

AIM 301 - 300 LEVEL

# Implement MLOps practices on AWS

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Amazon Web Services

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Practice Lead, Modern Data Platform  
Reply



# Agenda

## What is MLOps

People, Processes, Technology

## Why MLOps

Business Benefits and KPIs

## MLOps People & Processes

Team Structure and Personas

## MLOps Foundation Roadmap - Technology

MLOps Maturity: Initial, Repeatable, Reliable, Scalable

## MLOps Journey with Data Reply

Partnership, MLOps Accelerator and Customer Success Stories



# Customer Challenges, ML Lifecycle and Personas

CONSIDERATIONS & CHALLENGES LEAD TO ML AND OPERATIONS (MLOPS)

- Culture
- Lack of cross-functional teams
- Priorities & needs (personas)
- Organizational structure
- Skillsets
- Unique aspects of ML lifecycle

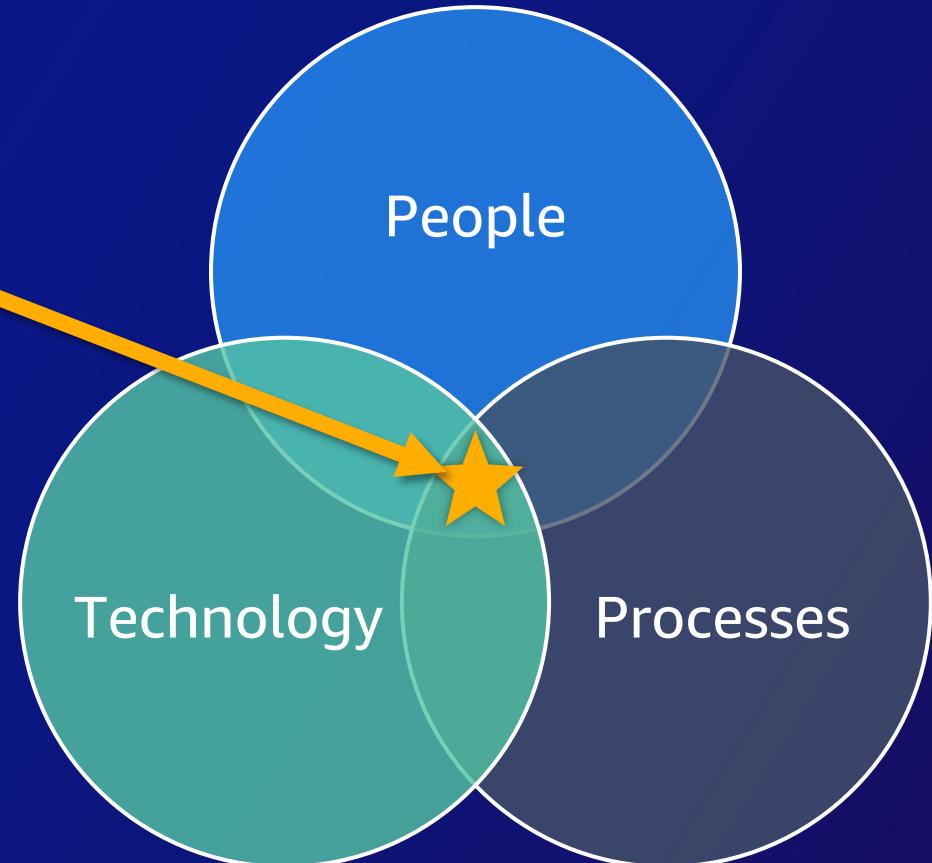
People	Processes	Technology
 Business Analysts Product Owner Business Stakeholders	Business decision making Business KPI evaluation	 QuickSight Visualisation
 Lead Data Scientist	Model KPI evaluation ML Solution QA	 SageMaker
 Data Scientists	Model building Model evaluation Model versioning Model retraining Model deployment Inference Code abstraction Code testing Code QA CI/CD development	 Notebooks
 ML Engineers	Data ingestion Data preparation Data partitioning Data governance Data quality	 Sagemaker Model Endpoints
 Data Engineers & Owners	Network orchestration Security hardening Infrastructure as code development Account instantiation	 ML Data
 IT Lead		

# What is MLOps?

**MLOps**  
Machine Learning  
& Operations

The combination of people,  
processes, and technology to  
productionize ML solutions  
efficiently.

## MLOps Definition



# Why MLOps? Expected Business Value

# MLOps Foundation Expected Outcomes

STANDARDIZE OPERATIONS AND INFRASTRUCTURE FOR YOUR DATA SCIENCE

Business Goal	Technical Metric	Before MLOps	MLOps Expected Outcomes	Business Value
1 Be more efficient in delivery	Time to value (from idea to production)	up to 12 months	< 3 months	Improve Speed-to-Value by 4x



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4	Standardize onboarding of new teams and ML use cases	Time to instantiate a new MLOps infrastructure & ML projects	40 days	< 1 hours	Accelerate ML adoption across all business areas

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5	Ensure high security standards	Execute the ML solutions without internet access in a private cloud	n/a	No internet	Your data is safe in your private cloud



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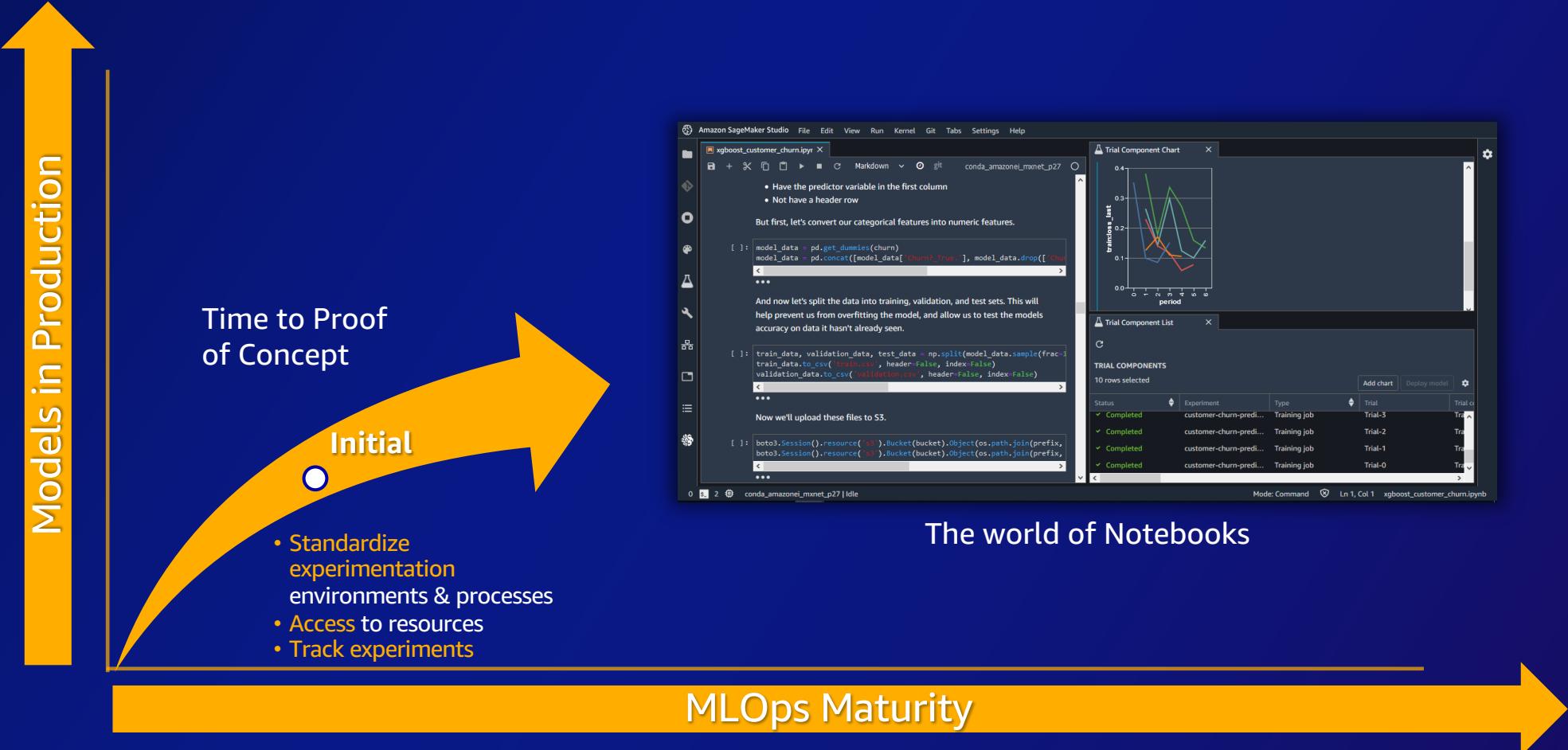
Reduce platform, people and operation costs

Customer references building MLOps foundation and business benefits:

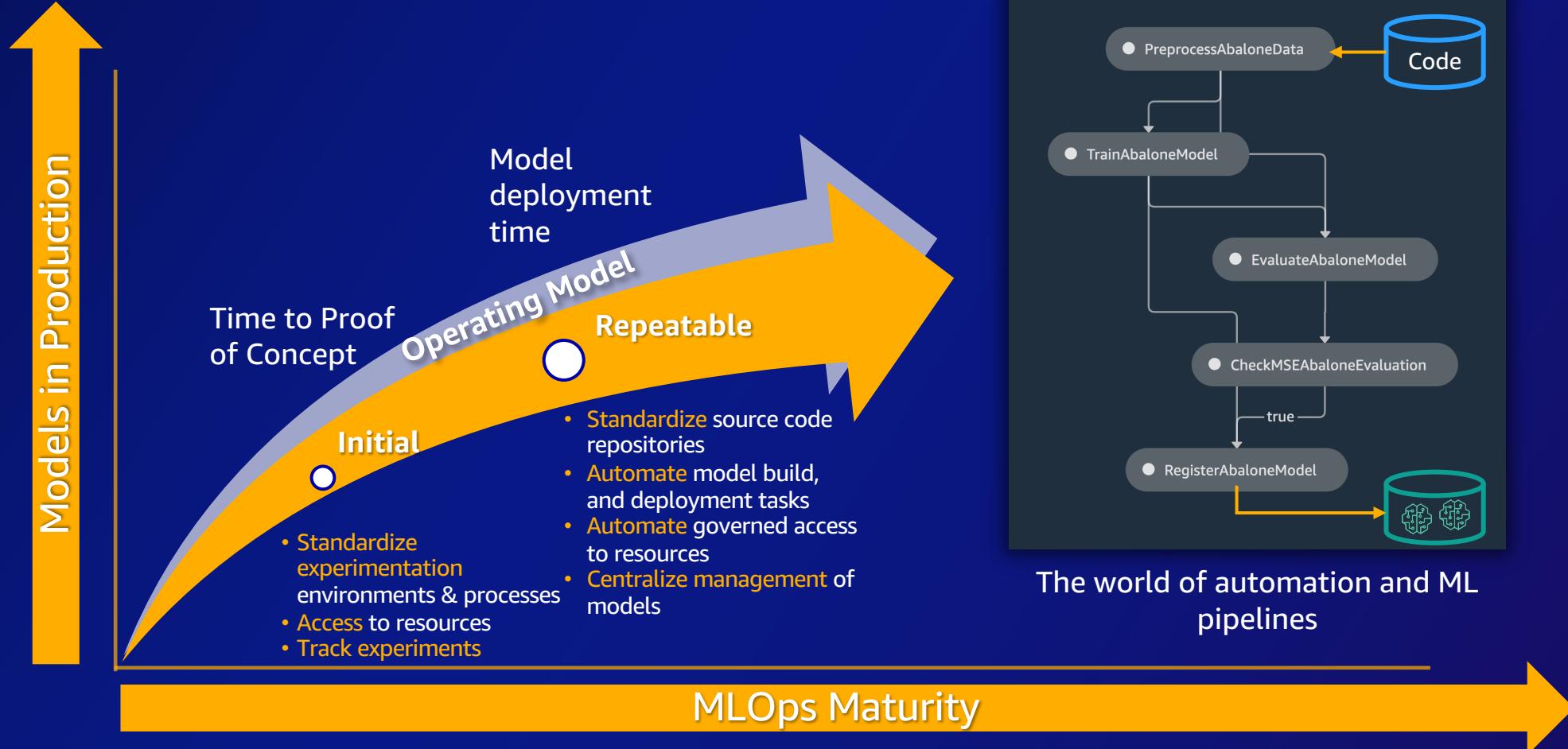
- NatWest: <https://aws.amazon.com/solutions/case-studies/natwest-group-case-study>
- BP: <https://aws.amazon.com/solutions/case-studies/bp-machine-learning-case-study>

