

## WHO ARE WE?

- Tori Tompkins
  - Senior Data Science Consultant
  - Cohost of Data Podcast, Totally Skewed



- Alex Billington
  - Senior Data Science Consultant
  - ML Engineer for 5 years

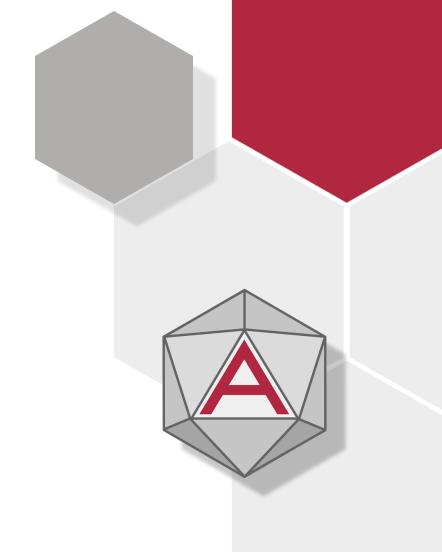






## **AGENDA**

- What is MLOps?
- What is the MLOps lifecycle?
- What is Databricks?
- Databricks features
  - Feature store
  - MLflow
  - Serving Endpoints





## **FOLLOW ALONG CODE**

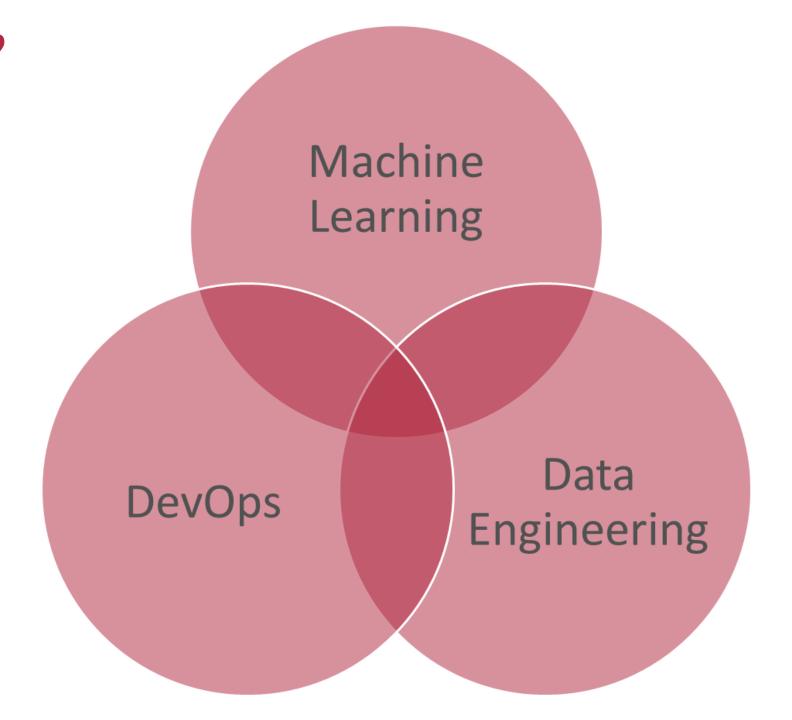
 https://github.com/ABillington96/MLOps in Databricks







## WHAT IS MLOPS?





#### WHY IS MLOPS IMPORTANT?

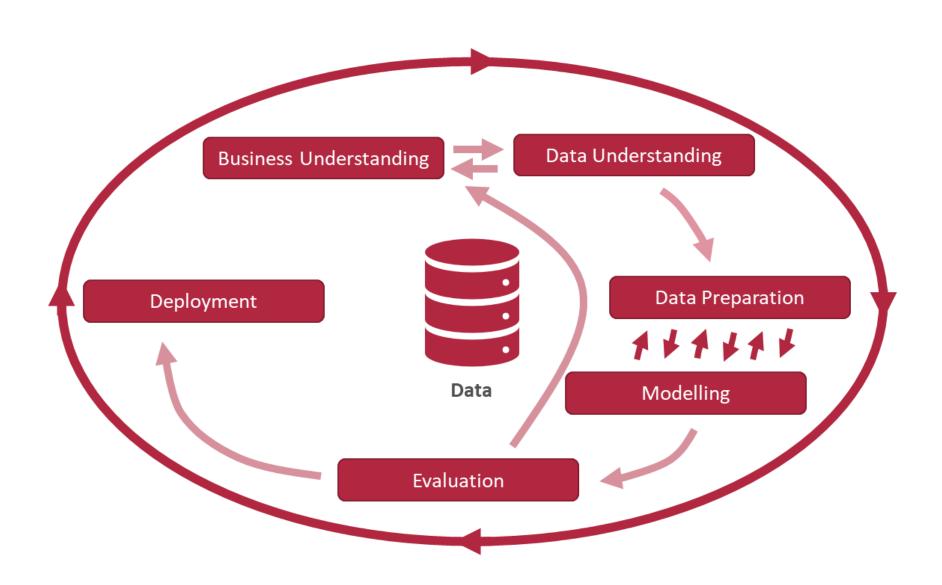
- Scaling
- Trust
- Better Integration
- Compliance
- Reduce Risk and Bias

The MLOps market could grow to around \$2 billion by 2025, up from about \$185 million in 2020.





