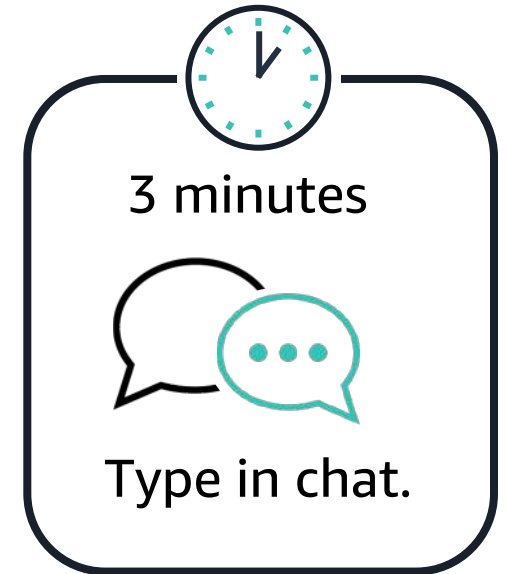


AWS Solutions Training for Partners: Machine Learning (ML) on AWS for ML Practitioners – Technical

“Machine Learning”

When you think about **machine learning**,
what is the **first word** that comes to mind?



Machine Learning on AWS – Technical

Course Introduction

Course Agenda

- Module 1: Introduction to Machine Learning
- Module 2: Artificial Intelligence Services on AWS
- Module 3: Machine Learning Process
- Module 4: Data Collection, Integration, Preparation and Visualization, and Analysis
- Module 5: Deep Learning Amazon Machine Images
- Module 6: Amazon SageMaker Concepts
- Module 7: Amazon SageMaker Notebooks
- Module 8: Amazon SageMaker Built-In Algorithms
- Module 9: Amazon SageMaker – Debugging and Monitoring
- Module 10: Introduction to MLOps
- Module 11: Next Steps and Additional Learning

Workbook 0.1: Personas

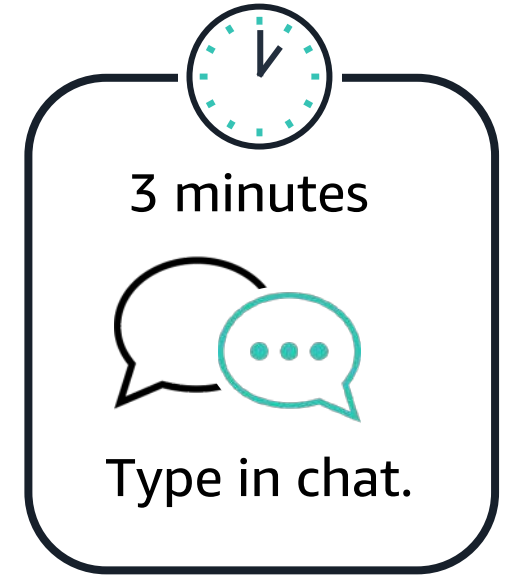


- Which persona are you?
- What do you want to take away from this course?

Your role and skill level

Type in the chat and let your colleagues know:

- Your role?
 - Data Scientist
 - TAM
 - Developer
 - Other
- Your skill level with AWS?
 - New
 - Beginner
 - Intermediate
 - Expert




Your role today

- Participate in class discussions and ask questions
- Complete individual and group exercises
- Be open to learn about AWS machine learning (ML), Amazon SageMaker services, ML Pipeline and related solutions
- Review case studies
- Answer knowledge check questions
- Complete the course assessment

Module 1: Introduction to Machine Learning

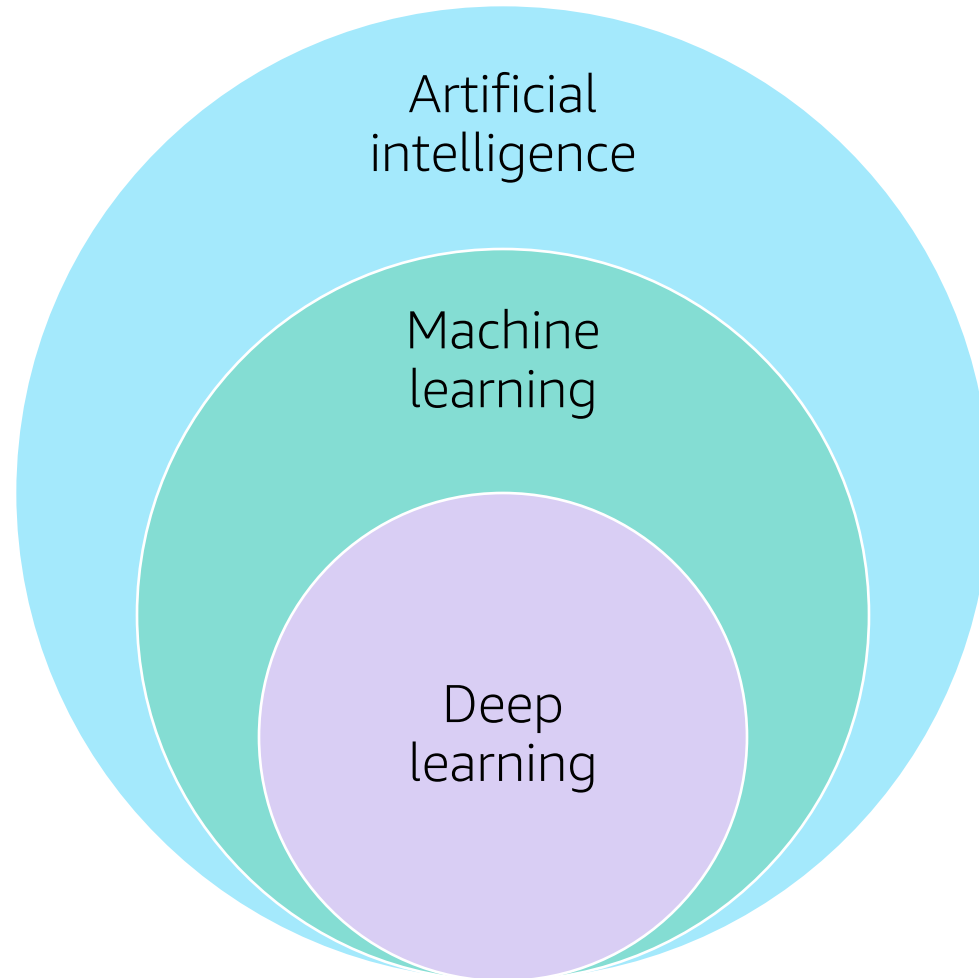
Module 1:

Introduction to Machine Learning



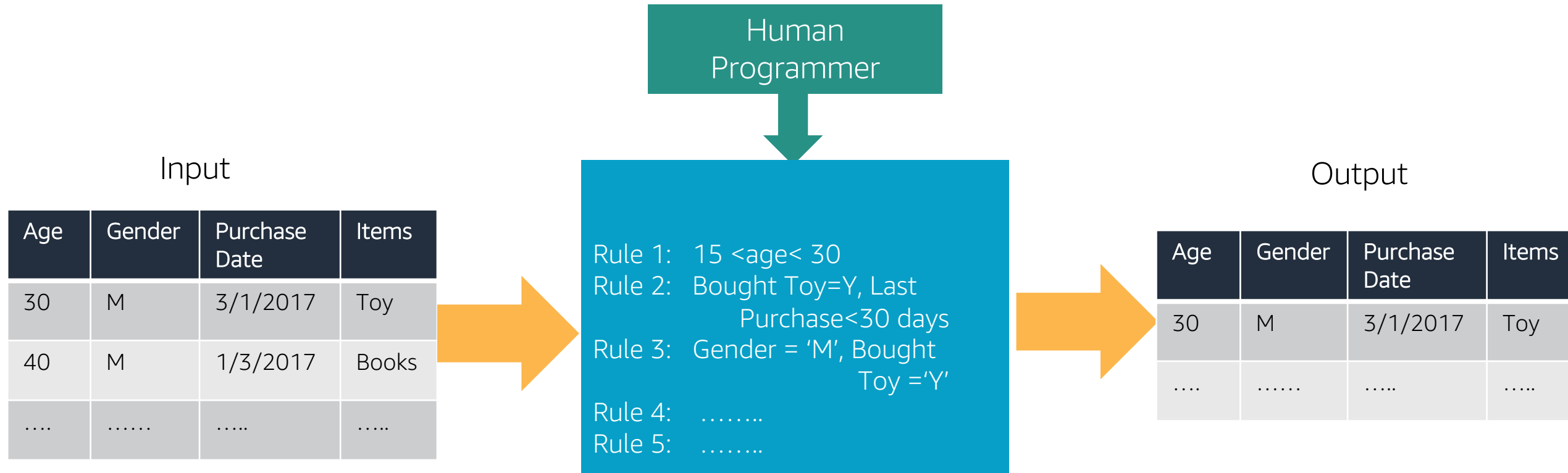
- Identify machine learning, artificial intelligence, and deep learning (DL)
- Explain how traditional programming differs from solving problems with machine learning
- List and explain the various types of machine learning
- Identify key machine learning terms
- Key Challenges and limitations of AI
- Insurance Fraud use case

Let's define AI, ML, and DL

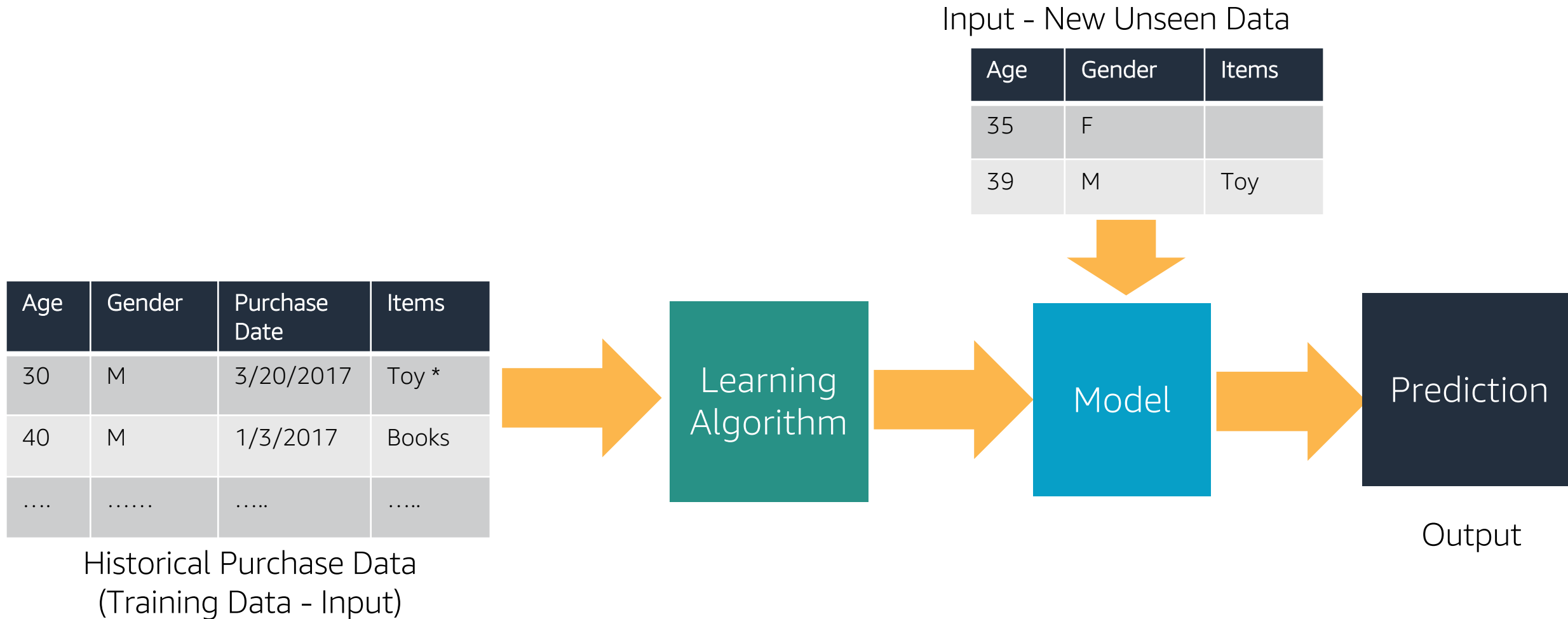


Traditional Programming vs. ML

Traditional programming: You write the business rules



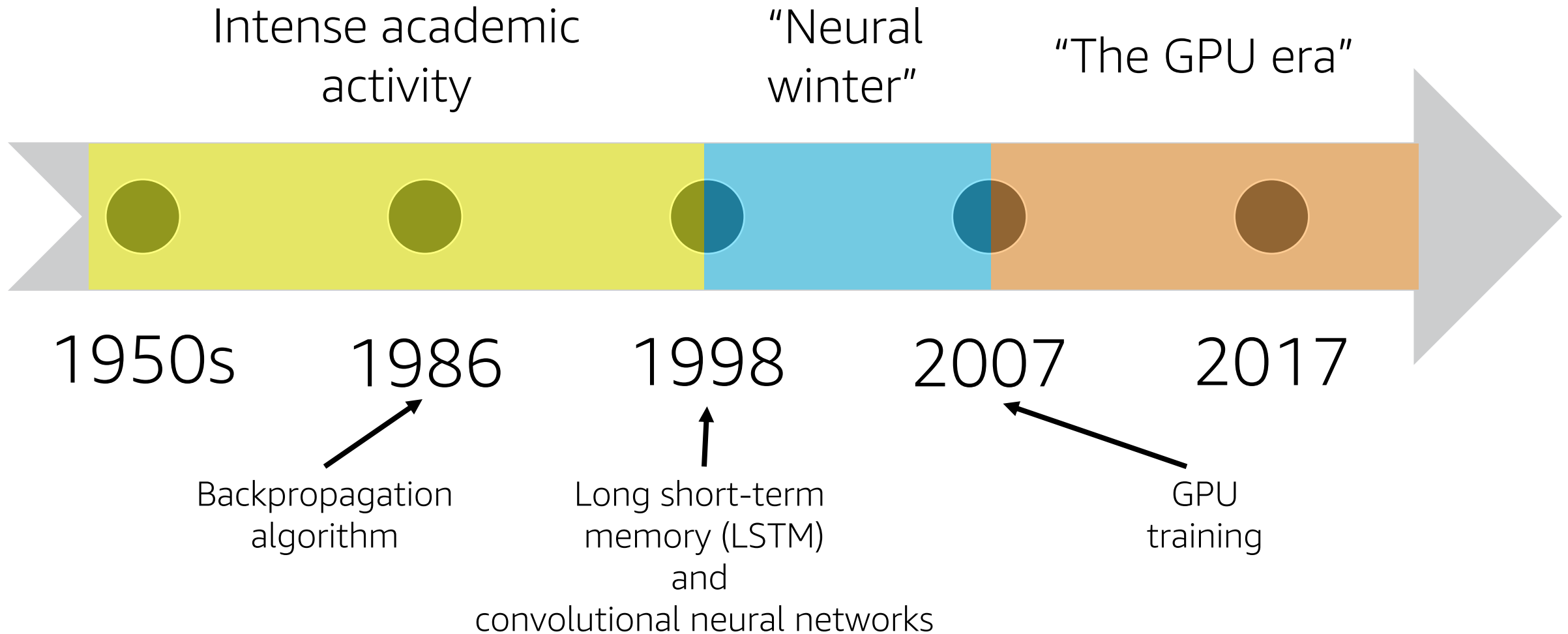
In ML: The data writes the business rules



When to use machine learning

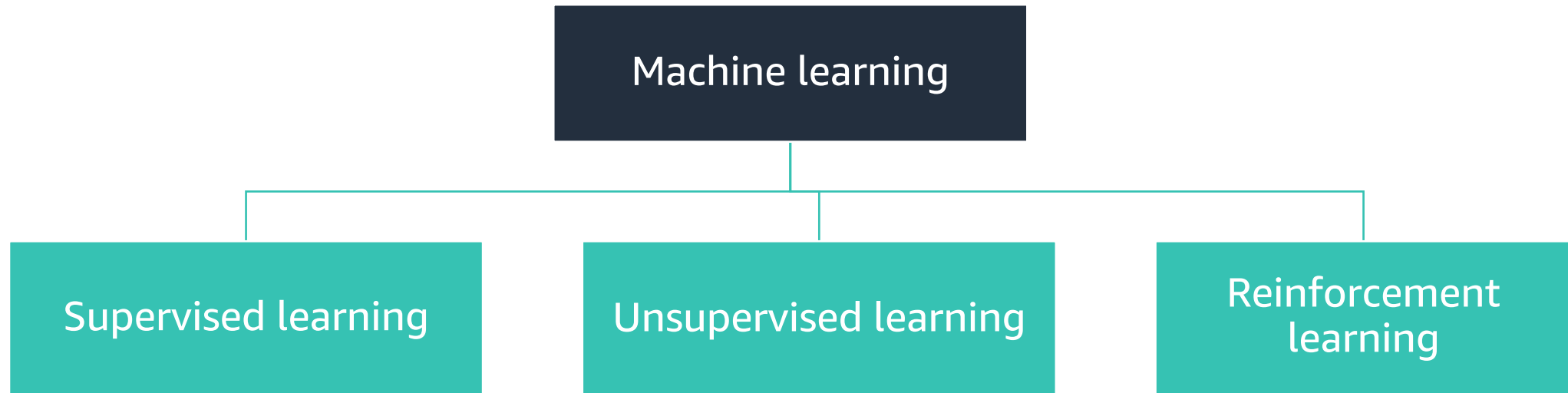
- Use ML when you **can't code it**
 - Complex tasks where deterministic solutions don't suffice
 - E.g., recognizing speech/images
- Use ML when you **can't scale it**
 - Replace repetitive tasks needing human-like expertise
 - E.g., recommendations, spam, fraud detection, machine translation
- Use ML when you have to **adapt/personalize**
 - E.g., recommendation and personalization
- Use ML when you **can't track it**
 - E.g., automated driving

ML timeline

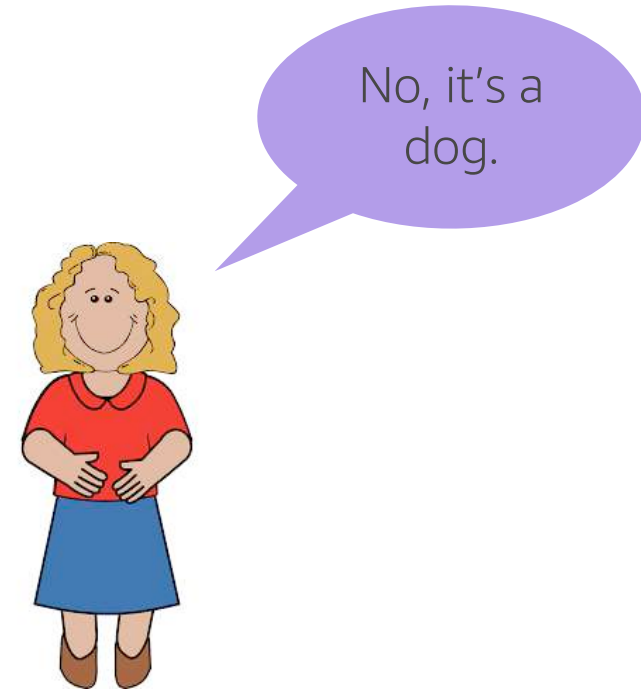
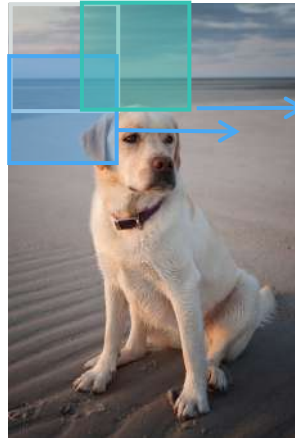
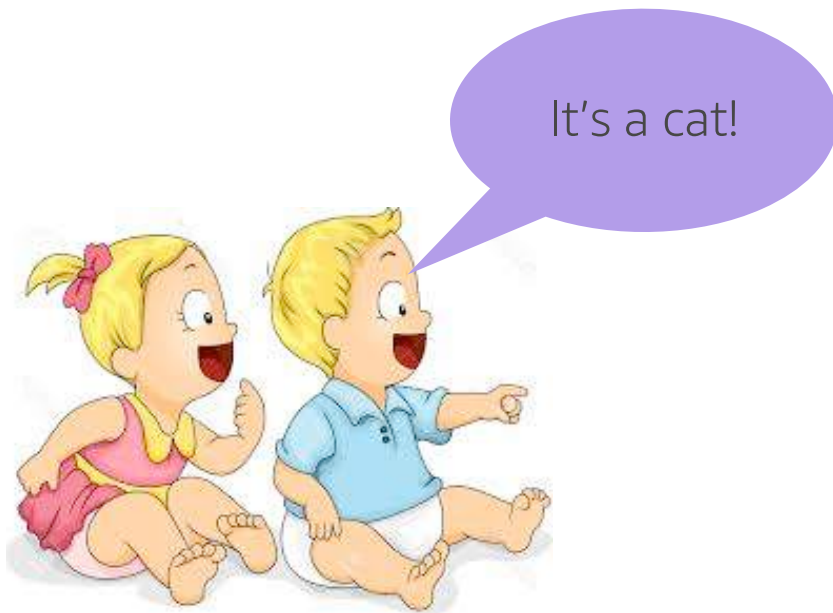


Types Of Machine Learning

Machine learning types

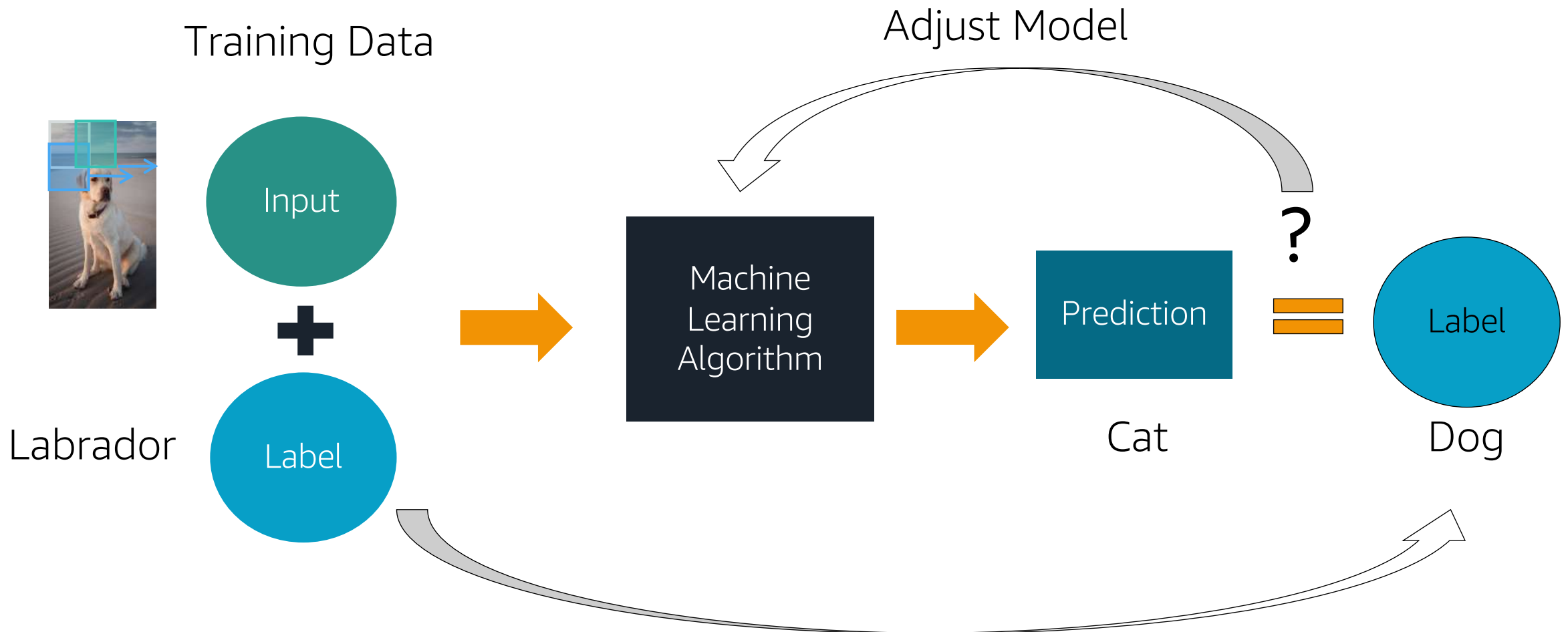


Supervised learning: How humans learn

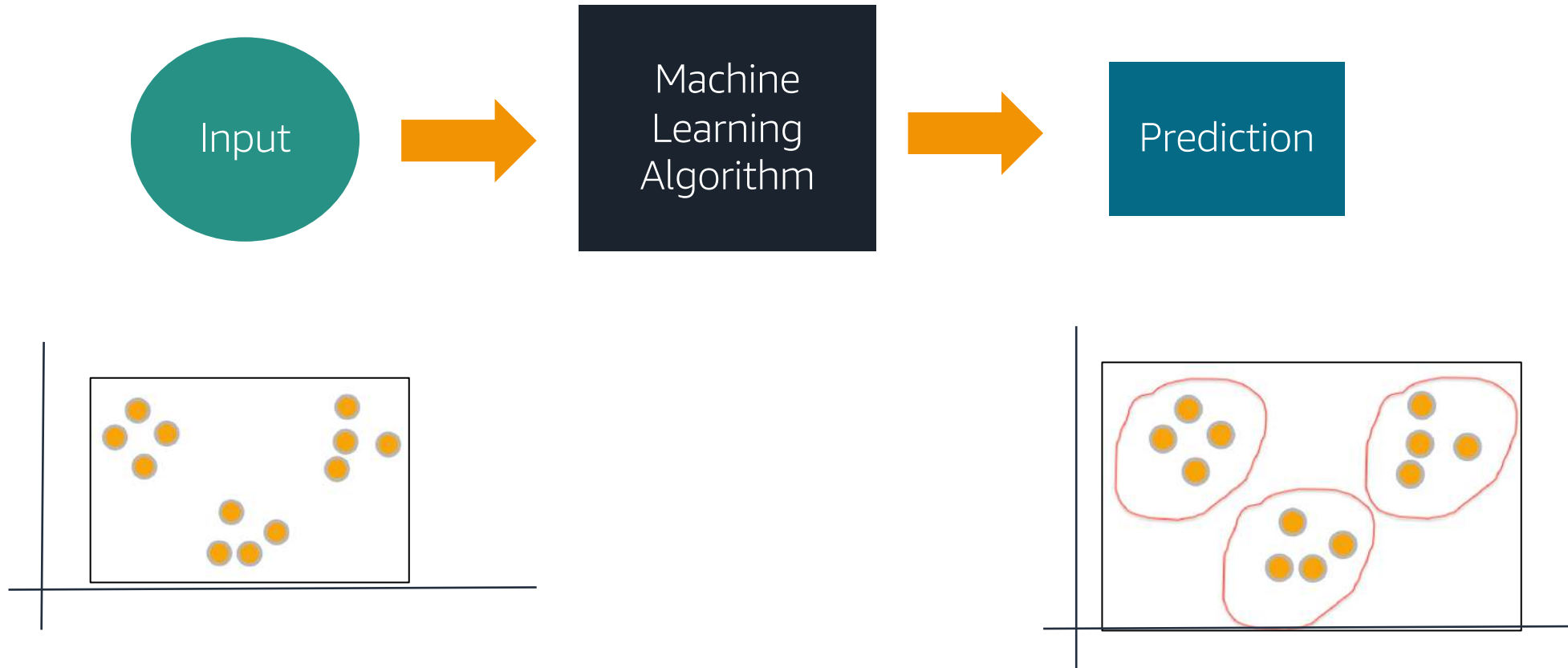


Supervised learning: How machines learn

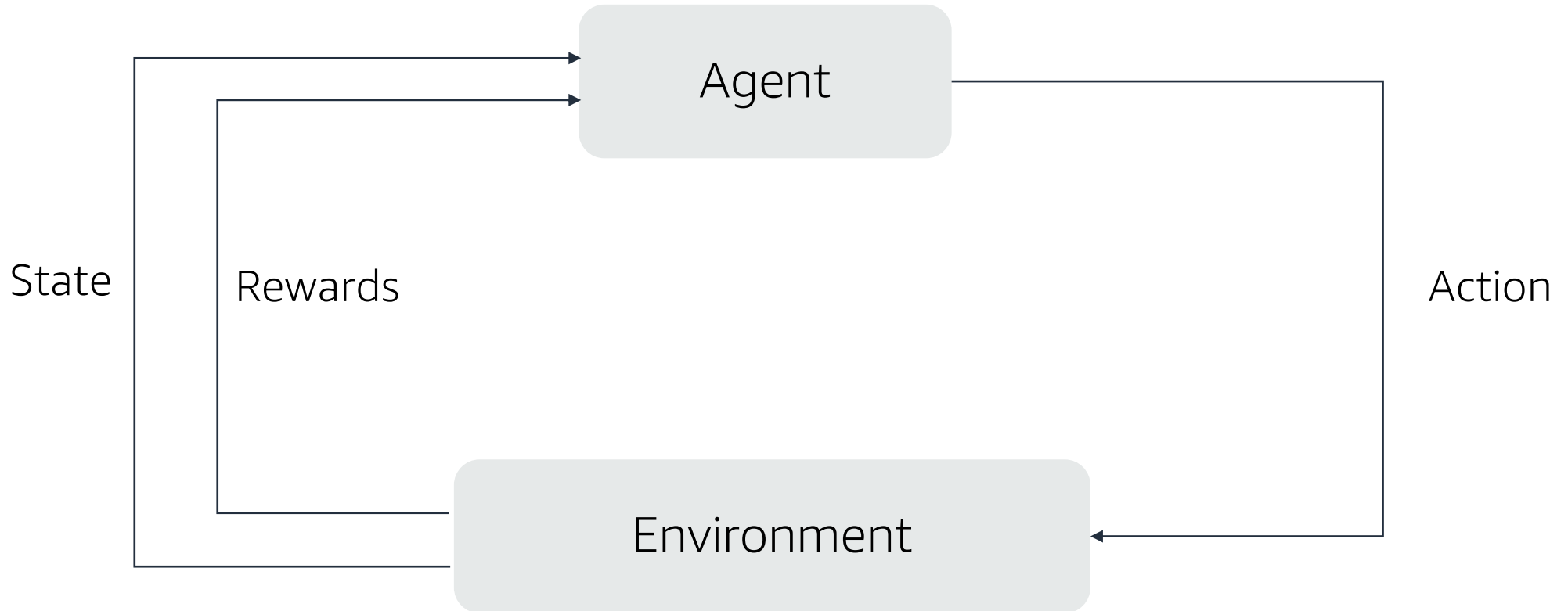
Human intervention and validation required; e.g., photo classification and tagging



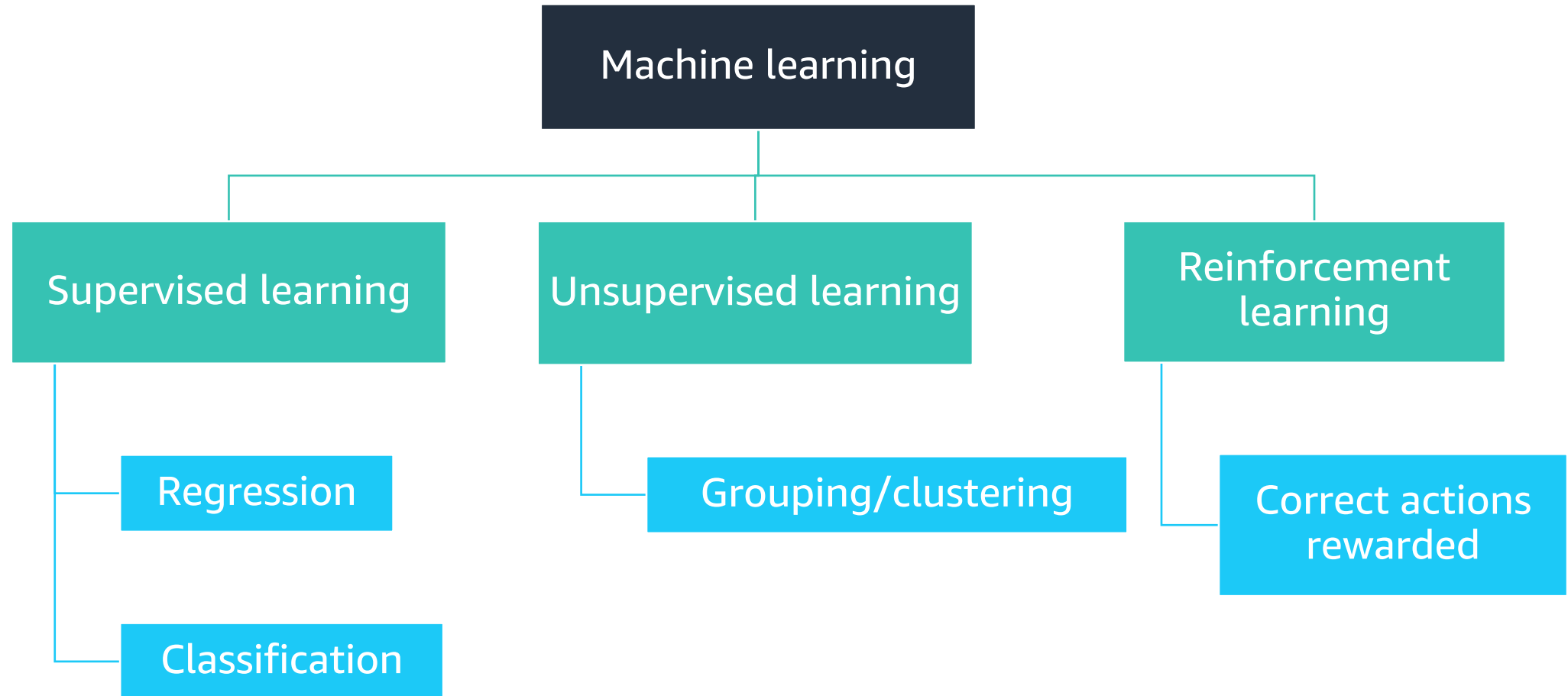
Unsupervised learning



Reinforcement learning



Machine learning types



Terminology and concepts

	Statistical Definition	Everyday Definition
Label/Target	Dependent variable	What you are trying to predict
Feature	Independent variable	Data that helps you make predictions
Feature Engineering	Data transformation	Process of reshaping data to get more value out of it
Feature Selection	Variable/subset selection	Process of using the most valuable data

ML: Common Use Cases

Common use cases

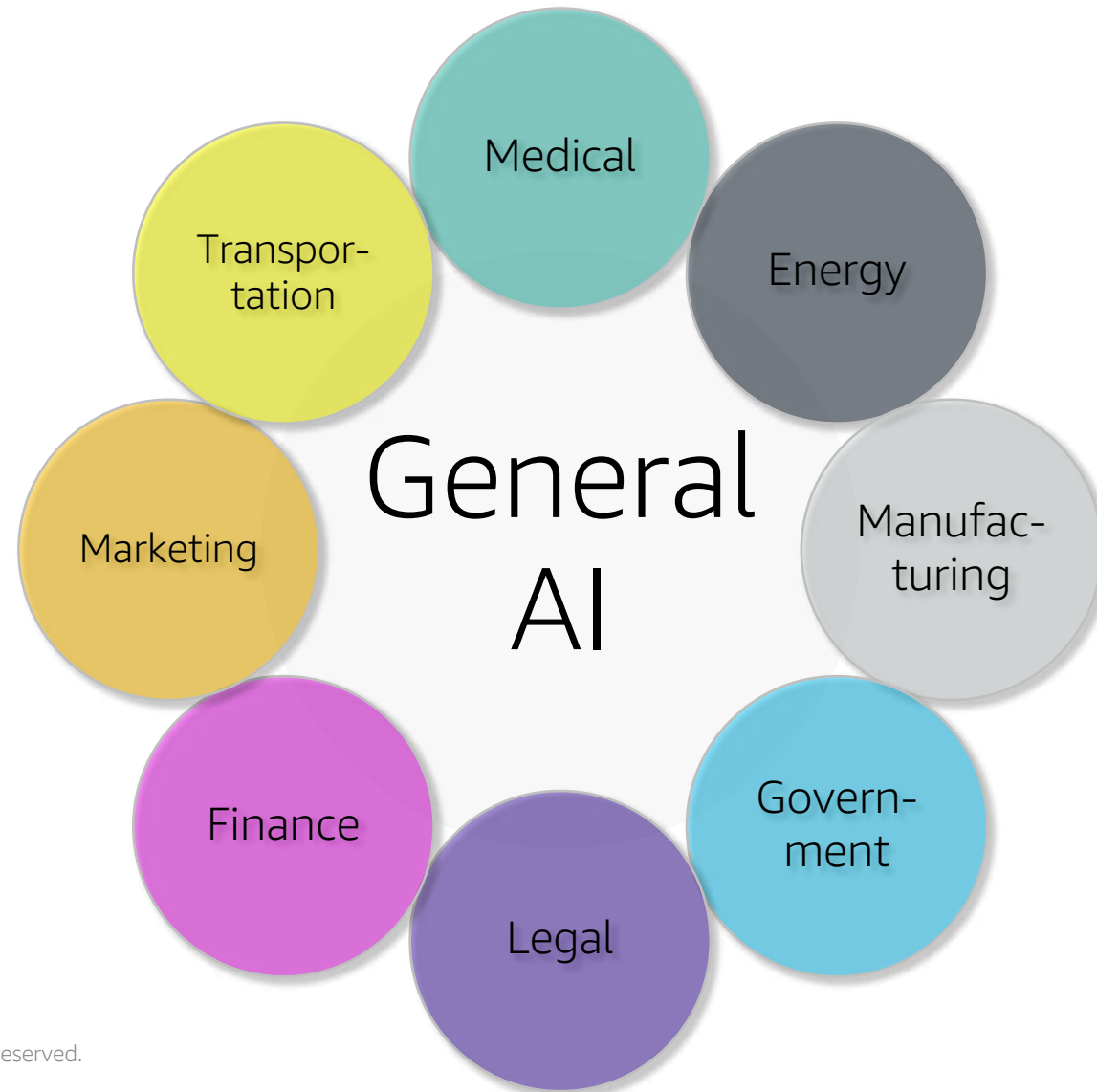


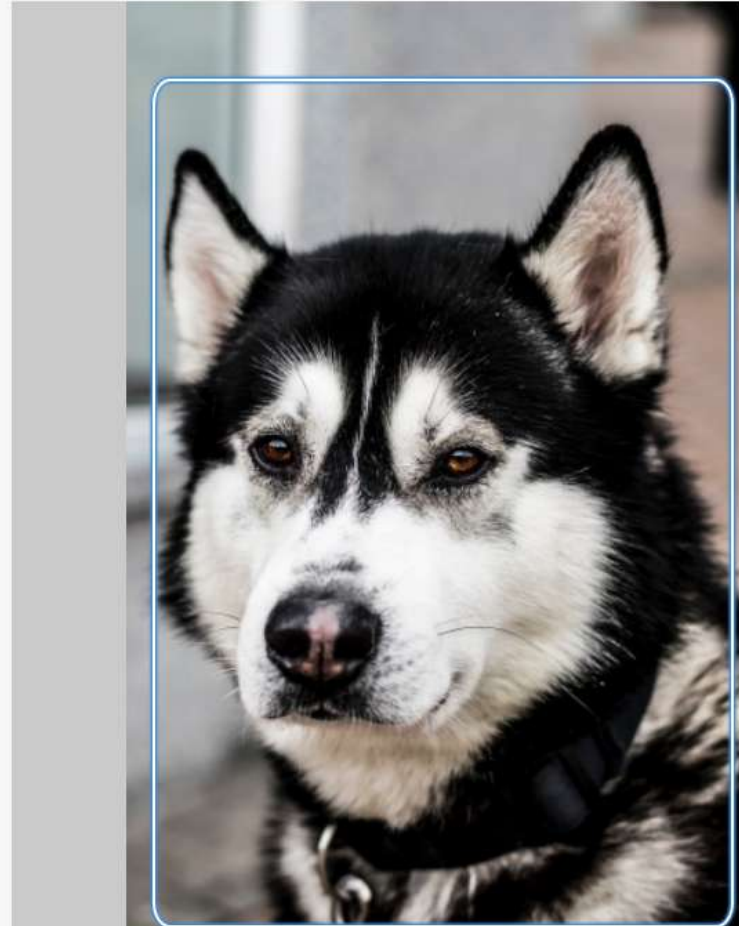
Image recognition



Amazon
Rekognition

Object and scene detection

Rekognition automatically labels objects, concepts and scenes in your images, and provides a confidence score.



