

# Al 3-in-1: Agents, RAG, and Local Models



Presented by Brent Laster &

### Tech Skills Transformations LLC

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### About me



- Founder, Tech Skills Transformations LLC
- https://getskillsnow.com
- info@getskillsnow.com
- Long career in corporate as dev, manager, and director in DevOps and other areas
- Author

\* \* \* 10 0

- O'Reilly "reports"
- **Books** 
  - Professional Git
  - Jenkins 2 Up and Running
  - Learning GitHub Actions
  - Learning GitHub Copilot
  - AI-Enabled SDLC
- Speaker
- Social media
- LinkedIn: brentlaster
- X: @BrentCLaster
- **□** Bluesky: brentclaster.bsky.social
- GitHub: brentlaster

















\$ ChatGPT

LISTED BELOW ARE A FEW OF THE TECHNOLOGIES FOR WHICH WE OFFER HANDS-ON TRAINING. THESE CAN BE **CUSTOMIZED FOR ANY** SIZE TEAM FROM 1-100 AND FOR ANY LEVEL FROM BEGINNER TO ADVANCED.

- ArgoCD
- Containers
- Docker
- Gerrit
- · Git
- GitHub Actions GitHub Codespaces
- GitHub Copilot
- GitHub Foundations
- GitHub Security
- GitLab
- GitOps • Gradle
- Grafana
- Helm
- Jenkins Kubernetes
- Kustomize
- LLMs
- Prometheus Tekton
- VS Code



































Running models locally



## Why run models locally?

- Privacy no need to share data
- Gives you control over setup, configuration, and customization options
  - Can tailor LLM to your needs, experiment with settings, integrate into your infra
- Can easily swap between different models for different tasks
- Work in offline mode
- Cost savings
  - No charges for subscriptions or API calls
- No censoring of results





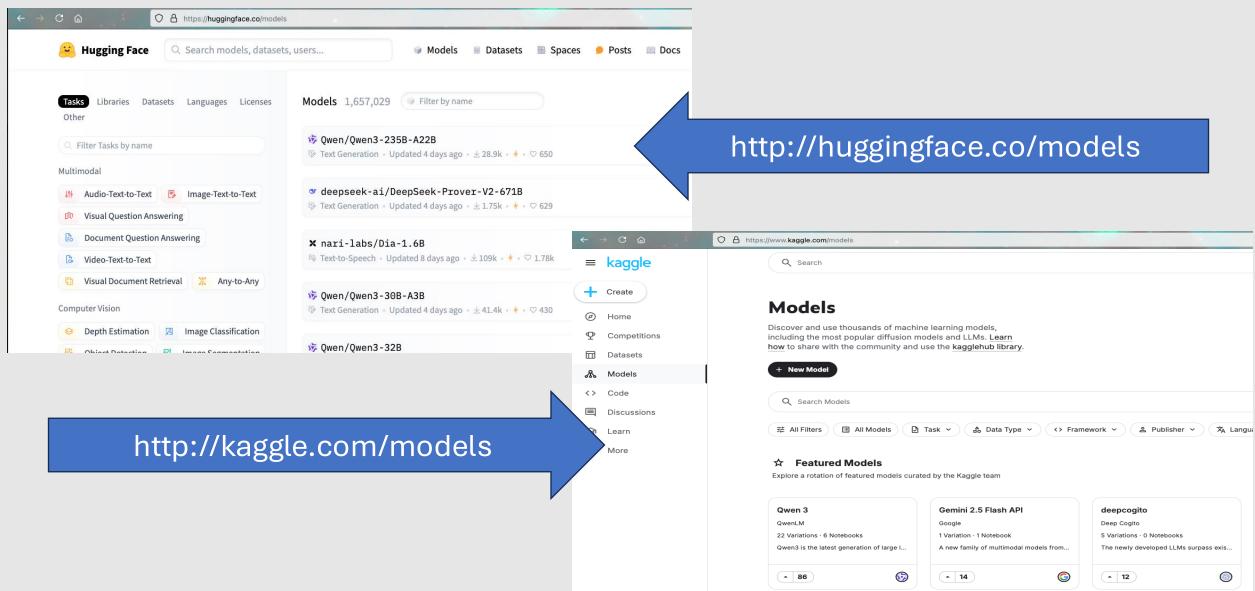








## Where to get models +



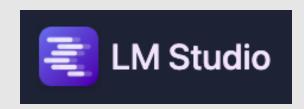


## Options for running LLMs locally

GPT4All 3.0

The Local LLM Desktop App
All new Ul and improved LocalDocs chat

- GPT4All <a href="https://github.com/nomic-ai/gpt4all">https://github.com/nomic-ai/gpt4all</a>
- LM Studio <a href="https://lmstudio.ai">https://lmstudio.ai</a>
- Jan AI <a href="https://jan.ai">https://jan.ai</a>
- llama.cpp https://github.com/ggerganov/llama.cpp
- LlamaFile <a href="https://github.com/Mozilla-Ocho/llamafile">https://github.com/Mozilla-Ocho/llamafile</a>
- Ollama <a href="https://ollama.com/">https://ollama.com/</a>
- HuggingFace Transformers https://huggingface.co/docs/transformers
- More!







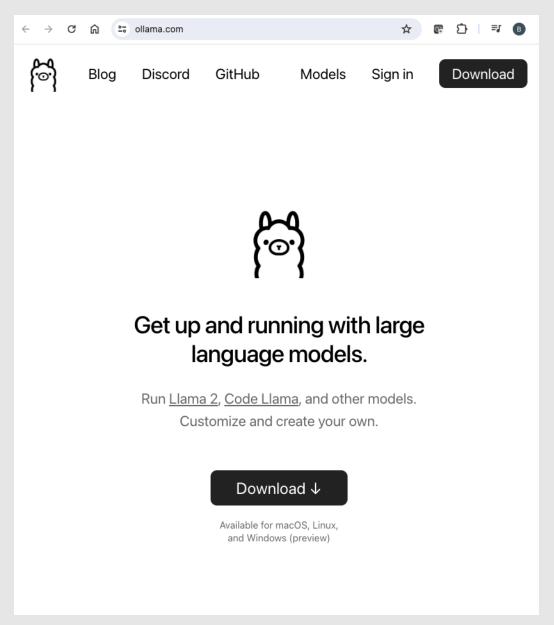






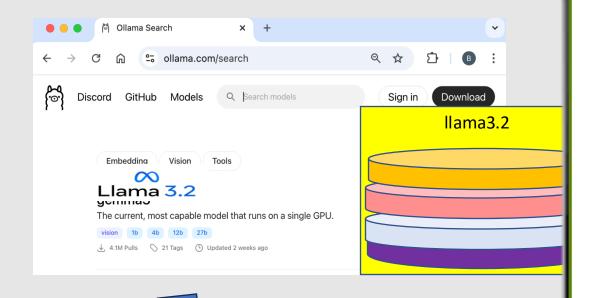


- Command line tool for downloading, exploring and using LLMs on local machine
- open source
- supports most of Hugging Face's popular models
- allows uploading new ones
- Links:
  - main site: <a href="https://ollama.com">https://ollama.com</a>
  - GitHub: <a href="https://github.com/ollama/">https://github.com/ollama/</a>
- Advantages
  - speeds up and simplifies
    - » model selection and download
    - » configuring endpoints
    - » integration with Python or JavaScript codebase





