

# Generative AI: Data Platform Architecture

IEEE-CNSV

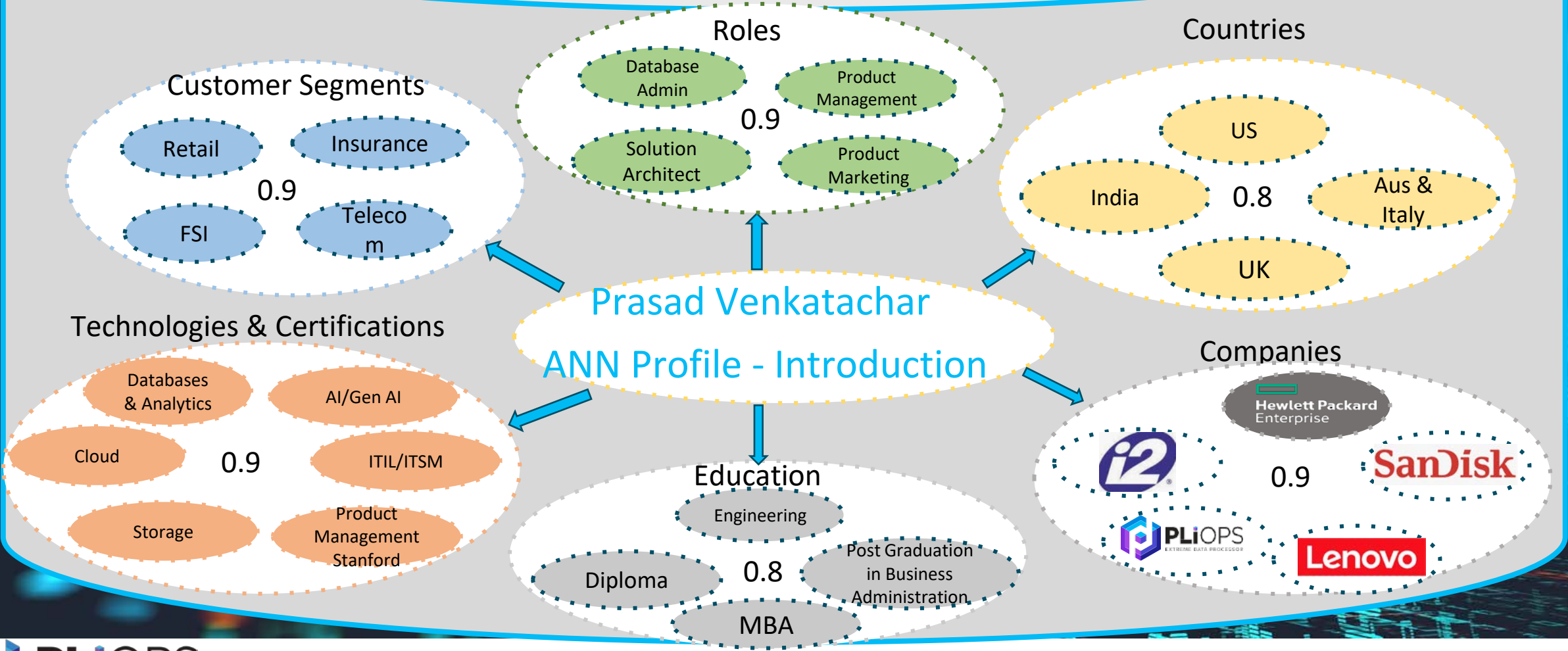
Milpitas, CA – Mar 12, 2024



Presented By:

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Products & Solutions @Pliops

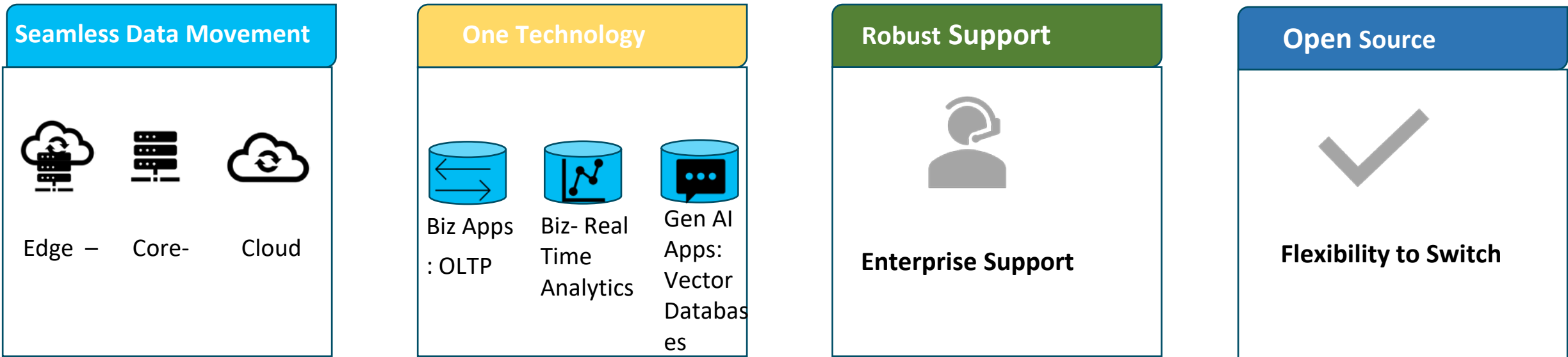
# Data Architecture in Gen AI Era



# Topics

- Data Platform Considerations
- Industry Verticals & Enterprise Functions
- Google AlloyDB Omni Solution
- How do I use it for Business Applications
  - Biz Apps: E-Commerce (Transaction Store)
  - Business Analytics
- Gen AI Intro & Adoption
- Vector Databases & RAG
- RAG Demo

# Next Data Platform Consideration



“71% of respondents in the Data and AI Trends Report plan to use databases integrated with gen AI capabilities.”

Google 2024 Survey

# Traditional Apps to Gen AI Apps Adoption

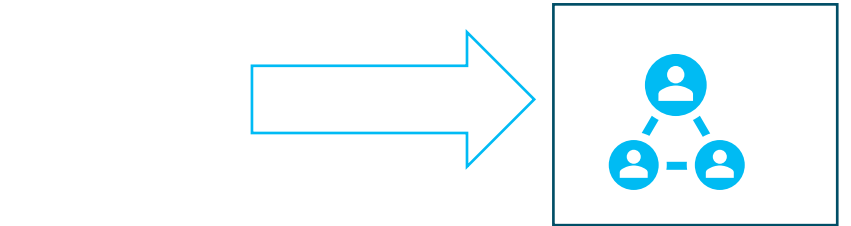
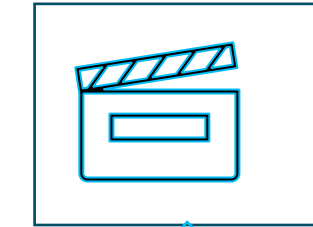
## Industry Verticals

## Content & Media

## Enterprise Functions

Retail

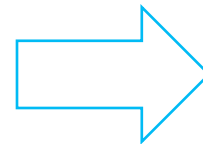
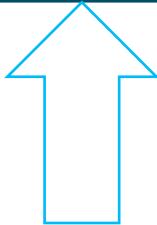
Banking & FSI



