Machine Learning on AWS: EC2 vs containers vs SageMaker

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And so it begins

- You’ve trained a model on a local machine, using a popular open source library.
- You’ve measured the model’s accuracy, and things look good.
- Now you’d like to deploy it to check its actual behaviour, to run A/B tests, etc.
- You’ve embedded the model in your business application.
- You’ve deployed everything to a single virtual machine in the cloud.
- Everything works, you’re serving predictions, life is good!

Score card

	Single EC2 instance
Infrastructure effort	C'mon, it's just one instance
ML setup effort	pip install tensorflow
CI/CD integration	Not needed
Build models	DIY
Train models	python train.py
Deploy models (at scale)	python predict.py
Scale/HA inference	Not needed
Optimize costs	Not needed
Security	Not needed

A few instances and models later…

- Life is not that good

- Too much manual work
  - Time-consuming and error-prone
  - Dependency hell
  - No cost optimization

- Monolithic architecture
  - Deployment hell
  - Multiple apps can’t share the same model
  - Apps and models scale differently

AWS Deep Learning AMIs and Containers

Optimized environments on Amazon Linux or Ubuntu

Conda AMI
For developers who want pre-installed pip packages of DL frameworks in separate virtual environments.

Base AMI
For developers who want a clean slate to set up private DL engine repositories or custom builds of DL engines.

Containers
For developers who want pre-installed containers for DL frameworks (TensorFlow, PyTorch, Apache MXNet)

Running a new EC2 instance with the Deep Learning AMI

```
aws ec2 run-instances \
    --image-id ami-02273e0d16172dbd1 \   # Deep Learning AMI in eu-west-1
    --instance-type p3.2xlarge \
    --instance-market-options '{"MarketType":"spot"}' \
    --tag-specifications 'ResourceType=instance,Tags=[{Key=Name,Value=dlami-demo}]' \
    --key-name $KEYPAIR \
    --security-group-ids $SECURITY_GROUP \
    --iam-instance-profile Name=$ROLE
```

Connecting to Jupyter

On your local machine

```
ssh -L 8000:localhost:8888 ec2-user@INSTANCE_NAME
```

On the EC2 instance

```
jupyter notebook --no-browser --port=8888
```

On your local machine

Open http://localhost:8000

Training with the Tensorflow Deep Learning container

List of image names: https://docs.aws.amazon.com/dlami/latest/devguide/deep-learning-containers-images.html

On the training machine

```
$(aws ecr get-login --no-include-email --region eu-west-1 --registry-ids 763104351884)

docker pull 763104351884.dkr.ecr.eu-west-1.amazonaws.com/tensorflow-training:1.15.2-
gpu-py36-cu100-ubuntu18.04

nvidia-docker run -it 763104351884.dkr.ecr.eu-west-1.amazonaws.com/tensorflow-
training:1.15.2-gpu-py36-cu100-ubuntu18.04
```

In the container

```
git clone https://github.com/fchollet/keras.git

python keras/examples/mnist_cnn.py
```

Scaling alert!

- More customers, more team members, more models, woohoo!
- Scalability, high availability & security are now a thing
- Scaling up is a losing proposition. You need to scale out
- Only automation can save you:
  IaC, CI/CD and all that good DevOps stuff
- What are your options?

Option 1: virtual machines

- Definitely possible, but:
  - Why? Seriously, I want to know.
  - Operational and financial issues await if you don't automate extensively
- Training
  - Build on-demand clusters with CloudFormation, Terraform, etc.
  - Distributed training is a pain to set up
- Prediction
  - Automate deployement with CI/CD
  - Scale with Auto Scaling, Load Balancers, etc.
- Spot, spot, spot

Score card

	More EC2 instances
Infrastructure effort	Lots
ML setup effort	Some (DL AMI)
CI/CD integration	No change
Build models	DIY
Train models	DIY
Deploy models	DIY (model servers)
Scale/HA inference	DIY (Auto Scaling, LB)
Optimize costs	DIY (Spot, automation)
Security	DIY (IAM, VPC, KMS)

Option 2: Docker clusters

- This makes a lot of sense if you're already deploying apps to Docker
  - No change to the dev experience: same workflows, same CI/CD, etc.
  - Deploy prediction services on the same infrastructure as business apps.
- Amazon ECS and Amazon EKS
  - Lots of flexibility: mixed instance types (including GPUs), placement constraints, etc.
  - Both come with AWS-maintained AMIs that will save you time
- One cluster or many clusters ?
  - Build on-demand development and test clusters with CloudFormation, Terraform, etc.
  - Many customers find that running a large single production cluster works better
- Still instance-based and not fully-managed
  - Not a hands-off operation: services / pods, service discovery, etc. are nice but you still have work to do
  - And yes, this matters even if « someone else is taking care of clusters »

