Compile and Train a Vision Transformer Model on the Caltech 256 Dataset using a Single Node

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SageMaker Training Compiler Overview

SageMaker Training Compiler is a capability of SageMaker that makes hard-to-implement optimizations to reduce training time on GPU instances. The compiler optimizes DL models to accelerate training by more efficiently using SageMaker machine learning (ML) GPU instances. SageMaker Training Compiler is available at no additional charge within SageMaker and can help reduce total billable time as it accelerates training.

SageMaker Training Compiler is integrated into the AWS Deep Learning Containers (DLCs). Using the SageMaker Training Compiler enabled AWS DLCs, you can compile and optimize training jobs on GPU instances with minimal changes to your code. Bring your deep learning models to SageMaker and enable SageMaker Training Compiler to accelerate the speed of your training job on SageMaker ML instances for accelerated computing.

For more information, see SageMaker Training Compiler in the *Amazon SageMaker Developer Guide*.

Introduction

In this demo, you'll use Amazon SageMaker Training Compiler to train the `Vision Transformer` model on the `Caltech-256` dataset. To get started, we need to set up the environment with a few prerequisite steps, for permissions, configurations, and so on.

NOTE: You can run this demo in SageMaker Studio, SageMaker notebook instances, or your local machine with AWS CLI set up. If using SageMaker Studio or SageMaker notebook instances, make sure you choose one of the TensorFlow-based kernels, `Python 3 (TensorFlow x.y Python 3.x CPU Optimized)` or `conda_tesorflow_p39` respectively.

NOTE: This notebook uses a `ml.p3.2xlarge` instance with a single GPU. However, it can easily be extended to multiple GPUs on a single node. If you don't have enough quota, see Request a service quota increase for SageMaker resources.