# How to Mature on MLOps?

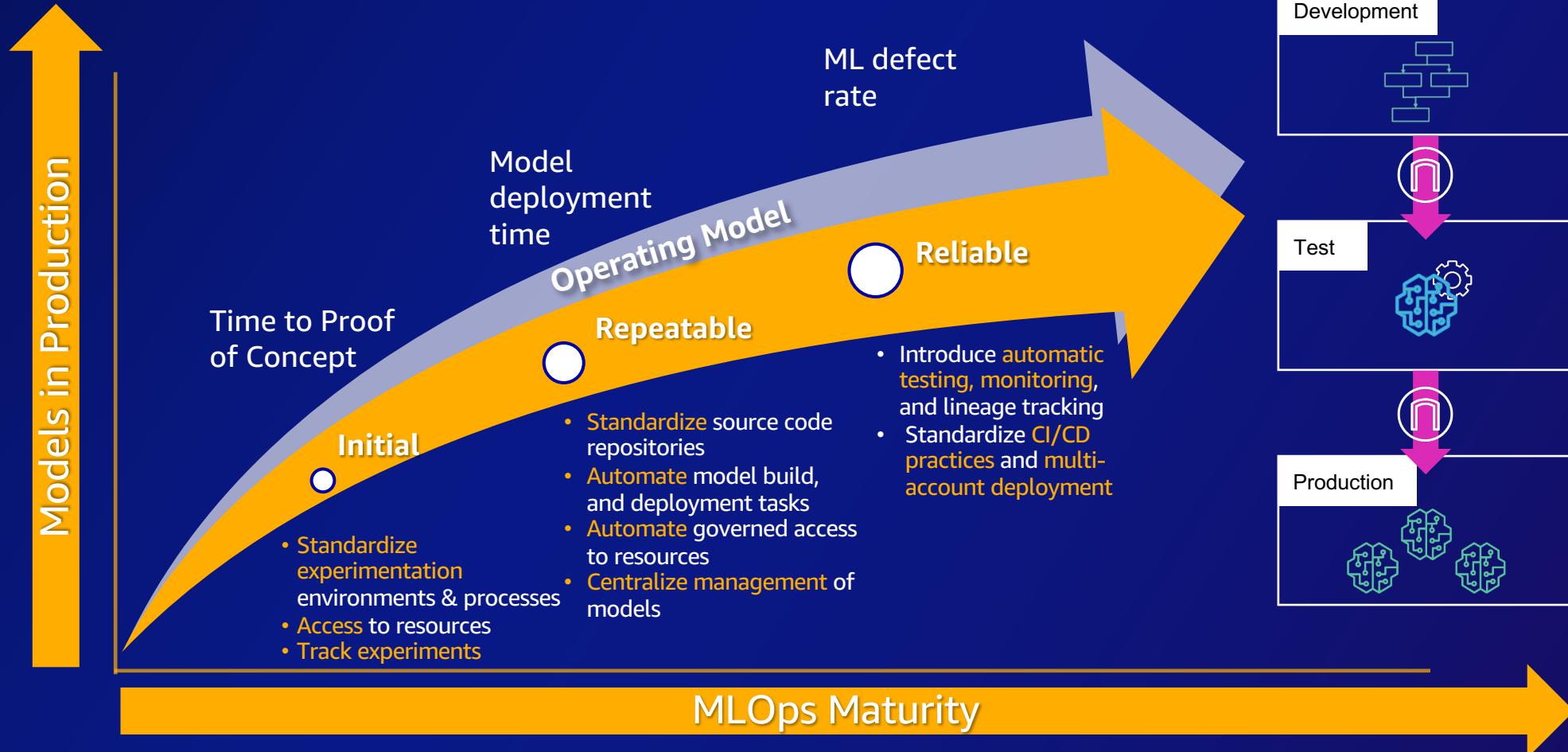
# MLOps Maturity Model



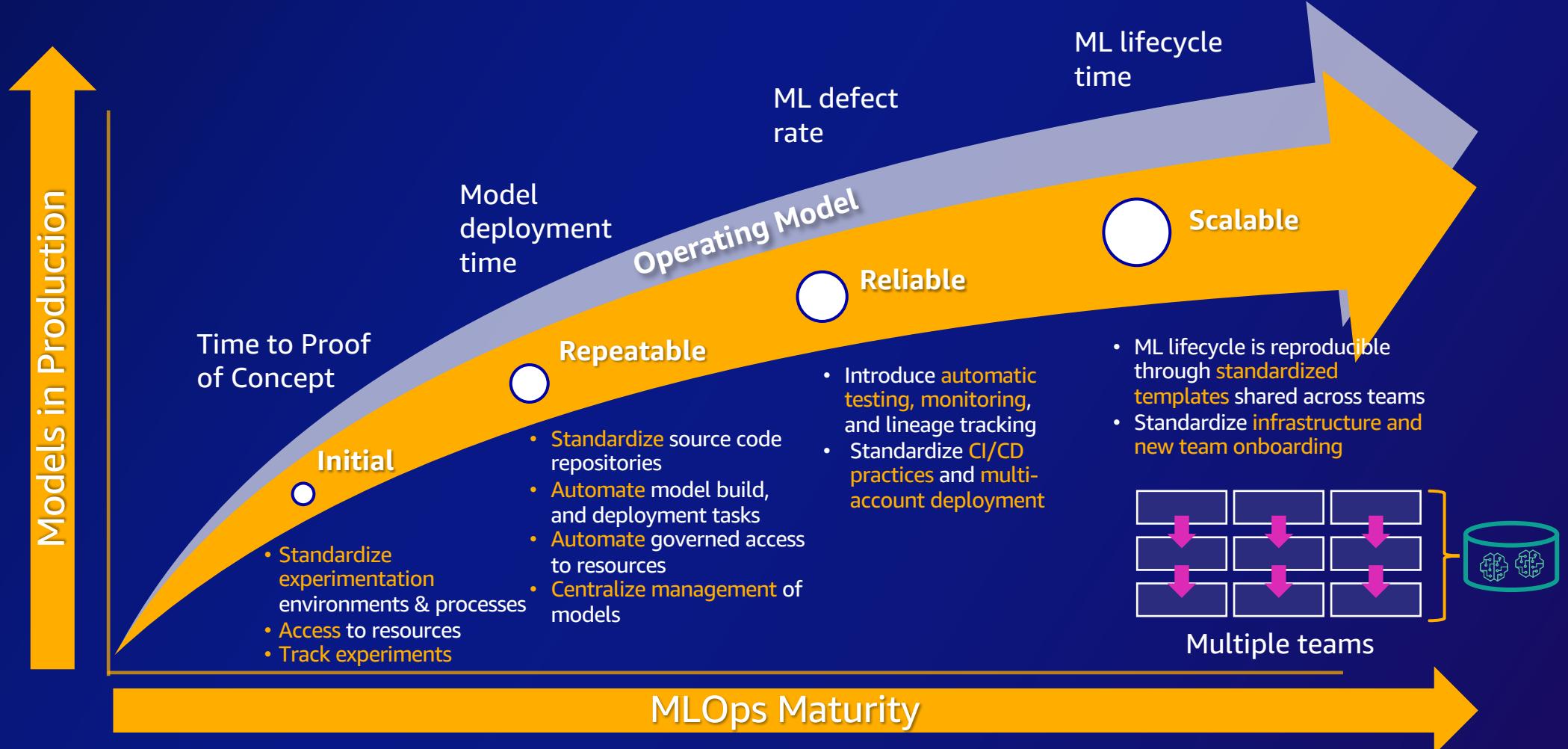
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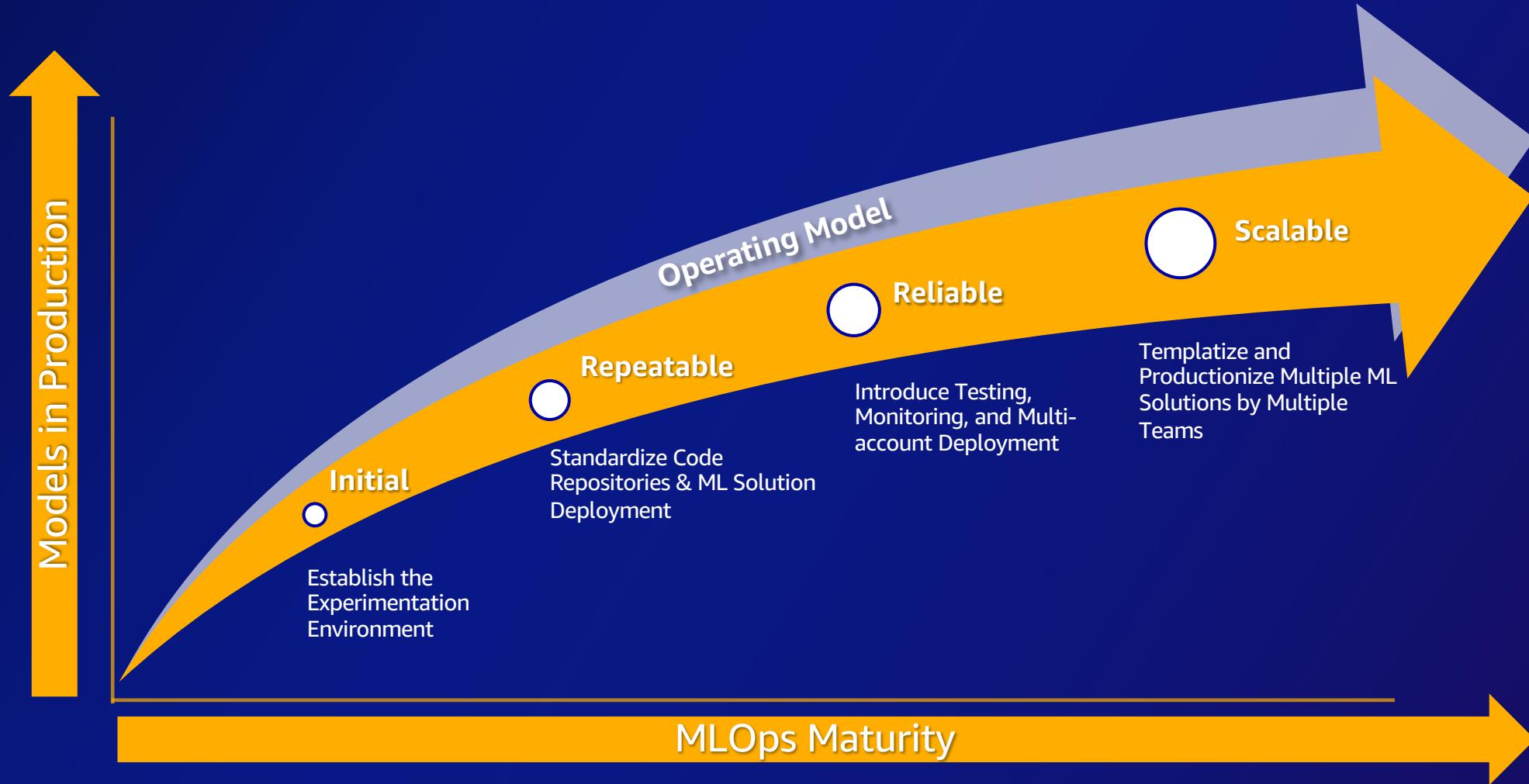
# MLOps Maturity Model



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# MLOps Maturity Model



# MLOps People & Processes

# MLOps Key Personas and Roles

## Advance Analytics Team Data Lake



### Data Engineer

Prepare & Ingest data building ETL pipelines



### Data Owners

Manage data sharing and provide access

## Data Science Team Experimentation & MLOps



### Data Scientist

Create the best ML models to solve business problems



### ML Engineer

Collaborate with DS to productionize ML

## Platform Team Secure Cloud/Data/ML Platform



### MLOps Engineer/Admin

Standardize CI/CD, user/service role, model consumption, testing and deployment methodology



