



# Mastering Amazon SageMaker

Model build, train and tune using Amazon SageMaker

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# Agenda

- Overview of Amazon SageMaker
- Module 2 – SageMaker Building ML models
  - SageMaker HPO
  - Spot Training
  - SageMaker Debugger
- Q&A
- Survey

# Support the responsible use of ML throughout the model lifecycle



## Build

Perform bias analysis during exploratory data analysis



## Train

Conduct bias and explainability analysis after training



## Deploy

Explain individual inferences from models in production



## Monitor

Validate bias and relative feature importance over time

# SageMaker Building ML models

# Build ML models

**Fully managed  
shareable notebooks on  
Amazon EC2**



## **Fully managed, sharable Jupyter notebooks**

Run notebooks on elastic compute resources



## **Built-in algorithms**

15 built-in algorithms available in prebuilt container images



## **Prebuilt solutions and open-source models**

Over 150 popular open-source models



## **AutoML**

Automatically create ML models with full visibility



## **Support for major frameworks and toolkits**

Optimized for popular deep learning (DL) frameworks such as TensorFlow, PyTorch, Apache MXNet, and Hugging Face

# Amazon SageMaker has built-in algorithms or bring your own

## Computer vision

Image classification | Object detection |  
Semantic segmentation

## Topic modeling

LDA | NTM

## Classification

Linear Learner | XGBoost | KNN

## Recommendation

Factorization machines

## Forecasting

DeepAR

## Working with text

BlazingText | Supervised | Unsupervised

## Regression

Linear Learner | XGBoost | KNN

## Clustering

KMeans

## Sequence translation

Seq2Seq

## Anomaly detection

Random cut forests | IP Insights

## Feature reduction

PCA

# SageMaker Training Deep Dive

# Train ML models

**Fast and cost-effective  
ML model training**



**Experiment management and model tuning**  
Save weeks of effort by automatically tracking training runs and tuning hyperparameters



**Debug and profile training runs**  
Use real-time metrics to correct performance problems



**Distributed training**  
Complete distributed training up to 40% faster



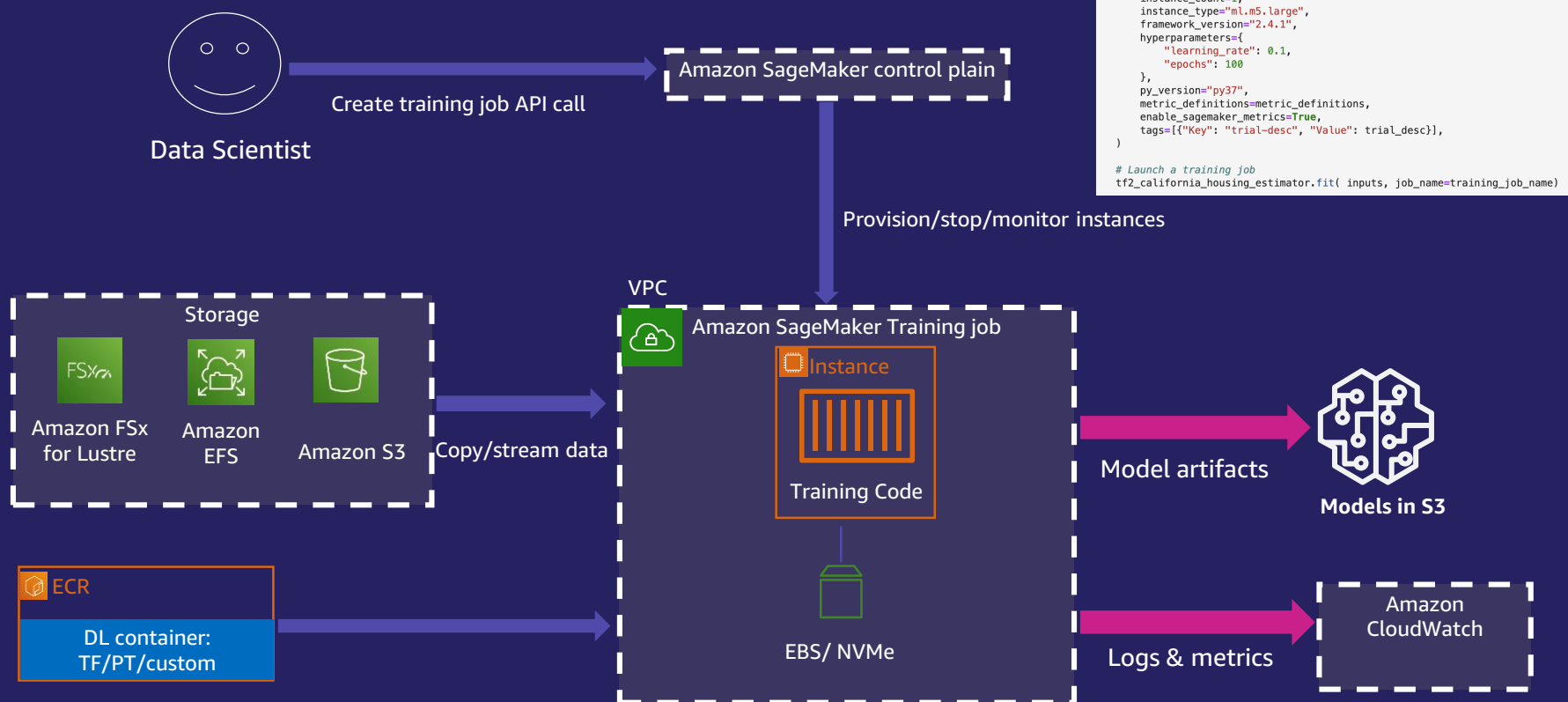
**Training compiler**  
Accelerate training times by up to 50% through more efficient use of GPUs



