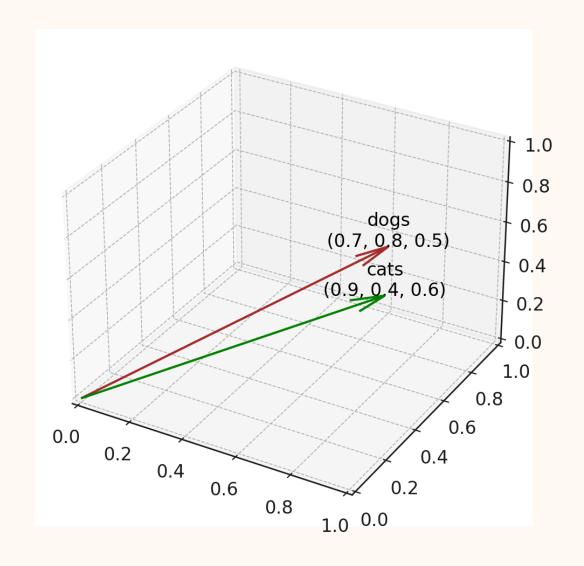
	id	1 11∆	name ↑↓▽	decision_date ↑↓▽	court_id ↑↓▽	opinion ↑↓▽
1	50	7122	Berschauer/Phillips Construction Co. v. Seattle Sc	1994-10-06	9029	"Guy, J.\nWe granted review to decide whether a gen
2	504	41745	Frisken v. Art Strand Floor Coverings, Inc.	1955-10-13	9029	"Rosellini, J.\nThe respondent, Florence Frisken, i
3	500	08733	Pate v. General Electric Co.	1953-09-04	9029	"Weaver, J.\nPlaintiff was injured while engaged in
4	500	07905	Cambro Co. v. Snook	1953-11-05	9029	"Donworth, J.\nPlaintiff instituted this action to
5	500	08594	Buttnick v. Clothier	1953-11-16	9029	"Donworth, J.\nThis action was instituted by plaint

# PostgreSQL AI Core Concepts

- Vectors
- Vector Indexes
- · Semantic Search

#### What is a Vector?

- Lists of numbers that represent items in a high-dimensional space.
- For example, a vector representing the string "dogs" might be [0.7, 0.8, 0.5].
- Each number in the vector is a dimension of the space.



## How to generate a vector?

Use a model to generate vectors for items:

Input	→ Model	$\rightarrow$	Vector
"dog"	text-embedding-3-small		[0.017198, -0.007493, -0.057982,]
"cat"	text-embedding-3-small		[0.004059, 0.06719, -0.093874,]

Model (bi-encoder)	Input types	Dimensions	
OpenAl: text-embedding-3-small	Text	1536	
OpenAl: text-embedding-3-large	Text	3072	
Mistral: e5-mistral-7b-instruct	Text	4096	

Popular models (find more on <u>HuggingFace</u>):

## What should we care about vectors?

## **Search & Similarity**

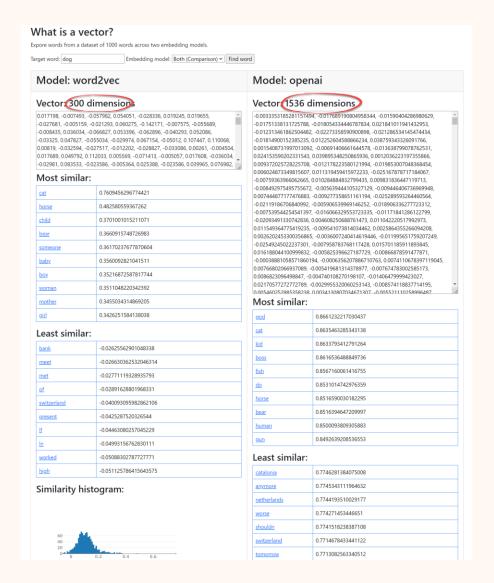
Search and retrieve items that are similar to what you're querying.