### Security

Assess data, user, and service access creating policies and guardrails



### Architects/ SysOps Engineer

Standardize account infrastructure, connectivity, user roles implementation

## Business Viz Dashboards, ML Adoption, & ROI



### Business Stakeholder Product Owners

Define business problem, business KPIs, and make business decisions



### Business Stakeholder Data & ML Consumers

Consumers of ML results from other BUs, driving business decision making

## Risk & Compliance Approve & Review Models

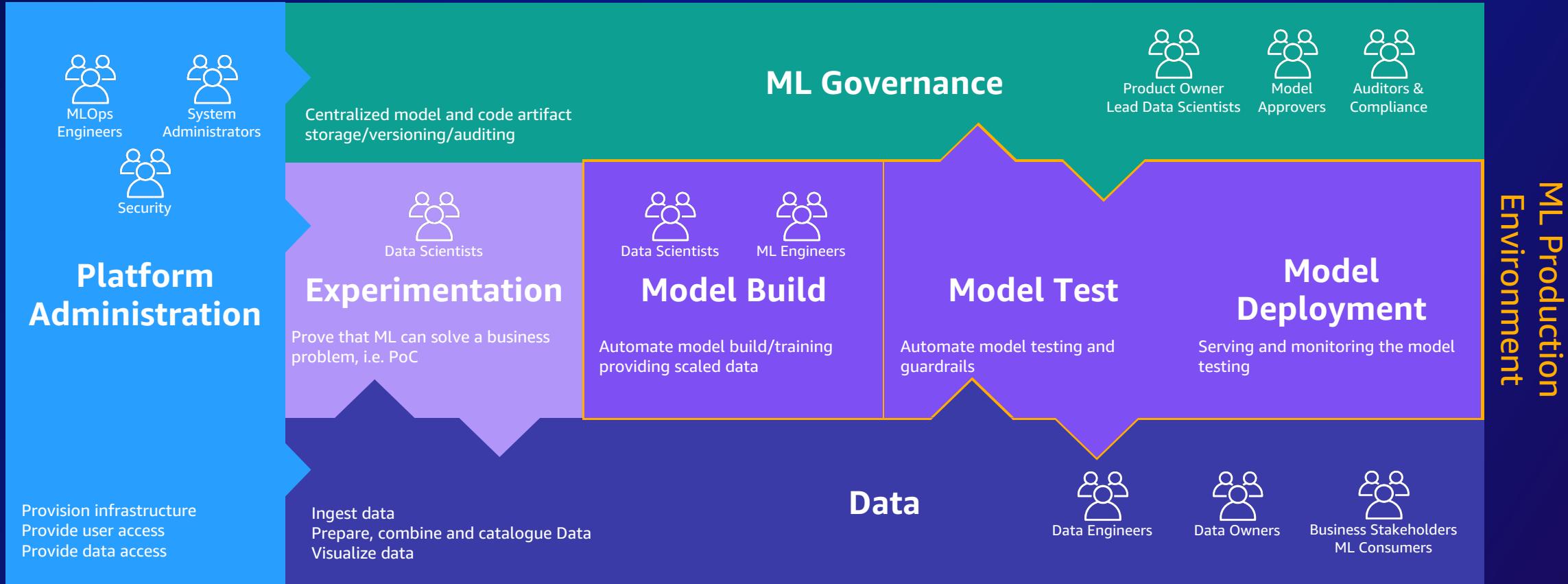


### Auditors/Risk & Compliance

Review models, data sources, code artifacts

# MLOps Foundation People & Processes

SEPARATION OF CONCERNS IS KEY FOR SUCCESS

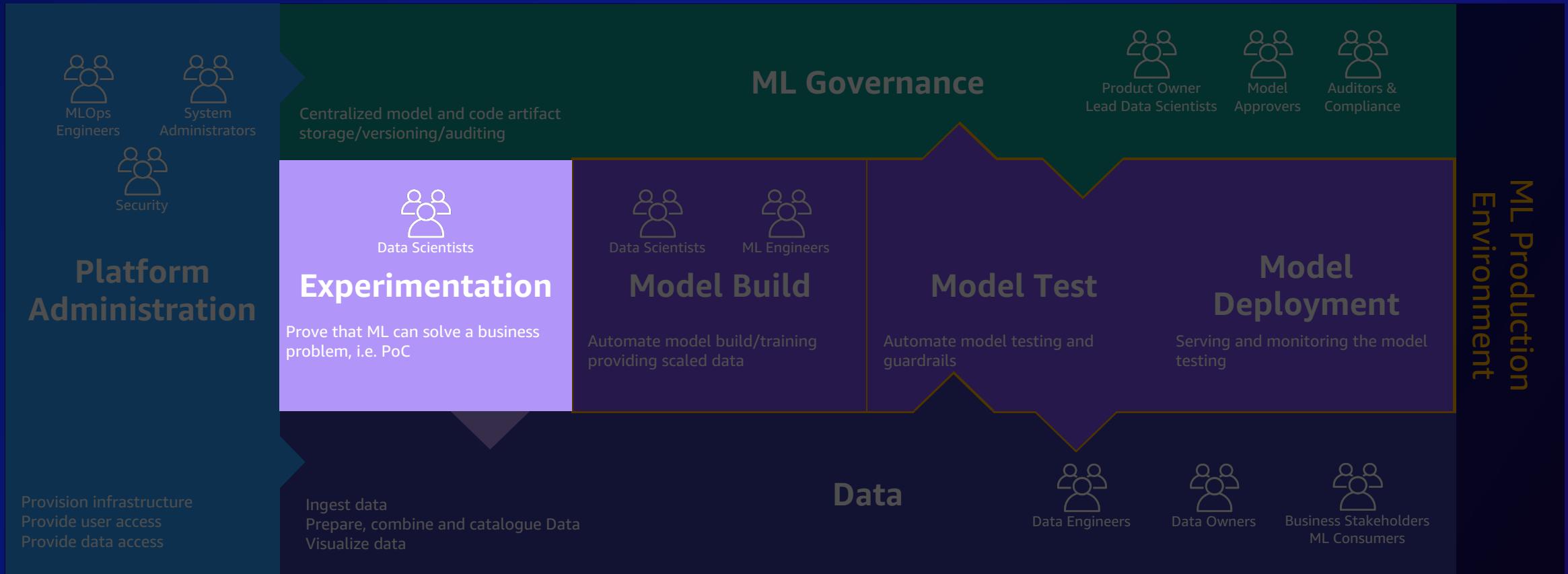


# MLOps Foundation Roadmap

## Technology

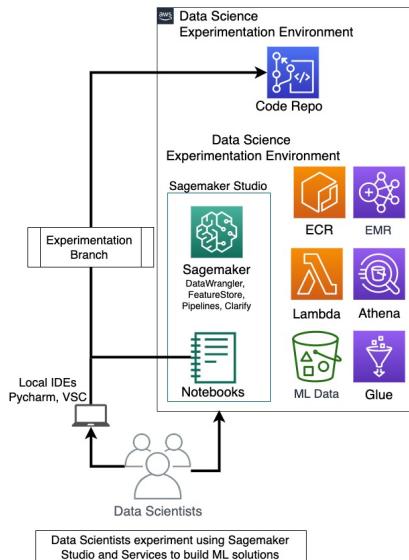
# MLOps Foundation People & Processes

## INITIAL PHASE



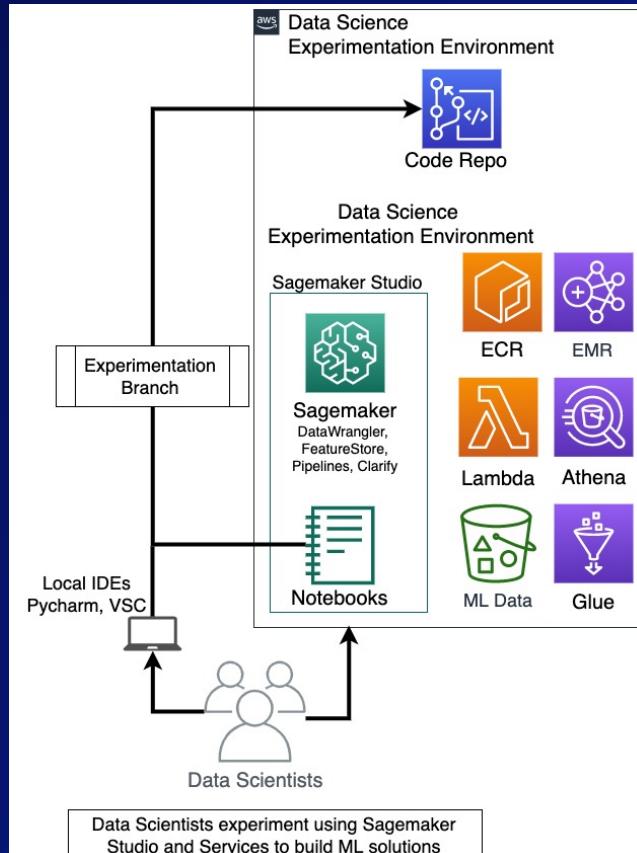
# MLOPs Initial Phase

ML EXPERIMENTATION ON AWS USING AMAZON SAGEMAKER STUDIO NOTEBOOKS



# Amazon SageMaker Studio

## ML EXPERIMENTATION ON AWS USING AMAZON SAGEMAKER STUDIO NOTEBOOKS



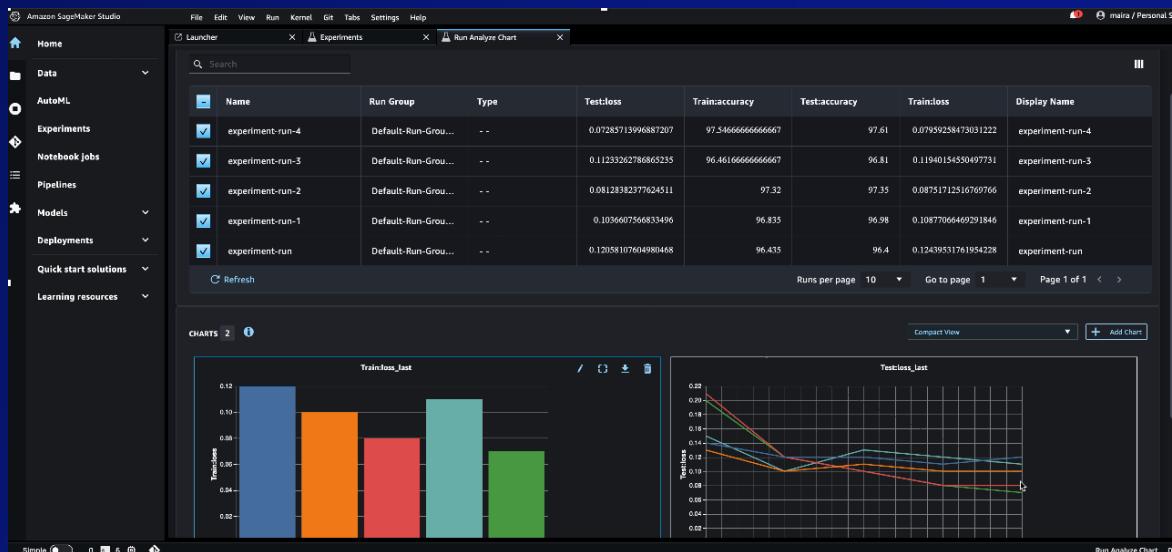
The screenshot shows the Amazon SageMaker Studio interface. The top navigation bar includes File, Edit, View, Run, Kernel, Git, Tabs, Settings, and Help. The left sidebar lists Home, Data, AutoML, Experiments, Pipelines, Models, Deployments, Quick start solutions, and Learning resources. The main area displays a 'Home' dashboard with 'Quick Actions' (Open Launcher, Connect to data sources, Read document), 'Prebuilt and automated solutions' (Deploy built-in algorithms, pre-built solutions, example notebooks, and build models from Sagemaker Studio), and a 'Training job summary' section. This section includes a pie chart of time spent in training phases (Initialization: 40%, Training loop: 30%, Finalization: 20%, Spot interruption: 10%), training job details (Start time: 2023-01-10 14:24:21, End time: 2023-01-10 15:05:00, Duration: 2408.501 seconds), and a table of metrics like Initialization, Training loop, Finalization, and Spot interruption. Below this is a code editor window showing Python code for pip installations and a terminal window displaying the output. The bottom right features a 'Manage endpoints and optimize performance' section with monitoring and profiling tools, and a 'Logs' tab.

# Amazon SageMaker Experiments

ORGANIZE, TRACK, AND COMPARE MACHINE LEARNING EXPERIMENTS

```
from sagemaker.experiments.run import Run
from sagemaker.session import Session
# create an experiment, start a new run and log a parameter
experiment_name = "experiment_name"
run_name = "run_name"
with Run(
    experiment_name=experiment_name,
    run_name=run_name,
    sagemaker_session=Session()
) as run:
    run.log_parameters({
        "normalization_mean": 0.1307,
        "normalization_std": 0.3081,
    })
```

```
from sagemaker.experiments.run import load_run
from sagemaker.session import Session
# load the run from context
with load_run(
    sagemaker_session=Session()
) as run:
    run.log_metric("precision", 0.9, step=step)
    run.log_confusion_matrix(
        target,
        pred,
        "Confusion-Matrix-Test-Data"
    )
```



## Tracking at scale

Track parameters and metrics across experiments and users



## Custom organization

Organize experiments by teams, goals, and hypotheses



## Visualization

Easily visualize experiments and compare



## Metrics and logging

Log custom metrics using the Python SDK and APIs

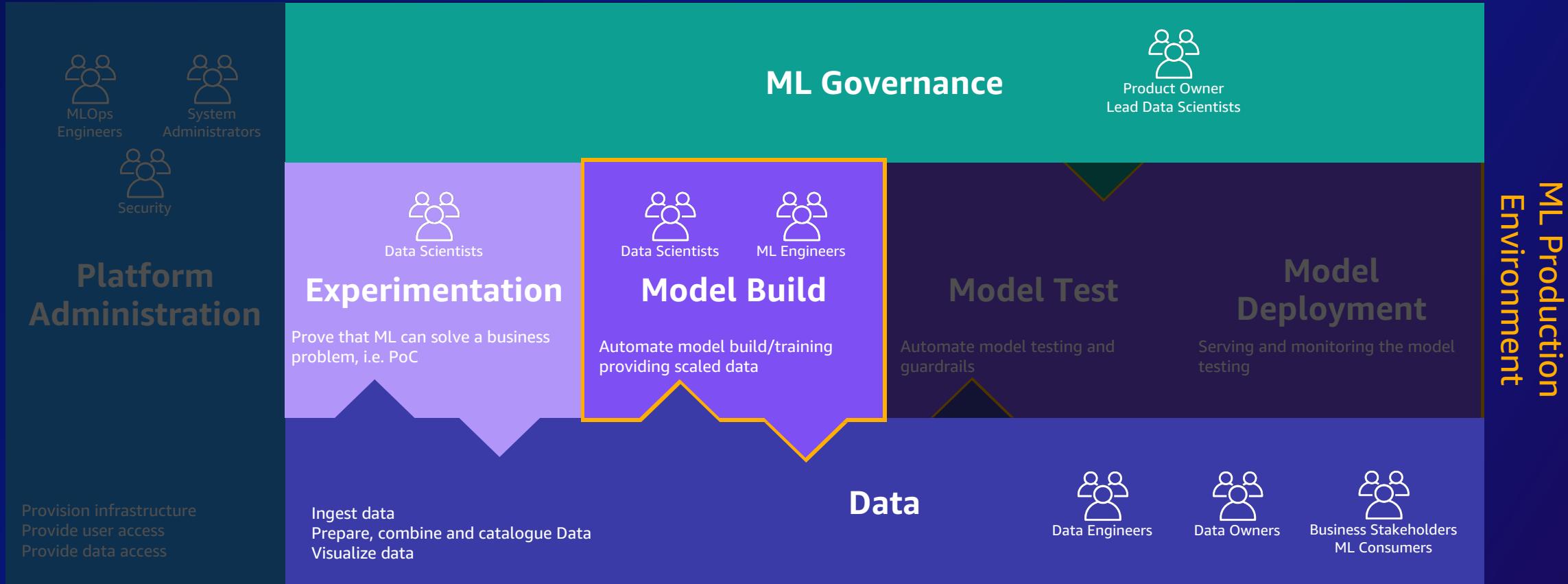


## Fast iteration

Quickly go back and forth, and maintain high-quality

# MLOps Foundation People & Processes

REPEATABLE PHASE



# ML Solution Lifecycle Automation

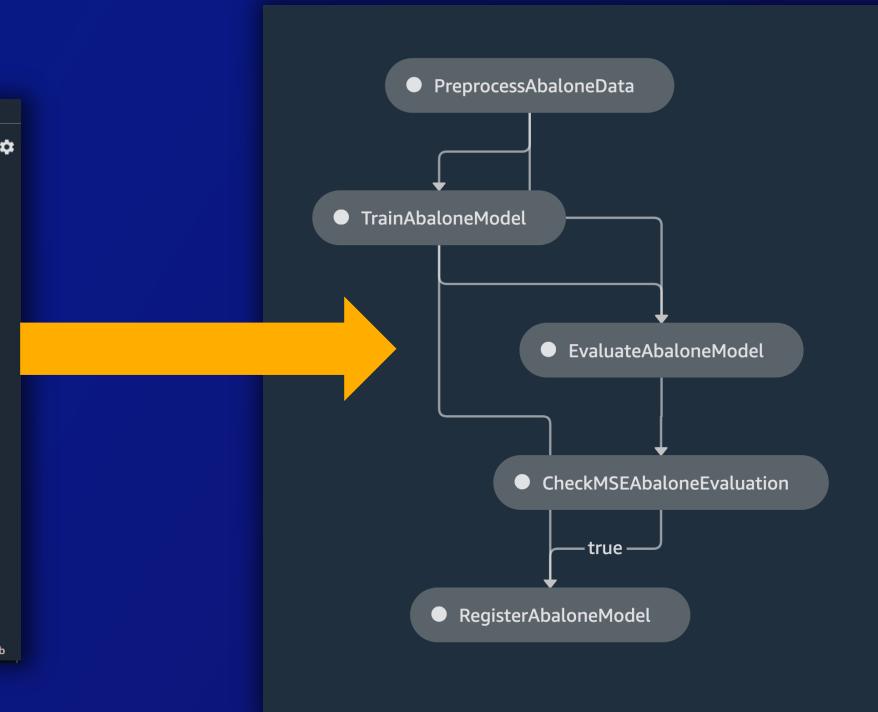
CREATING AUTOMATED WORKFLOWS ON AWS – ML PIPELINES

The screenshot shows the Amazon SageMaker Studio interface with a Jupyter notebook open. The notebook contains code for data preprocessing, model training, validation, and deployment. A 'Trial Component Chart' and 'Trial Component List' are also visible.

```
model_data = pd.get_dummies(churn)
model_data = pd.concat([model_data['Churn_>True'], model_data.drop(['Churn_>True'])], axis=1)

train_data, validation_data, test_data = np.split(model_data.sample(frac=1), [train_size, validation_size, len(model_data) - train_size - validation_size])
train_data.to_csv('train.csv', header=False, index=False)
validation_data.to_csv('validation.csv', header=False, index=False)
test_data.to_csv('test.csv', header=False, index=False)

boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train.csv')).upload_file('train.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'validation.csv')).upload_file('validation.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'test.csv')).upload_file('test.csv')
```



Move from the world of Notebooks...