HR & Finance

Marketing

Customer Support



# One Platform: OLTP/Analytics/Gen AI

E-Commerce Applications



Transaction Database



Real Time Biz Analytics



Columnar Engine



Gen AI Chatbots



Vector Database



 AlloyDB Omni

 AlloyDB



PLiOPS  
EXTREME DATA PROCESSOR

Lenovo

XDP Data Accelerator + SSDs



Lenovo Edge Server



XDP Data Accelerator + SSDs



Lenovo Datacenter Server



# Online Transaction Processing System

# Large number of users

1K – 1M users

Online Web Users

Mobile Users

Total Transaction per Second

Simple & Short duration Transaction

1 Row Insert: 2 Sec

Failover to Standynode:  
Primary Server/DB Failure

< Secs - Minutes

Database 1

Server 1

Database 2

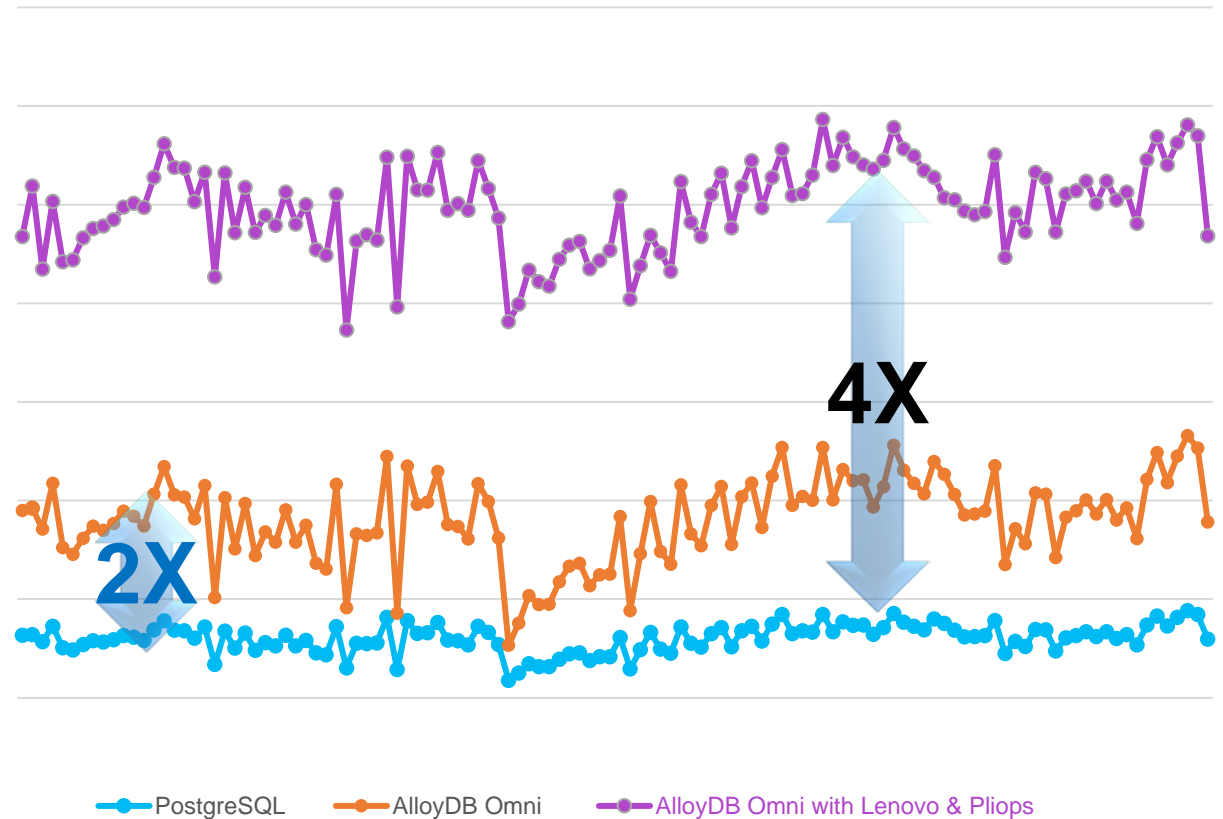
Server 2

Transaction Complete: User notified

Order Complete: 5 to 10 Seconds

# 4X PostgreSQL Performance: for Transactional Workloads

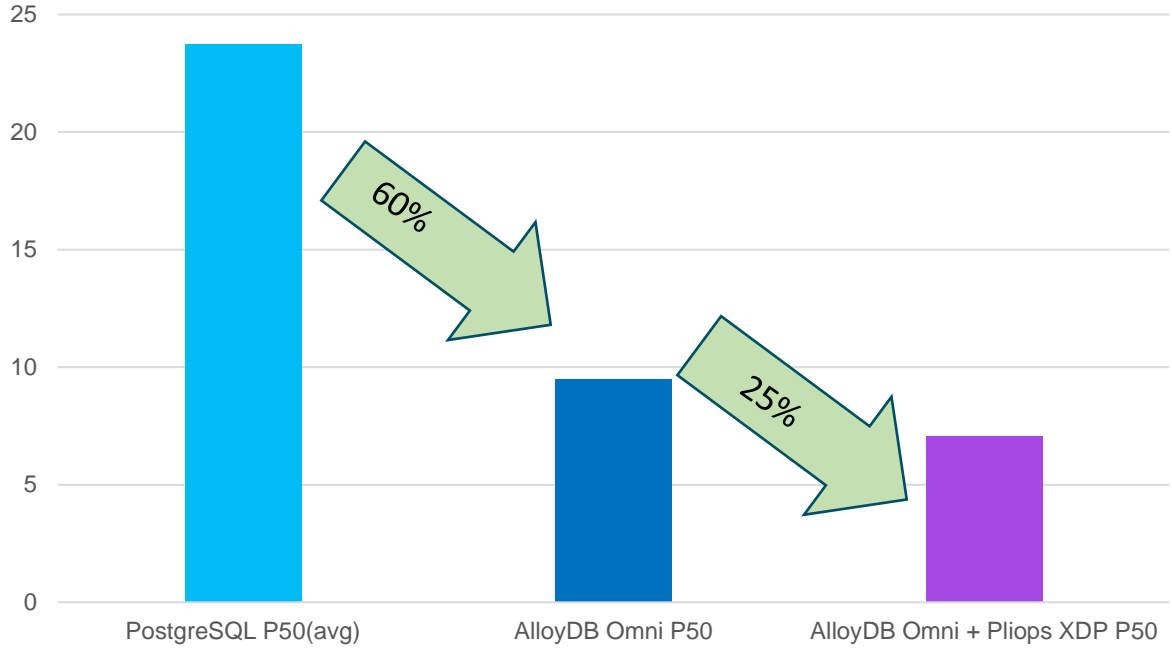
- Process more Transaction Requests
- 2X Higher Transaction Requests Postgres SQL to AlloyDB Omni
- Upto 4X Transaction Requests from PostgreSQL to AlloyDB Omni with Pliops & Lenovo
- Serve more Web and Mobile users



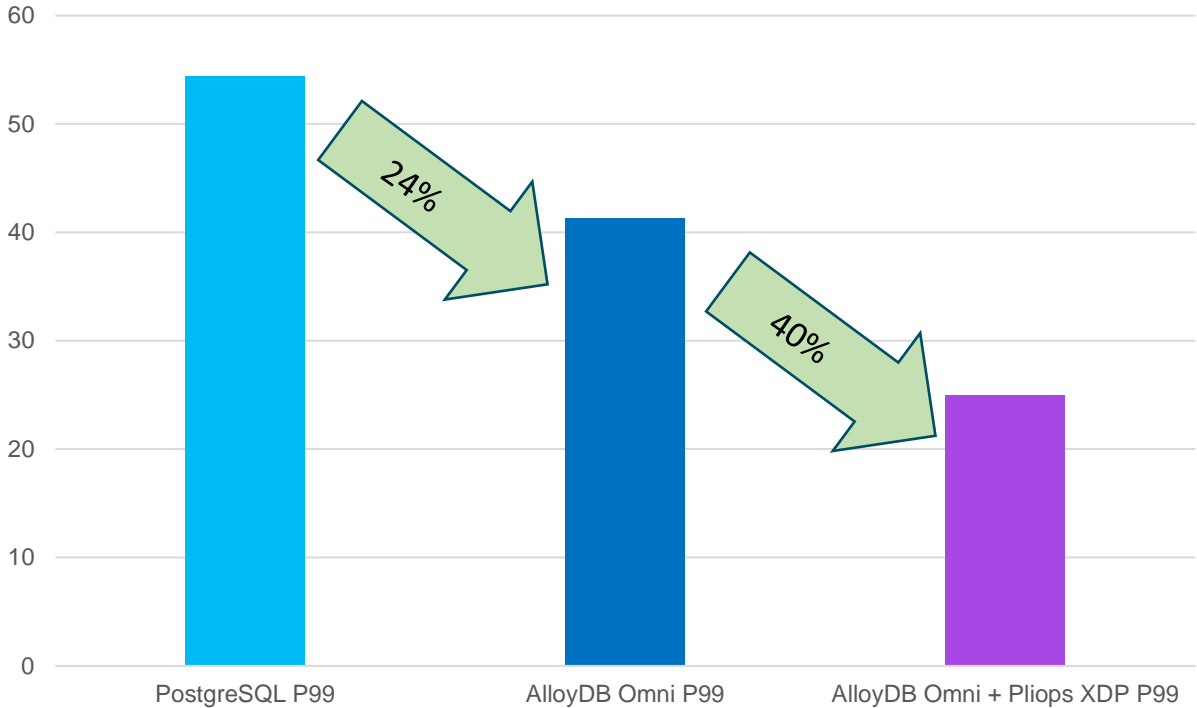


# User Experience: Average & Tail Latency Reduction

P50 : New Order Latency Avg (ms)

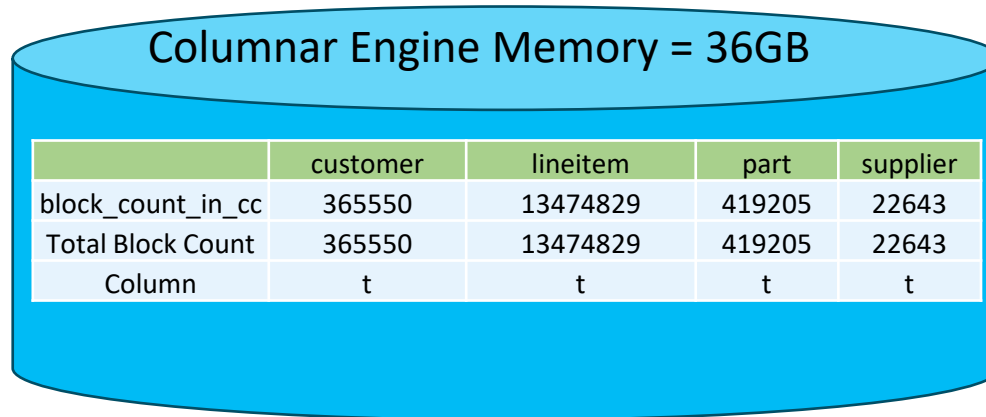
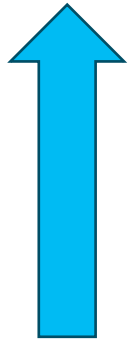