Creating an ECS cluster and adding instances

```
aws ecs create-cluster --cluster-name ecs-demo

# Add 4 p2.xlarge spot instances, ECS-optimized AMI with GPU support, default VPC
aws ec2 run-instances --image-id ami-0638eba79fcfe776e \
       --count 4 \
       --instance-type p2.xlarge \
       --instance-market-options '{"MarketType":"spot"}' \
       --tag-specifications 'ResourceType=instance,Tags=[{Key=Name,Value=ecs-demo}]’
       --key-name $KEYPAIR \
       --security-group-ids $SECURITY_GROUP \
       --iam-instance-profile Name=$ROLE
       --user-data file://user-data.txt

# Add 2 c5.2xlarge, ECS-optimized AMI, default VPC, different subnet
aws ec2 run-instances --image-id ami-09cd8db92c6bf3a84 \
       --count 2 \
       --instance-type c5.2xlarge \
       --instance-market-options '{"MarketType":"spot"}' \
       --subnet $SUBNET_ID \
       . . .
```

Defining the training task

```
"containerDefinitions": [{

    "command": [
      “git clone https://github.com/fchollet/keras.git && python keras/examples/mnist_cnn.py”],

    "entryPoint": [ "sh","-c"],

    "name": "TFconsole",

    "image": "763104351884.dkr.ecr.eu-west-1.amazonaws.com/tensorflow-training:1.13-horovod-gpu-py36-
cu100-ubuntu16.04",

    "memory": 4096,

    "cpu": 256,

    "resourceRequirements" : [ {"type" : "GPU”, "value" : "1”} ],

    . . .
```

Defining the inference task

```
"containerDefinitions": [{

    "command": [
      “git clone -b r1.13 https://github.com/tensorflow/serving.git && tensorflow_model_server
--port=8500 --rest_api_port=8501 --model_name=<MODEL_NAME> --model_base_path=<MODEL_PATH>”],

    "entryPoint": [ "sh","-c"],

    "name": "TFinference",

    "image": "763104351884.dkr.ecr.eu-west-1.amazonaws.com/tensorflow-inference:1.13-cpu-py36-
ubuntu16.04"",

    "memory": 4096,

    "cpu": 256,

    "portMappings": [{ "hostPort": 8500, "protocol": "tcp”, "containerPort": 8500},
                     { "hostPort": 8501, "protocol": "tcp”, "containerPort": 8501},

. . .
```

Running training and inference on the cluster

```
# Create task definitions for training and inference
aws ecs register-task-definition --cli-input-json file://training.json
aws ecs register-task-definition --cli-input-json file://inference.json


# Run 4 training tasks (the GPU requirement is in the task definition)
aws ecs run-task --cluster ecs-demo --task-definition training:1 --count 4

# Create inference service, starting with 1 initial task
# Run it on c5 instance, and spread tasks evenly
aws ecs create-service --cluster ecs-demo \
 --service-name inference-cpu \
 --task-definition inference:1 \
 --desired-count 1 \
 --placement-constraints type="memberOf",expression="attribute:ecs.instance-type =~ c5.*" \
 --placement-strategy field="instanceId",type="spread"

# Scale inference service to 2 tasks
aws ecs update-service --cluster ecs-demo --service inference-cpu --desired-count 2
```

Score card

	EC2	ECS / EKS
Infrastructure effort	Lots	Some (Docker tools)
ML setup effort	Some (DL AMI)	Some (DL containers)
CI/CD integration	No change	No change
Build models	DIY	DIY
Train models (at scale)	DIY	DIY (Docker tools)
Deploy models (at scale)	DIY (model servers)	DIY (Docker tools)
Scale/HA inference	DIY (Auto Scaling, LB)	DIY (Services, pods, etc.)
Optimize costs	DIY (Spot, RIs, automation)	DIY (Spot, RIs, automation)
Security	DIY (IAM, VPC, KMS)	DIY (IAM, VPC, KMS)

Option 3: go fully managed with Amazon SageMaker

Collect and prepare training data

Choose and optimize your ML algorithm

Set up and manage environments for training

Train and Tune ML Models

Deploy models in production

Scale and manage the production environment

Modular service and APIs, going from experimentation to production

Model options on Amazon SageMaker

AWS Marketplace for Machine Learning

Training code

Amazon SageMaker AutoPilot

Factorization Machines
Linear Learner
Principal Component Analysis
K-Means Clustering
Image classification
And more

mxnet Chainer
TensorFlow PyTorch
scikit learn dmlc XGBoost

Built-in Algorithms (17)

No ML coding required
No infrastructure work required
Distributed training
Pipe mode

Built-in Frameworks

Bring your own code: script mode
Open source containers
No infrastructure work required
Distributed training
Pipe mode

Bring Your Own Container

Full control, run anything!
R, C++, etc.
No infrastructure work required

aws

The Amazon SageMaker API

- Python SDK orchestrating all Amazon SageMaker activity
  - High-level objects for algorithm selection, training, deploying, automatic model tuning, etc. https://github.com/aws/sagemaker-python-sdk
  - Spark SDK (Python & Scala) https://github.com/aws/sagemaker-spark/tree/master/sagemaker-spark-sdk

- AWS SDK
  - For scripting and automation
  - CLI : '*aws sagemaker*'
  - Language SDKs: boto3, etc.