...to the world of automation

# Amazon SageMaker Processing

PREPROCESS DATA & OFFLOAD DATA SCIENTISTS ON MANAGING CONTAINERS

```
from sagemaker.sklearn.processing import SKLearnProcessor  
from sagemaker.processing import ProcessingInput, ProcessingOutput  
  
sklearn_processor = SKLearnProcessor(framework_version='0.20.0',  
                                     role=role,  
                                     instance_type='ml.m5.xlarge',  
                                     instance_count=1)  
  
sklearn_processor.run(code='preprocessing.py',  
                      inputs=[ProcessingInput(  
                           source='s3://path/to/my/input-data.csv',  
                           destination='/opt/ml/processing/input')],  
                      outputs=[ProcessingOutput(source='/opt/ml/processing/output/train'),  
                               ProcessingOutput(source='/opt/ml/processing/output/validation'),  
                               ProcessingOutput(source='/opt/ml/processing/output/test')])
```

Container

Code

Inputs

Outputs

s3://bucket/path/to/input\_data



s3://bucket/path/to/output\_data

Processing Container

Instance 1

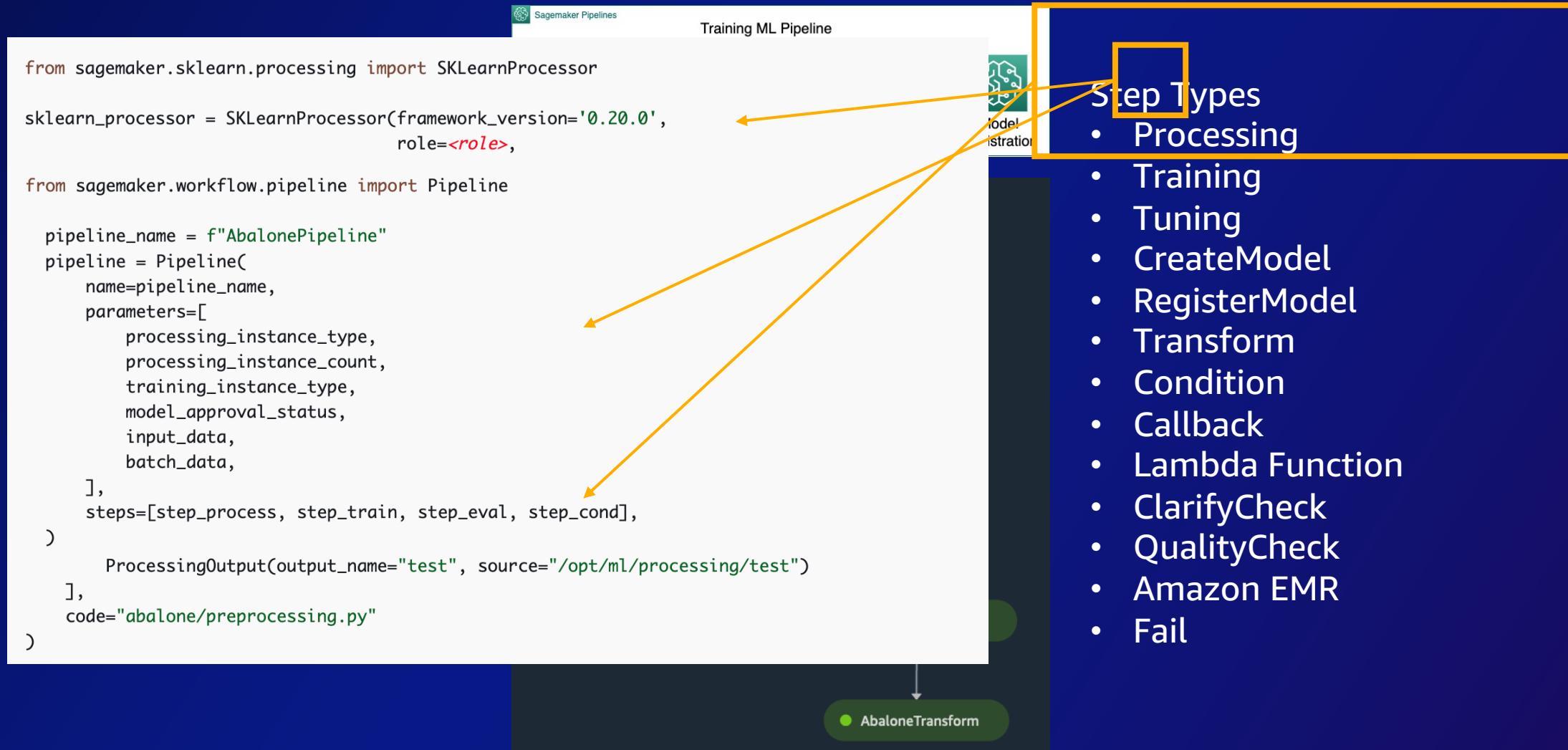
Cluster

Supported pre-built processors:



# Amazon SageMaker Pipelines

AUTOMATED WORKFLOWS TO PRE-PROCESS, TRAIN, EVALUATION, & REGISTER MODELS



# Amazon SageMaker Model Registry

STORE, VERSION, AND TRIGGER MODEL PROMOTION

The screenshot shows the 'Model registry' page in Amazon SageMaker Studio. It displays a table of model groups with columns: Model group name, Description, Status, Created on, and Created by. Two entries are visible: 'lineage-test-167...' with status 'Completed' and 'test-pipeline-project...' with status 'Completed'. The sidebar on the left provides navigation links for Home, Data, AutoML, Experiments, Notebook jobs, Pipelines, Models, Deployments, and Quick start solutions.

Create model groups in your model registry

The screenshot shows the 'test-pipeline-project-p-zkyabxnk9z7e' model group details page. It includes tabs for 'Versions' and 'Settings'. The 'Versions' tab lists two versions: '2' in 'None' stage and 'Pending' status, and '1' in 'prod' stage and 'Approved' status. A large yellow arrow points from the first screenshot to this one.

Benchmark and observe the model versions in your model group and promote versions of the model by changing their status

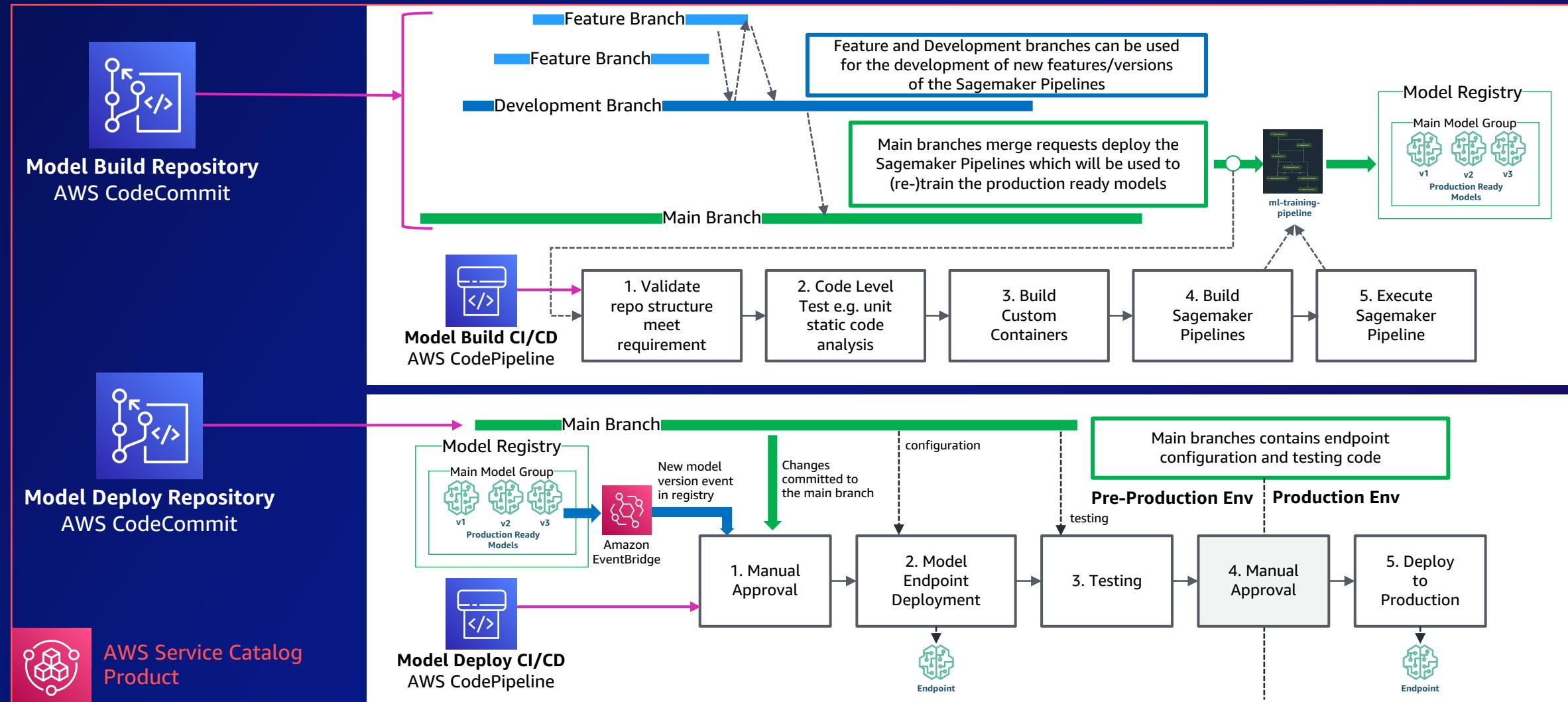
The screenshot shows the activity log for 'VERSION 1' and 'VERSION 2'. The log includes columns for Event type, Event, Comment, Modified by, Last modified, and Actions. Red boxes highlight specific entries: 'ModelDeployment' events for both versions with 'stage: prod' and 'stage: staging'; and 'Approval' entries for both versions with comments like 'Status updated to Approved' and 'Status updated to Pending'. A red box also highlights the 'Update status' button at the bottom right of the log table. Another red box highlights the 'Update status' button at the top right of the log table.