# Working with Ollama #1



o (py\_env) @gwstudent2 → /workspaces/3in1 (main) \$ □ \

ollama pull

Ollama





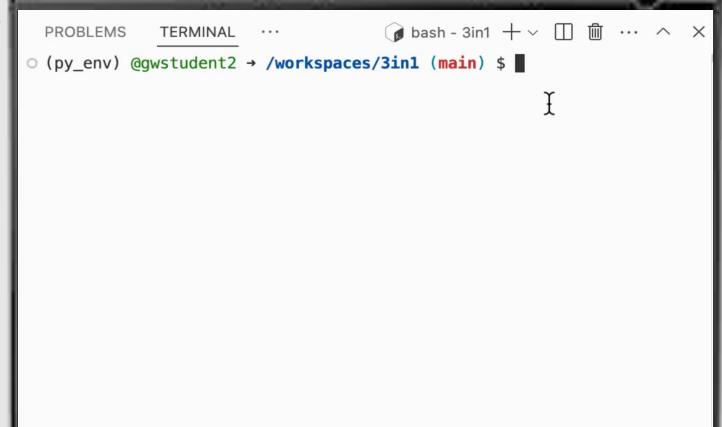
## Working with Ollama #2

>>> Briefly explain what an AI model is

### ollama run









# Working with Ollama #3

```
a bash - 3in1 <u>∧</u> + ∨ □ i ii
  PROBLEMS
               TERMINAL
o (py_env) @gwstudent2 → /workspaces/3in1 (main) $ □
```

## ollama serve



http://localhost:11434/v1

llama3.2



Demo #1 – Simple program to work with local model

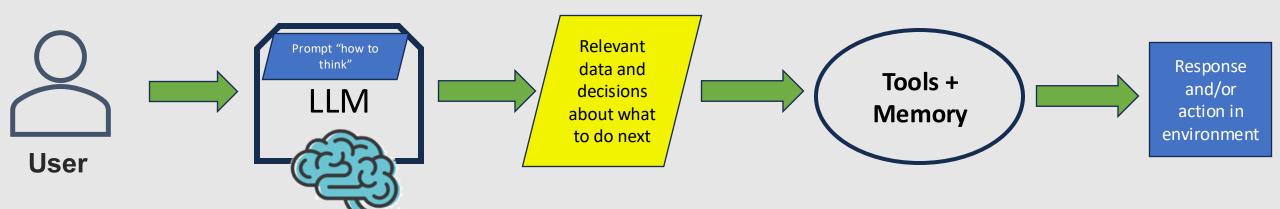


### Agents



## What is an Al Agent?

- A system that operates within an environment by using sensors to perceive information, a decision-making mechanism to process and reason about the data, and actuators to take actions that influence or update/respond to the environment
- This interaction enables the agent to achieve specific goals autonomously while continuously learning and adapting over time
- Agents use LLMs to identify key data, drive decisions, and communicate naturally





## Architectural Features of Al Agents

#### **Planning**



- Al autonomously outlines and executes a logical series of steps for accomplishing a given objective.
- Provides the AI with a way to dynamically adapt its approach based on real-time data and feedback..
- Might employ reflection to evaluate and improve responses
- Example: A research agent plans search → summarize → generate report.

#### Tool Use



- Al agents interact with external APIs, databases, and functions.
- Enhances LLMs by providing access to realworld knowledge.
- Reduces hallucinations by using retrievalaugmented generation (RAG).
- Example: Calling a Python function to perform complex calculations.

### Memory



- Short-term handles tasks; long term stores knowledge and experience
- Memory ensures consistency and efficiency in multi-step decisions
- Memory recalls preferences to enhance personalization and user experience
- Example: Storing user preferences for future reference or personalized responses



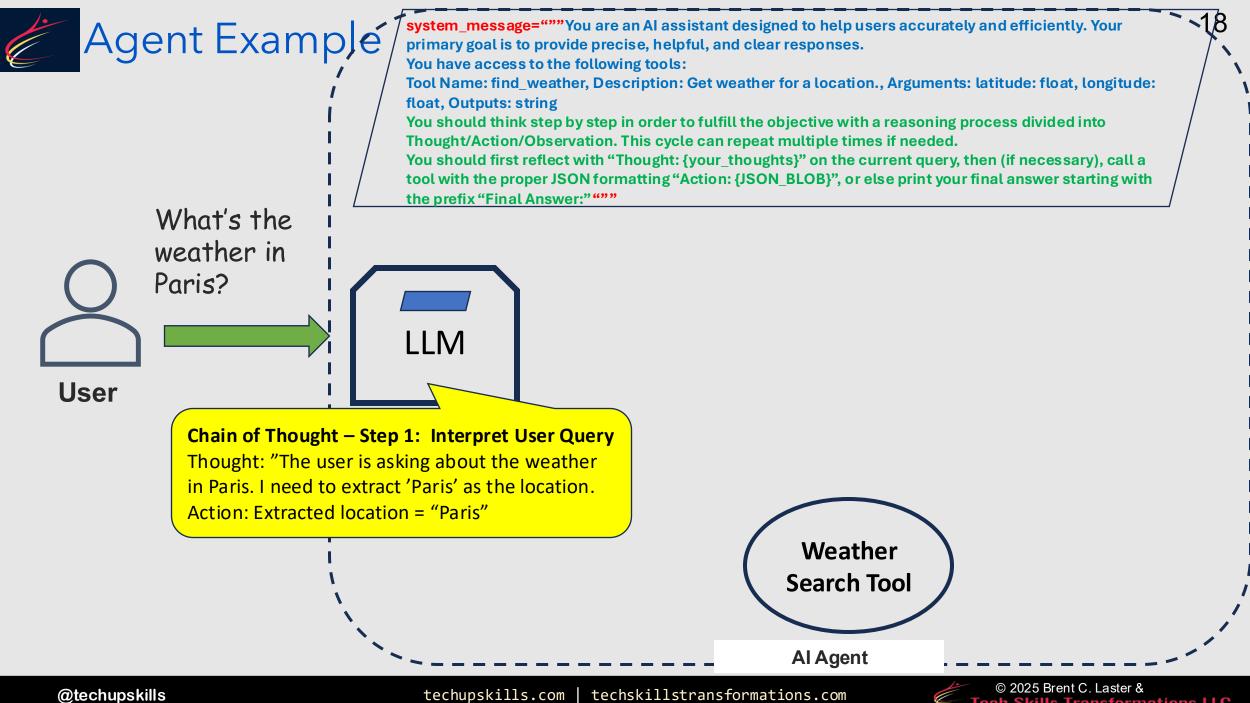
You have access to the following tools:

Tool Name: find\_weather, Description: Get weather for a location.,

Arguments: latitude: float, longitude: float, Outputs: string

You should think step by step in order to fulfill the objective with a reasoning process divided into Thought/Action/Observation. This cycle can repeat multiple times if needed.

You should first reflect with "Thought: {your\_thoughts}" on the current query, then (if necessary), call a tool with the proper JSON formatting "Action: {JSON\_BLOB}", or else print your final answer starting with the prefix "Final Answer:"""



You have access to the following tools:

Tool Name: find\_weather, Description: Get weather for a location., Arguments: latitude: float, longitude: float, Outputs: string

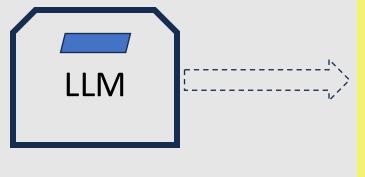
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Par

User

What's the weather in Paris?



```
AIResponse(
   tool calls=[{
      name:
"find_weather"
      parameters: {
          latitude:
"48.8566"
          longitude:
"2.3522"
                                  name:
                              "find_weather"
      id: "call tool123"
                                  parameters:
   Agent executes tool call
                                      latitude:
                              "48.8566",
                                      longitude:
         Weather
                              "2.3522",
        Search Tool
```

**Al Agent** 

You have access to the following tools:

Tool Name: find\_weather, Description: Get weather for a location., Arguments: latitude: float, longitude: float, Outputs: string

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AIResponse(

What's the weather in Paris?