Training and deploying

```
tf_estimator = TensorFlow(entry_point='mnist_keras_tf.py',
                          role=role,
                          train_instance_count=1,
                          train_instance_type='ml.c5.2xlarge’,
                          framework_version='1.12',
                          py_version='py3',
                          script_mode=True,
                          hyperparameters={
                                    'epochs': 10,
                                    'learning-rate': 0.01})

tf_estimator.fit(data)

# HTTPS endpoint backed by a single instance
tf_endpoint = tf_estimator.deploy(initial_instance_count=1, instance_type=ml.t3.xlarge)

tf_endpoint.predict(…)
```

Training and deploying, at any scale

```
tf_estimator = TensorFlow(entry_point='my_crazy_cnn.py',
                          role=role,
                          train_instance_count=8,
                          train_instance_type='ml.p3.16xlarge',   # Total of 64 GPUs
                          framework_version='1.12',
                          py_version='py3',
                          script_mode=True,
                          hyperparameters={
                                    'epochs': 200,
                                    'learning-rate': 0.01})

tf_estimator.fit(data)

# HTTPS endpoint backed by 16 multi-AZ load-balanced instances
tf_endpoint = tf_estimator.deploy(initial_instance_count=16, instance_type=ml.p3.2xlarge)

tf_endpoint.predict(…)
```

Score card

	EC2	ECS / EKS	SageMaker
Infrastructure effort	Maximal	Some (Docker tools)	None
ML setup effort	Some (DL AMI)	Some (DL containers)	Minimal
CI/CD integration	No change	No change	Some (SDK, Step Functions)
Build models	DIY	DIY	17 built-in algorithms
Train models (at scale)	DIY	DIY (Docker tools)	SDK: 2 LOCs
Deploy models (at scale)	DIY (model servers)	DIY (Docker tools)	SDK: 1 LOCs Kubernetes support
Scale/HA inference	DIY (Auto Scaling, LB)	DIY (Services, pods, etc.)	Built-in
Optimize costs	DIY (Spot, RIs, automation)	DIY (Spot, RIs, automation)	On-demand/Spot training, Auto Scaling for inference
Security	DIY (IAM, VPC, KMS)	DIY (IAM, VPC, KMS)	API parameters

Score card

Flame war in 3, 2, 1…

	EC2	ECS / EKS	SageMaker
Infrastructure effort	Maximal	Some (Docker tools)	None
ML setup effort	Some (DL AMI)	Some (DL containers)	Minimal
CI/CD integration	No change	No change	Some (SDK, Step Functions)
Build models	DIY	DIY	17 built-in algorithms
Train models (at scale)	DIY	DIY (Docker tools)	2 LOCs
Deploy models (at scale)	DIY (model servers)	DIY (Docker tools)	SDK: 1 LOCs Kubernetes support
Scale/HA inference	DIY (Auto Scaling, LB)	DIY (Services, pods, etc.)	Built-in
Optimize costs	DIY (Spot, RIs, automation)	DIY (Spot, RIs, automation)	Spot training, Auto Scaling for inference
Security	DIY (IAM, VPC, KMS)	DIY (IAM, VPC, KMS)	API parameters
Personal opinion	Small scale only, unless you have strong DevOps skills and enjoy exercising them.	Reasonable choice if you're a Docker shop, and if you're able and willing to integrate with the Docker/OSS ecosystem. If not, I'd think twice: Docker isn't an ML platform.	Learn it in a few hours, forget about servers, focus 100% on ML, enjoy goodies like pipe mode, distributed training, HPO, debugging, and more.

Conclusion

- Whatever works for you at this time is fine
  - Don't over-engineer, and don't « plan for the future »
  - Optimize for current business conditions, pay attention to TCO
- Models and data matter, not infrastructure
  - When conditions change, move fast: smash and rebuild
  - ... which is what cloud is all about!
  - « 100% of our time spent on ML » shall be the whole of the Law
- Mix and match if it makes sense
  - Train on SageMaker, deploy on ECS/EKS… or vice versa
  - Write your own story!