P99 : New Order Latency (ms)

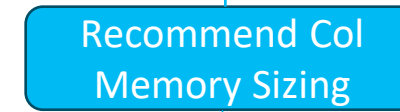


# AlloyDB Columnar Engine: Implementation & Benefits

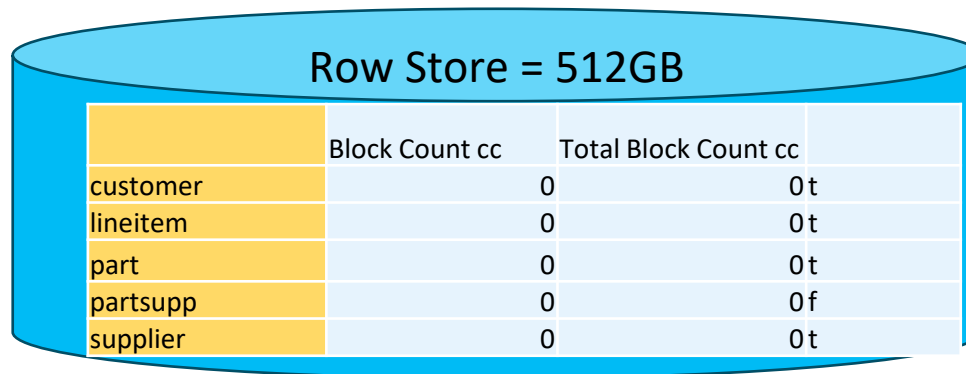
Real-time business insights



`google_columnar_engine.relations='TPC-H. Customer,,,,,,,,'`

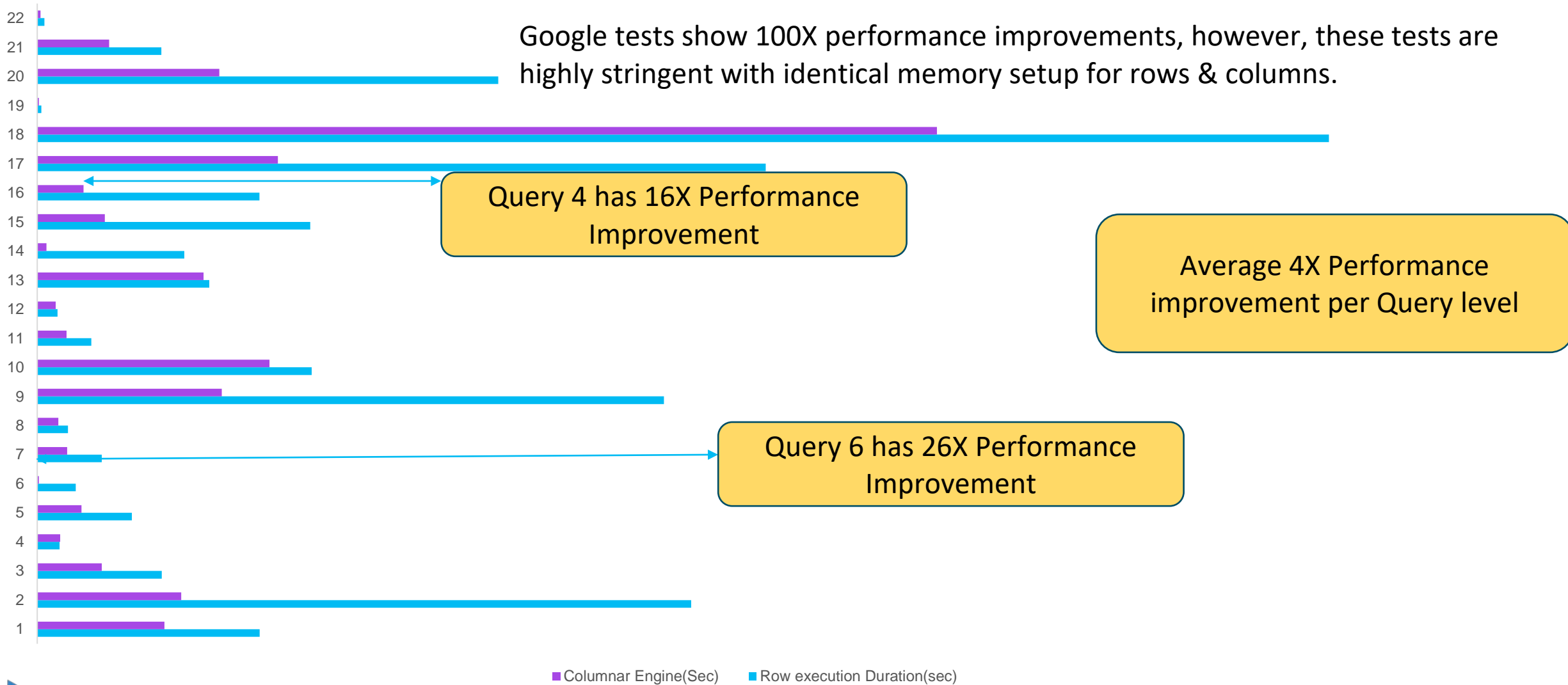


`columnar_engine.memory_size_in_mb=36GB`



# AlloyDB Omni : Row vs Columnar Execution

Google tests show 100X performance improvements, however, these tests are highly stringent with identical memory setup for rows & columns.



Query 4 has 16X Performance Improvement

Average 4X Performance improvement per Query level

Query 6 has 26X Performance Improvement

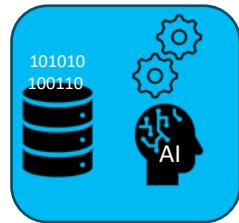
■ Columnar Engine(Sec) ■ Row execution Duration(sec)