Development Environment

Installation

This example notebook requires **SageMaker Python SDK v2.92.0**

In [310…

```
!pip install "sagemaker>=2.92" botocore boto3 awscli matplotlib --upgrade
```

```
Looking in indexes: https://pypi.org/simple, https://pip.repos.neuron.amazonaw
s.com
Requirement already satisfied: sagemaker>=2.92 in /home/ec2-user/anaconda3/env
s/tensorflow2_p38/lib/python3.8/site-packages (2.94.0)
Requirement already satisfied: botocore in /home/ec2-user/anaconda3/envs/tenso
rflow2_p38/lib/python3.8/site-packages (1.27.7)
Requirement already satisfied: boto3 in /home/ec2-user/anaconda3/envs/tensorfl
ow2_p38/lib/python3.8/site-packages (1.24.7)
Requirement already satisfied: awscli in /home/ec2-user/anaconda3/envs/tensorf
low2_p38/lib/python3.8/site-packages (1.25.7)
Requirement already satisfied: matplotlib in /home/ec2-user/anaconda3/envs/ten
sorflow2_p38/lib/python3.8/site-packages (3.5.2)
Requirement already satisfied: pathos in /home/ec2-user/anaconda3/envs/tensorf
low2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (0.2.8)
Requirement already satisfied: attrs==20.3.0 in /home/ec2-user/anaconda3/envs/
tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (20.3.0)
Requirement already satisfied: google-pasta in /home/ec2-user/anaconda3/envs/t
ensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (0.2.0)
Requirement already satisfied: protobuf<4.0,>=3.1 in /home/ec2-user/anaconda3/
envs/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (3.19.
1)
Requirement already satisfied: pandas in /home/ec2-user/anaconda3/envs/tensorf
low2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (1.3.4)
Requirement already satisfied: protobuf3-to-dict<1.0,>=0.1.5 in /home/ec2-use
r/anaconda3/envs/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=
2.92) (0.1.5)
Requirement already satisfied: smdebug-rulesconfig==1.0.1 in /home/ec2-user/an
aconda3/envs/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.9
2) (1.0.1)
Requirement already satisfied: importlib-metadata<5.0,>=1.4.0 in /home/ec2-use
r/anaconda3/envs/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=
2.92) (1.7.0)
Requirement already satisfied: packaging>=20.0 in /home/ec2-user/anaconda3/env
s/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (21.0)
Requirement already satisfied: numpy<2.0,>=1.9.0 in /home/ec2-user/anaconda3/e
nvs/tensorflow2_p38/lib/python3.8/site-packages (from sagemaker>=2.92) (1.20.
3)
Requirement already satisfied: jmespath<2.0.0,>=0.7.1 in /home/ec2-user/anacon
da3/envs/tensorflow2_p38/lib/python3.8/site-packages (from botocore) (0.10.0)
Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in /home/ec2-user/a
naconda3/envs/tensorflow2_p38/lib/python3.8/site-packages (from botocore) (2.
8.2)
Requirement already satisfied: urllib3<1.27,>=1.25.4 in /home/ec2-user/anacond
a3/envs/tensorflow2_p38/lib/python3.8/site-packages (from botocore) (1.26.8)
Requirement already satisfied: s3transfer<0.7.0,>=0.6.0 in /home/ec2-user/anac
onda3/envs/tensorflow2_p38/lib/python3.8/site-packages (from boto3) (0.6.0)
Requirement already satisfied: PyYAML<5.5,>=3.10 in /home/ec2-user/anaconda3/e
nvs/tensorflow2_p38/lib/python3.8/site-packages (from awscli) (5.4.1)
Requirement already satisfied: docutils<0.17,>=0.10 in /home/ec2-user/anaconda
3/envs/tensorflow2_p38/lib/python3.8/site-packages (from awscli) (0.15.2)
Requirement already satisfied: rsa<4.8,>=3.1.2 in /home/ec2-user/anaconda3/env
s/tensorflow2_p38/lib/python3.8/site-packages (from awscli) (4.7.2)
Requirement already satisfied: colorama<0.4.5,>=0.2.5 in /home/ec2-user/anacon
da3/envs/tensorflow2_p38/lib/python3.8/site-packages (from awscli) (0.4.3)
Requirement already satisfied: pillow>=6.2.0 in /home/ec2-user/anaconda3/envs/
tensorflow2_p38/lib/python3.8/site-packages (from matplotlib) (9.0.1)
Requirement already satisfied: fonttools>=4.22.0 in /home/ec2-user/anaconda3/e
nvs/tensorflow2_p38/lib/python3.8/site-packages (from matplotlib) (4.33.3)
Requirement already satisfied: pyparsing>=2.2.1 in /home/ec2-user/anaconda3/en
vs/tensorflow2_p38/lib/python3.8/site-packages (from matplotlib) (3.0.6)
```

```
Requirement already satisfied: kiwisolver>=1.0.1 in /home/ec2-user/anaconda3/e
nvs/tensorflow2_p38/lib/python3.8/site-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /home/ec2-user/anaconda3/envs/t
ensorflow2_p38/lib/python3.8/site-packages (from matplotlib) (0.11.0)
Requirement already satisfied: zipp>=0.5 in /home/ec2-user/anaconda3/envs/tens
orflow2_p38/lib/python3.8/site-packages (from importlib-metadata<5.0,>=1.4.0->
sagemaker>=2.92) (3.6.0)
Requirement already satisfied: six in /home/ec2-user/anaconda3/envs/tensorflow
2_p38/lib/python3.8/site-packages (from protobuf3-to-dict<1.0,>=0.1.5->sagemak
er>=2.92) (1.16.0)
Requirement already satisfied: pyasn1>=0.1.3 in /home/ec2-user/anaconda3/envs/
tensorflow2_p38/lib/python3.8/site-packages (from rsa<4.8,>=3.1.2->awscli) (0.
4.8)
Requirement already satisfied: pytz>=2017.3 in /home/ec2-user/anaconda3/envs/t
ensorflow2_p38/lib/python3.8/site-packages (from pandas->sagemaker>=2.92) (202
1.3)
Requirement already satisfied: ppft>=1.6.6.4 in /home/ec2-user/anaconda3/envs/
tensorflow2_p38/lib/python3.8/site-packages (from pathos->sagemaker>=2.92) (1.
6.6.4)
Requirement already satisfied: pox>=0.3.0 in /home/ec2-user/anaconda3/envs/ten
sorflow2_p38/lib/python3.8/site-packages (from pathos->sagemaker>=2.92) (0.3.
0)
Requirement already satisfied: dill>=0.3.4 in /home/ec2-user/anaconda3/envs/te
nsorflow2_p38/lib/python3.8/site-packages (from pathos->sagemaker>=2.92) (0.3.
4)
Requirement already satisfied: multiprocess>=0.70.12 in /home/ec2-user/anacond
a3/envs/tensorflow2_p38/lib/python3.8/site-packages (from pathos->sagemaker>=
2.92) (0.70.12.2)
WARNING: You are using pip version 22.0.4; however, version 22.1.2 is availabl
e.
You should consider upgrading via the '/home/ec2-user/anaconda3/envs/tensorflo
w2_p38/bin/python -m pip install --upgrade pip' command.
```

