Copyright Notice

Welcome to Course 3

DeepLearning.AI

aws

Advanced Model Training

Machine Learning Workflow

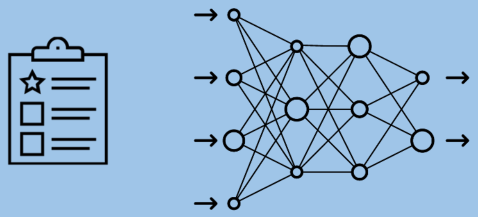
Ingest & Analyze	Prepare & Transform	Train & Tune	Deploy & Manage
Data exploration	Feature engineering	Automated ML	Model deployment
Bias detection	Feature store	Model train and tune	Automated pipelines
Amazon S3 & Amazon Athena	Amazon SageMaker Data Wrangler	Amazon SageMaker Autopilot	Amazon SageMaker 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

Model Tuning

Model Tuning

Model parameters

roberta-base
125M parameters



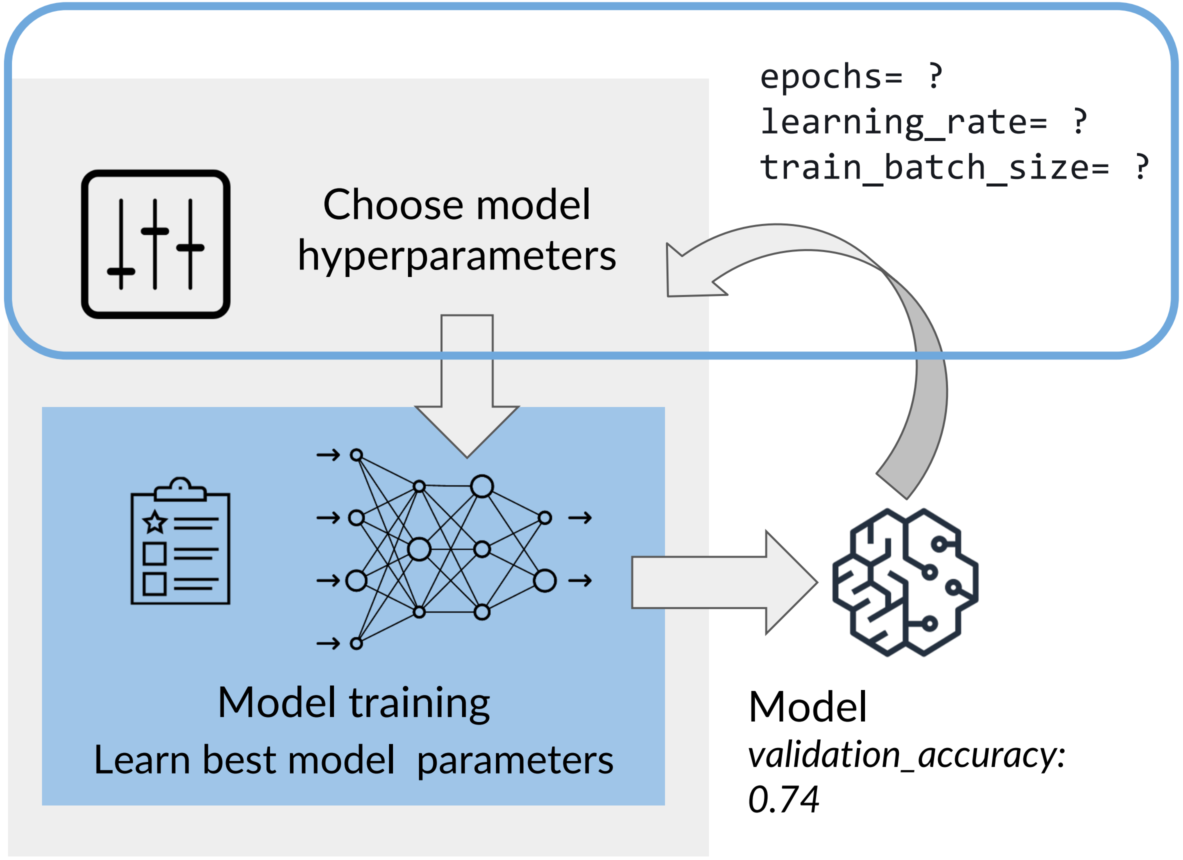
Model training
Learn best model parameters

Model
validation_accuracy: 0.74

Model Tuning

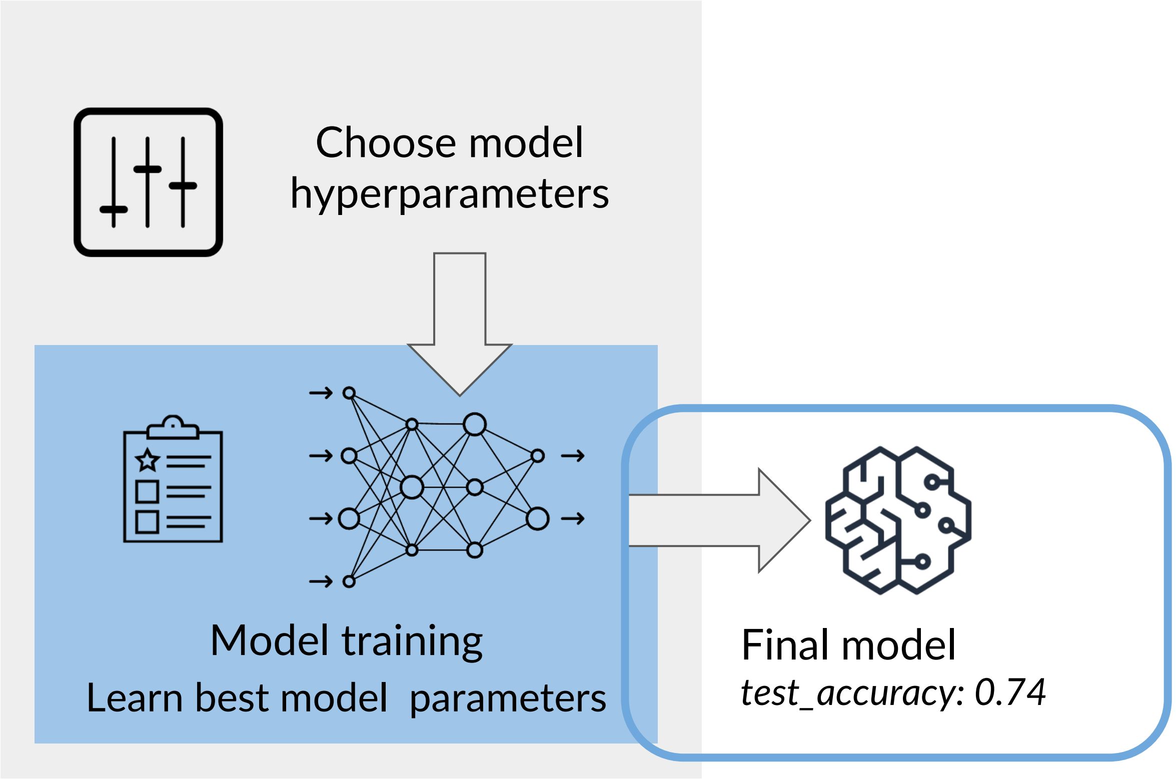
Model hyperparameters

Model parameters

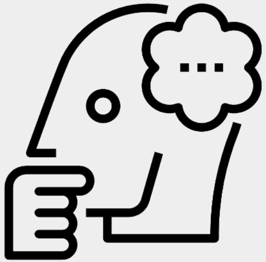


Model Evaluation

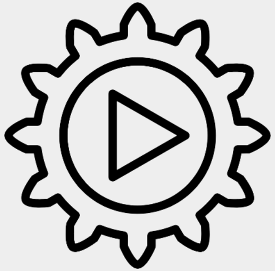
"If you can't measure it,
you can't improve it."
-- *Peter Drucker*



Manual vs. Automatic Model Tuning



Manual tuning



Automatic
model tuning

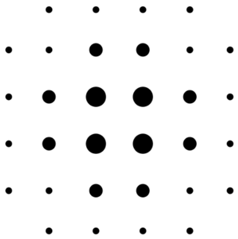
Popular Algorithms for Automatic Model Tuning

Automatic model tuning

- Grid search
- Random search
- Bayesian optimization
- Hyperband

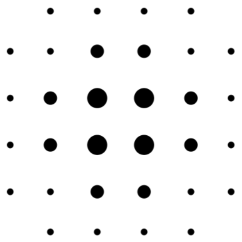
Grid Search

- Define sets of hyperparameters
- Test **every** combination
- Select the best performing hyperparameters



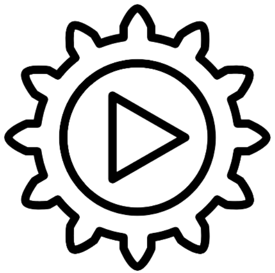
Grid Search

- Define sets of hyperparameters
- Test **every** combination
- Select the best performing hyperparameters

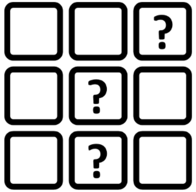


\+ Explores all combinations
\+ Works for small number of parameters
\- Time-consuming
\- Doesn't scale to large numbers of parameters

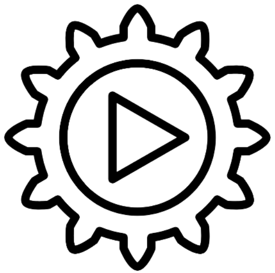
Random Search



- Define sets of hyperparameters
- Define search space & stop criteria
- Test **random** combinations within search space
- Select the best performing hyperparameters



Random Search



- Define sets of hyperparameters
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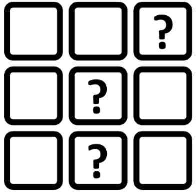
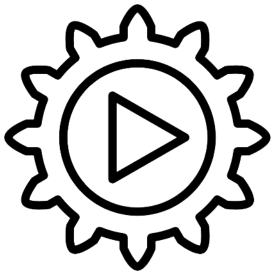


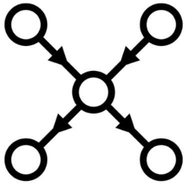
\+ Faster compared to grid search

\- Might miss better performing hyperparameters

Bayesian Optimization



- Treat HPT like a **regression** problem (surrogate model)
- Start from random hyperparameters
- Narrow down search space around better performing hyperparameters



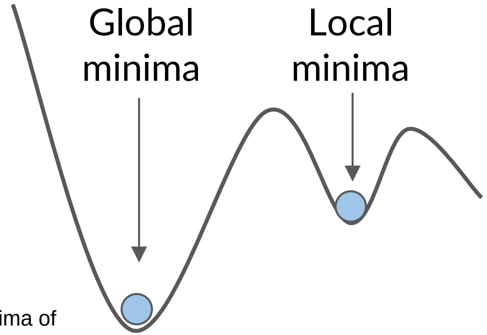
Bayesian Optimization

- Treat HPT like a **regression** problem (surrogate model)
- Start from random hyperparameters
- Narrow down search space around better performing hyperparameters

\+ More efficient in finding best hyperparameters

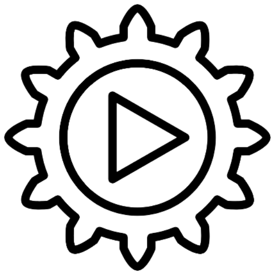
\- Requires sequential execution

\- Might get stuck in local minima

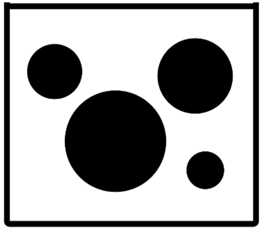


When you use gradient descent to minimize the Loss Function, it is a possibility that this algorithm might get stuck with a Local minima of the Loss Function and might not find the Global minima.