Track the activities, metrics, and settings per model version



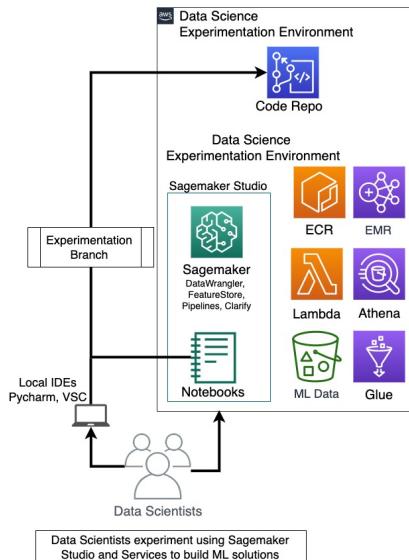
# Amazon SageMaker Projects

## EXAMPLE REPOSITORIES & CI/CD PIPELINES PER SAGEMAKER PROJECT



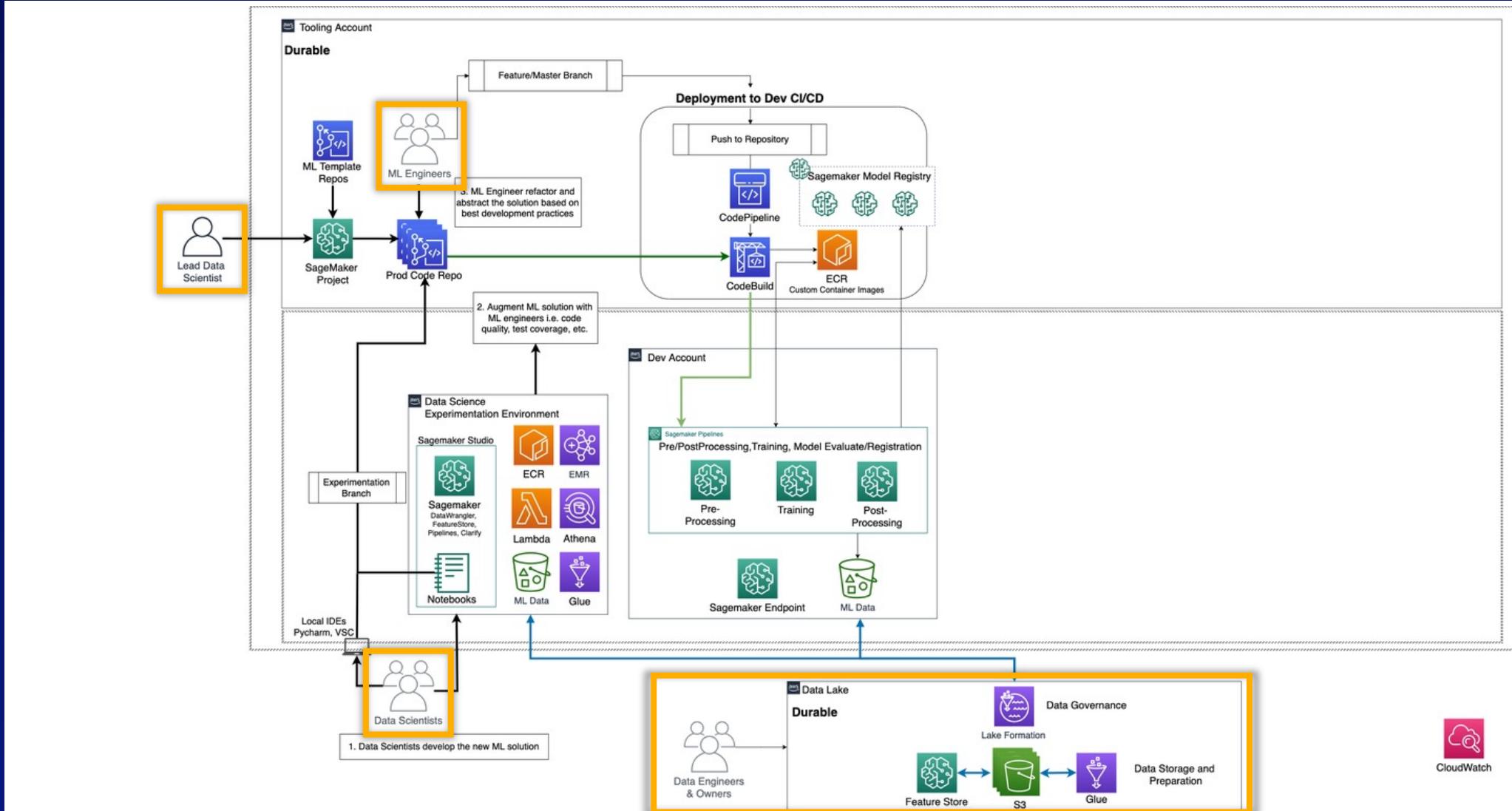
# MLOPs Initial Phase

ML EXPERIMENTATION ON AWS USING AMAZON SAGEMAKER STUDIO NOTEBOOKS



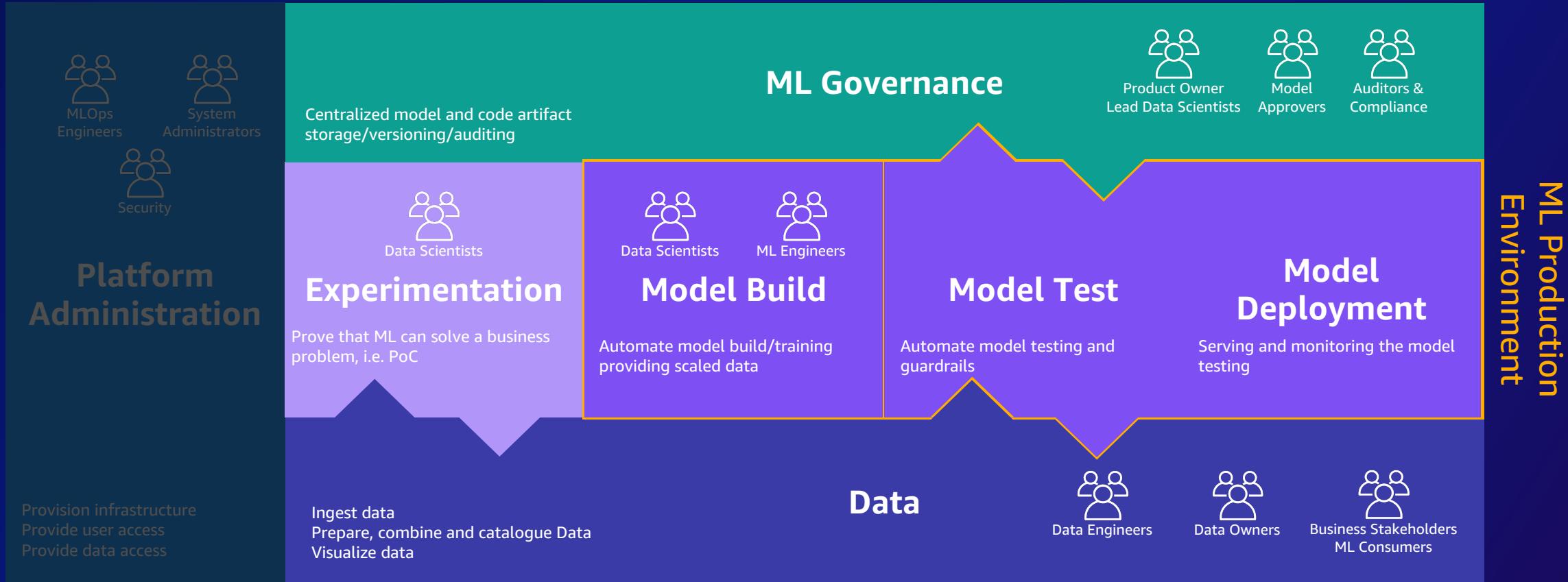
# MLOPs Repeatable Phase

FROM RESEARCH NOTEBOOKS TO ML PIPELINES & AUTOMATION



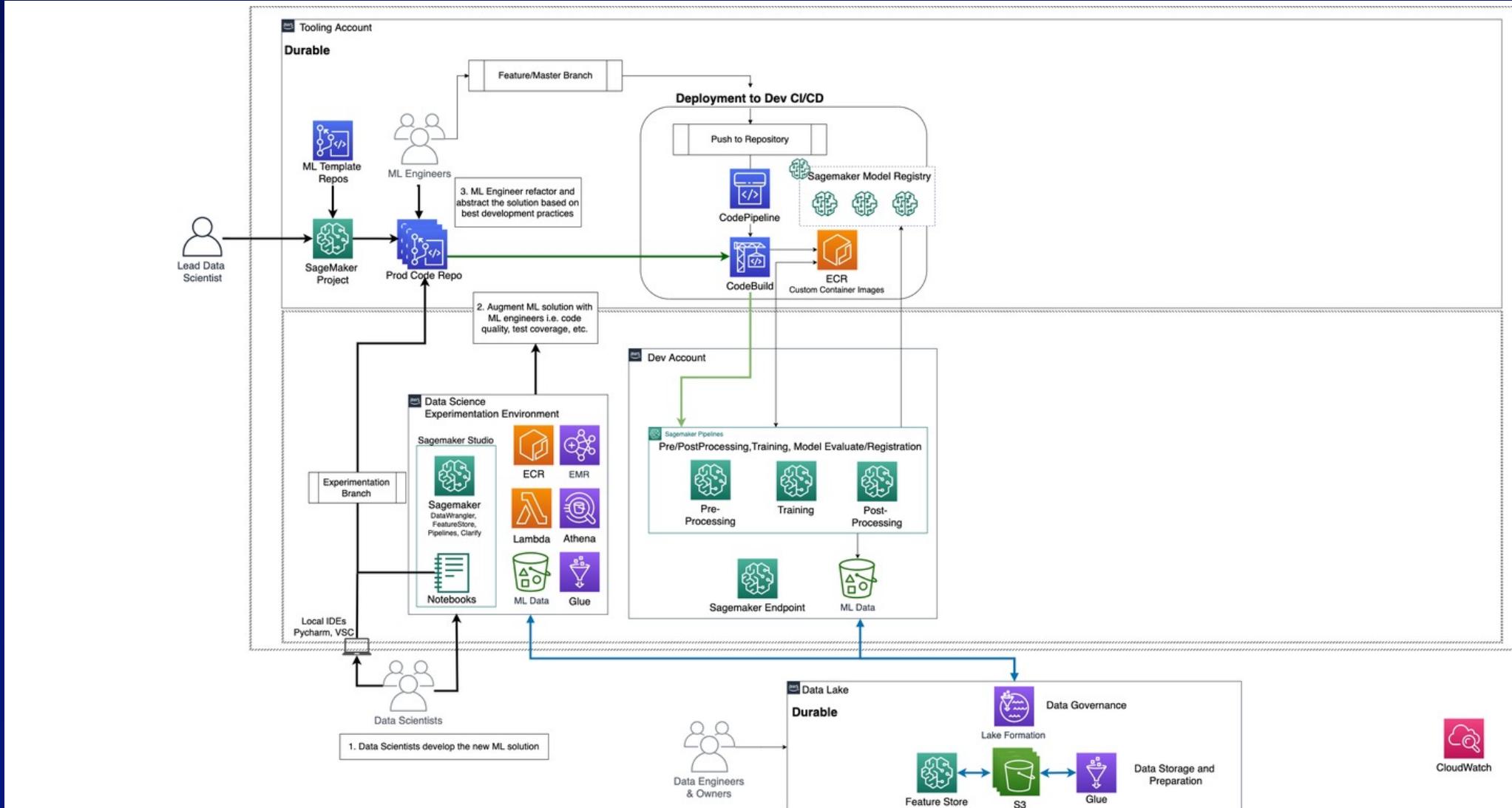
# MLOps Foundation People & Processes

## RELIABLE PHASE



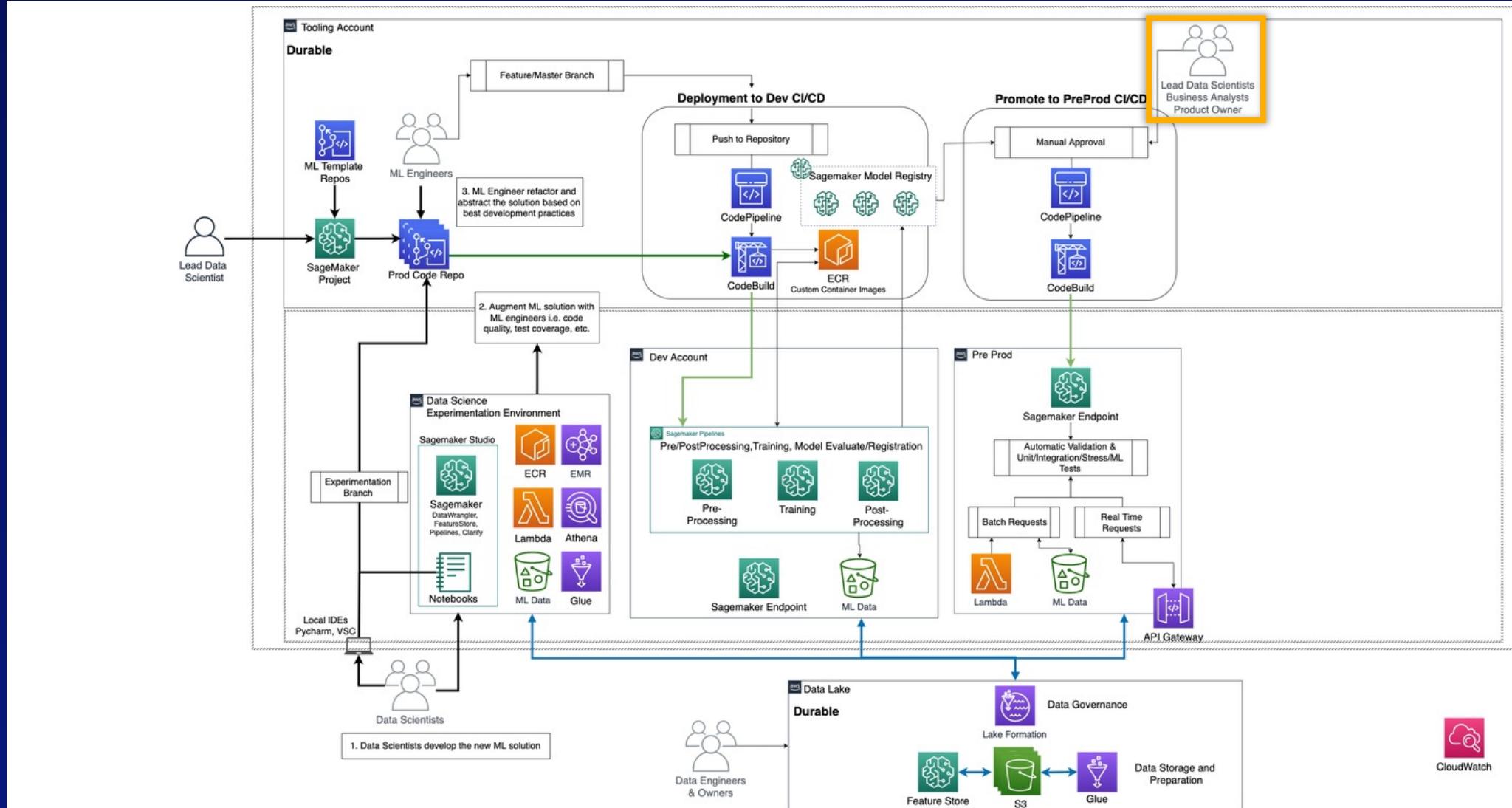
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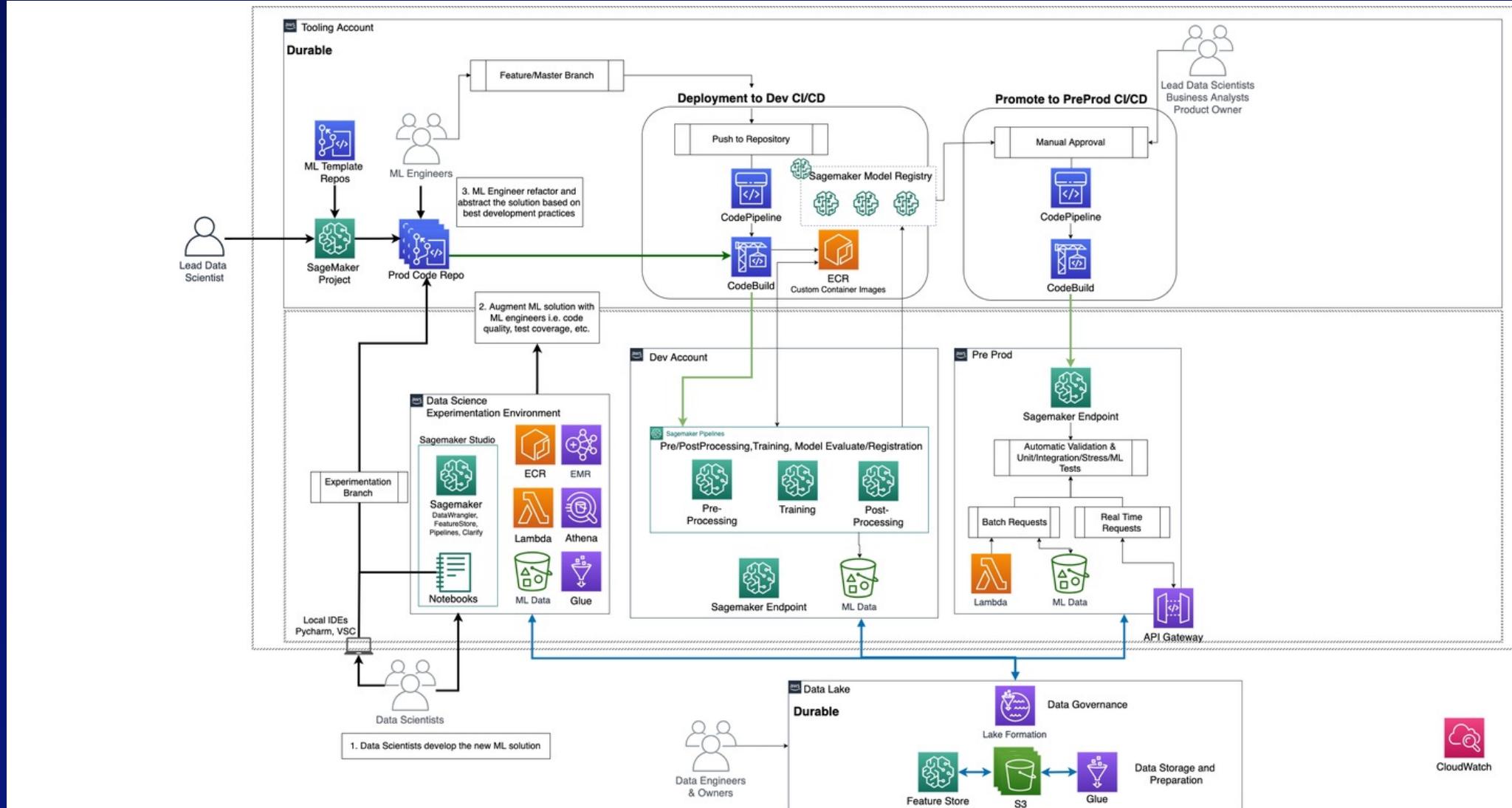
# MLOPs Reliable Phase 1/2

