



Mastering Amazon SageMaker

Distributed Training & Deployment using
Amazon SageMaker

Name: Mani Khanuja

Role: Sr. AI/ML Specialist SA

Email: mankhanu@amazon.com

Agenda

- SageMaker Training Deep Dive
 - Distributed Training
 - SageMaker Inference
 - Autoscaling
 - SageMaker Batch Transform
 - Async Inference
 - SageMaker Inference Pipelines
 - SageMaker Multi-model Endpoints
 - SageMaker Model Monitoring
- Q&A
- Survey

Distributed training

The fastest and easiest way to train large deep learning models



Reduced training time

Reduce training time by 25% with synchronization across GPUs



Optimized for AWS

Achieve near-linear scaling efficiency with data parallelism designed for AWS



Support for popular ML framework APIs

Re-use existing APIs such as Horovod without custom training code



Automatic and efficient model partitioning

Avoid experimentation with automated model profiling and partitioning



Minimal code change

Implement model parallelism with fewer than 10 lines of code change



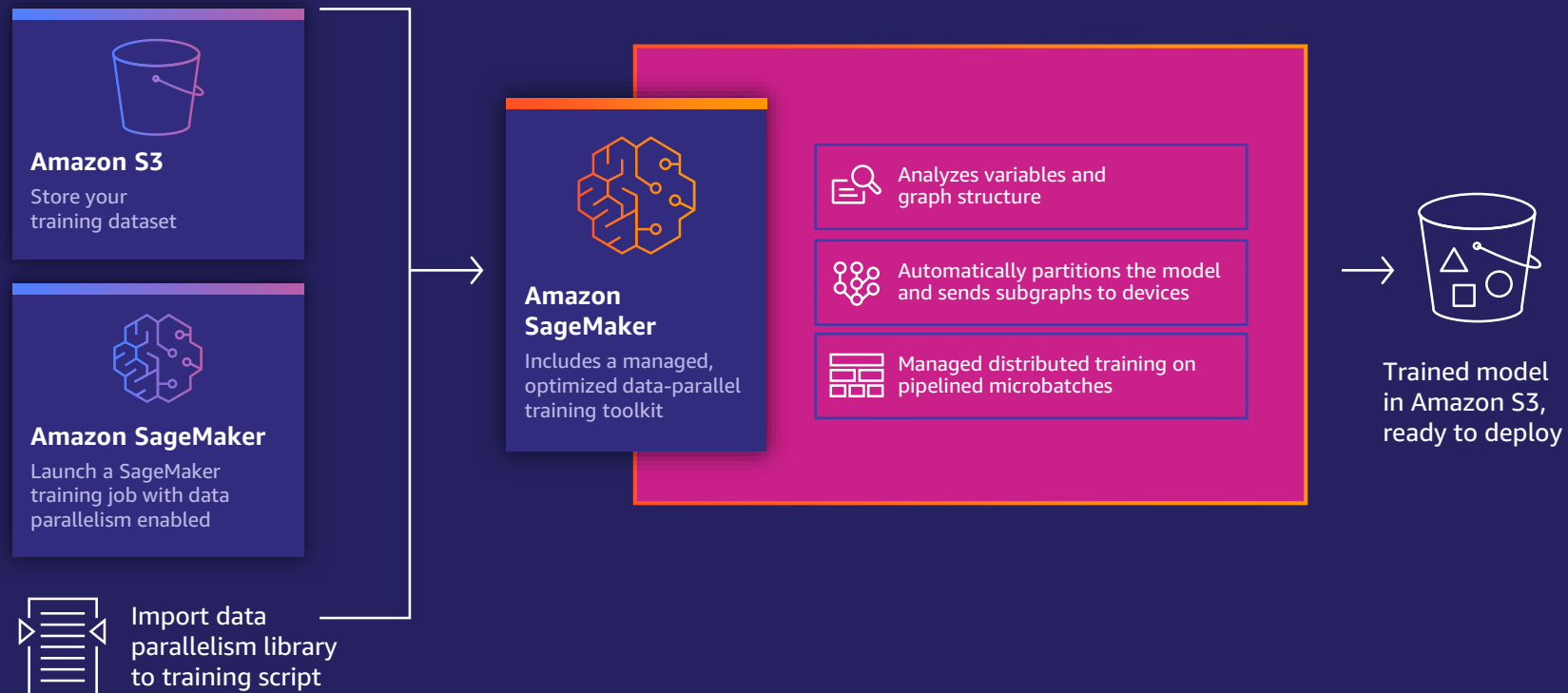
Efficient pipelining

Maximize resource usage with pipelining of micro-batches that keeps all GPUs active