Hyperband



- **Bandit-based** approach
- Start from random hyperparameters
- Explore sets of hyperparameters for few iterations
- Choose best and explore longer
- Repeat until `max_iterations` reached or one candidate left



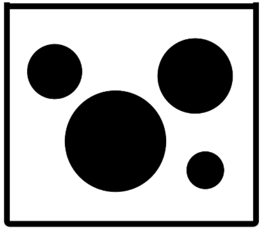
Bandit approaches typically use a combination of exploitation and exploration to find the best possible hyperparameters. The strength of the bandit approaches is that dynamic pull between exploitation and exploration.

You start with the larger space of random hyperparameter set and then you explore a random subset of these hyperparameters for a few iterations. After the first few iterations, you discard the worst performing half of the hyperparameter sets. In the subsequent few iterations, you continue to explore the best performing hyperparameters from the previous iteration. You continue this process until the set time is elapsed or you remain with just one possible candidate.

Hyperband clearly stands out by spending the time much more efficiently than other approaches we discussed to explore the hyperparameter values using the combination of exploitation and exploration. On the downside, it might discard good candidates very early on and these could be the candidate that converge slowly.

Hyperband

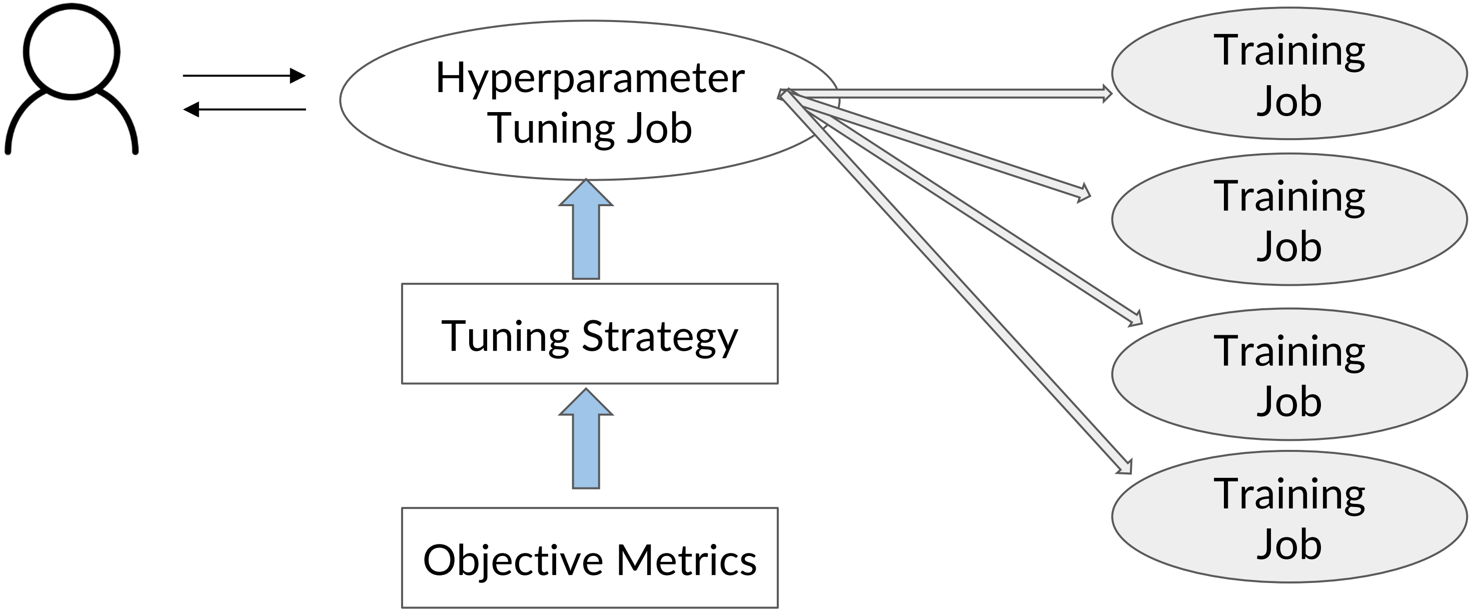
- **Bandit-based** approach
- Start from random hyperparameters
- Explore sets of hyperparameters for few iterations
- Choose best and explore longer
- Repeat until `max_iterations` reached or one candidate left



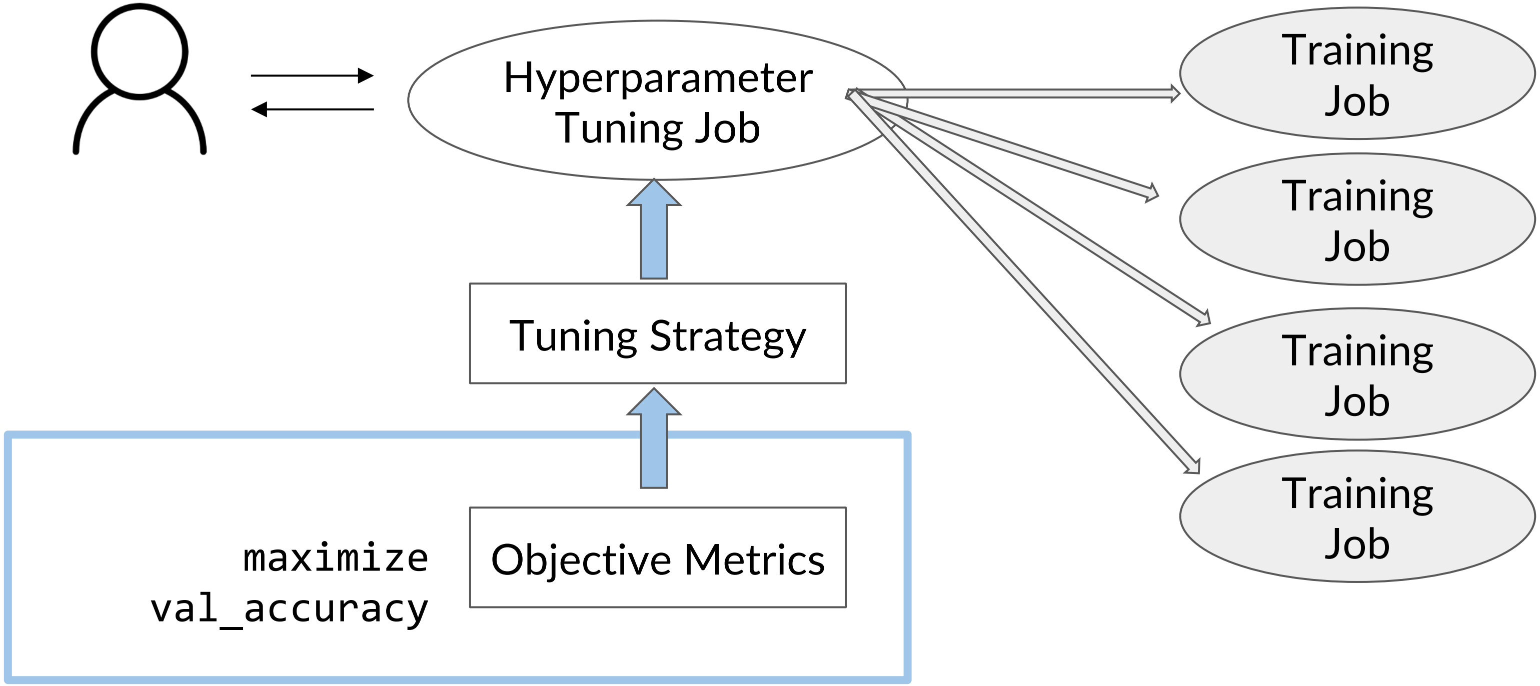
+ Spends time efficiently (explore-exploit theory)
- Might discard good candidates early that converge slowly