**Managed spot training**  
Reduce the costs of training by up to 90%



# Training on Amazon SageMaker



# Training Estimator

```
# Input data from s3
inputs = {"train": s3_inputs_train, "test": s3_inputs_test}

metric_definitions = [
    {"Name": "loss", "Regex": "loss: ([0-9\\.]+)"},
    {"Name": "accuracy", "Regex": "accuracy: ([0-9\\.]+)"},
    {"Name": "val_loss", "Regex": "val_loss: ([0-9\\.]+)"},
    {"Name": "val_accuracy", "Regex": "val_accuracy: ([0-9\\.]+)"},
]

# Create a TensorFlow Estimator
tf2_california_housing_estimator = TensorFlow(
    entry_point="california_housing_tf2.py",
    source_dir="code",
    role=sagemaker.get_execution_role(),
    instance_count=1,
    instance_type="ml.m5.large",
    framework_version="2.4.1",
    hyperparameters={
        "learning_rate": 0.1,
        "epochs": 100
    },
    py_version="py37",
    metric_definitions=metric_definitions,
    enable_sagemaker_metrics=True,
    tags=[{"Key": "trial-desc", "Value": trial_desc}],
)

# Launch a training job
tf2_california_housing_estimator.fit( inputs, job_name=training_job_name)
```

# Amazon SageMaker Automatic Model Tuning

Automatically tune  
hyperparameters in  
your algorithms



## Tuning at scale

Adjust thousands of different combinations of algorithm parameters



## Automated

Uses ML to find the best parameters



## Faster

Eliminate days or weeks of tedious manual work



## Decision trees

Tree depth | Max leaf nodes | Gamma | Eta | Lambda | Alpha

## Neural networks

Number of layers | Hidden layer width | Learning rate | Embedding dimensions | Dropout

# Amazon SageMaker Automatic Model Tuning

## Hyperparameter Tuning



# Setting up hyper parameter tuning job

1. Pick hyperparameters and ranges

```
: hyperparameter_ranges = {'eta': ContinuousParameter(0, 1),  
                             'min_child_weight': ContinuousParameter(1, 10),  
                             'alpha': ContinuousParameter(0, 2),  
                             'max_depth': IntegerParameter(1, 10)}
```