Done with the demo?

[Learn more](#)

▼ Results

Animal	99.8 %
Mammal	99.8 %
Canine	99.8 %
Dog	99.8 %
Husky	99.8 %
Pet	99.8 %

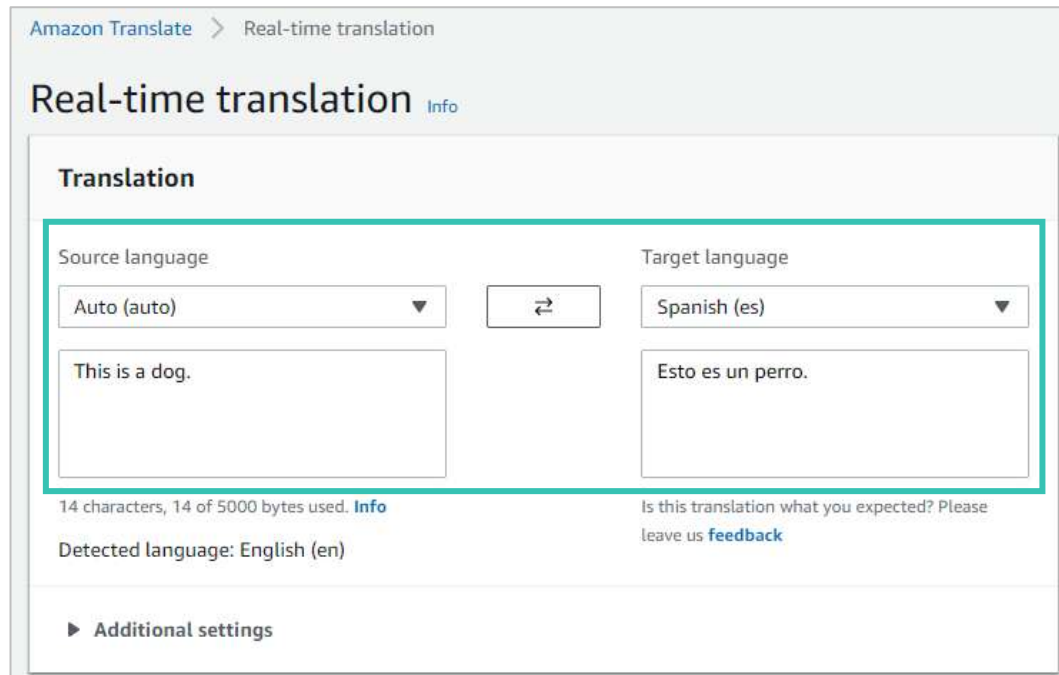
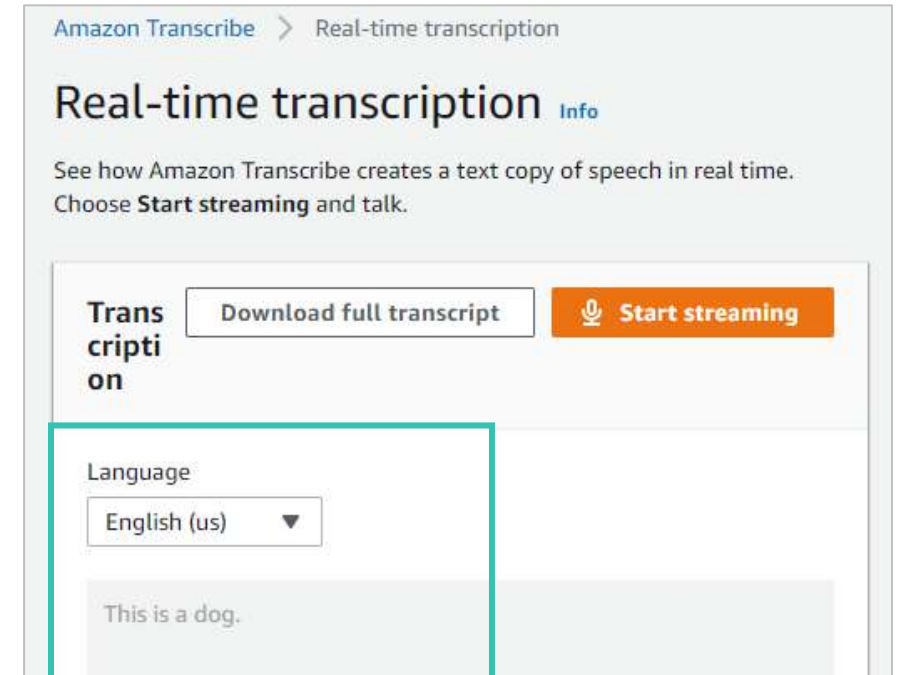
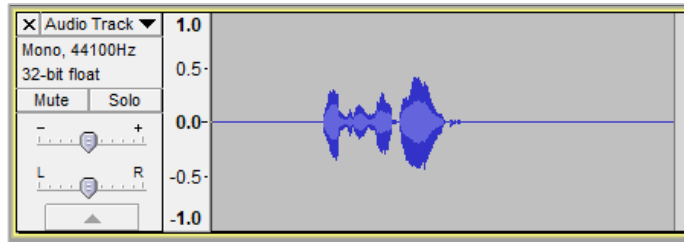
► Request

► Response

Translation and transcription



This is a dog.



Amazon Translate



Amazon Transcribe

Text analysis



Amazon
Comprehend

Input text
[Supported languages](#)

Hunter is a good dog! He likes to run, chase birds and play!



Insights [Info](#)

Entities | Key phrases | Language | **Sentiment** | Syntax

Analyzed text

Hunter is a good dog! He likes to run, chase birds and play!

▼ Results

Sentiment

Neutral	Positive	Negative	Mixed
0.02 confidence	0.97 confidence	0.00 confidence	0.00 confidence



Insights [Info](#)

Entities | **Key phrases** | Language | Sentiment | Syntax

Analyzed text

Hunter is a good dog! He likes to run, chase birds and play!

▼ Results

Key phrases	Confidence
Hunter	0.99+
a good dog	0.99+

Key Challenges and Limitations of AI

Some AI limitations

- **Data:** It fuels ML, so garbage-in / garbage-out still applies
- **Bias:** Poor predictions and decisions can be traced back to biased data
- **Explainability:** How and why the model makes certain predictions
- **Narrow AI:** Lack of generalized AI, where the current AI can only perform specific tasks within a narrow domain
- **Algorithm transparency:** Ability to see internal implementation used
- **Transfer learning:** Ability of ML models to take learning from one arena and apply to another
- **Emotional intelligence:** Basic human trait is still a challenge in ML

Key challenges in ML: Biases and responsible AI

- Biases in ML that we need to be aware of and deal with, such as
 - Sample bias
 - Prejudicial bias
 - Exclusion bias
 - Measurement bias
 - Algorithmic bias

<https://developer.ibm.com/technologies/machine-learning/articles/machine-learning-and-bias>

- Responsible AI: harnessing the power of AI in an ethical, fair, and responsible manner with full transparency, accountability, and freedom from bias.

<https://www.pwc.co.uk/issues/data-analytics/artificial-intelligence/what-is-responsible-ai.html>

Key challenges in ML: Transparency

- **Data lineage** tracks:
 - The origin of the data
 - What happens to it
 - Where it moves over time during data analytics processes
- **Reproducibility/Auditability**: Any results should be **documented** by making all data and code available in such a way that computations can be run again with identical results.
- Data lineage, reproducibility, and auditability are important to investigate potential bias in data and to ensure transparency.

Course use case

Workbook: AnyCompany use case



- Focused on many types of insurance
- Key challenge today is fraud
- Costing them millions of dollars per year
- Lots of historical data
- Wants to improve new claims fraud prediction
- Resolution needed by EOY

Knowledge check

Knowledge check 1

Which option uses deeply multilayered neural networks that perform tasks like speech and image recognition?



A. Artificial intelligence



B. Machine learning



C. Deep learning



D. Reinforcement learning



Knowledge check 2

Which ML algorithm would you use for forecasting the demand for a product?



A. Clustering



B. Classification



C. Regression



D. Correct Action Rewarded



Module 2: Artificial Intelligence Services on AWS

Module 2:

AI Services on AWS

- Overview of AWS ML/AI Portfolio
- Identify and describe key AWS AI services and Identify their use cases

Amazon Machine Learning stack

Our mission at AWS

Put machine learning in the
hands of every developer

Why AWS for ML?



Broad and deep set of ML and AI services

200+ new features and services launched within the last year

Solutions for everyone from ML scientists to application developers

Support for all three major frameworks



Machine learning with Amazon SageMaker

Single integrated development environment (IDE) for the entire ML workflow

At least 54% lower total cost of ownership (TCO)

In the last 2 years, 10,000 customers have adopted Amazon SageMaker



Comprehensive cloud offerings

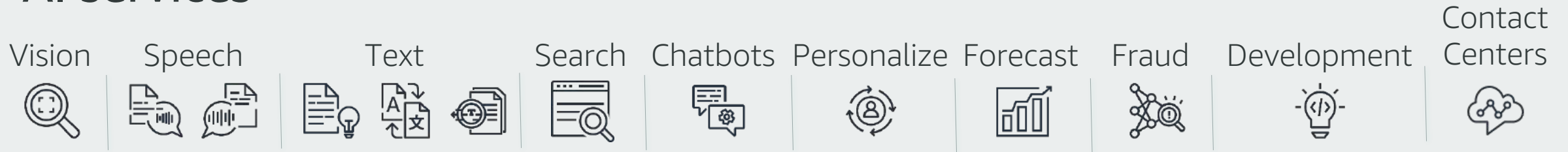
Highly secure, reliable, fully featured data store

Strong set of compute, storage, security, database, and analytics capabilities to build on

85% of TensorFlow in the cloud runs in the AWS Cloud

Amazon ML stack

AI services



ML services



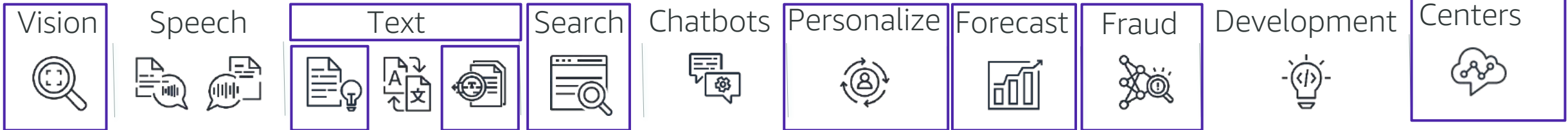
ML frameworks and infrastructure



AI services

Amazon ML stack – AI services

AI services



ML services



ML frameworks and infrastructure





Amazon
Rekognition

Function

Automate image and video analysis with machine learning

Use cases

- Media analysis
- Identity verification
- Content moderation

Key Features

Labels	Custom labels
Content moderation	Text detection
Facial detection	Face search and verification
Celebrity recognition	Pathing

<https://aws.amazon.com/rekognition>

Highlighted customer

C-SPAN



Amazon
Textract

Function

Extract any text and data from any document using machine learning and without manual effort

Use cases

- Create smart search indexes
- Build automated document processing workflows
- Maintain compliance in document archives

Benefits

Extract structured and unstructured data

Go beyond simple optical character recognition (OCR)

Security and compliance

Implement human reviews

<https://aws.amazon.com/textract/>

Highlighted customer

[Filevine](#)

Amazon Comprehend



Amazon
Comprehend

Function

Discover insights and relationships in text

Use cases

- Call center analytics
- Index and search product reviews
- Personalize content on a website

Benefits

Get answers from text

Organize documents by topics

Train models on your own data

Support general and industry-specific text

<https://aws.amazon.com/comprehend>

Highlighted customer

[FINRA](#)



Amazon
Personalize

Function

Create real-time, personalized user experiences fast, at scale

Use cases

- Retail – Help customers discover products
- Media and entertainment – Recommend new content, based on preference

Benefits

Deliver recommendations in real time

Implement personalized recommendations, in days

Personalize touchpoints along the customer journey

<https://aws.amazon.com/personalize>

Highlighted customers

[Retail – Subway](#)

[Media and Entertainment – Coursera](#)



Amazon
Kendra

Function

Enterprise search service powered by machine learning

Use cases

- Improve access to internal knowledge
- Enhance sales and customer support services
- Help customers find information efficiently

Benefits

Ask natural-language questions, get immediate answers

Bring data together with a few clicks

Constantly improve search results

<https://aws.amazon.com/kendra>

Highlighted customers

[CORD-19 Search](#)

COVID-19 Open
Research Dataset
(CORD-19)



Amazon
Forecast

Function

Time-series forecasting service

Use cases

- Product demand planning
- Financial planning
- Resource planning

Benefits

Reduce forecasting time from months to hours

Create any time series forecast

Secure business data

<https://aws.amazon.com/forecast>

Highlighted customer

[Puget Sound
Energy](#)

Amazon Fraud Detector



Amazon
Fraud Detector

Function

Detect more online fraud faster

Use cases

Detect common types of fraud:

- New account
- Online payment
- Guest checkout
- Online service and loyalty program abuse

Benefits

Prevent and detect online fraud

Fraud detection in minutes

Customized for your unique business needs

<https://aws.amazon.com/fraud-detector>

Highlighted customers

[Customers](#)

How you can help customers



- AWS AI services solve specific business problems.
- Customers can have little to no Amazon ML experience.
- Customers can use APIs to interact with AWS AI services.

Call to action

- Explore AI services in the AWS Management Console
- Complete tutorials

Course use case



- Return to the AnyCompany use case.
- Can a single AI service be used to address the problem?
- Can any combination of AI services be used?

3-minute individual exercise and
3-minute class discussion

Knowledge check

Knowledge check

Which AWS AI service can be used to discover insights and relationships in text?



Amazon Kendra



Amazon Textract



Amazon Comprehend



Amazon Personalize



Knowledge check

Which AWS AI service can be used to extract any text and data from any document without manual effort?



Amazon Kendra



Amazon Comprehend



Amazon Pinpoint



Amazon Textract



Module 3: Machine Learning Process

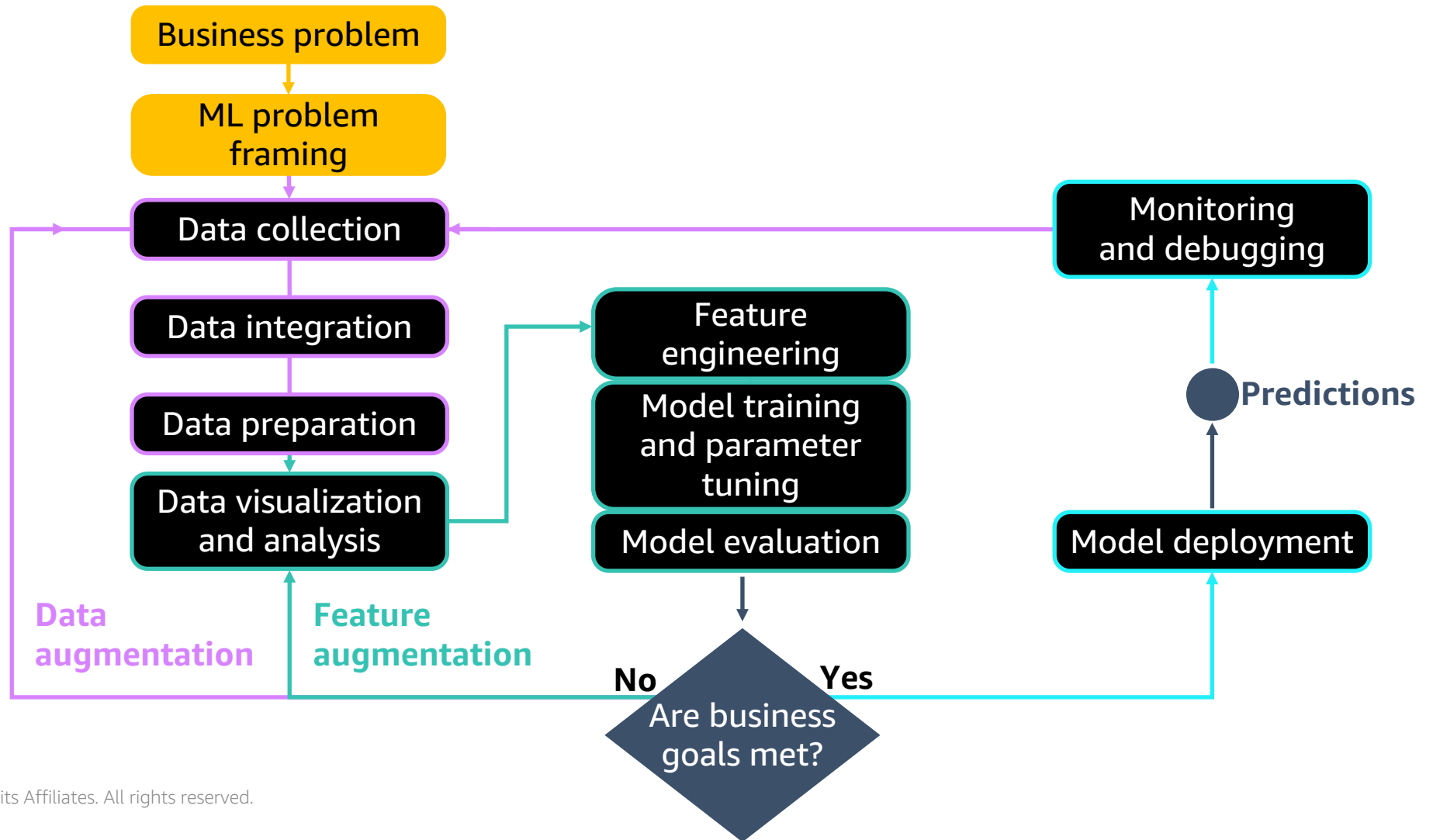
Module 3:

ML Process

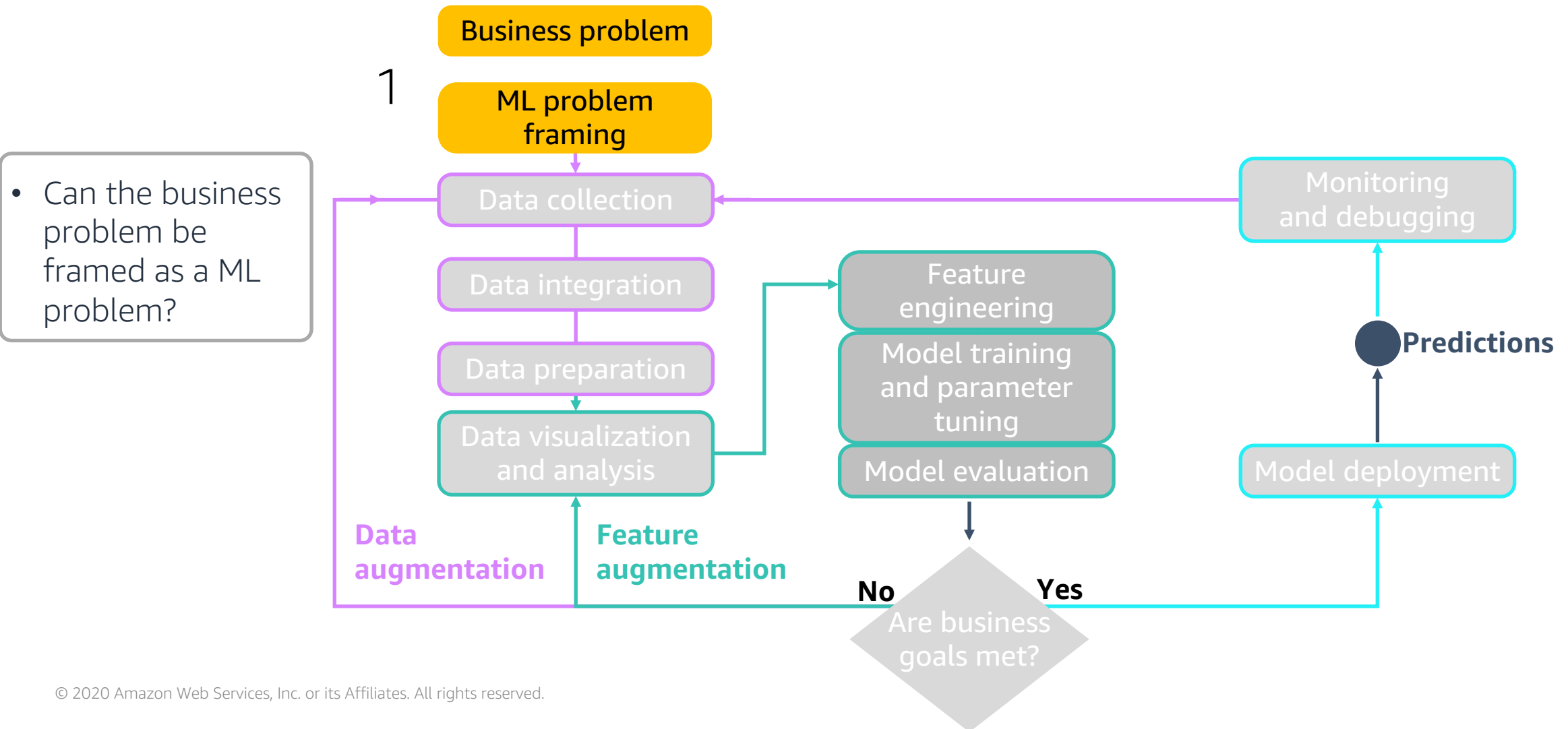
- Identify phases in the machine learning process
- Explain Machine Learning Pipeline
- Walk through the feature design process, requirements, and data dependencies for implementing ML on AWS
- Determine if a business problem can be solved with machine learning
- Identify your role, including how you can help customers
- Discuss Insurance Fraud Use Case

Phases of Machine Learning & ML Pipeline

ML process overview

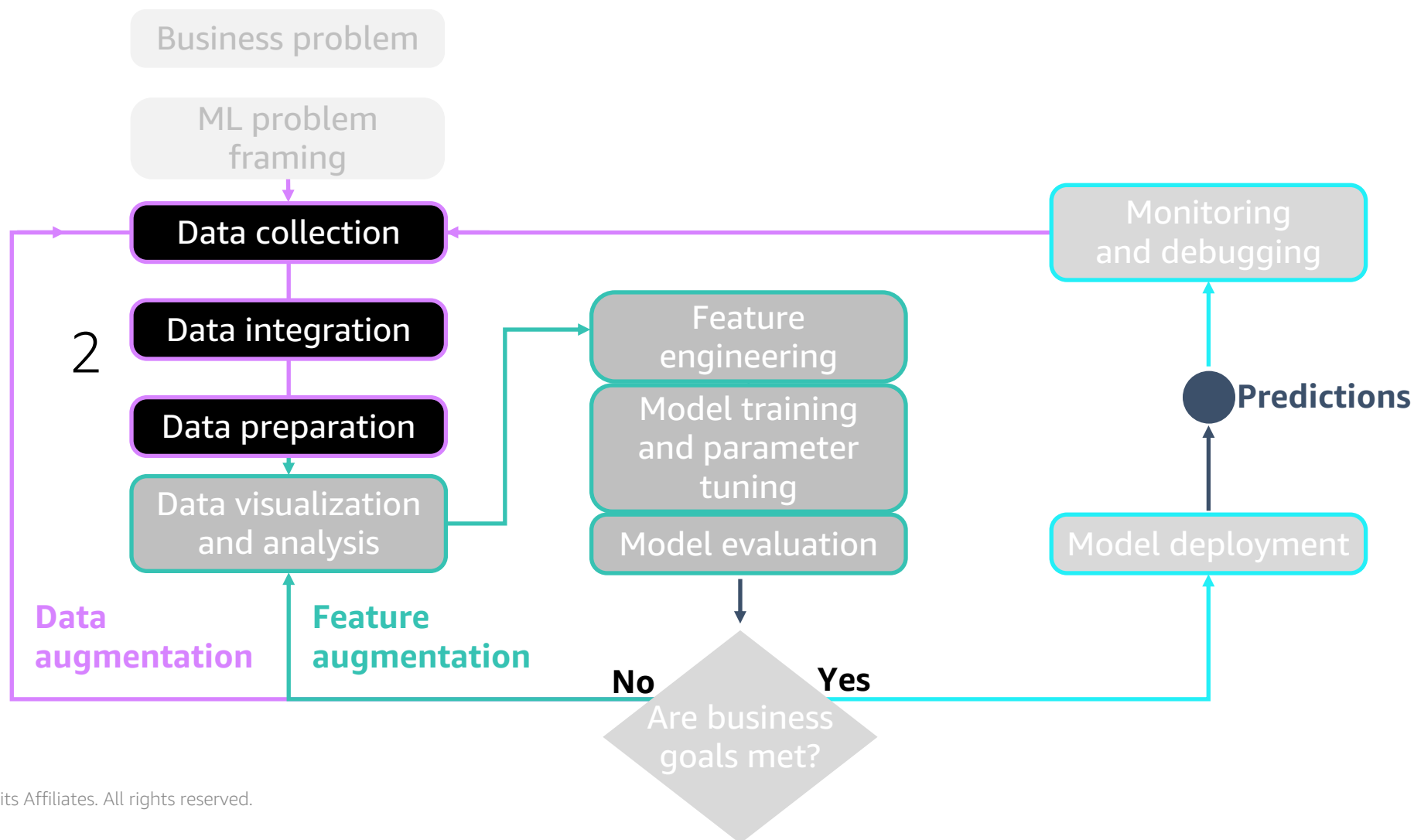


1. Business process: Framing a business problem



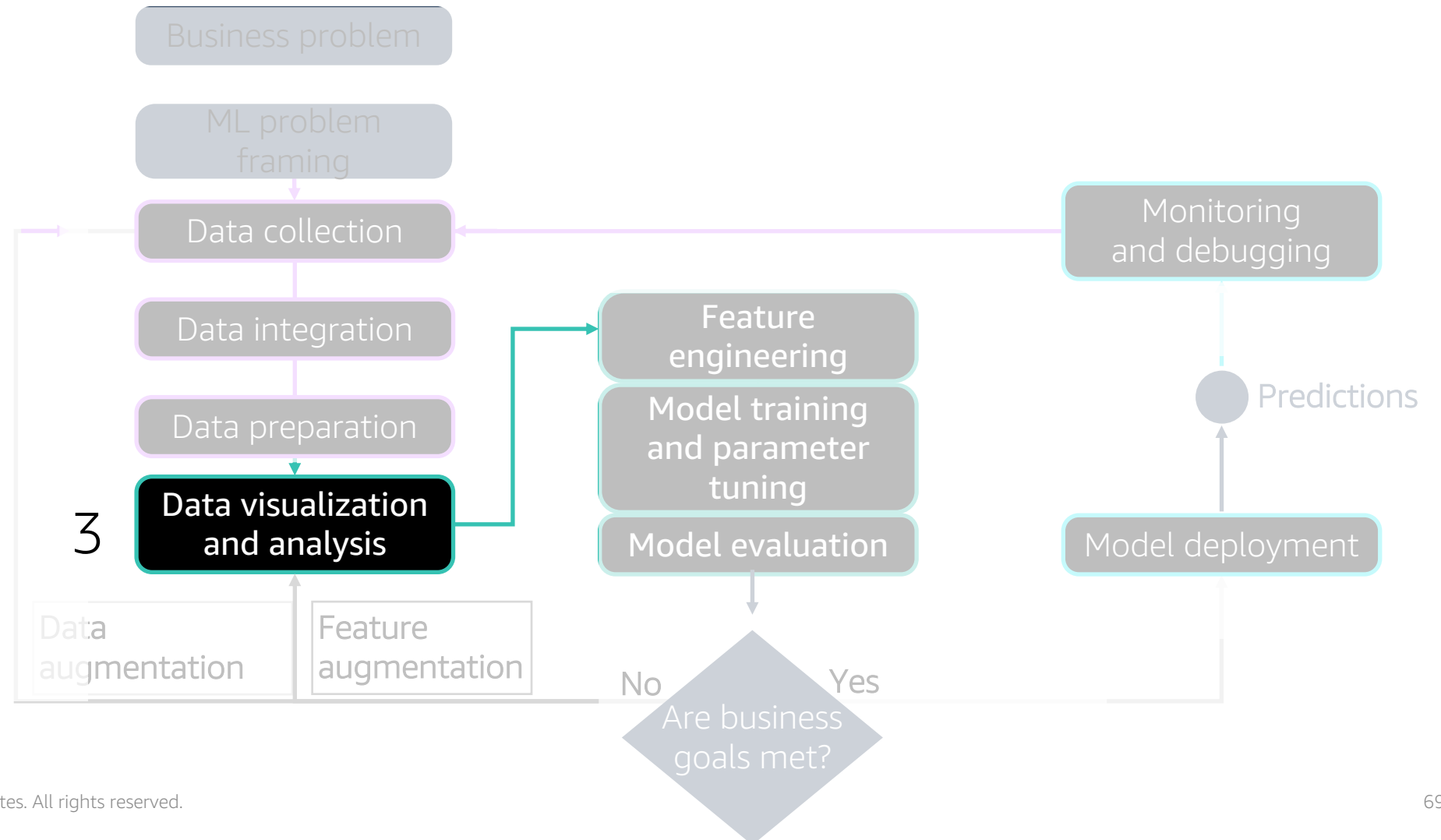
2. Data collection, integration, and preparation

- Set up Data Pipeline to
 - Collect data
 - Store data
- Cleanse, analyze and prepare data
- Use different tools for these tasks



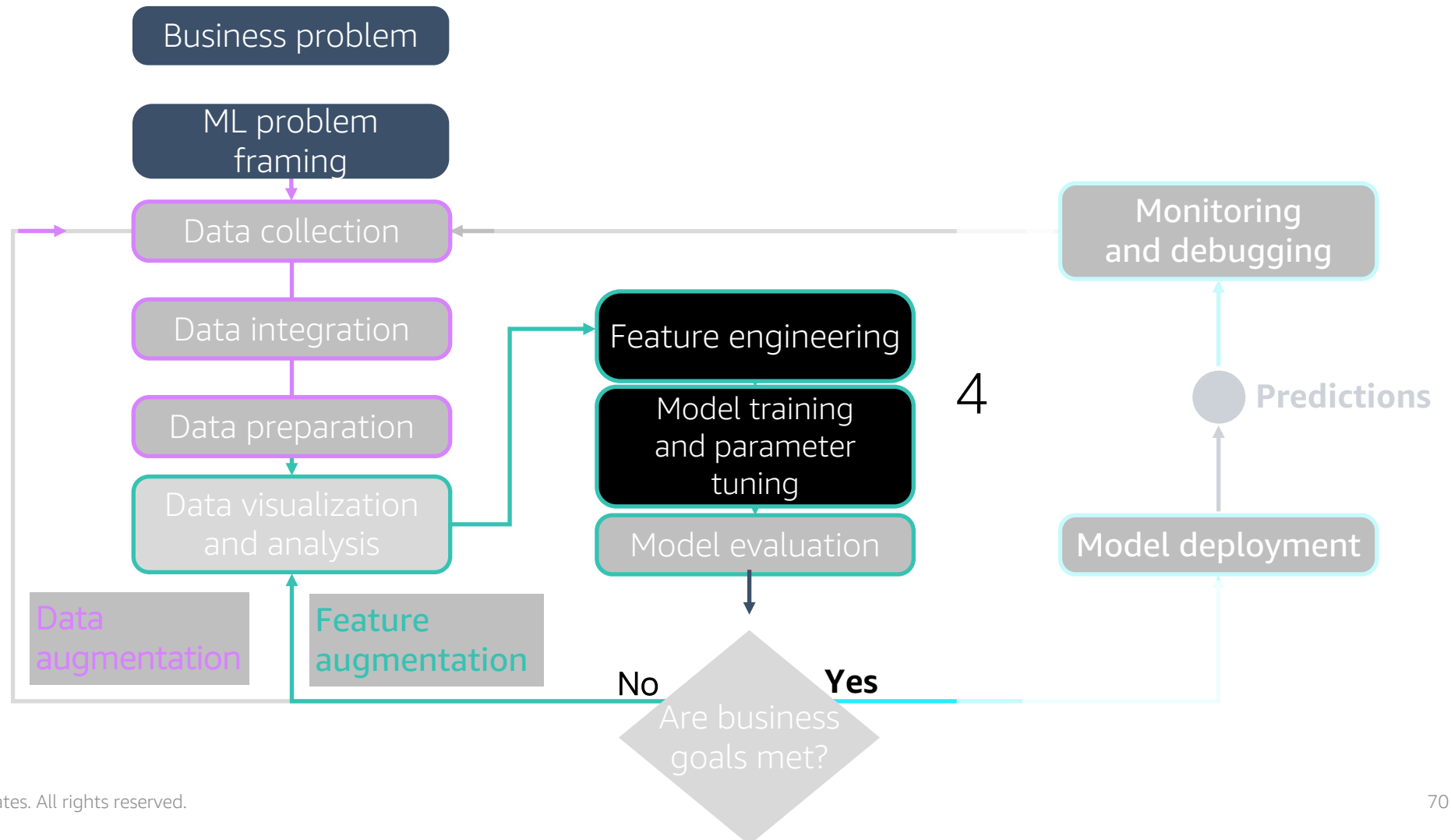
3. Data visualization

- Set up and manage
 - Notebook environments
- Use statistical tools to visualize and analyze data