How it works: Data parallelism library



How it works: Model parallelism library



Training time slows down development

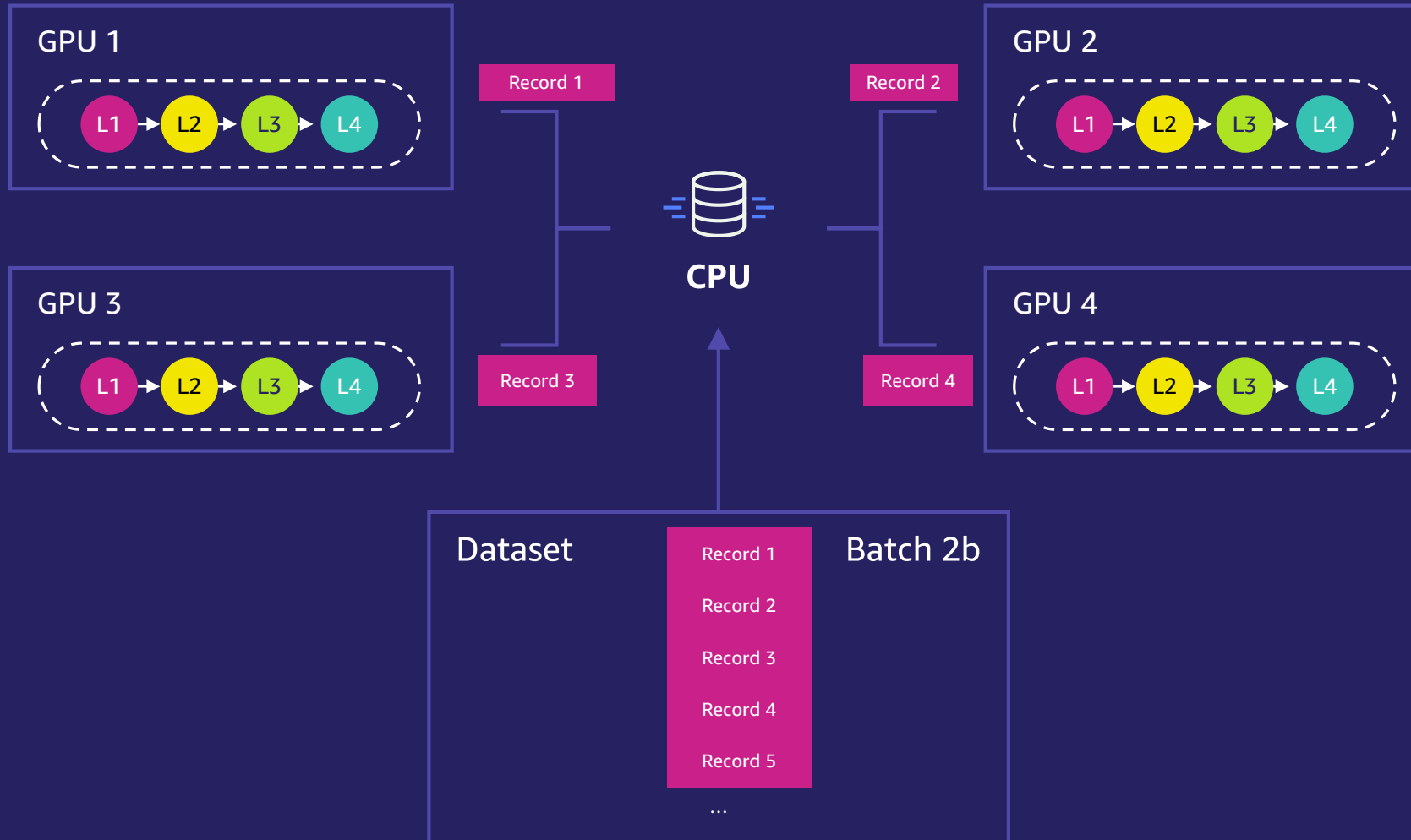


Credit: <https://xkcd.com/303/>



Model	RoBERTa
Dataset	300+ GB
Cluster	64 p3dn.24xl
Training time	Several days

Data parallelism in a nutshell



Model parallel – think “massive models”

Deep learning models are growing in size



MODEL

BERT
GPT-2
T5
GPT-3

RELEASED

Oct 2018
Feb 2019
Oct 2019
Jul 2020

PARAMETERS

340 M
1.5 B
11 B
175 B

But hardware improvements are not keeping up

- **HARDWARE CAPACITY GROWS TOO - BUT NOT AS FAST**



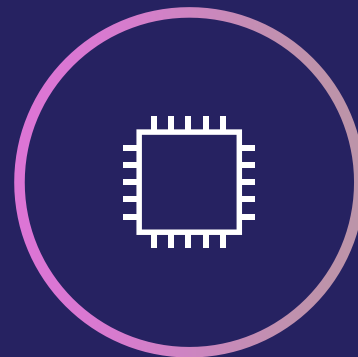
INSTANCE TYPE

P2.16xlarge
P3.16xlarge
P3dn.24xlarge
P4d.24xlarge



AVAILABLE

Sep 2016
Oct 2017
Dec 2018
Nov 2020



GPU

NVIDIA K80
NVIDIA V100
NVIDIA V100
NVIDIA A100



GPU MEMORY

12 GB
16 GB
32 GB
40 GB

The speed of model size growth is outpacing hardware improvements, leading to memory bottlenecks.

Memory bottlenecks in training large models

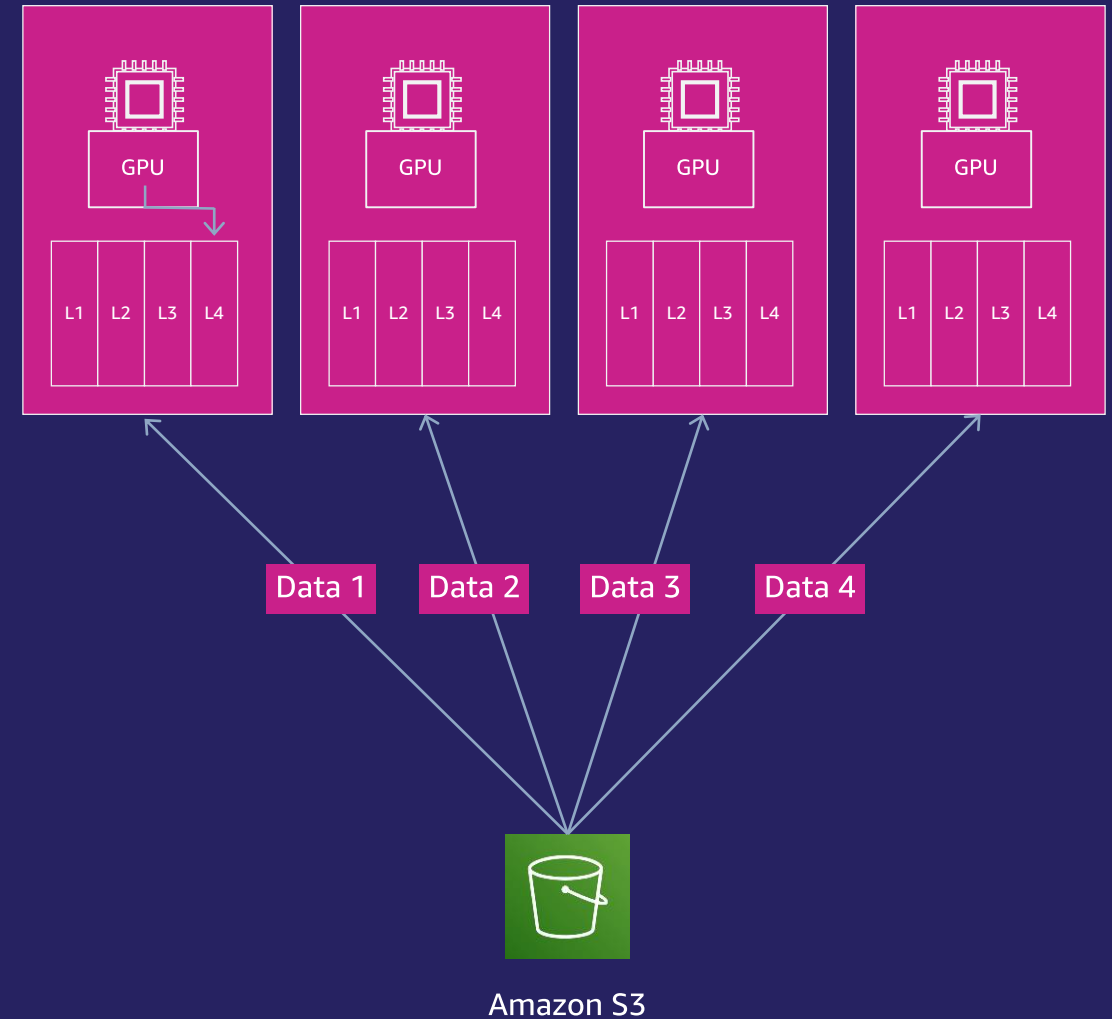
Model sizes can be limited by memory of a single GPU