2. Pick objective metric

```
: objective_metric_name = 'validation:auc'
```

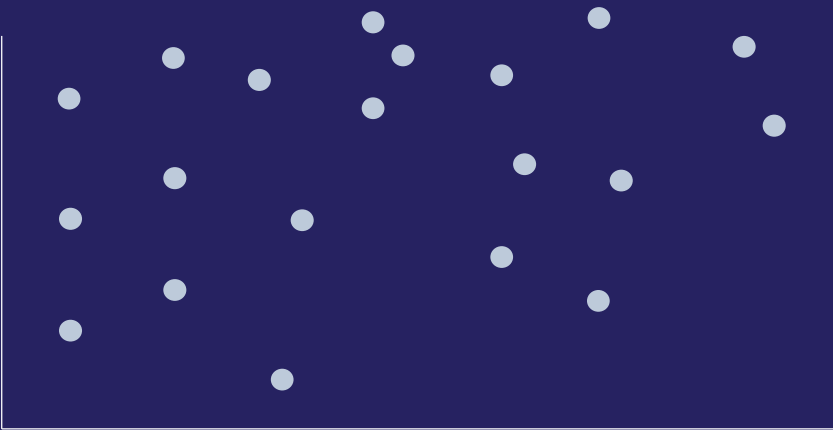
3. Pick job parameters

```
: tuner = HyperparameterTuner(xgb,  
                               objective_metric_name,  
                               hyperparameter_ranges,  
                               max_jobs=20,  
                               max_parallel_jobs=3)
```

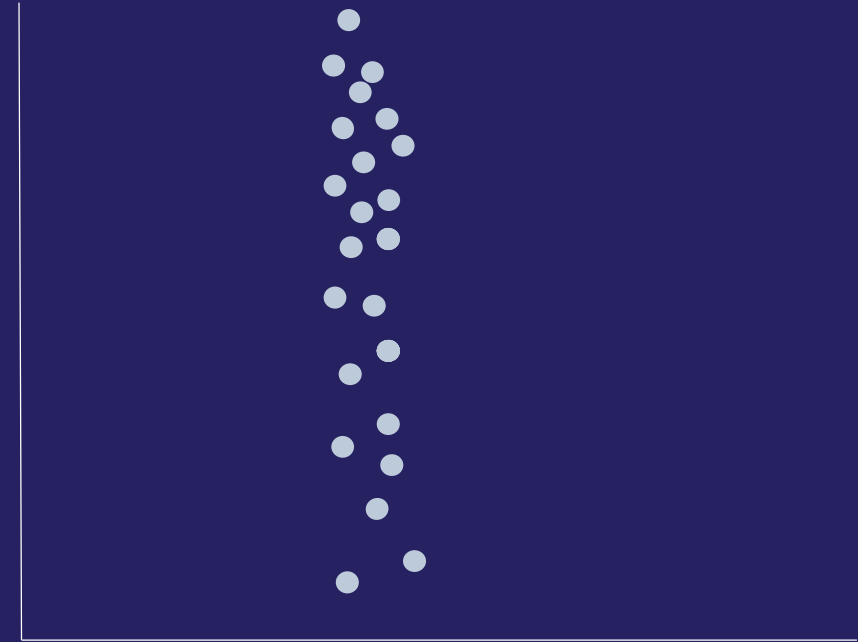
# Amazon SageMaker Automatic Model Tuning

What if I need all my jobs tuned at the same time ?

Bayesian Search



Random Search



# Random Search

```
{  
  "ParameterRanges": {...}  
  "Strategy": "Random",  
  "HyperParameterTuningJobObjective": {...}  
}
```

```
tuner = HyperparameterTuner(  
    sagemaker_estimator,  
    objective_metric_name,  
    hyperparameter_ranges,  
    max_jobs=20,  
    max_parallel_jobs=20,  
    strategy="Random"  
)
```

# Amazon SageMaker Automatic Model Tuning

## Can I use hyperparameter tuning with my own model ?

1

Built-in  
Algorithms

2

Docker

3

Script Mode

Fully Customizable



# Amazon SageMaker Automatic Model Tuning

## Can I use hyperparameter tuning with my own model ?

### Setting the hyperparameters

```
In [5]: hyperparameters = dict(batch_size=32, data_augmentation=True, learning_rate=.0001,  
                                width_shift_range=.1, height_shift_range=.1, epochs=1)  
hyperparameters
```

```
Out[5]: {'batch_size': 32,  
         'data_augmentation': True,  
         'learning_rate': 0.0001,  
         'width_shift_range': 0.1,  
         'height_shift_range': 0.1,  
         'epochs': 1}
```