## (Optional) Exploring Vectors

Generate Example Vectors

https://pamelafox.github.io/vectors-comparison/

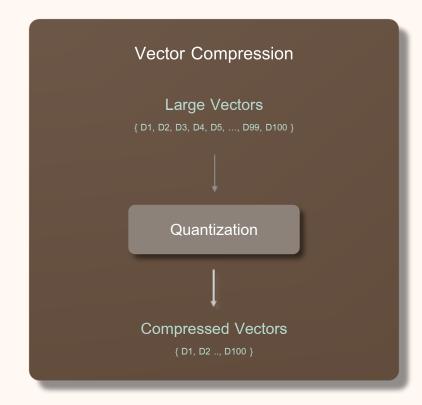


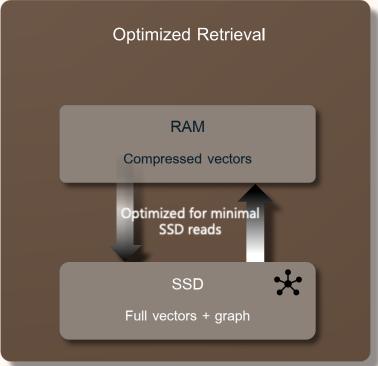
# Storing vectors in the PostgreSQL Table

Re	Results Messages					
	id ↑↓∇	7 name ↑↓▽	opinions_vector ↑↓▽			
1	507122	Berschauer/Phillips Construction Co. v. Seattle Sc	[-0.0077604363,0.034168452,0.022548927,0.058252566,0.0027358707,0.013302599,-0.04104158,-0.0011557909,-0.02792912,-0.00568652			
2	5041745	Frisken v. Art Strand Floor Coverings, Inc.	[0.008968134,0.04363906,-0.0017264026,0.0380413,0.006953235,0.0002628528,-0.022229837,-0.028633554,-0.011818302,0.0461009,0.0			
3	5008733	Pate v. General Electric Co.	[-0.009503542,0.052598044,-0.00058293104,0.051410984,0.013446276,0.017848289,-0.013997411,-0.02381185,-0.020533305,0.03219192			
4	5007905	Cambro Co. v. Snook	[0.02875072,0.033727877,0.00932174,0.004737335,0.037787456,0.01634954,-0.045406118,-0.019574959,-0.010670299,0.017281018,0.03			
5	5008594	Buttnick v. Clothier	[0.0077795624,0.035135385,0.029488107,0.02745043,-0.017844236,0.013717937,-0.023156751,-0.028396495,-0.03015763,-0.03202065,0			

## **Vector Indexing - DiskANN**

- Highly performant, scalable, and accurate index for vectors
- Superior to IVFLAT and HNSW
- Reduced memory footprint by storing vectors on SSD
- Compression and quantization improve speed and accuracy of vector search
- Accuracy retained as data changed





# Lab Part 0 – Login to Azure

- 1. Log into Azure Portal
- Verify Azure Services are provisioned

# Lab Part 0 – Login to Azure

#### **Azure Services:**

ResourceGroup1:

- · Azure OpenAl
- · Azure PostgreSQL Database

# Lab Part 1 – Setup your Azure PostgreSQL Database

(Work from the Lab Manual)

- 1. Open VS Code
- 2. Use Connection Dialog to Setup Database Connection
- 3. Launch PSQL Command Line Shell in VS Code
- 4. Populate the Database with Sample Data
- 5. Install and configure the azure\_ai extension
- 6. Explore the azure\_ai extension schema
- 7. Review the Azure OpenAI Schema

# Lab Part 2 – Using Al-driven Features in PostgreSQL

(Work from the Lab Manual)

- 1. Open New Query Editor in VS Code PosgreSQL Extension
- 2. Using Pattern matching for queries
- 3. Using Semantic Vector Search and DiskANN Index
  - · Create, Store, and Index Embedding Vectors
  - Perform a Semantic Search Query