UNDERSTAND THE NEEDS OF MLOPS & INTRODUCE AUTOMATED TESTING



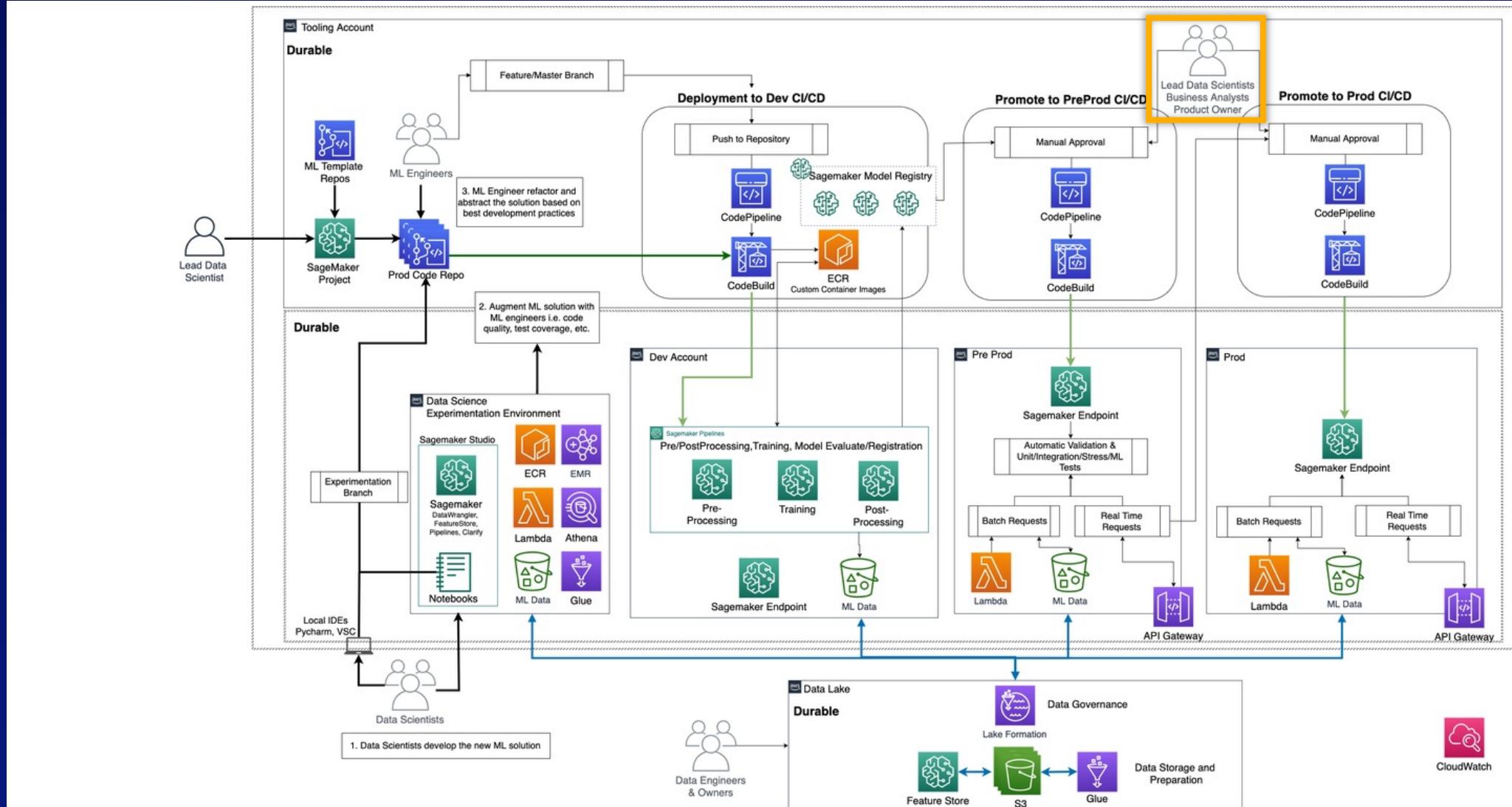
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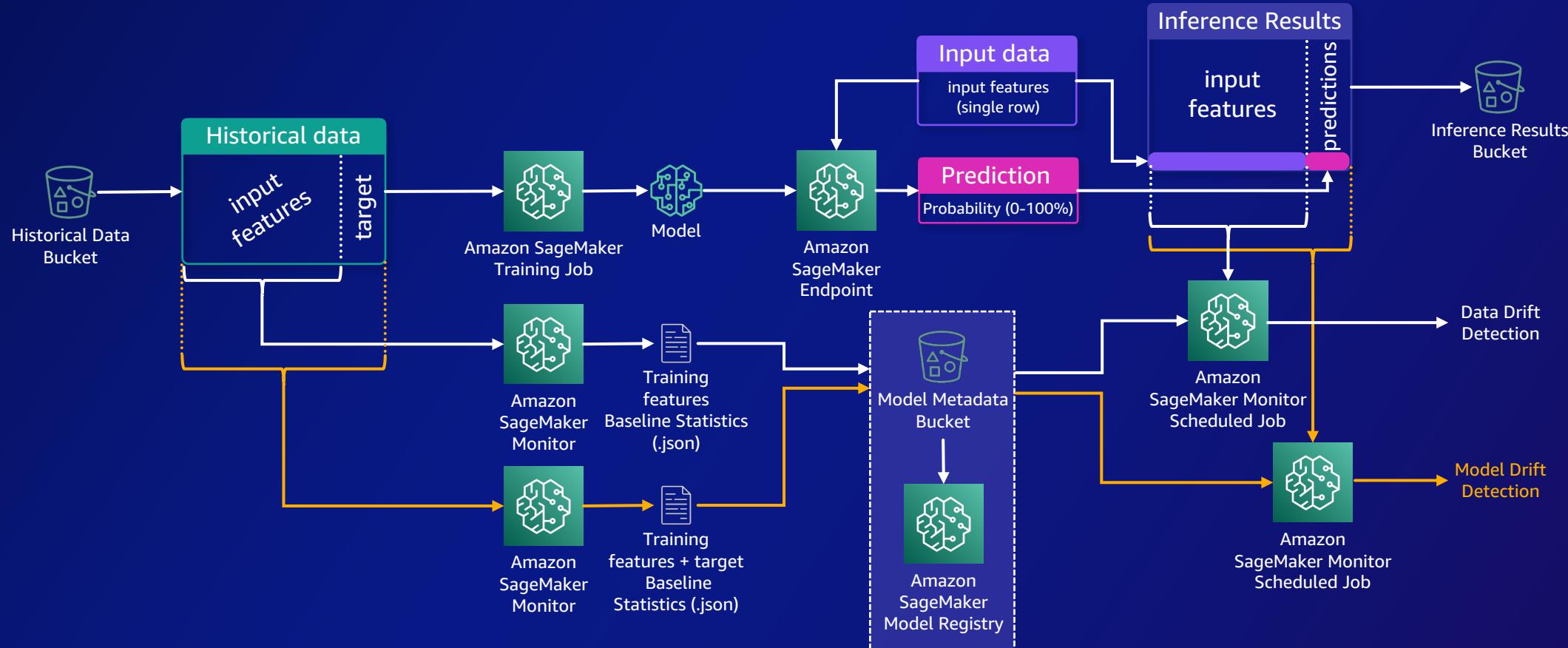
# MLOPs Reliable Phase 2/2

BEST PRACTICE ON MLOPS, ROBUST AND SECURE MODELS



# Amazon SageMaker Model Monitor

AUTOMATICALLY DETECT DATA AND MODEL QUALITY DRIFTS



# ML Governance – Model Dashboard

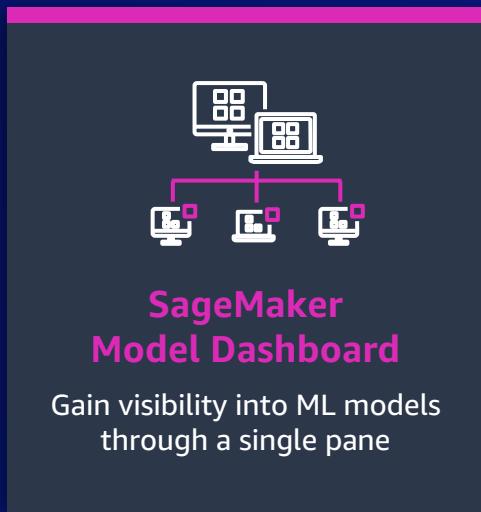
UNIFIED MONITORING ACROSS ALL YOUR MODELS IN PRODUCTION



Business Product  
Owners



Lead Data Scientist



The screenshot displays several components of the SageMaker Model Dashboard:

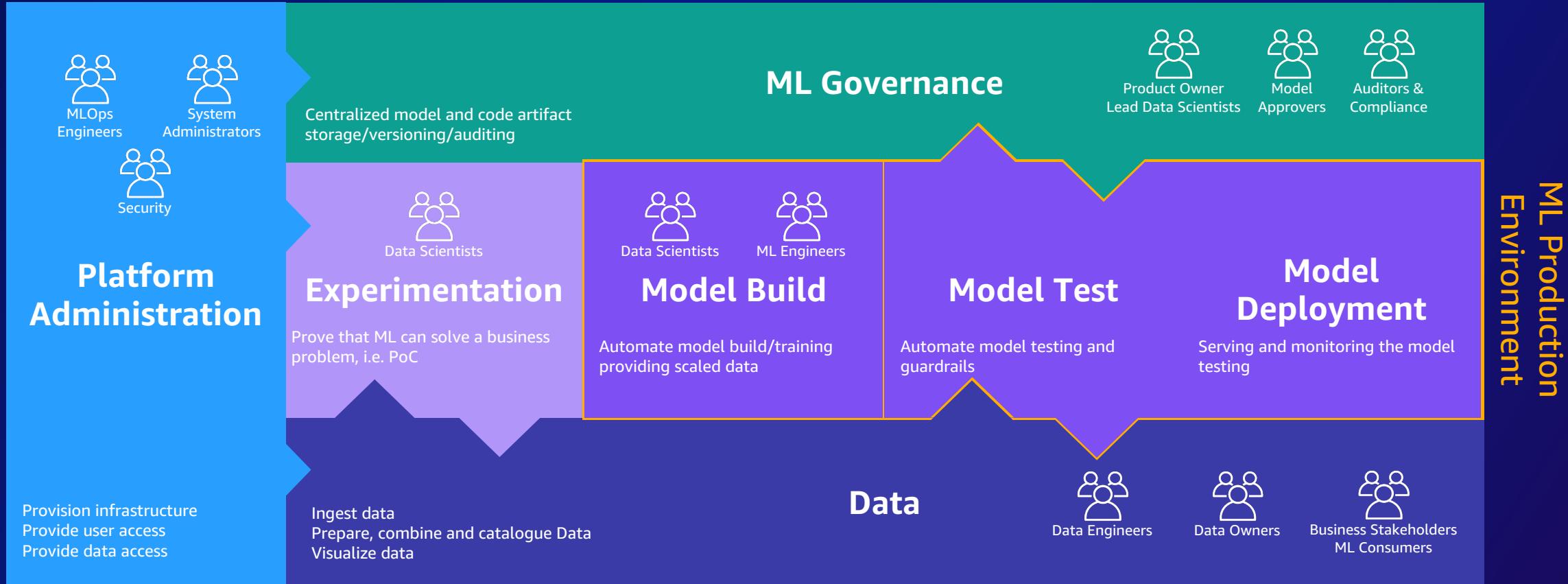
- SageMaker Models:** A card with two brain icons and the text "SageMaker Models".
- SageMaker Model Monitor (Real time & Batch):** A card with a brain icon and the text "SageMaker Model Monitor (Real time & Batch)". It includes a table with columns: Model name, Risk rating, Model quality, Data quality, Bias drift, Feature attribution drift, Endpoints, and Labels. The table lists nine models with varying risk ratings and status indicators (e.g., High, Medium, Inactive, Scheduled).
- SageMaker Clarify:** A card with a brain icon and the text "SageMaker Clarify".
- Model Card (Risk Rating):** A card with a brain icon and the text "Model Card (Risk Rating)". It shows a table with columns: Model name, Risk rating, Model quality, Data quality, Bias drift, Feature attribution drift, Endpoints, and Labels. The table lists multiple models with risk ratings like Medium, Inactive, and Scheduled.
- SageMaker Lineage Tracking:** A card with a brain icon and the text "SageMaker Lineage Tracking".