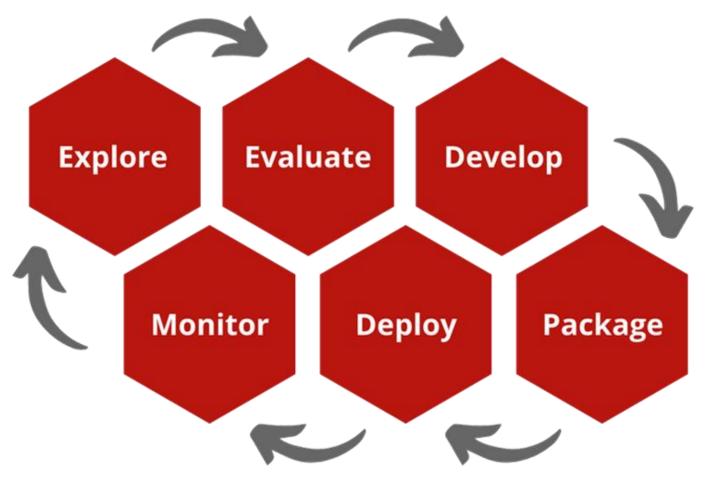
## WHY IS MLOPS DIFFERENT FROM DEVOPS?

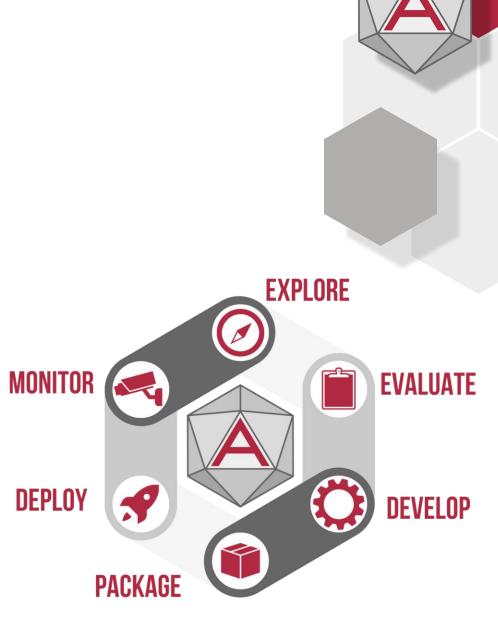




## WHY IS MLOPS DIFFERENT FROM DEVOPS? Evaluation Data Understanding **Business Understanding** Monitoring Data Preparation Deployment \*\*\*\* Data Modelling Re-Training **Evaluation**

## **MLOPS LIFECYCLE**





#### **EXPLORE**



- Experimental Phase for Data Scientists (DS) to try models
- MLOps should supply DS the environment they need to achieve this
- This can include leveraging feature stores, model experiment tracking and collaborative workspace



#### **EVALUATE**



- Testing phase for models to be evaluated for business value, accuracy and ethics
- MLOps should provide a platform and process to achieve this
- This can include leveraging libraries to analyse results, interpretability, explainability and fairness



#### **DEVELOP**



- Development phase to build robustness into the model inference pipeline
- MLOps should ensure models continuing to the next phase are production-ready
- This can include auditing, unit-testing, data and model versioning



#### **PACKAGE**



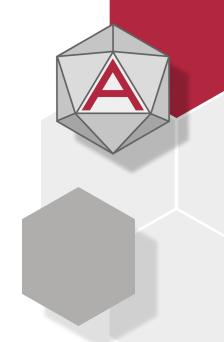
- Packaging phase to ensure the production environment resembles development
- MLOps should ensure resources are accurate and accessible to prevent unexpected behaviour
- This can include versioning of libraries and frameworks or packaging code into a wheel



#### **DEPLOY**



- Deployment phase to serve the model to user base
- MLOps should deploy the model according to business requirements
- This can include considering model complexity, size, importance, need for autoscaling or A/B testing etc