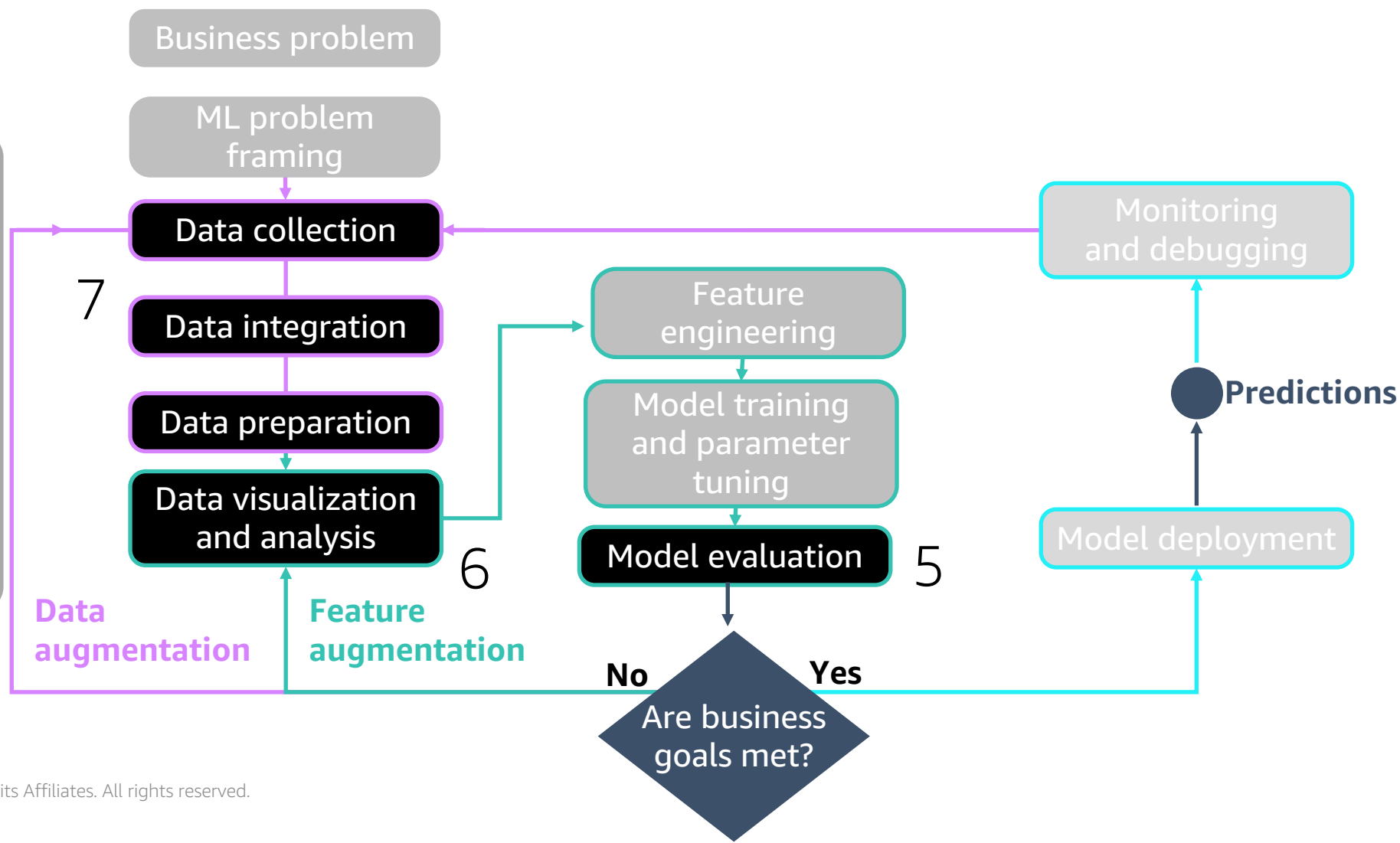
4. Feature engineering, model training, and parameter tuning

- Perform feature engineering
- Set up and manage inference clusters
- Manage and scale model inference APIs
- Train, monitor and debug model predictions
- Model versioning and performance tracking

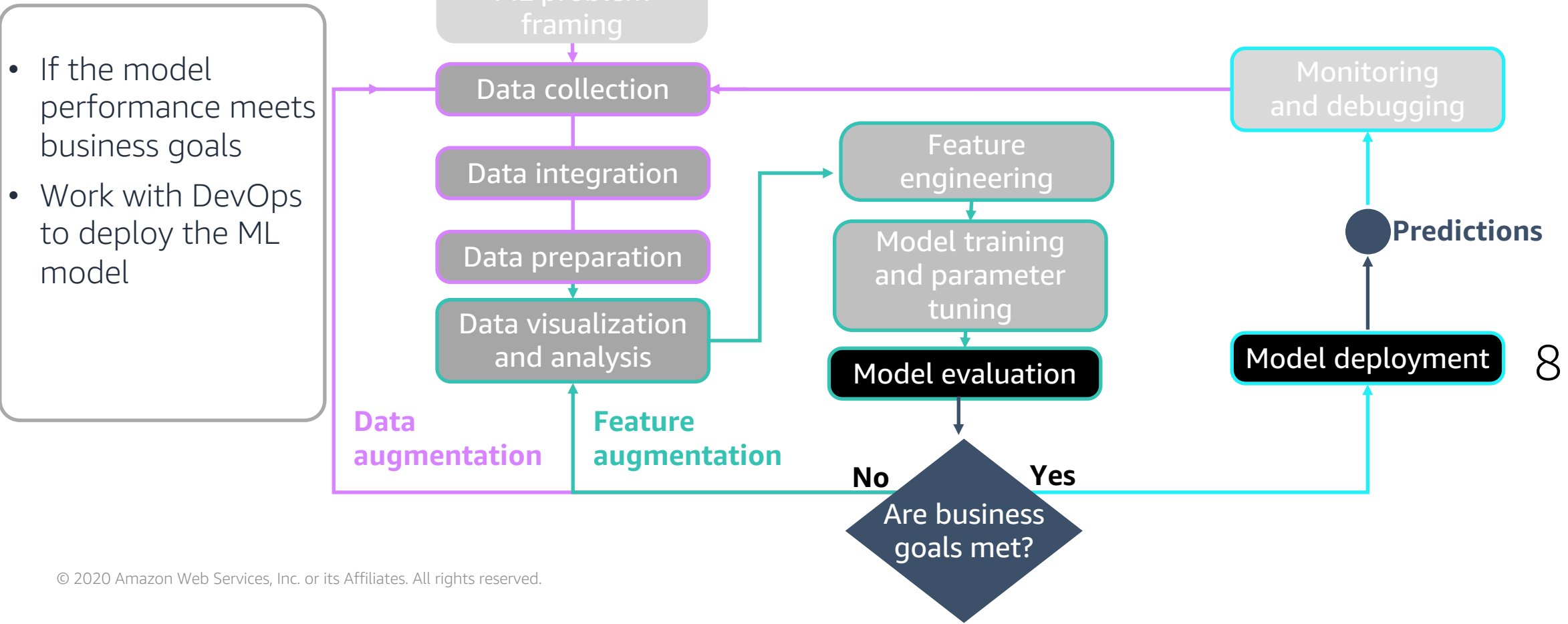


5, 6, 7 – Model evaluation, data and feature augmentations

- Evaluate if model performance meets business goals
- Will feature augmentations or data augmentations lead to improve model performance



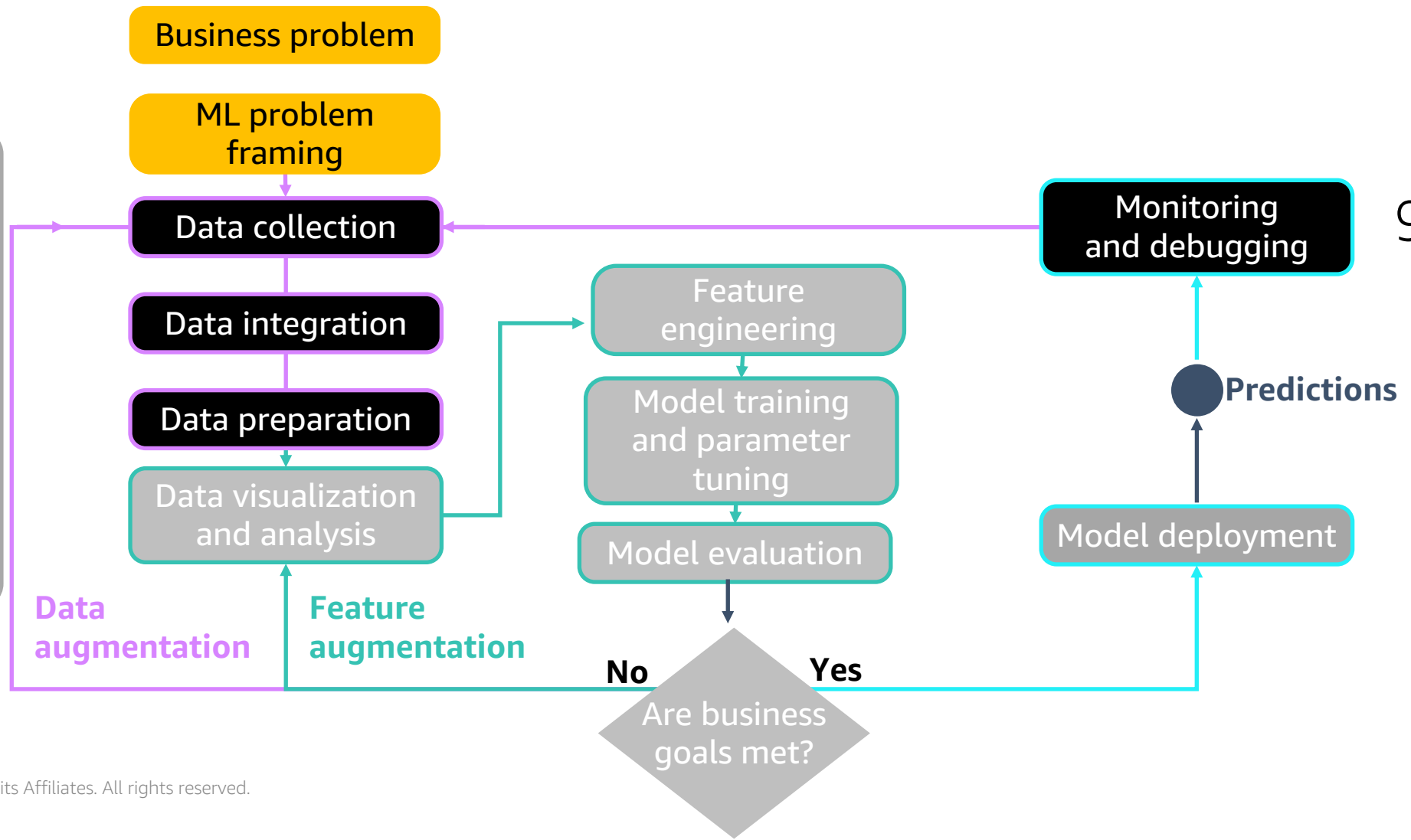
8. Model deployment



9. Model monitoring and debugging

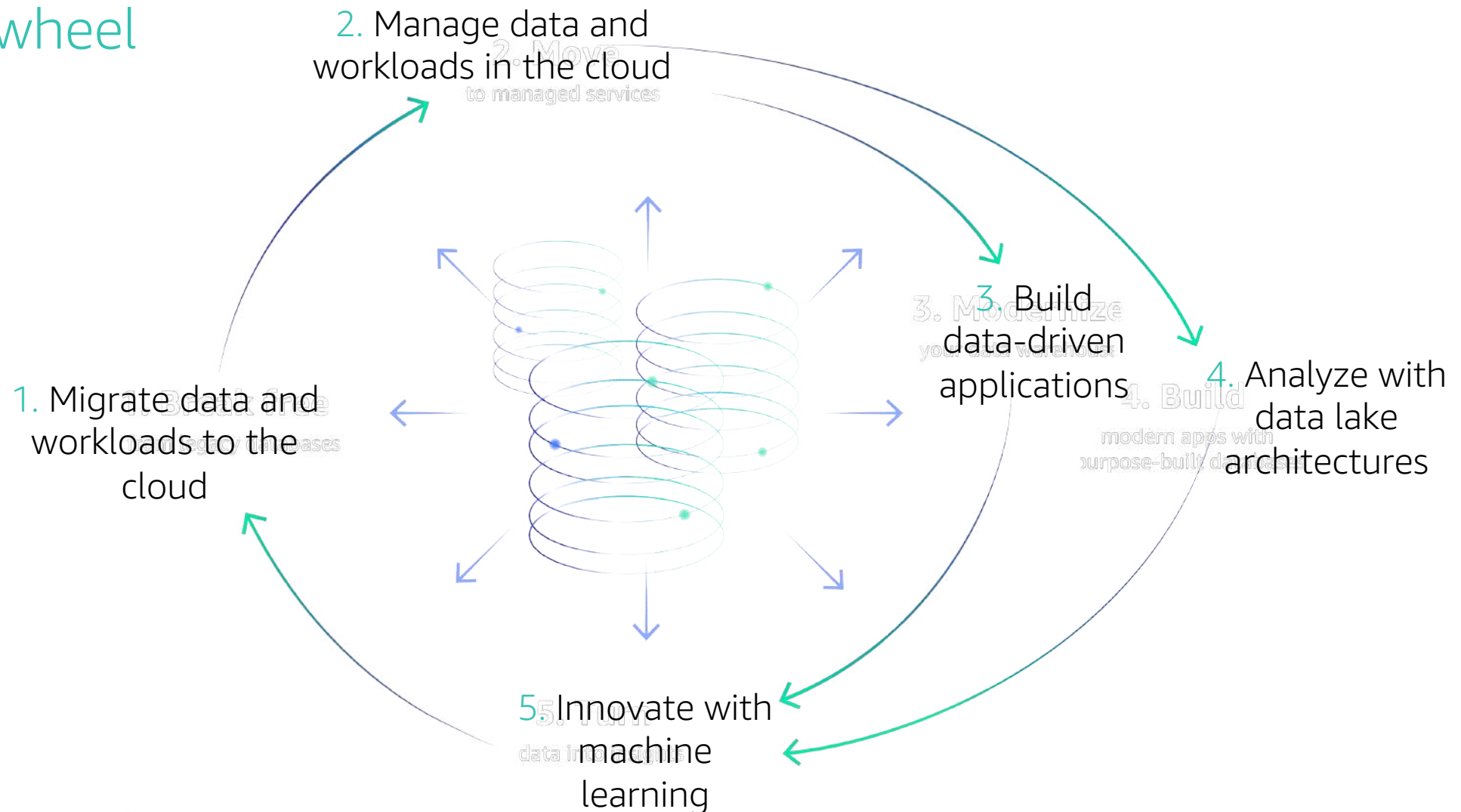
9

- Monitor for model performance and model drift
- To correct model drift, will need to go back to data collection and training phase



ML and the cloud journey

Data Flywheel

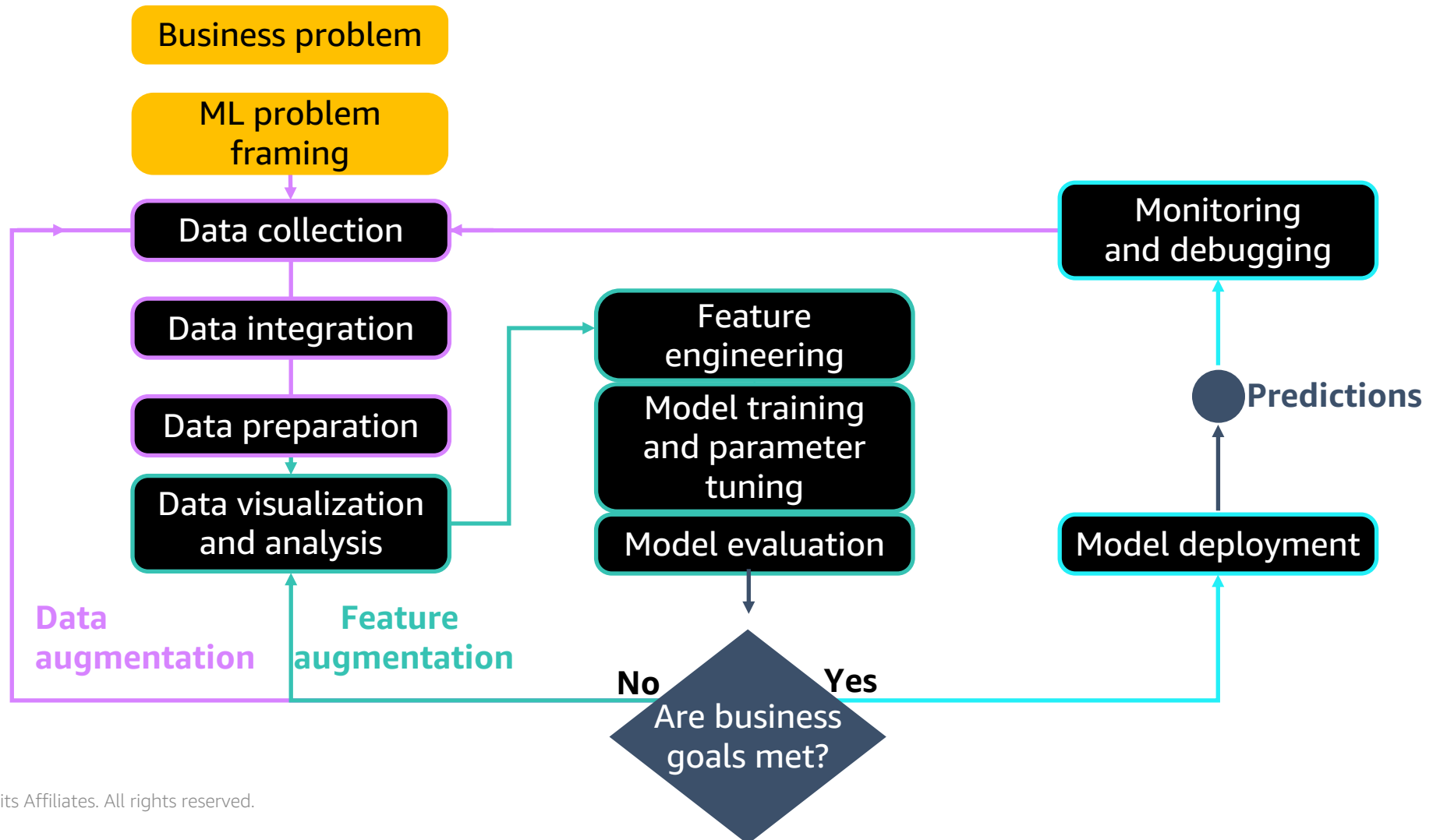




- Revisit the persona you affiliated with at the beginning of the course
- With this persona in mind, identify portions of the machine learning process where you could add value, including what you could do and how you would do it during each phase

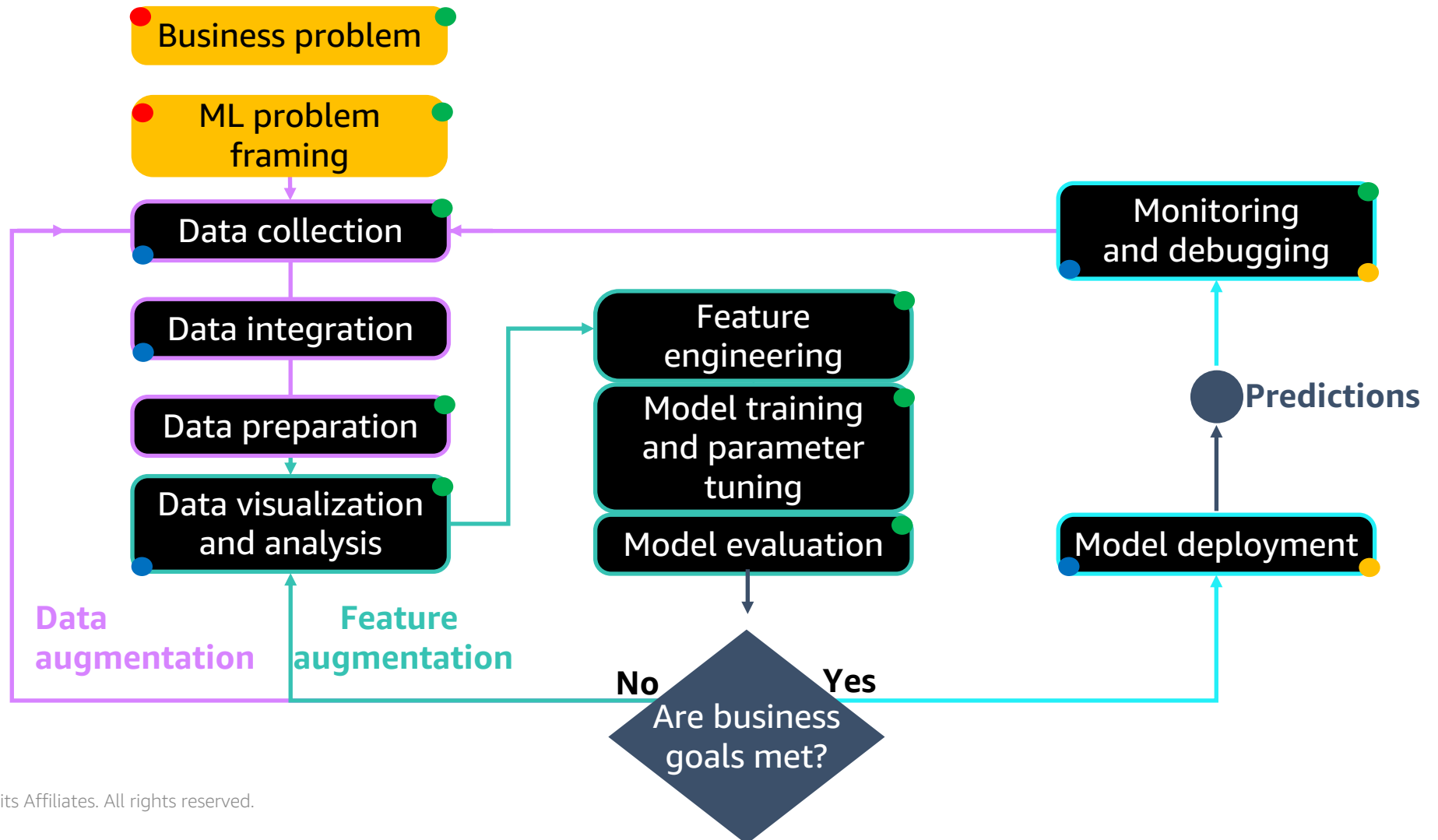
3-minute individual exercise and
3-minute class discussion

Workbook 3.1



Workbook 3.1

- TAM
- Data Scientist
- Developer
- DevOps



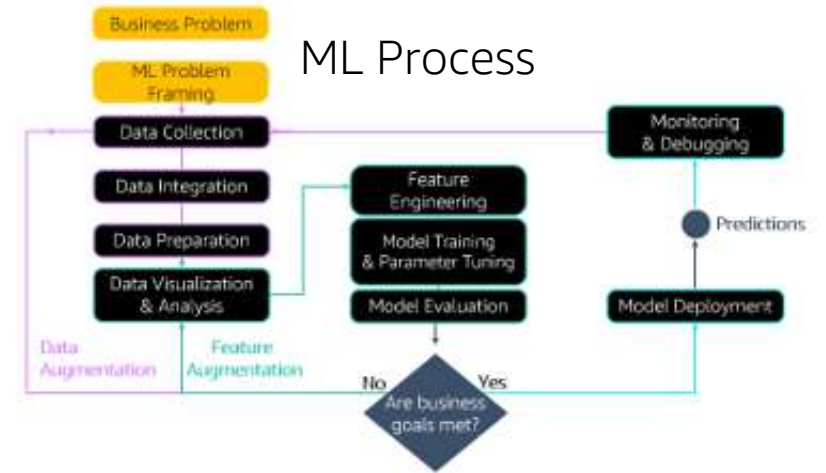
How you can help customers



Most business problems are not ML problems



Amazon AI/ ML



Pricing

Course use case

Workbook 3.2: Use case



- Focused on many types of insurance
- Key challenge today is fraud
- Costing them millions of dollars per year
- Lots of historical data
- Wants to improve new claims fraud prediction
- Resolution needed by EOY

Workbook 3.2

	months_ as_custome r	age	policy_n umber	policy_bi nd_date	policy_st ate	policy_cs l	policy_d eductabl e	policy_a nnual_pr emium	umbrella _limit	insured_ zip	police_re port_avai lable	total_clai m_amou nt	injury_cla im	property _claim	vehicle_c laim	auto_ma ke	auto_mo del	auto_yea r	fraud_re ported
0	328	48	521585	2014- 10-17	OH	250/500	1000	1406.91	0	466132	YES	71610	6510	13020	52080	Saab	92x	2004	Y
1	228	42	342868	2006- 06-27	IN	250/500	2000	1197.22	5000000	468176	?	5070	780	780	3510	Mercede s	E400	2007	Y
2	134	29	687698	2000- 09-06	OH	100/300	2000	1413.14	5000000	430632	NO	34650	7700	3850	23100	Dodge	RAM	2007	N
3	256	41	227811	1990- 05-25	IL	250/500	2000	1415.74	6000000	608117	NO	63400	6340	6340	50720	Chevrole t	Tahoe	2014	Y
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Knowledge check

Knowledge check

What is the most critical phase of the machine learning process?



Data Collection, Integration, and Preparation phase



Model Deployment phase



Feature Engineering, Model Training, and Parameter Tuning phase



Business Process phase



Knowledge check

When does the ML process end?



After model evaluation



After model deployment



After model monitoring and debugging



The ML process never ends

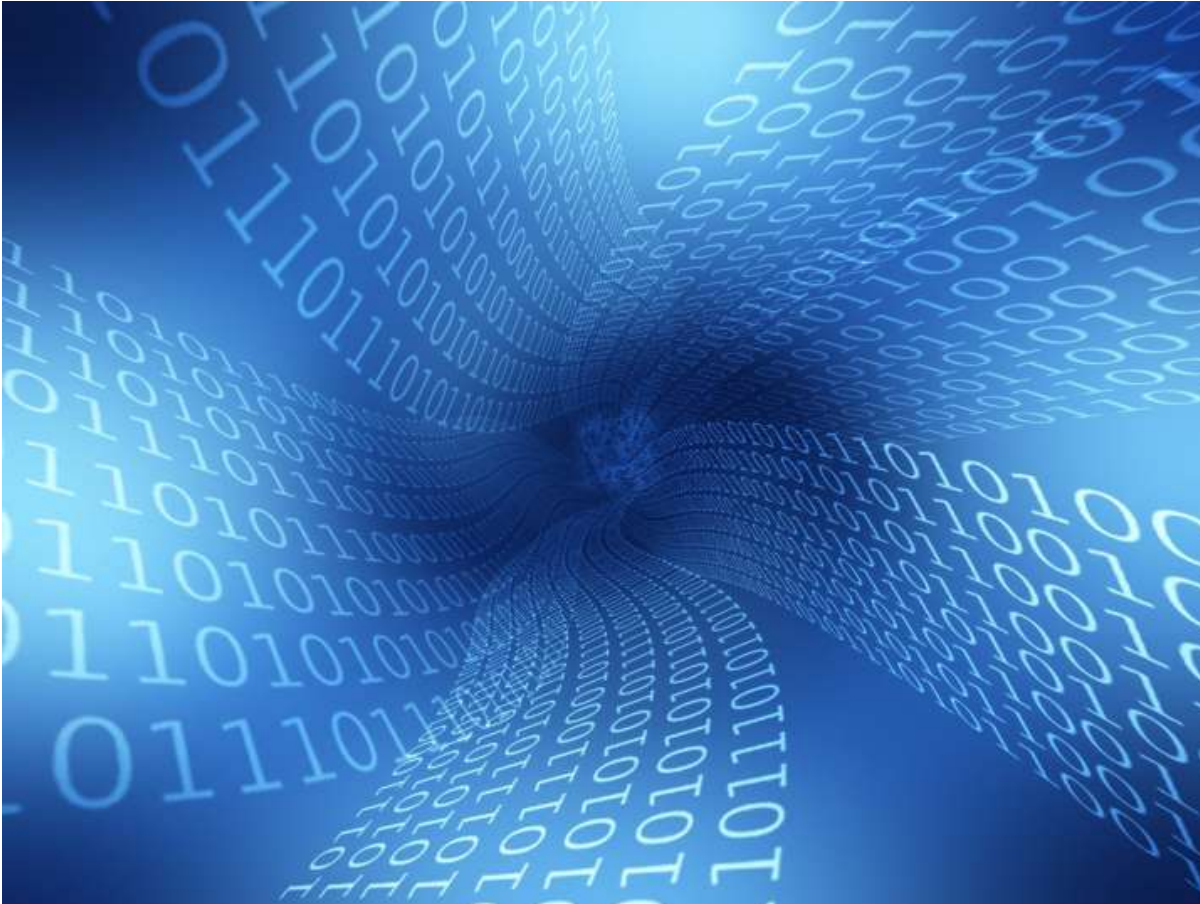


Module 4: Data Collection, Integration, Preparation, Visualization, and Analysis

Module 4: Data Collection, Integration, Preparation, Visualization, and Analysis

- Explain why data is critical to machine learning problems
- Explain structured and unstructured data
- Explain the purpose of data phases in the ML process
- Identify AWS services that are used during data collection, integration, preparation, and visualization
- Explain Amazon SageMaker Data Wrangler
- Explain Amazon SageMaker Feature Store
- Explain the purpose of Amazon SageMaker Ground Truth and identify its use cases

Data challenges in ML projects



- ML project requires lots of data
- **ML requires clean data.**
- More than 50% of project time is spent gathering, cleansing, and visualizing data.
- 36% see dirty data as the #1 challenge.