Tune a BERT-based Text Classifier

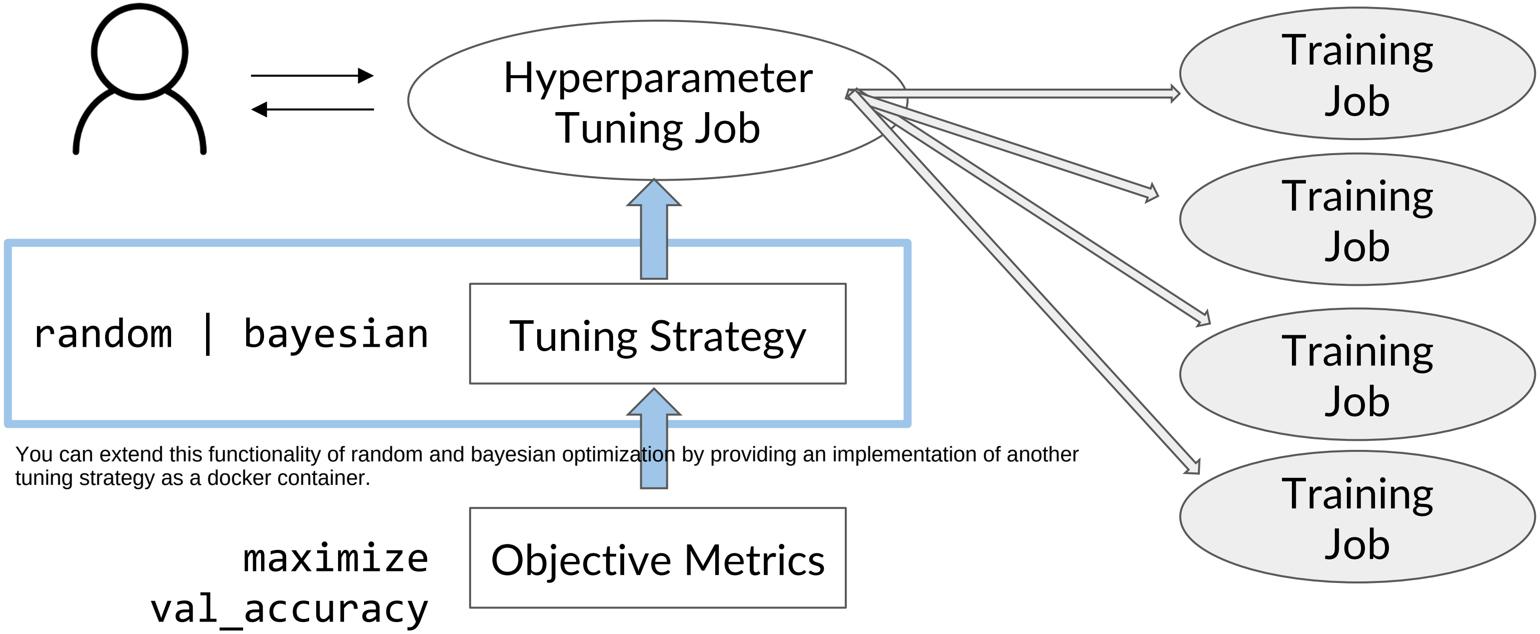
Amazon SageMaker Hyperparameter Tuning (HPT)



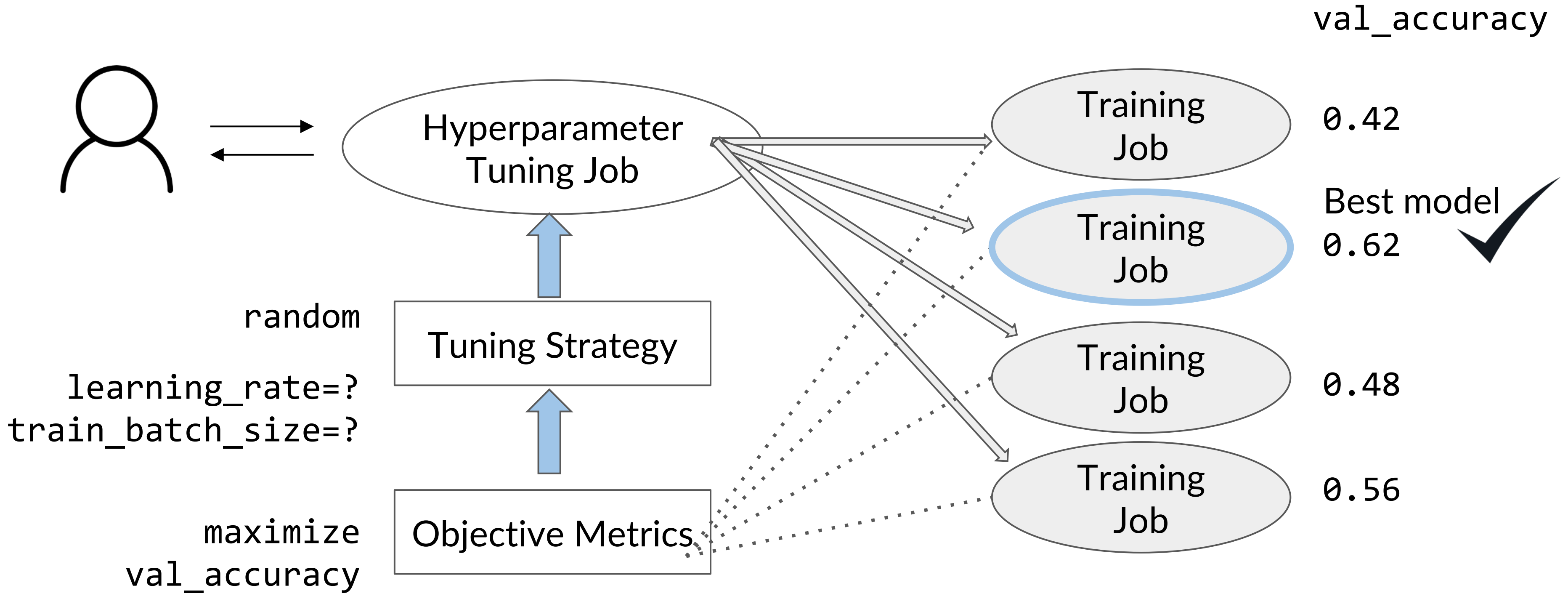
Amazon SageMaker Hyperparameter Tuning (HPT)



Amazon SageMaker Hyperparameter Tuning (HPT)



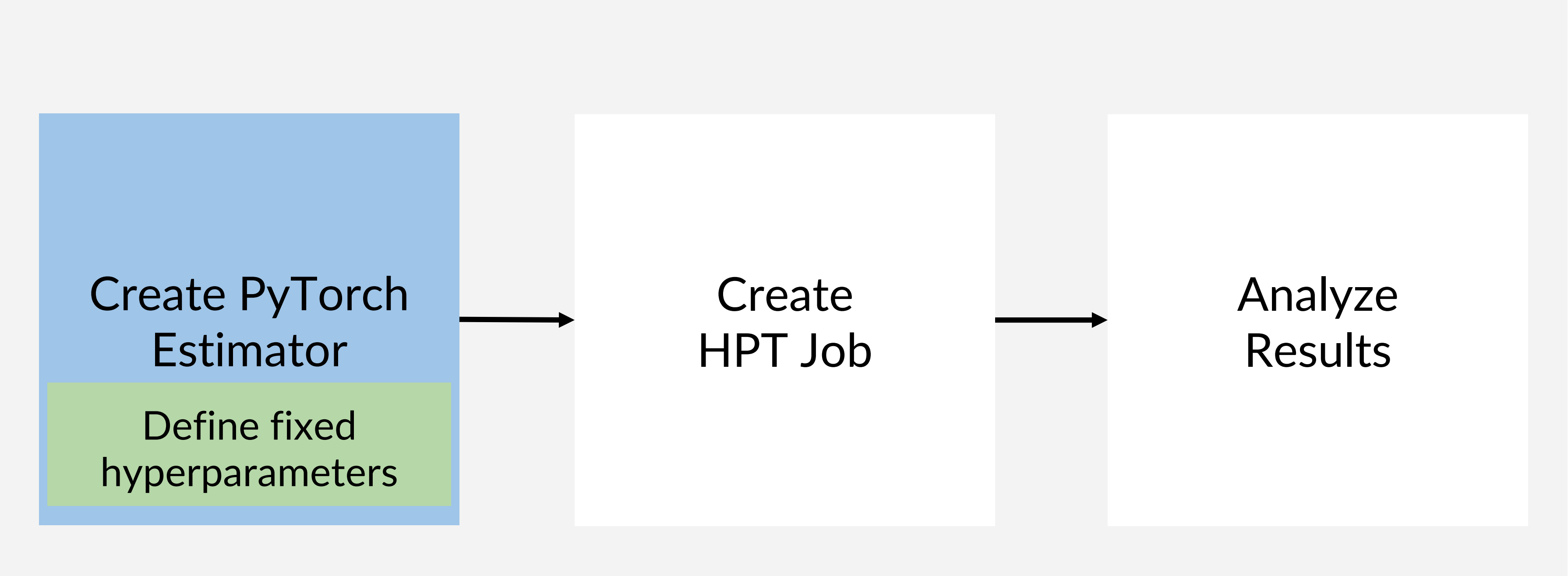
Tune BERT Text Classifier



Steps

Create PyTorch Estimator → Create HPT Job → Analyze Results

Steps



Create PyTorch Estimator
Define fixed hyperparameters
Create HPT Job
Analyze Results

Define Fixed Hyperparameters

Create PyTorch estimator

Define fixed hyperparameters

```
hyperparameters={
      'epochs': 3,
      'train_steps_per_epoch': 50,
      'validation_batch_size': 64,
      'validation_steps_per_epoch': 50,
      'freeze_bert_layer': False,
      'seed': 42,
      'max_seq_length': 64,
      'backend': 'gloo',
      'run_validation': True,
      'run_sample_predictions': False
}
```

Create PyTorch Estimator

Create PyTorch estimator

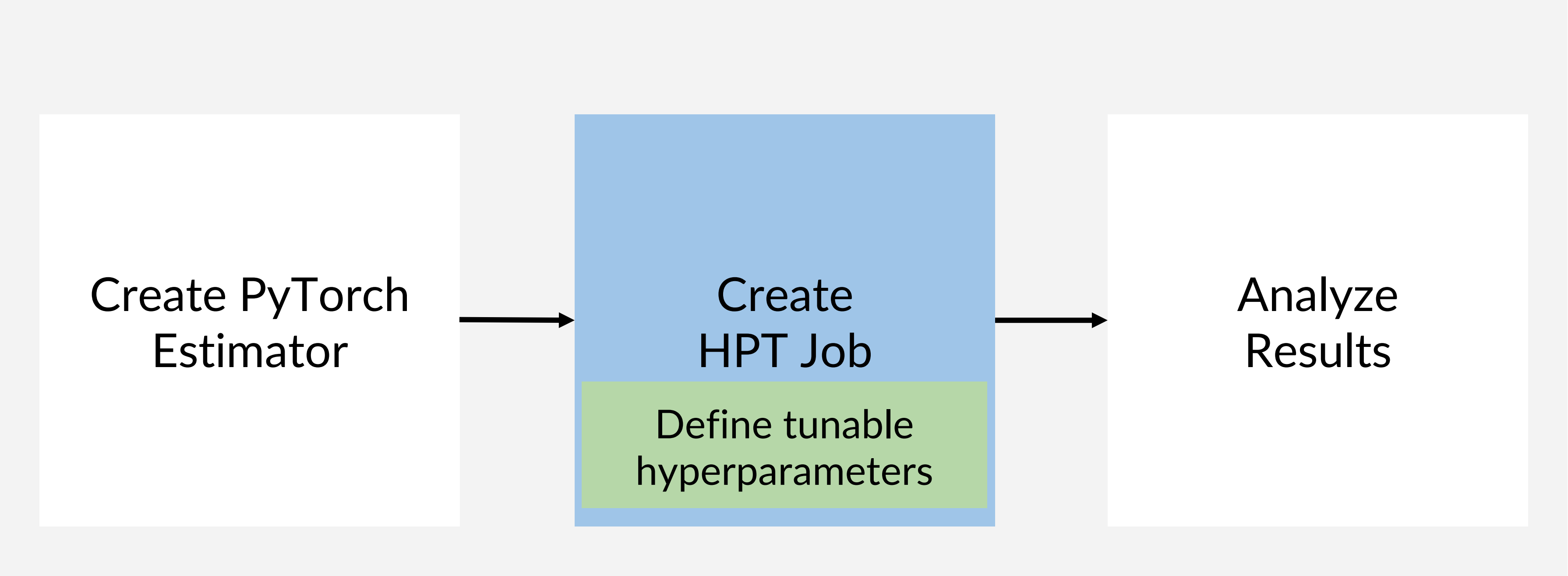
Define fixed hyperparameters

```
from sagemaker.pytorch import PyTorch as PyTorchEstimator

estimator = PyTorchEstimator(
    entry_point='train.py',
    ...
    hyperparameters=hyperparameters,

)
```