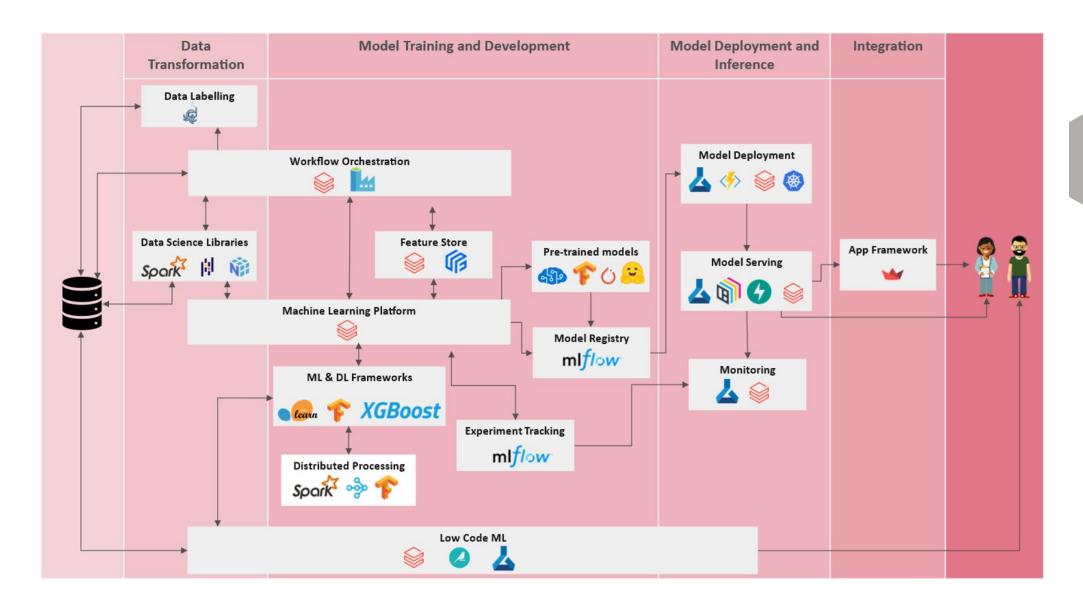
#### **MONITOR**



- Monitoring phase to ensure models remain accessible and accurate
- MLOps should monitor models for performance and data drift
- This can include tracking input and output data, performing drift analysis and automatic alerts

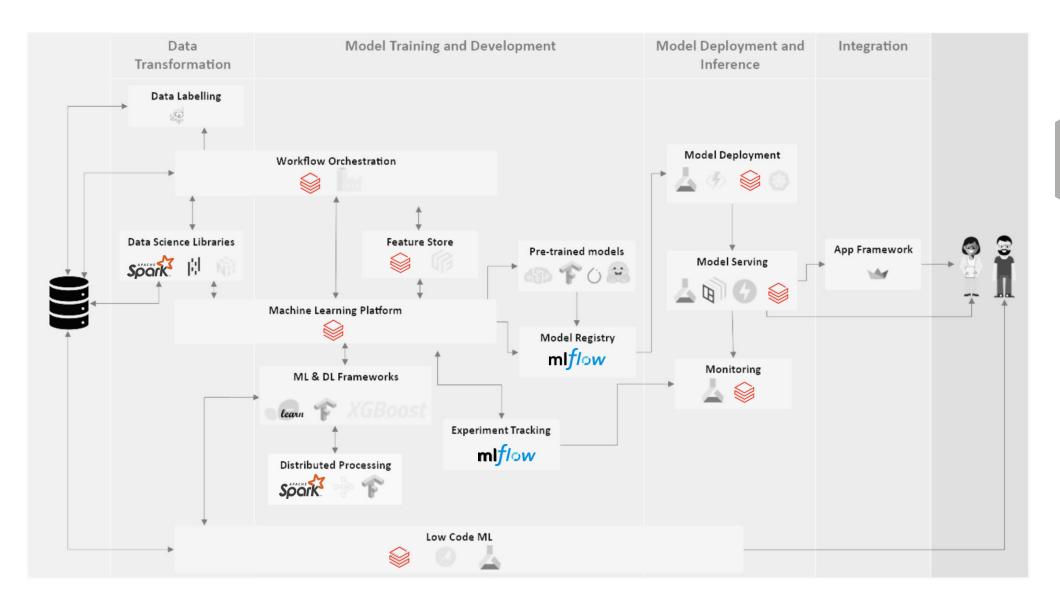


## **MLOPS TOOLS**





## **MLOPS TOOLS**





## **WHAT IS DATABRICKS?**



- Platform built on Spark
- Optimised for distributed computing
- Popular for Data Engineering, Analytics and Science workloads





## WHAT IS DELTA LAKE?



- Open-source storage layer designed to run on top of an existing data lake
- ACID transactions
- Scalable metadata handling
- Unified batch & streaming
- Schema enforcement
- Time travel (data versioning)
- Upserts and deletes
- Optimised file management



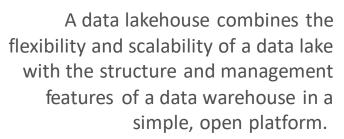




A delta lake, an evolution of data storage, preserves the integrity of your original data without sacrificing the performance and agility required for real-time analytics, artificial intelligence (AI), and machine learning (ML) applications.