User

```
LLM
```

"call\_tool123"

```
tool_calls=[{
    name:
    "find_weather"
        parameters: {
        latitude:
    "48.8566",
        longitude:
    "2.3522",
        },
        id: "call_tool123",
        type: "tool_invoke"
/eathedtool returns result
```

```
Weather tool returns result
```

```
Weather
Search Tool
```

```
Al Agent type: "t
```

ToolResponse(
content="53 and rainy",

name="find\_weather",
tool invoke id:

name:

"48.8566",

"2.3522",

"find\_weather"

parameters:

latitude:

longitude:

You have access to the following tools:

Tool Name: find\_weather, Description: Get weather for a location., Arguments: latitude: float, longitude: float, Outputs: string

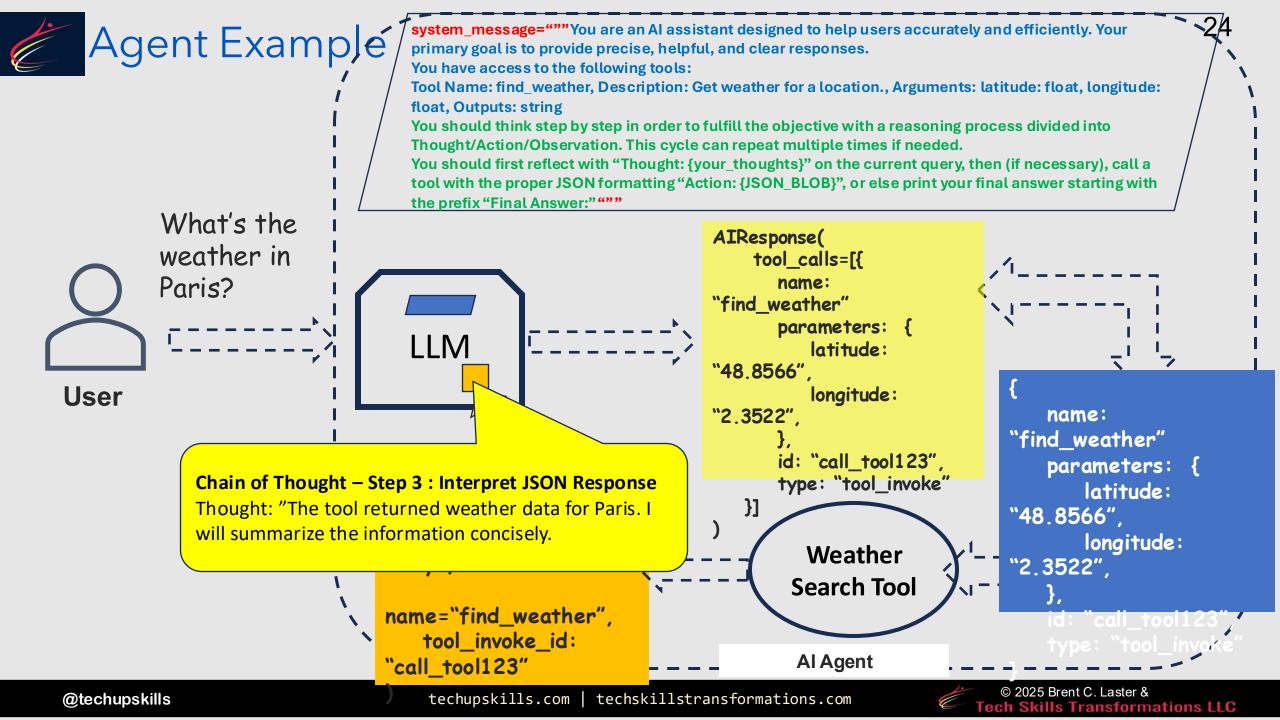
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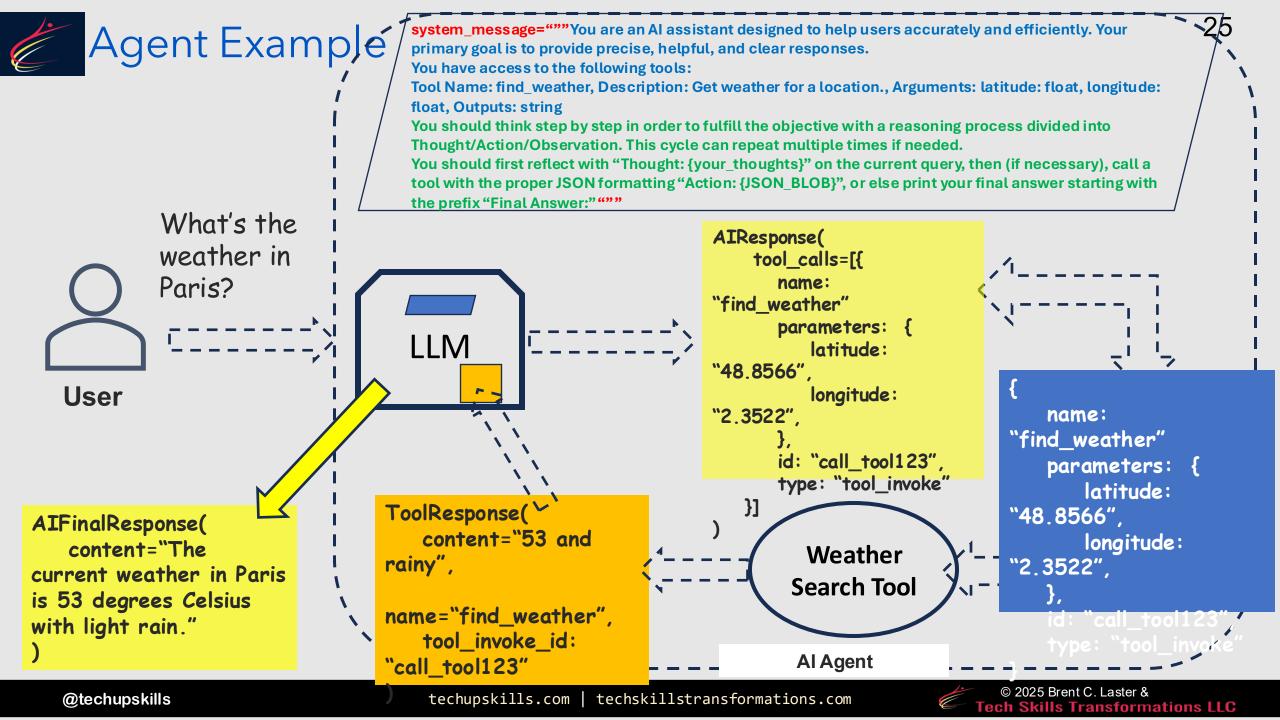
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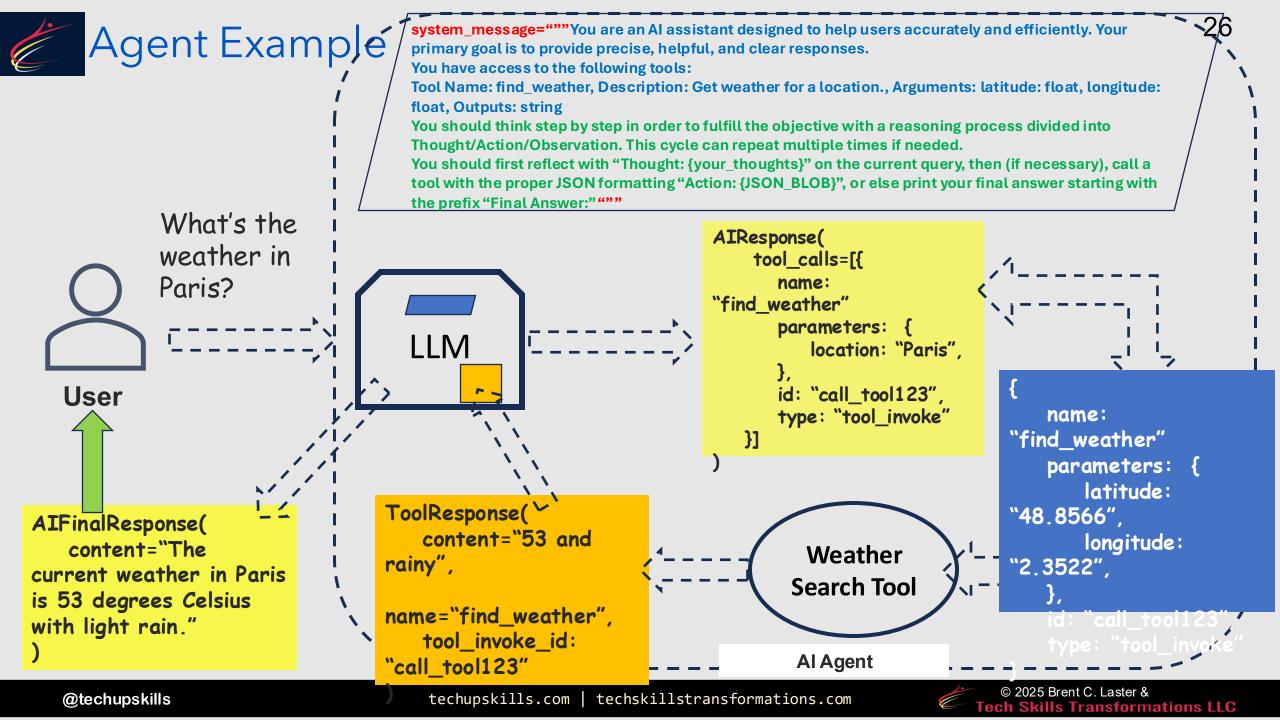
What's the weather in Paris?