- Large models cause OOM errors

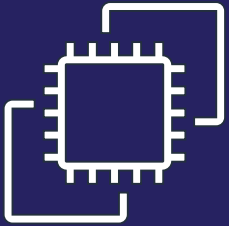
Naive approaches to model parallel replicate the entire model across all GPUS

- Wasteful when model is large, gets you even more OOM errors

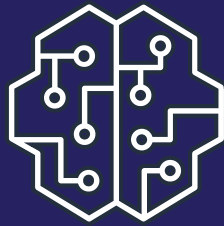
Hardware limitations without optimal usage can limit both research and applications



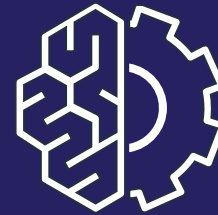
Model parallelism on Amazon SageMaker (SMP)



**Automated
model partitioning**



**Interleaved
pipelined training**



**Managed
SageMaker training**



**Clean
framework integration**

1. Use SMP to automate your model partitioning

ANALYZED MODEL



- Graph structure
- Sizes of trainable weights
- Sizes of exchanged tensors (using SageMaker Debugger)

RUN GRAPH PARTITIONING ALGORITHM



- Balance stored weights and activations
- Minimize communication

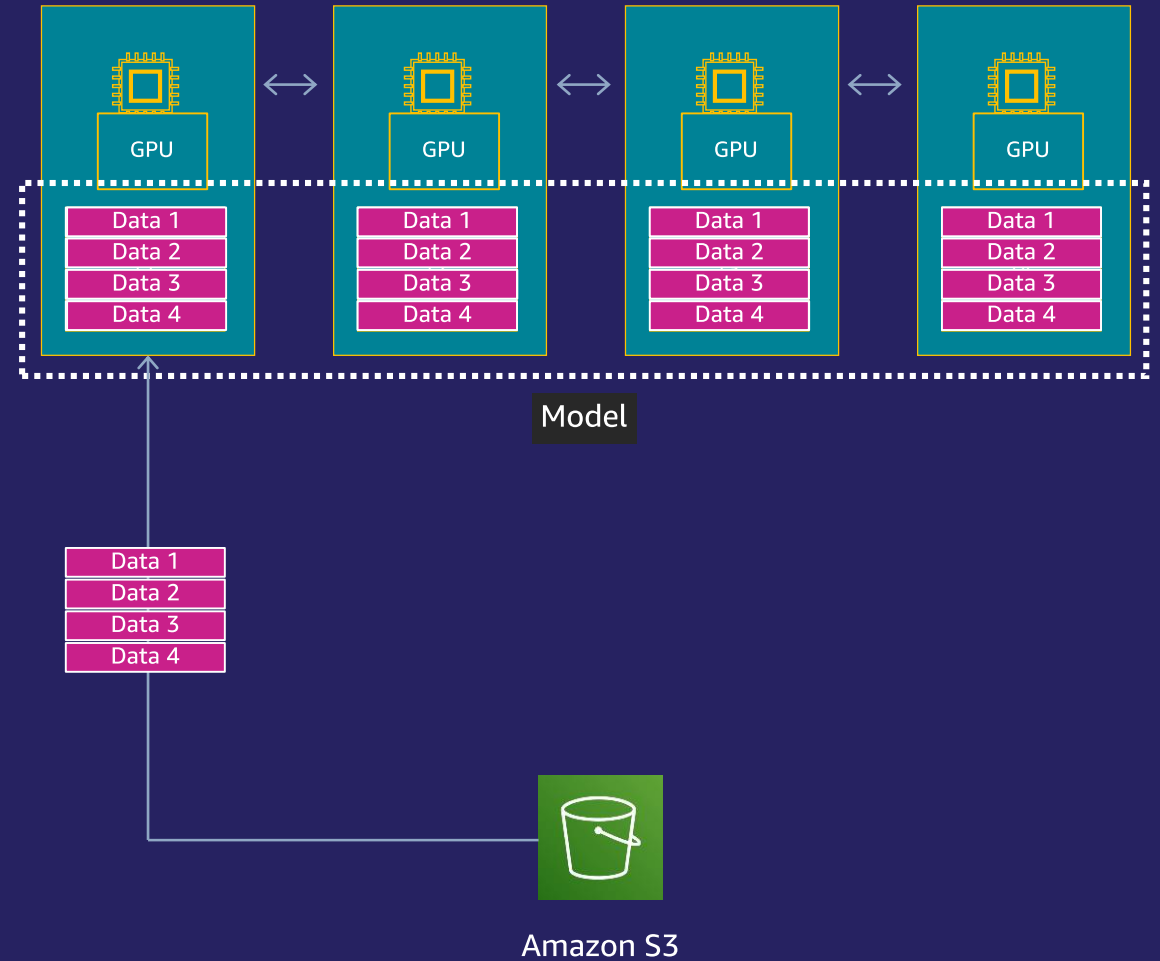
PLACE PARTITIONS ON DEVICES



- To be executed in a pipelined manner

2. Interleave pipeline execution to stabilize GPU utilization

- Split minibatches into N “**microbatches**”
- Feed microbatches sequentially, but process them to keep GPU utilization more even
- Minimize “idle” time on GPUs