Fixed hyperparameters in estimator

DeepLearning.AI

Steps


Create PyTorch Estimator
Create HPT Job
Define tunable hyperparameters
Analyze Results

Define Tunable Hyperparameters

Create HPT job

Define tunable hyperparameters

```
from sagemaker.tuner import CategoricalParameter
from sagemaker.tuner import ContinuousParameter
from sagemaker.tuner import IntegerParameter

hyperparameter_ranges = {
    'learning_rate': ContinuousParameter(0.00001, 0.00005,
scaling_type='Linear'),
    'train_batch_size': CategoricalParameter([128, 256]),
}
```

Specify parameters

Specify hyperparameter types

Specify ranges

How to Choose Hyperparameter Types

Categorical	
`'train_batch_size': CategoricalParameter([128, 256])`	`'freeze_bert_layer': CategoricalParameter([True, False])`

How to Choose Hyperparameter Types

Categorical

```
'train_batch_size':
CategoricalParameter([128, 256])
```

```
'freeze_bert_layer':
CategoricalParameter([True, False])
```

Integer

```
'train_batch_size':
IntegerParameter(16, 1024, scaling_type='Logarithmic')
```

If you need to explore large ranges quickly

'Logarithmic scales works well if you want to explore large ranges quickly.

How to Choose Hyperparameter Types

Categorical

```
'train_batch_size':
CategoricalParameter([128, 256])
```

```
'freeze_bert_layer':
CategoricalParameter([True, False])
```

Integer

```
'train_batch_size':
IntegerParameter(16, 1024, scaling_type='Logarithmic')
```

Continuous

```
'learning_rate':
ContinuousParameter(0.00001, 0.00005, scaling_type='Linear')
```

Create Amazon SageMaker HPT job

Create HPT job

Define tunable hyperparameters

```
from sagemaker.tuner import HyperparameterTuner

tuner = HyperparameterTuner(
    estimator=...,
    hyperparameter_ranges=...,
    objective_type=...,
    objective_metric_name=...,
    strategy=...,
)

tuner.fit(inputs={...}, ...)
```

Pass in estimator

Configure Hyperparameter ranges

Run HPT job with .fit()

Steps

Create PyTorch Estimator → Create HPT Job → Analyze Results

Analyze Results

Analyze Results

```
df_results = tuner.analytics().dataframe()
```

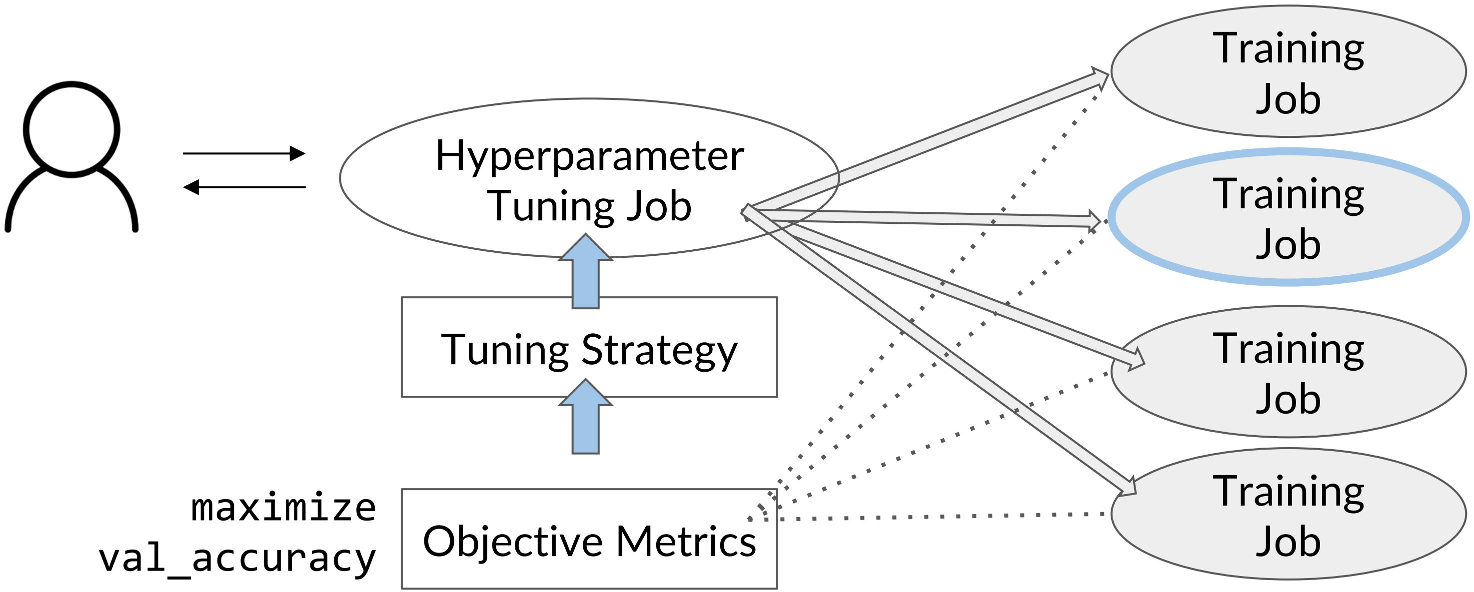
Analyze Results

Analyze Results

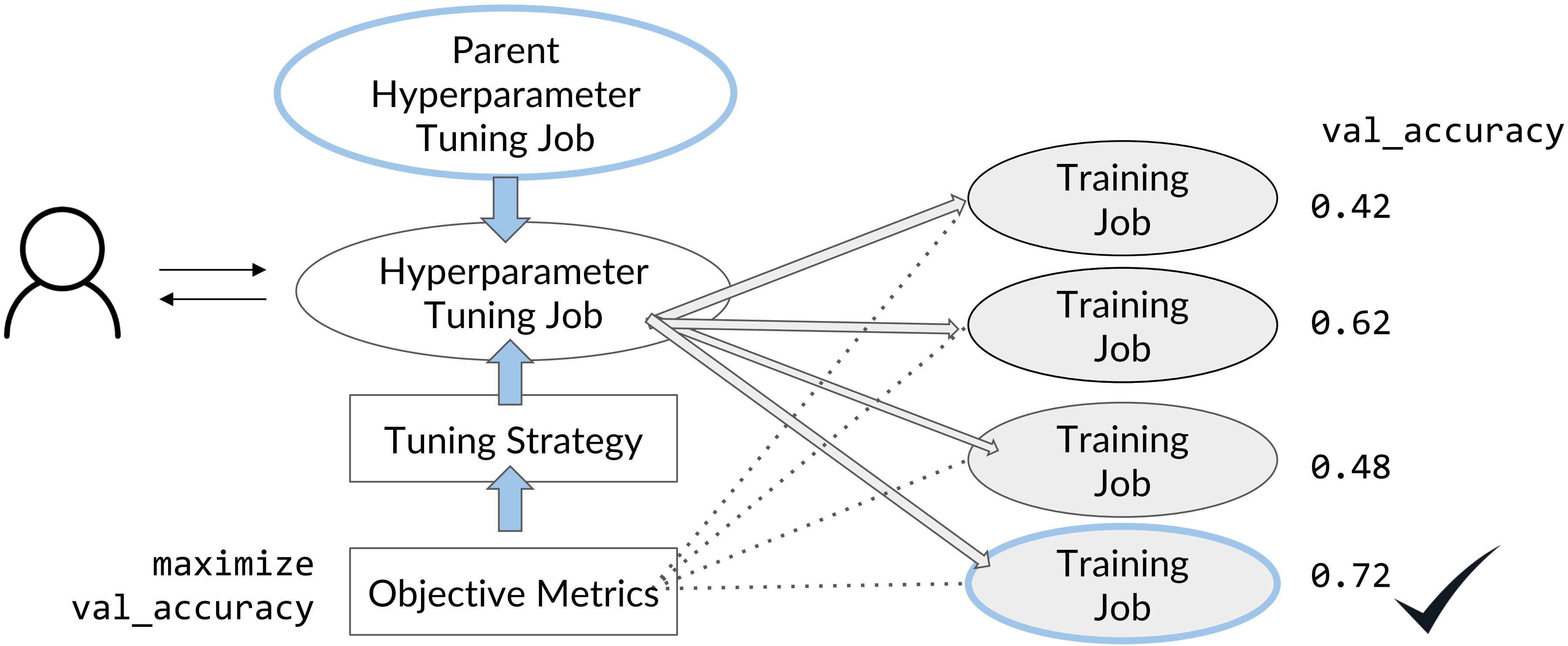
```
df_results = tuner.analytics().dataframe()
```

learning_rate	train_batch_size	TrainingJobName	TrainingJobStatus	FinalObjectiveValue
0.000021	"128"	pytorch-training-210225-1535-001-71394bc3	Completed	44.939999
0.000035	"128"	pytorch-training-210225-1535-002-cf437bad	Completed	41.580002

Warm Start HPT Job



Warm Start HPT Job



Warm Start HPT Job

- IDENTICAL_DATA_AND_ALGORITHM
  - Same input data and training data
  - Update hyperparameter tuning ranges and maximum number of training jobs
- TRANSFER_LEARNING
  - Updated training data and different version of training algorithm

Configure Warm Start

```
from sagemaker.tuner import WarmStartConfig
from sagemaker.tuner import WarmStartTypes

warm_start_config = WarmStartConfig(
     warm_start_type=WarmStartTypes.IDENTICAL_DATA_AND_ALGORITHM,
     parents=<PARENT_TUNING_JOB_NAME>)

tuner = HyperparameterTuner(
    ...
    warm_start_config=warm_start_config)

tuner.fit(...)
```

IDENTICAL_DATA_AND_ALGORITHM or TRANSFER_LEARNING

Specify parent tuning job

Pass warm start config in HyperparameterTuner

Best Practices - SageMaker HyperParameter Tuning

Hyperparameter Tuning is a time and computation intensive task.