In [311…

```
import botocore
import boto3
import sagemaker

print(f"botocore: {botocore.__version__}")
print(f"boto3: {boto3.__version__}")
print(f"sagemaker: {sagemaker.__version__}")
```

```
botocore: 1.27.7
boto3: 1.24.7
sagemaker: 2.94.0
```

SageMaker environment

In [312…

```
import sagemaker

sess = sagemaker.Session()

# SageMaker session bucket -> used for uploading data, models and logs
# SageMaker will automatically create this bucket if it does not exist
sagemaker_session_bucket = None
if sagemaker_session_bucket is None and sess is not None:
    # set to default bucket if a bucket name is not given
    sagemaker_session_bucket = sess.default_bucket()

role = sagemaker.get_execution_role()
```

```
sess = sagemaker.Session(default_bucket=sagemaker_session_bucket)

print(f"sagemaker role arn: {role}")
print(f"sagemaker bucket: {sagemaker_session_bucket}")
print(f"sagemaker session region: {sess.boto_region_name}")
```

```
sagemaker role arn: arn:aws:iam::875423407011:role/SageMakerRole
sagemaker bucket: sagemaker-us-west-2-875423407011
sagemaker session region: us-west-2
```

Working with the Caltech-256 dataset

We have hosted the Caltech-256 dataset in S3 in us-west-2. We will transfer this dataset to your account and region for use with SageMaker Training.

The dataset consists of JPEG images organized into directories with each directory representing an object cateogory.

In [313…

```
import os

source = 's3://sagemaker-sample-files/datasets/image/caltech-256/256_ObjectCate
destn = f's3://{sagemaker_session_bucket}/caltech-256'

os.system(f'aws s3 sync {source} {destn}')
```

Out[313]: 0

SageMaker Training Job

To create a SageMaker training job, we use a `TensorFlow` estimator. Using the estimator, you can define which training script should SageMaker use through `entry_point`, which `instance_type` to use for training, which `hyperparameters` to pass, and so on.

When a SageMaker training job starts, SageMaker takes care of starting and managing all the required machine learning instances, picks up the `TensorFlow` Deep Learning Container, uploads your training script, and downloads the data from `sagemaker_session_bucket` into the container at `/opt/ml/input/data`.

In the following section, you learn how to set up two versions of the SageMaker `TensorFlow` estimator, a native one without the compiler and an optimized one with the compiler.

Training Setup

Set up the basic configuration for training. Set `EPOCHS` to the number of times you would like to loop over the training data.

In [314…

```
TRCOMP_IMAGE_URI='763104351884.dkr.ecr.us-west-2.amazonaws.com/tensorflow-trair
EPOCHS = 10
```

Training with Native TensorFlow

The `BATCH_SIZE` in the following code cell is the maximum batch that can fit into the memory of an `ml.p3.2xlarge` instance while giving the best training speed. If you change the model, instance type, and other parameters, you need to do some experiments to find the largest batch size that will fit into GPU memory.

