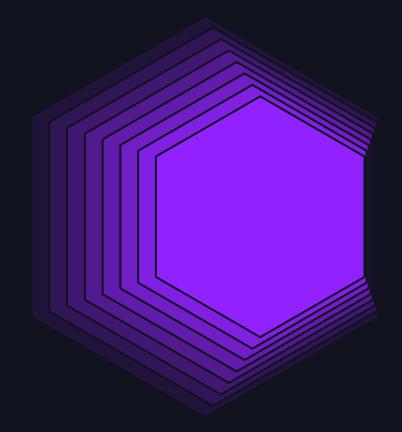


From Uncertainty to Certainty: Strategies for Deterministic LLMOps



Amanda Milberg, Dataiku June 2024

### Discussion Points



#### The LLM Landscape

- Discuss the growing LLM Landscape from 2018 present
- Outline key factors when building a LLM ecosystem to meet business needs



#### Strategies for LLMOps

- Define the term LLMOps
- Differences between AI / ML vs LLMs workflows
- Common problems and proposed solutions for monitoring LLMs



#### **Product Demo**

- Discuss an illustrative use case building a RAG application in Dataiku
- Mock up a LLMOps solution based on strategies disucssed



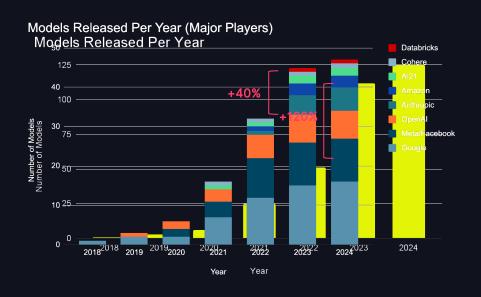
# The LLM Landscape



How many Large Language Models have been developed and released to date?

## The Growing LLM Landscape

#### There are over 125 LLMs available in the model landscape



- Expressation is that model
- Materials acting to the search of the s
- Aidleancements in both models with newer performannty and models replacing old ones

Source: https://informationisbeautiful.net/visualizations/the-rise-of-generative-ai-large-language-models-llms-like-chatgpt/

## One size *does not* fit all

#### An enterprise needs multiple LLMs to meet business needs

#### **Cost to Serve**

- Choose a models that is adaptive to your needs
  - Self Hosted vs. API Provider
  - Text vs Image
  - Task Specific vs. All Knowing
- Universal, all knowing LLMs can quickly rack up costs

#### Latency & Locality

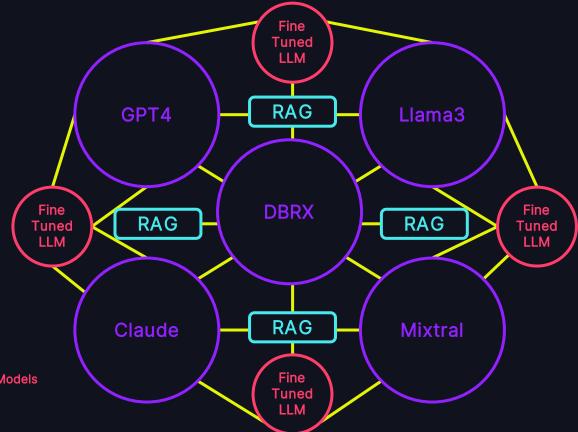
- Response time differs between models
- Models may need to be adapted to abide by regional laws
- Models may need to be local to an edge device (e.g. phone)

#### **Domain Specific Needs**

- Leverage or adapt models to a specific domain (e.g. FinGPT)
- Match a business problems with appropriate model in terms of cost / risk profile, relevance of data security