Source Kaggle Machine Learning and Data Science Survey 2017:
<https://www.kaggle.com/kaggle/kaggle-survey-2017>

Structured versus unstructured data

Name	Color	Vegetable
Apple	Red	No
Broccoli	Green	Yes
Spinach	Green	Yes
Grape	Purple	No
Squash	Yellow	Yes

Structured
(relational databases, .csv files)

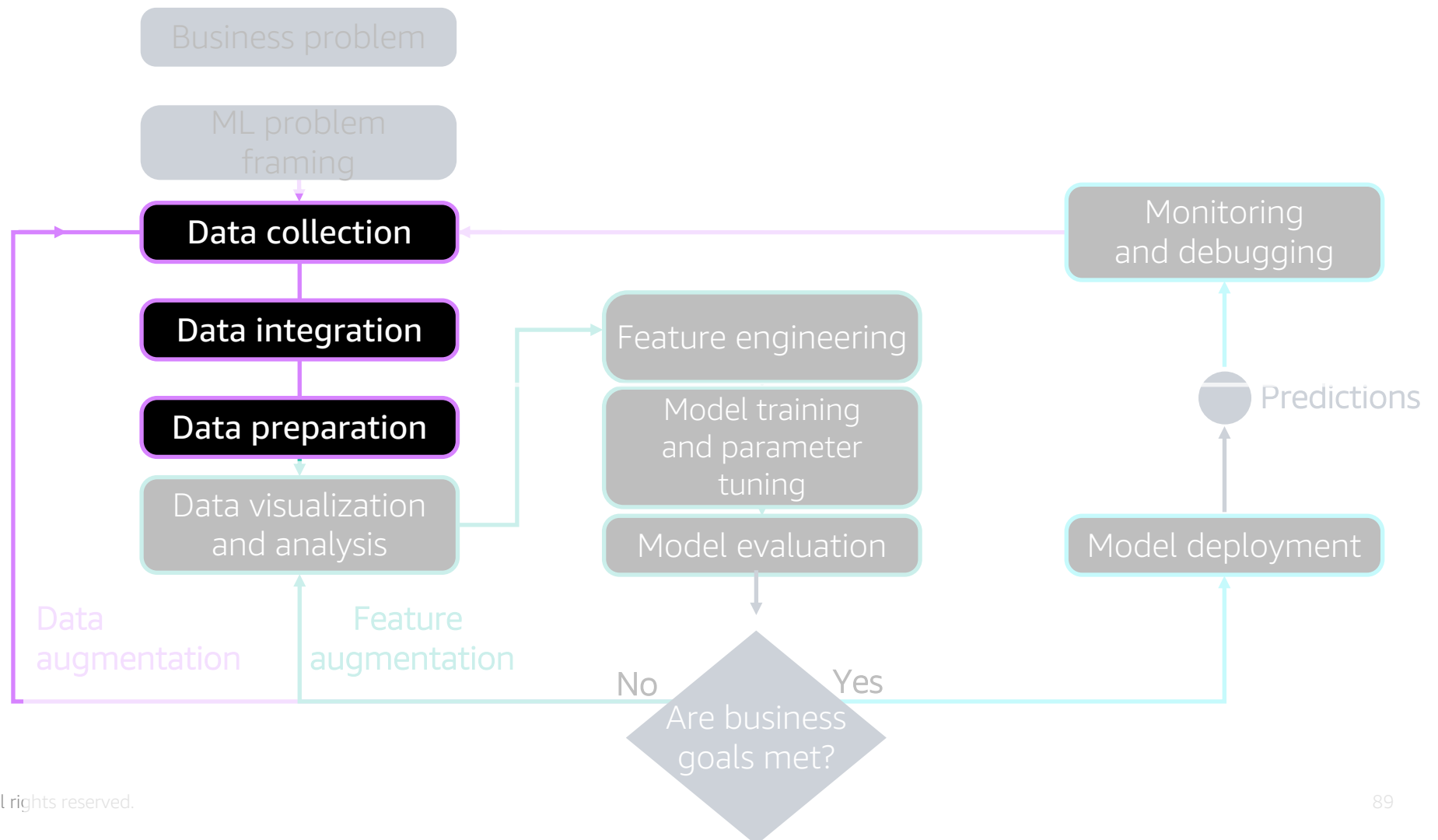


Unstructured
(documents,
audio, or video files)

ML process: Collection, Integration

Build the data platform:

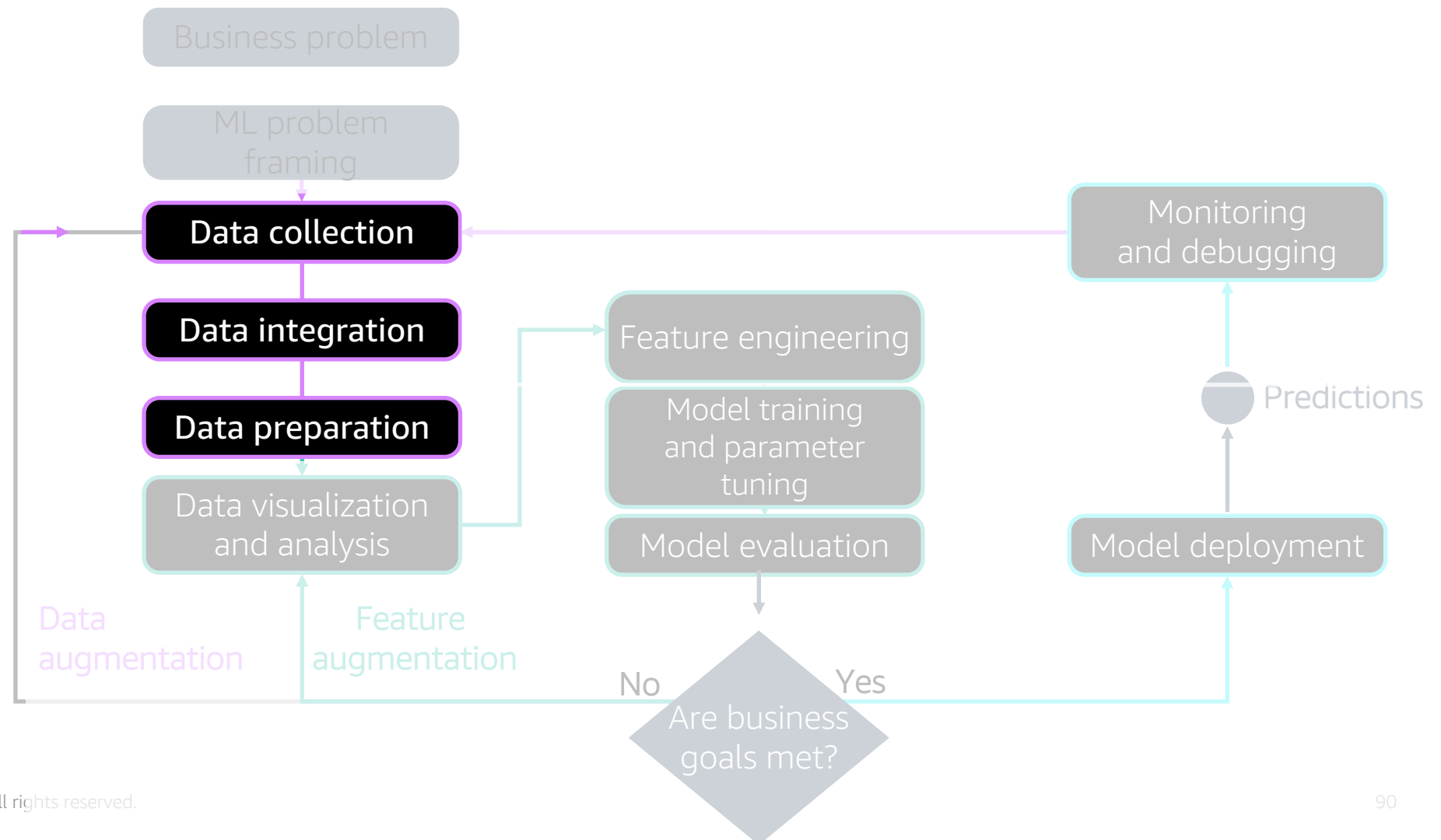
- Amazon Simple Storage Service (Amazon S3)
- Amazon Athena
- Amazon EMR
- AWS Glue
- Amazon QuickSight
- AWS Lake Formation
- Amazon Redshift



ML process: Preparation

Preparation steps:

- Data exploration and profiling
- Data formatting
- Data conversion
- Encoding
- Data cleaning
- Normalization
- Resampling (oversampling/undersampling)



Amazon SageMaker Data Wrangler

SageMaker Data Wrangler

The fastest and easiest way to prepare data for ML



With a **single click**

- Ingest data from various data sources
- Deploy data preparation workflows into production

Leverage **built-in feature** to

- Transform data with data transformations
- Data visually using visualization templates

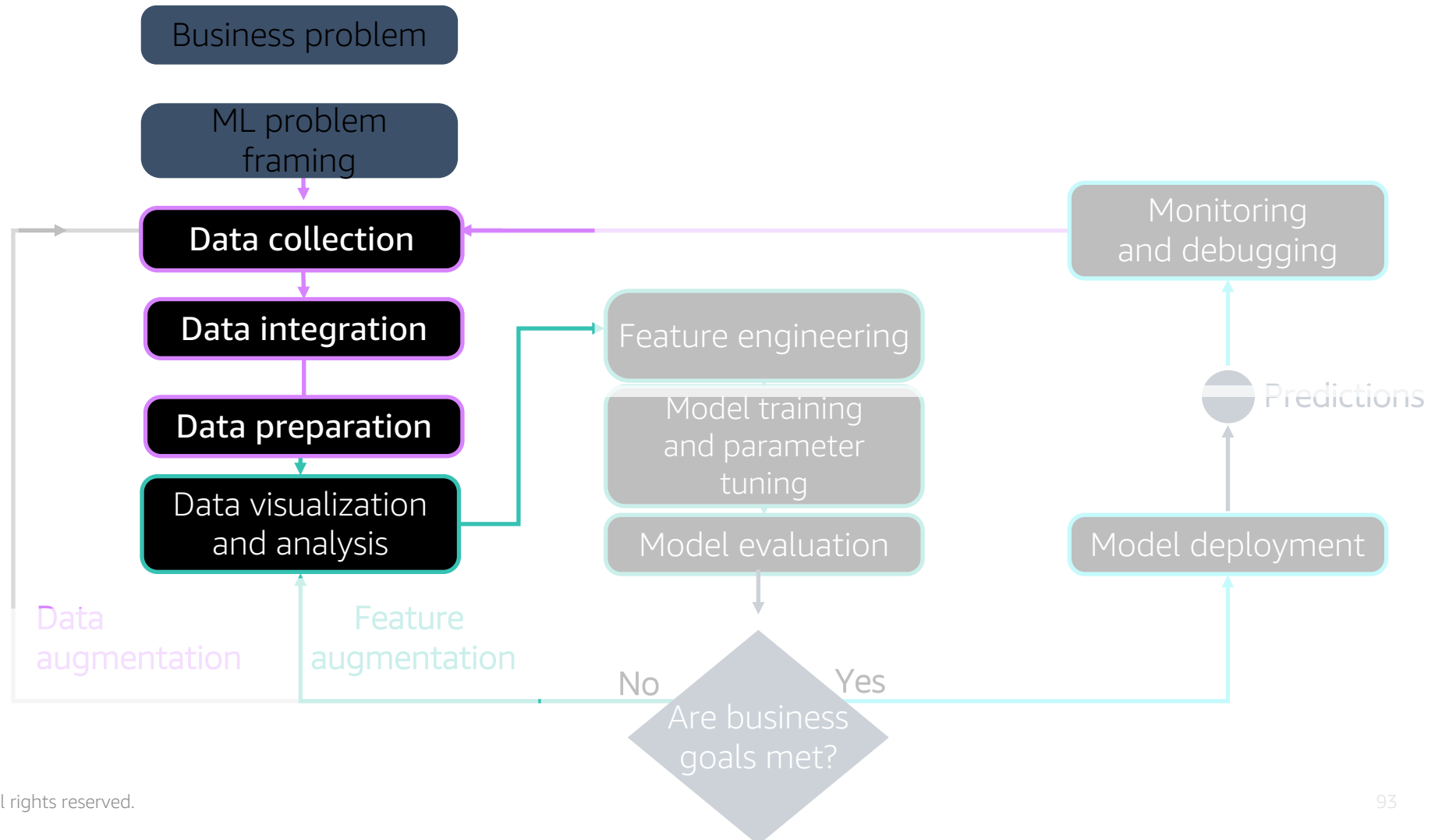
Ability to

- Bring your custom transformation
- Estimate ML model accuracy

Data collection, integration, preparation and visualization with Data Wrangler

Data Wrangler's

- Data Selection tool to import data in various formats from multiple sources
- Leverage 300+ data transformations to transform imported data
- Leverage pre-configured visualization template to visualize your data



Amazon SageMaker Feature Store

Challenges in Scaling ML Productivity

Long and
tedious feature
engineering

Redundant
feature
pipelines

No sharing or
discovery
mechanism

Troubleshooting
overhead due to
training inference
skew

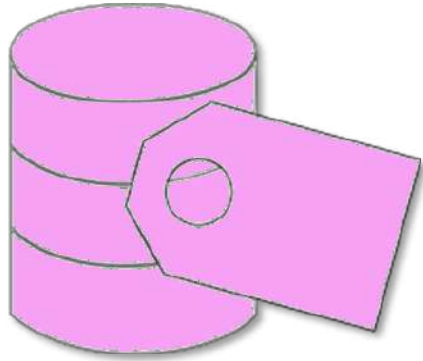
SageMaker Feature Store benefits



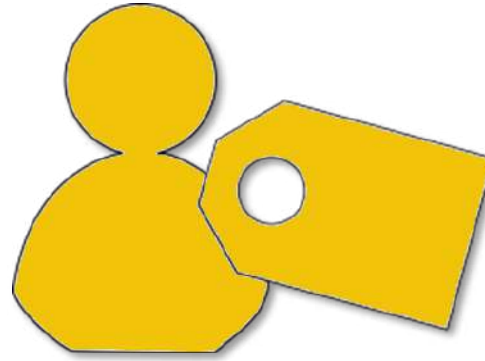
- Ingest features from many sources including Data Wrangler
- Search and discover features easily
- Ensure feature consistency for both training and for inferences
- Standardize with a single source of feature definition
- Integrate with SageMaker Pipeline

Amazon SageMaker Ground Truth

Amazon SageMaker Ground Truth Overview



Quickly label
training data



Easily integrate
human labelers



Get accurate
results

KEY FEATURES

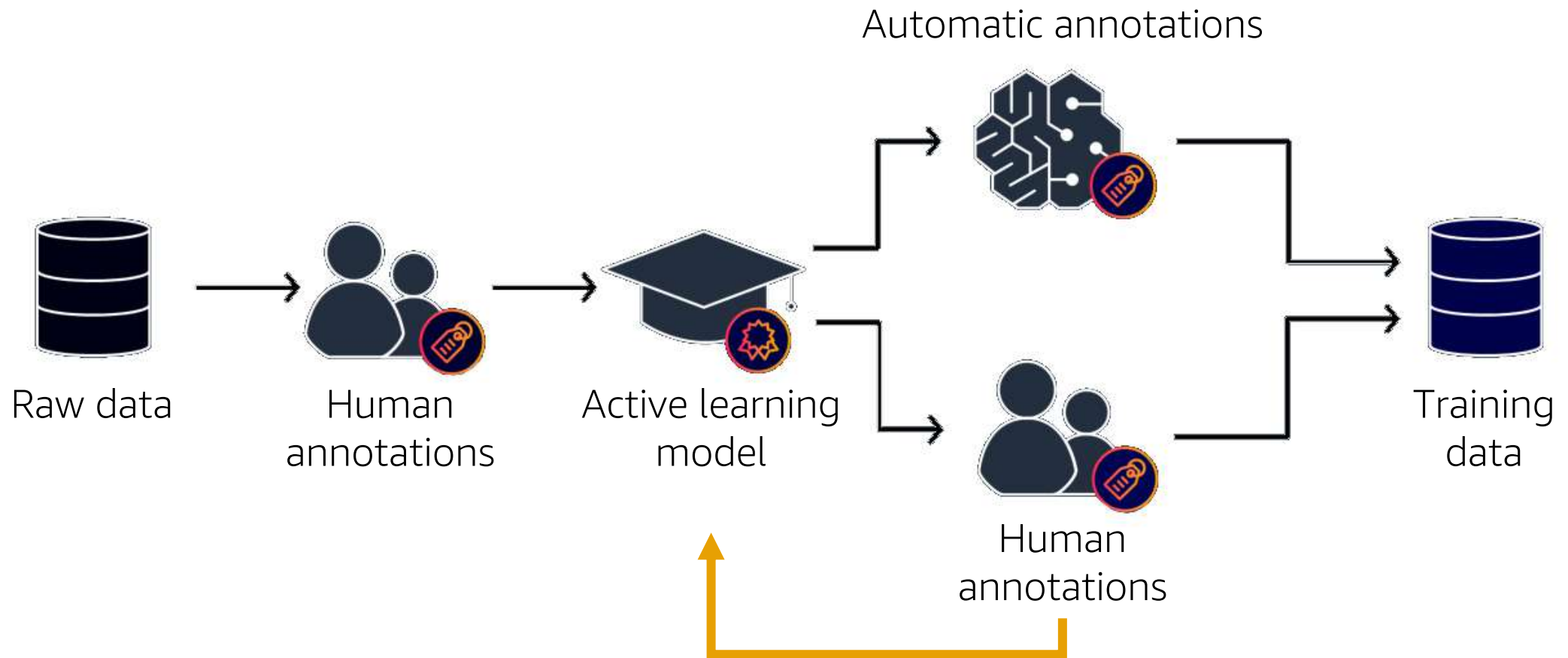
Automatic labeling by way of
machine learning

Ready-made and
custom workflows for
image bounding box,
segmentation, and text

Private and public
human workforce

Label
management

SageMaker Ground Truth: How it works



How you can help customers



- Understand the data structure and its purpose
- Understand where data comes from and how it is used today
- Devise the appropriate data processing solution

Clean, prepare, and visualize data first, before using it for ML!

Course use case

Workbook 4.1

	months_ as_custome r	age	policy_n umber	policy_bi nd_date	policy_st ate	policy_cs l	policy_d eductabl e	policy_a nnual_pr emium	umbrella _limit	insured_ zip	police_re port_avai lable	total_clai m_amou nt	injury_cla im	property _claim	vehicle_c laim	auto_ma ke	auto_mo del	auto_yea r	fraud_re ported
0	328	48	521585	2014- 10-17	OH	250/500	1000	1406.91	0	466132	YES	71610	6510	13020	52080	Saab	92x	2004	Y
1	228	42	342868	2006- 06-27	IN	250/500	2000	1197.22	5000000	468176	?	5070	780	780	3510	Mercede s	E400	2007	Y
2	134	29	687698	2000- 09-06	OH	100/300	2000	1413.14	5000000	430632	NO	34650	7700	3850	23100	Dodge	RAM	2007	N
3	256	41	227811	1990- 05-25	IL	250/500	2000	1415.74	6000000	608117	NO	63400	6340	6340	50720	Chevrole t	Tahoe	2014	Y
4	228	44	367455	2014- 06-06	IL	500/100 0	1000	1583.91	6000000	610706	NO	6500	1300	650	4550	Acura	RSX	2009	N

Knowledge check

Knowledge check

Which of these are the two main challenges data engineers face after data collection and before the data can be used for training?



Data integration and preparation



Data variety - different data formats



Data veracity - completeness, accuracy, or quality



Structured and unstructured data

Knowledge check

What are the three key benefits of Amazon SageMaker Ground Truth?



Speeds up model evaluation



Quickly labels training data



Easily integrates human labelers




Gets accurate labeling results



Module 5: Deep Learning

Amazon Machine Images

Module 5: Deep Learning Amazon Machine Images

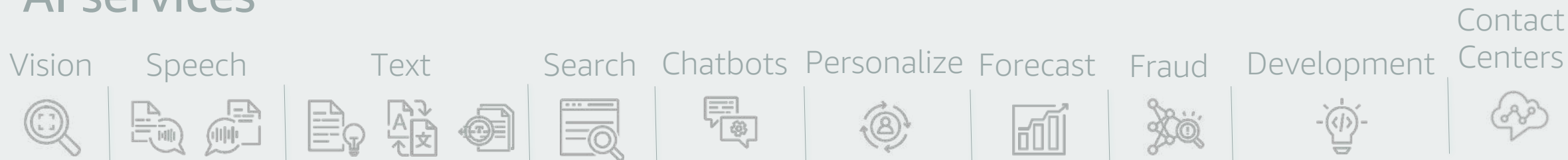


- Identify what deep learning AMIs are
- Identify the capabilities of AWS Deep Learning AMIs
- Identify use cases for AWS Deep Learning AMIs
- Explain when, how, and why to use AWS Deep Learning AMIs

ML infrastructure

Amazon ML stack

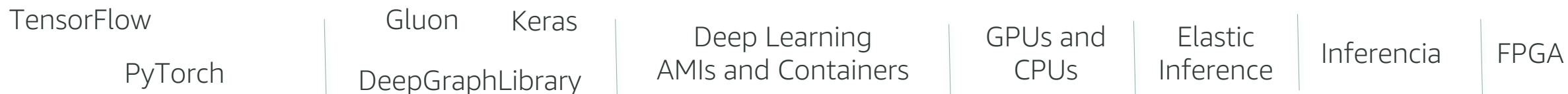
AI services



ML services



ML frameworks and infrastructure



AWS Deep Learning AMIs: Two choices



- Pre-configured environments to quickly build deep learning applications for ML practitioners and researchers
- Quickly launch Amazon EC2 instances pre-installed with popular deep learning frameworks and interfaces

Conda AMI

- Pre-installed pip package for deep learning framework
- Available in Ubuntu, Amazon Linux, and Windows 2016 versions

Base AMI

- Clean slate to set up custom private deep learning engine repository with no frameworks installed; only NVIDIA CUDA and other dependencies
- Available in Ubuntu and Amazon Linux versions

Supported deep learning frameworks



theano

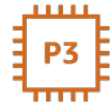


Provides access to the Amazon ML infrastructure

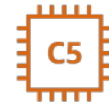
ML
infrastructure

TensorFlow
MXNet
PyTorch

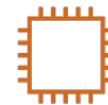
GLUON
Chainer
Keras



P3 instance



C5 instance



EC2 Inf1

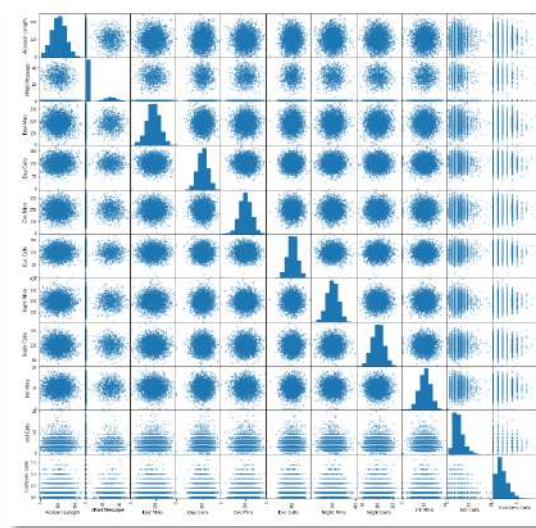


Amazon
Elastic
Inference

Use cases: DLAMI



Learning and app
development



Machine learning
and data analytics



Research

Cost optimization



Cost



Savings

- AMIs are free. Customers pay only for AWS infrastructure.
- Benefits are gained from using powerful compute instances.
- P3 instances speed up training and reduce costs.
- Anaconda Data Science Platform simplifies package management and deployment (everything is ready for you to get started).
- Customers can containerize their code to realize economies of scale.

DLAMI customers



- Machine learning experts
- Build custom algorithms
- Need more flexibility
- Building internal data science teams

Course use case



- Return to the AnyCompany use case.
- Could a DLAMI be used to predict future insurance claim fraud?
- Provide information to support your answer.

3-minute individual exercise and
3-minute class discussion

Knowledge check

Knowledge check

Conda-based AWS Deep Learning AMIs come installed with Jupyter Notebook loaded with which of the following kernels? (Select TWO)



Scikit-learn



SparkML



TensorFlow



Apache MXNet



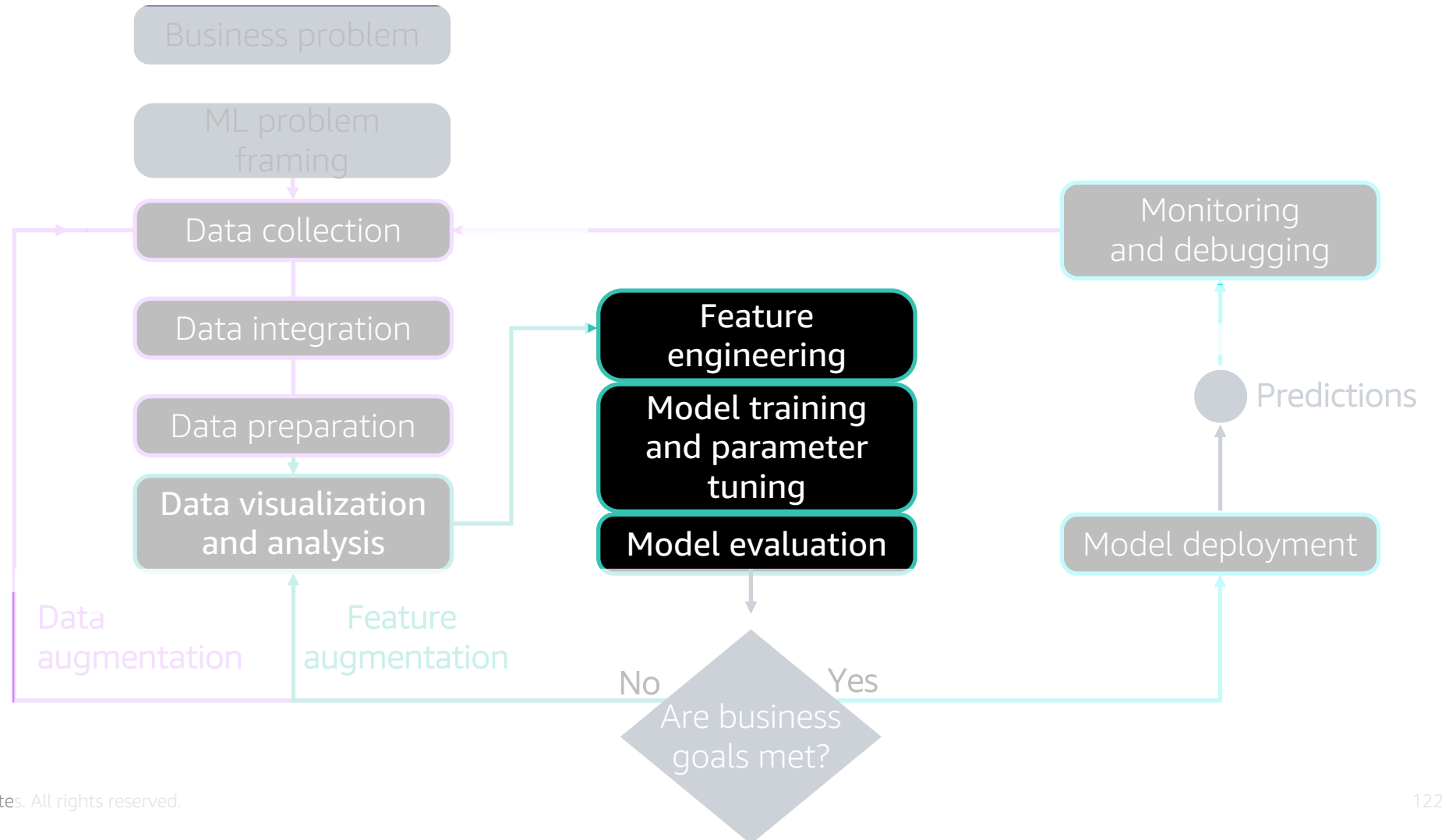
Module 6: Amazon SageMaker Concepts

Module 6: Amazon SageMaker Concepts

- Review a typical machine learning workflow using the AWS Deep Learning AMIs
- Identify what Amazon SageMaker is and explain how it works
- Identify the key components and features of Amazon SageMaker
- Discuss Amazon SageMaker Studio
- Identify use cases for Amazon SageMaker
- Identify the advantages of using Amazon SageMaker
- Summary of latest SageMaker services

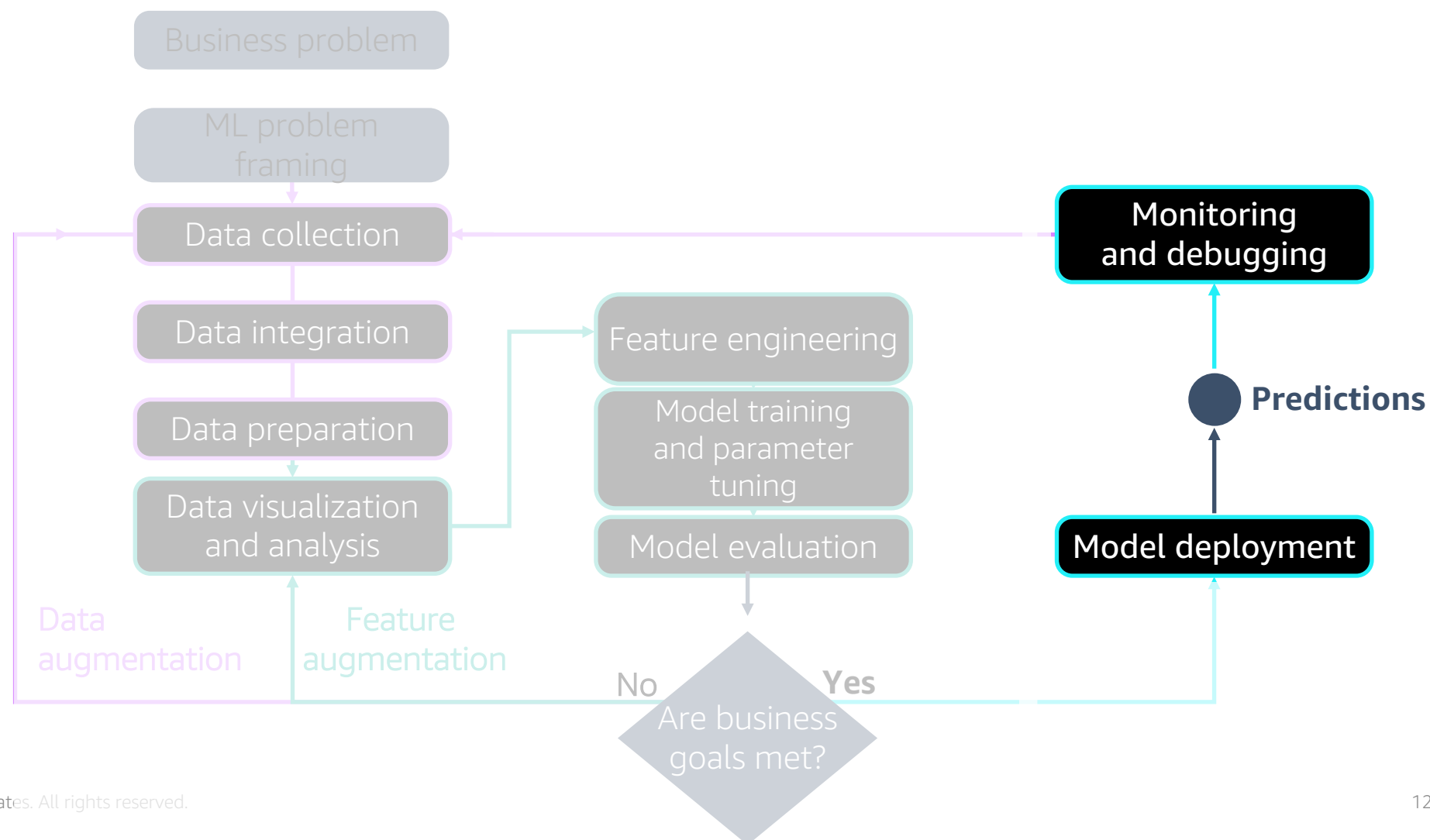
ML process: Model training

- Set up and manage
 - Notebook environments
 - Training clusters
- Write data connectors
- Scale ML algorithms to large datasets
- Distribute ML training algorithm to multiple machines
- Secure model artifacts



ML process: DevOps

- Set up and manage inference clusters
- Manage and scale model inference APIs
- Monitor and debug model predictions
- Model versioning and performance tracking
- Automate new model version promotion to production (A/B testing)



Challenges building and deploying an ML model

- ML development can be complex, cumbersome, time consuming, error prone, expensive, and a very iterative process.
- Different personas often use different tools in different phases of ML development, which can make collaboration and sharing work a challenge, affecting productivity.
- ML development lacked a robust integrated development environment (IDE) for the entire ML workflow until Amazon introduced Amazon SageMaker.

Amazon SageMaker

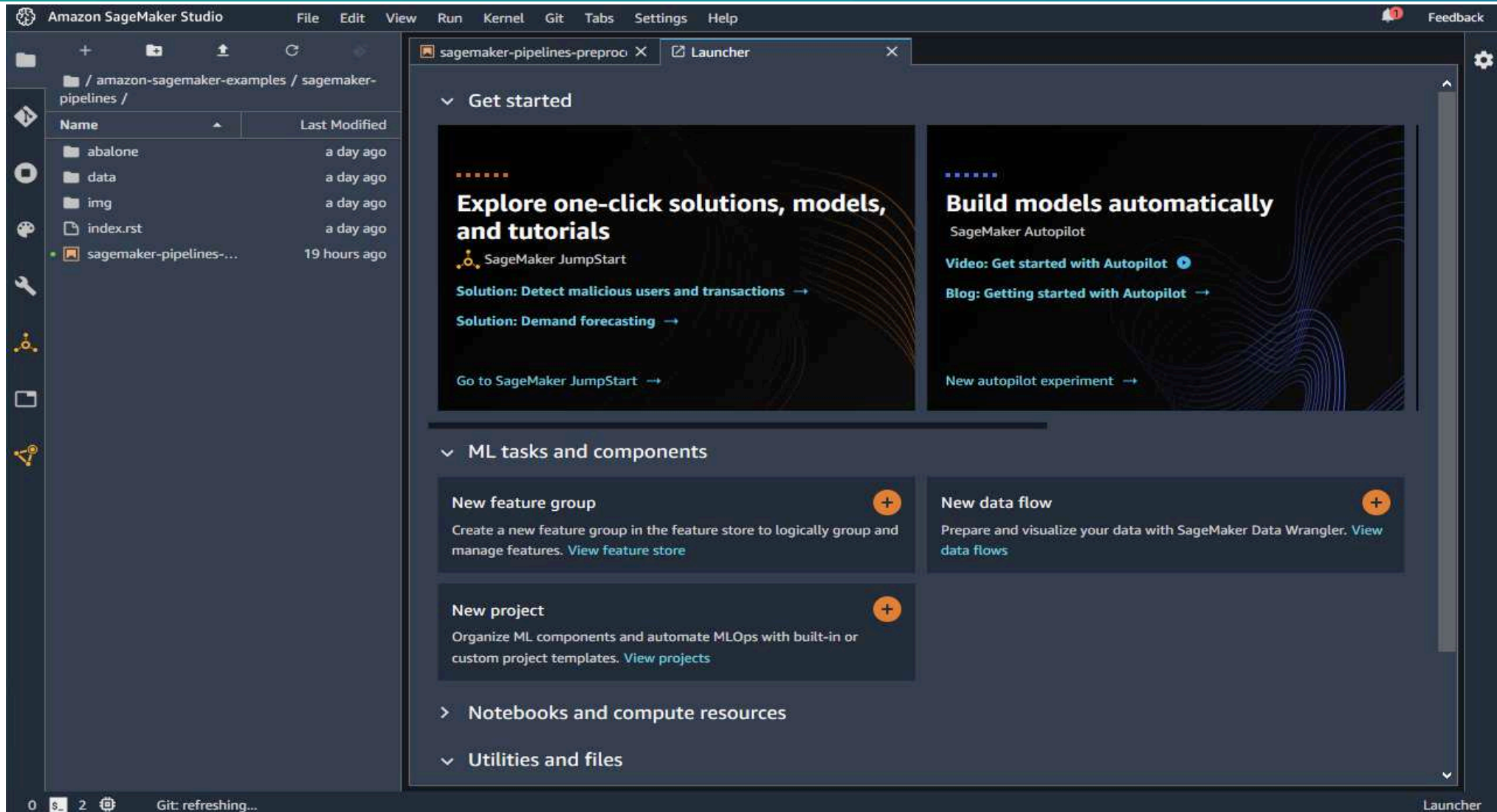
Amazon SageMaker Overview



Prepare	Build	Train & tune	Deploy & manage
SageMaker Ground Truth	SageMaker Studio Notebook	One-click Training	One-click Deployment
SageMaker Data Wrangler	Built-in and Bring-your-own Algorithms	SageMaker Experiments	Kubernetes & Kubeflow integration
SageMaker Processing	Local Mode	SageMaker Automatic Model Tuning	Multi-Model Endpoints
SageMaker Feature Store	SageMaker Autopilot	SageMaker Distributed Training	SageMaker Model Monitor
SageMaker Clarify	SageMaker JumpStart	SageMaker Debugger	SageMaker Edge Manager
		Managed Spot Training	SageMaker Pipeline

Amazon SageMaker Studio IDE

Fully integrated development environment (IDE) for Machine Learning



Amazon SageMaker Studio



Prepare	Build	Train & tune	Deploy & manage
SageMaker Ground Truth	SageMaker Studio Notebook	One-click Training	One-click Deployment
SageMaker Data Wrangler	Built-in and Bring-your-own Algorithms	SageMaker Experiments	Kubernetes & Kubeflow integration
SageMaker Processing	Local Mode	SageMaker Automatic Model Tuning	Multi-Model Endpoints
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SageMaker Clarify	SageMaker JumpStart	SageMaker Debugger	SageMaker Edge Manager
		Managed Spot Training	SageMaker Pipeline

— SageMaker Studio – Fully Integrated development environment (IDE) for ML —

Summary of new SageMaker services



SageMaker Jumpstart	SageMaker Clarify	Deep Profiling for SageMaker Debugger	SageMaker Distributed Training
Set of solutions for common ML use cases with one click deployable ML models and algorithms	Brings transparency to your models by detecting bias across the ML workflow and explaining model behaviors.	Optimizes ML models with real-time monitoring of training metrics and system resources	You can train large deep learning models faster by automatically partitioning your model and training data with distributed training.

<https://aws.amazon.com/sagemaker/features/>

Knowledge check

Knowledge check

Which Amazon SageMaker service enables ML Practitioners to build, train, tune and deploy ML model from a single interface?



Amazon SageMaker Experiments



Amazon SageMaker Studio



Amazon SageMaker Debugger



Amazon SageMaker Model Monitor



Knowledge check

Which Amazon SageMaker service enables one click hyperparameter tuning?



Amazon SageMaker Debugger



Amazon SageMaker Automatic Model Tuning



Amazon SageMaker Model Monitor



Amazon SageMaker Experiments



Module 7: Amazon SageMaker Notebooks

Module 7: Amazon SageMaker Notebooks

- Introduction to Jupyter Notebook and how Amazon SageMaker uses it
- Demo SageMaker notebooks - Create a notebook instance and explain how this is accomplished using Amazon SageMaker

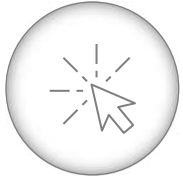
Amazon SageMaker Notebooks



Single Sign-On (SSO) - Access your notebooks in seconds



Access controls - Administrators manage access and permissions



Fully managed - Use your notebooks without manually spinning up or configuring compute resources



Collaboration - Share notebooks with a single click



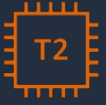
Scalability - Scale up or down compute resources as needed

Notebook instances



- Recommendations/personalization
- Fraud detection
- Forecasting
- Image classification
- Churn prediction
- Marketing email/campaign targeting
- Log processing and anomaly detection
- Speech to text
- More...

Amazon SageMaker Notebooks demonstration

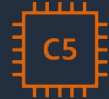


BUILD

```
algorithm = get_image_uri(...)  
model = Estimator(algorithm, role, instance_type)  
model.set_hyperparameters(...)
```

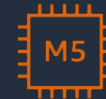
TRAIN

```
model.fit(train_data)
```



DEPLOY

```
endpoint = model.deploy(instance_type)  
endpoint.predict(test_data)
```



Knowledge check

Knowledge check

To avoid unnecessary charges, your customer should always shut down unused processes in a Jupyter Notebook instance. To do this, they select the Running tab, and click the shut down button for the active process.



