

MINT.

Bizmetric – MLOps Capability





- Established in 2011
- Microsoft Gold Partners
- Specialized into Azure Data Engineering, Data Science and Ops (Devops and MLOps) Projects
- Experienced team of Cloud Engineers and Data Scientist
- Large In-House Development Team
- Ability to provide extensive onshore and offshore services and Development Teams
- Specialized and experienced 100+ Consultants have since then joined globally from companies like Cognizant, Schlumberger, PROS, IBM, TCS, Infosys



50+ Certified Consultant



Global Project Locations includes <mark>USA</mark>, UK, Canada, Australia, India Project Success Rate 100%

Customer Retention (retained after 1 year or for the next project) 100%



Azure AI & Data Service Offerings





MLOps

Iterative Cycles for each task (ML, Dev, Ops)



Azure ML Life Cycle



Azure ML Pipeline Representation



Azure ML Architecture



Responsible Machine Learning

3

Mitigate

(how can I

improve my

model?)

Throughout the development and use of Al systems, trust must be at the core. Trust in the platform, process, and models. Responsible machine learning encompasses the following values and principles:

- Understand machine learning models
 - Interpret and explain model behaviour
 - Assess and mitigate model unfairness
- Protect people and their data
 - Prevent data exposure with differential privacy
 - Work with encrypted data using homomorphic encryption
- Control the end-to-end machine learning process
 - Document the machine learning lifecycle with datasheets

Fairlearn Is my model fair?

Unfairness mitigation to mitigate observed fairness issues

Perturb your datapoints using what-if to see how changing certain features impact your model's prediction

> Use individual feature importance to drill into which factor contributed towards single individual prediction



Azure Machine Learning

(what went wrong in my model?)

Use aggregate feature

importance to uncover which

factor overall contributed

towards your model's prediction

Diagnose

2

(why did my model make such errors?)

Fairness Assessment to highlight how model treats sensitive features

> Create dataset cohorts to understand different demographics

Analyze model performance

to see differences in model statistics across cohorts

Explore your dataset to observe data imbalances or other issues

Homomorphic Encryption

Homomorphic Encryption helps to protect the integrity of your data by allowing others to manipulate its encrypted form while no one (aside from you as the private key holder) can understand or access its decrypted values

- Securing Data Stored in the Cloud.
- Enabling Data Analytics in Regulated Industries.

Types of Homomorphic Encryption

- Partially Homomorphic Encryption
- Somewhat Homomorphic Encryption
- Fully Homomorphic Encryption

Homomorphic encryption-based data processing platform

> Third-party cloud service provider

Data owner





MLOps Maturity Model

Highlights

Technologies

Level 4 Full MLOps Automated Operations	 Full system automated and easily monitored Approaching a zero-downtime system 	 Automated model training and testing Verbose, centralized metrics from deployed model
Level 3 Automated Model Deployment	 Releases are low friction and automatic Full traceability from deployment back to original data Entire environment managed: train > test > production 	 Integrated A/B testing of model performance for deployment Automated tests for all code Centralized training of model training performance
Level 2 Automated Training	 Training environment is fully managed and traceable Easy to reproduce model Releases are manual, but low friction 	 Automated model training Centralized tracking of model training performance Model management
Level 1 DevOps but no MLOps	 Releases are less painful than No MLOps, but rely on Data Team for every new model Difficult to trace/reproduce results 	 Automated builds Automated tests for application code
Level 0 No MLOps	 Difficult to manage full machine learning model lifecycle The teams are disparate and releases are painful Most systems exist as "black boxes," little feedback during/post deployment 	 Manual builds and deployments Manual testing of model and application No centralized tracking of model performance Training of model is manual
		Gold Partner

MLOps Sample Project Plan

Sprint 1

- Manual builds and deployments
- Manual testing of model and application
- No centralized tracking of model performance
- Training of model is manual

Sprint 2

- Automated builds
- Automated tests for application code

Sprint 3

- •Automated model training
- •Centralized tracking of model training
- performance
- Model management

Sprint 4

- •Integrated A/B testing of model performance for deployment
- •Automated tests for all code
- •Centralized training of model training performance