The computational complexity is directly proportional to the number of hyperparameters that you tune.

- Select a small number of hyperparameters
- Select a small range for hyperparameters
- Enable warm start
- Enable early stop to save tuning time and costs
- Select a small number of concurrent training jobs

On one hand, if you use a larger number of concurrent jobs, the tuning process will be completed faster. But in fact, the hyperparameter tuning process is able to find best possible results only by depending on the previously completed training jobs.

Best Practices - Monitoring Training Resources

- Right size compute resources
- Requires empirical testing
- Amazon CloudWatch Metrics
- Insights from Amazon SageMaker Debugger

Checkpointing

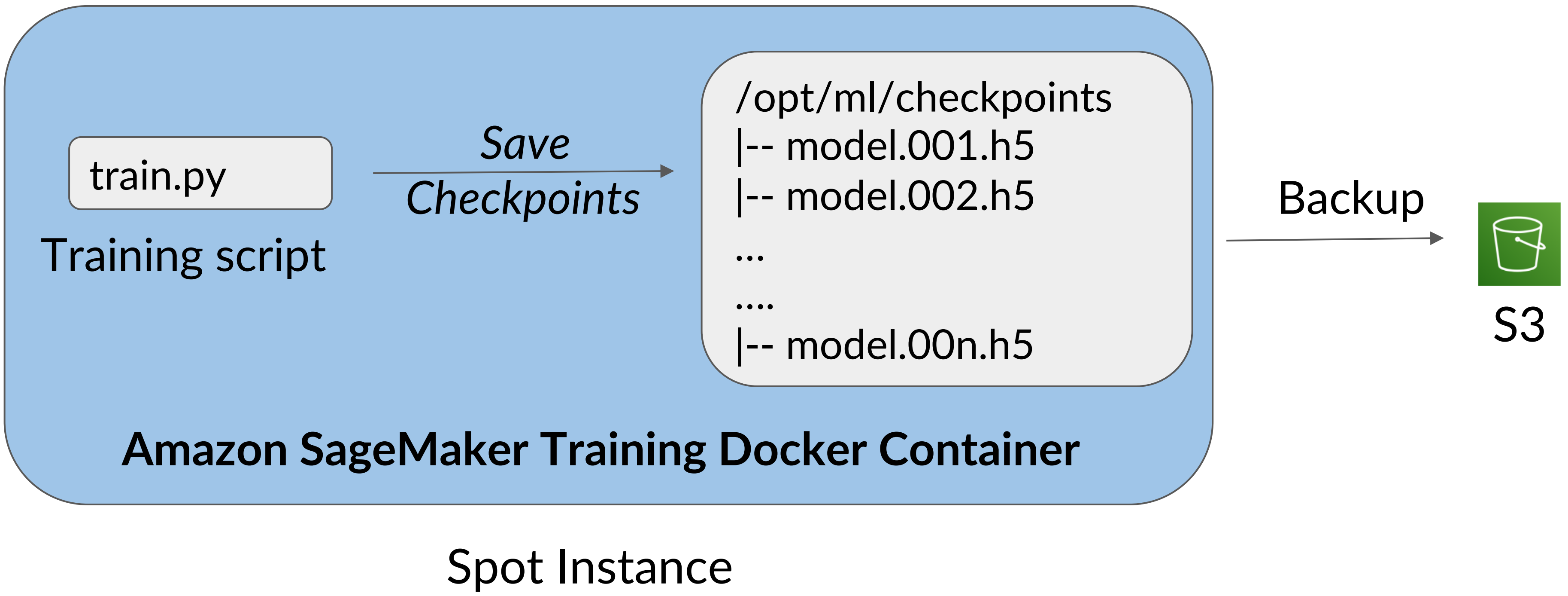
Machine Learning Checkpointing

- Save state of ML models during training
- Checkpoints : Snapshots of the model
  - Model architecture which allows you to recreate the model training once it stopped
  - Model weights that have been learned in the training process so far
  - Training configurations training configuration such as number of epochs that have been executed, and the optimizer used, and the loss observed so far in training, and other metadata information
  - Optimizer This optimizer state allows you to easily resume the training job from where it has stopped.
- Frequency and number of checkpoints

When configuring your new training job with checkpointing take two things into consideration, one is the frequency of checkpointing, and the second is the number of checkpoint files you are saving each time.

Amazon SageMaker Managed Spot

Managed Spot capability allows you to save training costs. Managed Spot is based on the concept of Spot Instances that offer speed and unused capacity to users at discount prices.



Amazon SageMaker Managed Spot

train.py

Training script

Save Checkpoints

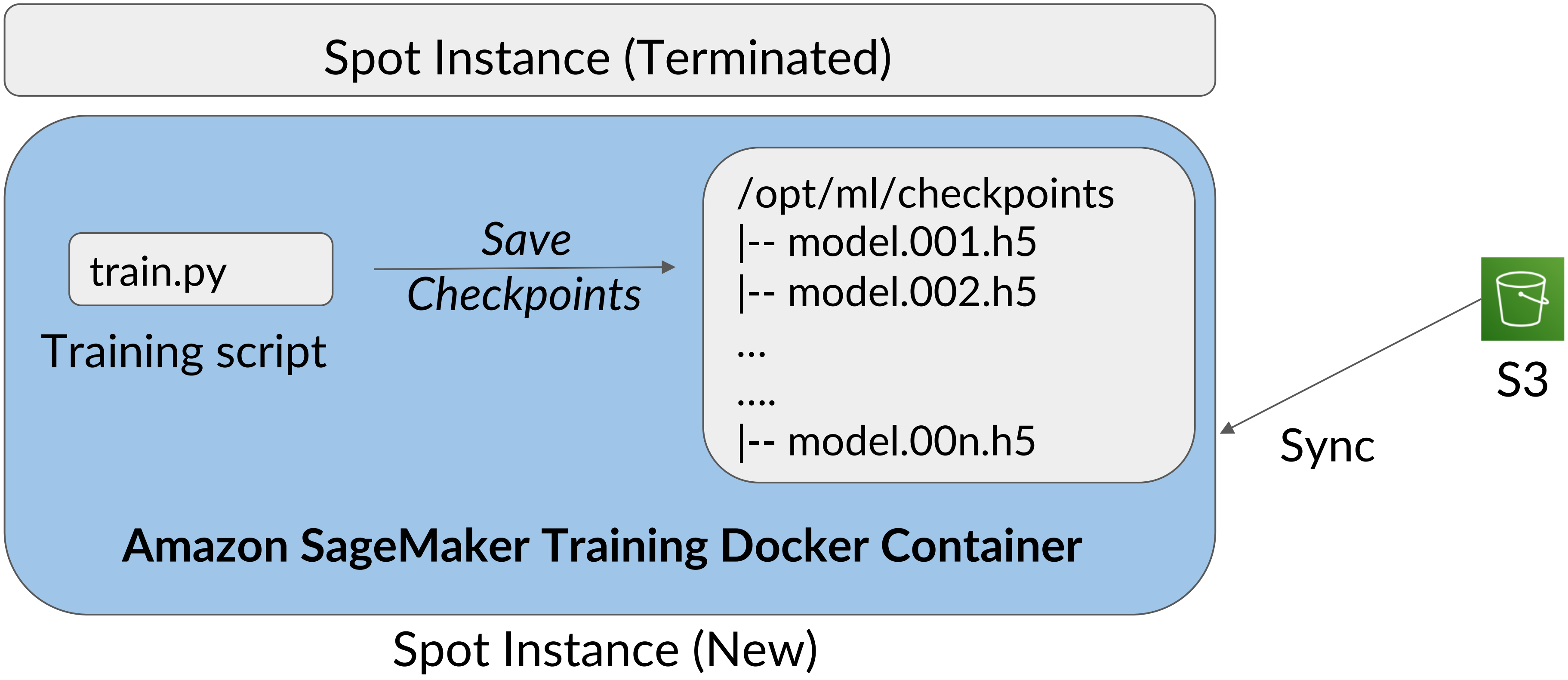
```
/opt/ml/checkpoints
|-- model.001.h5
|-- model.002.h5
...
....
|-- model.00n.h5
```

Amazon SageMaker Training Docker Container

S3

Spot Instance (Terminated)