True



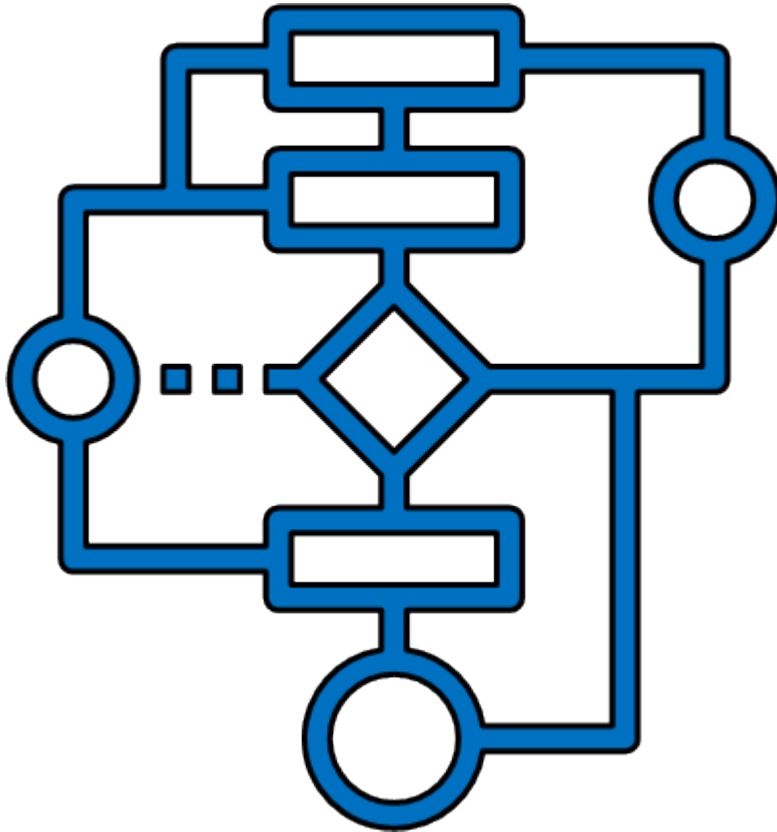
False



Module 8: Amazon SageMaker Built-In Algorithms

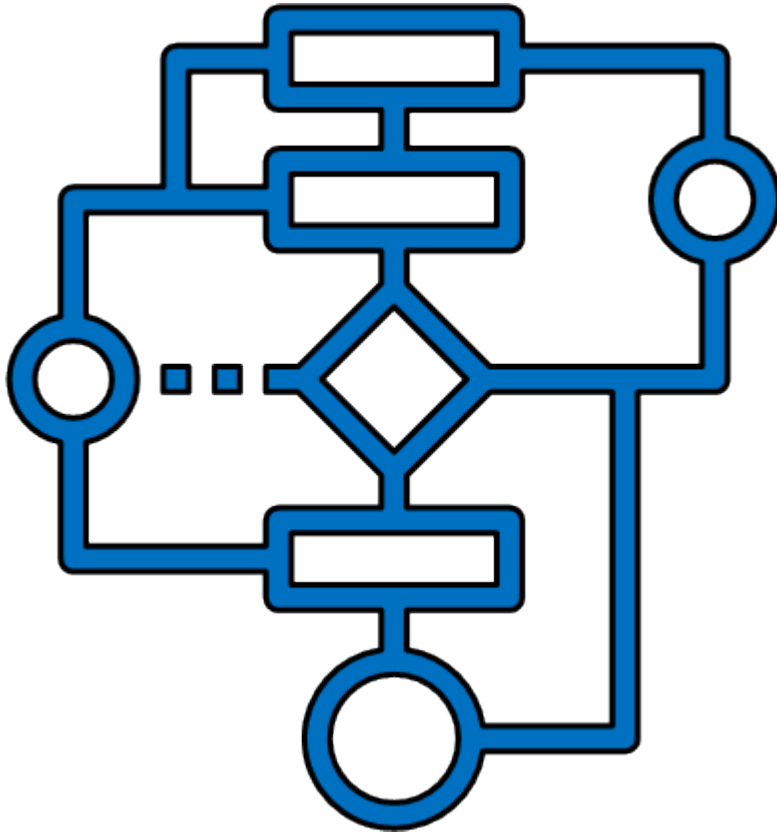
Module 8: SageMaker Built-In Algorithms

- Identify and explain the purpose of the Amazon SageMaker built-in algorithms
- Locate Amazon SageMaker algorithm examples in the console
- Select the appropriate algorithm for a business problem and data
- Configure and initiate a training job
- Associate a training job with an appropriate Amazon Simple Storage Service (Amazon S3) bucket
- Use queries with a model



- *Algorithms* are standardized methods used to train models.
- A *model* is a function that maps inputs to a set of predicted outcomes using algorithms.
- The exact definition of a model is unknown.
- Existing data is used to build a function, using rules, and this is called *training*.
- Algorithms define model rules.

Types of algorithms



- Linear regression
- Logistic regression
- Clustering
- Vectorization
- Image classification
- Encoding and decoding
- Language processing

Amazon SageMaker Built-in Algorithms

General purpose

Numerical regression or classification

- Linear Learner
- XGBoost
- K-Nearest Neighbors (K-NN)

Recommendation Factorization Machines

Group entities based on data K-Means

Detect anomalies in time series data Random Cut Forest (RCF)

Specific use cases

Classify images or find objects in images

- Image Classification
- Object Detection
- Semantic Segmentation

Classify, encode, and transform text data

- Sequence to Sequence (seq2seq)
- Neural Topic Model (NTM)
- Blazing Text
- Object2Vec

Predict future trends based on past history (time series) DeepAR Forecasting

Reduce dimensions in datasets with high numbers of attributes Principle Component Analysis (PCA)

Find usage patterns in network access logs IP Insights

Algorithms

Game Show



Mary



John

Algorithms

Game Show



- **Five** scenarios relating to Amazon SageMaker algorithms
- **Four** options
- **One** option addresses the scenario

Algorithms

Game Show

Scenario 1

- Real estate company
- Predict price of newly listed home
- Dataset has 100,000 records of selling prices of house in the area
- Dataset has 12 features

Question 1

Which Amazon SageMaker algorithm would be most appropriate to use?

DeepAR Forecasting

Linear Learner algorithm

Random Cut Forest algorithm

Factorization Machines

Algorithms

Game Show

Scenario 1

- Real estate company
- Predict price of newly listed home
- Dataset has 100,000 records of selling prices of house in the area
- Dataset has 12 features

Question 1

Which Amazon SageMaker algorithm would be most appropriate to use?

DeepAR Forecasting

Random Cut Forest algorithm

Linear Learner algorithm

Factorization Machines

Algorithms

Game Show

Scenario 2

- Home insurance company
- Estimating rebuild cost has been manual
- Goal is to automate this process using historical data
- Many features and some are more important than others

Question 2

Which Amazon SageMaker algorithm should you use?

Random Cut Forest algorithm

Linear Learner algorithm

XGBoost algorithm

K-Nearest Neighbors (k-NN) algorithm

Algorithms

Game Show

Scenario 2

- Home insurance company
- Estimating rebuild cost has been manual
- Goal is to automate this process using historical data
- Many features and some are more important than others

Question 2

Which Amazon SageMaker algorithm should you use?

Random Cut Forest algorithm

XGBoost algorithm

Linear Learner algorithm

K-Nearest Neighbors (k-NN) algorithm

Algorithms

Game Show

Scenario 3

- National bank
- Risk scoring clients based on parameters
- Current algorithm based on hand-coded business rules and 50 parameters
- Need to classify based on similarity of parameters

Question 3

Which Amazon SageMaker algorithm should you use?

Factorization Machines	K-Nearest Neighbors (k-NN) algorithm
K-Means algorithm	Random Cut Forest algorithm

Algorithms

Game Show

Scenario 3

- National bank
- Risk scoring clients based on parameters
- Current algorithm based on hand-coded business rules and 50 parameters
- Need to classify based on similarity of parameters

Question 3

Which Amazon SageMaker algorithm should you use?

Factorization Machines

K-Nearest Neighbors (k-NN) algorithm

K-Means algorithm

Random Cut Forest algorithm

Algorithms

Game Show

Scenario 4

- Credit union
- Basing lending decisions on credit score
- They have data on members and want to group based on low, medium, and high risk
- Want to predict which group a potential borrower fits into

Question 4

Which Amazon SageMaker algorithm should you use?

Linear Learner algorithm

K-Nearest Neighbors (k-NN) algorithm

K-Means algorithm

XGBoost algorithm

Algorithms

Game Show

Scenario 4

- Credit union
- Basing lending decisions on credit score
- They have data on members and want to group based on low, medium, and high risk
- Want to predict which group a potential borrower fits into

Question 4

Which Amazon SageMaker algorithm should you use?

Linear Learner algorithm

K-Means algorithm

K-Nearest Neighbors (k-NN) algorithm

XGBoost algorithm

Algorithms

Game Show

Scenario 5

- Manufacturing company, making 10 valves
- Products built in random order, need to be classified for labeling and packaging
- Need to automate classification robotics
- Using AWS IoT

Question 5

Which Amazon SageMaker algorithm should you use?

Object2Vec	Object Detection algorithm
Image Classification algorithm	K-Means algorithm

Algorithms

Game Show

Scenario 5

- Manufacturing company, making 10 valves
- Products built in random order, need to be classified for labeling and packaging
- Need to automate classification robotics
- Using AWS IoT

Question 5

Which Amazon SageMaker algorithm should you use?

Object2Vec

Object Detection algorithm

Image Classification algorithm

K-Means algorithm

Course use case

Workbook 8.1

	months_ as_custome r	age	policy_n umber	policy_bi nd_date	policy_st ate	policy_cs l	policy_d eductabl e	policy_a nnual_pr emium	umbrella _limit	insured_ zip	police_re port_avai lable	total_clai m_amou nt	injury_cla im	property _claim	vehicle_c laim	auto_ma ke	auto_mo del	auto_yea r	fraud_re ported
0	328	48	521585	2014- 10-17	OH	250/500	1000	1406.91	0	466132	YES	71610	6510	13020	52080	Saab	92x	2004	Y
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4	228	44	367455	2014- 06-06	IL	500/100 0	1000	1583.91	6000000	610706	NO	6500	1300	650	4550	Acura	RSX	2009	N

How you can help customers



- Understand the data structure and the data's purpose
- Determine which algorithm to use based on an ML problem and data
- Use the *Amazon SageMaker Developer Guide*
- Experiment with algorithms to find the optimal algorithm to solve an ML problem

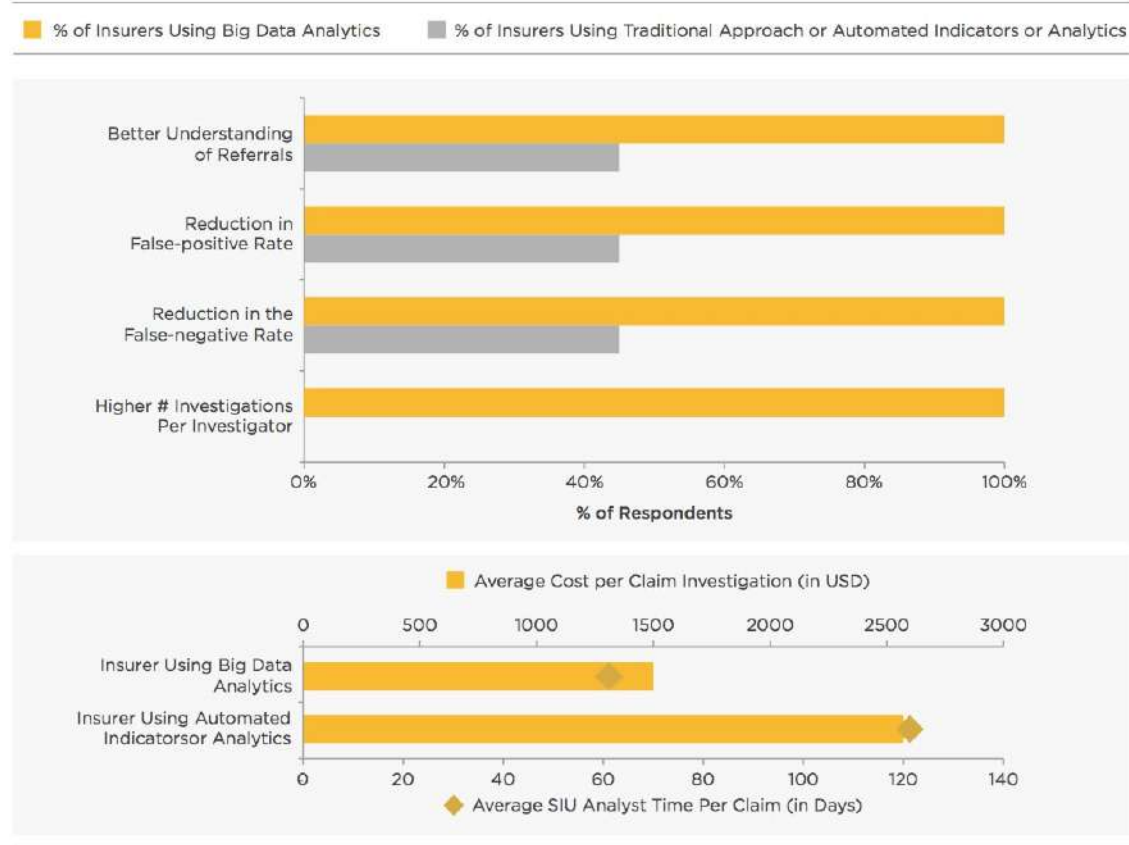
Insurance Fraud Notebook

Demo 1: Scikit-learn

Myth: Fraud is a victimless crime

Exhibit 17

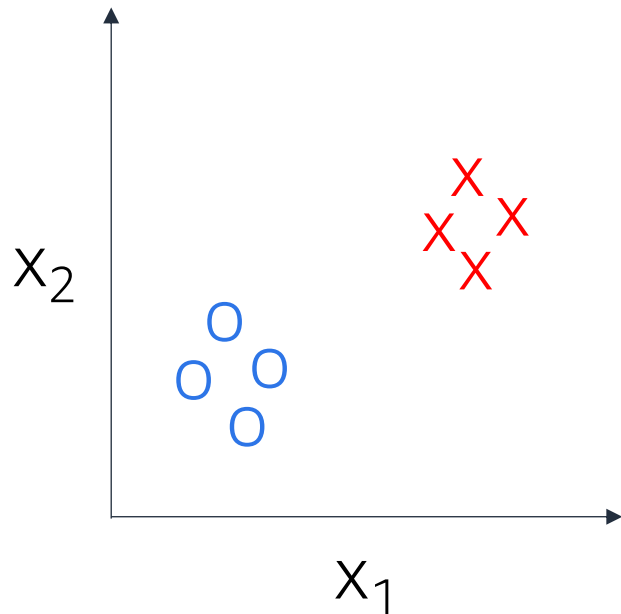
Benefits Generated at Investigation Stage



Source: WNS DecisionPoint™ Survey

- Insurance fraud costs \$80 billion per year.
- Detecting fraud uses significant resources and manpower.
- Insurers use big data to address fraud.
- ML helps insurers with fraud prediction accuracy.
- ML improves pricing accuracy, loss prevention, and customer relationships.

How ML can help



- Insurance fraud is a binary classification problem.
- The demonstration attempts to solve the problem.
- The dataset has 1,000 observations and 39 features.
- The goals are to train the classifier and predict whether claims are fraudulent.
- You can access the dataset [here](#).

Demo 1 – Outcomes



- Discover the ML problem data using scikit-learn
- Focus on collection, integration, visualization, and analysis locally
- Determine optimal algorithm in scikit-learn to address the problem
- Understand using scikit-learn saves customers money during the discovery phase



```
# BUILD
```

```
model1 = linear_model.LogisticRegression(hyperparams)
```

```
model2 = DecisionTreeClassifier(hyperparams)
```

```
# TRAIN
```

```
model1.fit(train_data)
```

```
model2.fit(train_data)
```

```
# TEST
```

```
model1.predict(test_data)
```

```
model2.predict(test_data)
```

Insurance Fraud Notebook

Demo 2: Data preparation and model training in Amazon SageMaker

Demo 2 – Outcomes



- Use Amazon SageMaker for heavy lifting after data discovery
- Configure the Amazon S3 bucket
- Ensure that cleaning and preparation steps occur in Amazon SageMaker
- Obtain container image for linear-learner algorithm
- Create a training job
- Set hyperparameters
- Monitor training job status



```
client = boto3.client('sagemaker')
runtime = boto3.client('sagemaker-runtime')
```

```
# BUILD
```

```
algorithm = get_image_uri(...)
hyperparams = ...
```

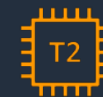
```
# TRAIN
```

```
client.create_training_job(
    algorithm, hyperparams, role, train_data, instance_type)
```



```
# DEPLOY
```

```
client.create_model(model_name, model_url, container)
client.create_endpoint_config(config_name, instance_type)
client.create_endpoint(config_name)
predictions = runtime.invoke_endpoint(test_data)
```





Many ways to train and deploy
a model in SageMaker...


- Jupyter Notebook

- Any platform: ScikitLearn, ...

- `from sklearn import linear_model` 

- Built-in Algorithms

- SageMaker API: `import sagemaker` 

- AWS SDK: `import boto3` 

- Script mode

managed Docker container

- 6 supported platforms: TensorFlow, Mxnet, PyTorch, Chainer, Spark, ScikitLearn.

- `from sagemaker.tensorflow import TensorFlow` 

- Docker container

unmanaged Docker container

- Marketplace

- Model or Algorithm

Module 9: Amazon SageMaker Training, Debugging and Monitoring

Module 9: Training, Debugging and Monitoring

- Explain how SageMaker AutoPilot, Experiments Debugger improve ML productivity
- Explain deployment option hosting service, or batch transform
- Identify what to do once a model is trained, specifically the steps required to use inference
- Demo Use case - How to Manage endpoints through the Amazon SageMaker console
- Explain Model Performance with Confusion Matrix
- Identify how to use a production variant for traffic weighting
- Explain how to monitor and log Amazon SageMaker events with Amazon CloudWatch

SageMaker Services

Amazon SageMaker Experiments



Organize, track, and compare training experiments:



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

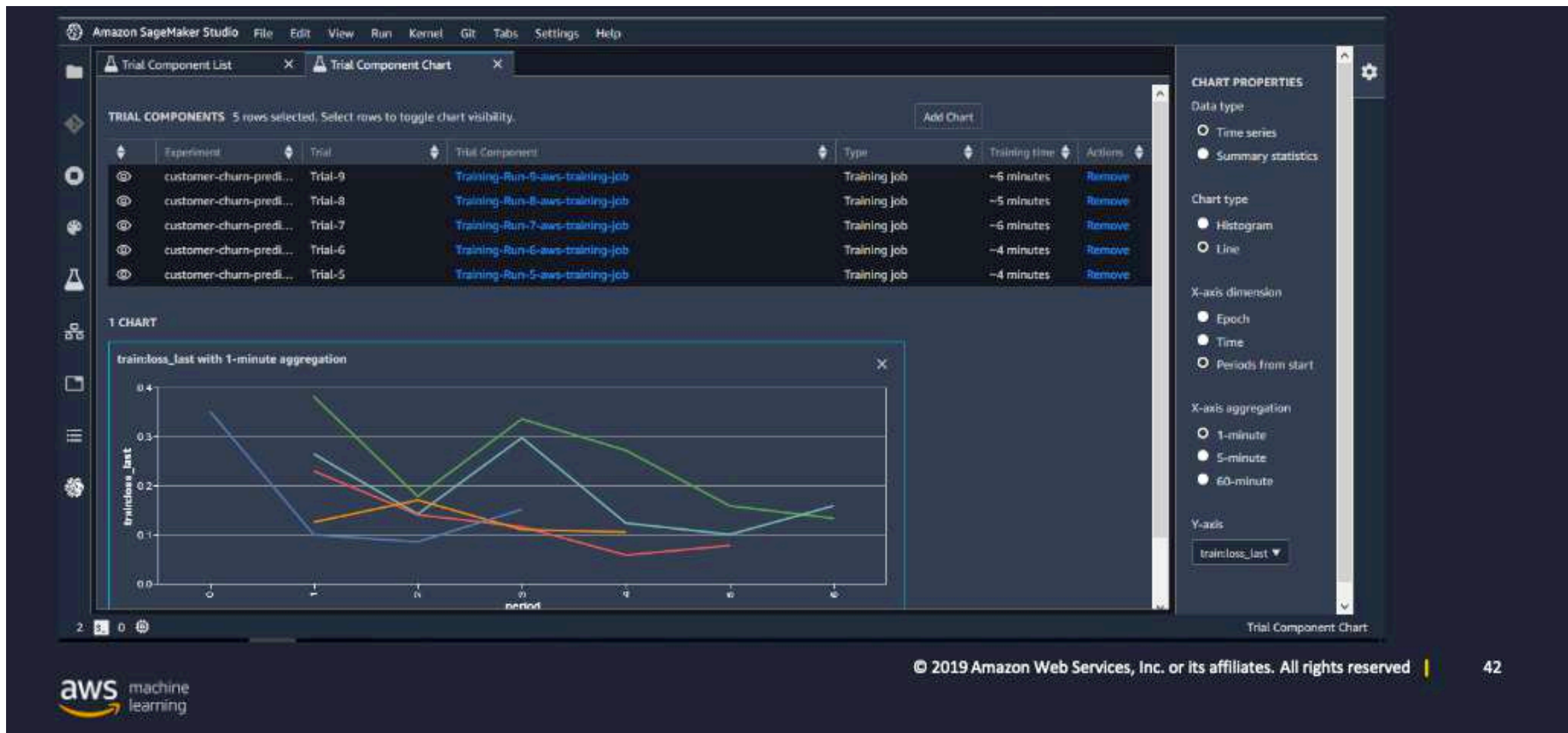
Log custom metrics using the Python SDK and APIs



Fast iteration

Quickly go back and forth and maintain high quality

Amazon SageMaker Experiments



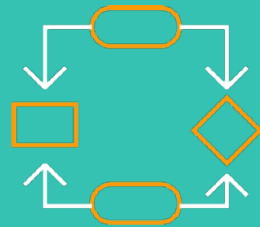
Amazon SageMaker Debugger

- Analysis and debugging, explainability, and alert generation



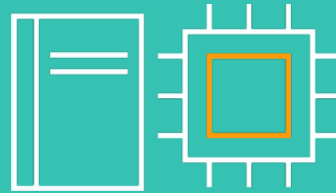
Relevant data capture

Data is automatically captured for analysis



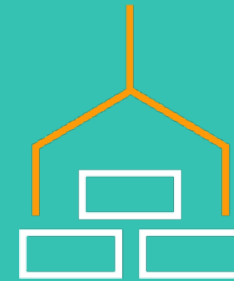
Data analysis and debugging

Analyze and debug data with no code changes



Automatic error detection

Errors are automatically detected based on rules



Improved productivity with alerts

Take corrective action based on alerts



Visual analysis and debugging

Visually analyze and debug from Amazon SageMaker Studio

Amazon SageMaker Debugger

Using SageMaker Rules

In this example we'll demonstrate how to use SageMaker rules to be evaluated against your training. You can find the list of SageMaker rules and the configurations best suited for using them here.

We specify a few rules that check for overfitting, decrease in loss across epochs and for saturated activations.

```
[8]: estimator = TensorFlow(
    role=sagemaker.get_execution_role(),
    base_job_name='mnist-tensorflow-example',
    train_instance_count=1,
    train_instance_type='ml.p3.2xlarge',
    image_name=cpu_training_image,
    entry_point=entrypoint_script,
    framework_version='1.15',
    py_version='py3',
    train_max_run=3600,
    script_mode=True,
    sagemaker_session=ss,
    ## New parameter
    rules = [ Rule.sagemaker(rule_configs.vanishing_gradient()),
              Rule.custom(name='Overfitting', # used to identify the rule
                           image_uri='759289512051.dkr.ecr.us-west-2.amazonaws.com',
                           instance_type='ml.p4.xlarge', # instance type to run the
                           source='py_custom_rule.py', # path to the rule source f
                           rule_to_invoke='CustomGradientRule', # name of the clas
                           volume_size_in_gb=400, # EBS volume size required to be
                           collections_to_save=[CollectionConfig(name='losses')],
                           rule_parameters={
                               "threshold": "28.0" # this will be used to initializ
                           }) ],
    hyperparameters = { 'num_epochs' : 100 }
)
```

Note that Sagemaker-Debugger is only supported for py_version='py3' currently.

Let's start the training by calling `fit()` on the MXNet estimator

```
[9]: # After calling fit, SageMaker will spin off 1 training job and 1 rule job for y
# The rule evaluation status(es) will be visible in the training logs
# at regular intervals
estimator.fit(wait=False)
```

Describe Trial Component

Experiment: Unassigned
Trial: Unassigned

Trial stages

Status	Last modified	Rule name	Job ARN
Issues Found	4 minutes ago	VanishingGradient	arn:aws:sagemaker:us-west-2:3
Issues Found	4 minutes ago	Overfitting	arn:aws:sagemaker:us-west-2:3

Trial Component Chart

TRIAL COMPONENTS 1 rows selected. Select rows to toggle chart visibility. [Add Chart](#)

Experiment	Trial	Trial Component	Type	Train
N/A	N/A	mnist-tensorflow-example-2019-12-02-09-52-13-126-aws-trainin...	Training job	~10

2 CHARTS

sparse_softmax_cross_entropy_loss/value:0_avg with 1-minute aggregation

trialComponentName
— mnist-tensorflow-example-2019-1...

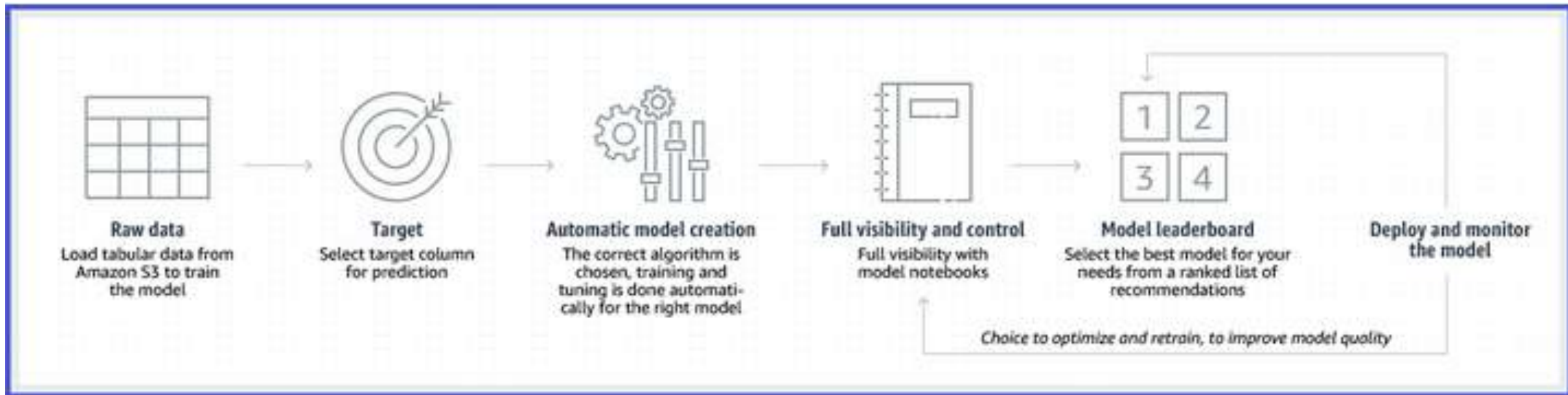
Hyperparameters are properties that **control the behavior** of a training algorithm. They are configured before training a model.

Choosing the right hyperparameters has a **significant impact** on model performance.

Amazon SageMaker automatic model tuning

- Adjusts various combinations of algorithm parameters
- Finds the best parameters automatically
- Speeds up processes
- Eliminates tedious manual work

Amazon SageMaker Autopilot – automates ML process

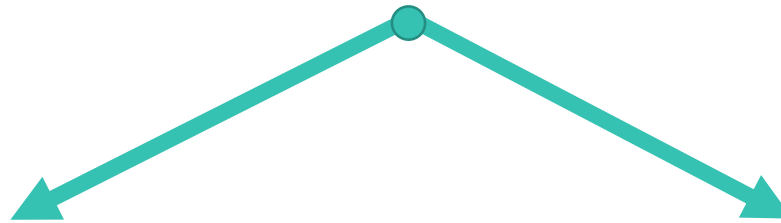


Deployment Options

Deployment options



Amazon SageMaker



Amazon SageMaker Hosting Services

Persistent endpoint

One prediction at a time

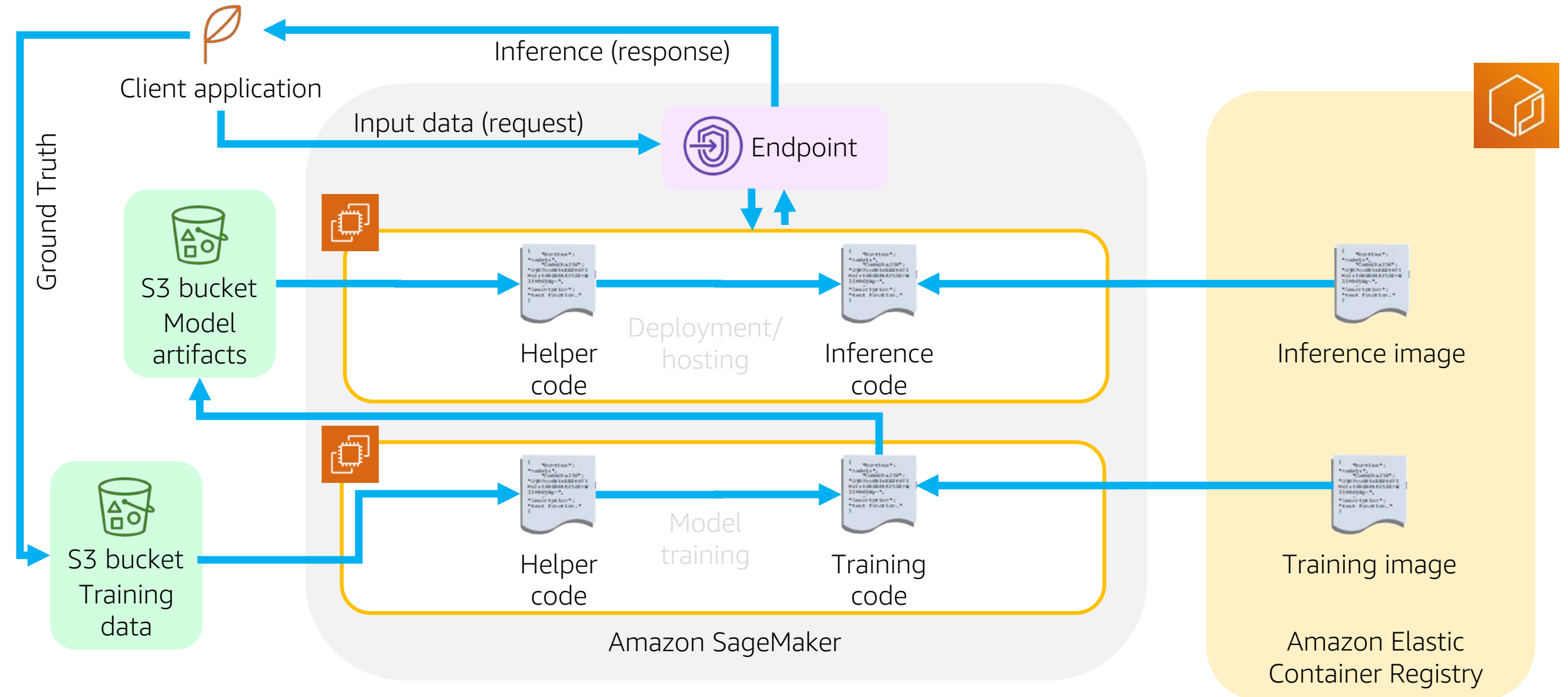
Amazon SageMaker Batch Transform

Predictions for an entire dataset

One after another

<https://docs.aws.amazon.com/sagemaker/latest/dg/how-it-works-deployment.html>

Amazon SageMaker hosting services



Amazon SageMaker Model Monitor



Continuous monitoring of models in production



Automatic data
collection

Data is automatically
collected from
your endpoints



Continuous
monitoring

Define a monitoring
schedule, and detect
changes in quality against
a predefined baseline



Flexibility
with rules

Use built-in rules to
detect data drift, or
write your own rules
for custom analysis



Visual
data analysis

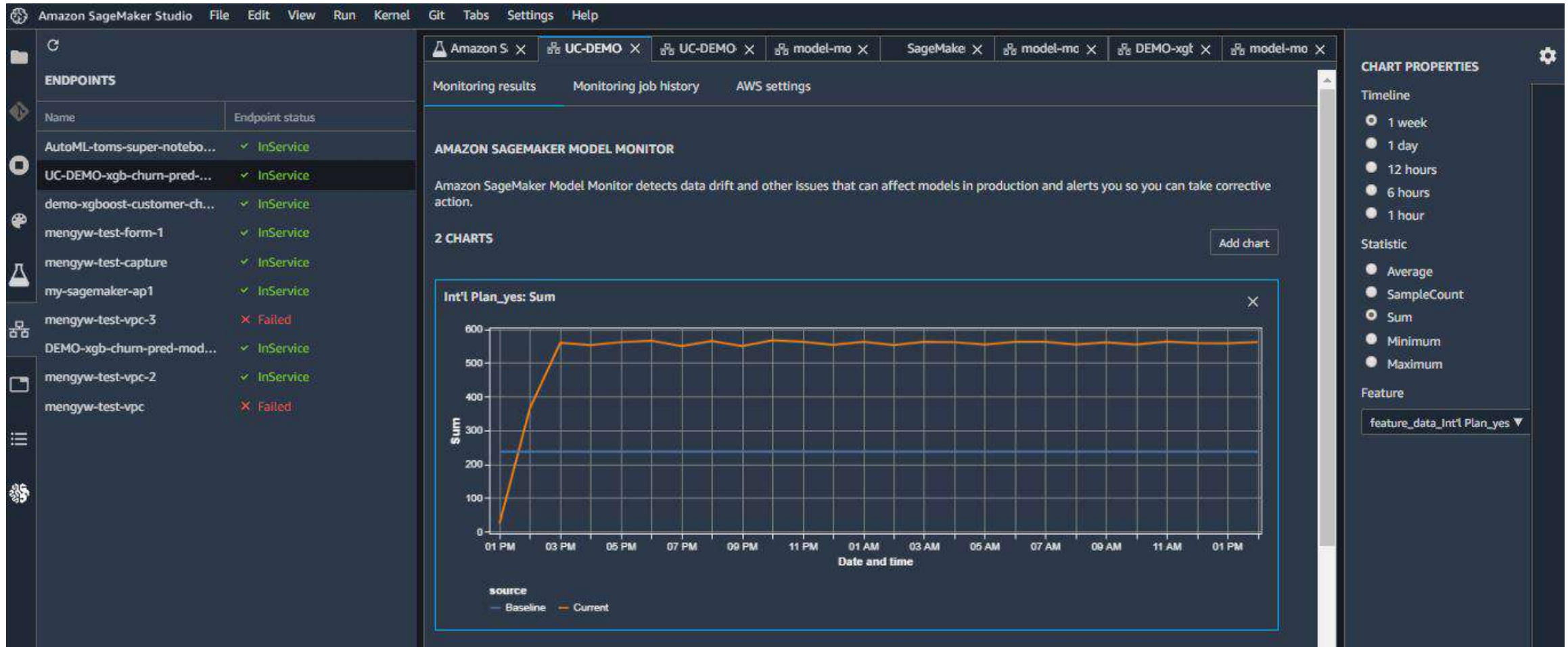
See monitoring results,
data statistics, and
violation reports in
Amazon SageMaker Studio