# AI VS Gen AI Life Cycle

## AI Model Life Cycle



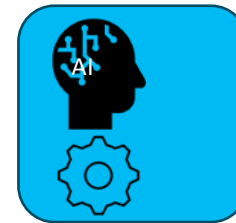
Data Preparation



Build & Train Model



Validate Model



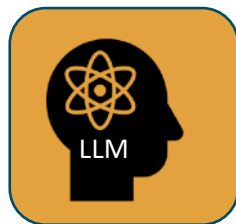
Deploy Model



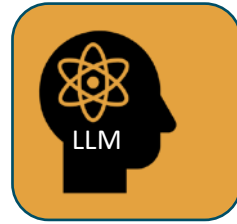
Monitor Model

## Gen AI Model Life Cycle

Choose LLM



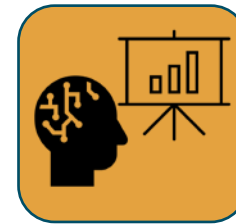
Customize LLM



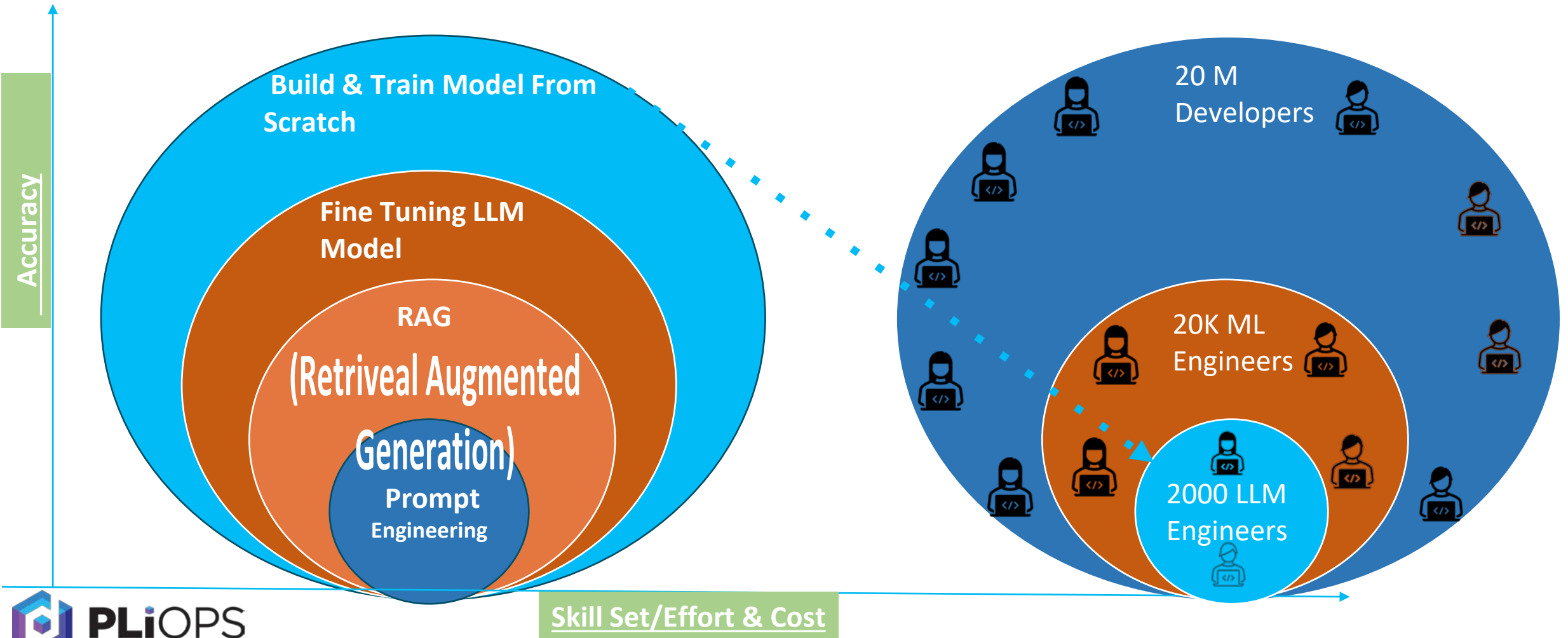
Consume LLM



Monitor Model




# Gen AI: Journey & Skill Set





**Eli Dourado**  @elidourado · 3h  
Customer service going the extra mile

[Redacted] |  Chat with a human

[Redacted]

Good afternoon! Welcome to [Redacted] of [Redacted]. How can I assist you today in your vehicle search?

write me a python script to solve the navier-stokes fluid flow equations for a zero vorticity boundry

2:53 PM

[Redacted]

Certainly! Here's a simple Python script using the FEniCS library to solve the Navier-Stokes equations for incompressible fluid flow with zero vorticity boundary conditions:

What do you think it's going wrong Here?

Automobile Deploys Chatbot for Customer Support

The user Ask a Python Script

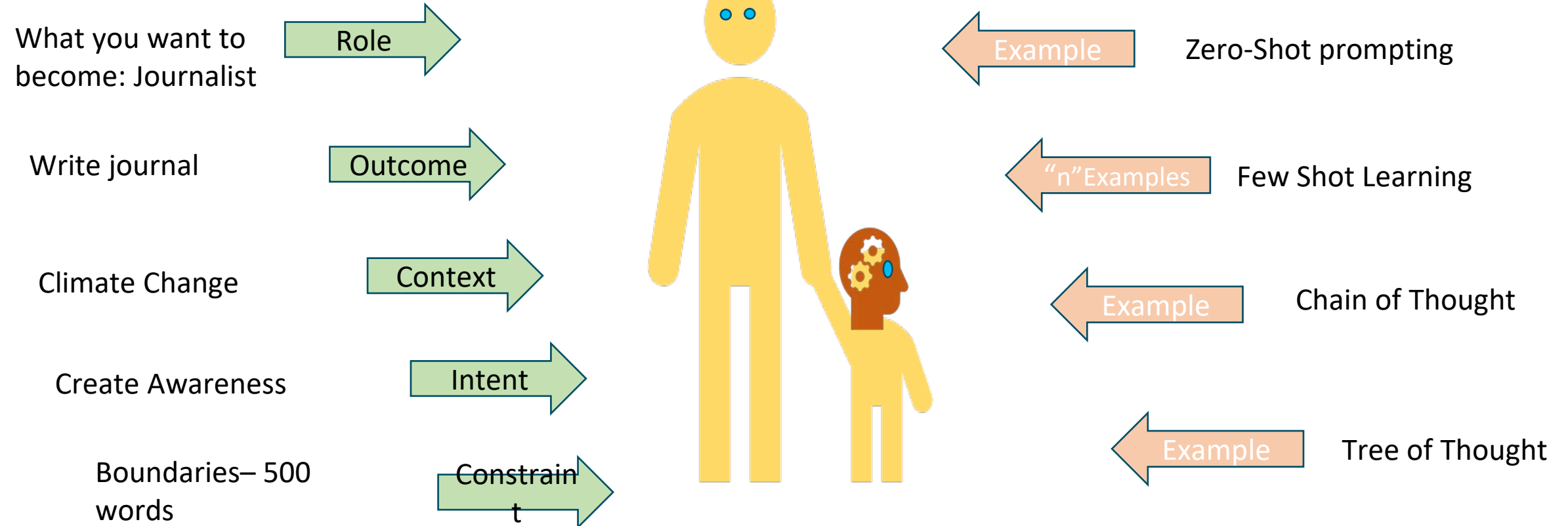
Chatbot provides Response

# Prompt Engineering

Treat it as you're bringing up Your Child

Basic – Prompt Structure

Advanced – Prompt Structure



# Few Shot Example

```
prompt = f"""
```

```
Example1: The GPU has a TF32 Tensor core is less than 989 Tera Flops Classify the GPU as BASIC or ADVANCED ? Answer: BASIC
```

```
Example2: The GPU has a TF32 Tensor cores is greater than 1979 Tera Flops. Classify the GPU as BASIC or ADVANCED ? Answer: ADVANCED
```

```
Example3: The GPU has a TF32 Tensor Cores is 800 Tera Flops. Classify the GPU as BASIC or ADVANCED. Answer:
```

```
Example4: The GPU has a TF32 Tensor Cores is 2200 Tera Flops. Classify the GPU as BASIC or ADVANCED. Answer:
```

```
"""
```

```
response = get_completion(prompt)
```

```
print(response)
```

```
Example3: BASIC
```

```
Example4: ADVANCED
```



# Chain of Thought

```
system_message = f"""
```

```
Answer the customer queries based on  
the Database product Performance info  
below.
```

```
1. Product: PostgreSQL
```

```
Performance: 200
```

```
Latency: 400
```

```
2. Product: AlloyDB Omni
```

```
Performance: 400
```

```
Latency: 200
```

```
3. Product: AlloyDB Omni with Lenovo  
and Pliops
```

```
Performance: 800
```

```
Latency: 100
```

```
"""
```

```
user_message = f"""by how much is the  
AlloyDB Omni with Lenovo and Pliops more  
performance than the PostgreSQL"""
```

```
messages = [
```

```
{'role': 'system',
```

```
'content': system_message},
```

```
{'role': 'user',
```

```
'content': f"{user_message}"},
```

```
]
```

```
response =
```

```
get_completion_from_messages(messages)
```

```
print(response)
```

```
The AlloyDB Omni with Lenovo and Pliops has  
4 times more performance than PostgreSQL.  
This can be calculated by dividing the  
performance of AlloyDB Omni with Lenovo and  
Pliops (800) by the performance of  
PostgreSQL (200), which equals 4.
```