## DATA LAKE

A data lake is a massive accumulation of raw data in multiple formats. The sheer volume and variety of information in a data lake can make analysis cumbersome and, without auditing or governance, the quality and consistency of the data can be unreliable.



## **DATA LAKEHOUSE**

A data warehouse gathers information from multiple sources, then reformats and organizes it into a large, consolidated volume of structured data that's optimized for analysis and reporting. Proprietary software and an inability to store unstructured data can limit its usefulness.

## **DATA WAREHOUSE**



#### DATABRICKS FOR MLOPS

- Extremely powerful Spark engine
- Supports R, SQL and Python
- Collaborative workspaces
- Powerful machine learning libraries
- Feature Store
- Serving Endpoints
- AutoML
- Git integration
- Fully managed version of MLflow
- NEW Dolly LLM

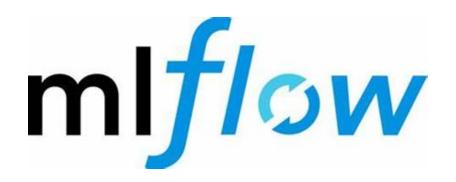






## WHY MLFLOW?

- Which dataset was used?
- Which ML algorithm did we use to train the model?
- What hyperparameter values were used?
- What were the performance like?
- How can we convey all these info to our team easily?

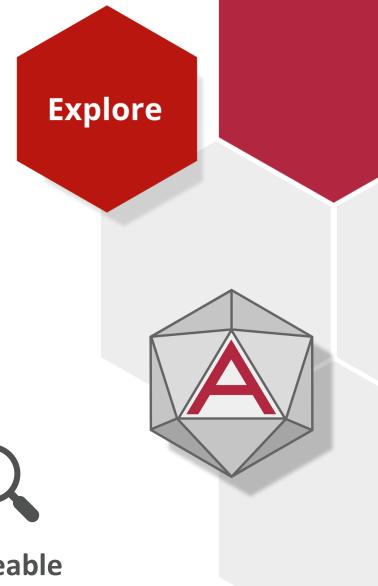








**Traceable** 





#### **MLFLOW - COMPONENTS**



Packaging format for reproducible runs on any compute platform

# **Tracking**

mlflow

**Models** 

**General model** 

format

that standardizes

deployment options

Record and query experiments: code, metrics, parameters, artifacts, models





## mlflow

**Model Registry** 

**Centralized and** collaborative model lifecycle management





## **DATABRICKS MLFLOW**

Experiment Tracking	Open Source MLflow	Managed MLflow on Databricks
MLflow tracking API		
MLflow tracking server	Self-hosted	Fully managed
Notebooks integration	×	
Workspace integration	×	
Reproducible Projects		
MLflow Projects	<b>✓</b>	
Git and Conda integration	<b>✓</b>	
Scalable cloud/clusters for project runs	×	
Model Management		
MLflow Model Registry		
Model versioning	<b>✓</b>	
ACL-based stage transition	×	
CI/CD workflow integrations	<b>✓</b>	



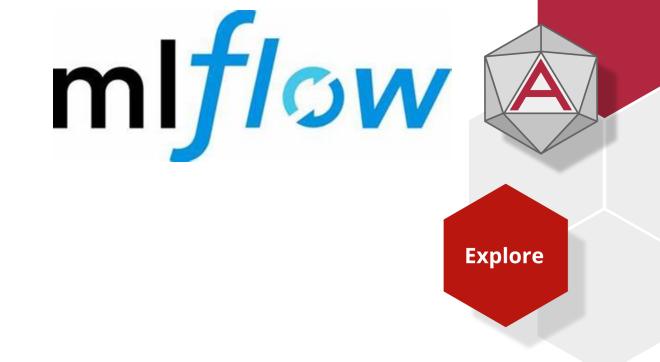
## **DATABRICKS MLFLOW**

Flexible Deployment		
MLflow Models	$\overline{\mathbf{v}}$	
Built-in batch inference	×	
Built-in streaming analytics	×	
Security and Management		
High availability	×	
Automated updates	×	
Role-based access control	×	