Integration
with Amazon
CloudWatch

Automate corrective
actions based on
CloudWatch alerts

Amazon SageMaker Model Monitor



Model performance and Confusion Matrix

Confusion matrix

Actual	Predicted Negative	Predicted Positive
Negative	True Negative	False Positive
Positive	False Negative	True Positive

Validating model with confusion matrix

Actual	Predicted Negative	Predicted Positive
Negative	True Negative	False Positive
Positive	False Negative	True Positive

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{F1} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Precision: Spam filtering with 1000 emails

Mail we want: Send to inbox [True Positive] = 650		
Failed to predict spam as spam [False Negative] = 75	Spam: Send to junk [True Negative] = 250	Wrongly predicted as spam but it's mail we want [False Positive] = 25

$$\text{Precision} = 650 / [650 + 25] = 0.96$$

$$\text{Recall} = 650 / [650 + 75] = 0.89$$

$$\text{F1 Score} = 2 * [0.96 * 0.89] / [0.96 + 0.89] = 0.94$$

Recall : COVID analysis of 1000 patients

Correct Healthy Predictions [True Positive] = 500		
Predicted a sick patient is healthy [False Negative]	Correct sick predictions [True Negative] = 400	Incorrectly Predicted a healthy patient is sick [False Positive] = 70

$$\text{Precision} = 500/[500 + 70] = 0.87$$

$$\text{Recall} = 500/[500 + 30] = 0.94$$

$$\text{F1 Score} = 2 * [0.87 * 0.94]/[0.87+0.94] = 0.90$$

Insurance Fraud Notebook

Demo 3: Deployment and endpoint management

Demo 3 – Outcomes



- Create a model definition
- Create an endpoint configuration
- Examine how a production variant can be used for distributing traffic (traffic weighting) to multiple models
- Create an endpoint
- Locate and manage endpoints in the console

Demo 3 – Outcomes



- Explain how to monitor and log events with Amazon CloudWatch
- Test the model with validation data

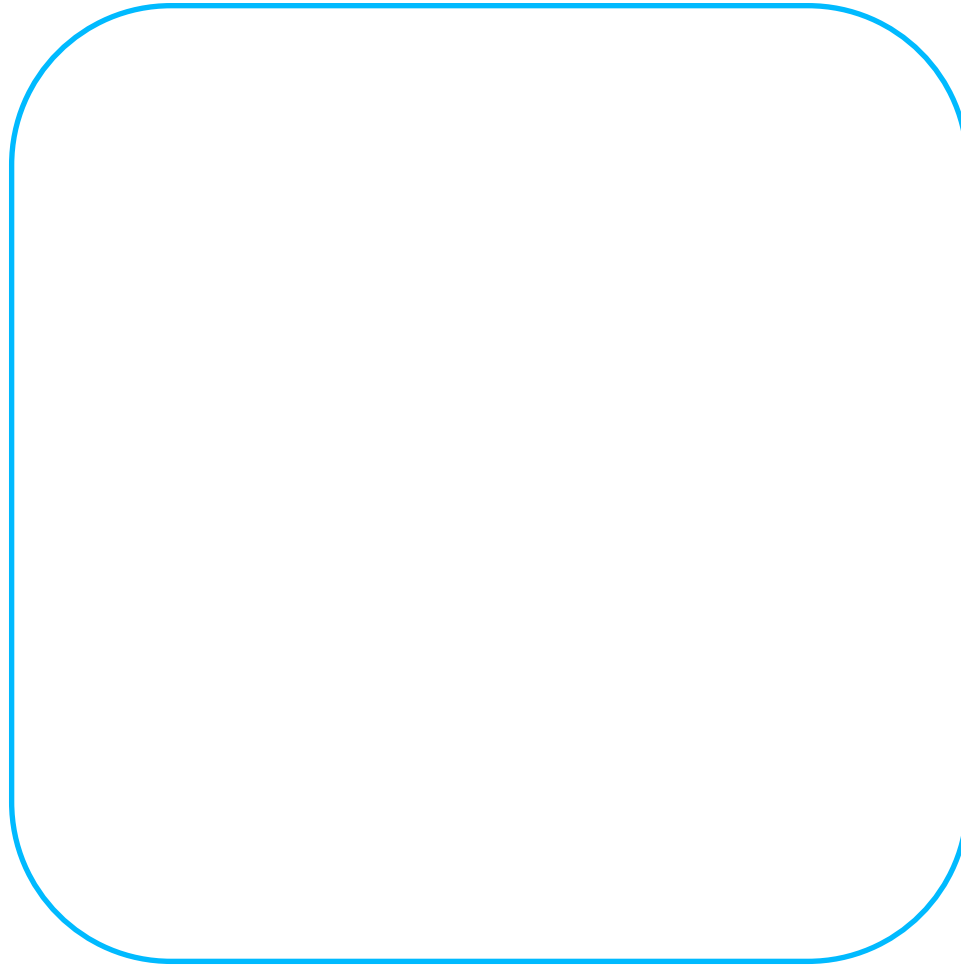
Production variants (traffic weighting)

Model deployment to Amazon SageMaker

Amazon Simple
Storage Service
bucket

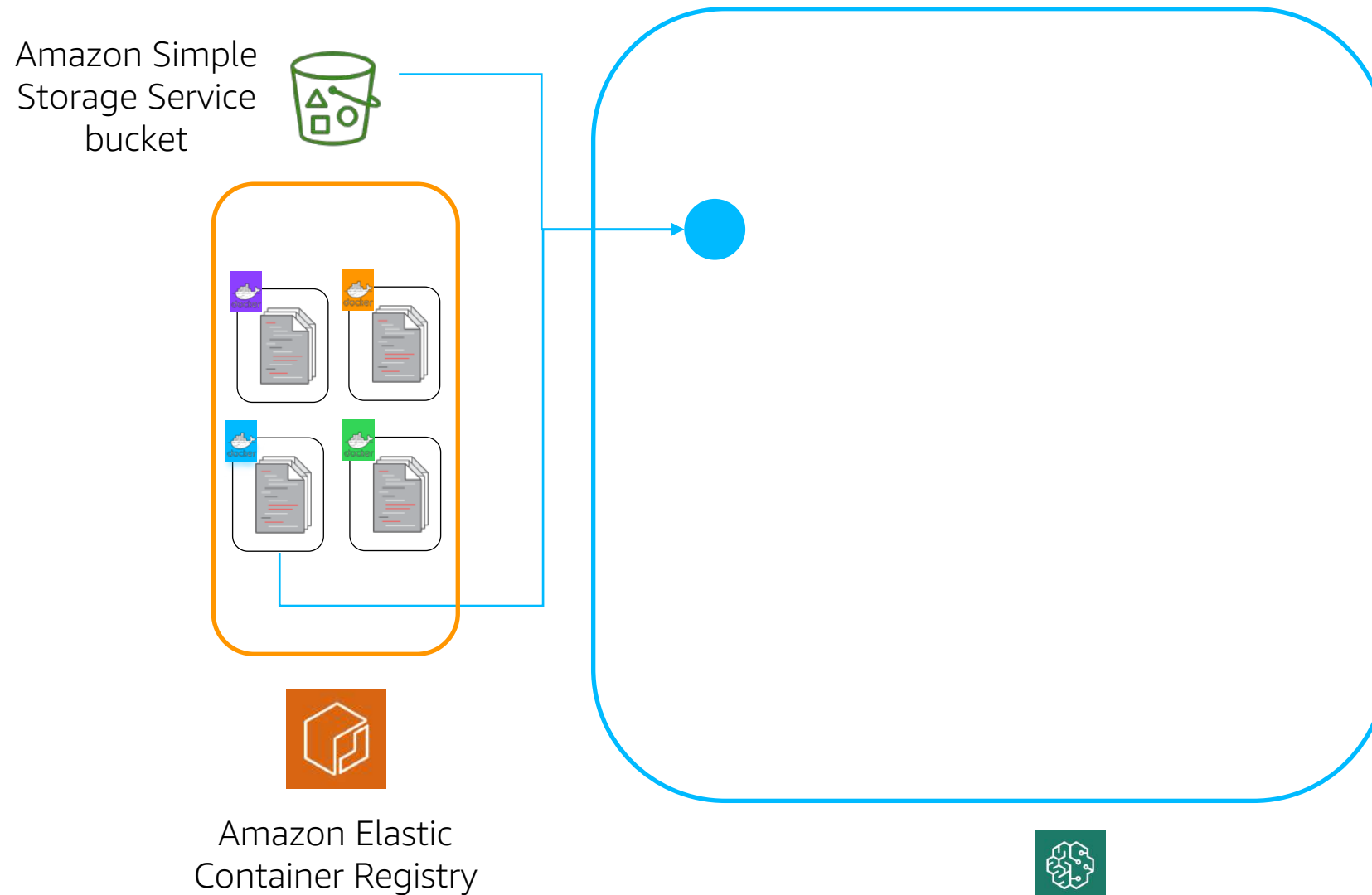


Amazon Elastic
Container Registry

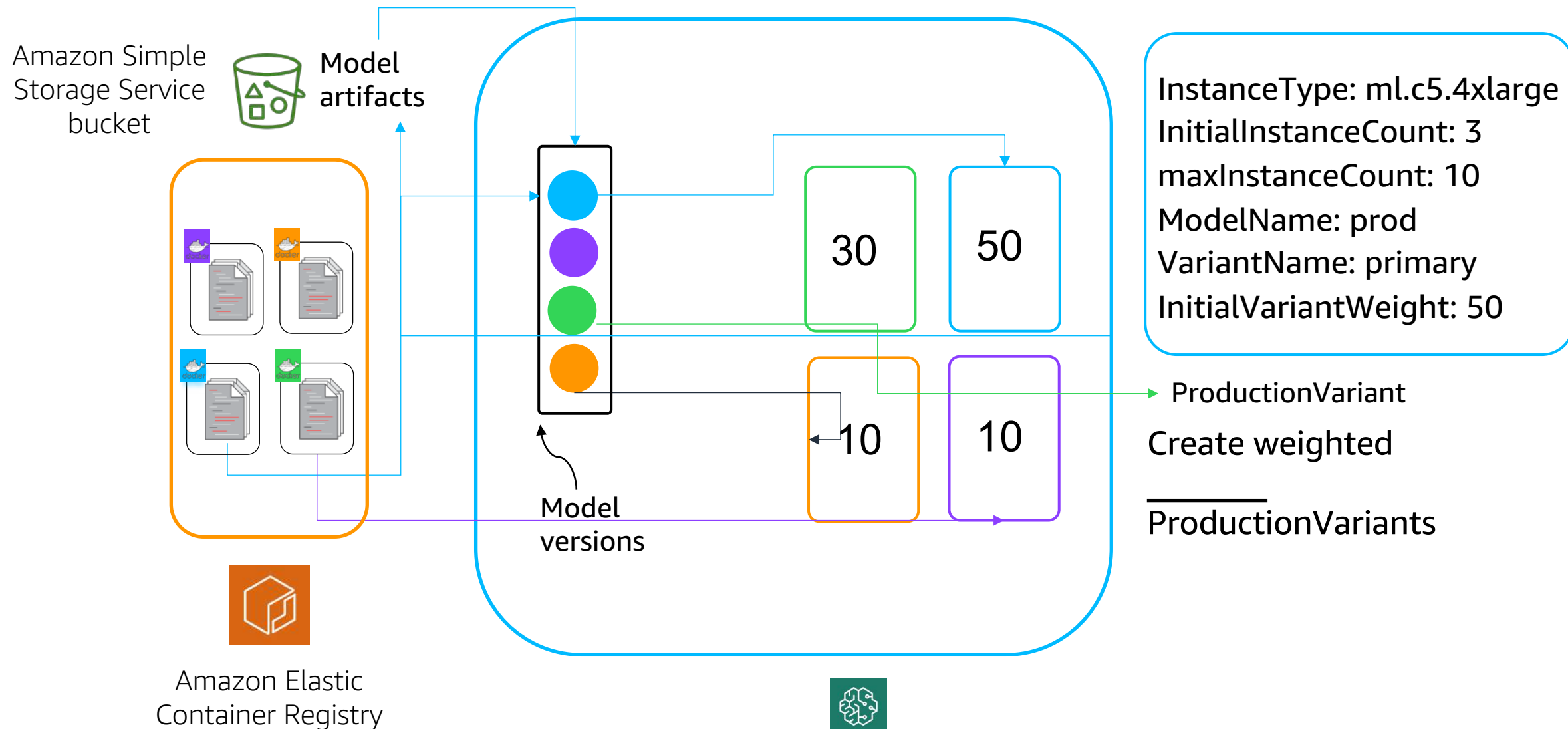


Amazon SageMaker

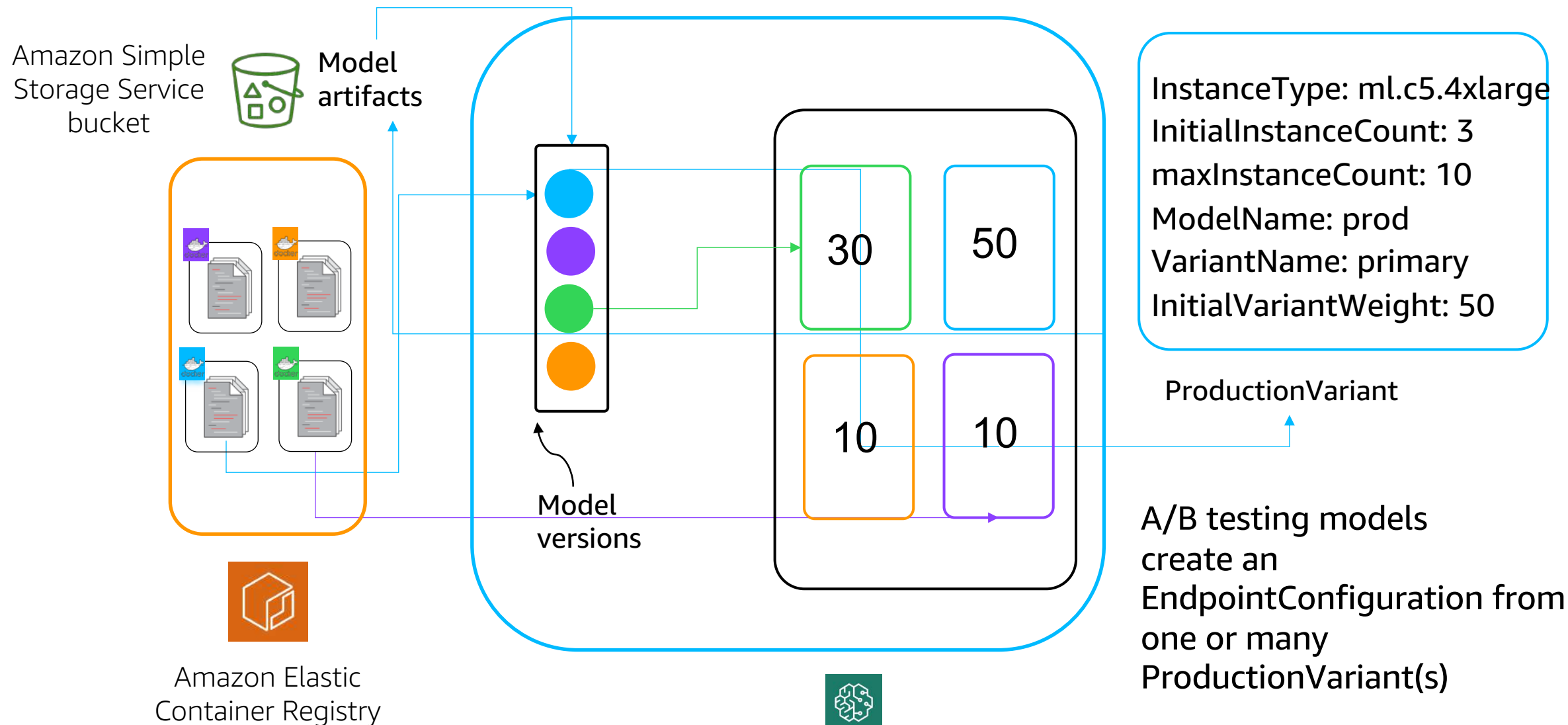
Model deployment to Amazon SageMaker



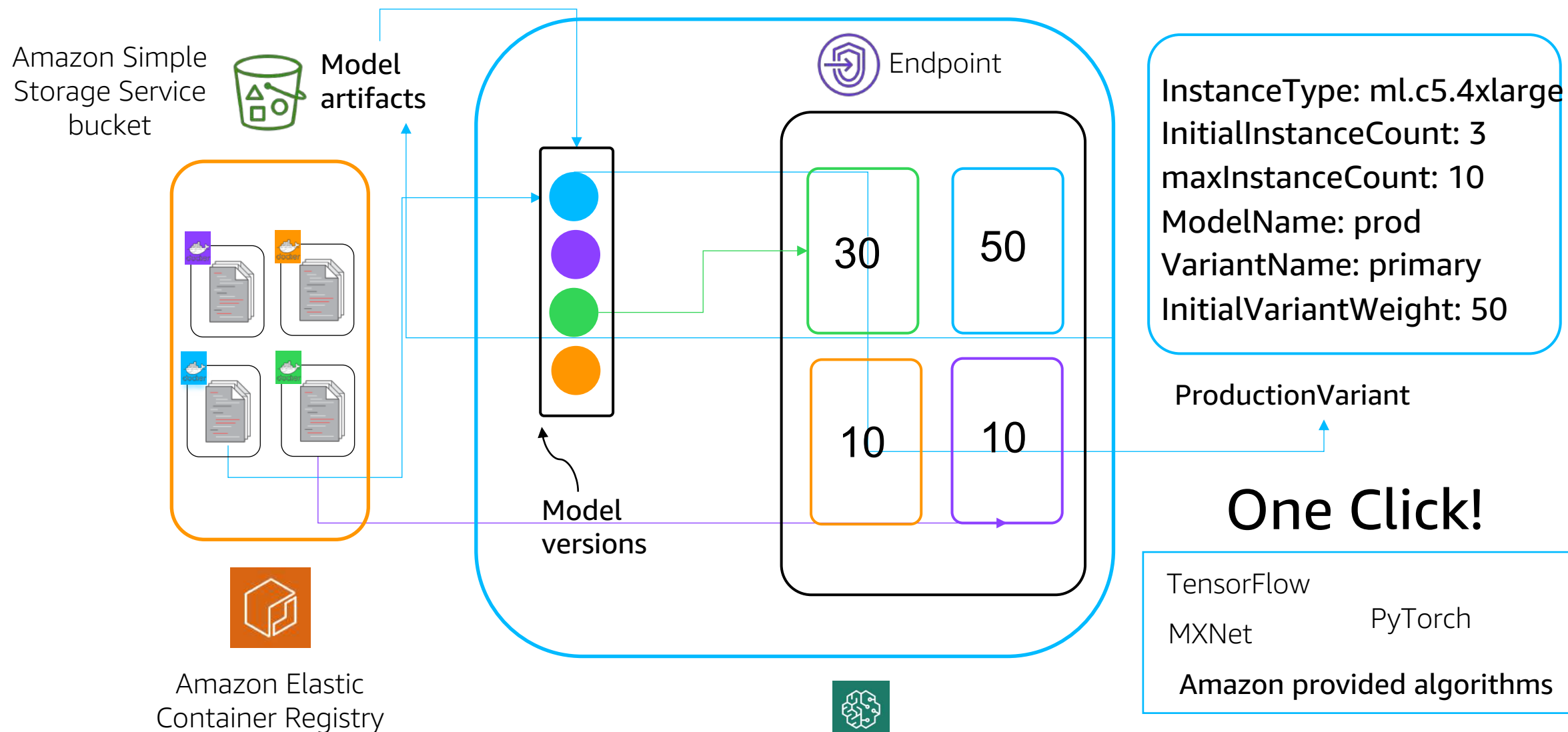
Model deployment to Amazon SageMaker



Model deployment to Amazon SageMaker



Model deployment to Amazon SageMaker



Production variant defined

```
# Get the current endpoint configuration
endpoint = sage_client.describe_endpoint(EndpointName=xgb_predictor.endpoint)
endpoint_config = sage_client.describe_endpoint_config(
    EndpointConfigName=endpoint['EndpointConfigName'])

# Change the current deployment weight to 0.5 (we'll move 50% of the traffic to
current_model_config = endpoint_config['ProductionVariants'][0]
current_model_config['InitialVariantWeight'] = 0.5
current_model_config['VariantName'] = 'XGBoost'
Variant = 'TunedXGBoost'

tuned_model_config = {'ModelName': model_name,
                      'InitialInstanceCount': 1,
                      'InstanceType': 'ml.m4.xlarge',
                      'VariantName': Variant,
                      'InitialVariantWeight': 0.5}
```

Production variant defined

```
# Create the new endpoint configuration
sage_client.create_endpoint_config(
    EndpointConfigName='AB-Config',
    ProductionVariants=[current_model_config,
                        tuned_model_config])

# Update the endpoint
sage_client.update_endpoint(
    EndpointName=endpoint['EndpointConfigName'],
    EndpointConfigName='AB-Config'
)
result = sess.wait_for_endpoint(endpoint['EndpointConfigName'])
```

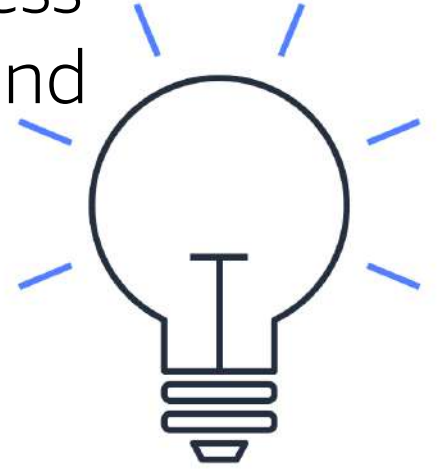
Model deployment features of Amazon SageMaker

- ✓ Auto Scaling Inference APIs
- ✓ A/B testing
- ✓ Low latency and high throughput
- ✓ Bring Your Own Model
- ✓ Python SDK

Knowledge check

Knowledge check

Pick an Amazon SageMaker service that automates ML process by preparing data for training, trains and tunes the models and selects best candidate mode for deployment?



Amazon SageMaker Experiments



Amazon SageMaker Model Monitor



Amazon SageMaker Automatic Model Tuning



Amazon SageMaker Autopilot

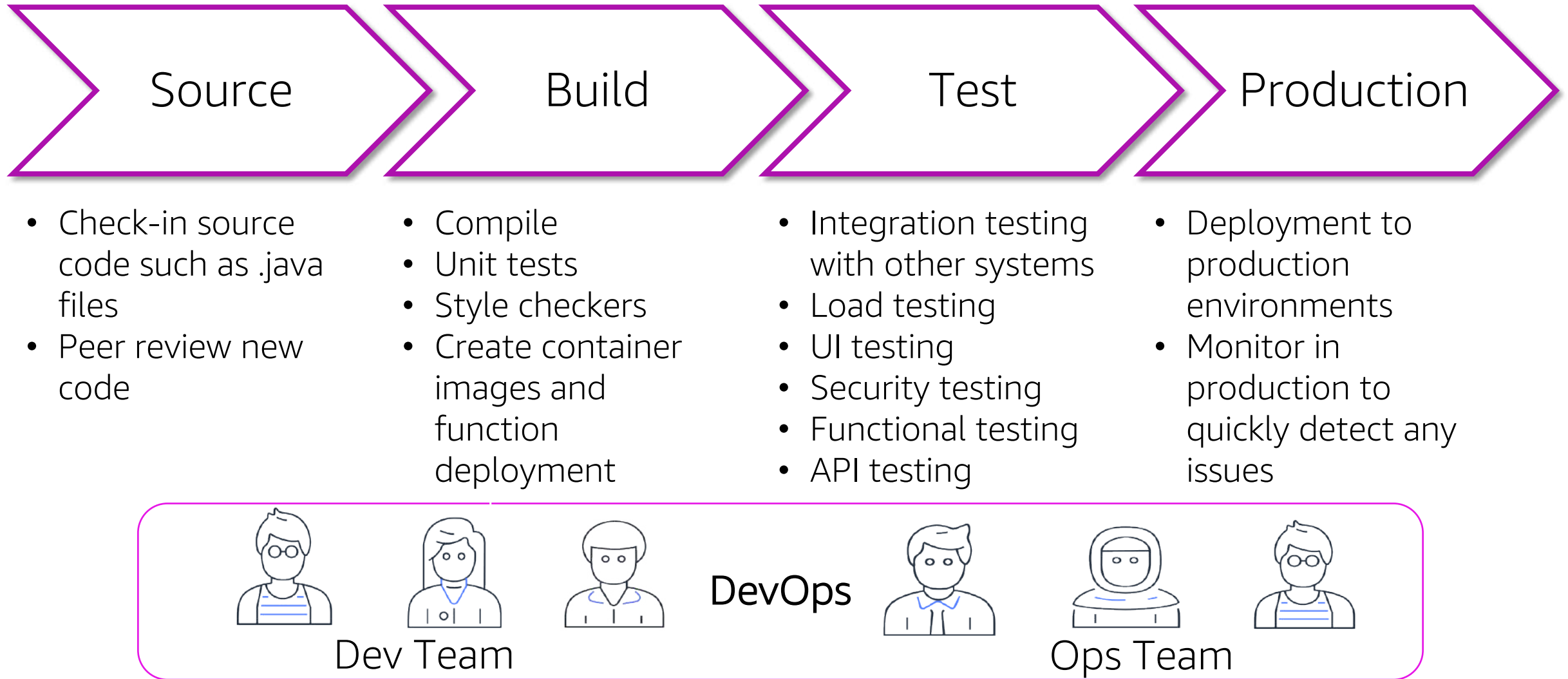
Module 10: Introduction to MLOps

Module 10: Introduction to MLOps

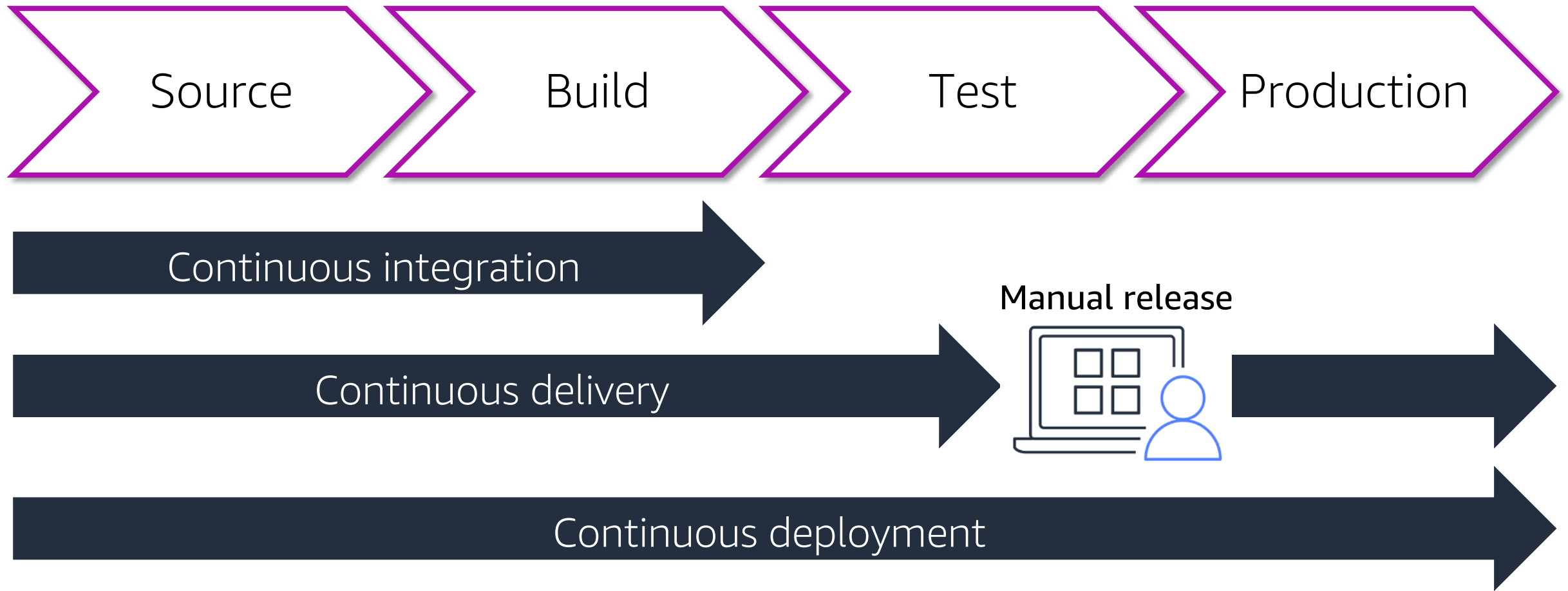
- DevOps and CI/CD pipelines
- Difference between MLOps and DevOps
- MLOps challenges
- MLOps process
- SageMaker Pipeline and other orchestration options
- Governance for ML on AWS

DevOps – CI/CD Pipeline

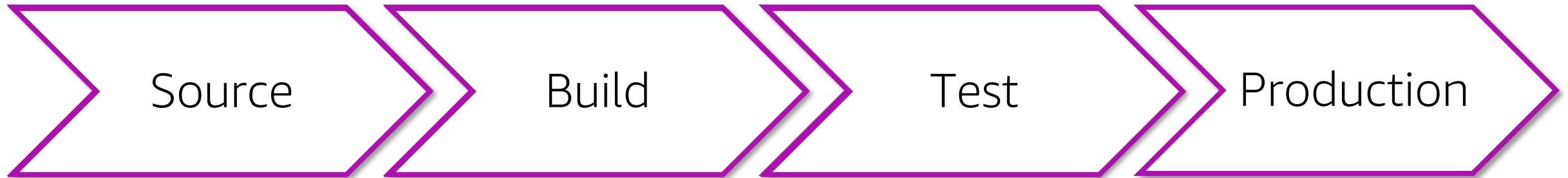
DevOps and Release Process



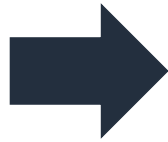
Automated CI/CD release process



Software release steps



AWS CodeCommit



AWS CodeBuild

OR



Third party



AWS CodeDeploy

Orchestration:



AWS CodePipeline

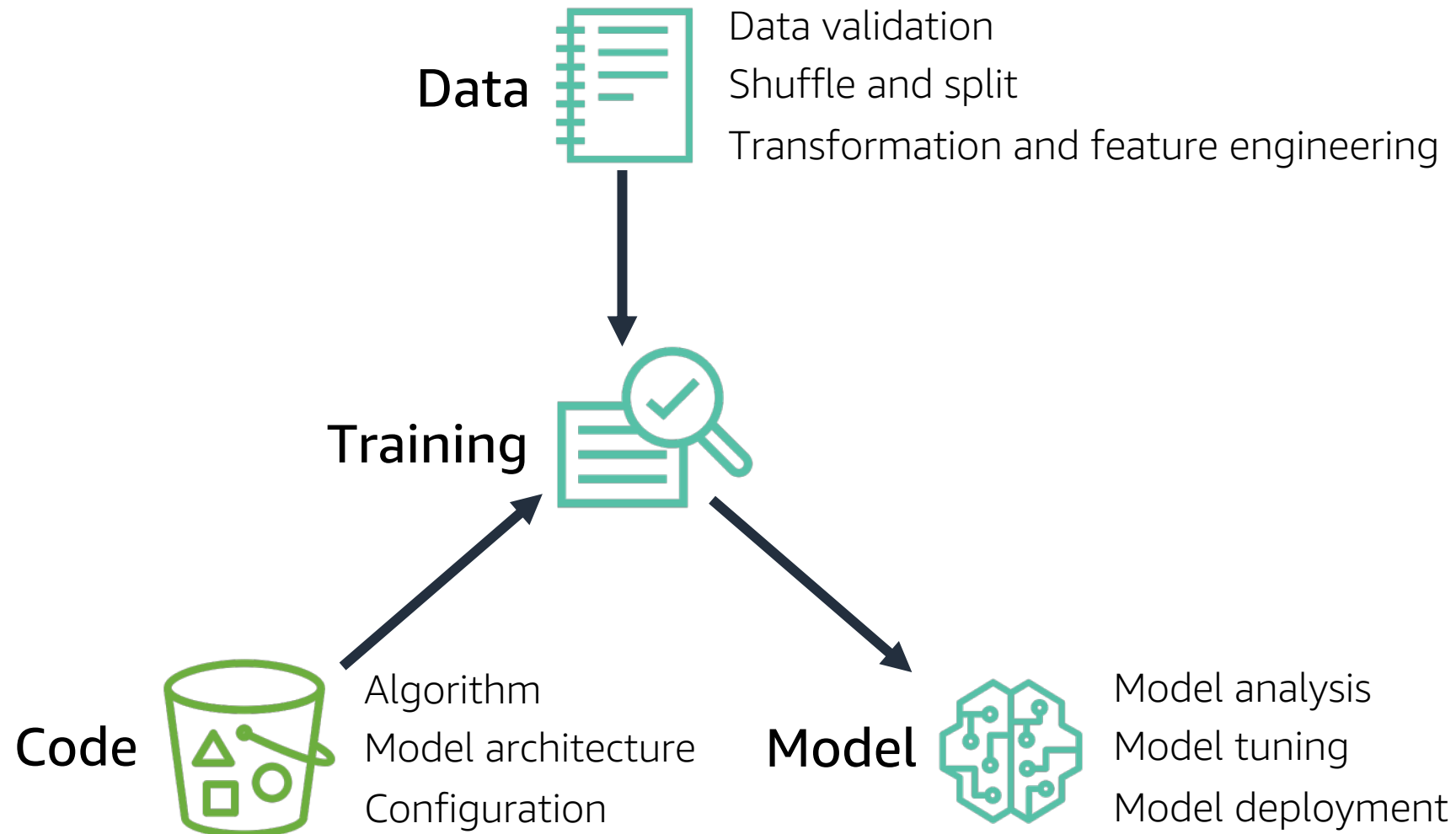
Artifact storage:



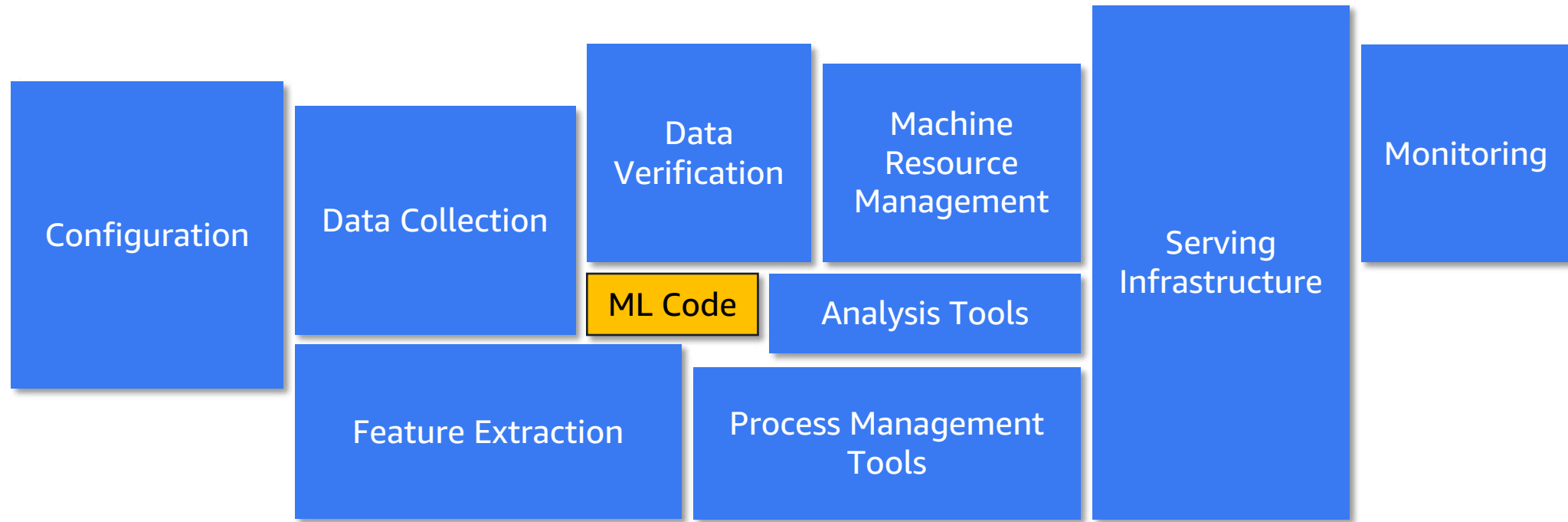
AWS CodeArtifact

ML is different

ML code and data are independent

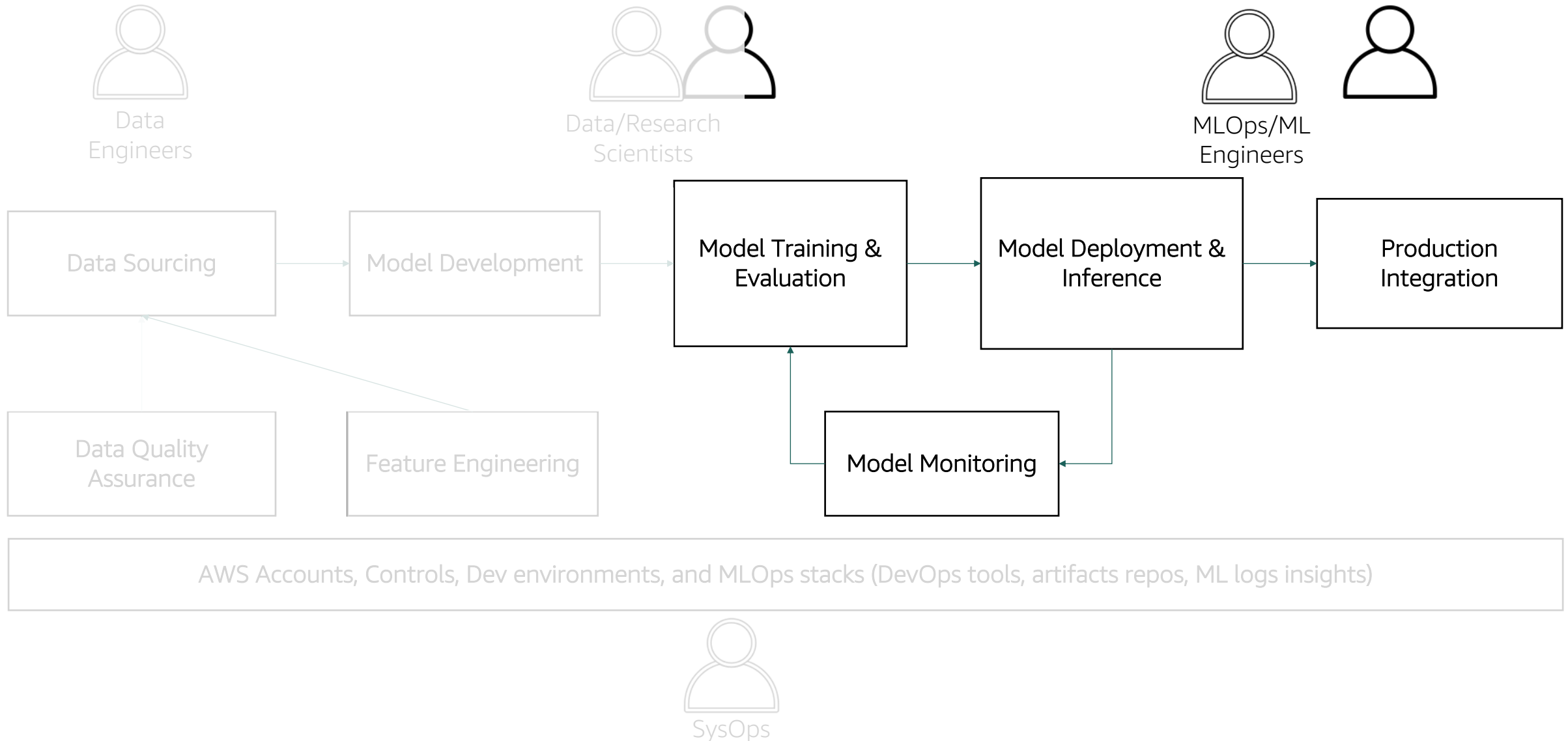


ML code is one small part of the solution



"Hidden Technical Debt in Machine Learning Systems" — Sculley et al.