User

```
AIResponse(
                                     tool calls=[{
                                       name:
                                 "find_weather"
                                       parameters: {
  LLM
                                           latitude:
                                 "48.8566"
                                           longitude:
                   Agent includes tool
                                                                  name:
                        output in
                                                               "find_weather"
                  message/prompt back
                                        d: "call_tool123",
                                                                   parameters: {
                        to model
                                       type: "tool_invoke"
                                                                      latitude:
ToolResponse(
                                                               "48.8566",
   content="53 and
                                                                      longitude:
                                          Weather
rainy",
                                                               "2.3522",
                                         Search Tool
name="find_weather",
   tool invoke id:
                                         Al Agent
"call_tool123"
```









Demo #2 – Adding agency to our code

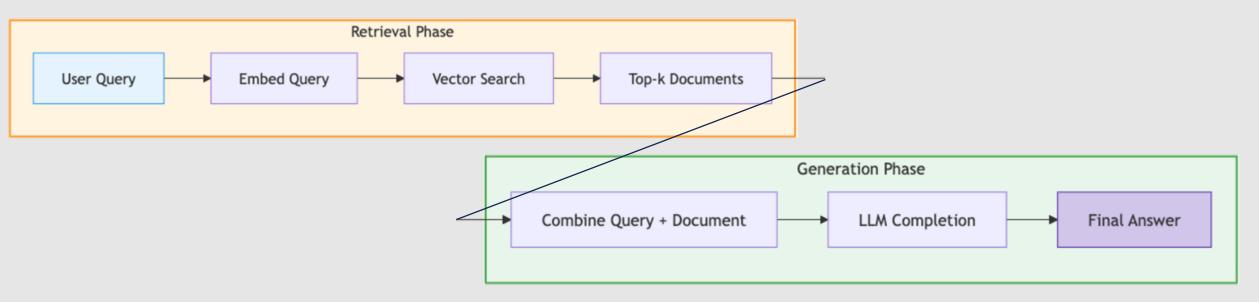


RAG



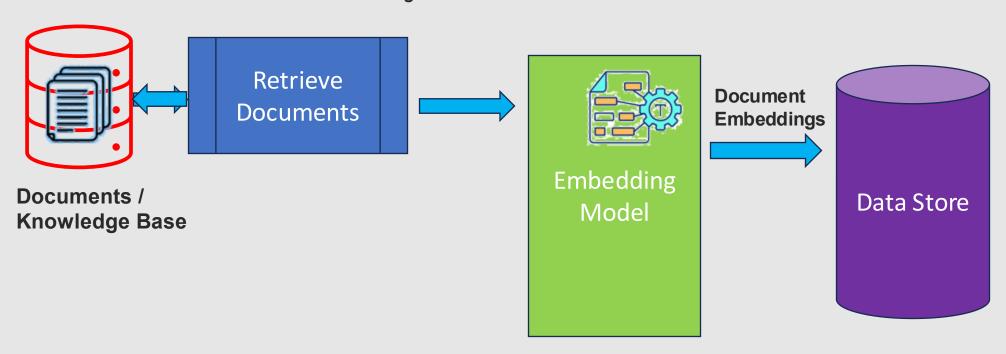
### What is RAG and how does it work?

- Combination of retrieval and generation: RAG combines information retrieval (like a search engine) with text generation (like a language model).
- **Uses external knowledge**: Instead of relying solely on pre-trained knowledge, RAG retrieves relevant documents or data from an external source (like a database or private knowledge bases) to generate more accurate and up-to-date responses.
- Improves factual accuracy: By pulling in real-time data or documents, RAG reduces the risk of generating factually incorrect or outdated information.
- Two-step process:
  - Retrieve: The model searches for relevant information from a knowledge source.
  - Generate: It then uses the retrieved data to create a coherent, contextually accurate answer.



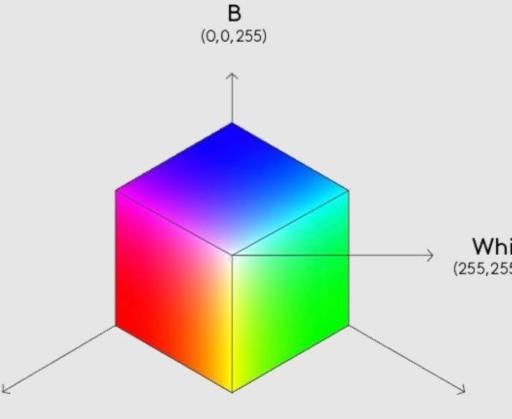
Source: https://blogs.nvidia.com/blog/what-is-retrieval-augmented-generation/

#### Doc Ingestion and Retrieval



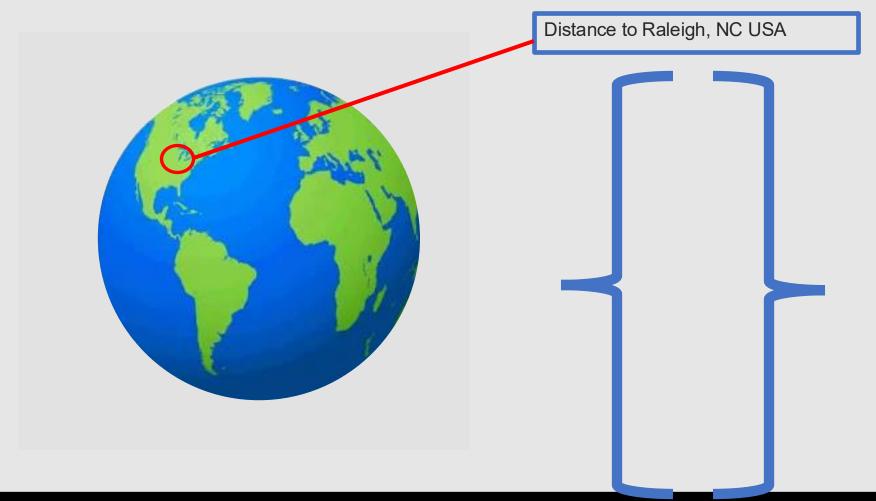
- You provide data sources and point application to them
- Info is retrieved from the data sources and tokenized, embedded and stored in a data store
- For queries/prompts, application gathers results (most relevant ones) from the vector database with your data