In [315…

```
from sagemaker.tensorflow import TensorFlow

BATCH_SIZE = 64
LEARNING_RATE = 1e-3
WEIGHT_DECAY = 1e-4

kwargs = dict(
    source_dir='scripts',
    entry_point='vit_b16_1.py',
    model_dir=False,
    instance_type='ml.p3.2xlarge',
    instance_count=1,
    image_uri=TRCOMP_IMAGE_URI,
    debugger_hook_config=None,
    disable_profiler=True,
    max_run=60*60, #60 minutes
    role = role,
    metric_definitions = [
        {'Name':'training_loss', 'Regex':'loss: ([0-9.]*?) '},
        {'Name':'training_accuracy', 'Regex':'accuracy: ([0-9.]*?) '},
        {'Name':'training_latency_per_epoch', 'Regex':'- ([0-9.]*?)s/epoch'},
        {'Name':'training_avg_latency_per_step', 'Regex':'- ([0-9.]*?)ms/step'}
    ]
)

# Configure the training job
native_estimator = TensorFlow(
                    hyperparameters={
                        'EPOCHS': EPOCHS,
                        'BATCH_SIZE' : BATCH_SIZE,
                        'LEARNING_RATE' : LEARNING_RATE,
                        'WEIGHT_DECAY' : WEIGHT_DECAY,
                    },
                    base_job_name='native-tf29-vit',
                    **kwargs,
                )

# Start training with our uploaded datasets as input
native_estimator.fit(inputs=destn, wait=False)

# The name of the training job.
native_estimator.latest_training_job.name
```

Out[315]:

```
'native-tf29-vit-2022-06-11-18-56-20-473'
```

Training with Optimized TensorFlow

Compilation through Training Compiler changes the memory footprint of the model. Most commonly, this manifests as a reduction in memory utilization and a consequent increase in the largest batch size that can fit on the GPU. But in some case the compiler intelligently promotes caching which leads to a decrease in largest batch size that can fit on the GPU. Note that if you want to change the batch size, you must adjust the learning rate appropriately.

Note: We recommend you to turn the SageMaker Debugger's profiling and debugging tools off when you use compilation to avoid additional overheads.

In [316…

```
# TODO: Change how TrainingCompilerConfig is used after SDK release

from sagemaker.tensorflow import TensorFlow
from sagemaker.training_compiler.config import TrainingCompilerConfig

OPTIMIZED_BATCH_SIZE = 48
LEARNING_RATE = LEARNING_RATE / BATCH_SIZE * OPTIMIZED_BATCH_SIZE
WEIGHT_DECAY = WEIGHT_DECAY * BATCH_SIZE / OPTIMIZED_BATCH_SIZE

# Configure the training job
optimized_estimator = TensorFlow(
                        hyperparameters={
                            TrainingCompilerConfig.HP_ENABLE_COMPILER : True,
                            'EPOCHS': EPOCHS,
                            'BATCH_SIZE' : OPTIMIZED_BATCH_SIZE,
                            'LEARNING_RATE' : LEARNING_RATE,
                            'WEIGHT_DECAY' : WEIGHT_DECAY,
                        },
                        base_job_name='optimized-tf29-vit',
                        **kwargs,
                    )

# Start training with our uploaded datasets as input
optimized_estimator.fit(inputs=destn, wait=False)

# The name of the training job.
optimized_estimator.latest_training_job.name
```

Out[316]:

```
'optimized-tf29-vit-2022-06-11-18-56-21-596'
```

Wait for training jobs to complete

The training jobs described above typically take around 40 mins to complete

Note: If the estimator object is no longer available due to a kernel break or refresh, you need to directly use the training job name and manually attach the training job to a new TensorFlow estimator. For example:

```
native_estimator = TensorFlow.attach("<your_training_job_name>")
```

In [329…

```
native_estimator = TensorFlow.attach(native_estimator.latest_training_job.name)
optimized_estimator = TensorFlow.attach(optimized_estimator.latest_training_jok
```

```
2022-06-11 19:26:36 Starting - Preparing the instances for training
2022-06-11 19:26:36 Downloading - Downloading input data
2022-06-11 19:26:36 Training - Training image download completed. Training in
progress.
2022-06-11 19:26:36 Uploading - Uploading generated training model
2022-06-11 19:26:36 Completed - Training job completed

2022-06-11 19:17:39 Starting - Preparing the instances for training
2022-06-11 19:17:39 Downloading - Downloading input data
2022-06-11 19:17:39 Training - Training image download completed. Training in
progress.
2022-06-11 19:17:39 Uploading - Uploading generated training model
2022-06-11 19:17:39 Completed - Training job completed
```

Analysis

Here we view the training metrics from the training jobs as a Pandas dataframe

Native TensorFlow

In [330…

```python
import pandas as pd

# Extract training metrics from the estimator
native_metrics = native_estimator.training_job_analytics.dataframe()

# Restructure table for viewing
for metric in native_metrics['metric_name'].unique():
    native_metrics[metric] = native_metrics[native_metrics['metric_name']==metr
native_metrics = native_metrics.drop(columns=['metric_name', 'value'])
native_metrics = native_metrics.groupby('timestamp').max()
native_metrics['epochs'] = range(1,11)
native_metrics = native_metrics.set_index('epochs')

native_metrics
```