Future enterprises will need to manage at least a dozen large language models

## An illustrative multi-model landscape



Foundational Models

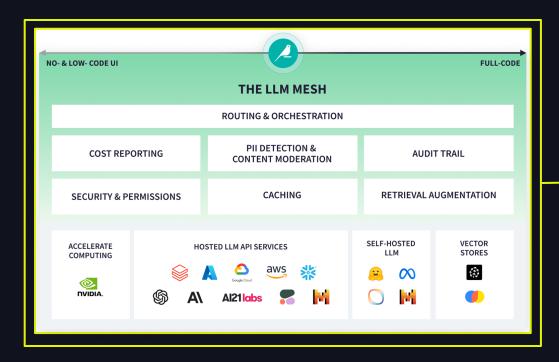
**Fine Tuned Large Language Models** 

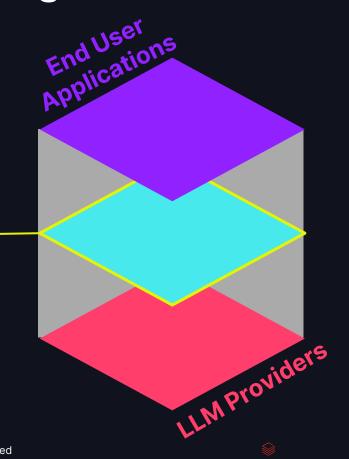
**RAG Pipelines** 

**LLM Mesh** 

## While the models may change...

...the challenge remains the same

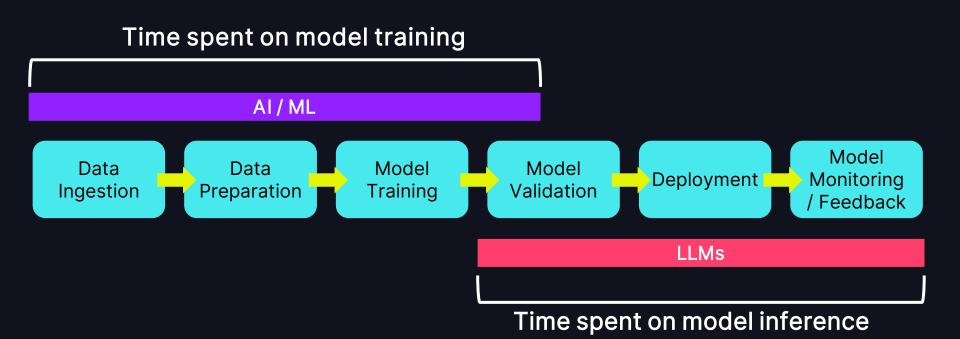




# Strategies For LLMOps

## The Model Development Lifecycle

AI / ML vs LLMs



## Areas of focus in LLMOps

#### Key Differentiators from AI / ML to LLMs

|                      | AI / ML                      | LLMs                     |
|----------------------|------------------------------|--------------------------|
| 1. Data Required     | Data Hungry                  | Zero / Few Shot Learning |
| 2. Compute Resources | Require CPUs                 | Require GPUs             |
| 3. Cost to Serve     | Constrained and              | Recurring Costs          |
|                      | Expected                     |                          |
| 4. Model Output      | Deterministic                | Non Deterministic        |
| 5. Model Metrics     | F1, Precision, Recall, AUC   | BERTScore Faithfullness  |
| O. HOUGE HELLICS     | T 1, 1 recision, Recall, ACC | BERTScore, Faithfuilless |

# Managing a LLM is like managing 100 interns

Problem Non Deterministic **Human Review Recurring Costs** Machines Solution Guardrails / **Automated LLM Cost Review** LLM-as-a-Judge **Monitoring** 

## Let's See It In Action



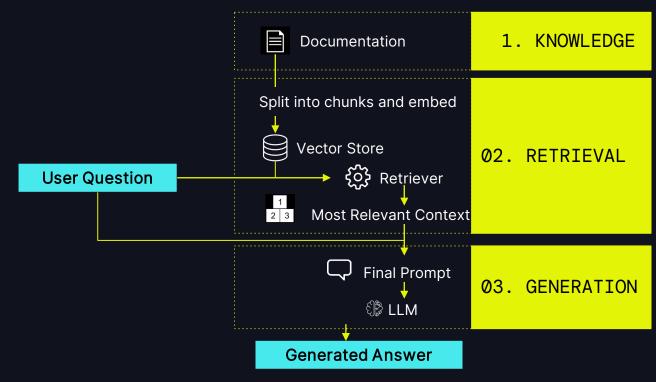
#### Illustrative Use Case

#### Build and Monitor a Chatbot in Dataiku

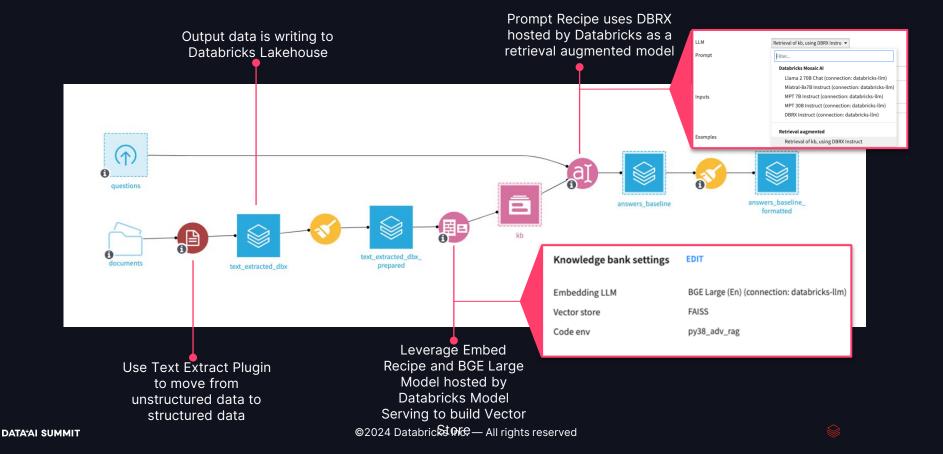
- Build out a RAG application in Dataiku using the LLM Mesh leveraging LLMs hosted by Databricks
- Implement LLM-as-a-Judge Approach using custom GenAl MLFlow Metrics and track them in a Evaluation Store
- Create metrics on overall pipeline performance and define a weighted score for model evaluation
- Monitor all LLM Costs across projects with LLM Cost Review Dashboard