- Embeddings represent text as sets of numeric data tensors (lots of dimensions)
- Each dimension stores some info about the text's meaning, context, or syntactical aspects
- Words or sentences with similar meanings are stored closer together in the vector space
  - If two pieces of text are similar syntactically, they will have similar embeddings (smaller distance between their vectors)
- During training, models learn to place text with similar meanings closer together in the embedding space
- Common pre-trained models used for generating embeddings include BERT and variants (RoBERTa, DistilBERT)
- Once you have embeddings, you can use them for NLP tasks like semantic search, text classification, sentiment analysis

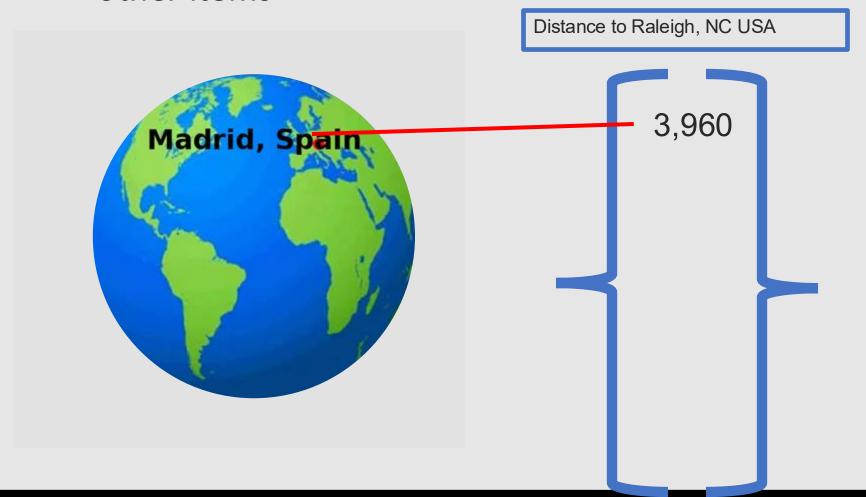


R (255,0,0)