Out[330]:

	training_loss	training_accuracy	training_latency_per_epoch	training_avg_latency_per
epochs				
1	5.8042	0.0187	149.0	
2	5.7577	0.0197	116.0	
3	5.7547	0.0218	117.0	
4	5.7739	0.0204	116.0	
5	5.7613	0.0218	116.0	
6	5.7600	0.0230	116.0	
7	5.7640	0.0216	116.0	
8	5.7234	0.0220	116.0	
9	5.4523	0.0285	116.0	
10	5.4006	0.0301	116.0	

Optimized TensorFlow

In [331…

```
import pandas as pd

# Extract training metrics from the estimator
optimized_metrics = optimized_estimator.training_job_analytics.dataframe()

# Restructure table for viewing
for metric in optimized_metrics['metric_name'].unique():
    optimized_metrics[ metric] = optimized_metrics[optimized_metrics['metric_na
optimized_metrics = optimized_metrics.drop(columns=['metric_name', 'value'])
optimized_metrics = optimized_metrics.groupby('timestamp').max()
optimized_metrics['epochs'] = range(1,11)
optimized_metrics = optimized_metrics.set_index('epochs')

optimized_metrics
```

Out[331]:

epochs	training_loss	training_accuracy	training_latency_per_epoch	training_avg_latency_per
1	5.7542	0.0201	115.0	
2	5.7203	0.0220	66.0	
3	5.7126	0.0216	66.0	
4	5.7175	0.0207	66.0	
5	5.7053	0.0233	66.0	
6	5.5634	0.0254	66.0	
7	5.3941	0.0293	66.0	
8	5.3260	0.0340	66.0	
9	5.1929	0.0407	66.0	
10	4.9748	0.0579	66.0	

Savings from Training Compiler

Let us calculate the actual savings on the training jobs above and the potential for savings for a longer training job.

Actual Savings

To get the actual savings, we use the describe_training_job API to get the billable seconds for each training job.

In [332…

```
# Billable seconds for the Native TensorFlow Training job

details = sess.describe_training_job(job_name=native_estimator.latest_training_
native_secs = details['BillableTimeInSeconds']

native_secs
```

Out[332]:

```
1714
```

In [333…
```
# Billable seconds for the Optimized TensorFlow Training job

details = sess.describe_training_job(job_name=optimized_estimator.latest_traini
optimized_secs = details['BillableTimeInSeconds']

optimized_secs
```

Out[333]:
```
1176
```

In [334…
```
# Calculating percentage Savings from Training Compiler

percentage = (native_secs-optimized_secs)*100/native_secs

f"Training Compiler yielded {percentage:.2f}% savings in training cost."
```

Out[334]:
```
'Training Compiler yielded 31.39% savings in training cost.'
```

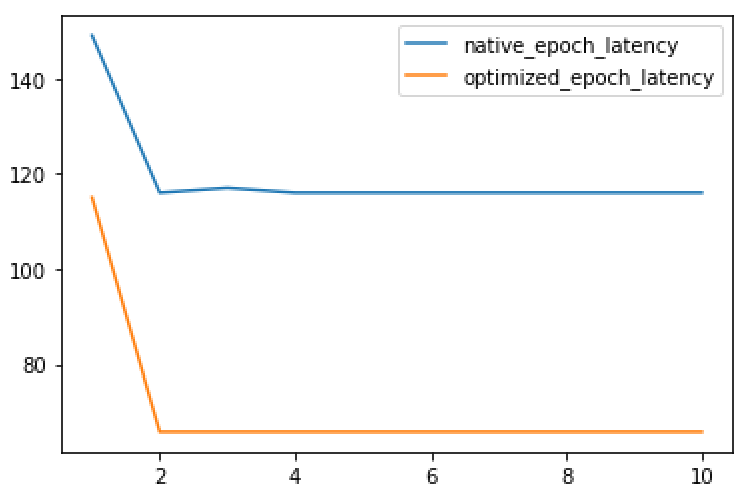
Potential savings

The Training Compiler works by compiling the model graph once per input shape and reusing the cached graph for subsequent steps. As a result the first few steps of training incur an increased latency owing to compilation which we refer to as the compilation overhead. This overhead is amortized over time thanks to the subsequent steps being much faster. We will demonstrate this below.

