Copyright Notice

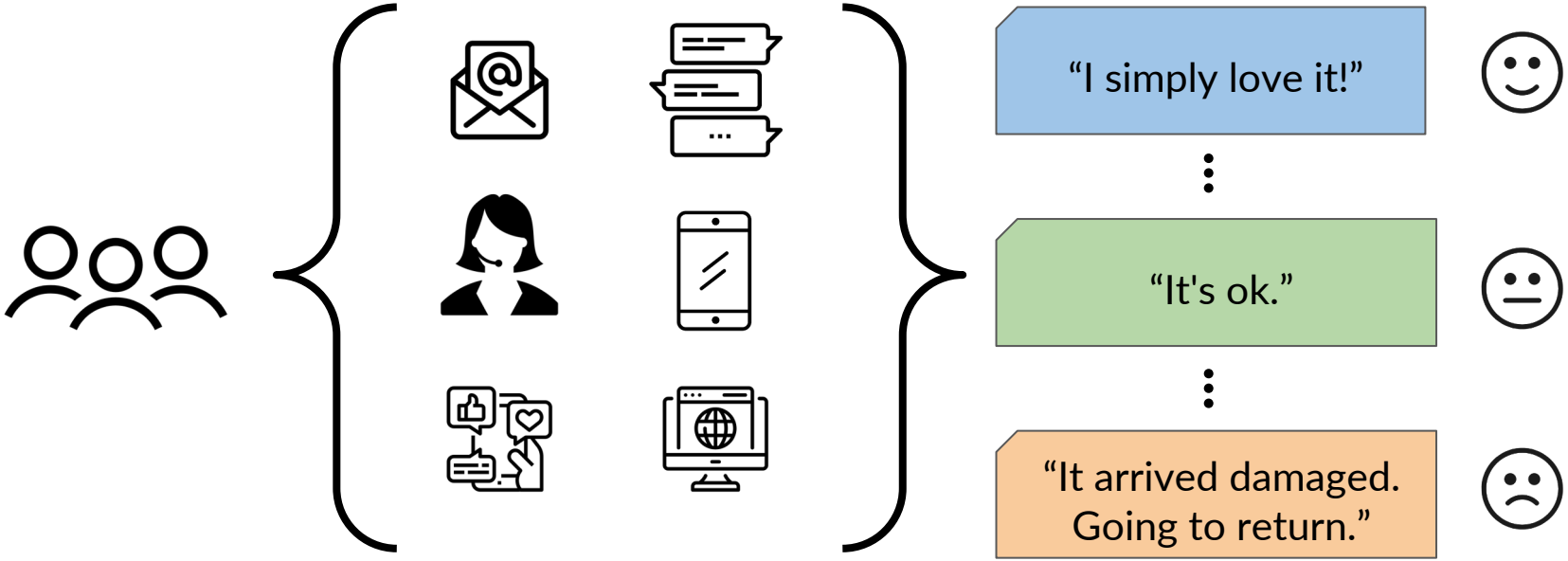
DeepLearning.AI

Train and Debug a Custom Machine Learning Model

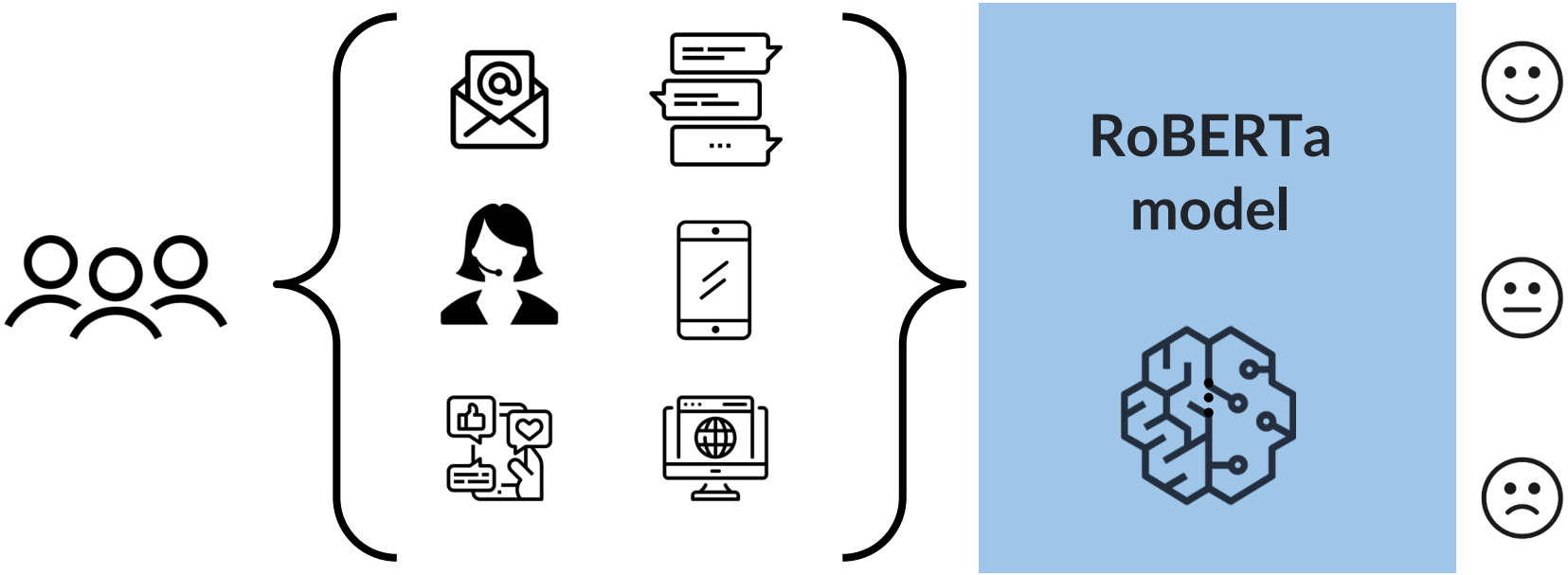
Machine Learning Workflow

Ingest & Analyze	Prepare & Transform	Train & Tune	Deploy & Manage
Data exploration	Feature engineering	Automated ML	Model deployment
Bias detection	Feature store	Model train and tune	Automated pipelines
Amazon S3 & Amazon Athena	Amazon SageMaker Data Wrangler	Amazon SageMaker Autopilot	Amazon SageMaker Endpoints
AWS Glue	Amazon SageMaker Processing Jobs	Amazon SageMaker Training & Debugger	Amazon SageMaker Batch Transform
Amazon SageMaker Data Wrangler & Clarify	Amazon SageMaker Feature Store	Amazon SageMaker Hyperparameter Tuning	Amazon SageMaker Pipelines

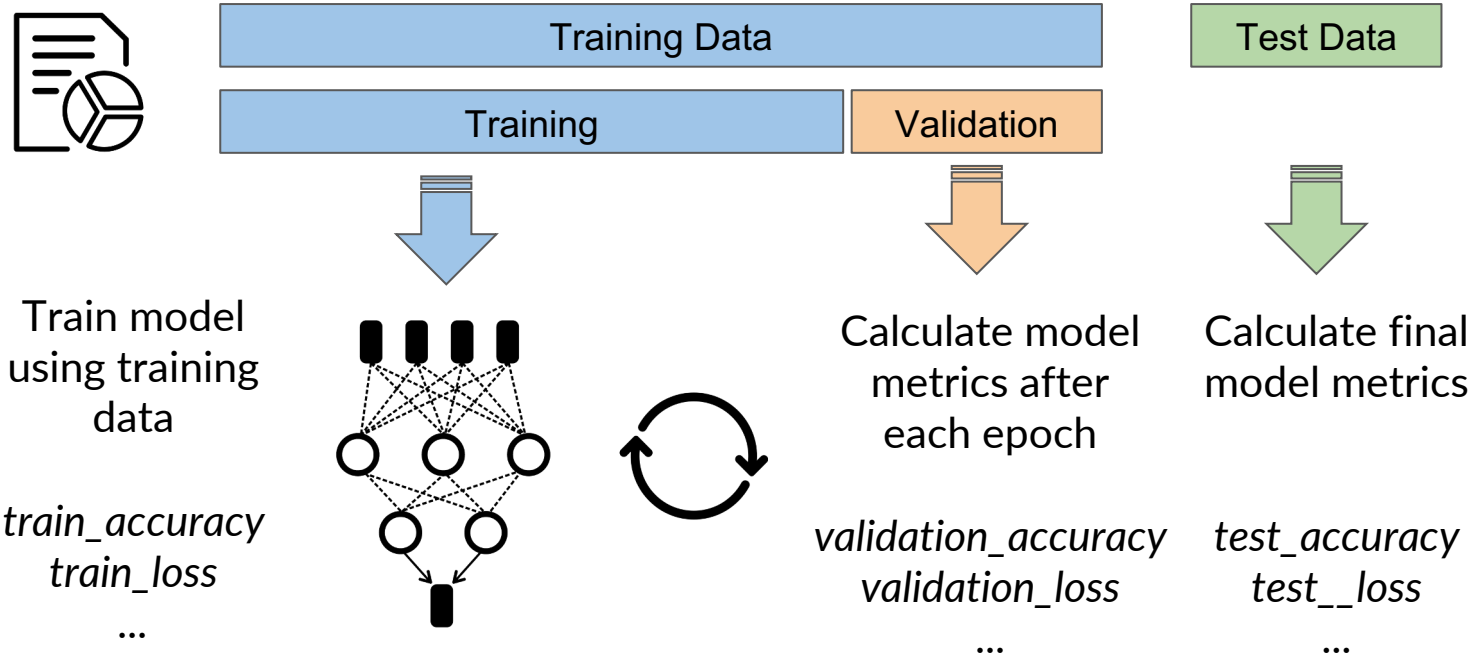
Multi-class classification for sentiment analysis of product reviews