SageMaker Hosting Deep Dive

Deploy ML models

Fully managed deployment
for inference at scale



Wide selection of infrastructure

70+ instance types with varying levels of compute and memory to meet the needs of every use case



Single-digit millisecond overhead latency

For use cases requiring real-time responses



Asynchronous inference

Supports large models with long-running processing times



Cost-effective deployment

Multi-model/multi-container endpoints, serverless inference, and elastic scaling



Built-in integration for MLOps

ML workflows, CI/CD, lineage tracking, and catalog



Automatic deployment recommendations

Optimal instance type/count and container parameters, and fully managed load testing

SageMaker inference options

NEW

Real-time inference

Low latency
Ultra high throughput
Multi-model endpoints
A/B testing

Batch transform

Process large datasets
Job-based system

Asynchronous inference

Near real-time
Large payloads (1 GB)
Long timeouts (15 mins)

Serverless Inference

Fully managed offering



Managed infrastructure

Security
Monitoring
Logging
Built in availability
and fault tolerance



Serverless

No need to select instance
types or provision capacity
Choose memory options based
on inference processing needs

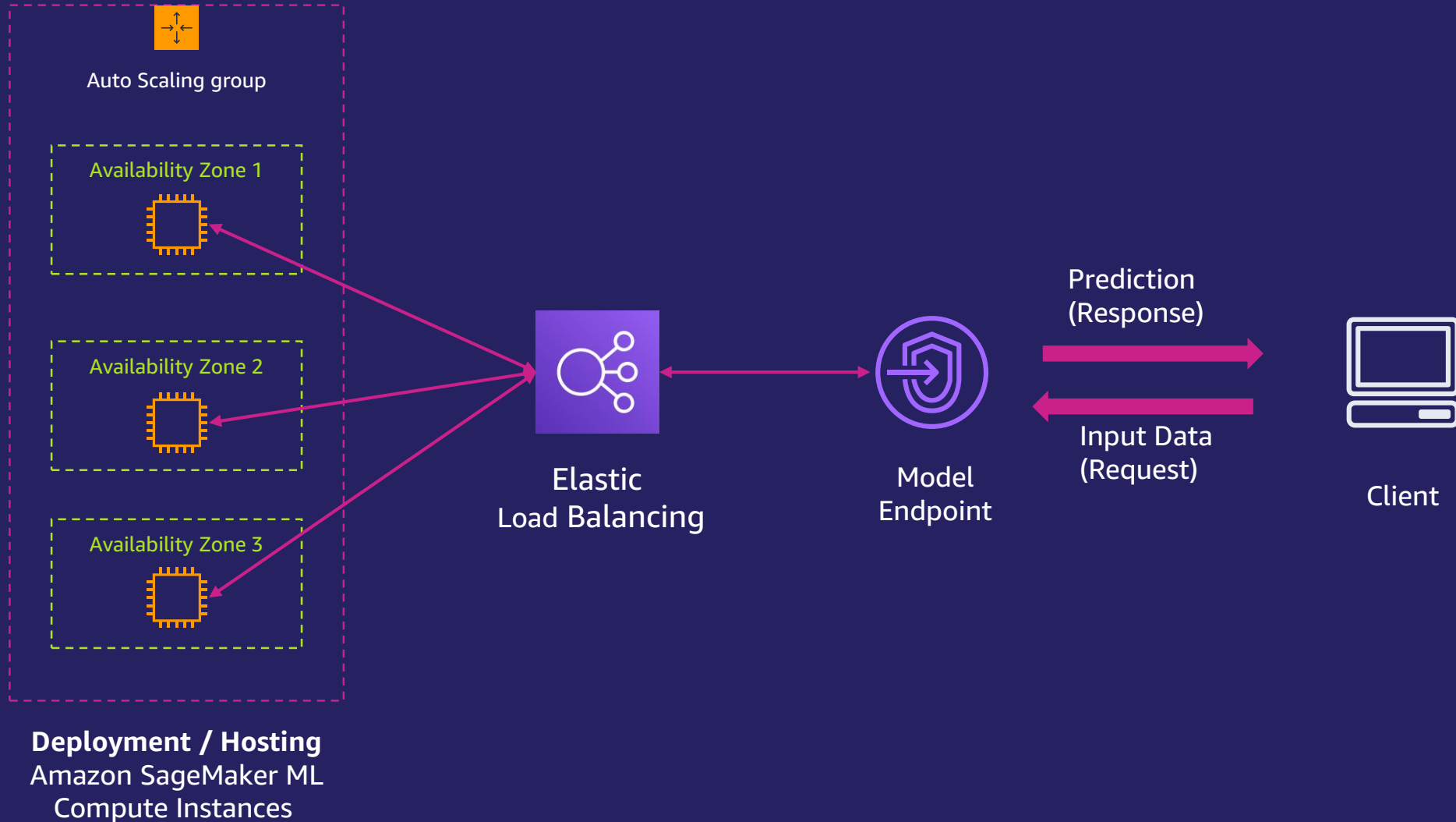


Automatically scale out, in, and down to 0

No need to set
scaling policies

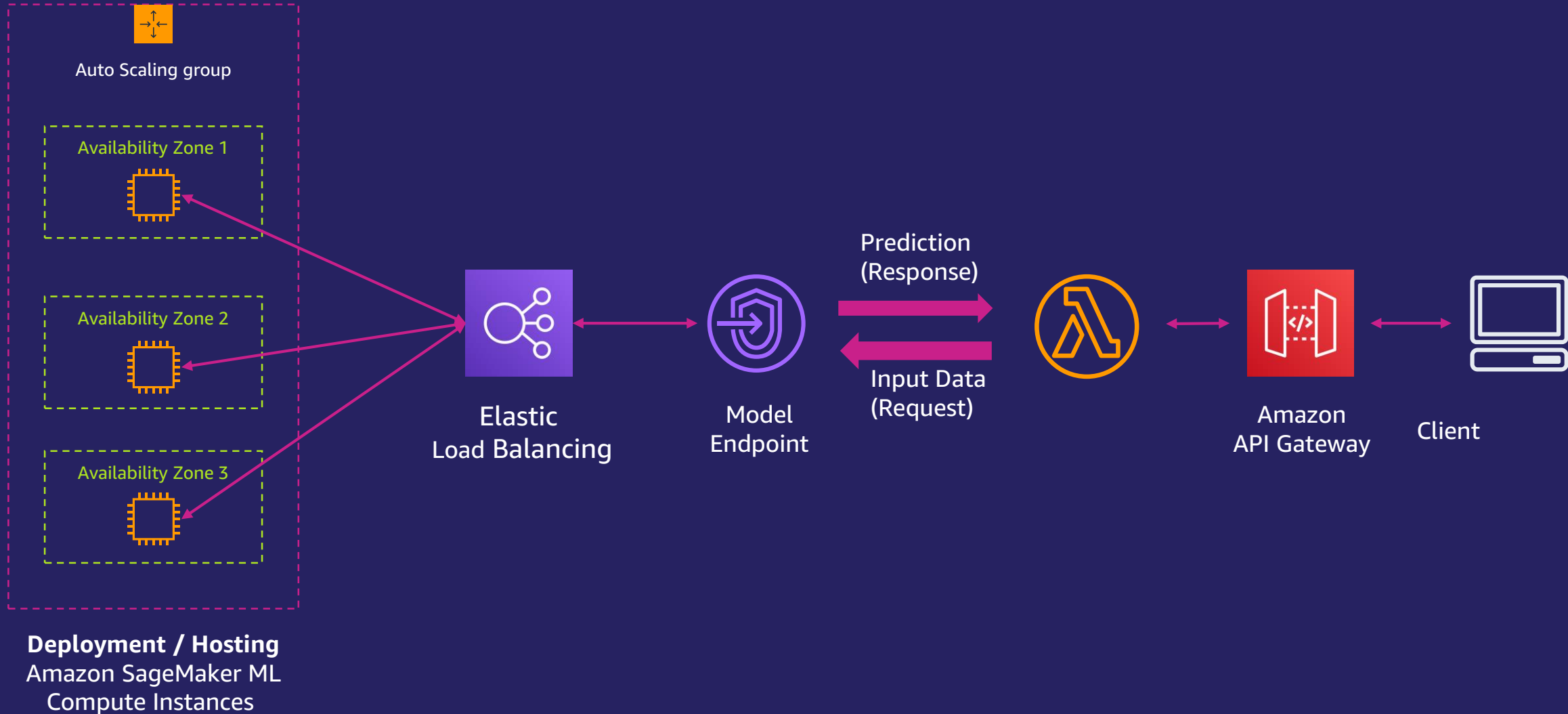
Amazon SageMaker Deployment

SageMaker Endpoints (Private API)



Amazon SageMaker Deployment

SageMaker Endpoints (Public API)



Real time Inference

```
from time import gmtime, strftime
from sagemaker.tensorflow.model import TensorFlowModel

tensorflow_model = TensorFlowModel(model_data=model_path,
                                   role=role,
                                   framework_version="2.3.1")