## Step 1: Build out a RAG Pipeline

#### **Illustrative Use Case**

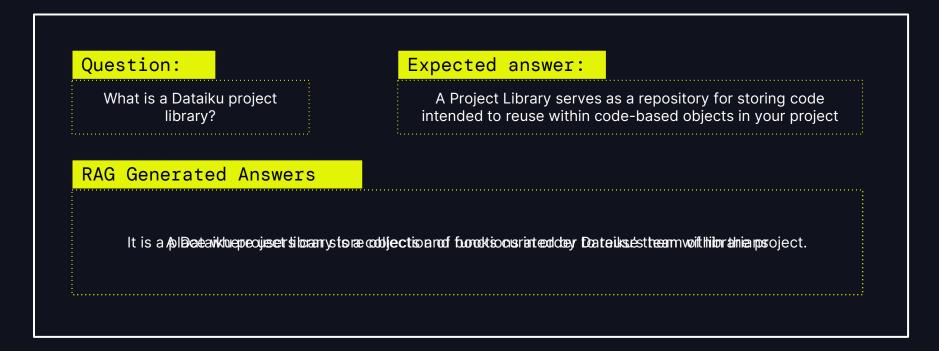


## Step 1: Build out a RAG Pipeline



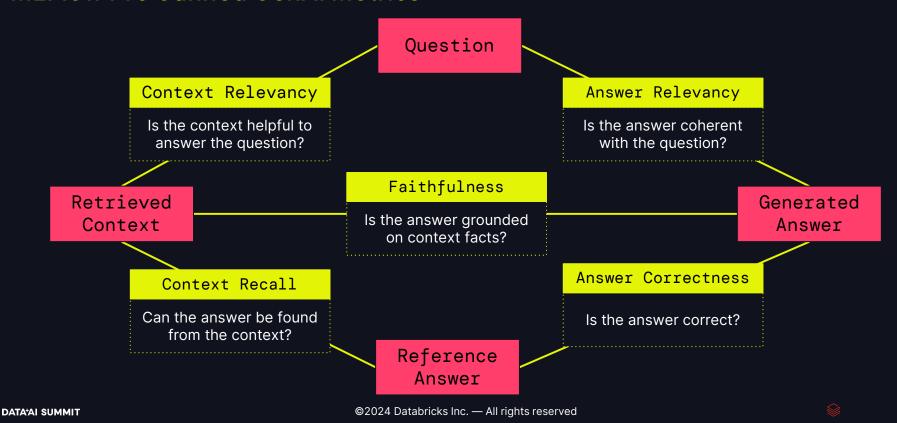
## Step 2: Implementing LLM-as-a-Judge

#### **Illustrative Use Case**



## Step 2: Implementing LLM-as-a-Judge

#### **MLFlow Pre Canned GenAl Metrics**



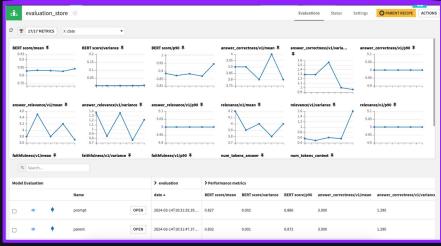
## Step 2: Implementing LLM-as-a-Judge

#### **Evaluation Stores in Dataiku**



Experiment Tracking with MLFlow

Track metrics overtime in Evaluation Store



## LLM-as-a-Judge Framework

#### Tips and Tricks

## Implement a Weighting System

Create a weighting system that factors your business needs. This may be tuned for each application.