Multi-class classification for sentiment analysis of product reviews

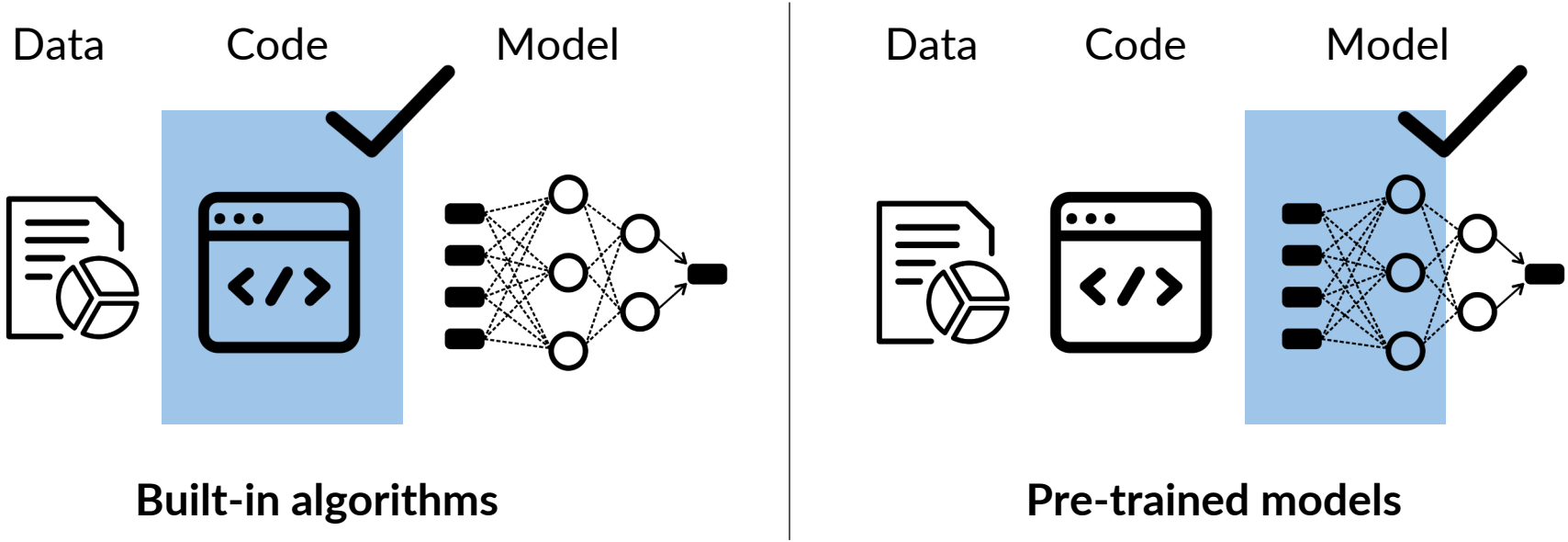


Model training - Fit the model to your data

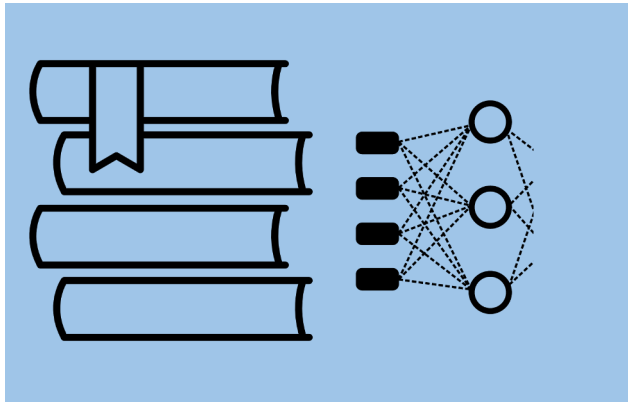


Pre-trained models

Built-in algorithms versus pre-trained models

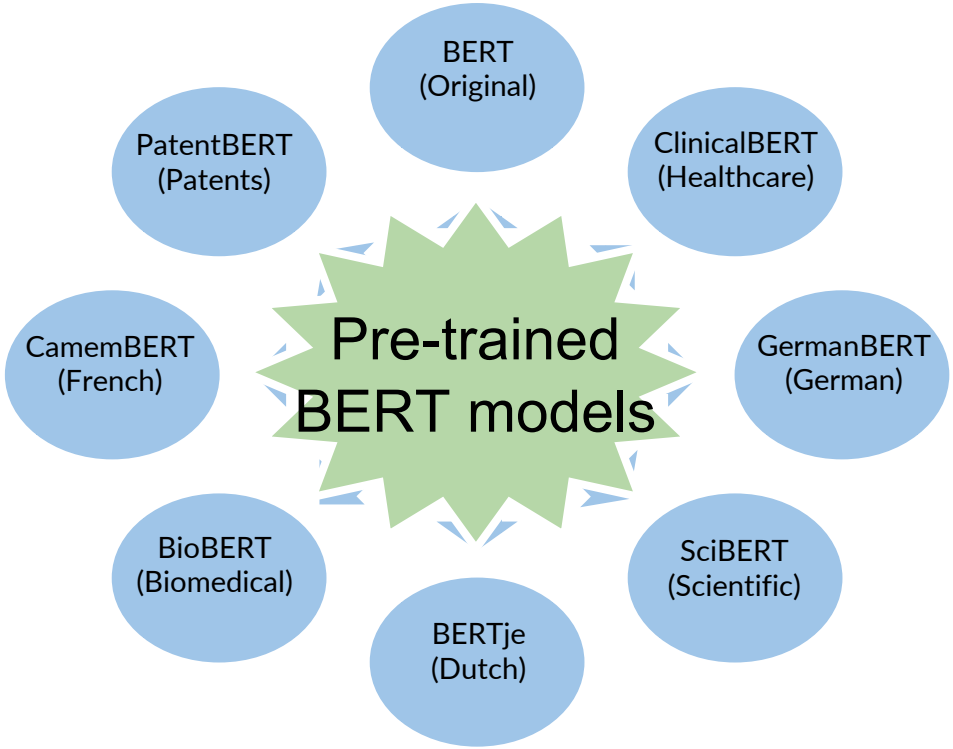


Model pre-training and fine-tuning

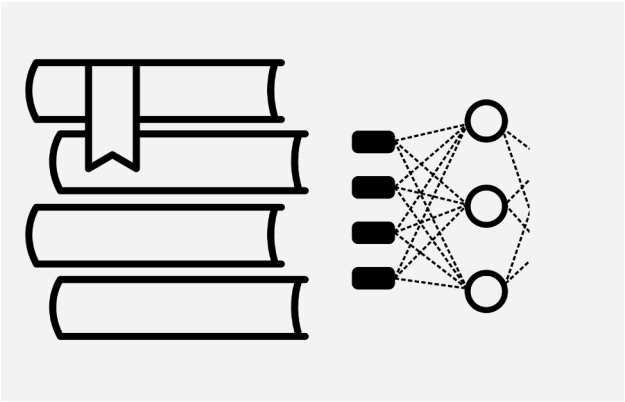


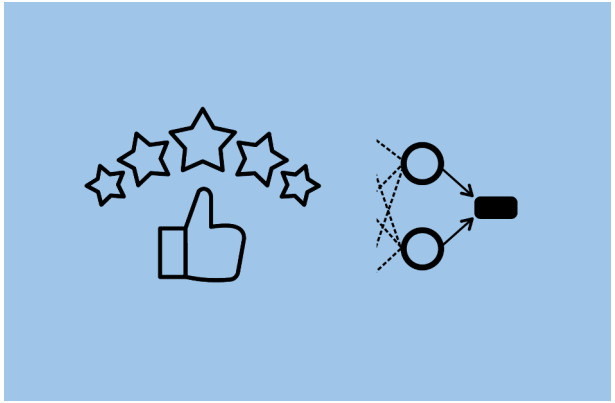
Unsupervised Learning

Pre-Training



Model pre-training and fine-tuning





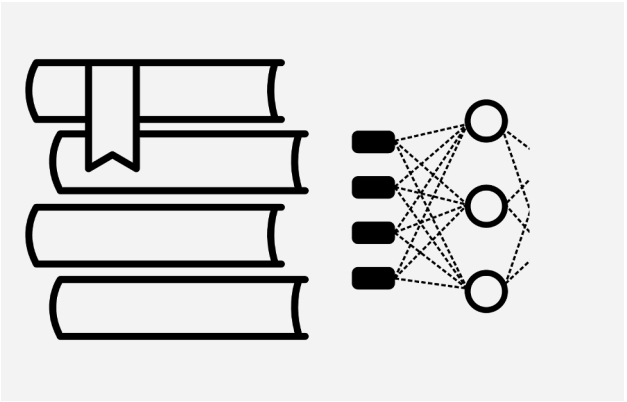
Unsupervised Learning

Pre-Training

Supervised Learning

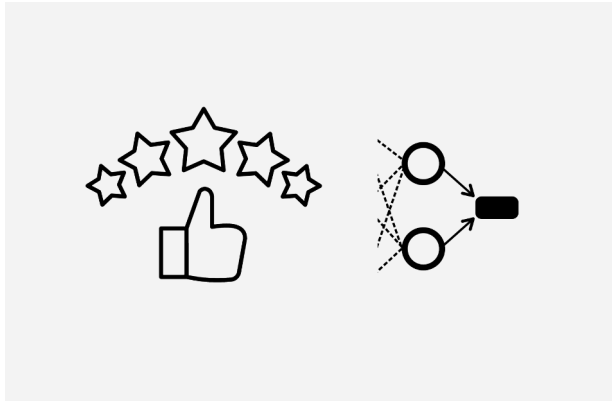
Fine-Tuning

Model pre-training and fine-tuning



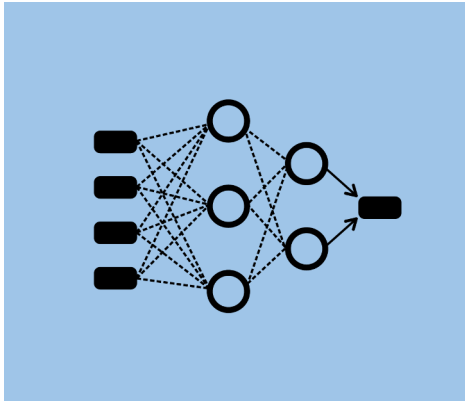
Unsupervised Learning

Pre-Training



Supervised Learning

Fine-Tuning



Fine-Tuned Model

Where to find pre-trained models

Where to find pre-trained models

PyTorch HUB

mxnet

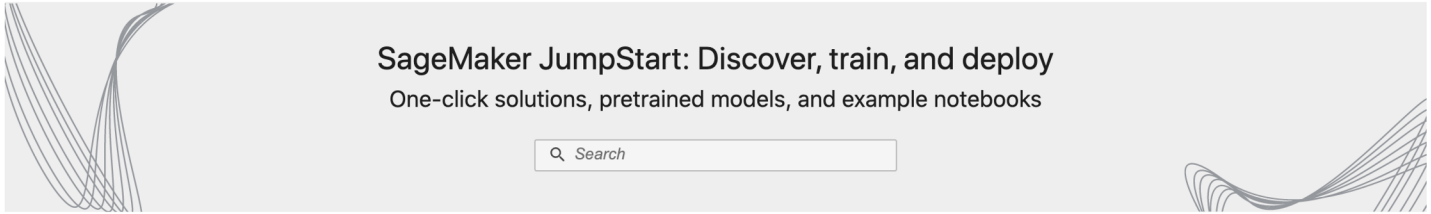
Gluon Model Zoo

TensorFlow Hub

Hugging Face
Model Hub

It has 8000 pre-trained NLP models.