Integrates with Feature Store Facilitates Databricks Serving Endpoints

## **MLFLOW DEMO**





#### **EVALUATION**

- mlflow.evaluate
- Built in metrics
  - Regressor models: example\_count, mean\_absolute\_error, mean\_squared\_error, root mean squared error, sum on target, mean on target, r2 score, max error, mean\_absolute\_percentage\_error.
  - **Binary classifiers:** true\_negatives, false\_positives, false\_negatives, true\_positives, recall, precision, f1\_score, accuracy\_score, example\_count, log\_loss, roc\_auc, precision\_recall\_auc.
  - Multiclass classifiers: accuracy\_score, example\_count, f1\_score\_micro, f1\_score\_macro, log\_loss
- Custom metrics
- Explainability metrics
  - SHAP
- Fairness metrics
  - Fairlearn







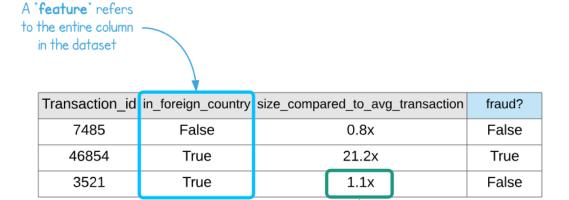
= Fairlearn



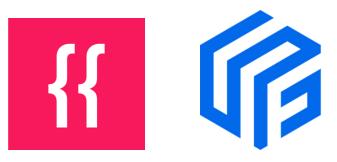




## **DATABRICKS FEATURE STORE**



A "feature value" refers to a single value of a feature column







COTOP





#### FEATURE STORE CONCEPTS

- Registry Central interface for managing feature definitions + metadata
- Offline Store Store large volumes of feature data used train and test
- Online Store Low latency database for realtime inference







#### WHY DO YOU NEED A FEATURE STORE?

- Easily reuse new features
- Easily explore features
- Data pipelines can be shared across both training and serving
- Constant features across teams
- Provides lineage
- Feature tracking





## **DATABRICKS FEATURE STORE**

- Backed by Delta Lake
- Feature Store Library
- Feature Store UI
- Offline Store
- Online Store Compatability
- Training Set Functionality





## **DATABRICKS FEATURE STORE DEMO**







#### **DEVOPS**











# Package

#### Admin workflow

Set up top-level repos folders (for example, Test or Production)

Set up Git automation to update Repos on merge

#### User workflow in Databricks

Clone remote repository to a user folder

Create a new branch based on the main branch

Create and edit code

Commit and push to the feature branch

#### Merge workflow in Databricks

Pull request and review process

Merge into main branch

Git automation calls to the Databricks Repos API

#### Production job workflow in Databricks

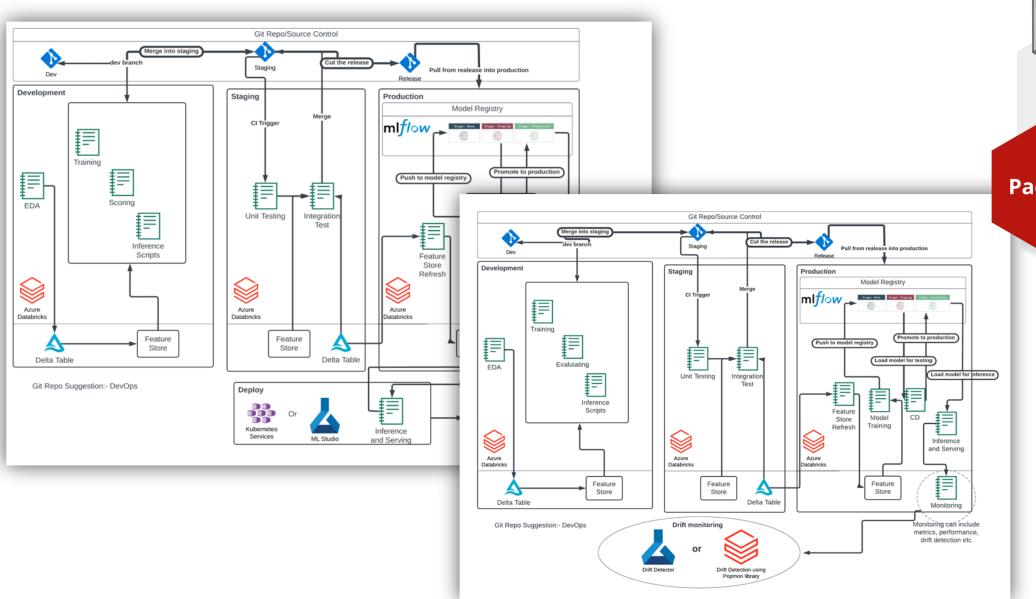
API call brings the repo in the Production folder to the latest version

Run a Databricks job based on a repo in a Production folder.