endpoint_name = "DEMO-tf2-california-housing-model-monitor-" + strftime(
    "%Y-%m-%d-%H-%M-%S", gmtime()
)

predictor = tensorflow_model.deploy(
    initial_instance_count=1,
    instance_type="ml.m5.xlarge",
    endpoint_name=endpoint_name,
)
```

Serverless Inference

Step1 : Create Model

```
from time import gmtime, strftime

model_name = "xgboost-serverless" + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print("Model name: " + model_name)

# dummy environment variables
byo_container_env_vars = {"SAGEMAKER_CONTAINER_LOG_LEVEL": "20", "SOME_ENV_VAR": "myEnvVar"}

create_model_response = client.create_model(
    ModelName=model_name,
    Containers=[
        {
            "Image": image_uri,
            "Mode": "SingleModel",
            "ModelDataUrl": model_artifacts,
            "Environment": byo_container_env_vars,
        }
    ],
    ExecutionRoleArn=role,
)

print("Model Arn: " + create_model_response["ModelArn"])
```

Step2 : Create Endpoint Configuration

```
xgboost_epc_name = "xgboost-serverless-epc" + strftime("%Y-%m-%d-%H-%M-%S", gmtime())

endpoint_config_response = client.create_endpoint_config(
    EndpointConfigName=xgboost_epc_name,
    ProductionVariants=[
        {
            "VariantName": "byoVariant",
            "ModelName": model_name,
            "ServerlessConfig": {
                "MemorySizeInMB": 4096,
                "MaxConcurrency": 1,
            },
        },
    ],
)

print("Endpoint Configuration Arn: " + endpoint_config_response["EndpointConfigArn"])
```

Step3 : Create Endpoint

```
endpoint_name = "xgboost-serverless-ep" + strftime("%Y-%m-%d-%H-%M-%S", gmtime())

create_endpoint_response = client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=xgboost_epc_name,
)

print("Endpoint Arn: " + create_endpoint_response["EndpointArn"])
```