Amazon SageMaker JumpStart

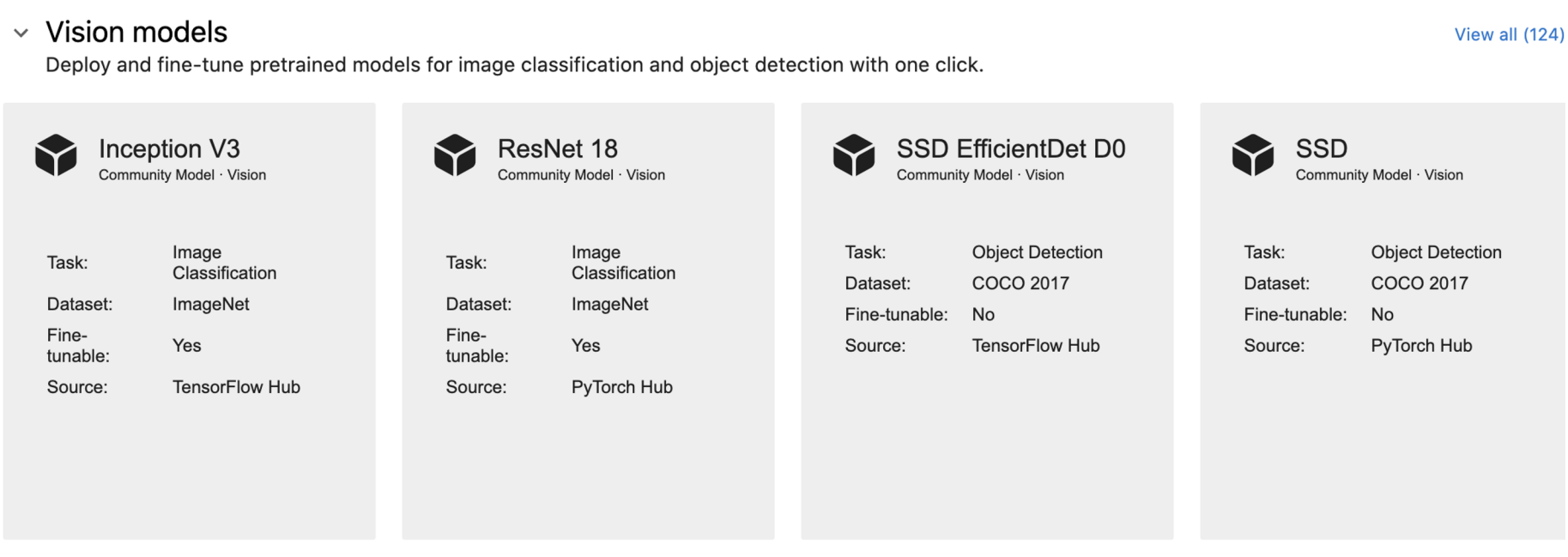


Solutions View all (14)
Launch end-to-end machine learning solutions that tie SageMaker to other AWS services with one click.

Text models View all (39)
Deploy and fine-tune pretrained transformers for various natural language processing use cases.

Vision models View all (124)
Deploy and fine-tune pretrained models for image classification and object detection with one click.

Amazon SageMaker JumpStart vision models



Amazon SageMaker JumpStart text models

Text models

Deploy and fine-tune pretrained transformers for various natural language processing use cases.

View all (39)

BERT Large Cased
Community Model · Text

Task:	Extractive Question Answering
Pre-training Dataset:	English Text
Fine-tunable:	Yes
Source:	PyTorch Hub

RoBERTa Base
Community Model · Text

Task:	Extractive Question Answering
Pre-training Dataset:	English Text
Fine-tunable:	Yes
Source:	PyTorch Hub

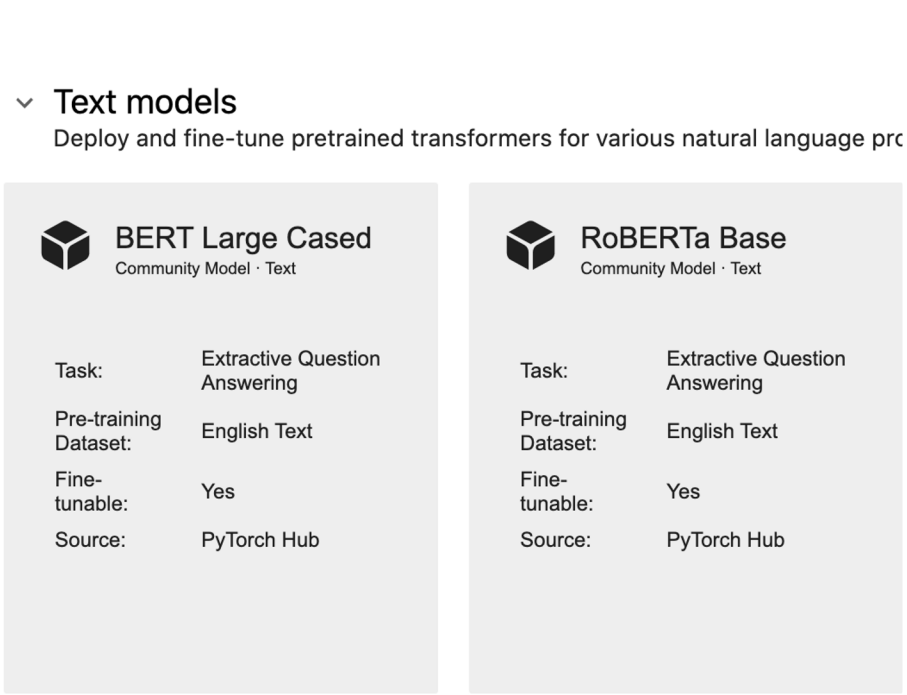
BERT Base Uncased
Community Model · Text

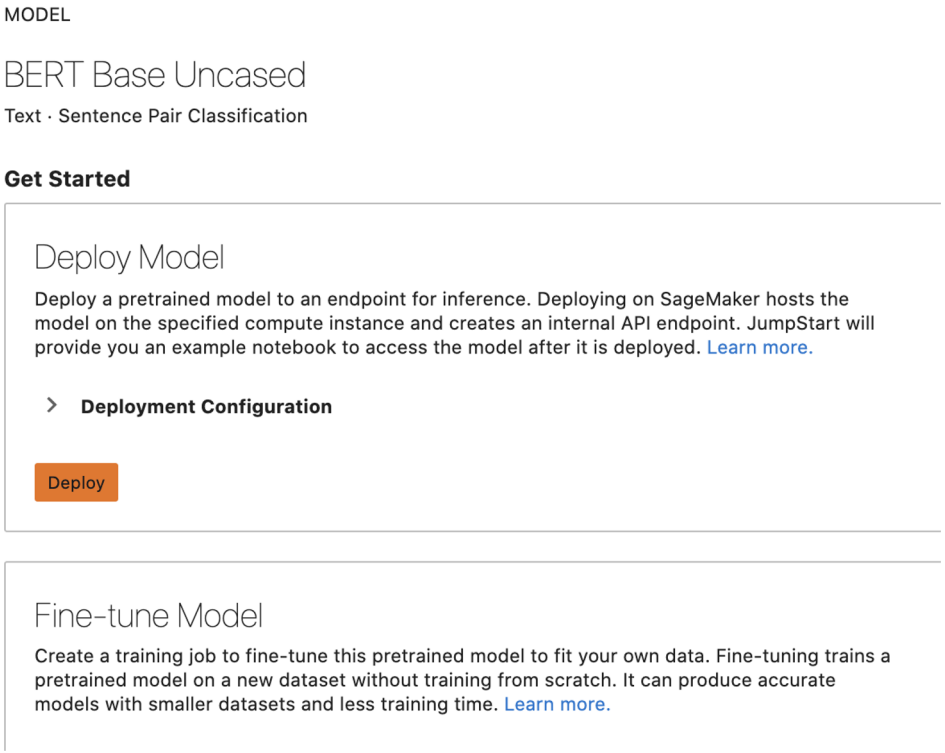
Task:	Extractive Question Answering
Pre-training Dataset:	English Text
Fine-tunable:	Yes
Source:	PyTorch Hub

BERT Base Uncased
Community Model · Text

Task:	Sentence Pair Classification
Pre-training Dataset:	English Text
Fine-tunable:	Yes
Source:	PyTorch Hub

Amazon SageMaker JumpStart text models





Amazon SageMaker JumpStart solutions

Solutions

Launch end-to-end machine learning solutions that tie SageMaker to other AWS services with one click.

View all (14)

Fraud Detection in Financial Transactions

Financial Services

Use Deep Graph Library (DGL) to train a graph neural network model to detect fraud in finacial transactions.

Explain Credit Decisions

Financial Services

Predict credit default in credit applications and provide explanations.

Predictive Maintenance

Manufacturing

Use historical sensor readings to predict the remaining useful life for each sensor.

Detect Malicious Users and Transactions

Financial Services

Automate the detection of potentially fraudulent activity in transactions.

Where to find pre-trained models

PyTorch HUB

mxnet

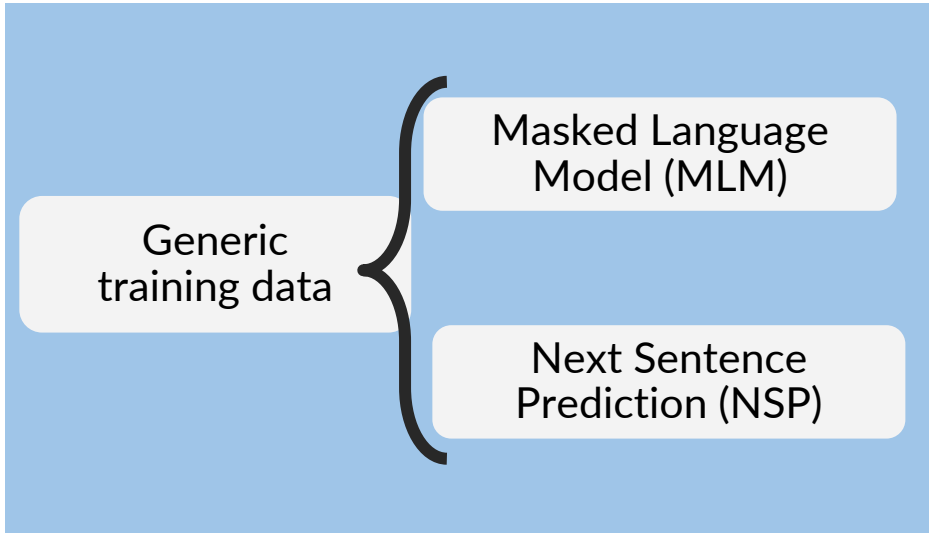
Gluon Model Zoo

TensorFlow Hub

Hugging Face
Model Hub

Pre-trained BERT models

BERT model pre-training and fine-tuning steps



Unsupervised Learning
Pre-Training

BERT model uses Masked Language Model (MLM) and Next Sentence Prediction to learn and understand language.