Steps in Databricks

Steps in your Git provider

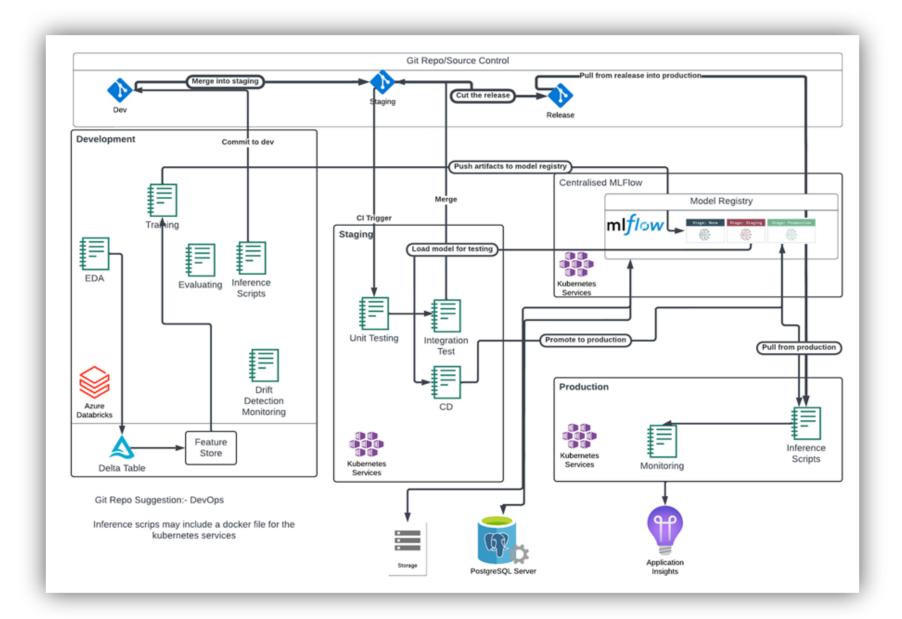
#### **CODE-FIRST DEPLOYMENT**





**Package** 

#### **MODEL-FIRST DEPLOYMENT**





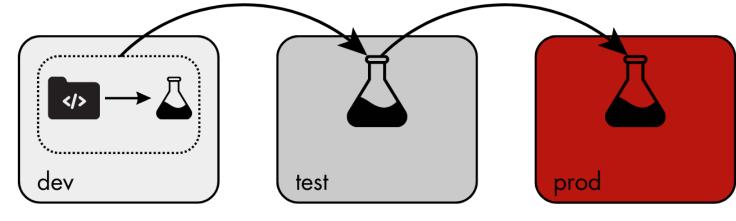
#### **CODE-FIRST VS MODEL-FIRST**



</>
training code

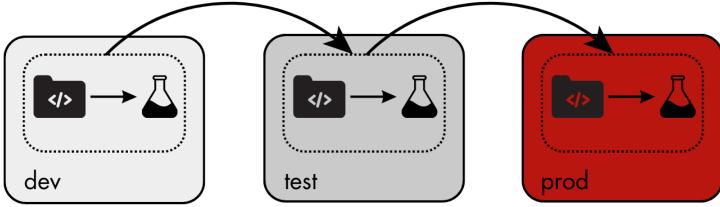


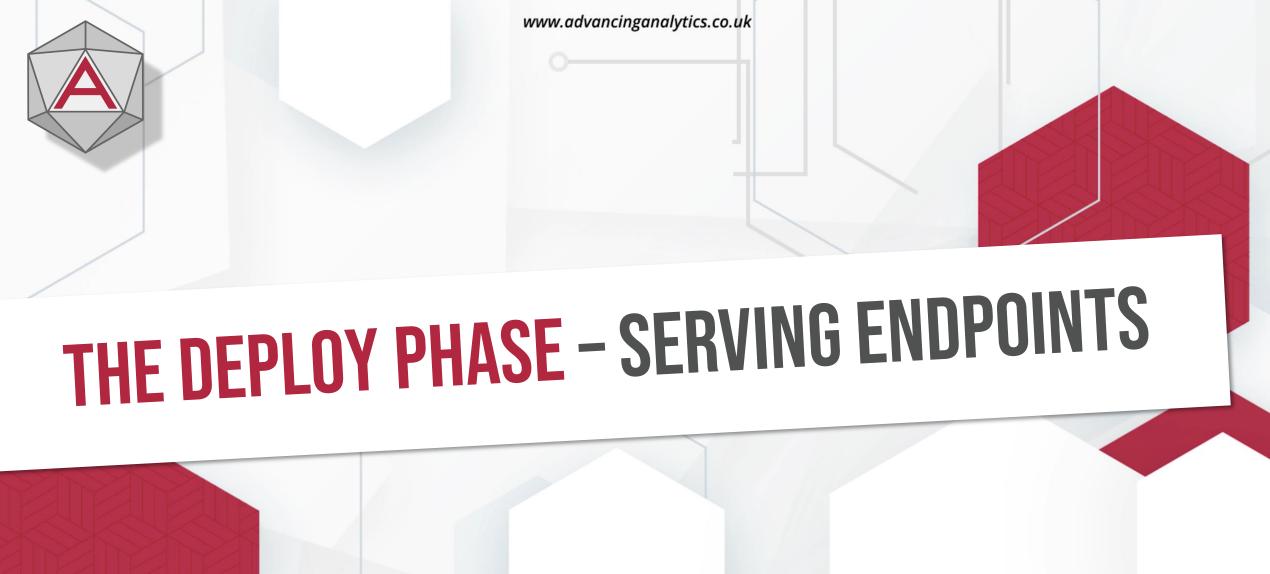
model deployment



Package

code deployment







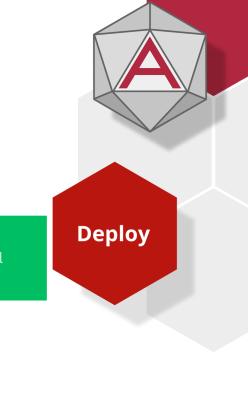
#### **MODEL SERVING**

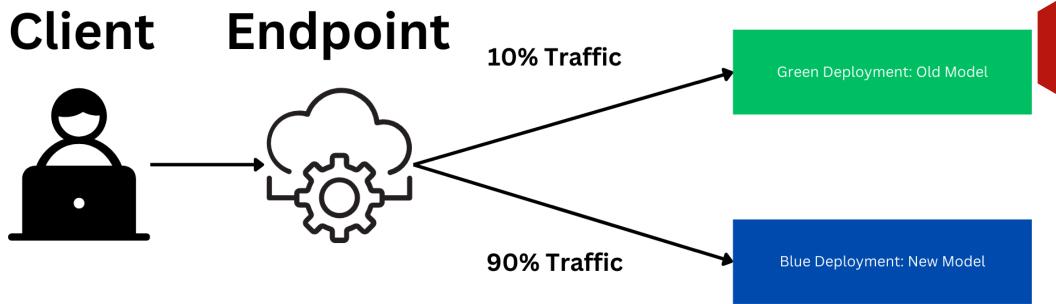