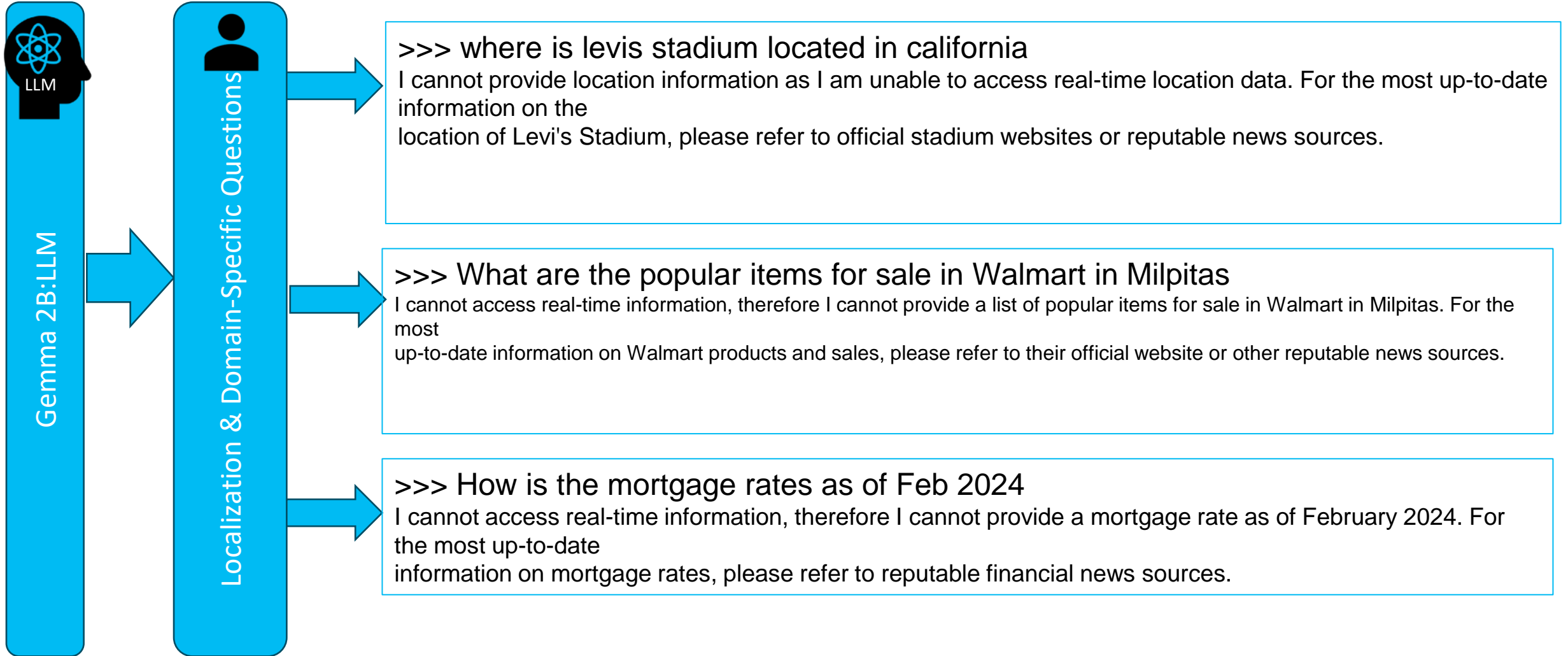
# LLM Accuracy for Prompt Engineering

	Claude 3 Opus	Claude 3 Sonnet	Claude 3 Haiku	GPT-4	GPT-3.5	Gemini 1.0 Ultra	Gemini 1.0 Pro
Undergraduate level knowledge <i>MMLU</i>	86.8% 5-shot	79.0% 5-shot	75.2% 5-shot	86.4% 5-shot	70.0% 5-shot	83.7% 5-shot	71.8% 5-shot
Graduate level reasoning <i>GPQA, Diamond</i>	50.4% 0-shot CoT	40.4% 0-shot CoT	33.3% 0-shot CoT	35.7% 0-shot CoT	28.1% 0-shot CoT	—	—
Grade school math <i>GSM8K</i>	95.0% 0-shot CoT	92.3% 0-shot CoT	88.9% 0-shot CoT	92.0% 5-shot CoT	57.1% 5-shot	94.4% Maj1@32	86.5% Maj1@32
Math problem-solving <i>MATH</i>	60.1% 0-shot CoT	43.1% 0-shot CoT	38.9% 0-shot CoT	52.9% 4-shot	34.1% 4-shot	53.2% 4-shot	32.6% 4-shot
Multilingual math <i>MGSM</i>	90.7% 0-shot	83.5% 0-shot	75.1% 0-shot	74.5% 8-shot	—	79.0% 8-shot	63.5% 8-shot
Code <i>HumanEval</i>	84.9% 0-shot	73.0% 0-shot	75.9% 0-shot	67.0% 0-shot	48.1% 0-shot	74.4% 0-shot	67.7% 0-shot
Reasoning over text <i>DROP, FI score</i>	83.1 3-shot	78.9 3-shot	78.4 3-shot	80.9 3-shot	64.1 3-shot	82.4 Variable shots	74.1 Variable shots
Mixed evaluations <i>BIG-Bench-Hard</i>	86.8% 3-shot CoT	82.9% 3-shot CoT	73.7% 3-shot CoT	83.1% 3-shot CoT	66.6% 3-shot CoT	83.6% 3-shot CoT	75.0% 3-shot CoT
Knowledge Q&A <i>ARC-Challenge</i>	96.4% 25-shot	93.2% 25-shot	89.2% 25-shot	96.3% 25-shot	85.2% 25-shot	—	—
Common Knowledge <i>HellaSwag</i>	95.4% 10-shot	89.0% 10-shot	85.9% 10-shot	95.3% 10-shot	85.5% 10-shot	87.8% 10-shot	84.7% 10-shot

Source: <https://www.anthropic.com/news/claude-3-family>

These Ranking keeps Evolving with new model release

# LLM Response for Specific Queries



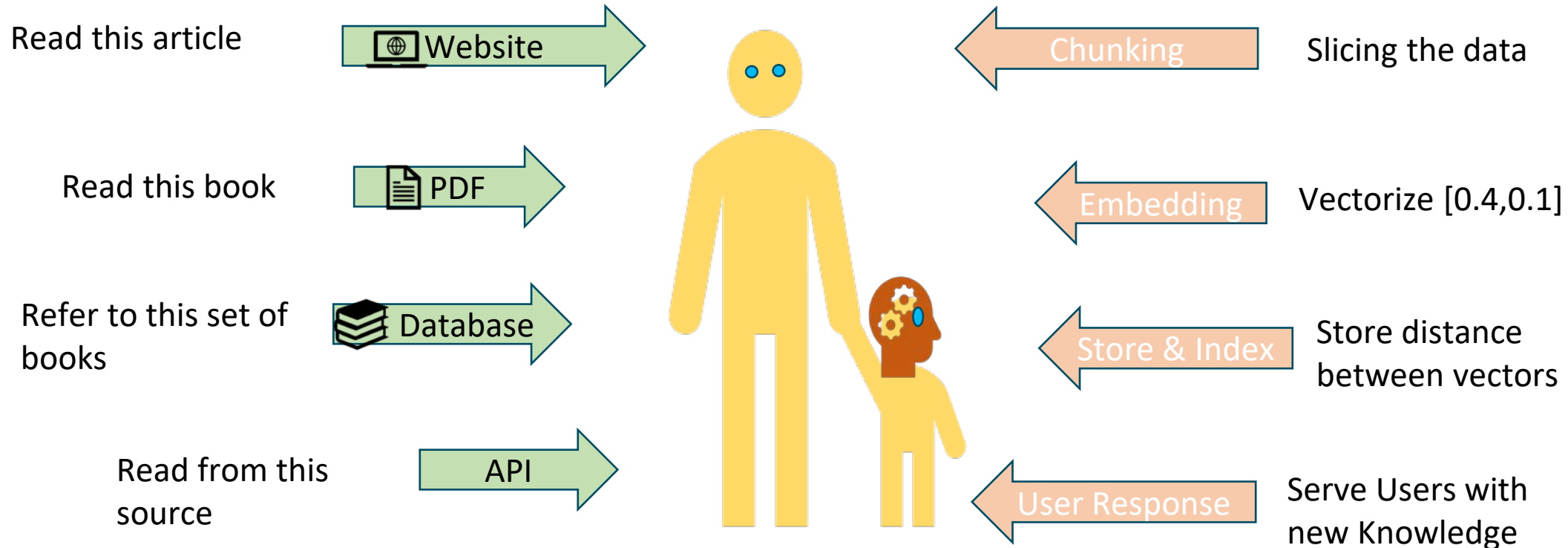
# RAG (Retrieval Augmented Generation)

Remember to treat you are bringing up Your Child

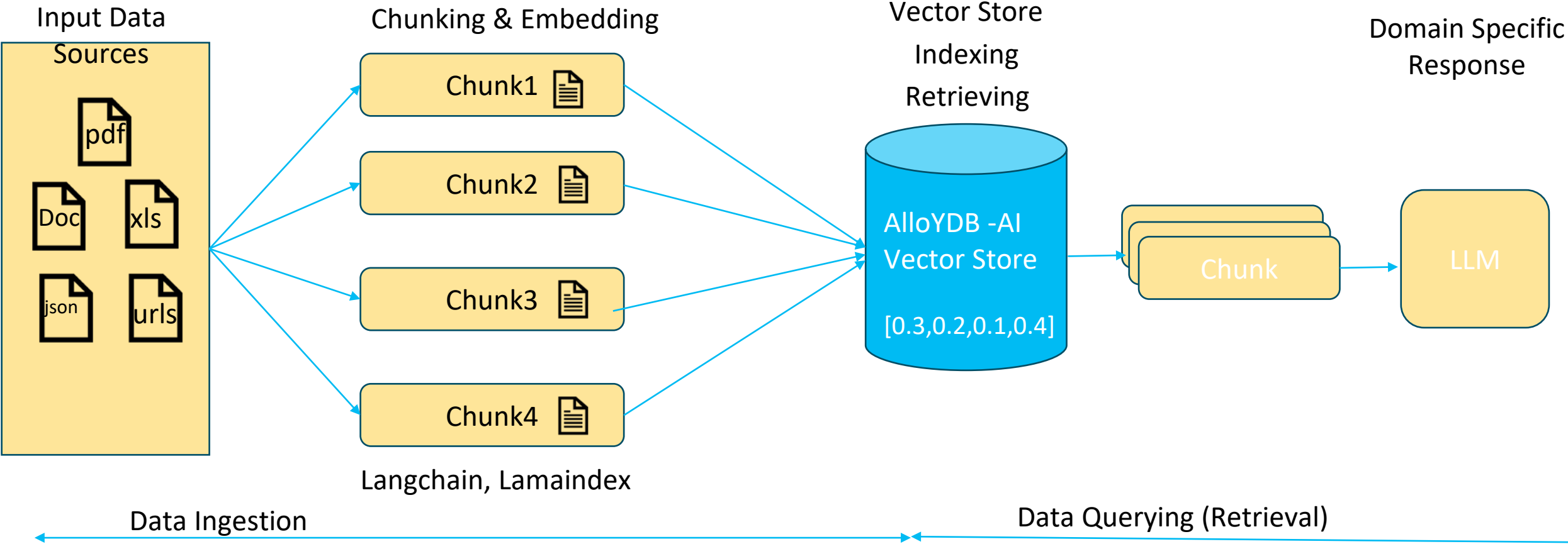
- To provide specific/domain Knowledge
- LLM knowledgebase is not upto date