Getting started

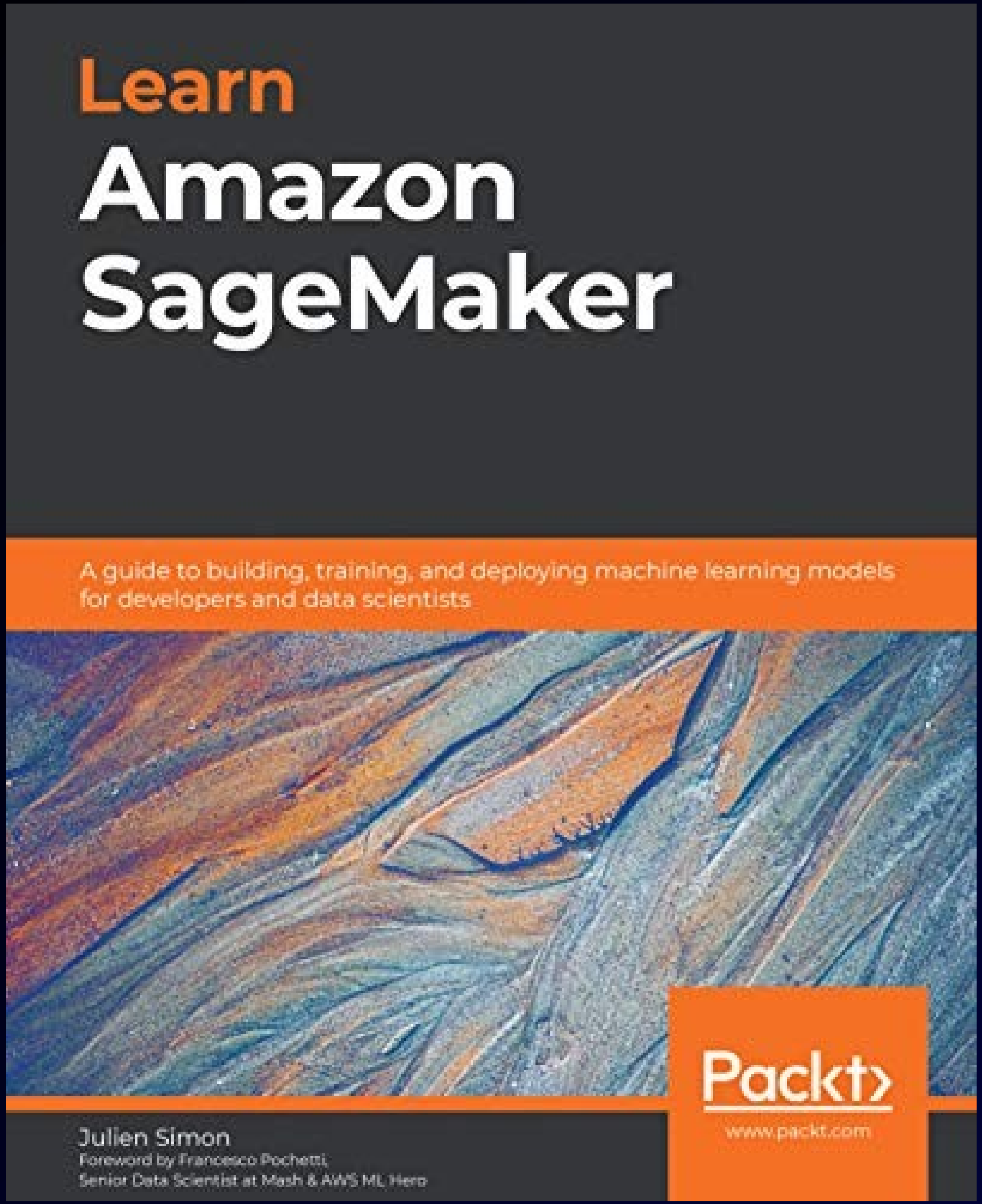
https://aws.amazon.com/machine-learning/amis/
https://aws.amazon.com/machine-learning/containers/

https://aws.amazon.com/sagemaker
https://github.com/aws/sagemaker-python-sdk
https://github.com/awslabs/amazon-sagemaker-examples

https://sagemaker.readthedocs.io/en/stable/amazon_sagemaker_operators_for_kubernetes.html

https://medium.com/@julsimon
https://youtube.com/juliensimonfr

https://gitlab.com/juliensimon/dlcontainers DL AMI / container demos
https://gitlab.com/juliensimon/dlnotebooks SageMaker notebooks



Published August 2020

13 chapters, 481 pages, 62 original notebooks based on the latest SDK (2.x)

Discount link for the paper edition on Amazon (US only):
https://www.amazon.com/gp/mpc/AOHJSZC7A0AV5

Discount code for the e-book edition on Packt:
20SAGEMAKER
https://www.packtpub.com/product/learn-amazon-sagemaker/9781800208919

Thank you!

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