Different teams might own part of process



ML has additional requirements

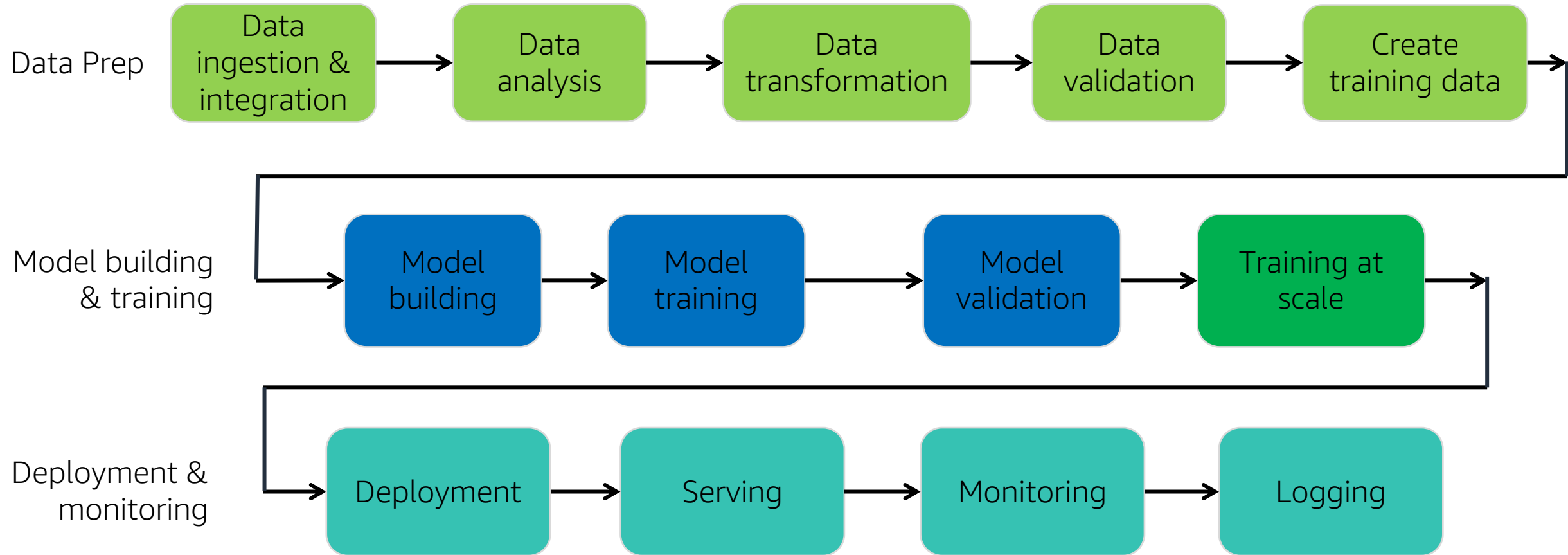
- Consistency: Minimal variance between environments (i.e. using containers)
- Flexibility: Can accommodate most frameworks
- Reproducibility: Can recreate past experiments/training
- Reusability: Components are reusable across projects
- Scalability: Able to scale resources to efficiently meet demand
- Auditability: Logs, versions, and dependencies of artifacts are available
- Explainability: Decision transparency

MLOps = DevOps for ML

	DevOps	DevOps for ML
Code versioning	✓	✓
Compute environment	✓	✓
Continuous integration/delivery	✓	✓
Monitoring in production	✓	✓
Data provenance		✓
Datasets		✓
Models		✓
Hyperparameters		✓
Metrics		✓
Workflows		✓

ML pipeline is more complex

Phases:



ML Pipeline Orchestration

ML pipeline orchestration options

- Amazon SageMaker Pipeline
- AWS Step Functions and AWS CodePipeline
- Kubeflow: ML toolkit for Kubernetes
- Apache Airflow: Platform to author, schedule, and monitor workflows
- MLflow: Platform to manage the ML lifecycle

Automate ML workflows with Amazon SageMaker Pipeline

Amazon SageMaker Pipelines



- Orchestrating workflows across each step of the ML process can take months of coding.
- SageMaker Pipeline - purpose-built CI/CD service for machine learning
- With SageMaker Pipelines you
 - Can use Python interface for creating pipelines to automate different steps of the ML workflow, including data loading, data transformation, training and tuning, and deployment.
 - Can build dozens of ML models a week, manage massive volumes of data, thousands of training experiments, and hundreds of different model versions.
 - Can share and re-use workflows to recreate or optimize models, helping you scale ML throughout your organization
 - Can manage dependencies, build correct sequences and automate steps without coding

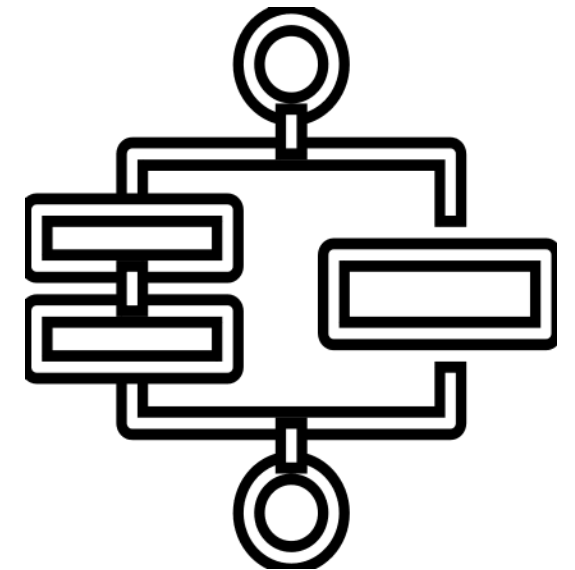
Amazon SageMaker Pipeline benefits



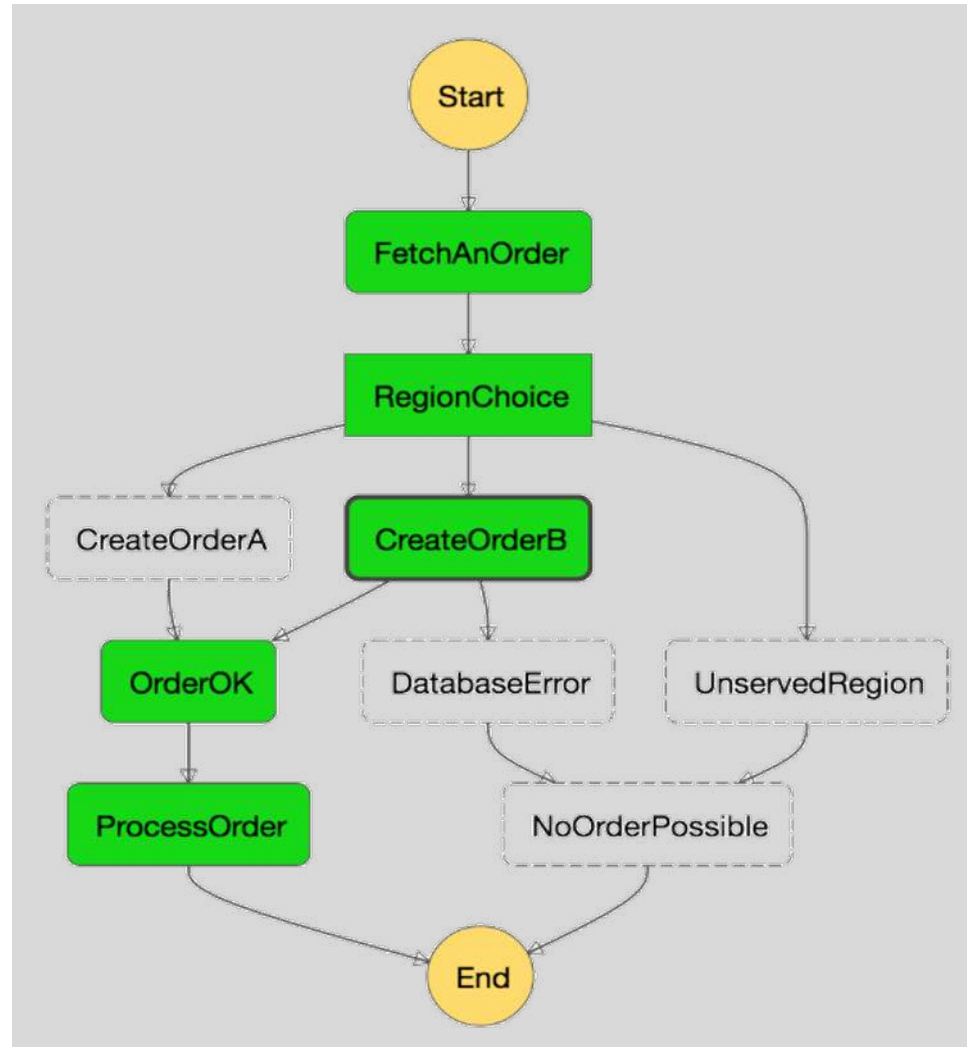
- Compose and manage ML workflows
- Track model lineage for governance and audits
- Replay and re-run workflows
- Visually compare, select, and deploy models
- Access a central registry of trained models
- Fully managed ML Ops with built-in CI/CD support

Automate ML workflows with AWS Step Function and AWS CodePipeline

- Resilient serverless workflows orchestration service
- Build visual workflows: Less code to write and maintain
- Can be used to:
 - Author and visualize your ML pipeline using Python and your Jupyter notebook
 - Leverage AWS CodePipeline for CI/CD



Easy to create workflow with Step Functions

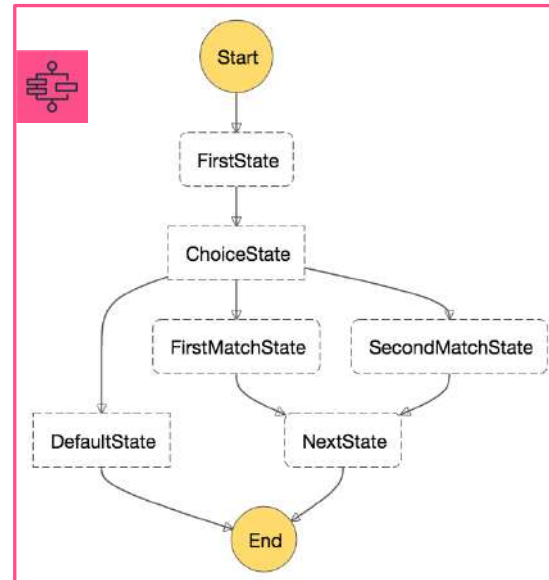


AWS Step Functions: Visual workflows

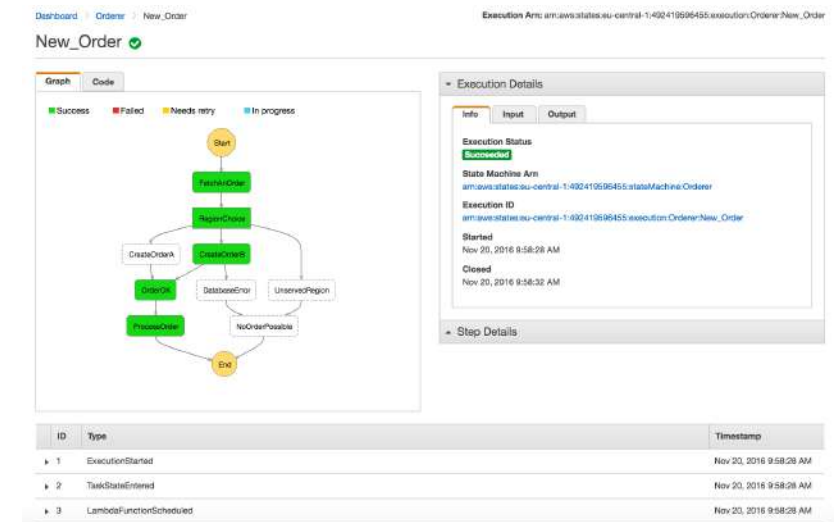
Define in JSON

```
Code
1 {
2   "Comment": "An AWS example using a choice state.",
3   "StartAt": "FirstState",
4   "States": {
5     "FirstState": {
6       "Type": "Task",
7       "Resource": "arn:aws:lambda:REGION:ACCOUNT_ID:function:FUNCTION_NAME",
8       "Next": "ChoiceState"
9     },
10    "ChoiceState": {
11      "Type": "Choice",
12      "Choices": [
13        {
14          "Variable": "$?.id",
15          "Match": "Equals",
16          "Next": "FirstMatchState"
17        },
18        {
19          "Variable": "$?.id",
20          "Match": "NotEquals",
21          "Next": "SecondMatchState"
22        },
23        {
24          "Default": "DefaultState"
25        }
26      ]
27    },
28    "FirstMatchState": {
29      "Type": "Task",
30      "Resource": "arn:aws:lambda:REGION:ACCOUNT_ID:function:FUNCTION_NAME",
31      "Next": "NextState"
32    },
33    "SecondMatchState": {
34      "Type": "Task",
35      "Resource": "arn:aws:lambda:REGION:ACCOUNT_ID:function:FUNCTION_NAME",
36      "Next": "NextState"
37    },
38    "DefaultState": {
39      "Type": "Task",
40      "Resource": "arn:aws:lambda:REGION:ACCOUNT_ID:function:FUNCTION_NAME",
41      "Next": "NextState"
42    },
43    "NextState": {
44      "Type": "Task",
45      "Resource": "arn:aws:lambda:REGION:ACCOUNT_ID:function:FUNCTION_NAME",
46      "Next": "End"
47    },
48    "End": {
49      "Type": "End"
50    }
51  }
52 }
```

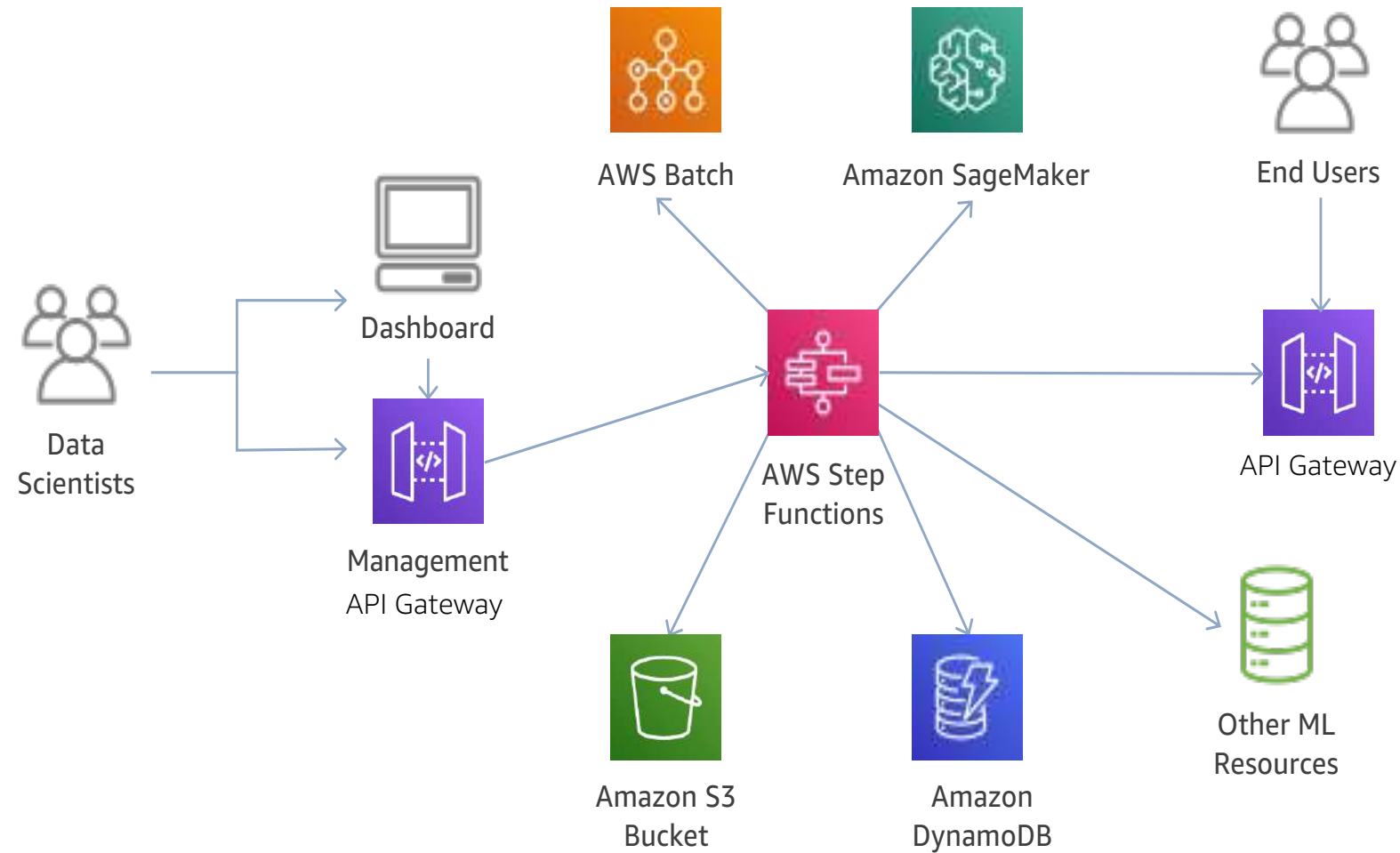
Visualize in the Console



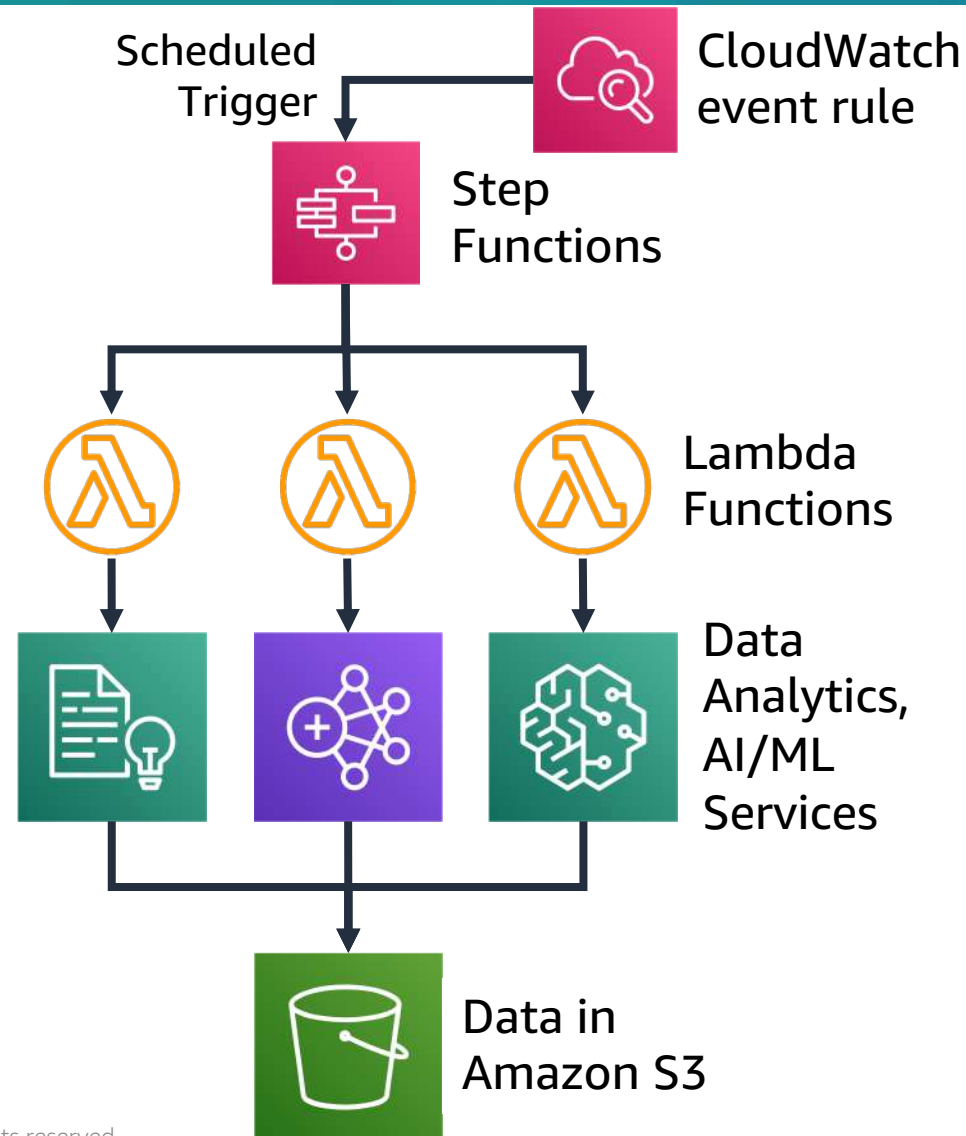
Monitor Run-time



AWS Step Functions: Build flexible and repeatable ML workflows



AWS Step Functions: Build flexible and repeatable ML workflows



Enable auditability, reproducibility, traceability, and verifiability

Versioned Code: Amazon SageMaker

Experiments

- Python notebooks
- Python code

ML Training

- Python code
- Docker files
- BuildSpec Files
- CF Templates/CDK

ML Deployment

- Python code
- Docker files
- BuildSpec files
- CF templates/CDK

Code Repo

Versioned Data: Amazon S3

Data Files

- Raw data
- Processed data
- Labelled data
- Training data
- Validation data
- Inference data (batch)
- Inference feedback

Data Repo

Versioned Containers: Amazon ECR

Docker Images

- Data processing
- Model training
- Model deployment

Uniquely IDed Models: Amazon S3

Model Binaries

- model.tar.gz

Model Registry

Versioned Manifests: Amazon SageMaker

Release

- Container IDs
 - Model name
 - Model binary path
 - Instance type
 - Instance count
 - Monitoring config
 - Data feedback
- ### Build
- Container IDs
 - Input data
 - Data processing
 - Compute
 - Training data
 - Artefact registry
 - Run-time outputs

ML Process Logs: Amazon CloudWatch

Logs Store

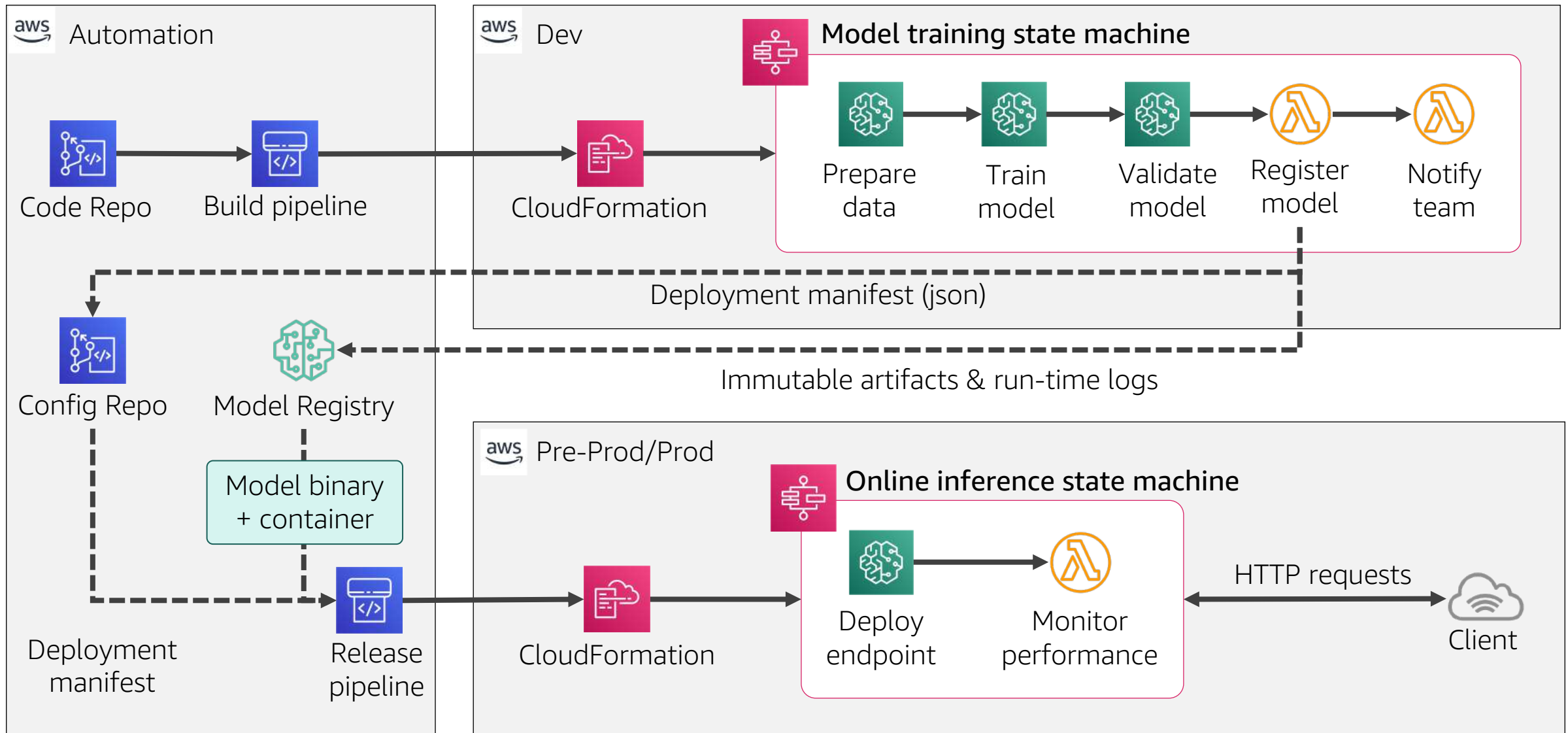
- Step Functions logs
- Data processing
- Training
- Validation
- Model fingerprint
- Deployment
- Monitoring

Logs Dashboard

- Project dashboard

ML Logs Insights

MLOps pipeline orchestration for automated deployments



Automate ML workflows with Kubeflow

Kubeflow: ML Toolkit for Kubernetes



Kubeflow

Notebook

Pipeline

Training

Serving

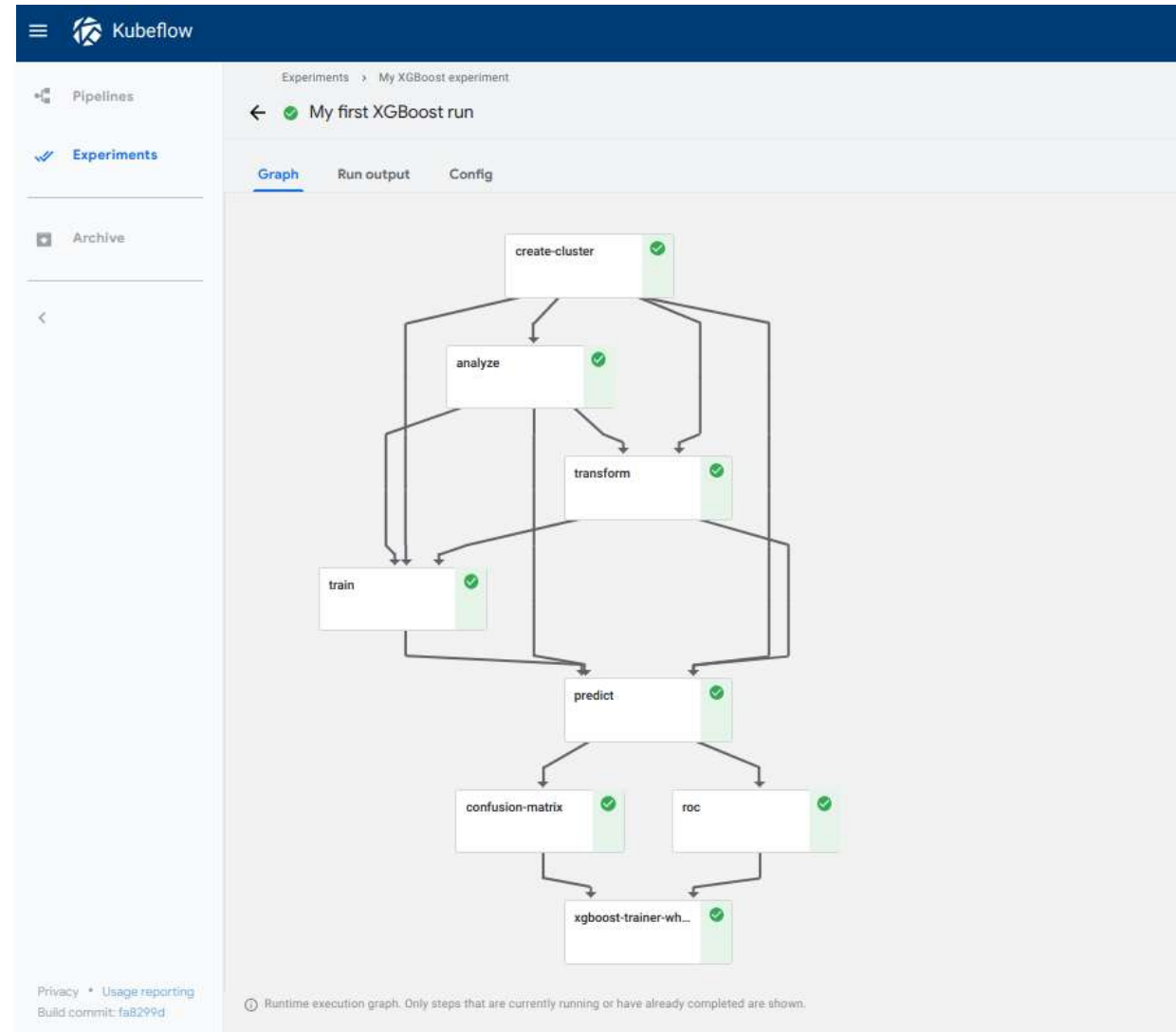
Kubeflow Pipelines

You can use Kubeflow Pipelines platform to compose, deploy, and manage end-to-end Kubernetes ML workflows