Amazon SageMaker Spot Training



Distributed Training Strategies

Challenges

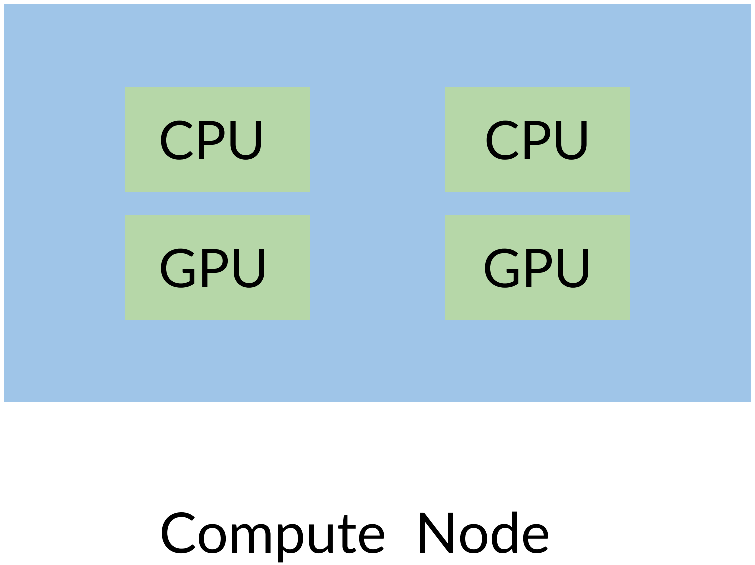
Increased training data volume

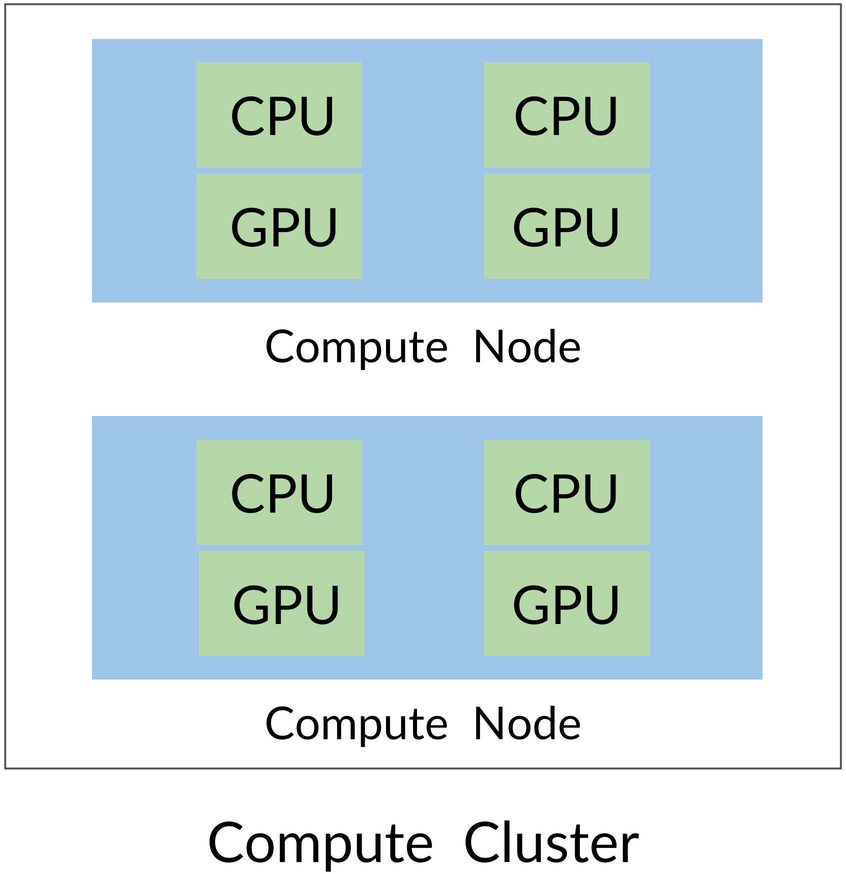
Increased model size and complexity

Distributed Training

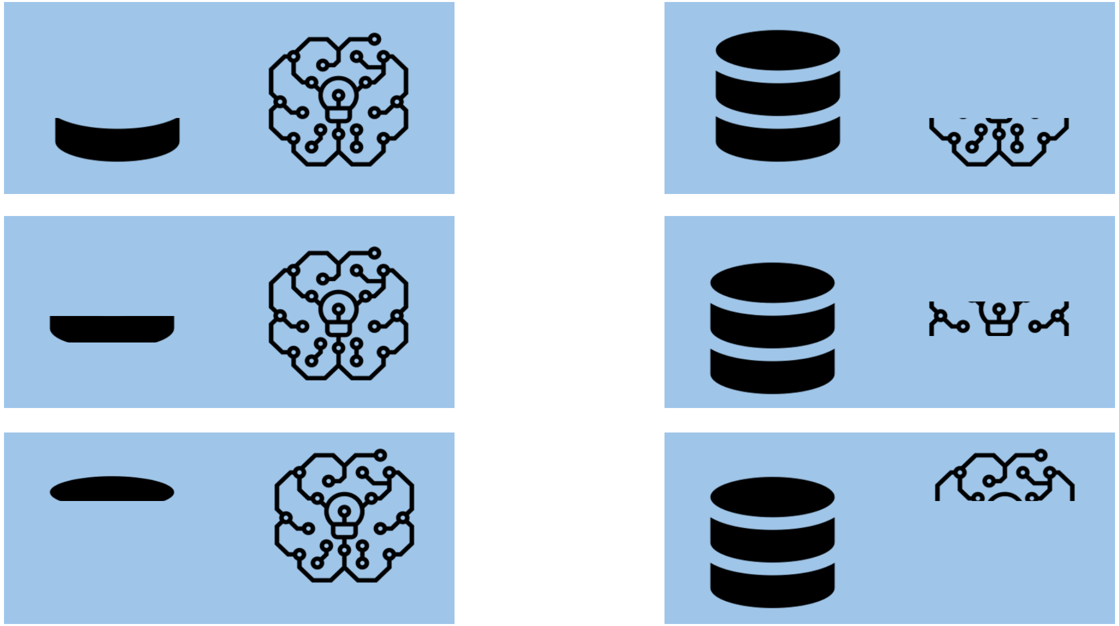
The training load is split across multiple CPUs and GPUs, also called as devices within a single Compute Node.

Or the node can be distributed across multiple compute nodes or compute instances that form a compute cluster.





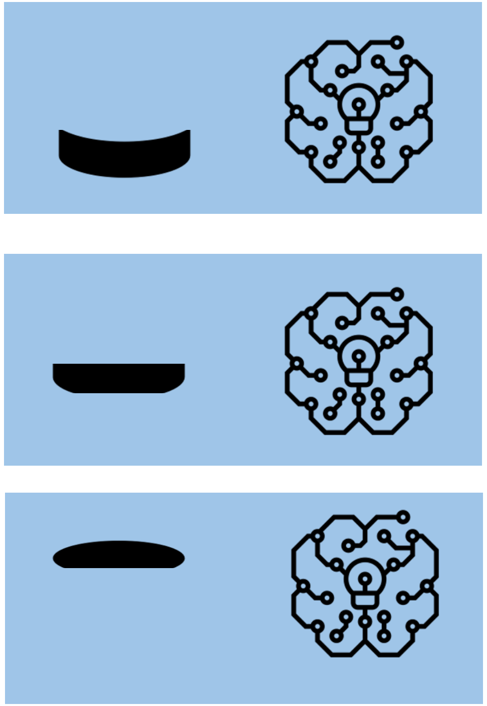
Distributed Training Strategies



Data Parallelism | Model Parallelism

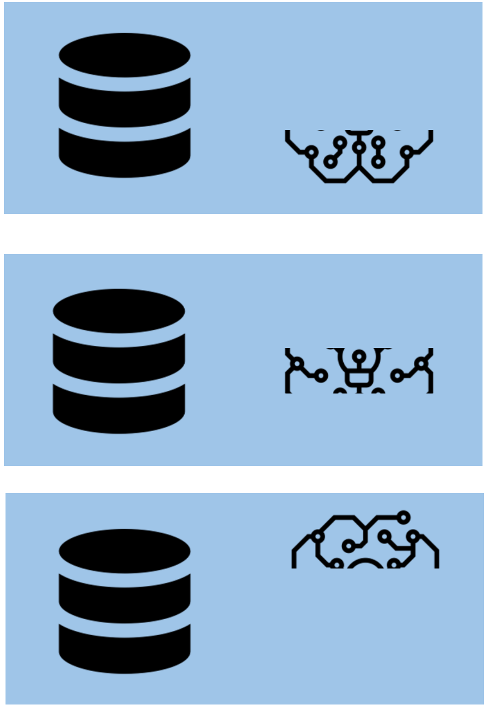
Distributed Training Strategies - Data Parallelism

- Training data split up
- Model replicated on all nodes



Distributed Training Strategies - Model Parallelism

- Training data replicated
- Model split up on all nodes



Amazon SageMaker Estimator

```
from sagemaker.pytorch import PyTorch
estimator = PyTorch(
    entry_point='train.py',
    role=sagemaker.get_execution_role(),
    framework_version='1.6.0',
    py_version='py3',
    instance_count=3,
    instance_type='ml.p3.16xlarge',
    distribution={'smdistributed':{'dataparallel':{enabled': True}}}
)
estimator.fit()
```

Data Parallelism

Distribution Strategy

Amazon SageMaker Estimator

```
from sagemaker.pytorch import PyTorch
estimator = PyTorch(
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    py_version='py3',
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    instance_type='ml.p3.16xlarge',
    distribution={'smdistributed':{'modelparallel':{enabled': True}}}
)
estimator.fit()
```

Model Parallel Distribution Strategy

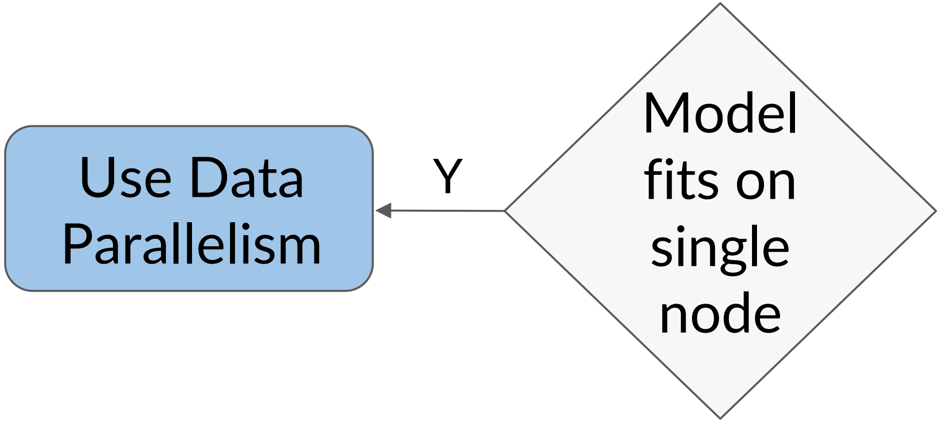
Model Parallelism

Choosing a Distribution Strategy

When choosing a distributed training strategy always keep in mind that if your training across multiple nodes or multiple instances, there is always a certain training overhead. The training overhead comes in the form of internode communication because of the data that needs to be exchanged between the multiple nodes of the cluster.