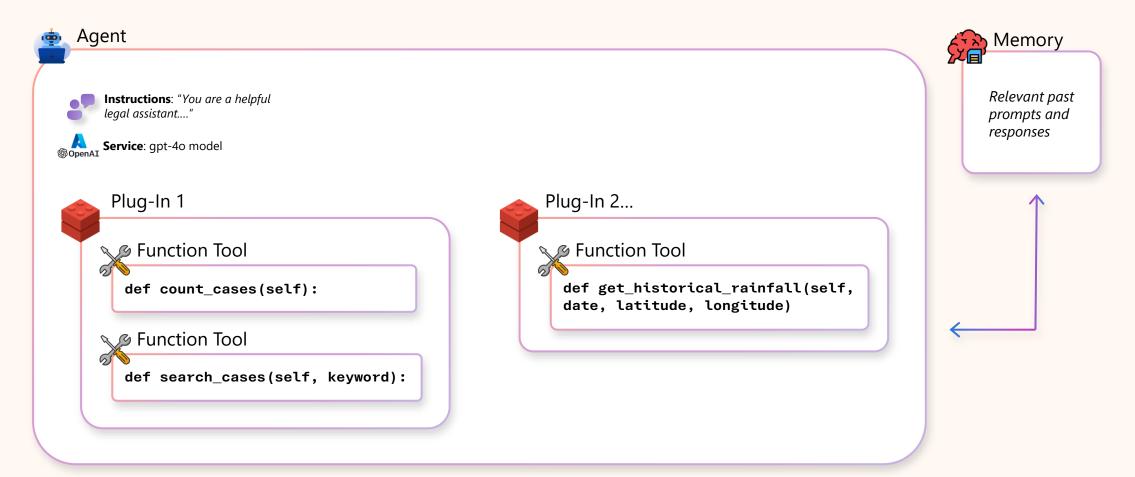
## Lab Part 3 – Build an Agentic App

(Work from the VS Code Notebook)

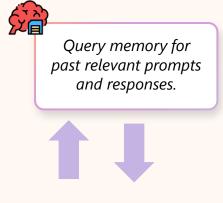
- 1. Setup Python Imports
- 2. Setup environmental connection variables
- 3. Create Semantic Kernel Plugin for Basic Database Queries
- 4. Test Run our New Agent
- 5. Improve Agent Accuracy with Semantic Re-ranking
- 6. Add GraphRAG Plug-In to Agent
- 7. Re-assemble our Agent with new GraphRAG Plug-In
- 8. Add a Weather Service Plug-In
- 9. Re-Test our Agent with all Plug-Ins Together
- 10. Add memory into the Agent

## Agents

#### Semantic Kernel

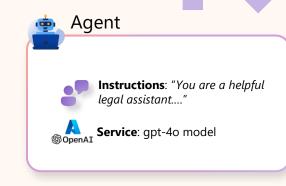


# **Agents**Logical Flow



#### Prompt:

"How many cases are there, and high accuracy is important, help me find 10 highly relevant cases related to water leaking in client's apartment."



OpenAl Functions
Mode. Decide which
Function Tools to call

Chosen Functions Invoked. Responses gathered.



Final Response provided, bringing all elements together.



Completed Composite Prompt ran through LLM a final time.



Composite Prompt created with Agent Instructions and Function Responses.

## Semantic Re-Ranking

#### Process

- 1. Takes top 100 vector search results
- 2. Re-ranks them using crossencoder model
- 3. Return top 10 most relevant items

#### Pros/cons

- Cross-encoder model performs deeper comparison at text level
- Better relevance on good models
- Requires GPU hardware to run the model

## Semantic Re-Ranking

#### **Cross Encoders**

#### Process:

 A cross-encoder model (e.g., BERT, T5, or Cohere Rerank) compares each retrieved document with the query jointly, considering context from both before ranking.

#### Efficiency:

 Higher computational cost, as every document-query pair is encoded dynamically.