Masked Language Model (MLM) or Masked LM:
As BERT sees texts, it masks 15% of the words in each sentence.
BERT then predicts the masked words and corrects itself - by updating the model weights when it predicts incorrectly.

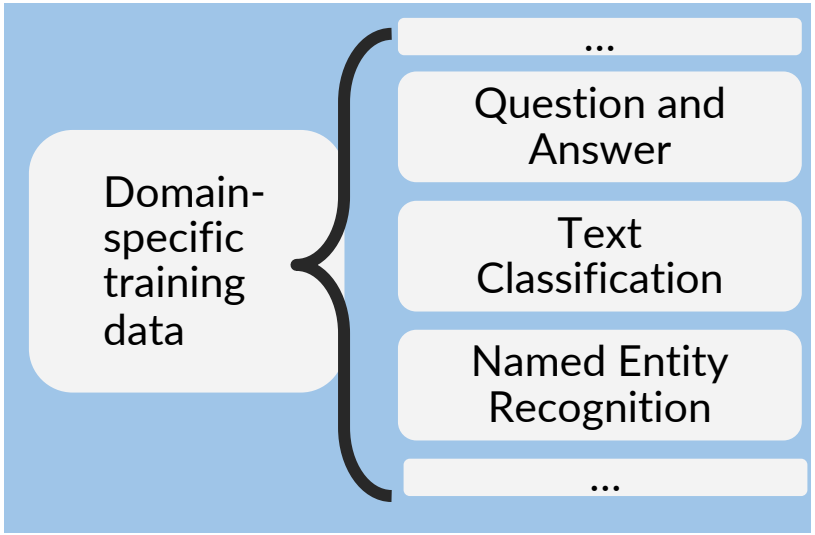
It is also performing Next Sentence Prediction (NSP) on pairs of input sequences.
To perform NSP BERT chooses 50% of the sentence pairs and replaces one of the 2 sentences with a random sentence from another part of the document.
BERT then predicts if the two sentences are a valid sentence pair or not. BERT corrects itself when it predicts incorrectly.

Both of the training tasks are performed in parallel to produce a single accuracy score for the combined training efforts. This results in a more robust model capable of performing word and sentence level predictive tasks.

Note that this pre-training step is implemented as unsupervised learning. The input data is large collections of unlabeled text.

BERT model pre-training and fine-tuning steps

Fine-tuning is implemented as supervised learning and no masking or next sentence prediction happens. Hence, this step is very fast and requires a relatively small number of samples.

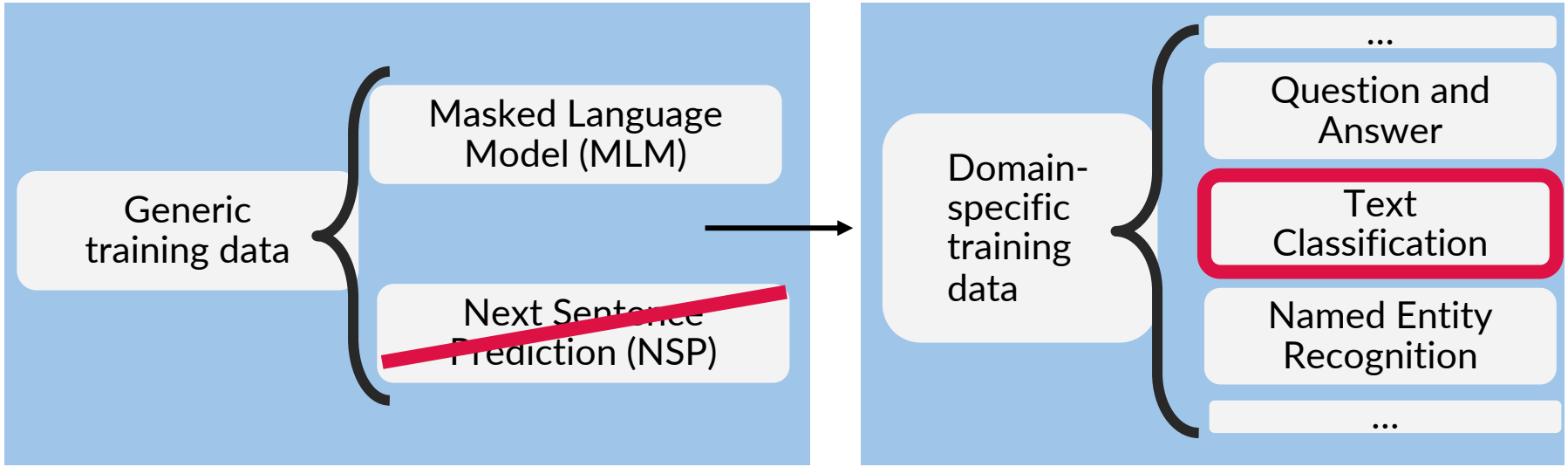


Supervised Learning
Fine-Tuning

RoBERTa model

It builds on BERT's language masking strategy, but removes the next sentence pre-training objective.

It also trains on much larger mini-batches and
learning rates and with a 160GB of text - uses a larger training data.