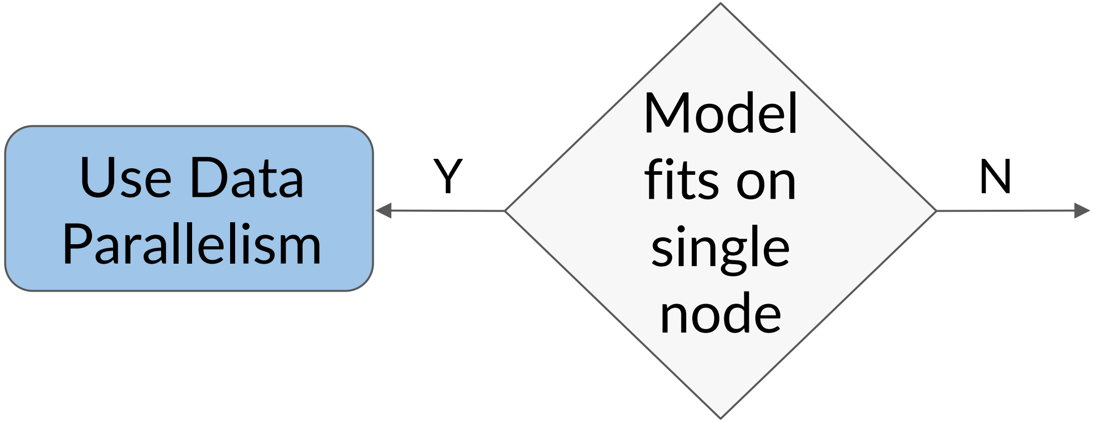
Model fits on single node

Choosing a Distribution Strategy

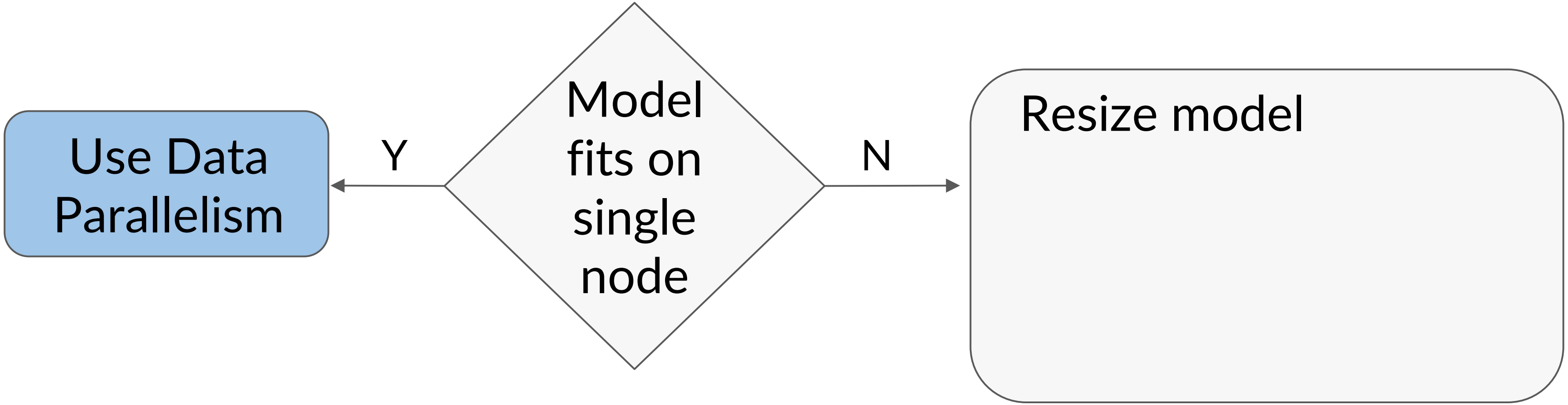


If the train model can fit on a single node's memory, then use data parallelism. In the situations where the model cannot fit on a single node's memory, you have some experimentation to do to see if you can reduce the model size to fit on that single node. All of these experimentations will include an effort to resize the model.