#### Example Models:

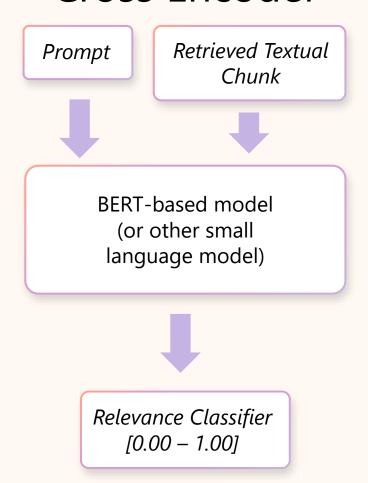
 BGE-reranker-v2-m3, MS MARCO-trained BERT Cross-Encoders, Cohere Rerank Models, T5-based Rerankers

## 2021 was a major year for efficiency improvements, making them more viable at scale.

#### Key papers:

ColBERT (2020) – Khattab & Zaharia, MonoBERT & DuoBERT (2020) – MacAvaney et al., TAS-B (2021) – Hofstätter et al., ColBERTv2 (2021) – Santhanam et al.

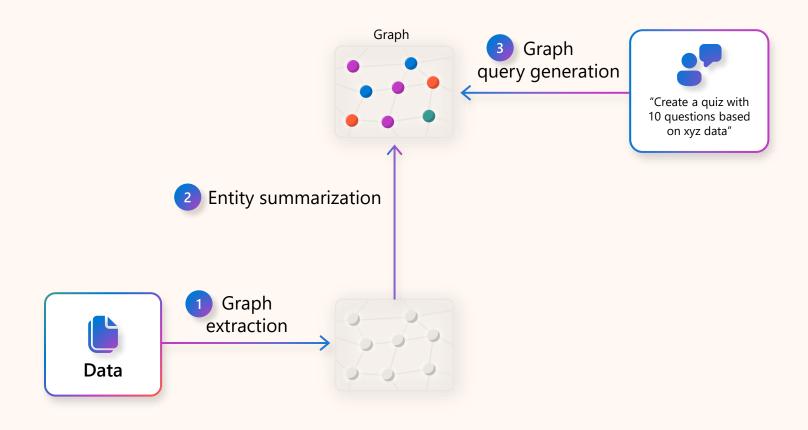
#### Cross Encoder



## **GraphRAG – Option 1**

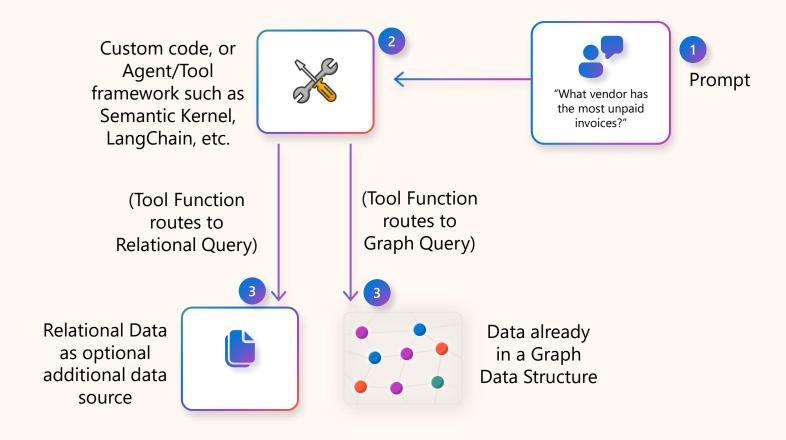
GraphRAG via Post-Processing Graph Construction

(Knowledge Graph Generation)



## **GraphRAG – Option 2**

GraphRAG via Native Graph Data Querying



## **Related Sessions**

**BRK211** 

Develop Smarter Agentic Apps with PostgreSQL, GraphRAG & LangChain

Date: Tuesday, May 20

**Time**: 11:45 AM - 12:45 PM Pacific Daylight Time

Location: Arch, 705 Pike, Level 4, Room 4C-4

# GitHub Repo

https://github.com/jjfrost/pg-sk-agents-lab

## **Evals**

https://aka.ms/build/evals