A pink arrow points from the "SageMaker Model Dashboard" section towards the "Model Card (Risk Rating)" table, indicating its integration with the main dashboard.



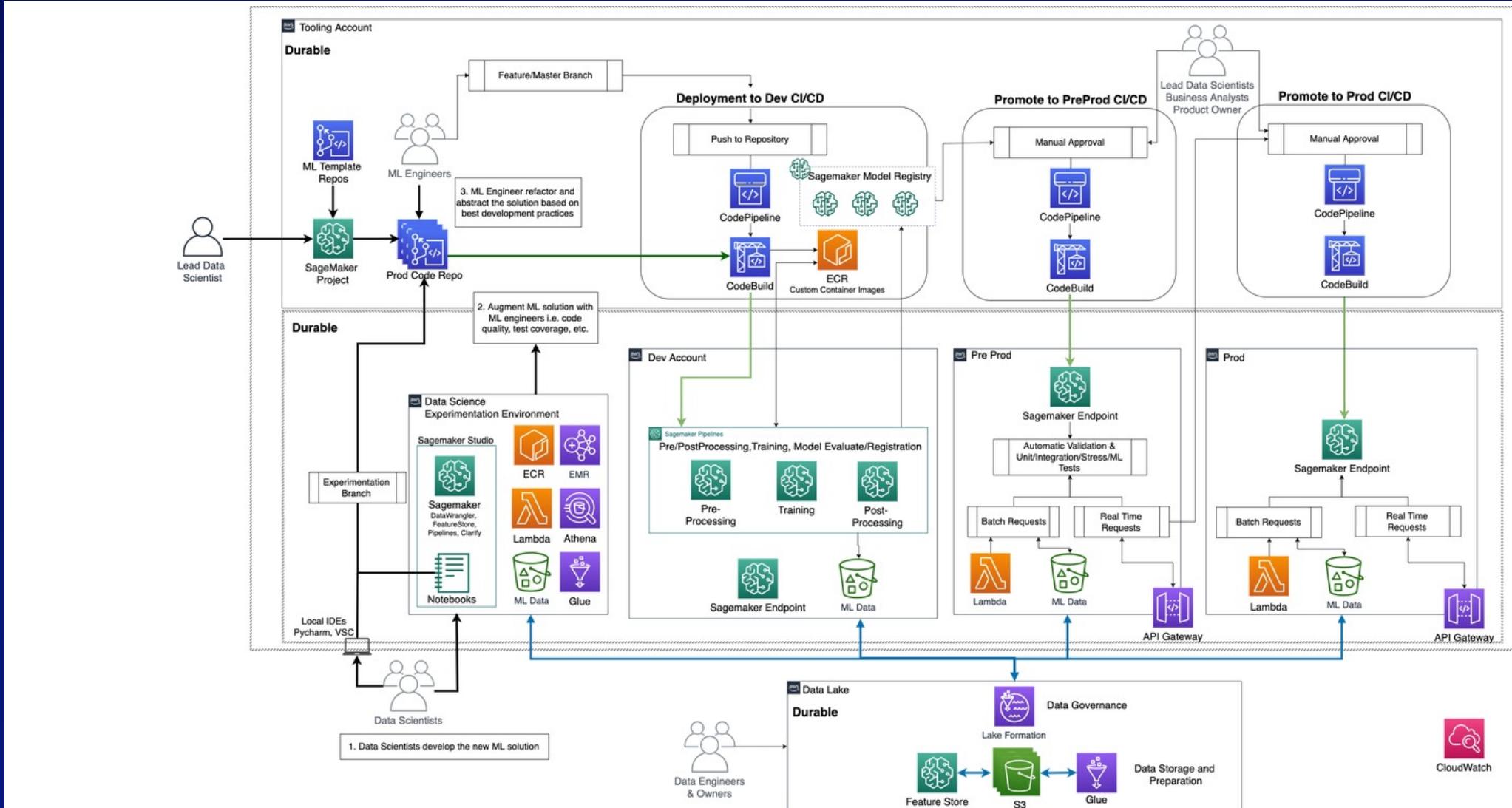
# MLOps Foundation People & Processes

## SCALABLE PHASE



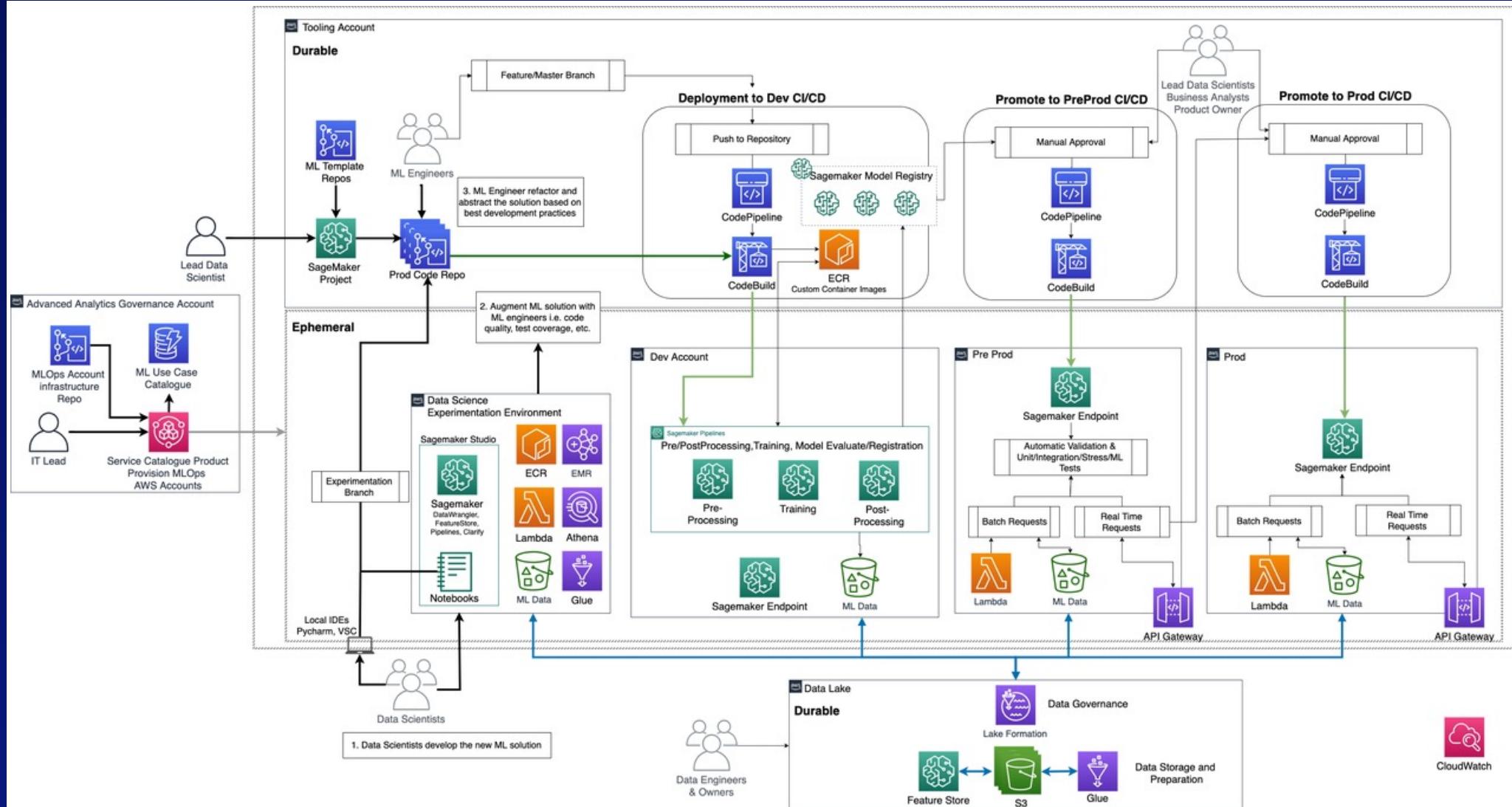
# MLOPs Reliable Phase

BEST PRACTICE ON MLOPS, ROBUST AND SECURE MODELS



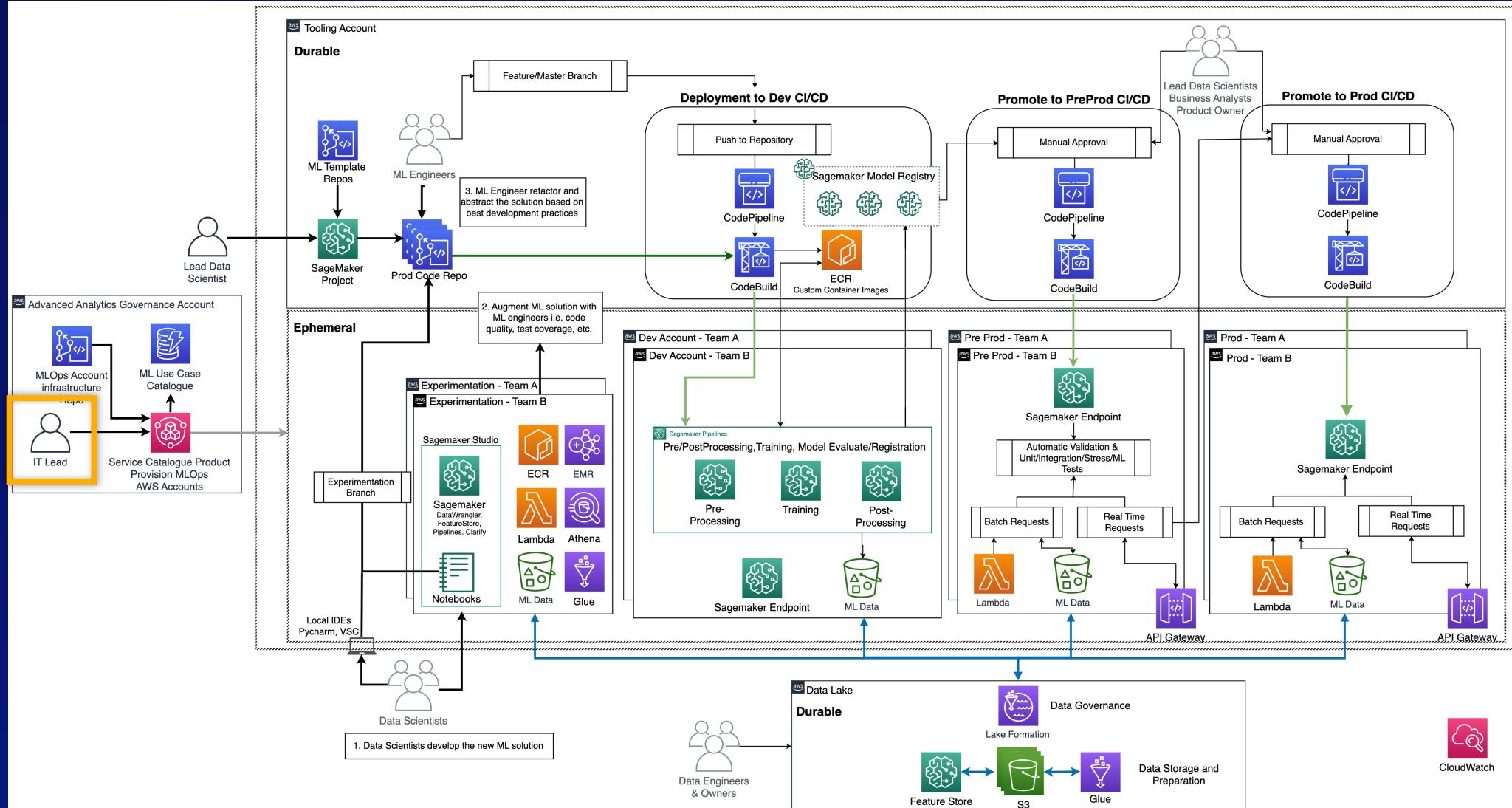
# MLOPs Scalable Phase

MULTIPLE TEAMS AND ML USE CASES ADOPT MLOPS



# MLOPs Scalable Phase

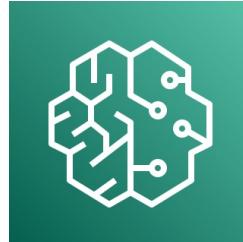
MULTIPLE TEAMS AND ML USE CASES ADOPT MLOPS



# MLOPs Foundation Technology

MULTIPLE TEAMS AND ML USE CASES ADOPT MLOPS

Large architecture but data scientists need to be enabled only on ....