In [335…
```
import matplotlib.pyplot as plt

plt.plot(native_metrics['training_latency_per_epoch'], label='native_epoch_late
plt.plot(optimized_metrics['training_latency_per_epoch'], label='optimized_epoc
plt.legend()
```

Out[335]:
```
<matplotlib.legend.Legend at 0x7f38099a93a0>
```



We calculate the potential savings below from the difference in steady state epoch latency between native TensorFlow and optimized TensorFlow

In [336…
```
native_steady_state_latency = native_metrics['training_latency_per_epoch'].iloc

native_steady_state_latency
```

Out[336]: 116.0

In [337…
```
optimized_steady_state_latency = optimized_metrics['training_latency_per_epoch'

optimized_steady_state_latency
```

Out[337]: 66.0

In [338…
```
# Calculating potential percentage Savings from Training Compiler

percentage = (native_steady_state_latency-optimized_steady_state_latency)*100/r

f"Training Compiler can potentially yield {percentage:.2f}% savings in training
```

Out[338]: 'Training Compiler can potentially yield 43.10% savings in training cost for a longer training job.'

Convergence of Training

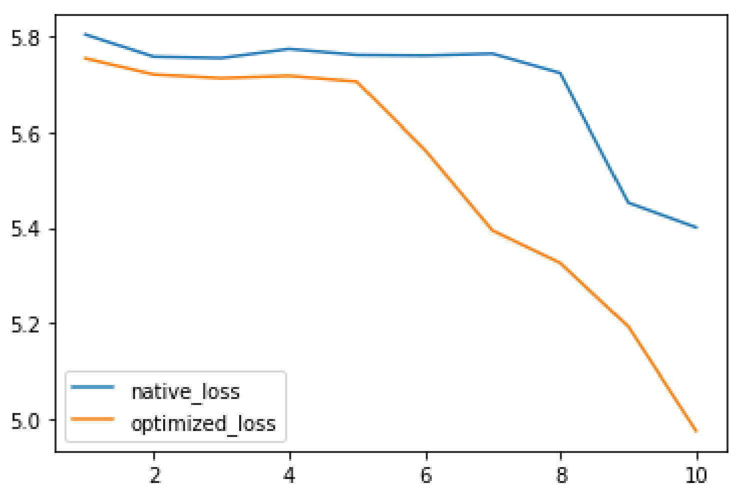
Training Compiler brings down total training time by intelligently choosing between memory utilization and core utilization in the GPU. This does not have any effect on the model arithmetic and consequently convergence of the model.

However, since we are working with a new batch size, hyperparameters like - learning rate, learning rate schedule and weight decay might have to be scaled and tuned for the new batch size

In [339…
```
import matplotlib.pyplot as plt

plt.plot(native_metrics['training_loss'], label='native_loss')
plt.plot(optimized_metrics['training_loss'], label='optimized_loss')
plt.legend()
```

Out[339]: <matplotlib.legend.Legend at 0x7f3848c5c1f0>



We can see that the model's convergence behavior is similar with and without Training Compiler. Here we have tuned the batch size specific hyperparameters - Learning Rate and Weight Decay using a linear scaling.

Learning rate is directly proportional to the batch size:

```
new_learning_rate = old_learning_rate * new_batch_size/old_batch_size
```

Weight decay is inversely proportional to the batch size:

```
new_weight_decay = old_weight_decay * old_batch_size/new_batch_size
```

Better results can be achieved with further tuning. Check out Automatic Model Tuning for tuning.

Clean up

Stop all training jobs launched if the jobs are still running.

In [340…

```
def stop_training_job(name):
    status = sess.describe_training_job(name)["TrainingJobStatus"]
    if status == "InProgress":
        sm.stop_training_job(TrainingJobName=name)


stop_training_job(native_estimator.latest_training_job.name)
stop_training_job(optimized_estimator.latest_training_job.name)
```

Also, to find instructions on cleaning up resources, see Clean Up in the *Amazon SageMaker Developer Guide*.