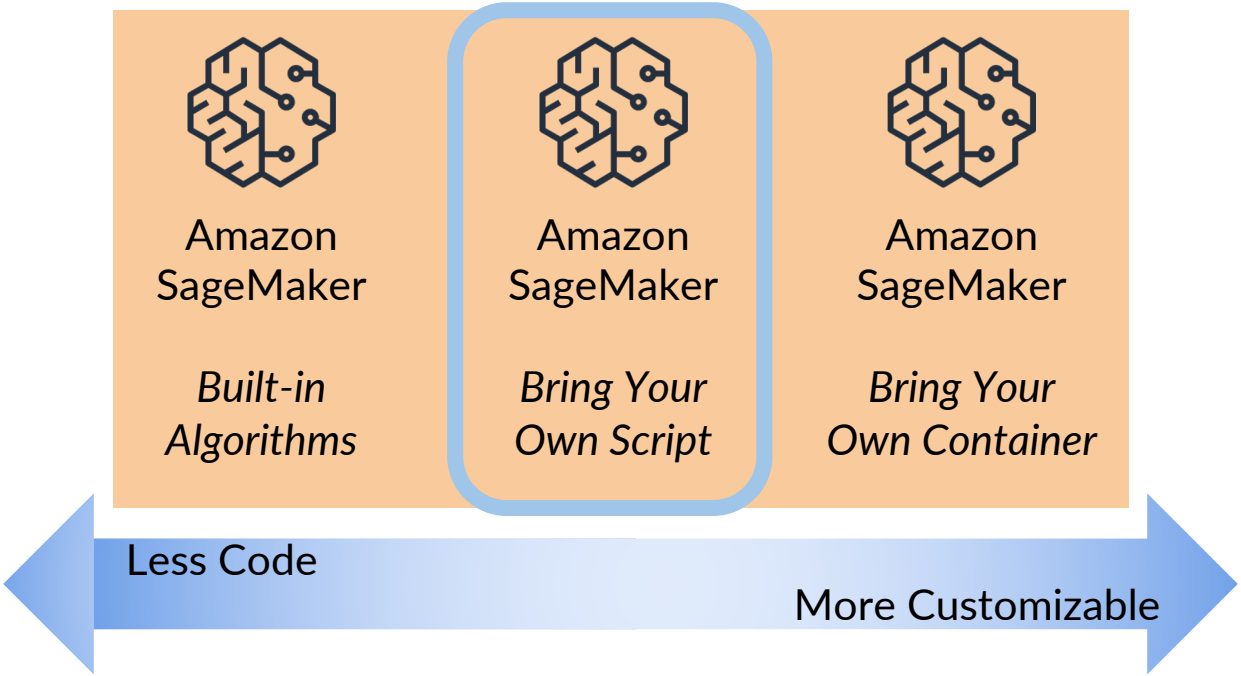
Unsupervised Learning
Pre-Training

Supervised Learning
Fine-Tuning

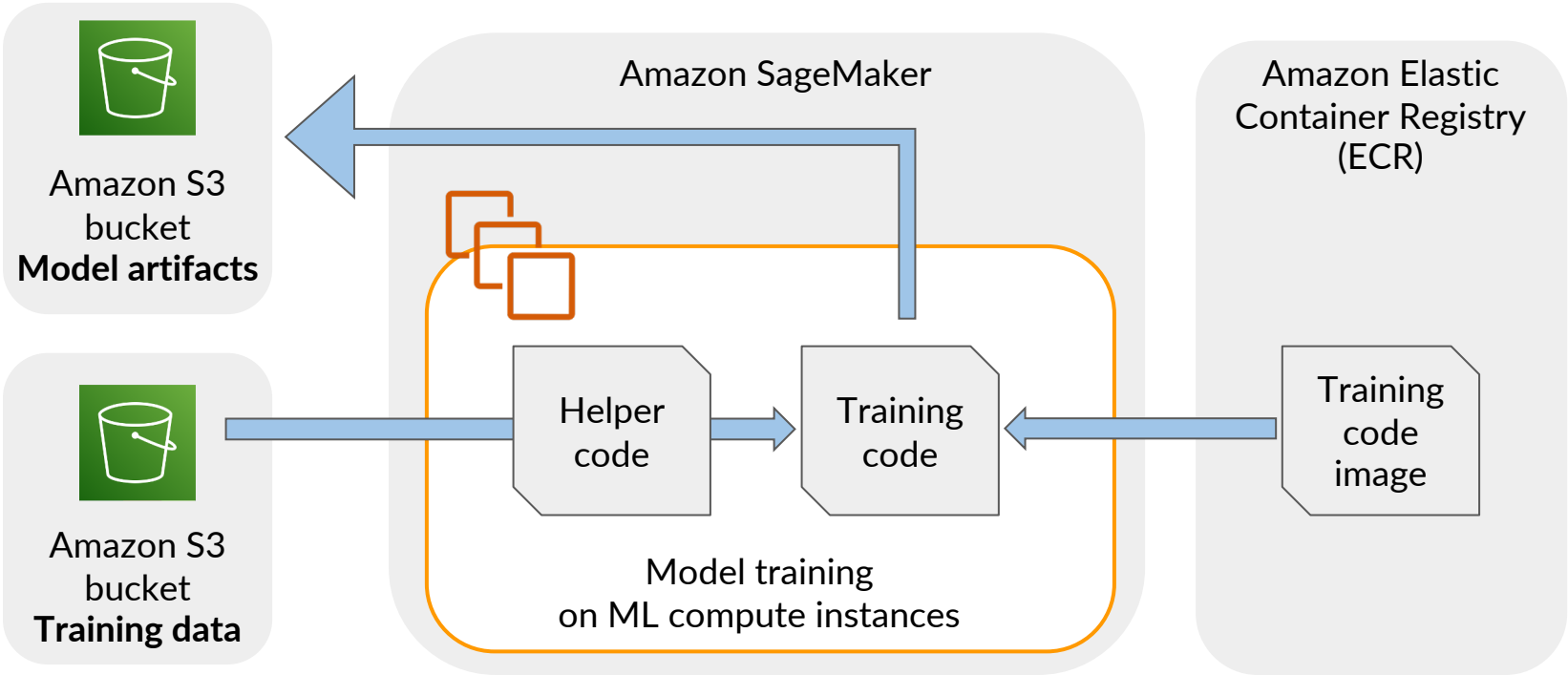
Train a custom model

with Amazon SageMaker

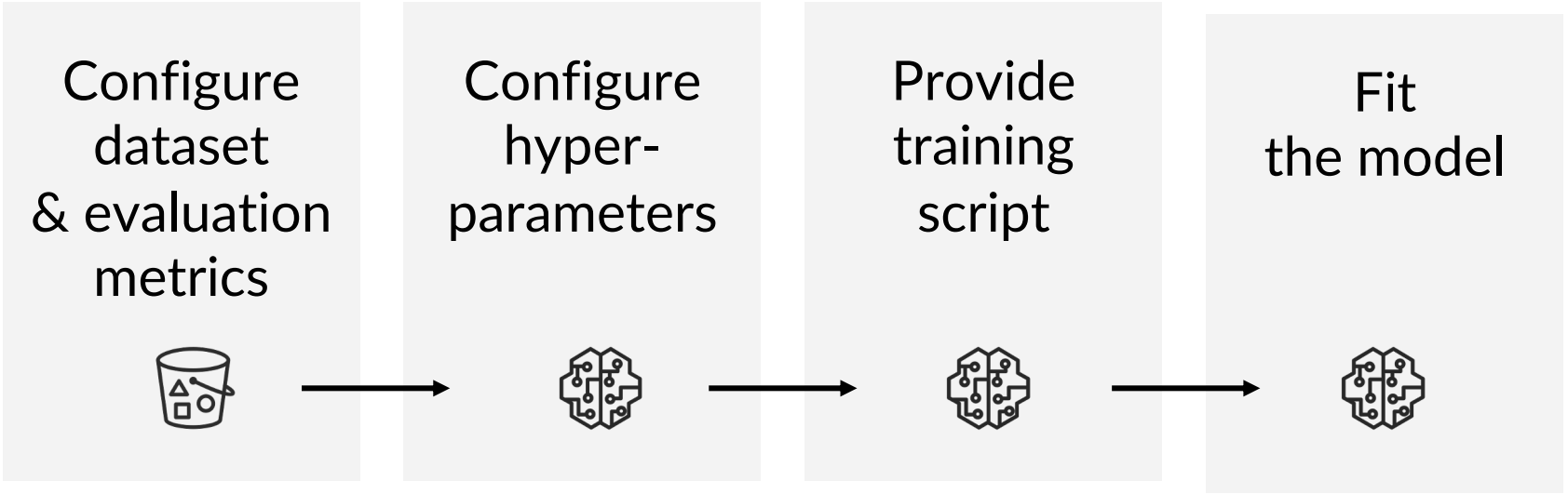
Model training options



Amazon SageMaker "Bring Your Own Script"



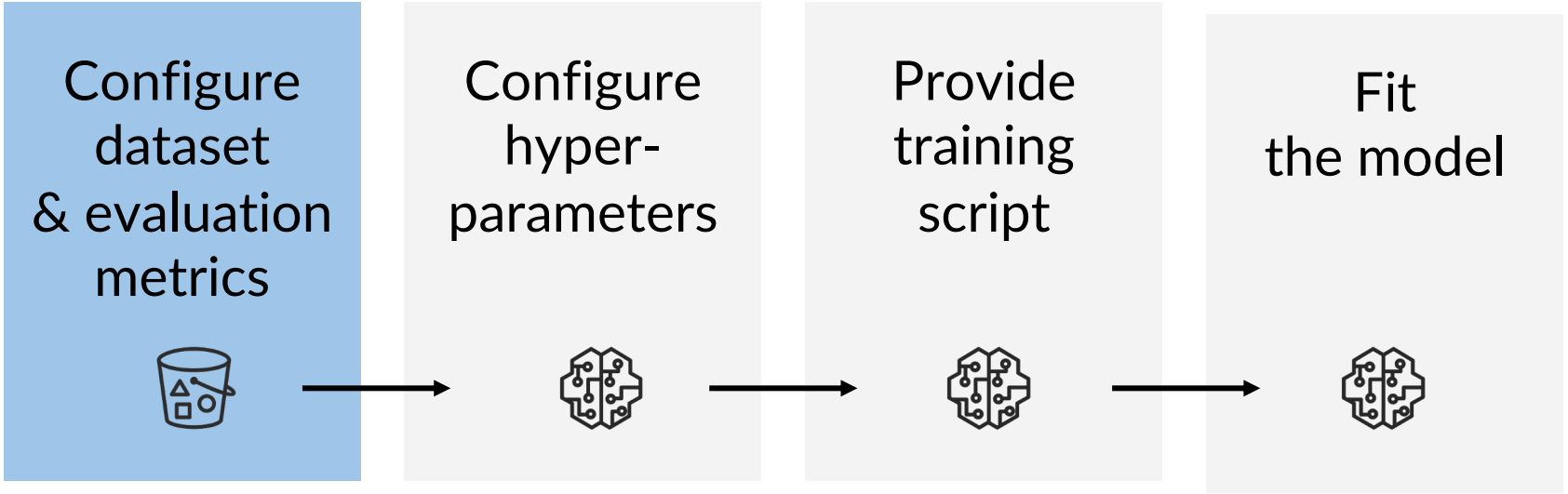
Steps



Evaluation Matrix could be:
- Validation loss, or
- Validation Accuracy

Number of epocs, Learning rate, etc.

Steps


Configure dataset & evaluation metrics
Configure hyper-parameters
Provide training script
Fit the model

Configure dataset and metrics

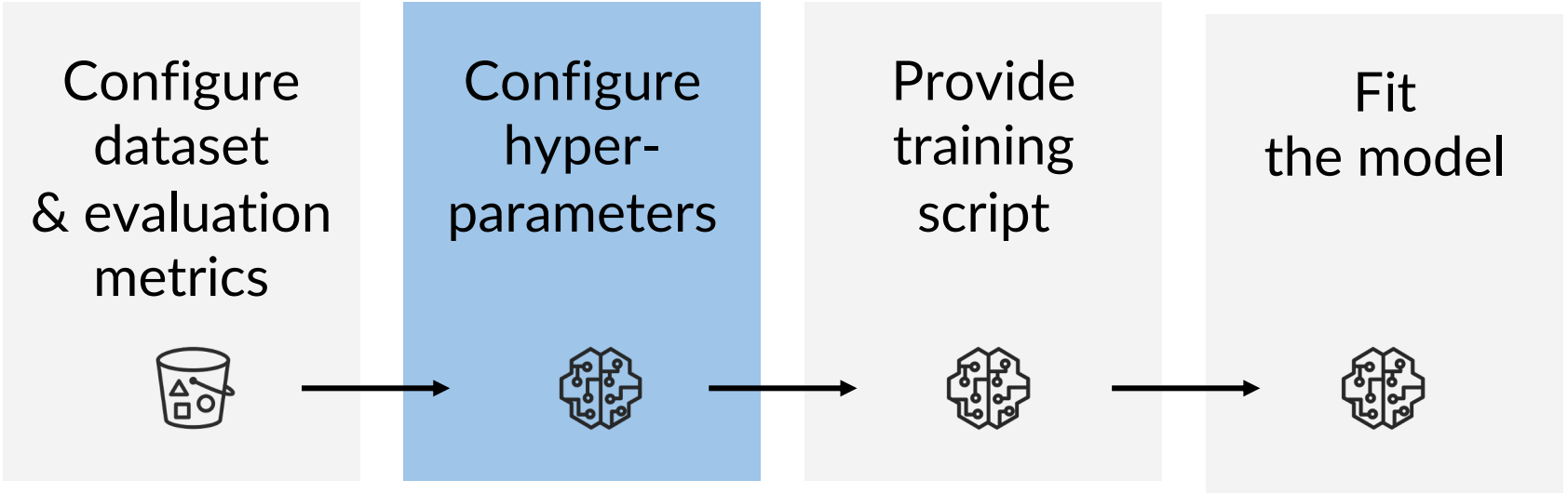
```
from sagemaker.inputs import TrainingInput

s3_input_train_data = TrainingInput(s3_data="s3://...")
s3_input_validation_data = TrainingInput(s3_data="s3://...")
s3_input_test_data = TrainingInput(s3_data="s3://...")
```

Amazon S3

```
metric_definitions = [
     {'Name': 'validation:loss', 'Regex': 'val_loss: ([0-9\\.]+)'},
     {'Name': 'validation:accuracy', 'Regex': 'val_acc: ([0-9\\.]+)'}
]
```

Amazon CloudWatch Logs

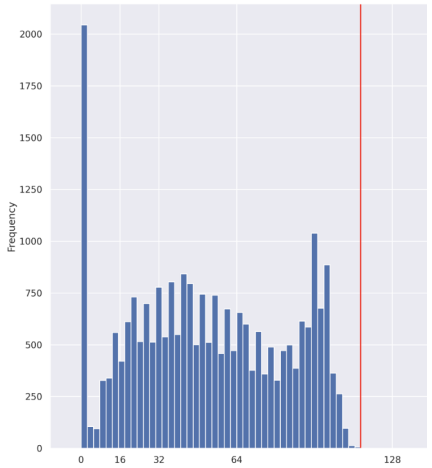
Steps


Configure dataset & evaluation metrics
Configure hyper-parameters
Provide training script
Fit the model