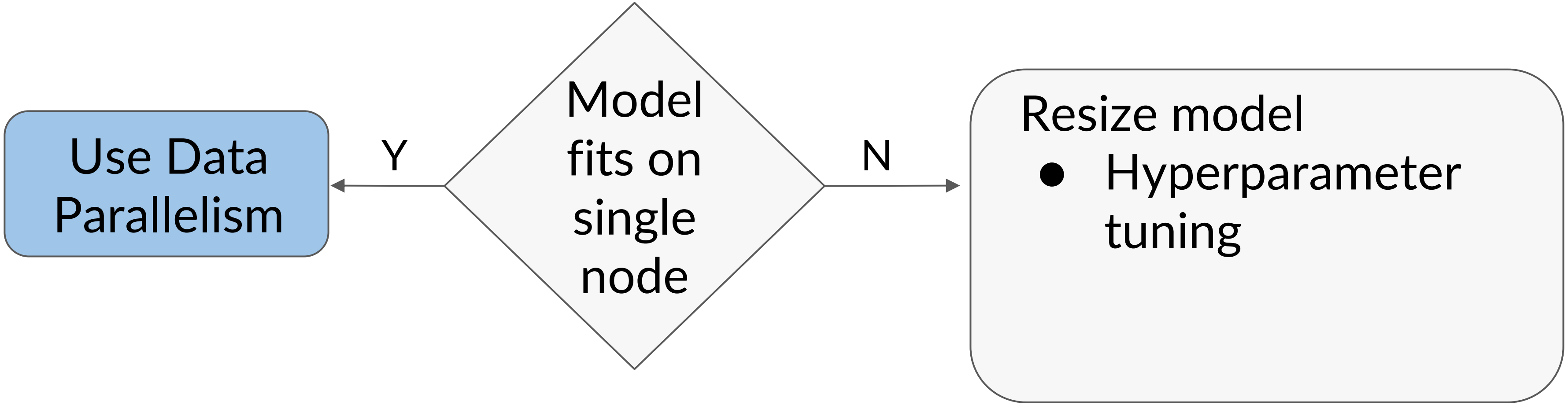
Choosing a Distribution Strategy



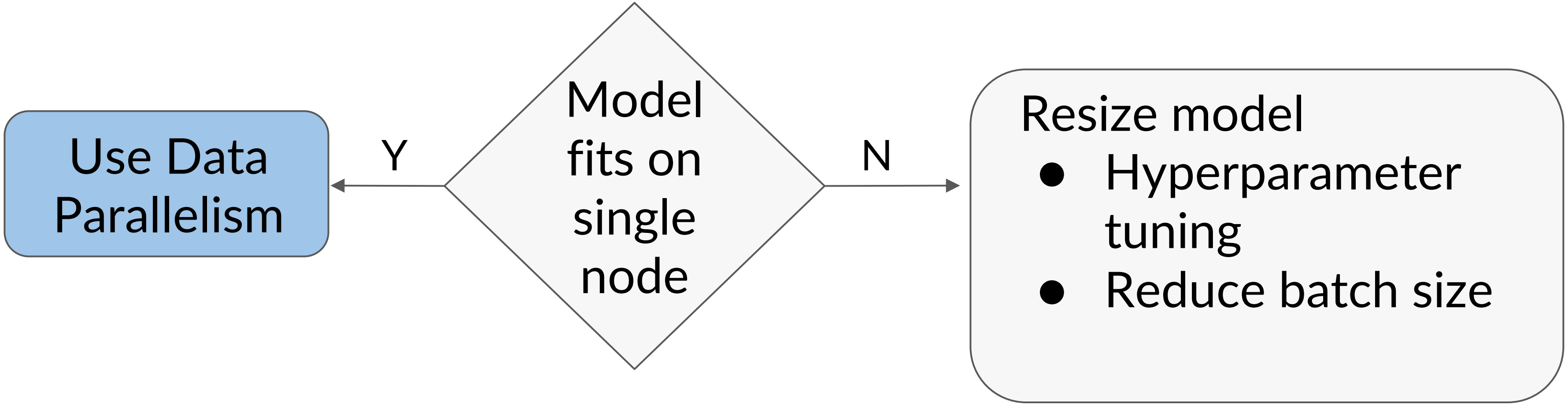
Choosing a Distribution Strategy



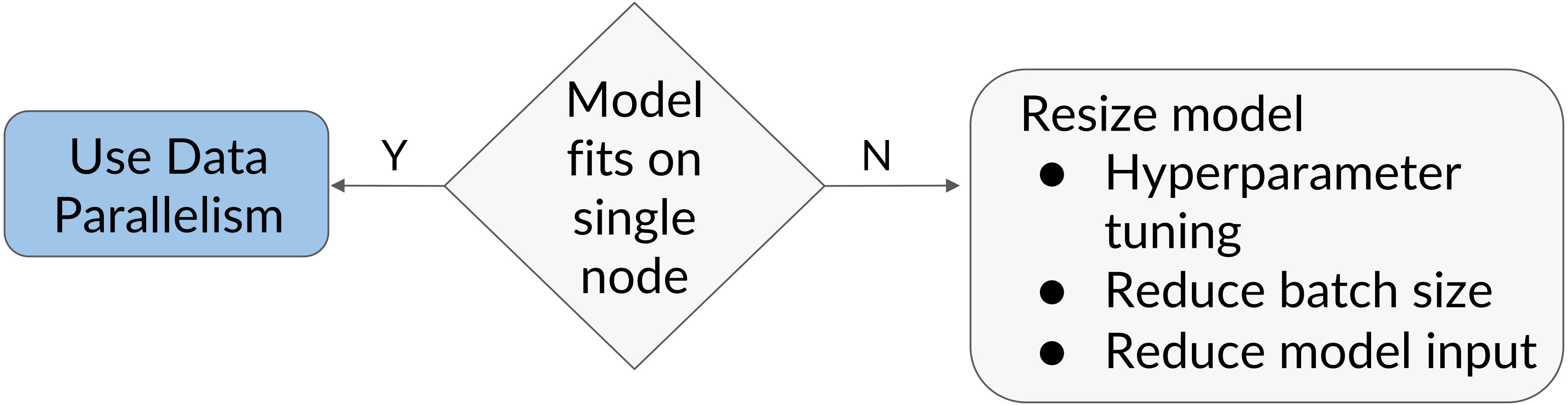
Choosing a Distribution Strategy



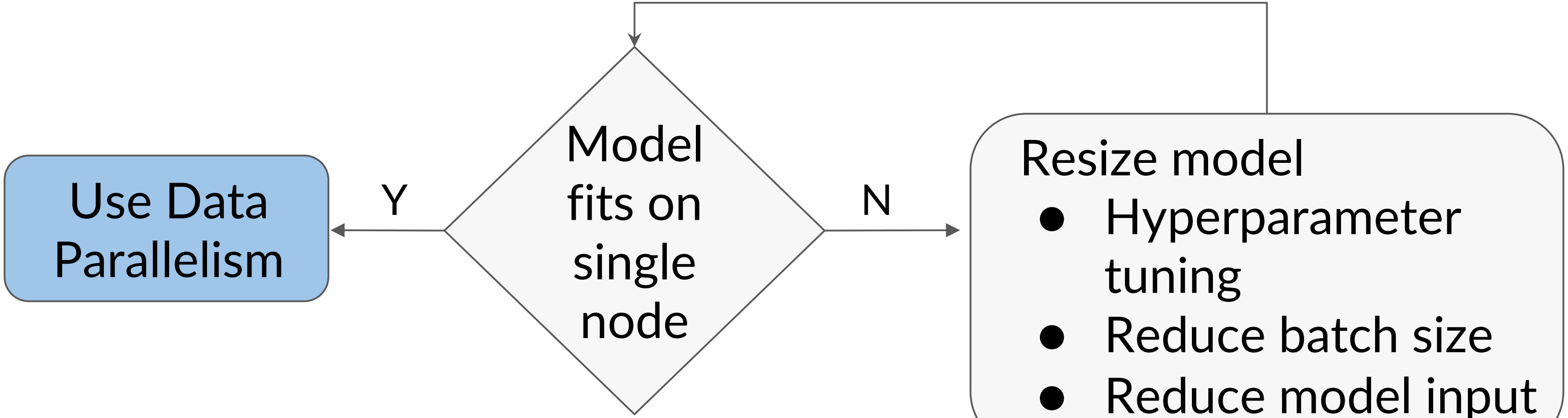
Choosing a Distribution Strategy



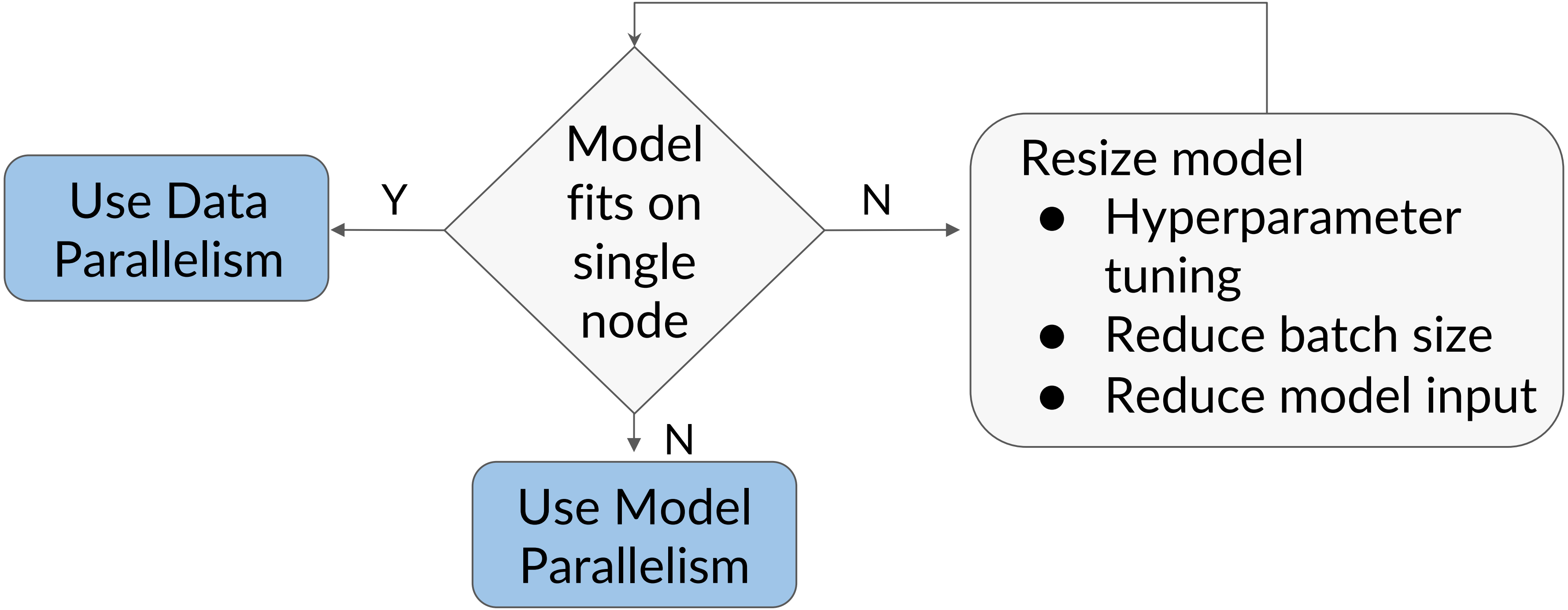
Choosing a Distribution Strategy



Choosing a Distribution Strategy



Choosing a Distribution Strategy



Custom Algorithms with Amazon SageMaker

Options on Amazon SageMaker

Amazon SageMaker	Amazon SageMaker	Amazon SageMaker
Built-in Algorithms	*Bring Your Own Script*	*Bring Your Own Container*

Less Code

More Customizable

Amazon SageMaker Estimator

```
estimator =
sagemaker.estimator.Estimator(image_uri=image_uri, ...)
estimator.set_hyperparameters(...)
estimator.fit(...)
```

Built-In Algorithms

Options on Amazon SageMaker

Amazon SageMaker	Amazon SageMaker	Amazon SageMaker
Built-in Algorithms	*Bring Your Own Script*	*Bring Your Own Container*

Less Code

More Customizable

Amazon SageMaker Estimator

```
estimator =
sagemaker.estimator.Estimator(image_uri=image_uri, ...)
estimator.set_hyperparameters(...)
estimator.fit(...)
```

Built-In Algorithms

```
from sagemaker.pytorch import PyTorch
pytorch_estimator = PyTorch(
    entry_point='train.py',
    ...
)
```

Script Mode
PyTorch Container

Training Options on Amazon SageMaker

Amazon SageMaker	Amazon SageMaker	Amazon SageMaker
Built-in Algorithms	*Bring Your Own Script*	*Bring Your Own Container*

Less Code

More Customizable

Bring Your Own Container - Steps

Code → **Containerize** → **Register with Amazon ECR** → **Create Estimator**

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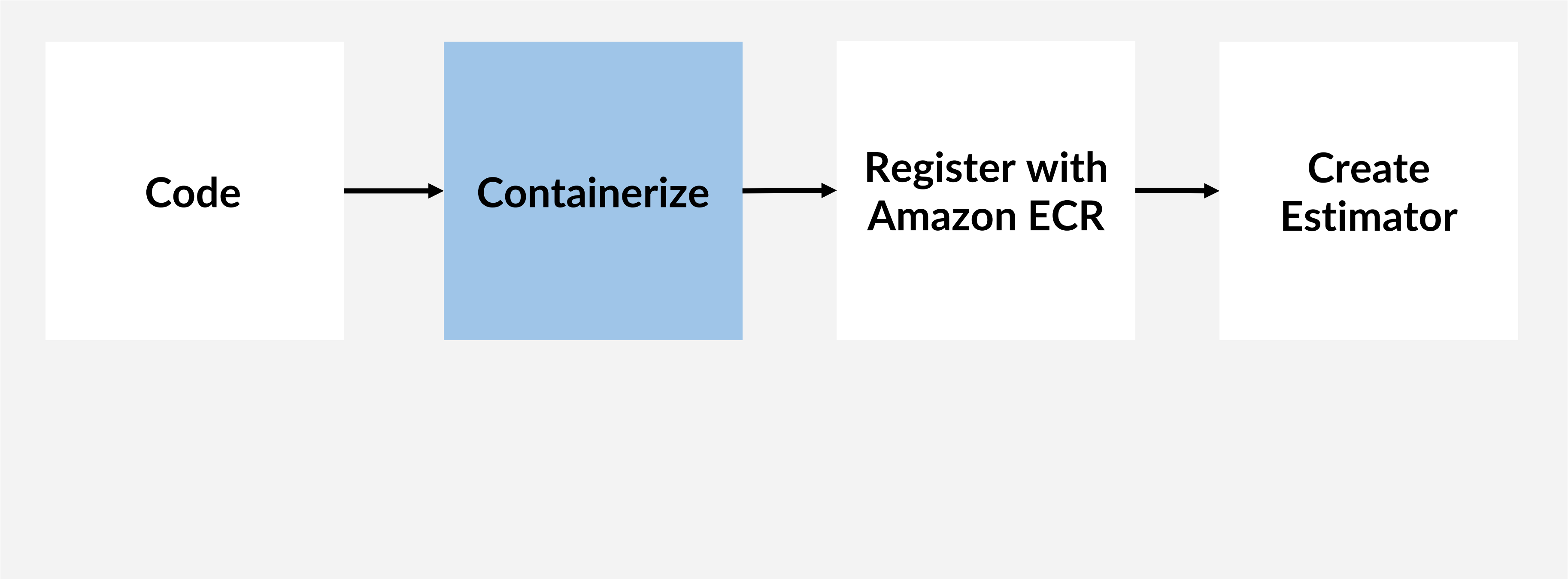
- Algorithm
- Training
- Inference

Bring Your Own Container - Steps



Bring Your Own Container - Steps

Code → **Containerize** → Register with Amazon ECR → Create Estimator

- algorithm_name=tf-custom-container-test
- docker build -t ${algorithm_name} .

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Code → Containerize → **Register with Amazon ECR** → Create Estimator

- aws ecr create-repository --repository-name "${algorithm_name}" > /dev/null
- fullname="${account}.dkr.ecr.${region}.amazonaws.com/${algorithm_name}:latest"
- docker push ${fullname}

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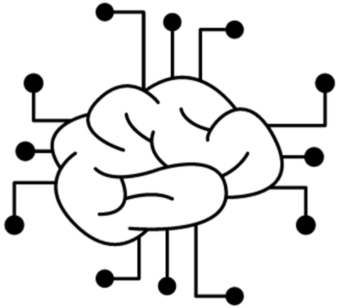
- byoc_image_uri = '{}.dkr.ecr.{}.{}/{}'.format(account_id, region, uri_suffix, ecr_repository + tag)
- estimator = Estimator (image_name=byoc_image_uri, ...   )

Summary

Summary



- Tune and evaluate a model
- Model tuning
- Tune a BERT-based text classifier
- Model evaluation
- Evaluate a BERT-based text classifier
- TODO: Script Mode?
- TODO: Bring Your Own Container?