Sprint 5

Automated model training and testing
Verbose, centralized metrics from deployed model





Use Case :- 1

- A USA based Steel Production company. We Implemented the time series forecasting model which forecasts the amount of steel which will be bought by the customers on monthly basis on Microsoft Azure Using ADF and ML Studio.
- Azure Data Factory was used for data ingestion from different database SQL server and Postgres server database for extracting data using SQL.
- Perform EDA and feature analysis on the datasets with data collection and preparation for different machine learning models.
- Implementation of different MLOps levels starting from level 0 to level 4 by achieving complete automation.
- Create a python framework to forecast the Amount of steel which is going to be purchased by the customers.
- Training steel-purchase models for Organization, Customer and Material level predictions.
- Create end to end pipelines for fetching the data, transforming the data, retraining the model, and deploying the ML pipelines using Azure Devops.

Use Case :- 2

Client is a multi-disciplinary mining, infrastructure, and oil & gas services company with a track record of achievement in Indonesia. The project was about using Advance Analytics, Data Engineering & Data Science to improve their operational efficiency hence reduce overall cost for mining.

Use Cases - To achieve man, machine & environment operational efficiency different advance analytics, data science & machine learning solutions were designed and implemented.

- Azure DevOps was used to implement MLOPs for Continuous Integration, Continuous Delivery and Continuous Training.
- Kedro frameworks was used for creating pipelines of Data Engineering and different Machine learning use cases, which were used for automated training, scoring, testing and deployment of best models.
- Different MLOps maturity levels starting from level 0 to level 4 were achieved.
- Various prediction result was populated on Azure PostgreSQL for Backend, Frontend and Power BI reports deployment.





ExxonMobil MLOps Case Study

About the Industry

The recent years in the oil and gas industry have evolved considerably. It's been six years since the oil price saw a decent rise in the price. Many energy firms have decided to streamline their resource portfolio, considering the disruptions occurring now and then. Commitment to delineated climate change, an initiative to drive a transformed business model, and a greater emphasis on healthier financial results have created a new arena of opportunities for the organizations. As per the current scenario analysis, the energy transition plans will see a tremendous boost due to the increasing oil prices.

About the Client

Our client is one of the world's largest publicly traded energy service provider companies. They deploy next-gen technologies in producing high-quality chemical products. Our client has a specific governance framework that makes the business more viable and productive. The company holds excellence in producing unleaded gasoline and diesel fuel products. They have an array of service-offering products such as credit cards, gift cards, and mobile payment applications to cater to the daily needs of the customer segment. Our client has also targeted many untapped geographies across the globe for their business expansion.

The Business Challenges

- Absence of solutions to automate the manual and redundant processes
- Delayed deployment of ML-enabled solutions by weeks
- Absence of extra features like multiple experiments execution, hyperparameter tuning, code versioning etc.
- Need for user Interface Application that interacts with the model API and makes predictions for production data
- Retraining the Machine Learning Model in case of trivial circumstances data drift was the crucial enterprise need
- End-to-end tracking of the entire model lifecycle was one of the significant roadblocks for our client

The Business Solution

- Proposed an MLOps solution on Microsoft Azure cloud platform solution to develop a scalable solution
- Modularized the project code to set up the orchestration of data engineering & data science pipelines
- Helped the client with Service Creation, Hyperparameter Tuning, Continuous Integration, Continuous Training, Continuous Deployment & UI Application deployment pipelines for the project
- The Hyperparameter tuning of the model using "Optuna" automated the trial-anderror process, and helped client obtain the best parameters for the BERT model
- Developed the Dash UI Application to make predictions for production data

Key Results

- Automated MLOps process eliminated the manual dependencies and reduced the project cycle time to a great extent
- Streamlined the ML lifecycle from developing models to the deployment and management of ML apps
- Auto retraining of the model critically reduced the occurrence of the problems like data drifting and prediction inaccuracies
- Our client can now focus on building new models and conducting meaningful experiments
- Technical documentation helped the organization in understanding the entire framework very effectively



Architecture Diagram





Thank You

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