Docker



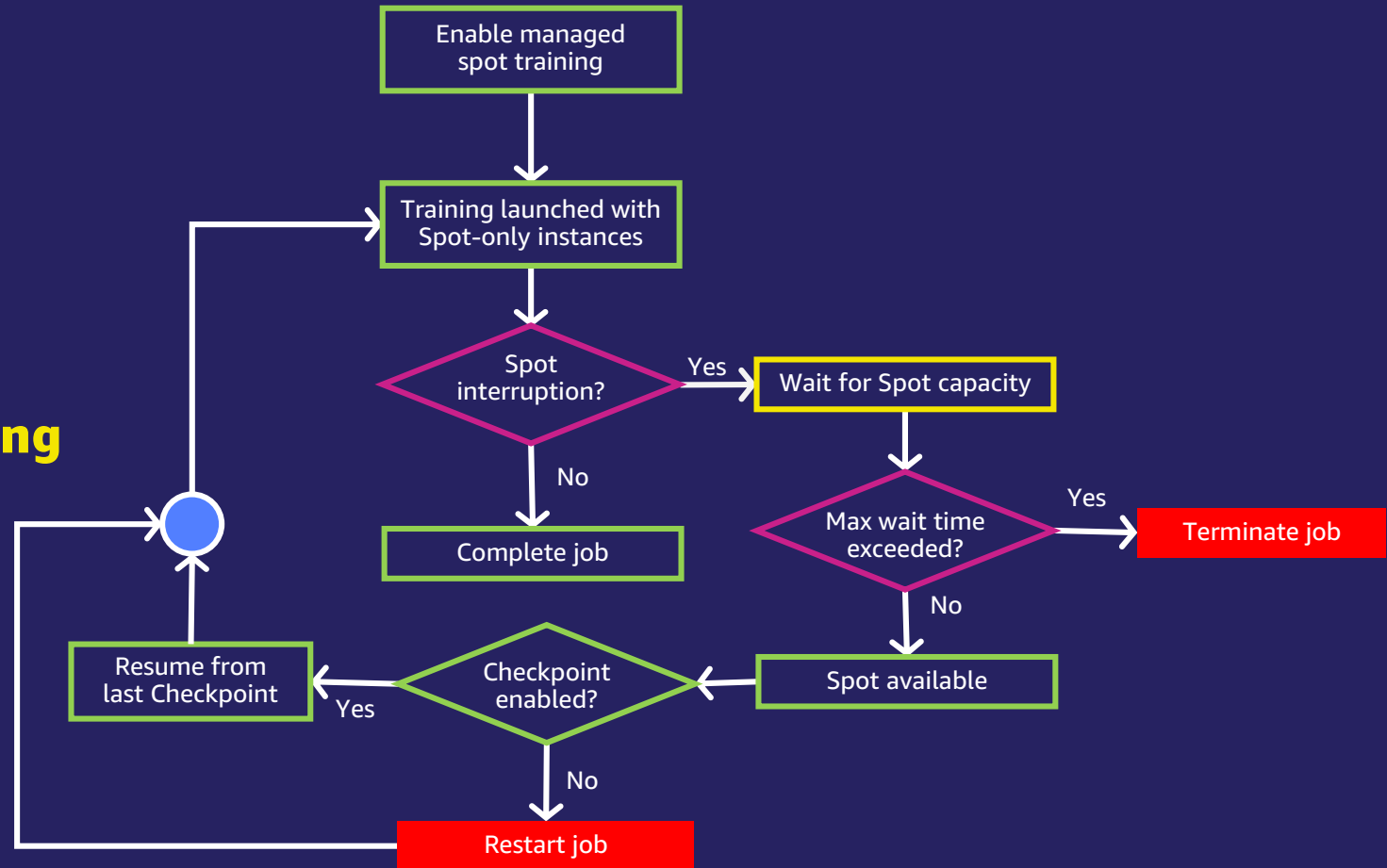
Script Mode



# Managed Spot Training

# Managed Spot Training

Save up to 90% on model training costs



# Key considerations



## Training with only Spot

Interrupted jobs resume if checkpointed and if Spot instances become available;  
Jobs restart if not checkpointed\*

Works with Automated Model Tuning

Training jobs can run only with a single instance - type in a single - AZ

Does not integrate with Spot Fleet and Spot Block today



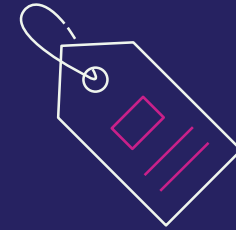
## Checkpoint

Built-in algorithms checkpoint automatically

For custom models, checkpointing should be enabled

Checkpoints are saved to S3

Models that don't checkpoint are subject to *MaxWaitTime* of 60 mins



## Pricing

View savings on AWS console or use DescribeTrainingJob API

Charged for the run duration before completion or termination;  
not charged for idle time, billing starts when instances are ready

Charged for data download time only once even if the job is interrupted multiple times