60% Correctness 20% Faithfulness 20% Professionalism

#### Compare LLM-as-Judges

Use a less robust model for grading system and keep that system on a small scale (e.g. 1-5)

GPT 3.5 drives down the cost of the judge by 10x and increased the speed by 3x

## Leverage Combined Strategies

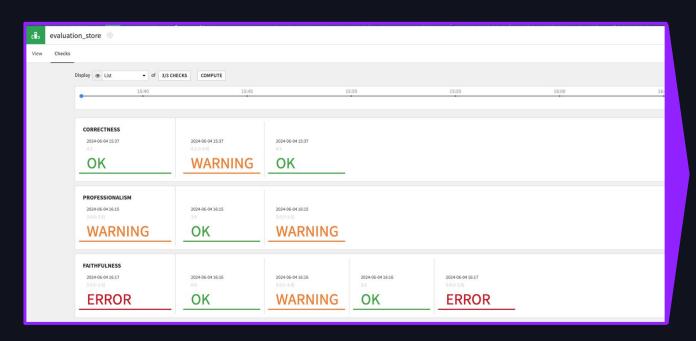
Compare Prompt
Engineering strategies to
avoid bias and improve
reliability

Low Temperature (0.1)
Chain of Thought
Prompting
Few Shot Learning



## Step 3: Monitoring and Alerting

Add metrics / checks to alert overall performance of RAG pipeline

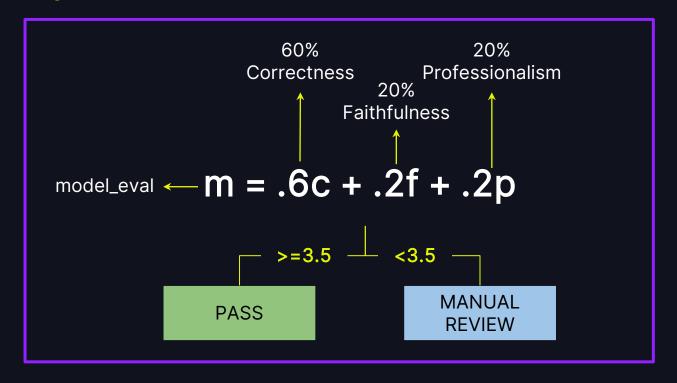


Set Thresholds to
Track Metrics
Overtime with
Metrics and Checks



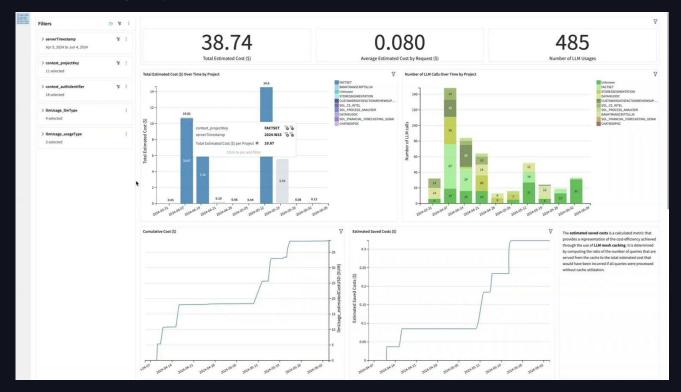
## Step 3: Monitoring and Alerting

Develop a weighted scored on record level



## Step 4. LLM Cost Review Dashboard

#### Monitor individual projects and overall LLM Costs



# To Wrap Up



## Key Takeaways

#### Final thoughts..

## LLM Mesh Enables Scalability

Enterprises need a meshtype architecture to scale to a multi-model ecosystem

## Evaluate LLMs with Guardrails

LLM-as-a-Judge is a promising approach to achieve human like evaluation in an automated way

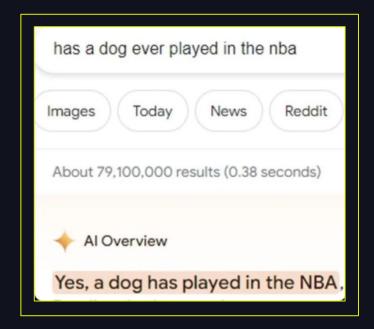
## Monitor and Alert with LLM Cost Review

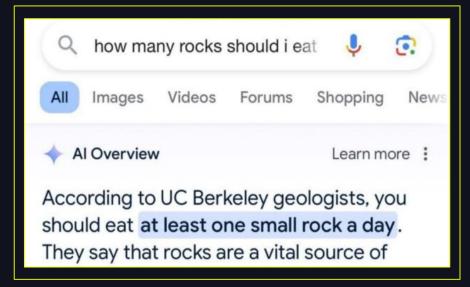
Enabling insights to track and review LLM costs is key to finding ROI and proving value



## Implement an LLMOps Strategy...

...Or your company will be the next viral internet meme









## Thank You

Amanda Milberg Dataiku, Booth #85 amanda.milberg@dataiku.com