- Real time scoring provides near real-time results on small records
  - Fraud Detection
  - Predictive Maintenance
  - Recommender systems
- Batch scoring provides results for a large volume of records in a single operation
  - Churn Prediction
  - Credit Risk Analysis
  - Forecasting





#### **GREEN BLUE DEPLOYMENT**





#### DATABRICKS SERVING/SERVERLESS ENDPOINTS

Serverless doesn't mean no servers!

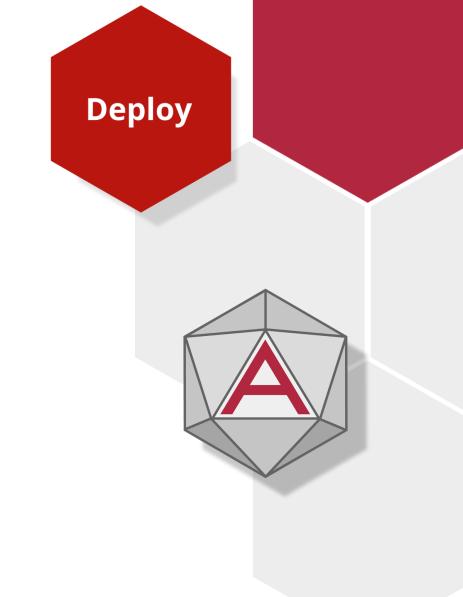
The cloud providers take care of underlying infrastructure