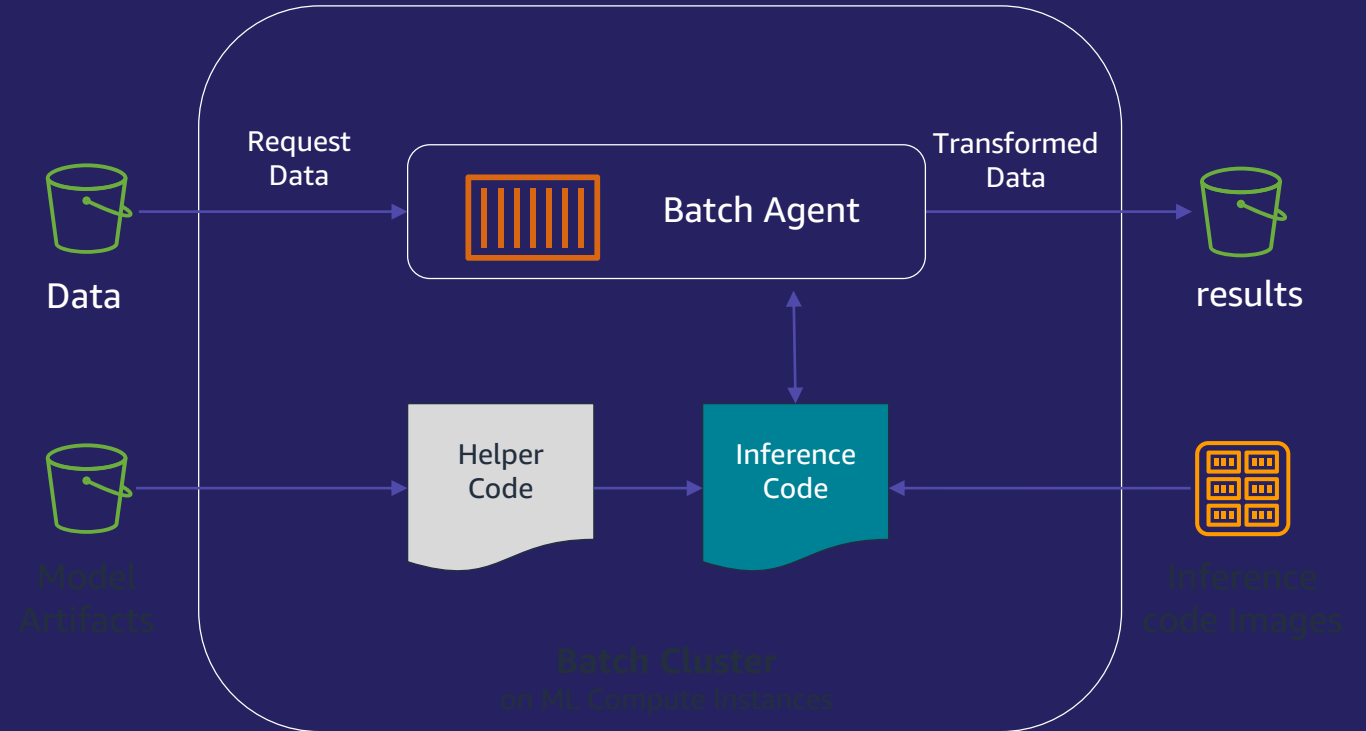
Amazon SageMaker Deployment

Batch Hosting



Batch Transform

- Predictions for an entire dataset
- Transient resources (instances provisioned and terminated once job is done)
- No infrastructure to manage
- Can associate prediction results with input
- Supports Built-In/Bring-Your-Own