Configure model hyperparameters

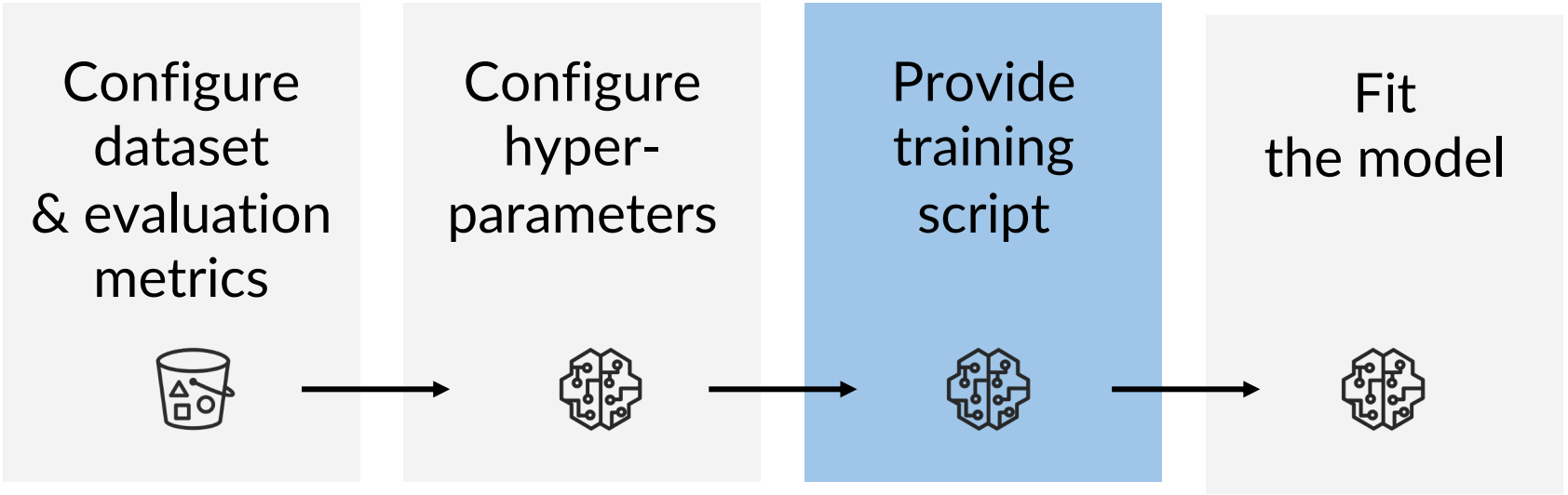
```
hyperparameters={
    'epochs': 3,
    'learning_rate': 2e-5,
    'train_batch_size': 256,
    'train_steps_per_epoch': 50,
    'validation_batch_size': 256,
    'validation_steps_per_epoch': 50,
        ...
    'max_seq_length': 128
}
```

Max. number of input tokens passed to BERT model



mean	52.51
std	31.38
min	1.00
10%	10.00
20%	22.00
30%	32.00
40%	41.00
50%	51.00
60%	61.00
70%	73.00
80%	88.00
90%	97.00
100%	**115.00**

Steps


Configure dataset & evaluation metrics
Configure hyper-parameters
Provide training script
Fit the model

Provide training script *src/train.py*

```
from transformers import RobertaModel, RobertaConfig
from transformers import RobertaForSequenceClassification
...

config = RobertaConfig.from_pretrained('roberta-base', num_labels=3,
                                       id2label={ 0: -1, 1: 0, 2: 1},
                                       label2id={-1: 0, 0: 1, 1: 2})
```

Import Hugging Face transformer libraries (pip install transformers)

Download model config

Specify number of labels and id2label mappings

Provide training script *src/train.py*

```
model = RobertaForSequenceClassification.from_pretrained(
                                        'roberta-base',
                                        config=config)

...

model = train_model(model, ...)
```

Download pre-trained model

Fine-tune model

Hugging Face
Model Hub

Provide training script *src/train.py*

```
def train_model(model, train_data_loader, df_train, val_data_loader, df_val, args):


    loss_function = nn.CrossEntropyLoss()
    optimizer = optim.Adam(params=model.parameters(), lr=args.learning_rate)
    ...
```

Define loss function

We have defined CrossEntryLoss as our loss function

Creating optimizer

Adam optimizer is used

Provide training script *src/train.py*

```
for epoch in range(args.epochs):
    print('EPOCH -- {}'.format(epoch))
    for i, (sent, label) in enumerate(train_data_loader):
        if i < args.train_steps_per_epoch:
            model.train()
            optimizer.zero_grad()
            sent = sent.squeeze(0)
            output = model(sent)[0]
            _, predicted = torch.max(output, 1)
            loss = loss_function(output, label)
            loss.backward()
            optimizer.step()
    ...
return model
```

Loop through epochs

Put model in train mode

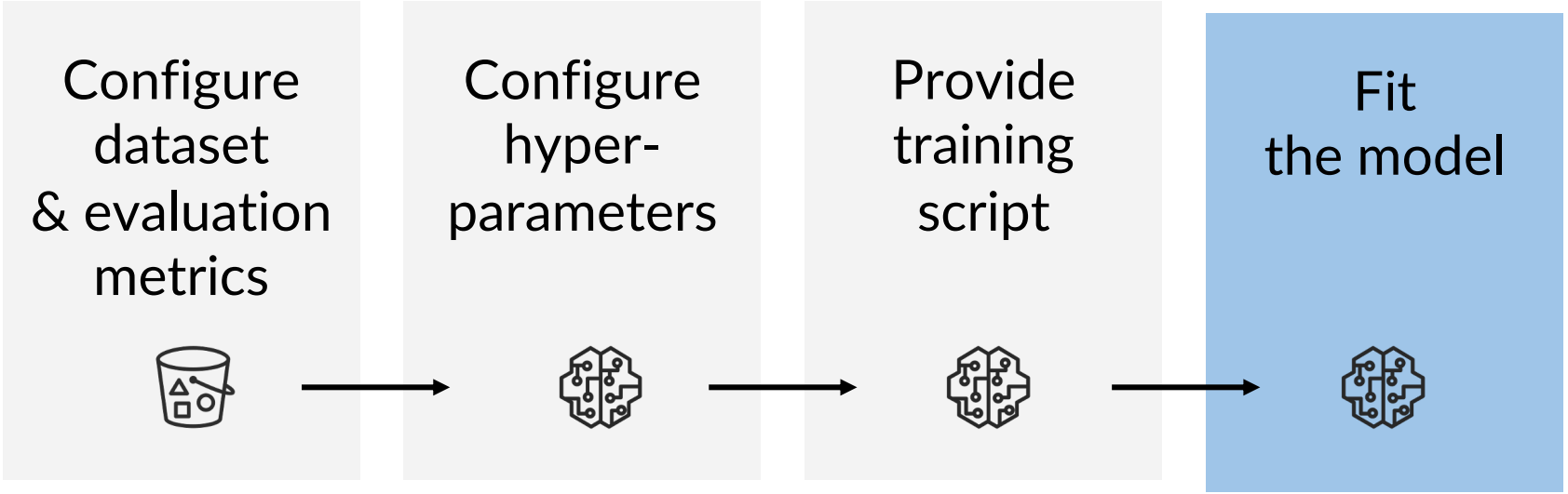
Clear gradients

Get prediction result

Compute gradients via backpropagation

Update the parameters

Steps


Configure dataset & evaluation metrics
Configure hyper-parameters
Provide training script
Fit the model

Fit the model

```
from sagemaker.pytorch import PyTorch as PyTorchEstimator

estimator = PyTorchEstimator(
    entry_point='train.py',
    source_dir='src',
    role=role,
    instance_count=1,
    instance_type='ml.c5.9xlarge',
    ...
```

Model training script

Directory containing additional assets such as requirements.txt

Compute instance types and count

Fit the model

```
from sagemaker.pytorch import PyTorch as PyTorchEstimator

estimator = PyTorchEstimator(
    ...
    framework_version=<PYTORCH_VERSION>,
    hyperparameters=hyperparameters,
    metric_definitions=metric_definitions)

estimator.fit(...)
```

PyTorch version

Define the Pytorch framework version that you are using.

Pass in hyperparameters and metrics

Start model training

Debug and profile models

Debug and profile models

Detect common training errors

"Are my gradient values becoming too large or too small?"

Detect common training errors

- Vanishing gradients
- Exploding gradients
- Bad initialization
- Overfitting
- ...

Deep Neural Networks typically learn through back propogation, in which the models losses trace back through the network. The neurons weights are modified in order to minimize the loss.

If the network is too deep, however, the learning algorithm can spend its whole loss patches on the top layers and waits in the lower layers, never get updated. - Vanishing Gradient problem

In return, learning algorithm might trace a series of errors to the same neuron resulting in a large modification to the neuron weights that it imbalances the network. - Exploding Gradient Problem

Initializations assign random values to the model parameters.
If all parameters have the same initial value, they receive the same gradient and the model is unable to learn.
Initializing parameters that are too large or too small may lead to vanishing and exploding gradients.

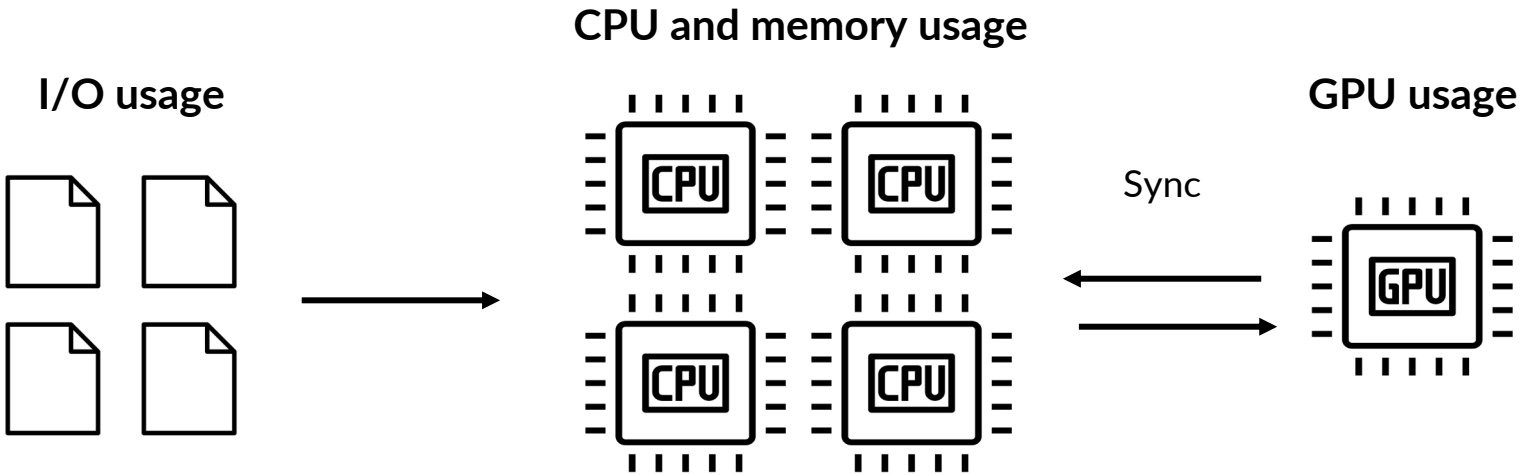
The training loop consists of training and validation. If the model's performance improves on a training set but not on a validation data set, it is a clear indication that the model is overfitting.
If the model's performance initially improves on the validation set but then begins to fall off, training needs to stop to prevent the overfitting.