Amazon SageMaker

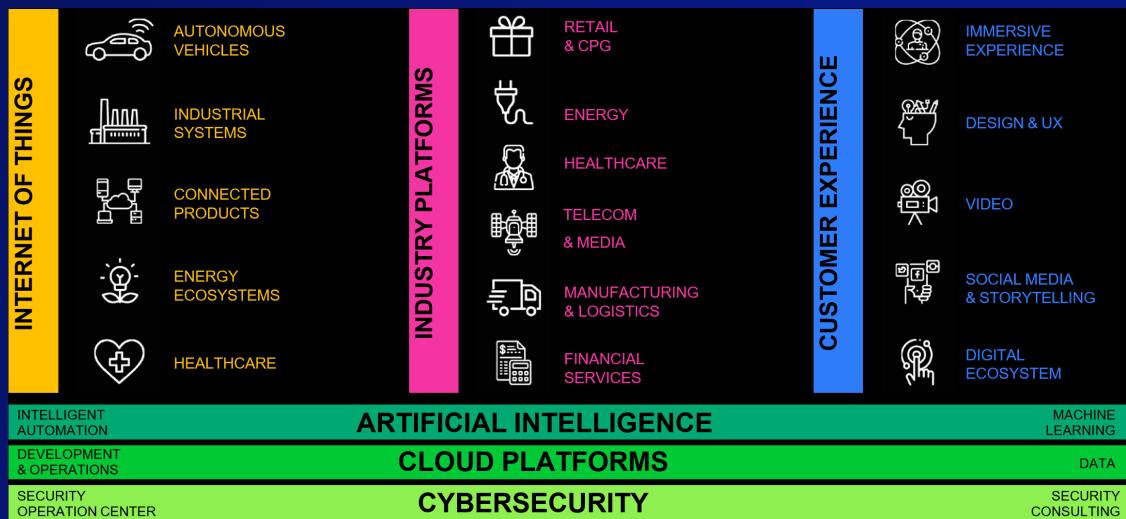


# The Data Reply UK MLOps Journey

# REPLY in A Nutshell



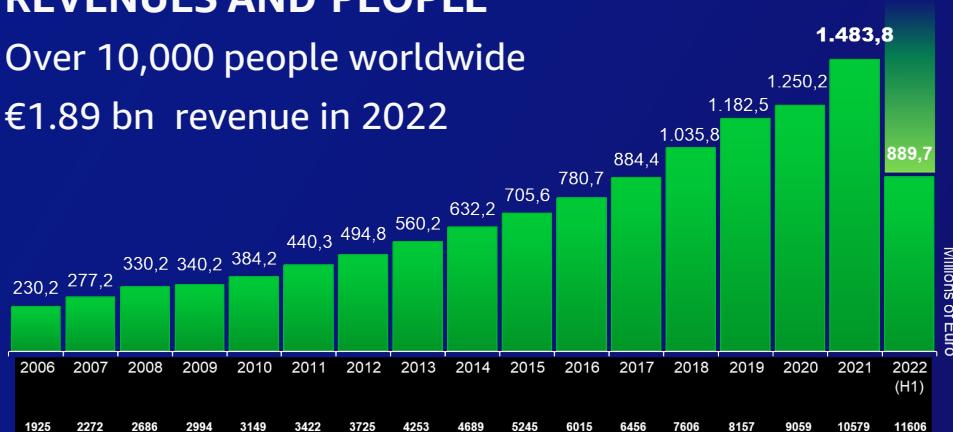
Founded in 1996, Reply is a company specialized in **System integration, Digital Services and Consulting** with a focus on solutions **design and implementation**.



## REVENUES AND PEOPLE

Over 10,000 people worldwide

€1.89 bn revenue in 2022



# Reply and AWS Partnership

A PASSION FOR TECHNOLOGY

Reply is among the companies with the most extensive number of competencies, including in **Data and Analytics** and **Machine Learning**, Service Delivery Validations, Certifications and programmes participation.

Data Reply is a **Launch partner of the AWS MLOps Competency** in 2021



**13**  
AWS  
Competencies

**16**  
AWS Service  
Delivery  
Validations

**9**  
AWS  
Programmes

**700+**  
AWS  
Certifications

# Data Reply and AWS MLOPs Partnership

Data Reply is an AWS trusted partner in MLOps, through AWS MLOps partner enablement program

We developed an MLOps accelerator using native AWS services and successfully leveraged with a number of our customers



## OUTCOMES

### MLOps Platform Implementation

9-12 Months

3 Months

### ML Route to Live

3 Months

<2 Weeks

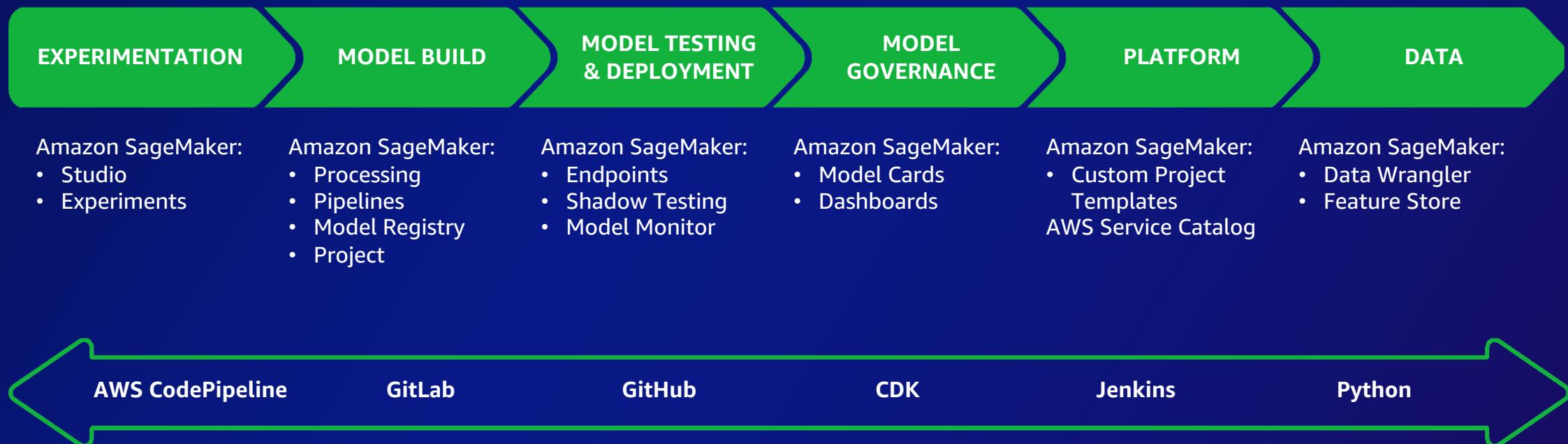
### Onboarding Data Science Teams

2 Months

<2 Weeks

# MLOps Accelerator

MLOps Accelerator is a framework which aims to industrialise and operationalise ML lifecycle on AWS using best practices and Amazon SageMaker as the key principles.



# Why Choose Our MLOps Accelerator



It allows customer to implement the MLOps capabilities up to 50% faster



Based on AWS native services, but can be integrated with your existing cloud platform



Modular and reusable across different use cases and environments



Adheres to AWS's best practices (AWS WAF ML Lens)



Validated & Trusted by AWS MLOps Solutions Architects

# Case Study: ML Modernisation & MLOps

INDICIA  
WORLDWIDE

## Client:

Indicia Worldwide, a global marketing agency.

## Goal:

To standardise and scale ML capabilities on AWS improving productivity, repeatability and time to market with acceptable ROI



### Challenge:

- Gap in capabilities to productionise ML use cases
- Manual input to deploy models
- Slow speed of development
- Frustration for internal teams, lack of collaboration
- Lack of cloud operations for ML platform



### Solution:

- Transitioned ML development from on-prem to Amazon SageMaker
- The MLOps journey began with the MLOps Assessment followed by MLOps solution implementation
- AWS Sagemaker services used to automate the build, test, and deploy models in production



### Results:

- Successfully **productionised 15 use cases** on the cloud, with several more in the pipeline.
- Reduced 'time-to-market' by **60-70%**
- Data scientists can **focus on clients**, not infrastructure
- Happier, more productive staff

# Customer Quotes



“ The platform that Data Reply built for us has massively reduced our time to value. What used to take months, we can now do in weeks. It's not just about the models. It's about testing, deploying, and scaling, as well as integrating them into existing systems. ”

**Graham Lannigan**

Head of Data Platform at Indicia Worldwide

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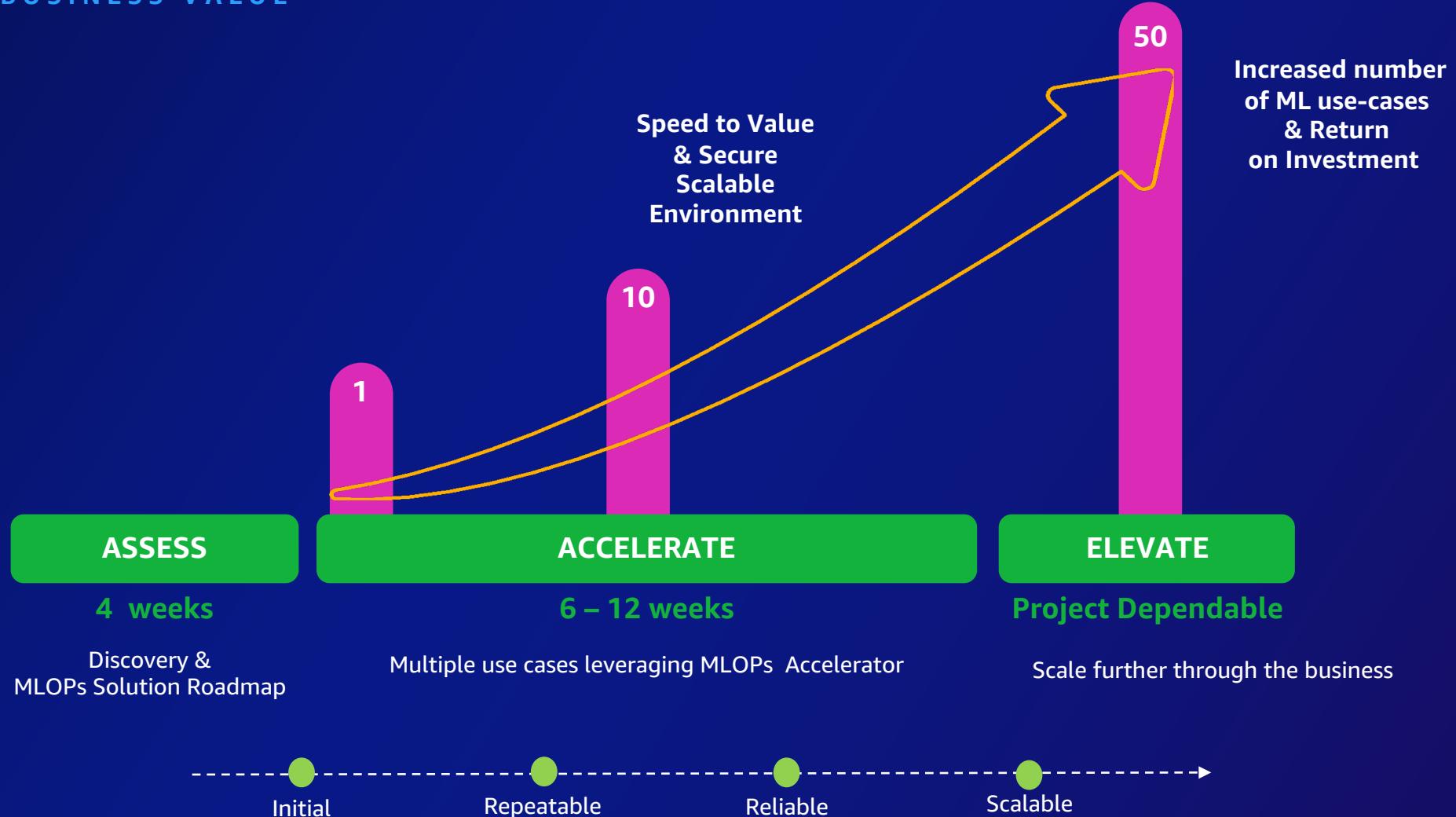
“ Data Reply UK is helping us with streamlining and standardising our end-to-end ML processes. With the new MLOPs Framework leveraging Amazon CDK and Amazon SageMaker services, we are set to productionise 10 ML models in the next 6 months , scaling to tens of models next year. This will help with optimising the recommendation system on the TUI's web app and the website leading to an increased customer engagement and a seamless customer experience! ”

**Stefan Grossman**

Customer Analytics Lead at TUI

# Our MLOps Engagement Approach

FOCUSING ON BUSINESS VALUE



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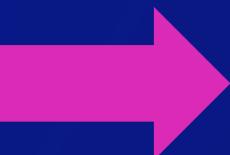
# MLOps Discovery Workshop Offer

A HALF DAY WORKSHOP AT ZERO COST TO THE CUSTOMER

## Workshop overview

### Why attend?

A customer is looking to accelerate and scale their ML initiatives but has limited capability, skills and resources



### Outcomes

- Key ML development challenges and pain points identified
- Understanding MLOps value
- Initial use case(s) for MLOps is identified
- Stakeholders identified for the MLOps project mobilisation

### Who should attend?

Head of Data Science/ML, Head of Data Platform, Engineering, DevOps

# Thought Leadership & Additional Resources

Data Reply is a Launch Partners Of The AWS MLOPs category Of The ML Competency.



[Our MLOps Whitepaper](#)



[APN Blog Post – Leveraging MLOps on AWS](#)



[Our offering is featured on AWS Marketplace](#)



[Our video Case Study with Indicia Worldwide is on APN TV](#)

These clients have trusted Data Reply with MLOps

INDICIA  
WORLDWIDE



St  
James's  
Place



LAVAZZA

nexi



Scan for more information  
about the Data Reply  
MLOps Capability  
Assessment



# MLOps Resources

# MLOps Resources



MLOps on AWS by Amazon SageMaker  
<https://aws.amazon.com/sagemaker/mlops>



Amazon SageMaker documentation  
<https://docs.aws.amazon.com/sagemaker/index.html>



MLOps foundation roadmap for enterprises  
<https://aws.amazon.com/blogs/machine-learning/mlops-foundation-roadmap-for-enterprises-with-amazon-sagemaker>



Secure multi-account MLOPs platform source code examples  
<https://github.com/aws-samples/sagemaker-custom-project-templates/tree/main/mlops-multi-account-cdk>

# Thank you!

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Please complete the session  
survey in the mobile app