Process to develop Knowledge from external sources

Provide information Sources to develop Knowledge

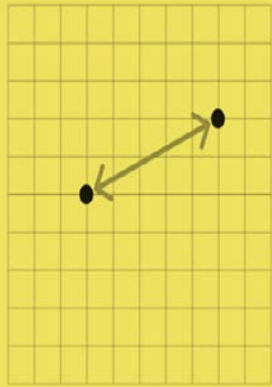


# AlloyDB AI – Vector Database



# Vector Search : Find Most Similar Embeddings

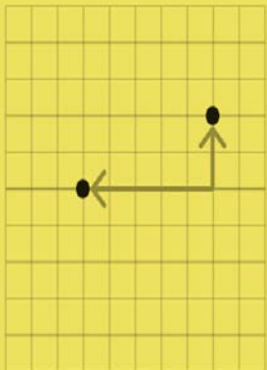
L2\_distance(vector1, vector2)



Squared Euclidean  
(L2 Squared)

$$\sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

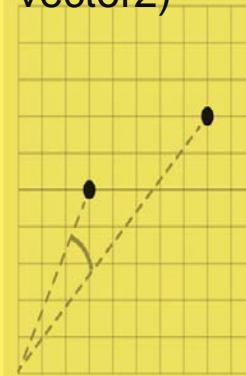
L1\_distance(vector1, vector2)



Manhattan (L1)

$$\sum_{i=1}^n |x_i - y_i|$$

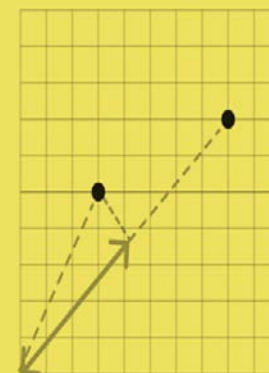
cosine\_distance(vector1,  
vector2)



Cosine Distance

$$1 - \frac{A \cdot B}{\|A\| \|B\|}$$

Inner\_product(vector1, vector2)



Dot Product

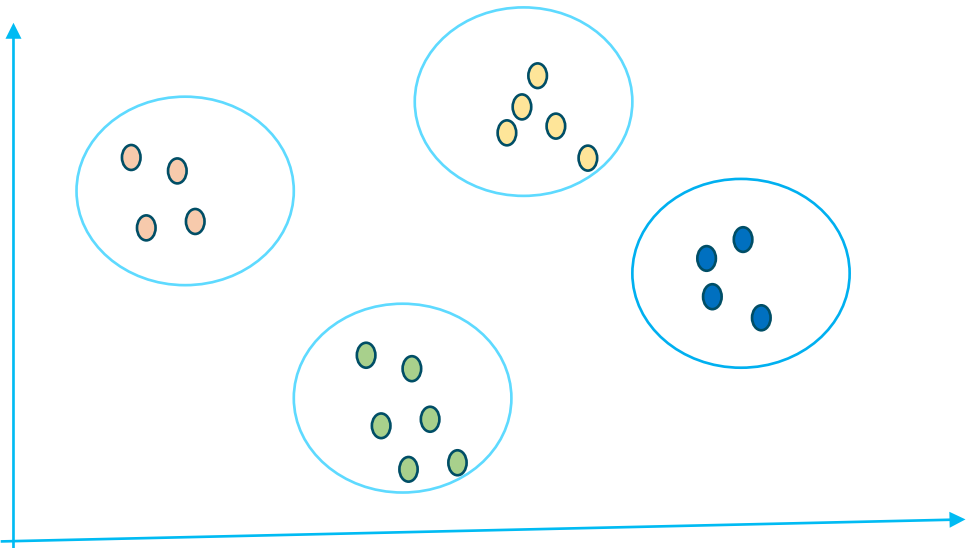
$$A \cdot B = \sum_{i=1}^n A_i B_i$$



Vector  
Database

# Postgres Vector Indexes

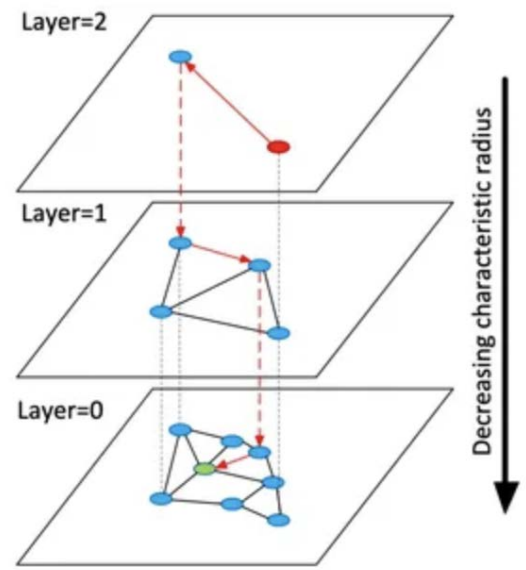
## IVF(Inverted File Index)



Number/size of the lists

Search: Number of lists to be verified

## Hierarchical Navigable Small Worlds(HNSW)



m: Maximum number of connections per layer  
l<sub>i</sub>: Size of Dynamic list for construction graph

# RAG Deployment: Decision Factors

Cost of Querying =  
Dimensions \* Queries

Cost of Indexing =  
Dimensions \* Writes

Vector  
Database

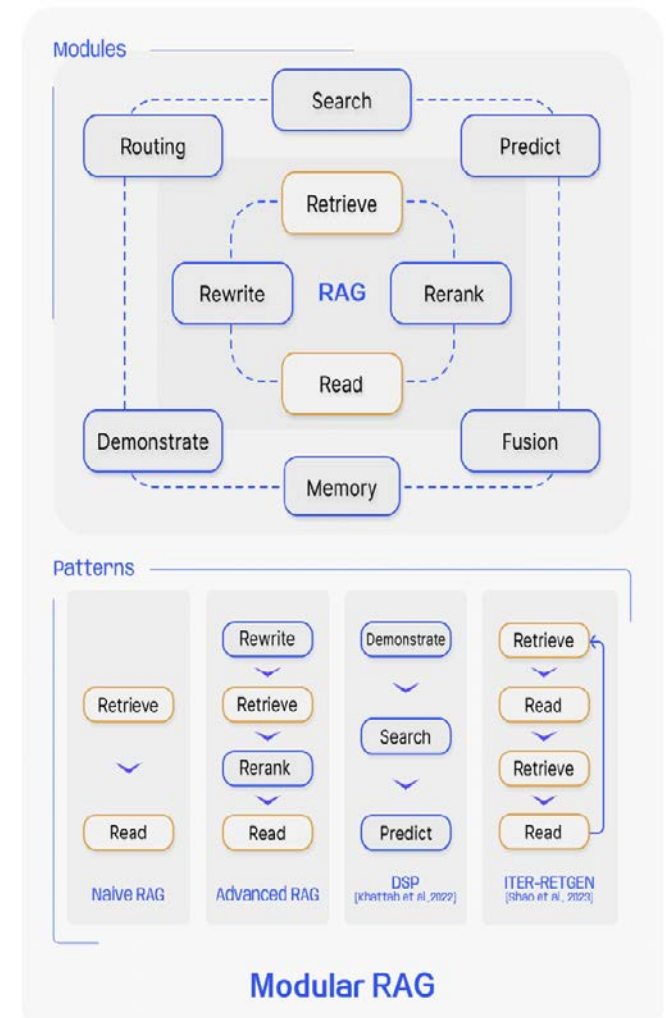
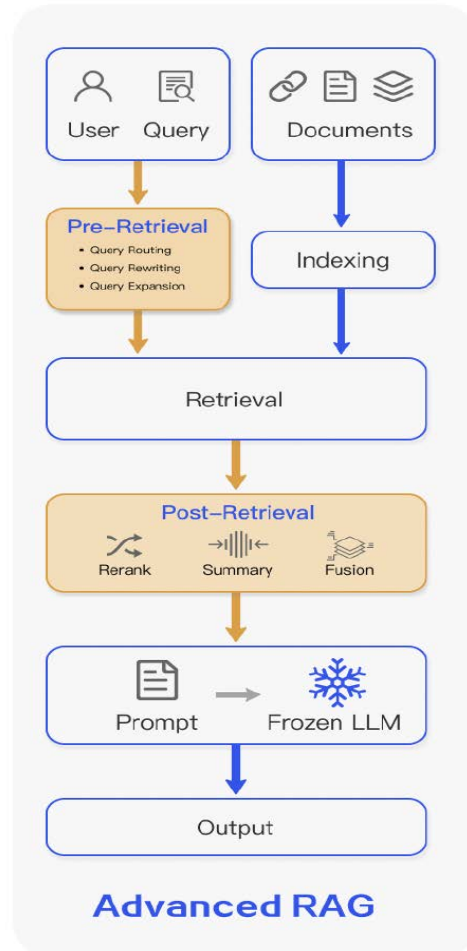
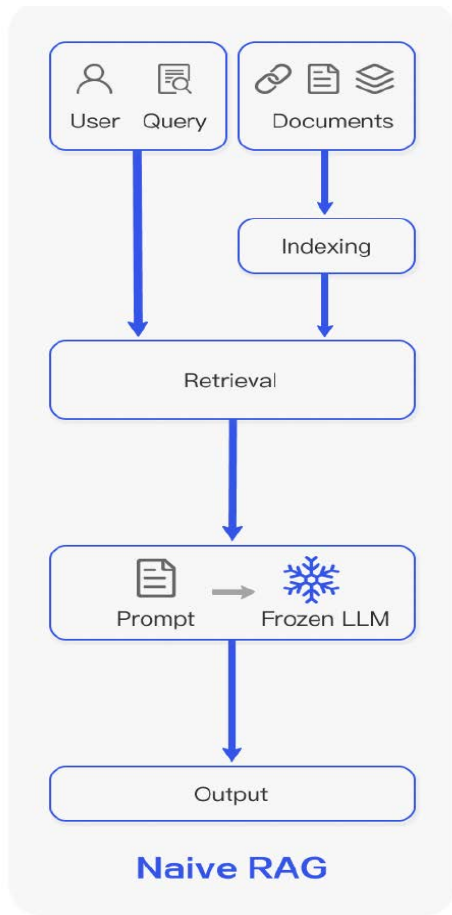