Debug and profile models

Detect common training errors	"Are my gradient values becoming too large or too small?"
Monitor and profile system resource utilization	"How much GPU, CPU, network, and memory does my model training consume?"

Monitor and profile system resource utilization

Potential bottlenecks:



Debug and profile models

Detect common training errors	"Are my gradient values becoming too large or too small?"
Monitor and profile system resource utilization	"How much GPU, CPU, network,and memory does my model training consume?"
Analyze errors and take action	"Stop the model training if the model starts overfitting!"

Analyze errors and take action

- Stop model training when an issue is found

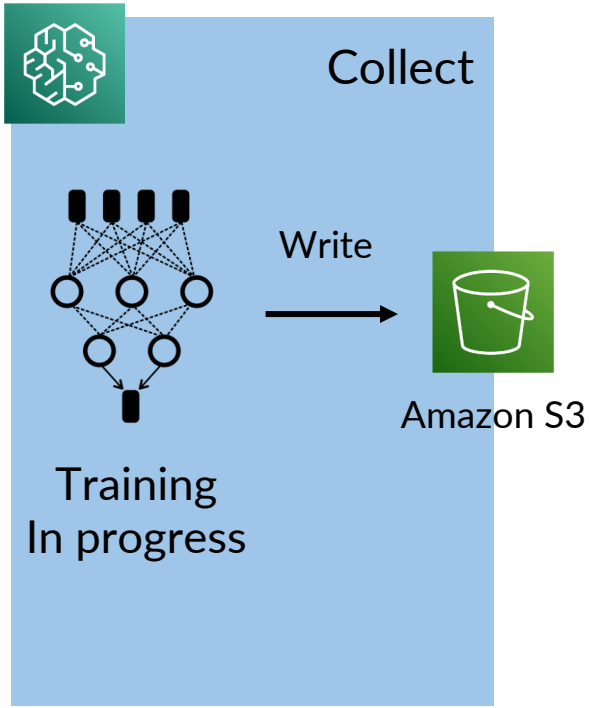
- Send a notification via email an issue is found

- Send a notification via text message when an issue is found

Debug and profile models

with Amazon SageMaker Debugger

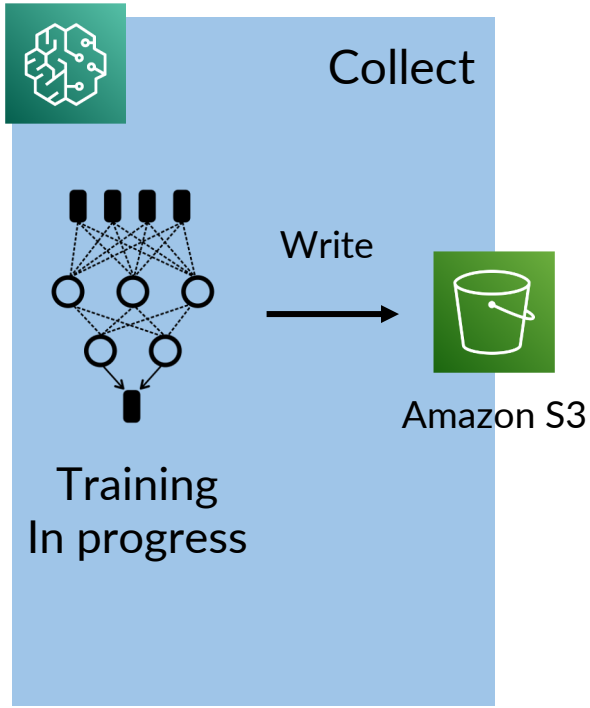
Amazon SageMaker Debugger



Capture real-time debugging data during model training in Amazon SageMaker

- System metrics — Stores hardware resource utilization data such as CPU, GPU, and memory utilization. Network Metrics and O/P and I/P metrics.
- Framework metrics — Convolutional operations in the forward pass, batch normalization operations in backward pass, data loader processes and gradient descent algo operations
- Output tensors — Output tensors are collections of model parameters that are continuously updated during the back propagation and optimization process of training ML and deep learning models.
accuracy, loss, weight metrics, gradient metrics, input and output layers.

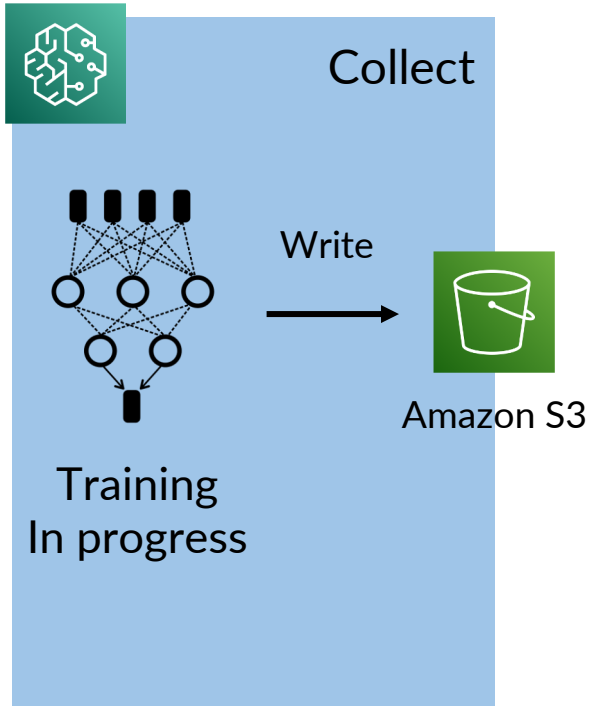
Amazon SageMaker Debugger



Capture real-time debugging data during model training in Amazon SageMaker

- System metrics
  - CPU and GPU (and memory) utilization
  - Network metrics
  - Data input and output (I/O) metrics

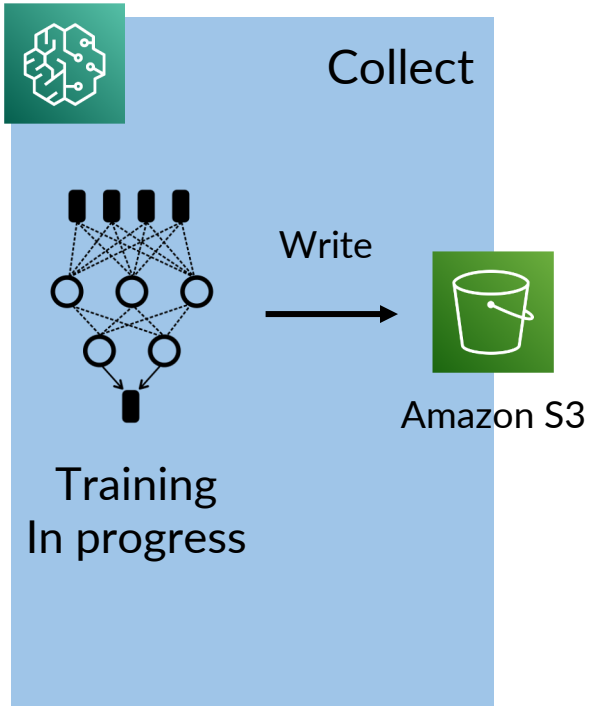
Amazon SageMaker Debugger



Capture real-time debugging data during model training in Amazon SageMaker

- Framework metrics
  - Convolutional operations in forward pass
  - Batch normalization operations in backward pass
  - Data loader processes between steps
  - Gradient descent algorithm operations

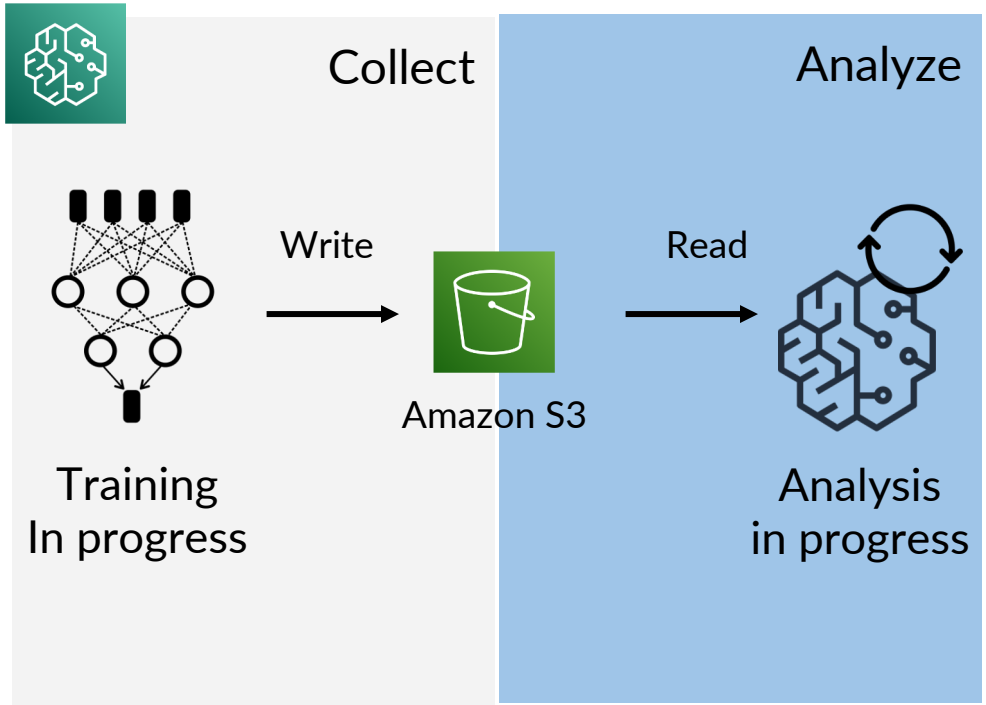
Amazon SageMaker Debugger



Capture real-time debugging data during model training in Amazon SageMaker

- Output tensors
  - Scalar values (accuracy and loss)
  - Matrices (weights, gradients, input layers, and output layers)