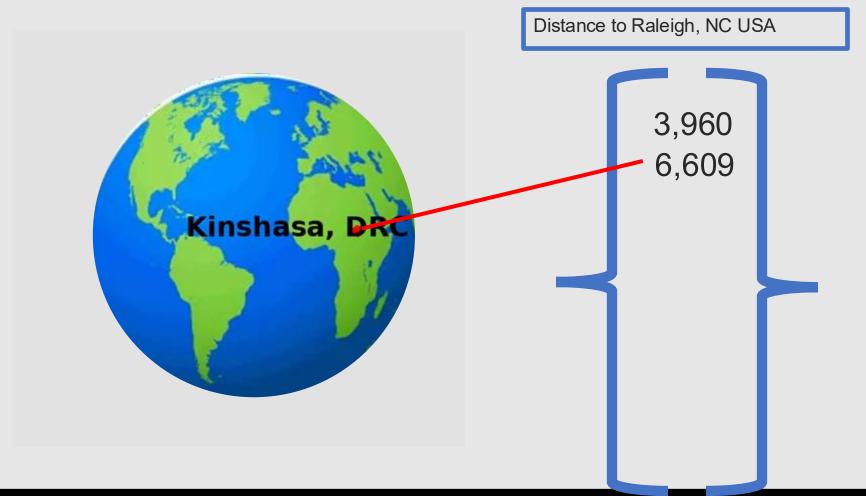




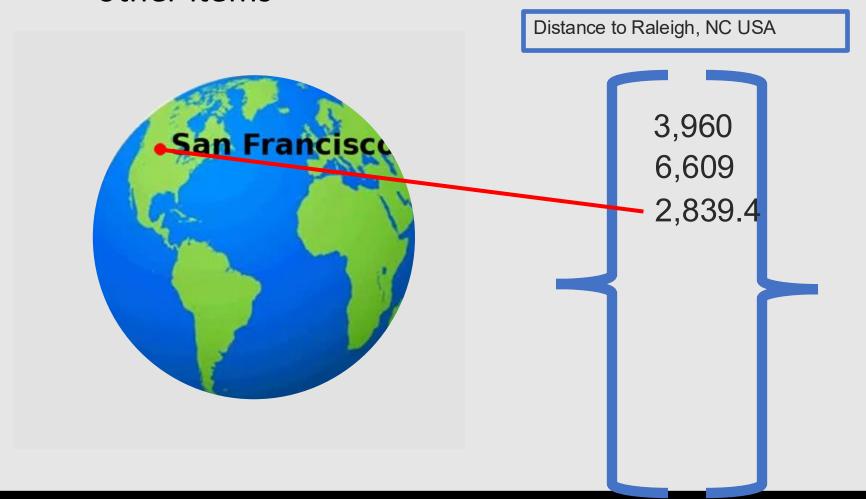




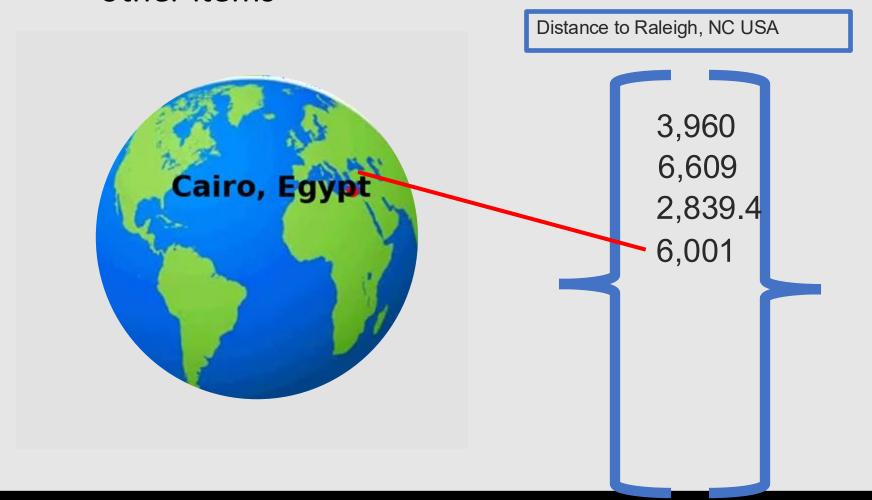




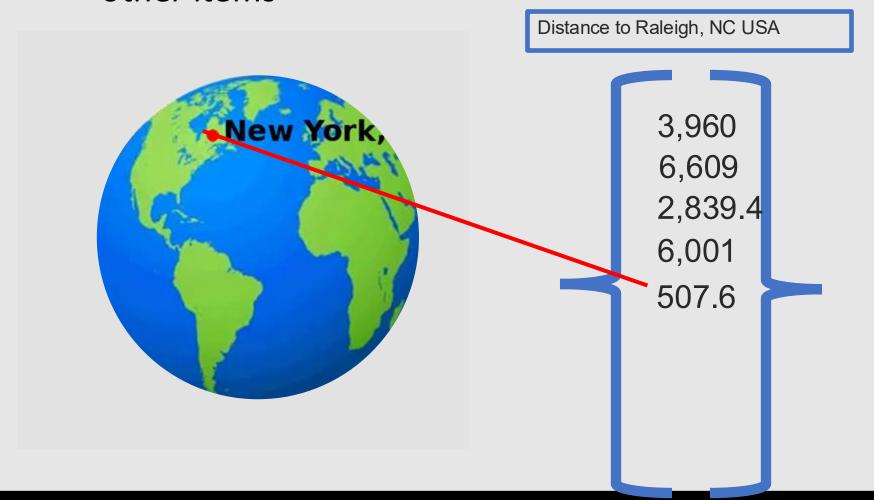




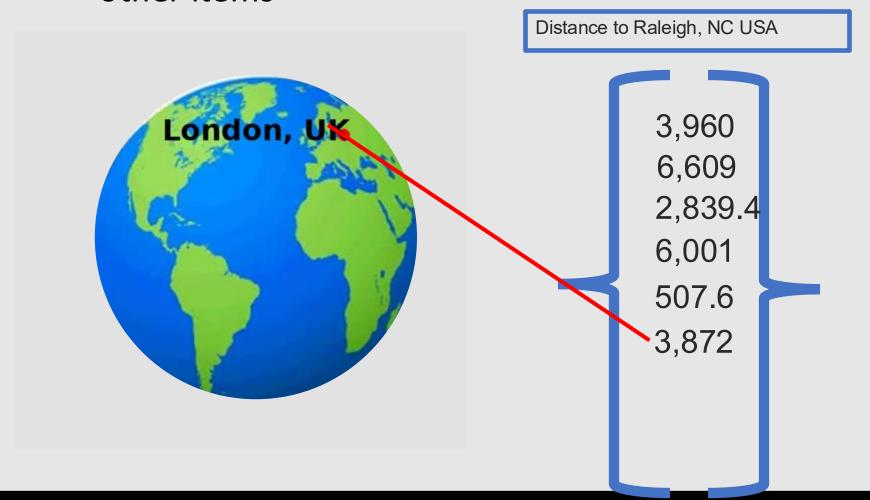








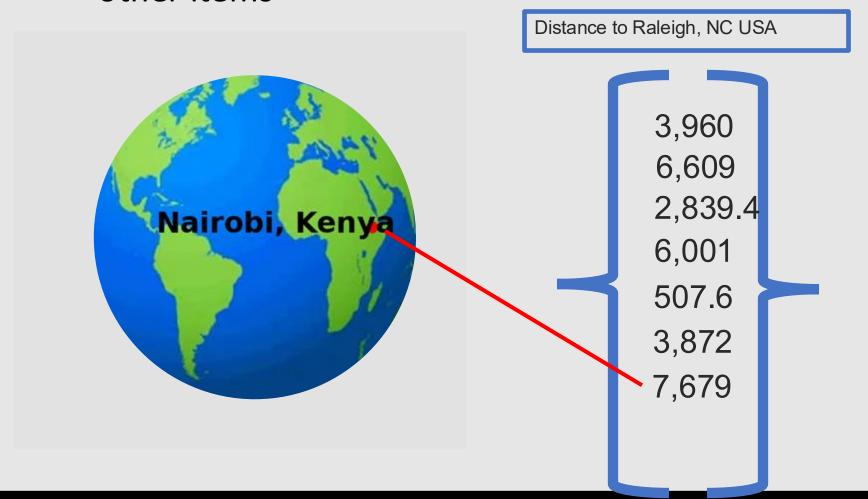






## Understanding vectors in Al

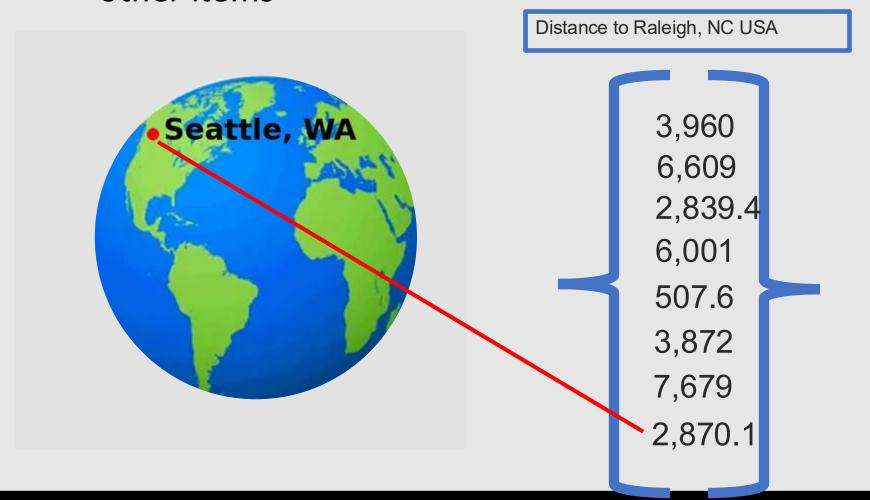
 Collection of data points that encapsulate an item's relationship to other items





## Understanding vectors in Al

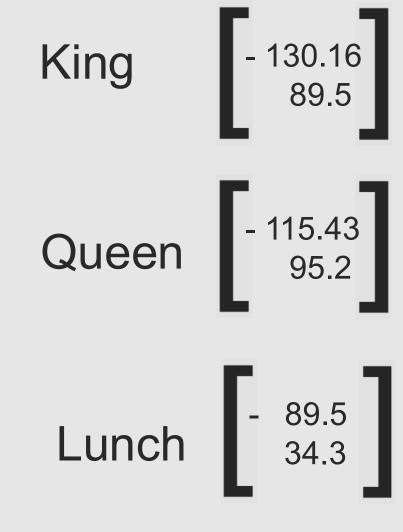
 Collection of data points that encapsulate an item's relationship to other items





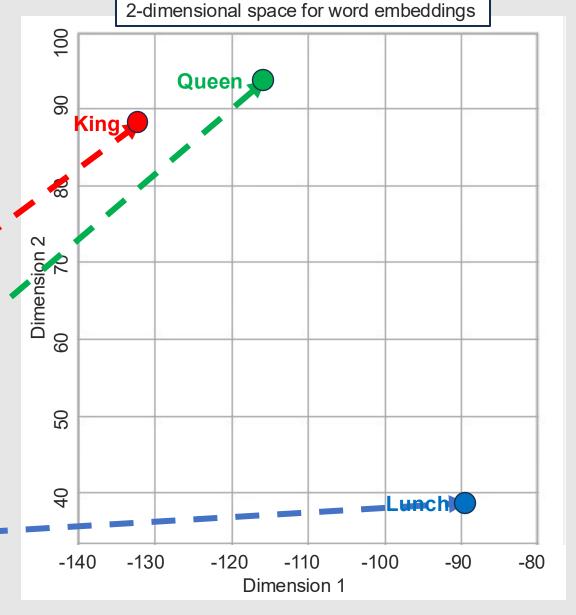
## Semantic meaning / relationships

- Suppose we have 3 words
- King and Queen are more similar to each other than they are to lunch
- In order for neural net to understand the relationships, each word needs to be represented as a vector
- Suppose each word is represented by a 2dimensional vector



- Plotting in 2-dimensional embedding space shows relationships
- Way to let NN understand relationships between words
- We want the NN to learn that King and Queen are more similar to each other than they are to lunch

King [-130.16]
Queen [-115.43]
Lunch [-89.5]
----



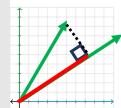


# Searching for Vectors - similarity metrics

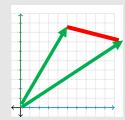
3 metrics commonly used to determine similarity of two vectors (2-dimensional representation)



**Cosine similarity** - measure the angle between two vectors; values from -1 to 1; 1 = both point in same direction; -1 point in opposite directions; 0 = orthogonal (perpendicular)