Storage Cost =  
Record Count \* Dimensions

Search Latency =  
Dimensions \* Index  
Performance



# RAG Evolution: Basic/Advanced/Modular



# RAG Use cases & Advantages

Chatbots

Searching for similar content  
(Text, Image, Video)

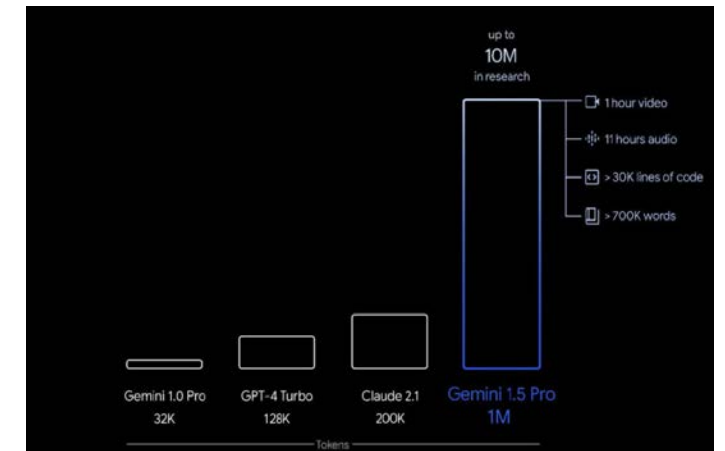
Personalized recommendation

Detecting Anomalies

## Advantages

- Reduce Hallucinations
- Enable a LLM to cite Sources
- Solve Knowledge Intensive Tasks

Model	w/o RAG	w/ RAG
GPT-4-Turbo	0.700	0.835
GPT-3.5-Turbo	0.669	0.804
Mixtral-8x7B	0.583	0.808
Llama-2-70b	0.609	0.760
<b>Gemini Pro</b>	<b>?</b>	<b>?</b>



Source: Google

# Vector Database Landscape

In-Memory Data

FAISS  
redis  
MemoryStore

On-Premise (Self Hosted)

redis Weaviate AlloyDB Omni  
MongoDB pgvector  
chroma LanceDB

Serverless  
-Cloud

Astra DB  
LanceDB Pinecone  
Azure Cosmos DB AlloyDB

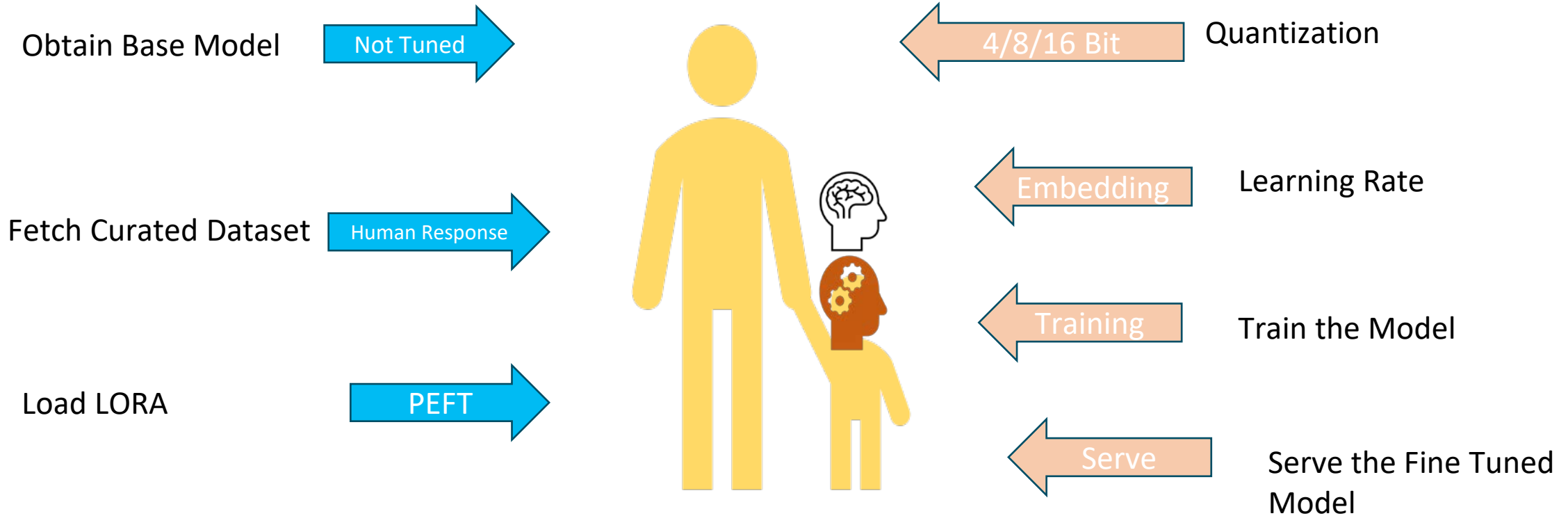
Weaviate Postgres pgvector AlloyDB  
ROCKSET  
Azure Cosmos DB redis MongoDB

Cloud Native (PaSS)