Batch Inference

```
from sagemaker.tensorflow import TensorflowModel

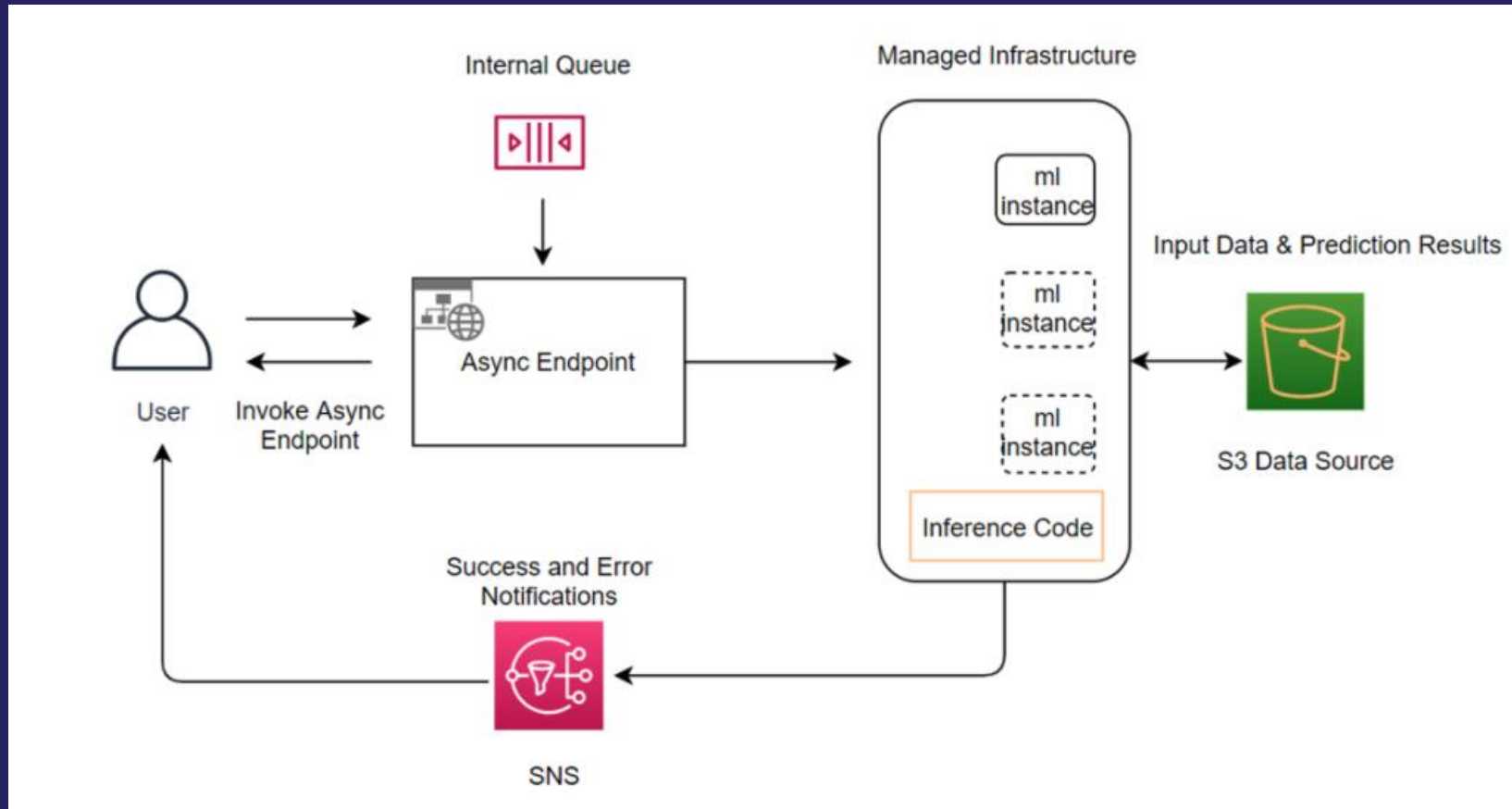
serving = TensorflowModel(
    model_data = 's3 location',
    role=role,
    framework_version="2.3",
    sagemaker_session=sagemaker_session,
    entry_point = 'inference.py',
    source_dir = 'code'
)

input_data_path = "s3://sagemaker-sample-data-{}/tensorflow/california_housing_data/batch.csv".format(
    sagemaker_session.boto_region_name
)
output_data_path = "s3://{}/{}/{}".format(bucket, prefix, "batch-predictions")
batch_instance_count = 2
batch_instance_type = "ml.g4dn.2xlarge"
concurrency = 32
max_payload_in_mb = 1

transformer = serving.transformer(
    instance_count=batch_instance_count,
    instance_type=batch_instance_type,
    max_concurrent_transforms=concurrency,
    max_payload=max_payload_in_mb,
    output_path=output_data_path,
)

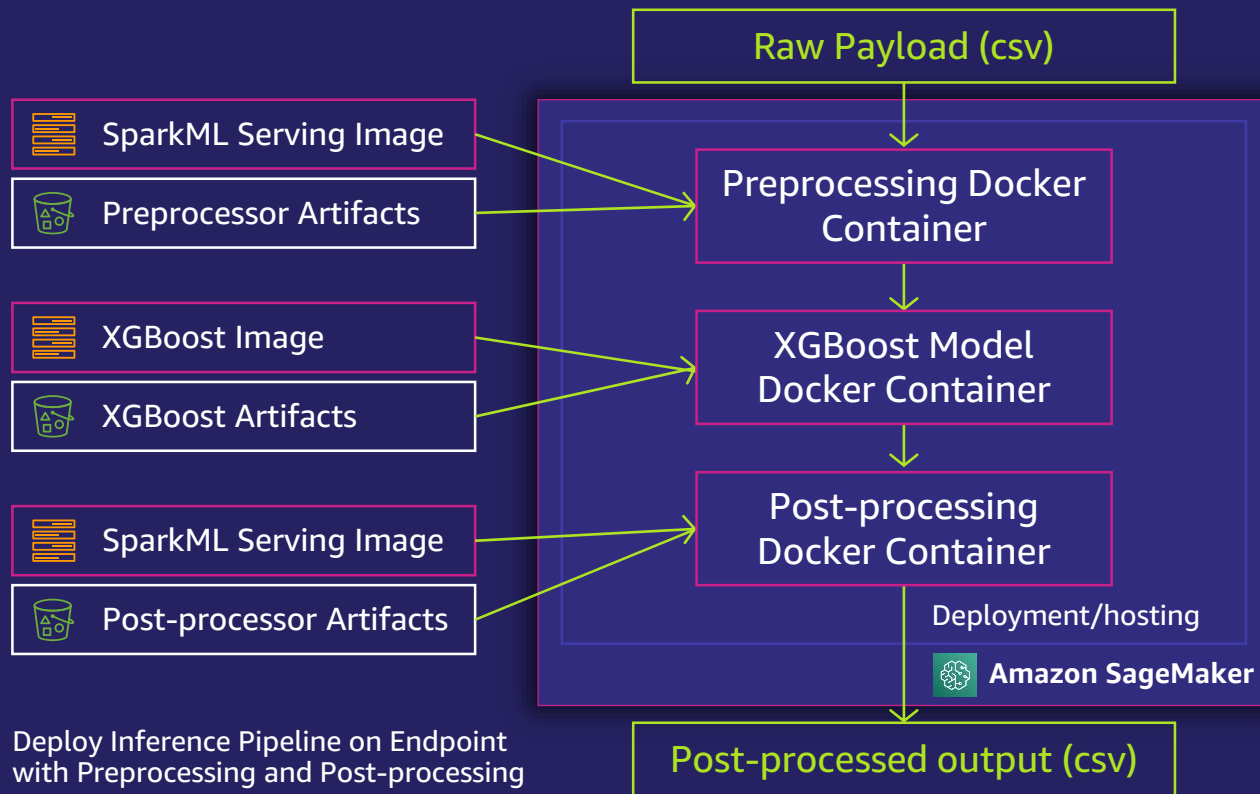
transformer.transform(data=input_data_path, content_type="text/csv")
transformer.wait()
```


Async Inference



Inference Pipelines for sequential execution of models

Execute data processing on inference requests, maintain single copy of data processing code for training and inference