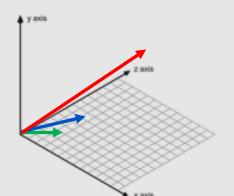
Dot product / inner product - measures how well 2 vectors align with each other; values from - ∞ to ∞; positive values indicate vectors are in same direction; negative values indicate opposite directions; 0 = orthogonal



**Euclidean distance** - measures the distance between two vectors; values from 0 to  $\infty$ ; 0 = identical; larger numbers farther apart

#### imagine 3 vectors - a,b,c

$$a = \begin{bmatrix} .01 \\ .07 \\ .1 \end{bmatrix}$$
  $b = \begin{bmatrix} .01 \\ .08 \\ .11 \end{bmatrix}$   $c = \begin{bmatrix} .91 \\ .57 \\ .6 \end{bmatrix}$ 



#### Cosine similarity

$$sim(u,v) = \frac{u \cdot v}{\|u\| \|v\|} = \frac{\sum_{i=1}^{n} a_n b_n}{\sqrt{\sum_{i=1}^{n} u_n^2} \sqrt{\sum_{i=1}^{n} v_n^2}}$$

$$sim(a,b) = \frac{(d_1 * b_1) + (a_2 * b_2) + (a_3 * b_3)}{\sqrt{a_1^2 + a_2^2 + a_3^2} \sqrt{b_1^2 + b_2^2 + b_3^2}}$$

$$= \frac{(0.01 * 0.01) + (0.07 * 0.08) + (0.1 * 0.11)}{\sqrt{0.01^2 + 0.07^2 + 0.1^2} \sqrt{0.01^2 + 0.08^2 + 0.11^2}}$$

#### Dot product / inner product

$$u \cdot v = |u||v|\cos\theta = \sum_{i=1}^{n} a_n b_n \qquad a \cdot b = (a_1 b_1) + (a_2 b_2) + (a_3 b_3)$$
  
=  $(0.01 * 0.01) + (0.07 * 0.08) + (0.1 * 0.11)$ 

0.0167

$$d(u, v) = \sqrt{\sum_{i=1}^{n} (u_i - v_i)^2}$$

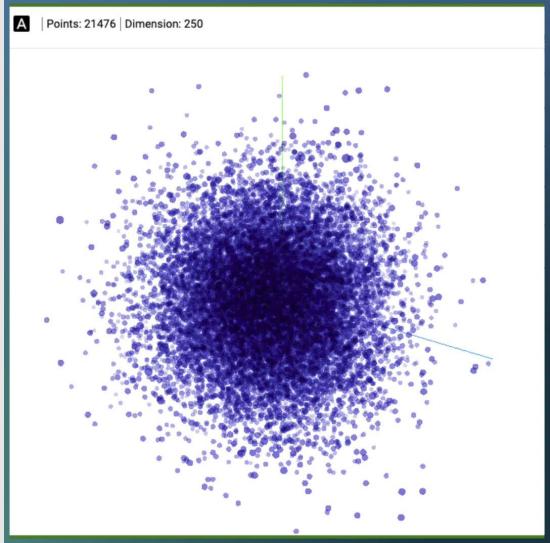
0.9998

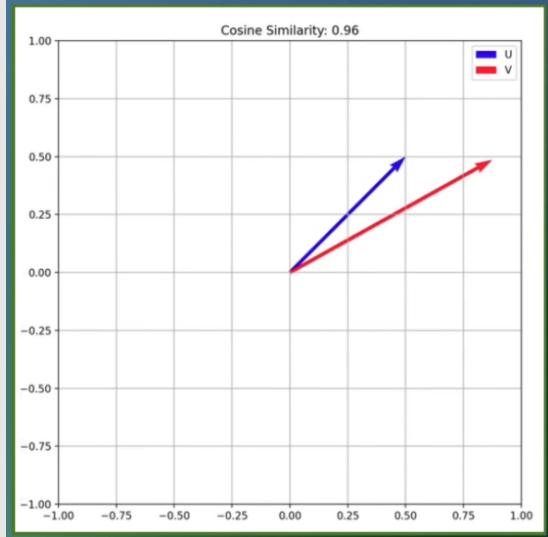
Euclidean distance  $\overline{d(a,b)} = \sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2 + (b_3 - a_3)^2}$  $= \sqrt{(0.01 - 0.01)^2 + (0.08 - 0.07)^2 + (0.11 - 0.1)^2}$ 

edit: https://towardsdatascience.com/similarity-metrics-in-nlp-acc0777e234c



# Visualizing Embeddings and Vector Similarity





source: https://projector.tensorflow.org/?config=https://gist.githubusercontent.com/martin-

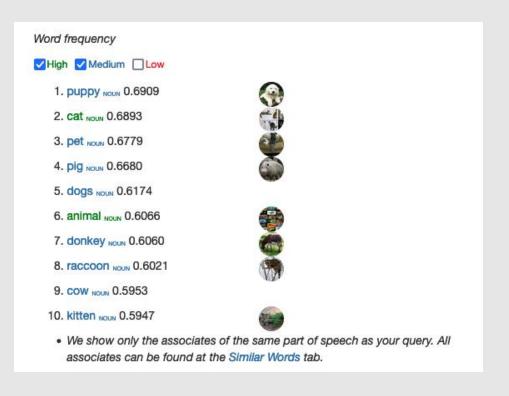
labrecque/4483ff5a104f0b56417585c3bc9a12f1/raw/57348e12a70c8d70c2c573d3dbc0122ac077556b/journaux\_config.json

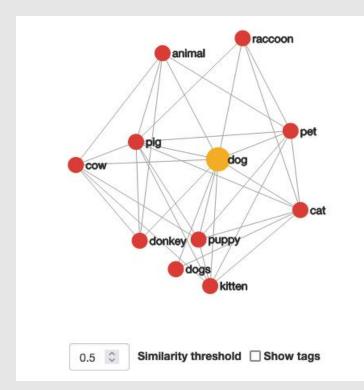




## Vectors and relationships example

Query - what words are related to "dog" in model "English Wikipedia"?





#### Show the raw vector of «dog» in model MOD enwiki upos skipgram 300 2 2021:

[-0.03301828354597092, 0.05134638026356697, 0.0036009703762829304, -0.04066073149442673, 0.10361430048942566, 0.013021323829889297, 0.028161464259028435, -0.0027567853685468435, 0.03388035297393799, -0.044882044196128845, 0.005169689189642668, -0.05818631127476692, 0.0533536821603775, 0.016616210341453552, 0.02030780538916588, -0.008570297621190548, -0.10925538837909698, -0.0708925873041153, 0.04675082117319107, -0.03091960959136486, -0.05172094330191612,0.04471702128648758. 0.008674593642354012. -0.01816382259130478. 0.05909318849444389, 0.10409023612737656, 0.05633684620261192, -0.024881813675165176, 0.01872968301177025, 0.007228093687444925, -0.023127363994717598, 0.01528552919626236, -0.0643191784620285, -0.010359424166381359, -0.06104437634348869, -0.13868044316768646, -0.023004498332738876, 0.0038427673280239105, -0.021551262587308884 -0.03467748314142227, 0.010687021538615227, -0.017304275184869766, 0.026886526495218277, -0.0030398862436413765, -0.03685504570603371, -0.06017328053712845, 0.047442398965358734, -0.10714898258447647, 0.14808930456638336, -0.06579480320215225, -0.004342162515968084, 0.06226382404565811, 0.08031187951564789, -0.055930640548467636, -0.07030591368675232, 0.015474628657102585, 0.05367768555879593, 0.0917837843298912, 0.031899698078632355, 0.055091146379709244, -0.025078952312469482, -0.048126623034477234, -0.09730836749076843, -0.07128141075372696, 0.019415033981204033, -0.025872433558106422, -0.01761292852461338, 0.015608762390911579, -0.029876720160245895, -0.008602319285273552, 0.049825914204120636, 0.06784739345312119,0.005586292129009962, -0.07148509472608566, -0.03097137063741684, -0.020296750590205193, 0.05099814385175705, 0.14920306205749512,