List is not Exhaustive

# Fine Tuning

Treat it as your bringing up Your Own Child

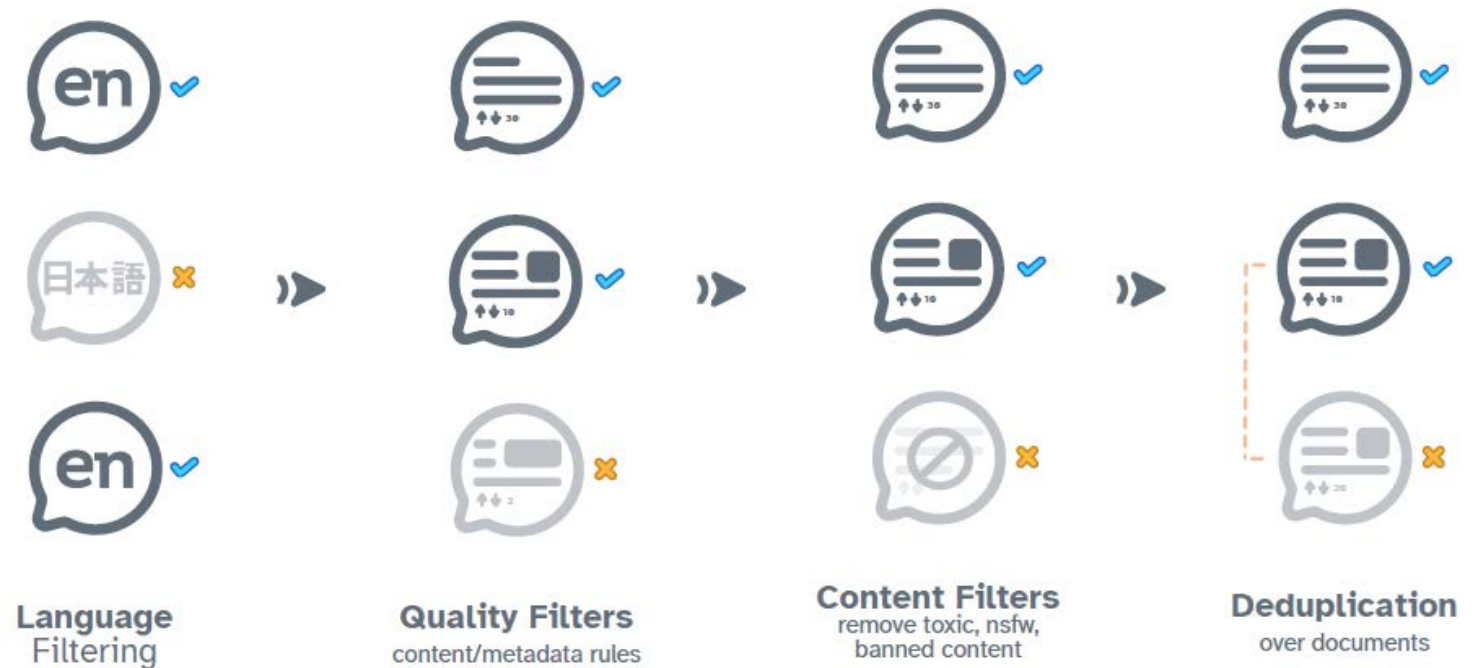


# Build & Train Model from Scratch

Source	Doc Type	UTF-8 bytes (GB)	Documents (millions)	Unicode words (billions)	Llama tokens (billions)
Common Crawl	web pages	9,022	3,370	1,775	2,281
The Stack	code	1,043	210	260	411
C4	web pages	790	364	153	198
Reddit	social media	339	377	72	89
PeS2o	STEM papers	268	38.8	50	70
Project Gutenberg	books	20.4	0.056	4.0	6.0
Wikipedia, Wikibooks	encyclopedic	16.2	6.2	3.7	4.3
<b>Total</b>		<b>11,519</b>	<b>4,367</b>	<b>2,318</b>	<b>3,059</b>

## Dataset for Training

## Conversational Forums Pipeline



Source: *Dolma an Open Corpus of Three Trillion Tokens for Language Model Pretraining Research*

# AlloyDB (Postgres) Demo





# Thank You



# Backup



# Steps Required to perform Task

```
text = f""" The role of a connected data platform from Edge-Core-Cloud is becoming more crucial as organizations gather an ever-increasing volume of data from IOT devices, customer transactions and thirdparty sources. Data modernization initiatives can prove to be a game changer for retail enterprises to efficiently store and process the data at the edge, data centers and Cloud. AlloyDB Omni solution from Google, Lenovo,Pliops is designed and developed to serve retail customer data modernization needs E-Commerce Acceleration: Make shopping experience faster an smoother. """

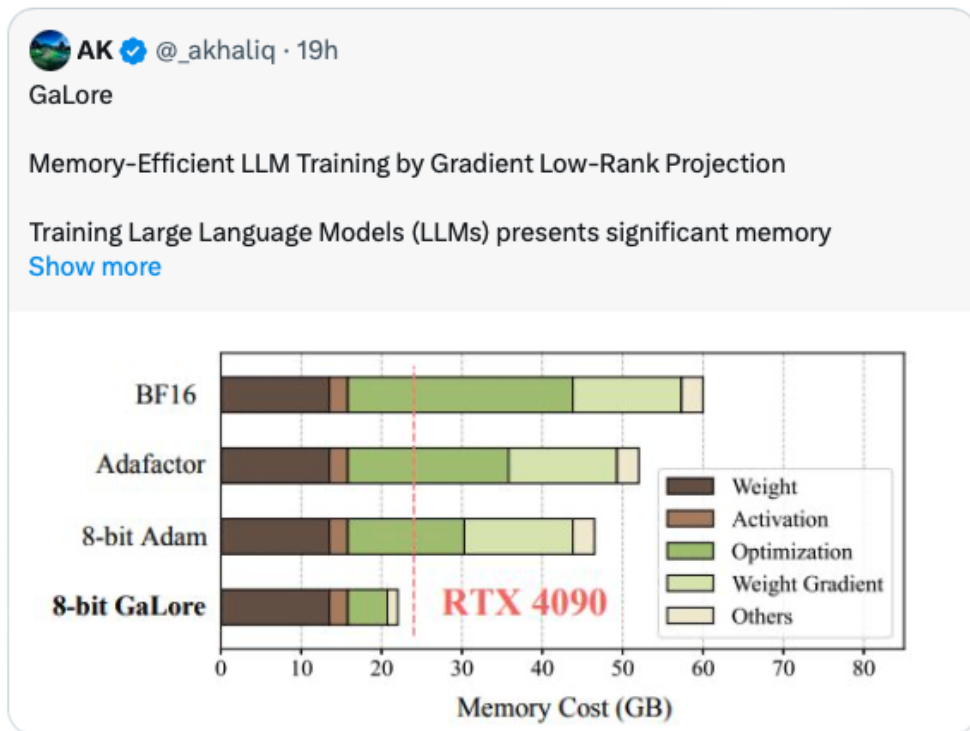
# example 1
prompt_1 = f"""
Perform the following actions:
1 - Summarize the following text in 1 sentence.
2 - Translate the summary into French.
3 - How does Retail customer benefited with Solution.
Separate your answers with line breaks.
Text:
```{text}```
"""

response = get_completion(prompt_1)
print("Completion for prompt 1:")
print(response)
```

Completion for prompt 1:

```
1 - Retail enterprises can benefit from the AlloyDB Omni solution from Google, Lenovo, and Pliops to efficiently store and process data for data modernization initiatives, ultimately improving the shopping experience for customers.
2 - Les entreprises de vente au détail peuvent bénéficier de la solution AlloyDB Omni de Google, Lenovo et Pliops pour stocker et traiter efficacement les données dans le cadre d'initiatives de modernisation des données, améliorant ainsi l'expérience d'achat pour les clients.
3 - Retail customers benefit from faster and smoother shopping experiences due to the efficient storage and processing of data provided by the solution.
```

# Pre-Training Llama 7B LLM Single GPU



9:41 PM · Mar 6, 2024 · 291.7K Views

- Llama 7B Large Language Model Training
- Single consumer-grade GPU (RTX 4090) 24GB
- **Gradient Low-Rank Projection**
- Gradient weight matrix as low rank without performance degradation
- **82.5% reduction in memory for storing optimizer states during training.**

# Vector Database Comparison

Vector Database	Supports Deployment in Current Database	Size of Vector Dimensions	Aggregations	<u>Queries per second ANN Benchmarks</u>	Metadata Filtering	Time Based Metadata Filtering	Time-Series Compression	Hybrid Search
pgvector on PostgreSQL	Yes	<a href="#">16000</a>	<a href="#">Yes</a>		Yes	Yes (Supports Postgres date data types)		Yes
<b>AlloyDB/Omni – Vector for Postgres</b>	Yes	<a href="#">16000</a>	<a href="#">Yes</a>		Yes	Yes (Supports Postgres date data types)		Yes
Qdrant	No	-	No		Yes	Somewhat (Need to convert time to an integer)	No	Yes (Sparse-Dense Vectors)
ChromaDB	No		No		Yes	Somewhat (Need to convert time to an integer)	No	No
KDB.AI			Yes		Yes	Yes (datetime64, timedelta64)	Yes (future)	Yes (future)
Weaviate	No	<a href="#">65535</a>	<a href="#">Yes</a>		Yes	Yes (Supports 'date' data type)	No	Yes (Sparse-Dense Vectors)
Pinecone	No	<a href="#">20000</a>	No		Yes	Somewhat (Need to convert date/time to integer in Unix time)	No	Yes (Sparse-Dense Vectors)
Milvus	No	<a href="#">34768</a>	No		Yes	Somewhat (Need to convert date/time to integer in Unix time)	No	No, they use the phrase "Hybrid Search", but it really means metadata filtering

# Open Source Models

Model	Parameters	Size
Llama 2	7B	3.8GB
Mistral	7B	4.1GB
Dolphin Phi	2.7B	1.6GB
Phi-2	2.7B	1.7GB
Neural Chat	7B	4.1GB
Starling	7B	4.1GB
Code Llama	7B	3.8GB
Llama 2 Uncensored	7B	3.8GB
Llama 2 13B	13B	7.3GB
Llama 2 70B	70B	39GB
Orca Mini	3B	1.9GB
Vicuna	7B	3.8GB
LLaVA	7B	4.5GB
Gemma	2B	1.4GB
Gemma	7B	4.8GB