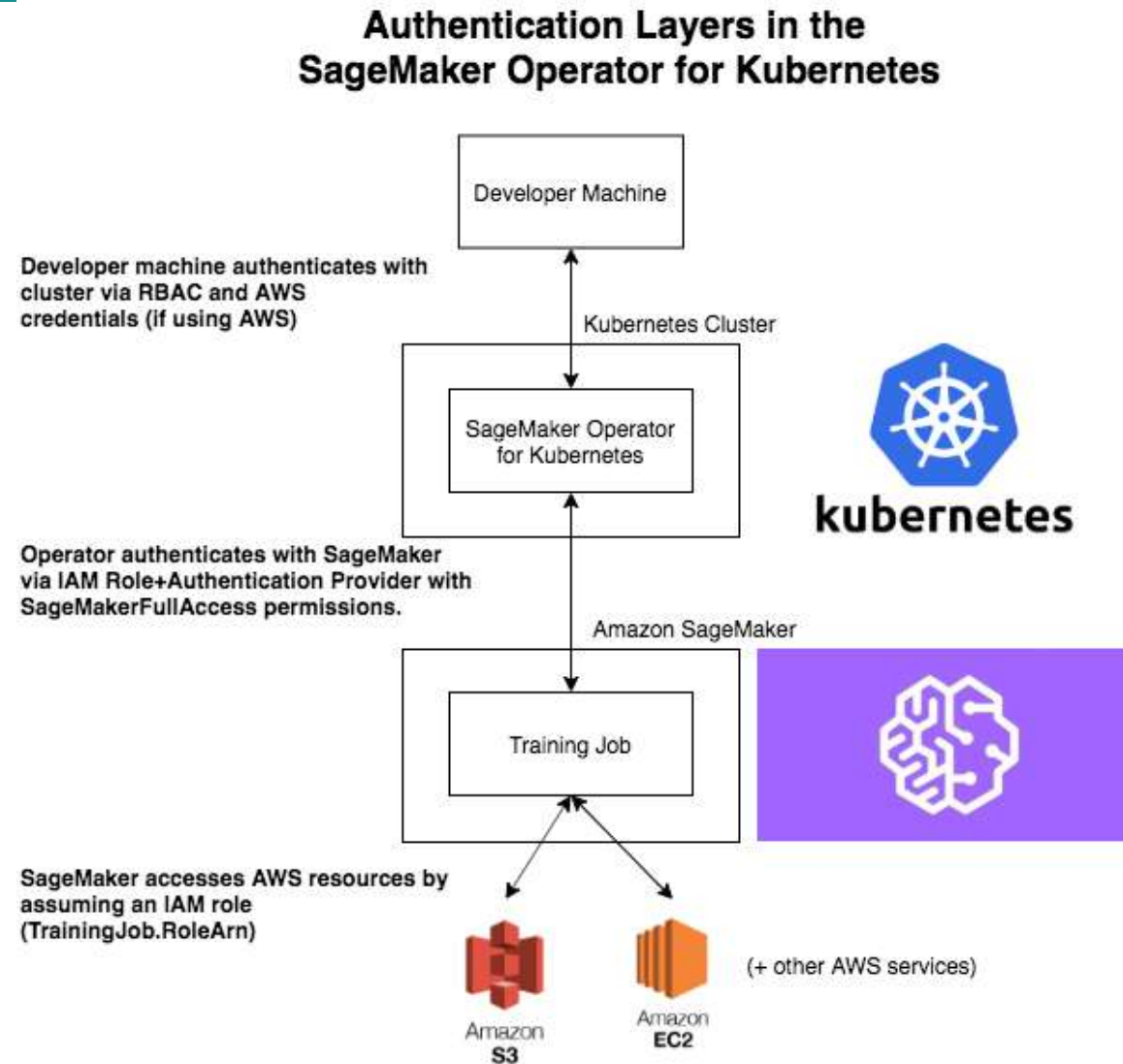
Leverage Kubeflow Pipelines SDK

- `kfp.compiler`,
`kfp.components`, `kfp.Client`

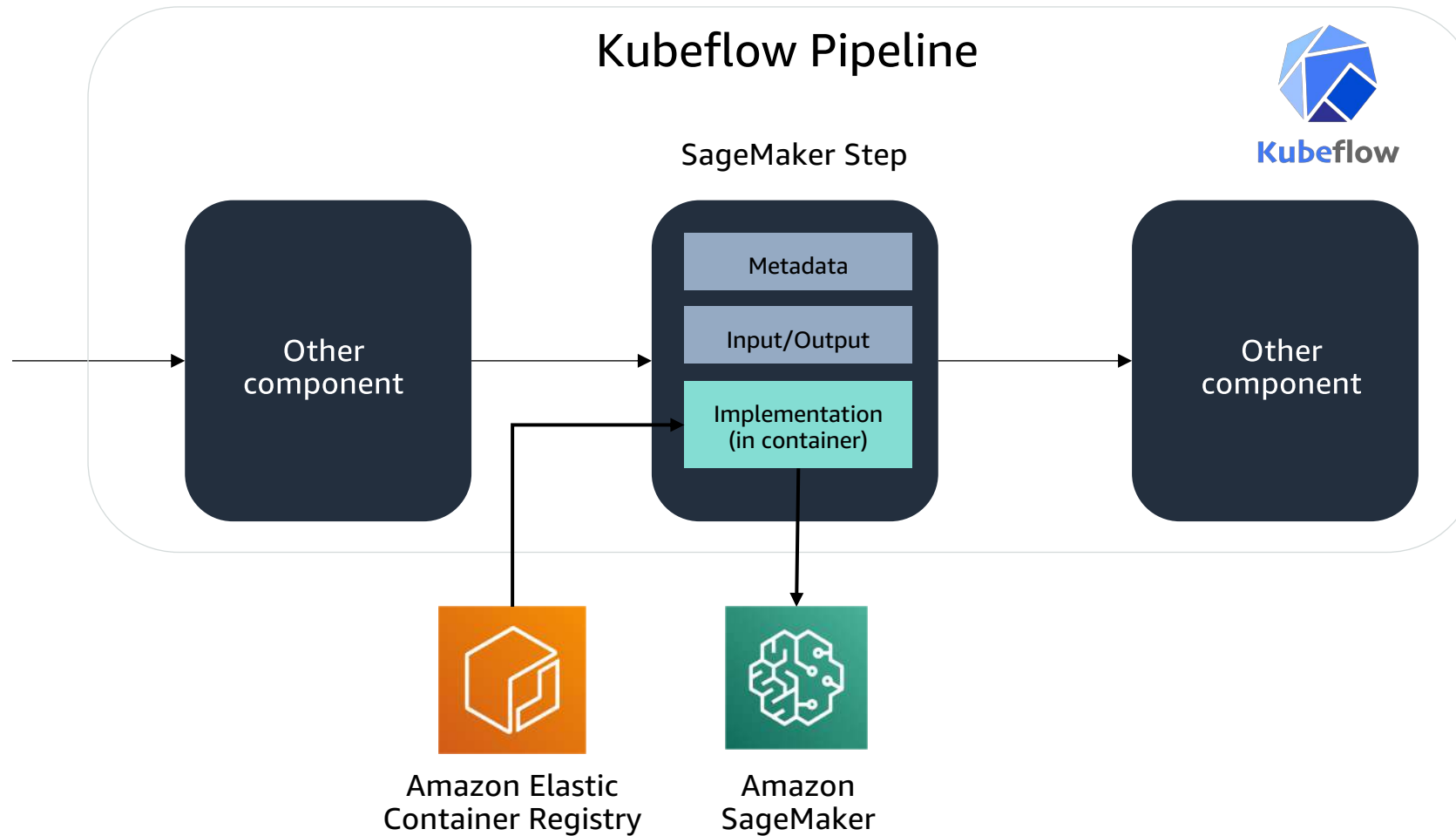
Uses Argo under the hood to orchestrate resources



Amazon SageMaker Operators for Kubernetes



Running SageMaker – pipeline components



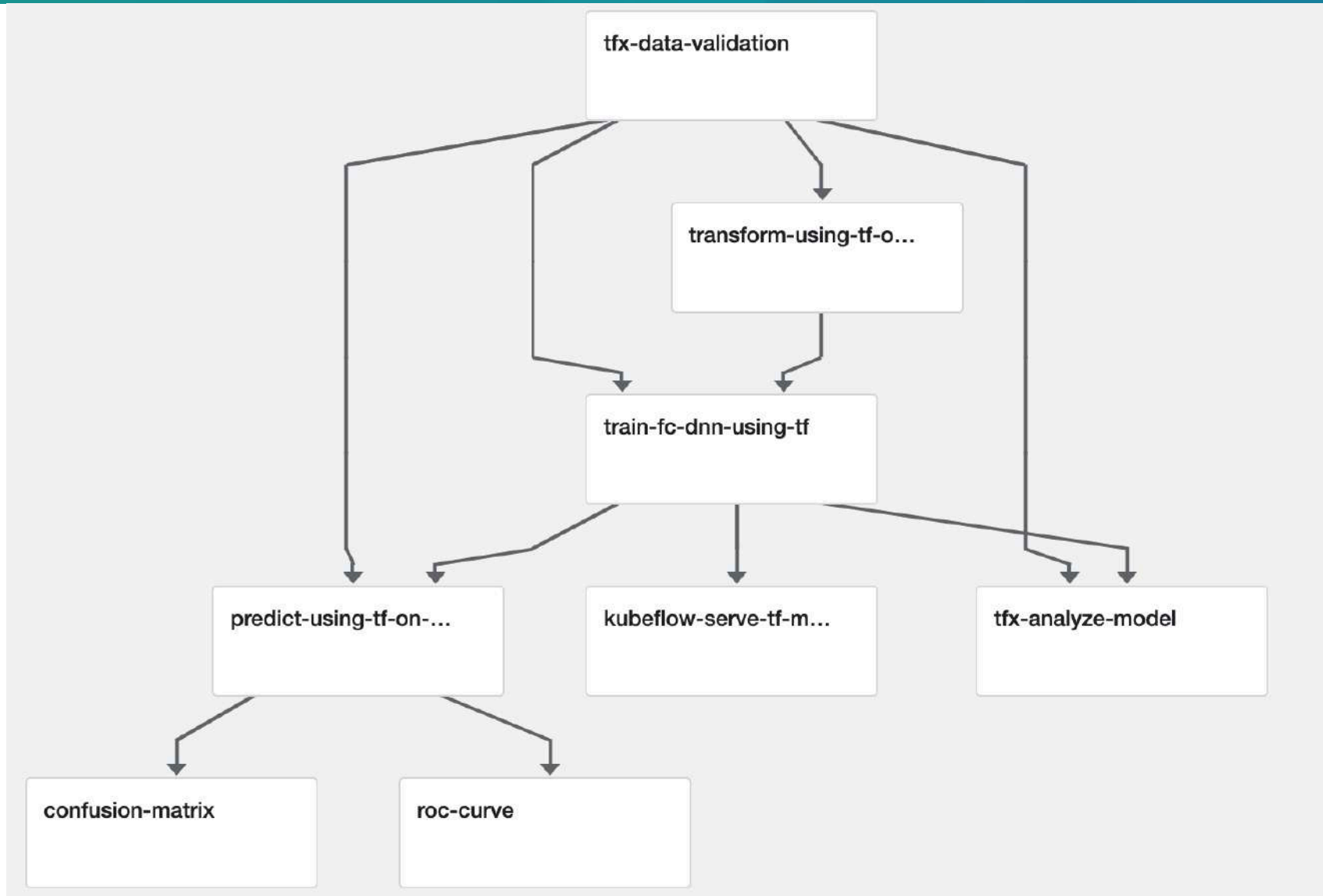
Supported components

- Training
- Model generation
- Hyperparameter tuning
- Model deployment
- Batch transform

<https://github.com/kubeflow/pipelines/tree/master/components/aws/sagemaker>

Kubeflow ML pipeline orchestration

Taxi Tip
Prediction
Model trainer
using TF DNN



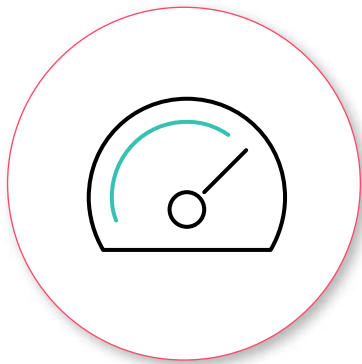
Governance at Scale for ML on AWS

Enable self-service, governed ML development environments

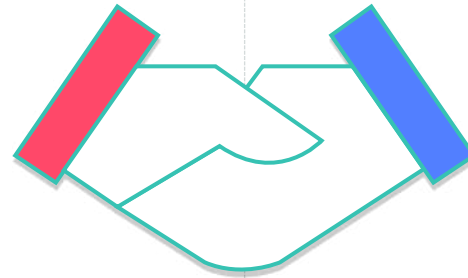
Balancing the needs of ML builders and central cloud IT

ML Builders

Stay agile

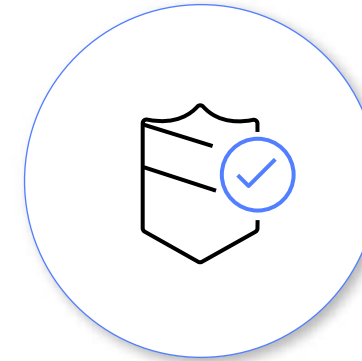


Innovate with the speed and agility of AWS
Self-service access
Experiment fast
Respond quickly to change



Cloud IT

Establish governance

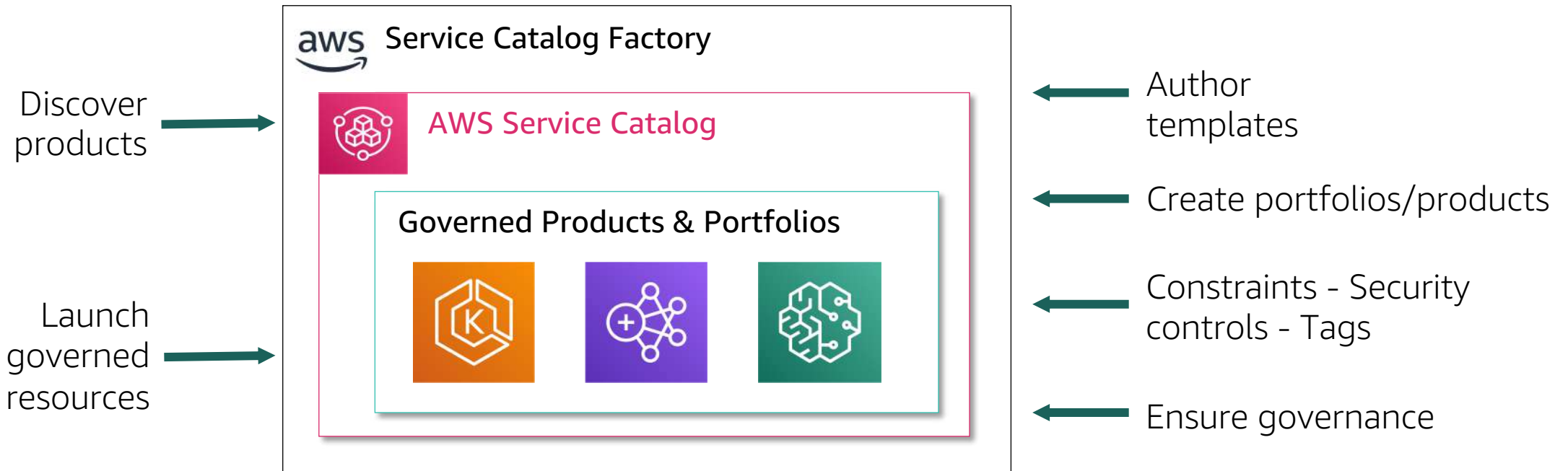


Govern at scale with central controls
Security
Compliance
Operations
Spend management

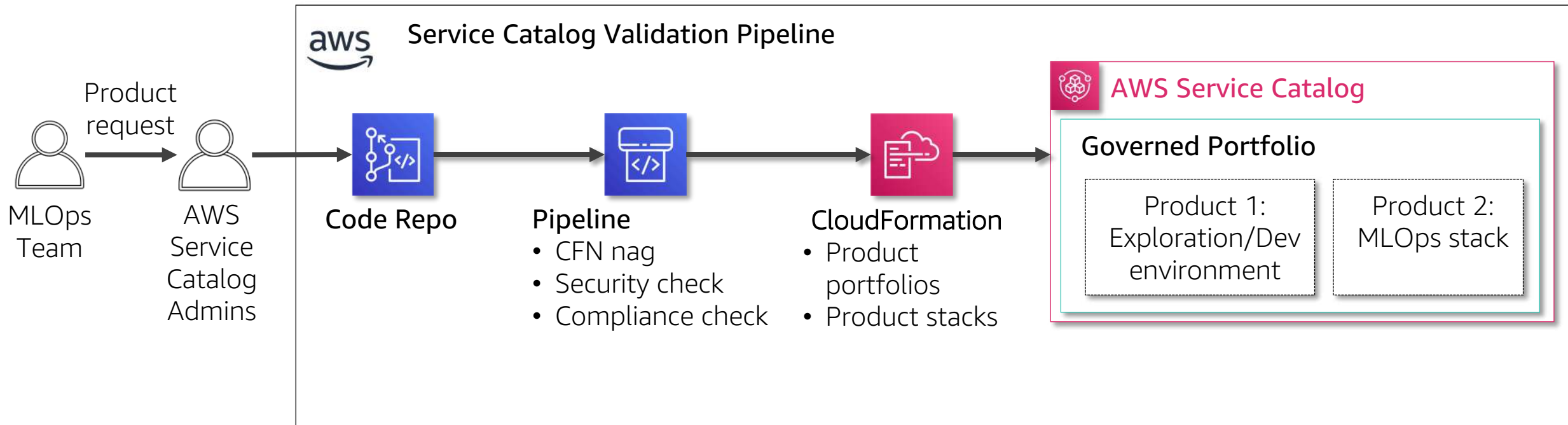
Enable MLOps/development teams to innovate at speed while ensuring governance

MLOps team

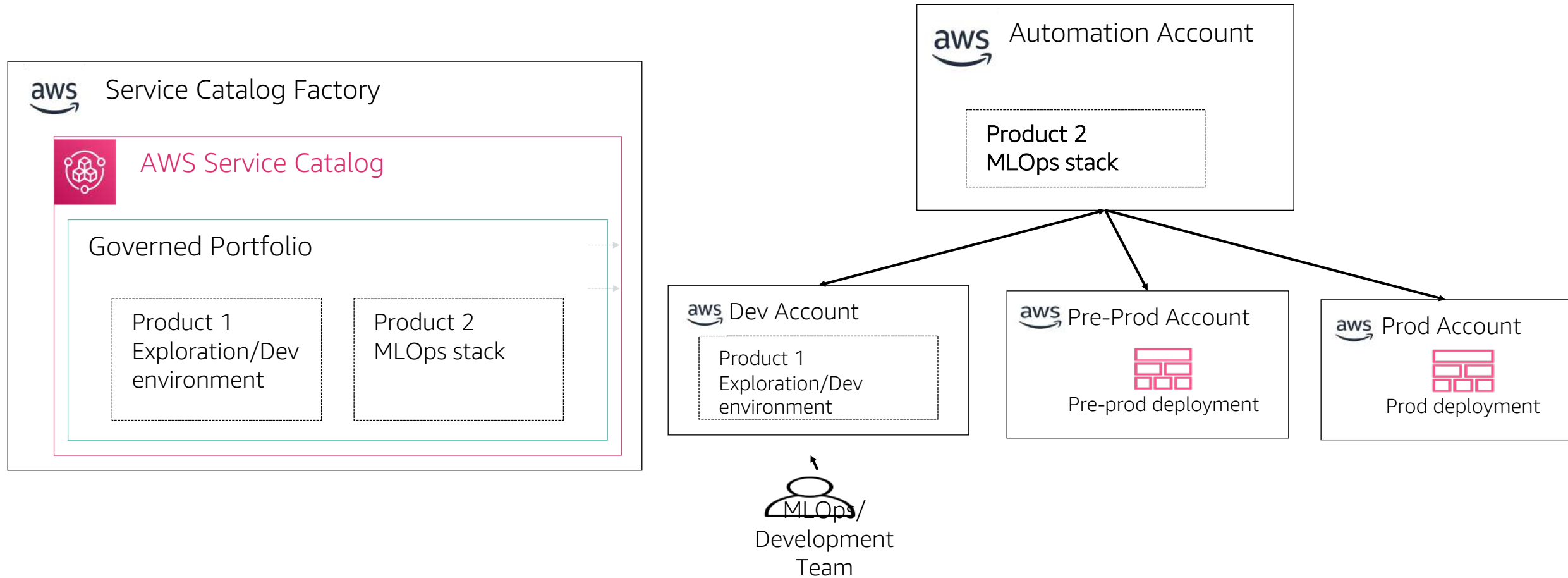
AWS Service Catalog Administrator



Create governed environments with AWS Service Catalog



Launch governed ML environments in a few clicks



Knowledge Check

Knowledge check

Select two ways we identified that MLOps is different from traditional DevOps:



In ML, code and data are independent



In ML, the code is what usually requires the most work



ML code is only a small part of the ML solution



MLOps doesn't use CI/CD pipelines



Knowledge check

Pick two AWS services that can be used together to orchestrate an MLOps pipeline:



AWS CodePipeline



AWS AppSync



AWS Step Functions



Amazon AppFlow



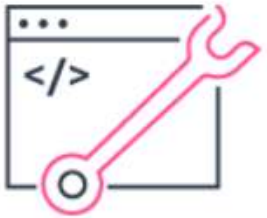
Module 11: Next Steps and Additional Learning

Module 11: Next Steps and Additional Learning

- Identify and describe the AWS Machine Learning Competency Program
- Explain how the AWS Machine Learning Competency Program impacts independent software vendors (ISVs) and consulting partners
- Locate resources for additional learning on ML topics

ML learning paths

Pick Your Learning Path



Developer



**Business Decision
Maker**



Data Scientist



**Data Platform
Engineer**



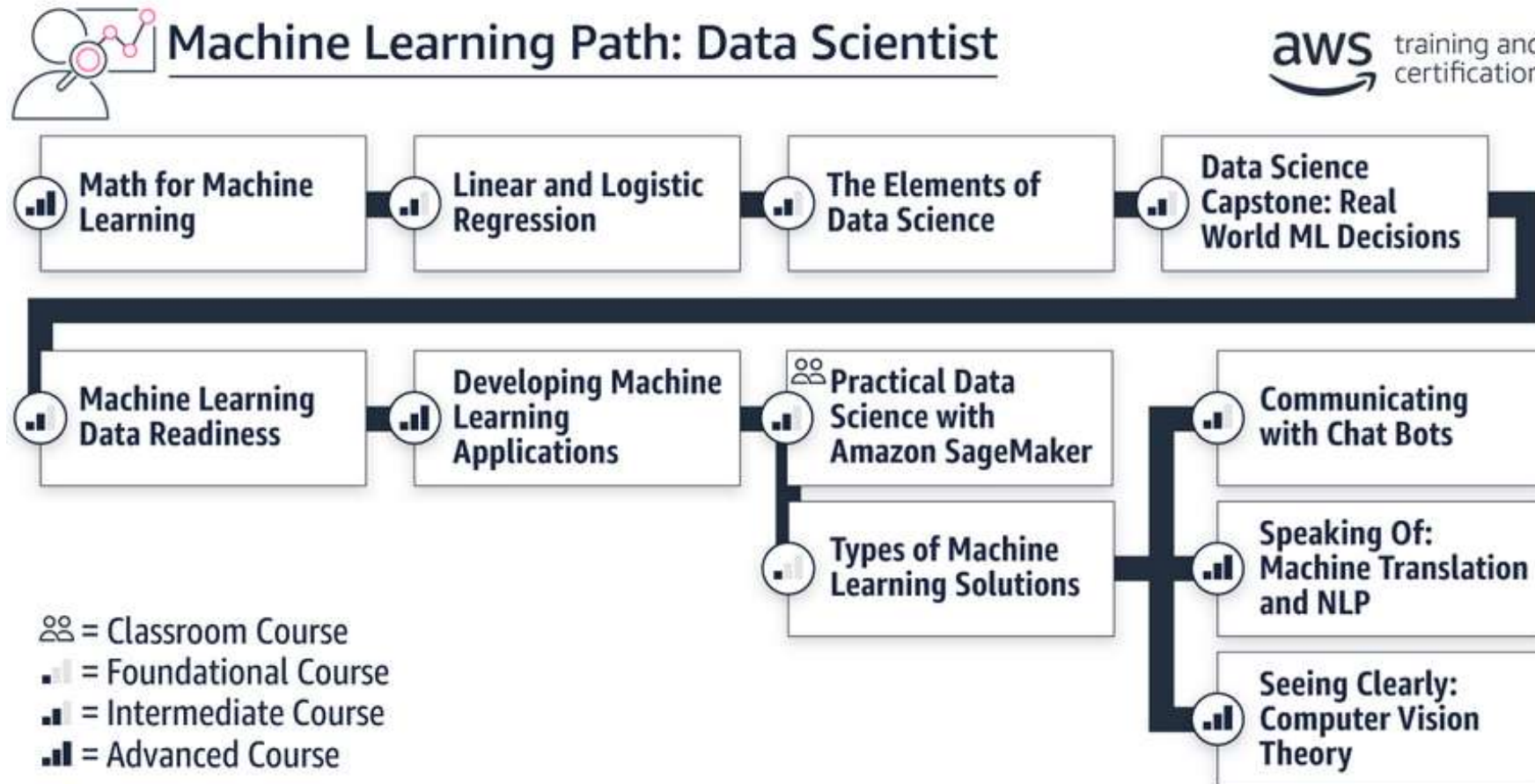
Exam Preparation



**Browse all Machine
Learning classes**

<https://pages.awscloud.com/AWS-Partner-Learning-Path-Tool.html>

Learning path: ML for data scientists



<https://aws.amazon.com/training/learning-paths/machine-learning>

Machine Learning Certification



AWS Certified Machine Learning – Specialty

Validate your ability to build, train, tune, and deploy machine learning models using the AWS Cloud.

[Schedule an exam](#)

A promotional banner for the AWS Certified Machine Learning – Specialty exam. It features a dark blue background with a subtle pattern of light blue and white geometric lines. The title "AWS Certified Machine Learning – Specialty" is in large, bold, white sans-serif font. Below it, the description "Validate your ability to build, train, tune, and deploy machine learning models using the AWS Cloud." is in a smaller white font. At the bottom, there is an orange rectangular button with the text "Schedule an exam" in white.

<https://aws.amazon.com/certification/certified-machine-learning-specialty/>

AWS ML Community



Learn from the ML Community

Whether you're just getting started with ML, already an expert, or something in between there is always something to learn. Choose from community created and ML focused blogs, videos, eLearning guides and much more.



VIDEO

How I started a career in machine learning – no PhD required

Alex Schultz

Level 100



BLOG

How to win at the AWS Deep Racer League (code and model included)?

Vaibhav Malpani

Level 200



BOOK

AWS Machine Learning in Motion (gated content)

Kesha Williams

Level 300



TUTORIAL

Learn how to find relevance from 1,000 wine descriptors using Amazon SageMaker

Roald Schuring

Level 300

<https://aws.amazon.com/machine-learning/ml-community>



AWS Pop-up Loft Munich

<https://aws.amazon.com/start-ups/loft>

<https://aws.amazon.com/start-ups/loft/fag>




AWS Machine Learning Competency Technology Partner Validation Checklist

<https://aws.amazon.com/blogs/apn/new-look-aws-competency-validation-checklists-for-apn-technology-partners/>

AWS Competency benefits

AWS Competency Partner Benefits

In addition to the benefits you receive as an APN member, partners that qualify for AWS Competencies will receive a number of valuable benefits, which may include:

Special Access Benefits	Go-To-Market Benefits	Selective Eligibility	Event Specific Benefits
<ul style="list-style-type: none">◦ Increased discount through the AWS Solution Provider Program◦ Shared customer opportunities◦ Preferred access to Market Development Funds◦ Direct and prioritized access to AWS Partner Network reference team	<ul style="list-style-type: none">◦ AWS Competency spotlight guest series on the APN Blog◦ APN Partner spotlight opportunities◦ AWS Sales enablement◦ Preferred Partner recommendations		 <p>Terry Wise Vice President, Channels & Alliances amazon web services</p> <p>Special Access Benefits</p>

https://aws.amazon.com/partners/competencies/#AWS_Competency_Partner_Benefits



Getting Started with the APN Navigate Specialization Track



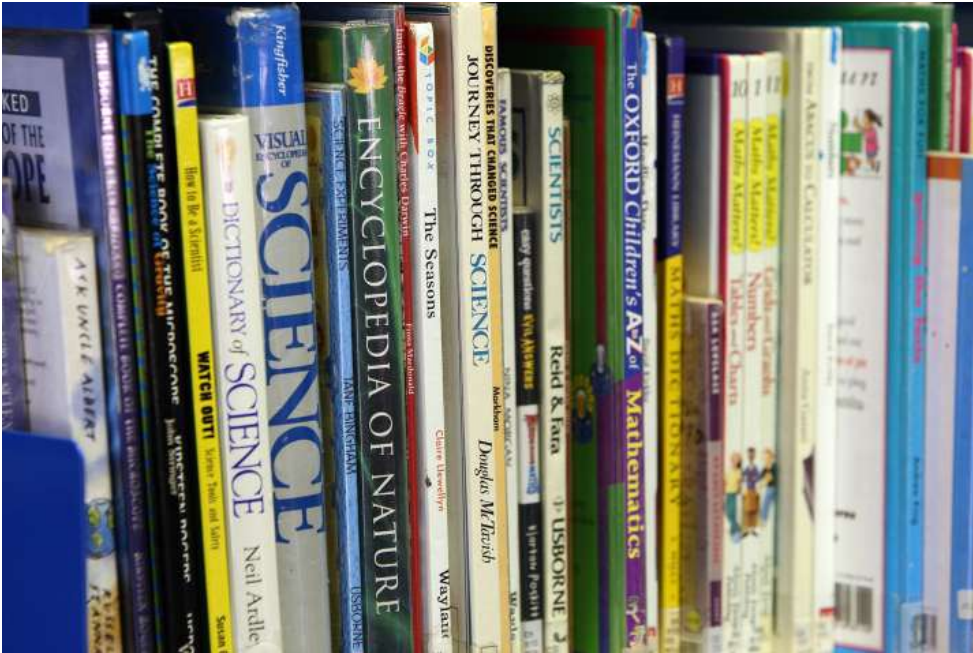
<https://aws.amazon.com/partners/navigate/>

APN Navigate for Machine Learning



<https://aws.amazon.com/partners/navigate/machine-learning/>

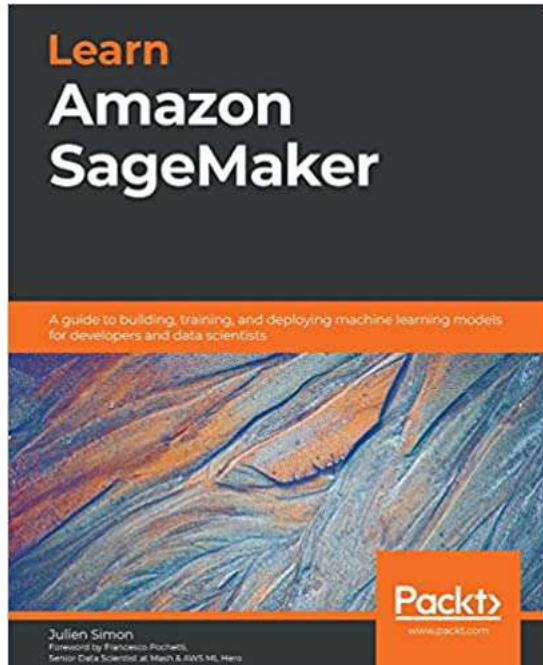
Resources and references



- Located in your participant guide
- Websites and references
- Please review
- **Subject to change**

Book - *Learn Amazon SageMaker*

A guide to building, training, and deploying machine learning models for developers and data scientists



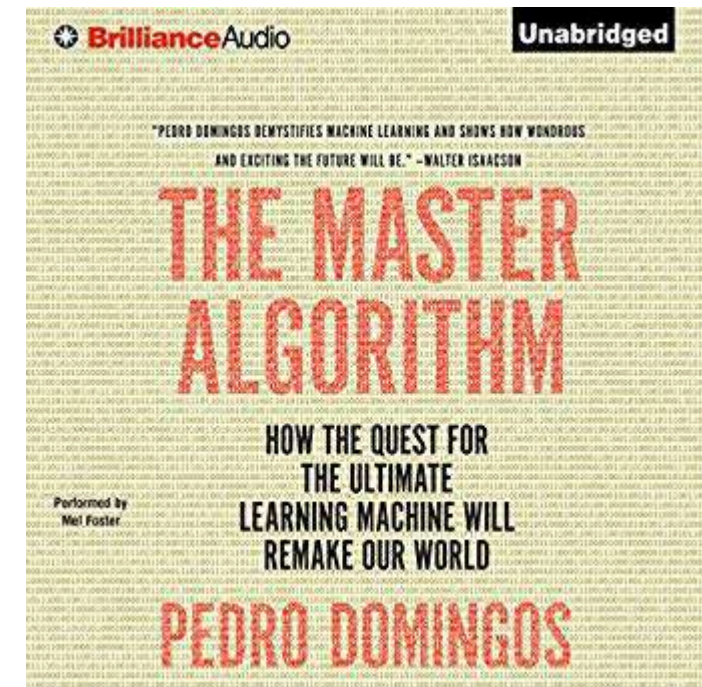
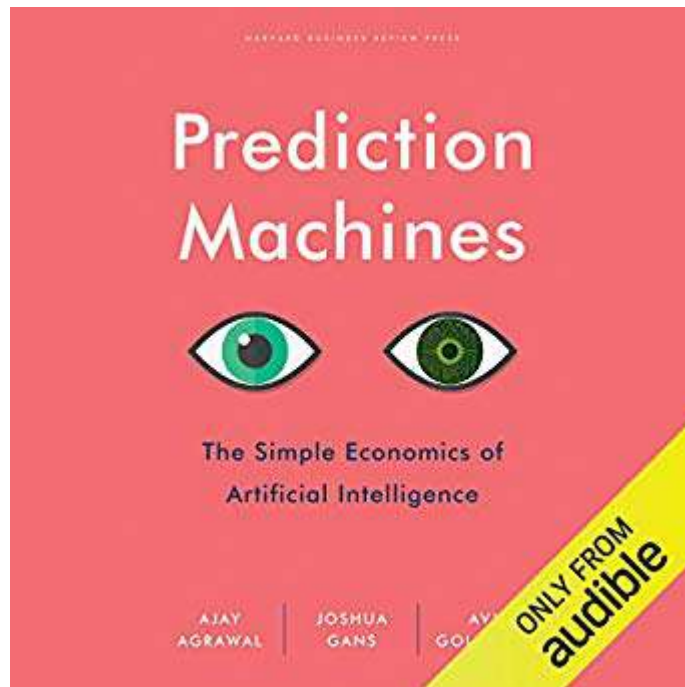
September 2020

Julien Simon

Principal Advocate, ML/AI

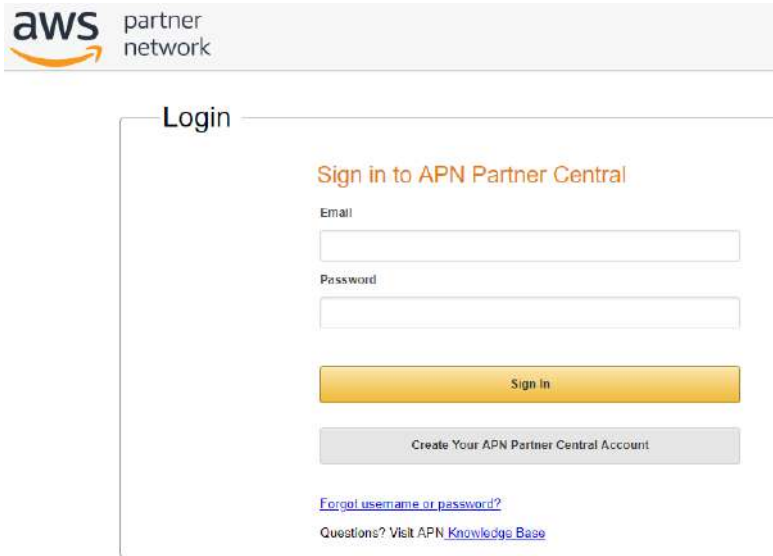
1. Getting Started with Amazon SageMaker
2. Handling Data Preparation Techniques
3. AutoML with Amazon SageMaker AutoPilot
4. Training Machine Learning Models
5. Training Computer Vision Models
6. Training Natural Language Processing Models
7. Extending Machine Learning Services Using Built-In Frameworks
8. Using Your Algorithms and Code
9. Scaling Your Training Jobs
10. Advanced Training Techniques
11. Deploying Machine Learning Models
12. Automating Machine Learning Workflows
13. Optimizing Prediction Cost and Performance

Further learning



End of class

Assessment and course evaluation



The screenshot shows the AWS Partner Central login interface. At the top left is the 'aws partner network' logo. Below it, the word 'Login' is displayed. The main heading is 'Sign in to APN Partner Central'. There are two input fields: 'Email' and 'Password'. Below these fields is a yellow 'Sign in' button and a grey 'Create Your APN Partner Central Account' button. At the bottom, there are two links: 'Forgot username or password?' and 'Questions? Visit APN Knowledge Base'.

1. <https://partnercentral.awspartner.com>



2. Click the Training tab.



3. Click the learn more link.



4. Click the Dashboard tab.

5. Solutions Training for Partners: Introduction to Machine Learning on AWS – Technical will be in progress.

Select the resume button, locate the assessment and click launch.

Thank You

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