- Scalable
- Cost-effective
- Flexible
- Easy to deploy & manage

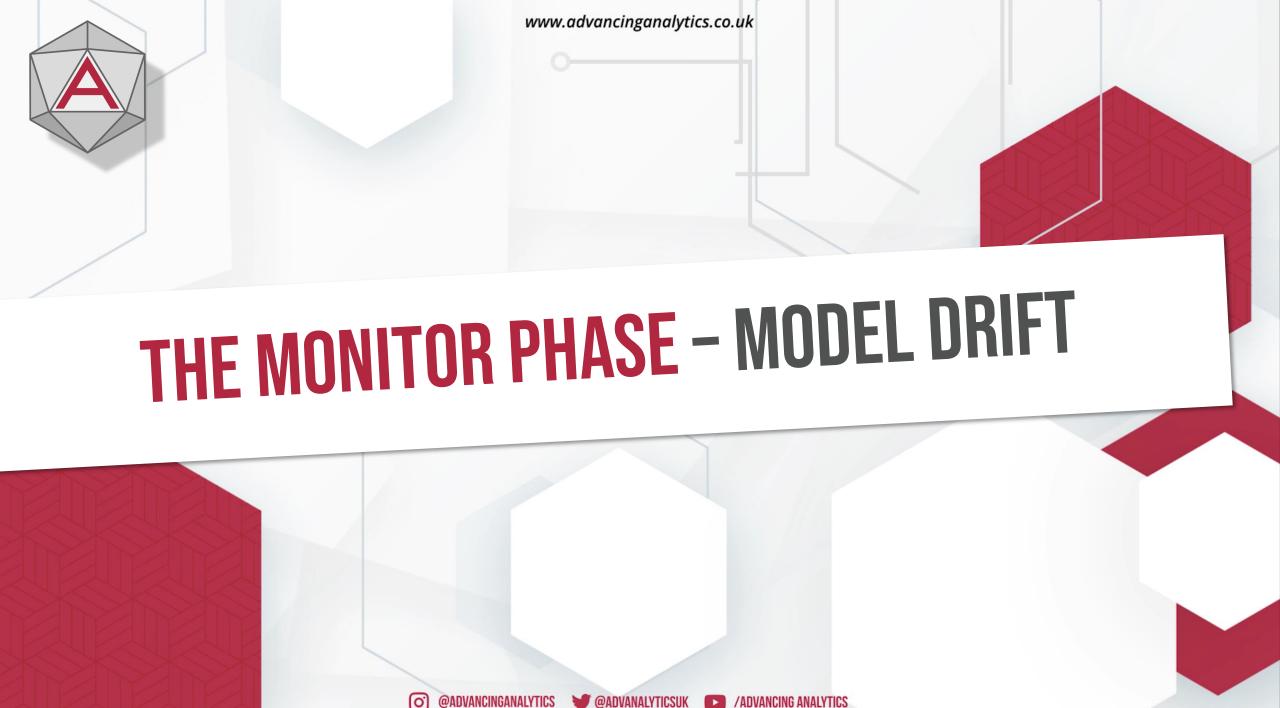




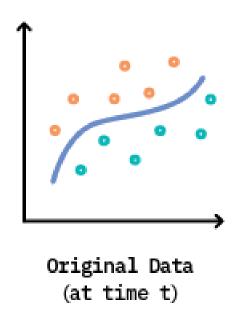
### DATABRICKS SERVING ENDPOINT DEMO

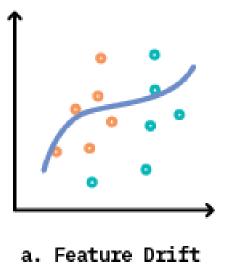






#### **MODEL DRIFT**





(at time t+1)

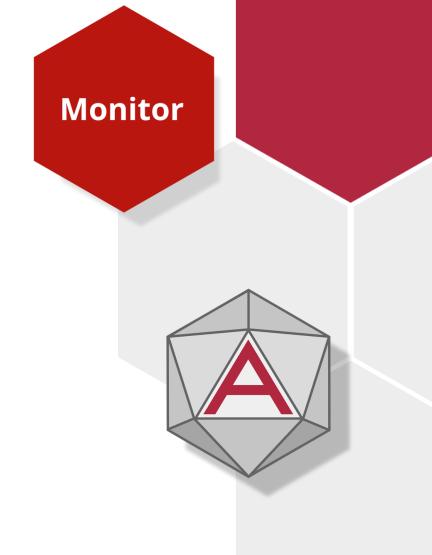


**Monitor** 

- Data drift
- Label drift
- Prediction drift
- Concept drift

#### **DRIFT TRACKING IN DATABRICKS**

- No current explicit support
- Log data with Delta
- Custom notebooks:
  - Summary statistics
  - Correlation statistics
  - Kullback-Liebler Divergence/ Jenson-Shannon
     Divergence
  - Chi-Squared test





# DATABRICKS AS AN END-TO-END PLATFORM







**Collaborative Workspace** 

Explore Evaluate Develop

Monitor Deploy Package

Databricks Feature Store





Code vs Model Deployment

## **DELTA LAKE**

**Custom Drift Notebooks** 

Databricks Serverless Endpoints

#### **LEARN MORE**





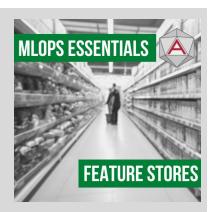
FEATURE STORES, MOVIES, ICECREAM AND S'MORE





DESIGNING THE RIGHT ML PLATFORM WITH MLOPS





FEATURE STORES AND WHY YOU NEED THEM





WHAT IS MLOPS AND WHY DO YOU NEED IT?





HOW TO FIX
DIFFERENT TYPES OF
MODEL DRIFT



# **QUESTIONS?**