\* Checkpointing is a best practice and is highly recommended

# Debugger



## **Generate ML models faster**

Detect bottlenecks and issues during training in real-time and correct problems to deploy models faster, with a single, unified tool



## **Optimize resources with no additional code**

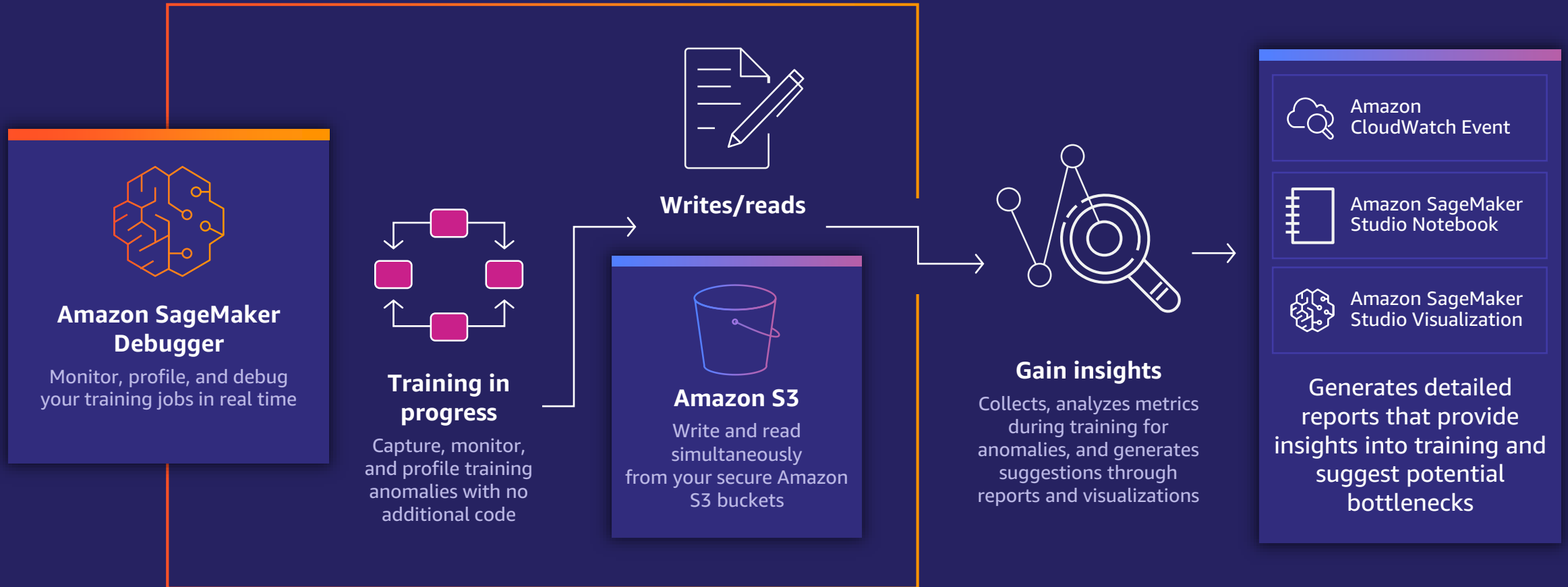
Monitor and profile system resources without code and get recommendations to optimize resources effectively