Source: http://vectors.nlpl.eu/explore/embeddings/en/MOD enwiki upos skipgram 300 2 2021/dog NOUN/



Vector Databases

- Specialized database that index and stores vector embeddings
- Useful for
  - fast retrieval
  - similarity search
- Offer comprehensive data management capabilities
  - metadata storage
    Vector Database
  - filtering
  - dynamic querying based on associate metadata
- Scalable and can handle large volumes of vector data
- Support real-time updates
- Play key role in AI and ML applications

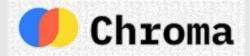










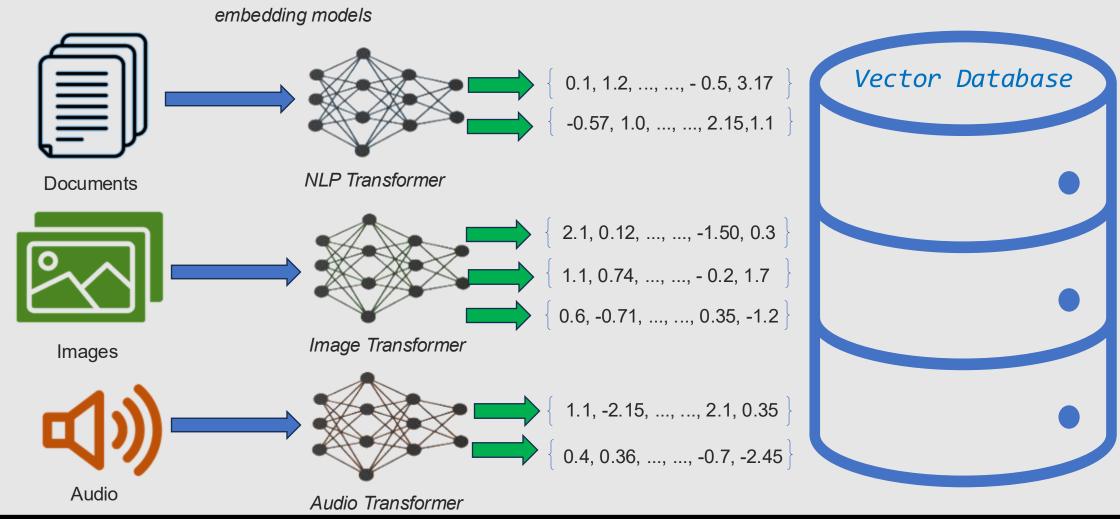






## How data gets into Vector Databases

- Data is input, converted to embeddings (vectors) and stored
- Queries are input, converted to embeddings (vectors) and then similarity metrics are used to find results ("nearest neighbors")



LLM

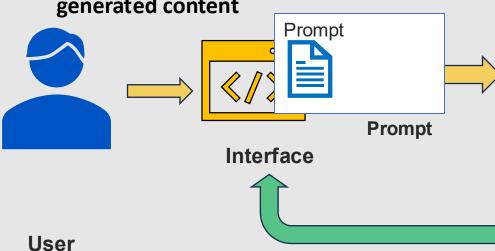
LLM Response



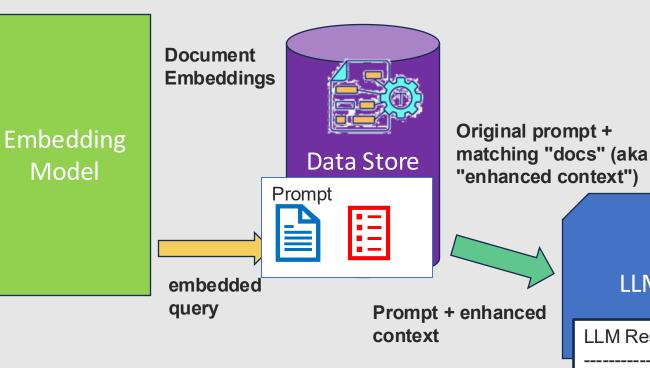
### How does RAG work?

- For queries/prompts, application gathers results (most relevant ones) from the vector database with your data
- Adds results to your regular LLM query/prompt
- Asks the LLM to answer based on the augmented/enriched query/prompt

NOTE: Items returned via RAG search are existing items from the data store, not generated content



User Query and Response Generation



response (generative)

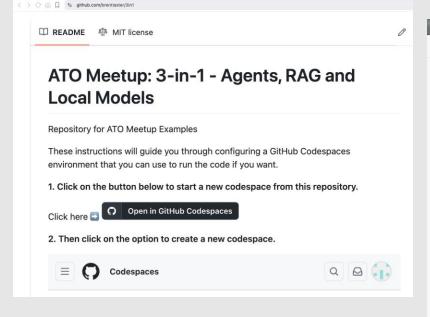


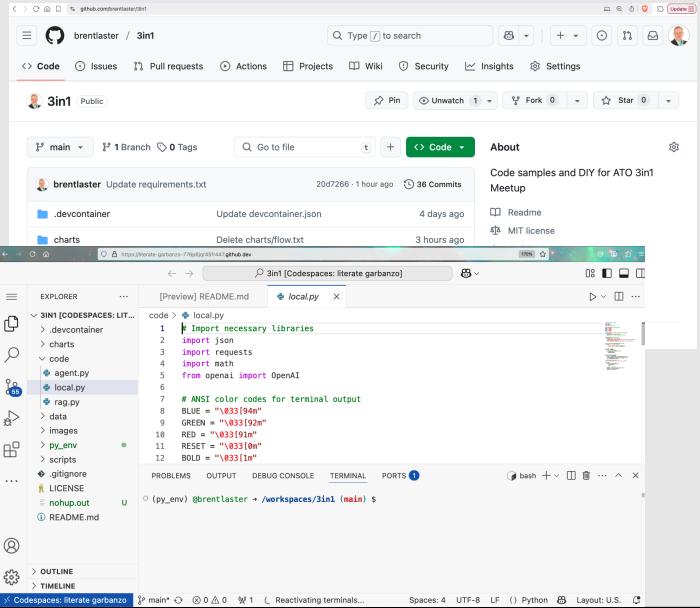
Demo #3 – Adding RAG to our code



## DIY - github.com/brentlaster/3in1

- Fork if desired
- Click on button in README to start codespace
- Follow guide.md

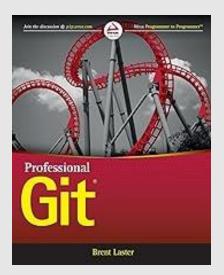


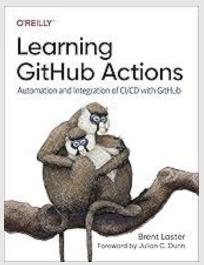


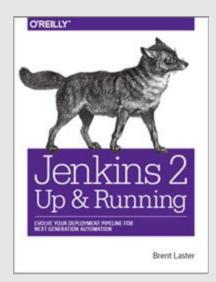


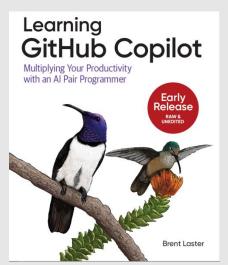
### Contact: training@getskillsnow.com

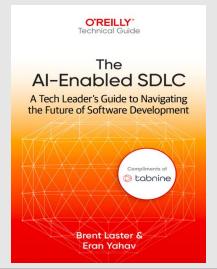
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