Built-in containers—
Scikit-Learn and
Apache Spark MLlib

Add up to 5 containers;
execute sequentially

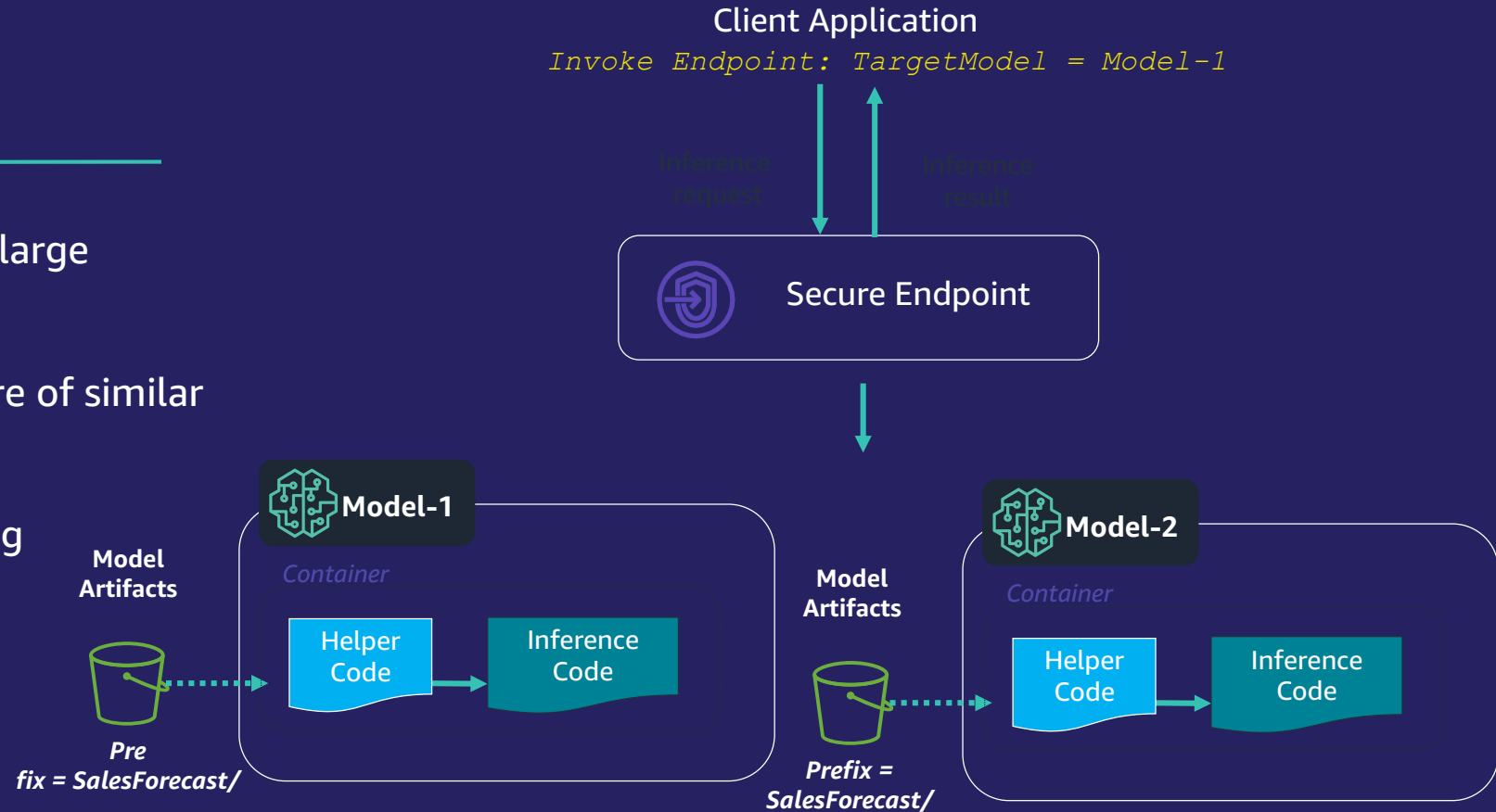
Containers co-located on
instance for low latency

Amazon SageMaker Deployment

Multi-Model Endpoints

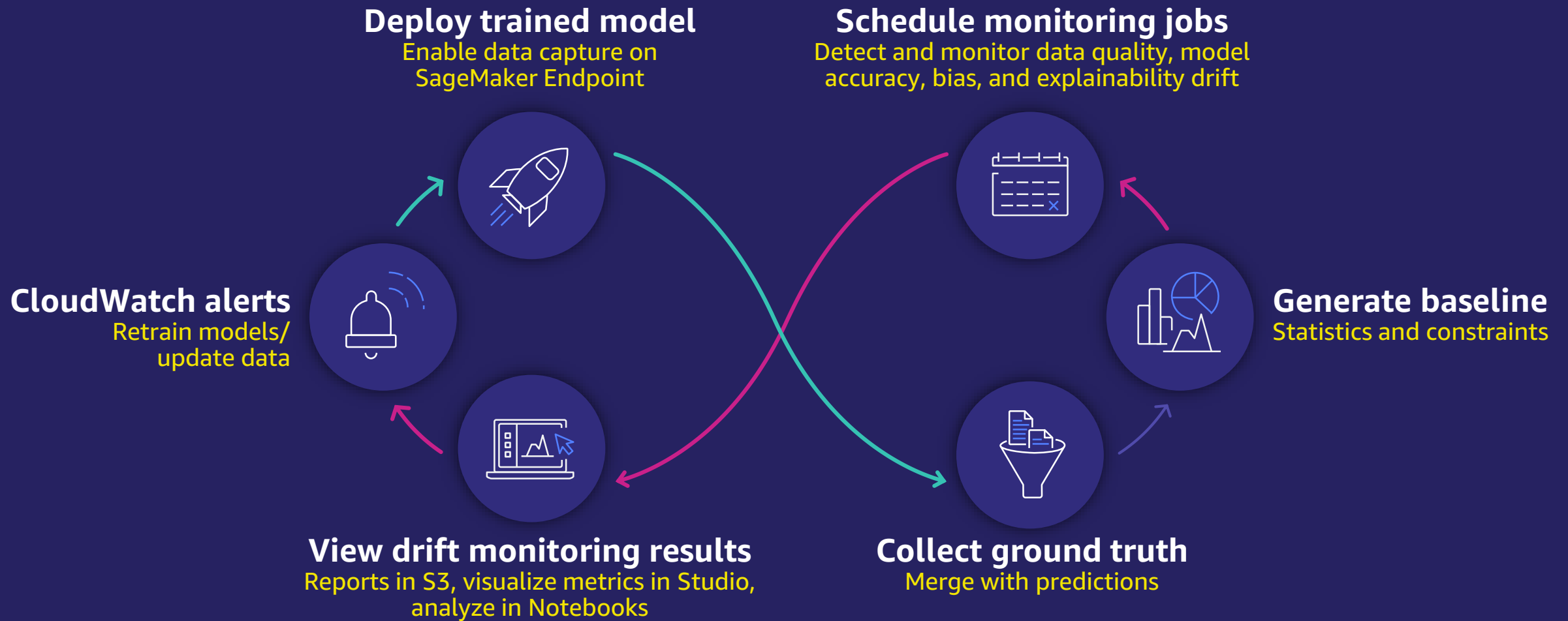


- Scalable/Cost Effective for large number of models
- Works best when models are of similar size and latency
- Automatic memory handling



SageMaker Model Monitoring

Model Monitor: how it works



DEMO

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!