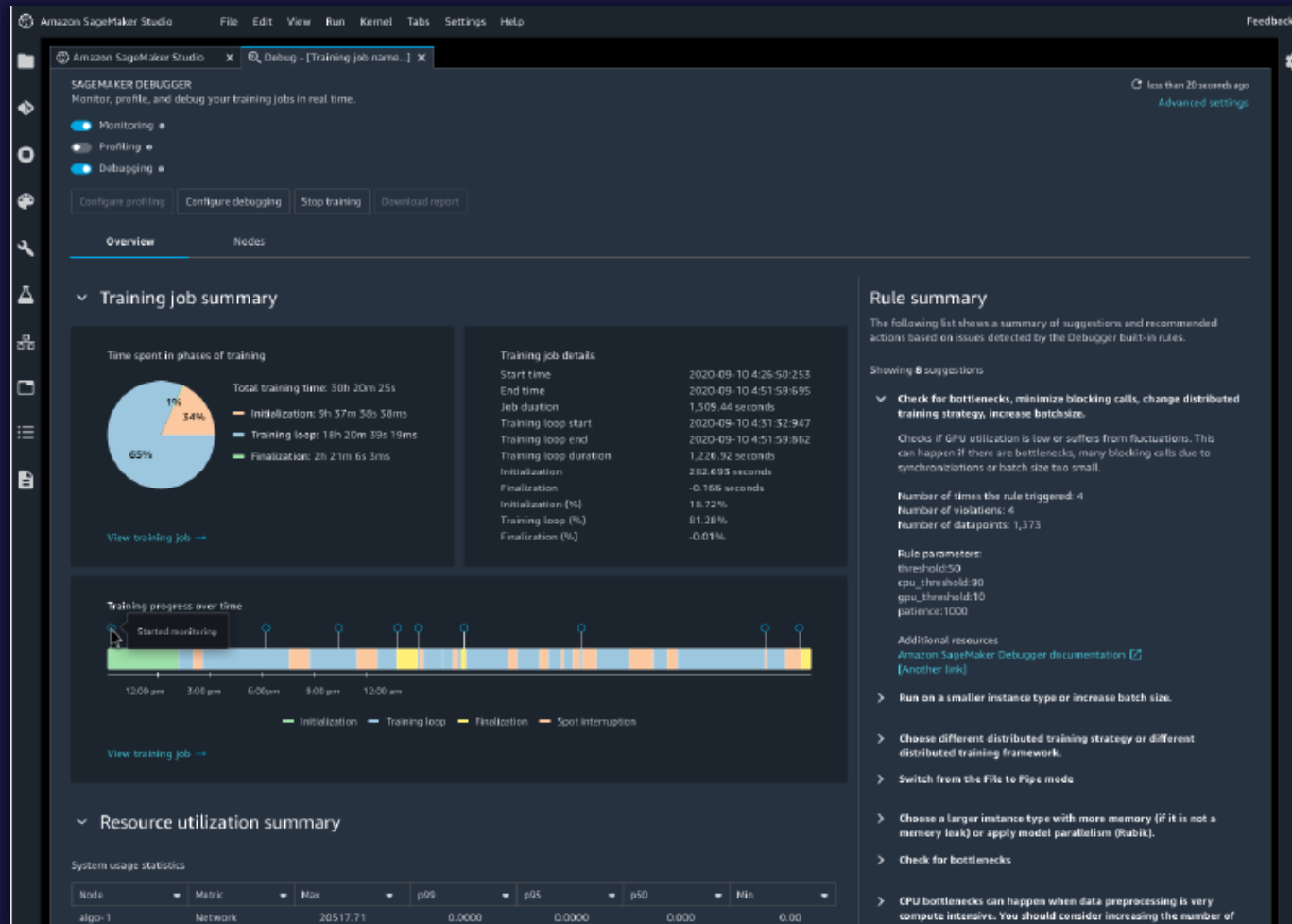
## **Make ML training transparent**

Get complete insights into the ML training process in real-time and offline

# Amazon SageMaker Debugger—How it works

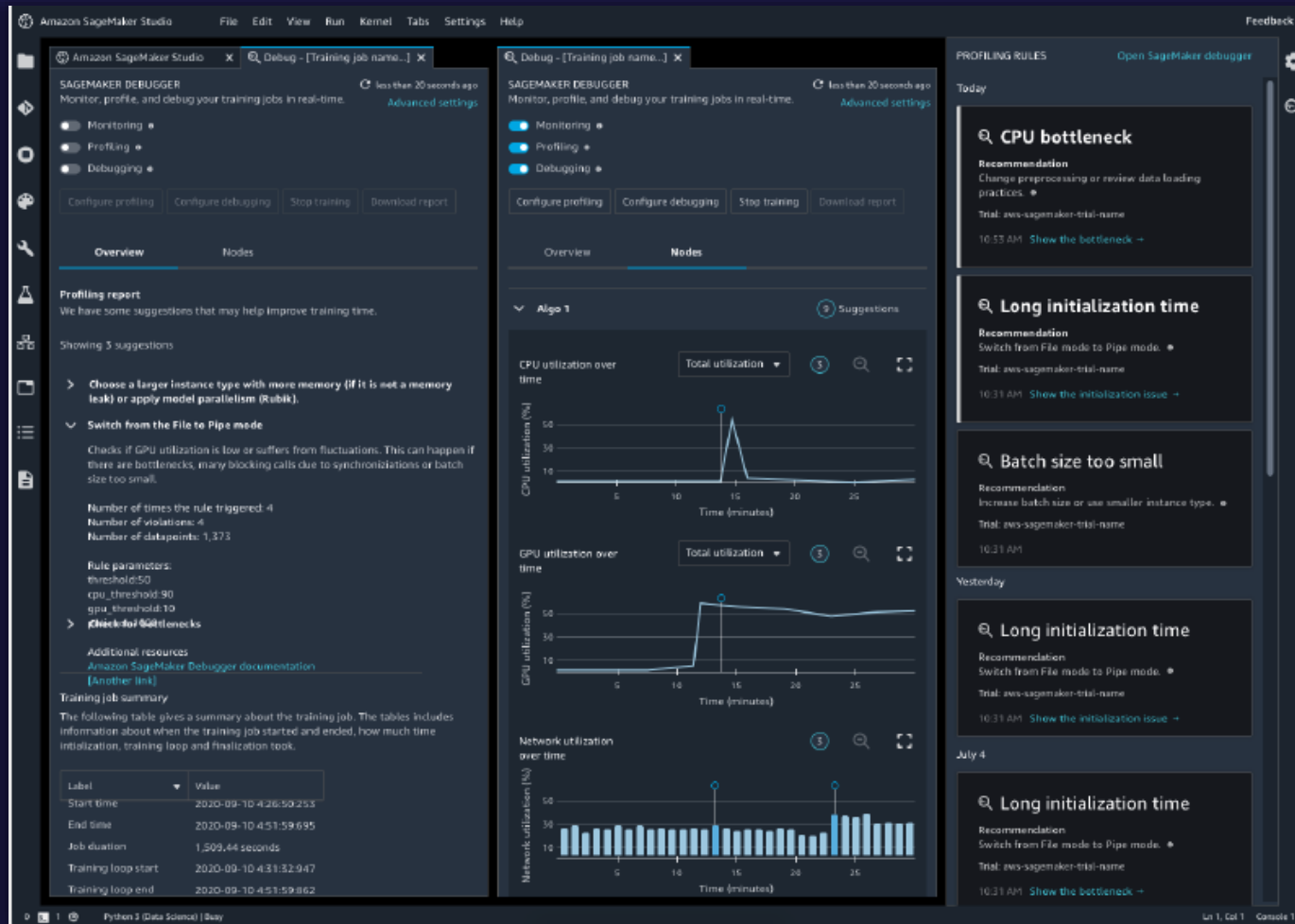


# Monitor and profile system resource utilization



- Automatically monitor system resource utilization
- Profile training jobs to collect ML framework metrics
- Visualize system resource utilization for GPU, CPU, network, memory within SageMaker Studio

# Analyze errors and take action



- Built-in analysis in the form of rules
- Automatically analyze training data including inputs, outputs, tensors
- Detect if a model is overfitting or overtraining, or determine if gradient values are incorrect
- Specify custom actions to stop training or send alerts



# Broad support across algorithms and frameworks



**1 Supports** popular ML algorithms such as XGBoost and deep learning frameworks such as TensorFlow, PyTorch, Apache MXNet, and Keras, with SageMaker built-in containers

**2 Integrated** with AWS Lambda to act on results from alerts

**3 Invoke actions** to automatically stop a training job when you detect a non-converging action such as losses increasing continuously

# Amazon SageMaker

## Next Steps

### Onboarding & Processing

- <https://docs.aws.amazon.com/sagemaker/latest/dg/gs-studio-onboard.html>
- <https://docs.aws.amazon.com/sagemaker/latest/dg/processing-job.html>

### Training

- <https://docs.aws.amazon.com/sagemaker/latest/dg/train-model.html>
- <https://docs.aws.amazon.com/sagemaker/latest/dg/distributed-training.html>
- <https://aws.amazon.com/sagemaker/debugger>

### Deployment

- <https://docs.aws.amazon.com/sagemaker/latest/dg/realtime-endpoints.html>
- <https://docs.aws.amazon.com/sagemaker/latest/dg/serverless-endpoints.html>
- <https://docs.aws.amazon.com/sagemaker/latest/dg/async-inference.html>
- <https://docs.aws.amazon.com/sagemaker/latest/dg/batch-transform.html>

<https://github.com/aws/amazon-sagemaker-examples>

<https://sagemaker.readthedocs.io/en/stable/index.html>

# Q & A



**Please Complete  
the session Survey**



# Thank you!