Amazon SageMaker Debugger



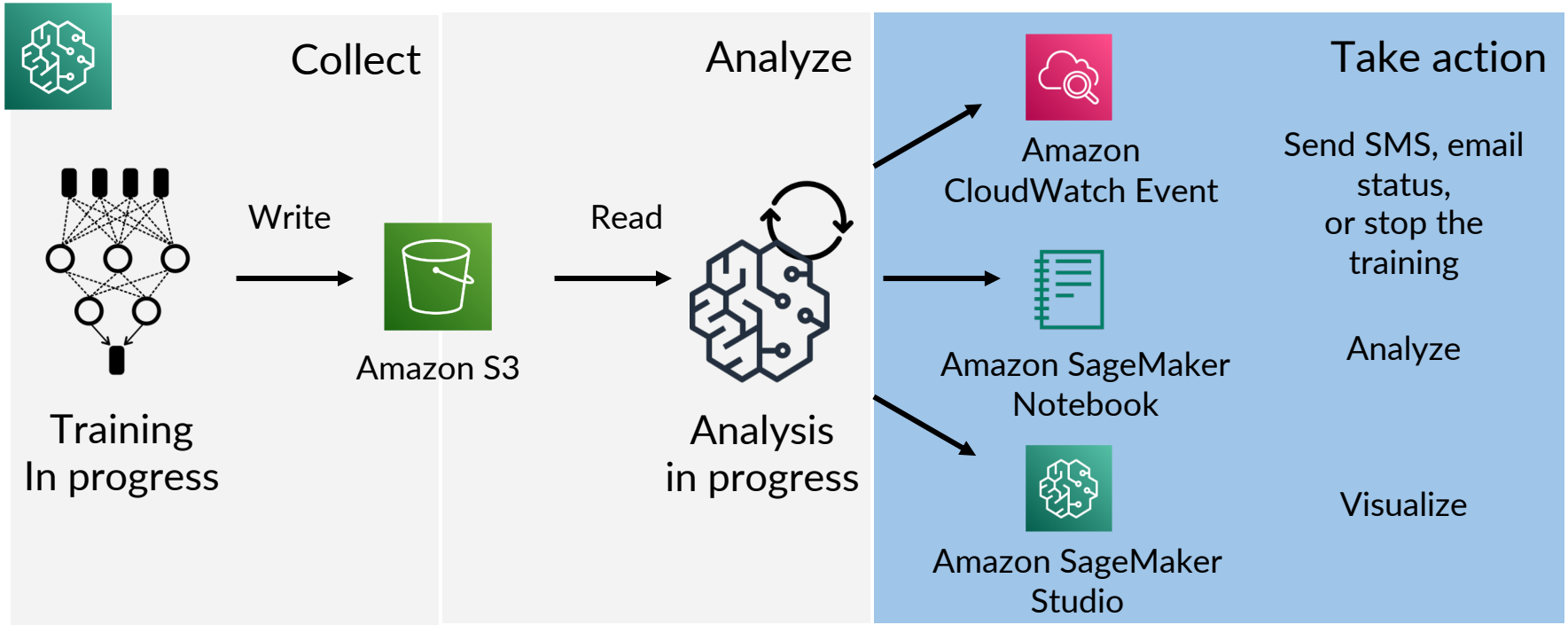
Continuous analysis through rules

Amazon SageMaker Debugger: Built-in rules

Problem class	Rules
Datasets	Class imbalance Data not normalized Ratio of tokens in sequence
Loss and accuracy	Loss not decreasing Overfitting Underfitting Overtraining Classifier confusion
Weights	Poor initialization Updates too small

Problem class	Rules
Tensor	All values zero Variance of values too small Values not changing across steps
Activation function	Tanh saturation Sigmoid saturation Dying ReLU
Decision trees	Depth of tree too large Low feature importance
Gradients	Vanishing Exploding

Amazon SageMaker Debugger



Code example

Debug model training: Configuration

```
from sagemaker.debugger import Rule, rule_configs
rules=[
    Rule.sagemaker(rule_configs.loss_not_decreasing()),
    Rule.sagemaker(rule_configs.overtraining())
    ...
]
```

Select (built-in) rules to evaluate

Overtraining prevents model from overfitting

Debug model training: Add config to estimator

```
from sagemaker.pytorch import PyTorch as PyTorchEstimator
estimator = PyTorchEstimator(
    entry_point='train.py',
    ...
    rules=rules
)
```

Pass rules in estimator

Profile training job: Configuration

```
from sagemaker.debugger import ProfilerRule, rule_configs
rules=[
    ProfilerRule.sagemaker(rule_configs.LowGPUUtilization()),
    ProfilerRule.sagemaker(rule_configs.ProfilerReport()),
    ...]
```

Select rules for profiling

```
from sagemaker.debugger import ProfilerConfig, FrameworkProfile
profiler_config = ProfilerConfig(
    system_monitor_interval_millis=500,
    framework_profile_params=FrameworkProfile(num_steps=10))
```

Configure profiler

Profile training job: Add config to estimator

```
from sagemaker.pytorch import PyTorch as PyTorchEstimator
estimator = PyTorchEstimator(
    entry_point='train.py', ... ,
    rules=rules,
    profiler_config=profiler_config)
```

Pass rules and config in estimator

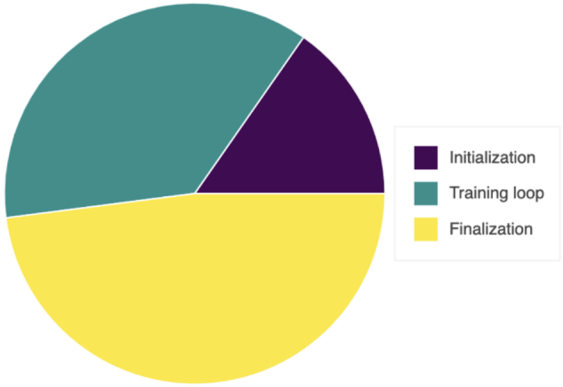
Analyze results

Profiling Report

Training job summary

The following table gives a summary about the training job. The table includes information about when the training job started and ended, how much time initialization, training loop and finalization took. Your training job started on 05/06/2021 at 17:53:36 and ran for 323 seconds.

#		Job Statistics
0	Start time	17:53:36 05/06/2021
1	End time	17:58:59 05/06/2021
2	Job duration	323 seconds
3	Training loop start	17:54:26 05/06/2021
4	Training loop end	17:56:26 05/06/2021
5	Training loop duration	119 seconds
6	Initialization time	49 seconds
7	Finalization time	153 seconds
8	Initialization	15 %
9	Training loop	36 %
10	Finalization	47 %



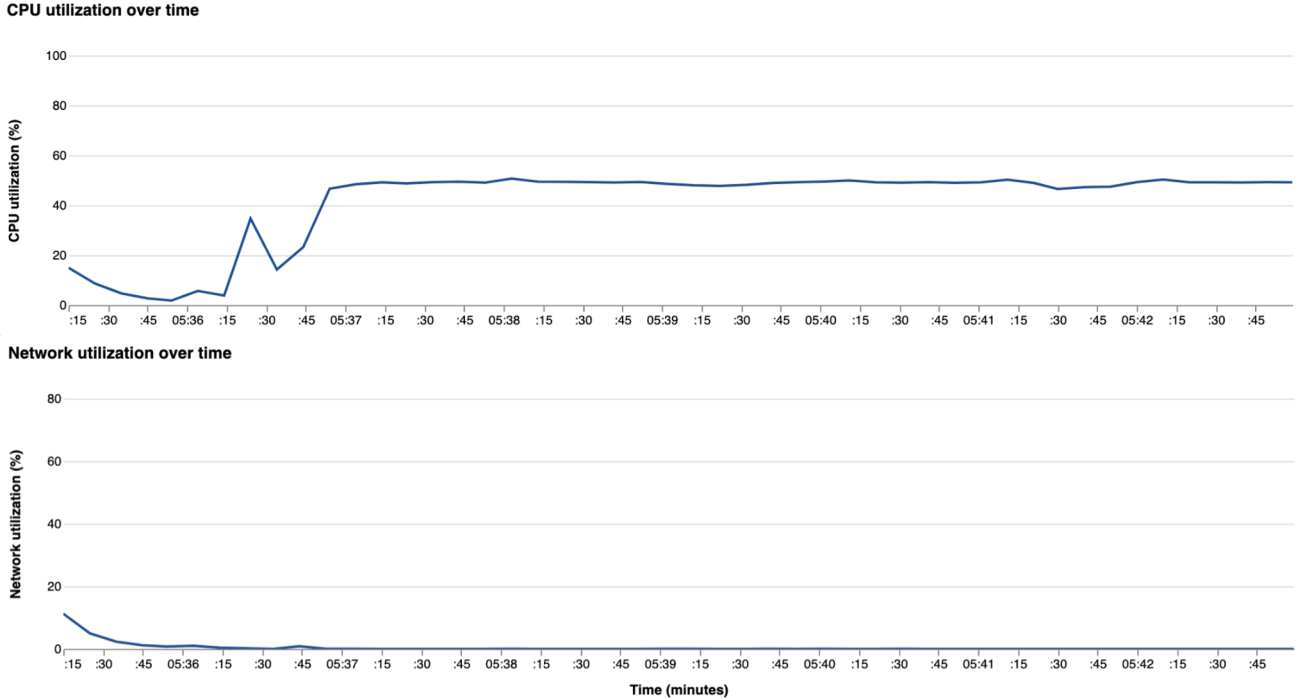
Profiling Report - Rules summary

Rules summary

The following table shows a profiling summary of the Debugger built-in rules. The table is sorted by the rules that triggered the most frequently. During your training job, the MaxInitializationTime rule was the most frequently triggered. It processed 295 datapoints and was triggered 0 times.

	Description	Recommendation	Number of times rule triggered	Number of datapoints	Rule parameters
MaxInitializationTime	Checks if the time spent on initialization exceeds a threshold percent of the total training time. The rule waits until the first step of training loop starts. The initialization can take longer if downloading the entire dataset from Amazon S3 in File mode. The default threshold is 20 minutes.	Initialization takes too long. If using File mode, consider switching to Pipe mode in case you are using TensorFlow framework.	0	295	threshold:20
GPUMemoryIncrease	Measures the average GPU memory footprint and triggers if there is a large increase.	Choose a larger instance type with more memory if footprint is close to maximum available memory.	0	0	increase:5 patience:1000 window:10
StepOutlier	Detects outliers in step duration. The step duration for forward and backward pass should be roughly the same throughout the training. If there are significant outliers, it may indicate a system stall or bottleneck issues.	Check if there are any bottlenecks (CPU, I/O) correlated to the step outliers.	0	295	threshold:3 mode:None n_outliers:10 stddev:3
BatchSize	Checks if GPUs are underutilized because the batch size is too small. To detect this problem, the rule analyzes the average GPU memory footprint, the CPU and the GPU utilization.	The batch size is too small, and GPUs are underutilized. Consider running on a smaller instance type or increasing the batch size.	0	930	cpu_threshold_p95:70 gpu_threshold_p95:70 gpu_memory_threshold_p95:70 patience:1000 window:500

Profiling Report - CPU/network utilization



Profiling Report - System utilization