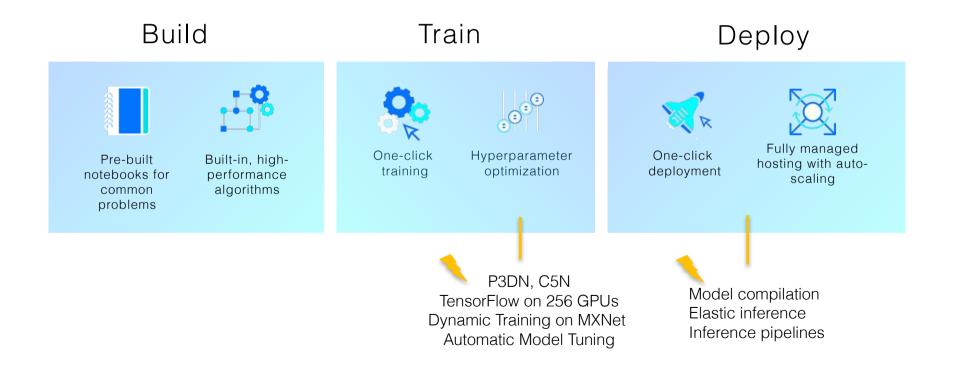
# Optimize your Machine Learning workloads

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## Amazon SageMaker



# Optimizing infrastructure

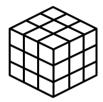


#### Amazon EC2 P3dn

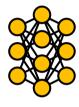
https://aws.amazon.com/blogs/aws/new-ec2-p3dn-gpu-instances-with-100-gbps-networking-local-nvme-storage-for-faster-machine-learning-p3-price-reduction/



Reduce machine learning training time



Better GPU utilization



Support larger, more complex models

100Gbps of networking bandwidth

KEY
FEATURE §2GB of
8 NVIDIA Tesla
V100 GPUs

Memory per
GPU
(2x more P3)

96 Intel Skylake vCPUs (50% more than P3) with AVX-512

#### Amazon EC2 C5n

https://aws.amazon.com/blogs/aws/new-c5n-instances-with-100-gbps-networking/

Intel Xeon Platinum 8000

Up to 3.5GHz single core speed

Up to 100Gbit networking

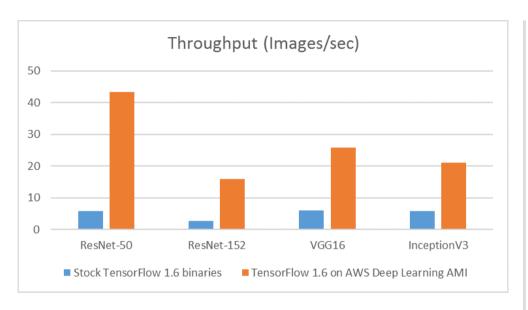
Based on Nitro hypervisor for bare metal-like performance

Instance Name	vCPUs	RAM	EBS Bandwidth	Network Bandwidth
c5n.large	2	5.25 GiB	Up to 3.5 Gbps	Up to 25 Gbps
c5n.xlarge	4	10.5 GiB	Up to 3.5 Gbps	Up to 25 Gbps
c5n.2xlarge	8	21 GiB	Up to 3.5 Gbps	Up to 25 Gbps
c5n.4xlarge	16	42 GiB	3.5 Gbps	Up to 25 Gbps
c5n.9xlarge	36	96 GiB	7 Gbps	50 Gbps
c5n.18xlarge	72	192 GiB	14 Gbps	100 Gbps

## Optimizing frameworks



## Making TensorFlow faster



Training a ResNet-50
benchmark with the synthetic
ImageNet dataset using our
optimized build of TensorFlow 1.11
on a c5.18xlarge instance type is
11x faster than training on the
stock binaries.

https://aws.amazon.com/blogs/machine-learning/faster-training-with-optimized-tensorflow-1-6-on-amazon-ec2-c5-and-p3-instances/ (March 2018)

https://aws.amazon.com/about-aws/whats-new/201 8/10/chainer4-4 theano 1-0-2 launch deep learnin g ami/ (October 2018)

#### Scaling TensorFlow near-linearly to 256 GPUs

https://aws.amazon.com/about-aws/whats-new/2018/11/tensorflow-scalability-to-256-gpus/



Available with Amazon SageMaker and the AWS Deep Learning AMIs

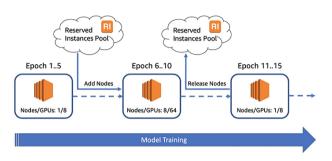
#### Dynamic training with Apache MXNet and RIs

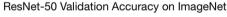
https://aws.amazon.com/blogs/machine-learning/introducing-dynamic-training-for-deep-learning-with-amazon-ec2/

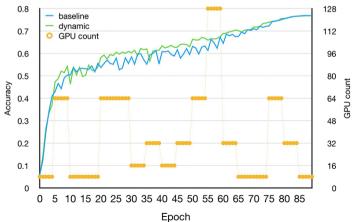
Use a variable number of instances for distributed training

No loss of accuracy

Coming soon spot instances, additional frameworks







## Optimizing models



## Examples of hyperparameters

#### **XGBoost**

Tree depth

Max leaf nodes

Gamma

Eta

Lambda

Alpha

. . .

#### **Neural Networks**

Number of layers

Hidden layer width

Learning rate

Embedding

dimensions

Dropout

. . .

### Automatic Model Tuning

Finding the optimal set of hyper parameters

- Manual Search ("I know what I'm doing")
- Grid Search ("X marks the spot")
  - Typically training hundreds of models
  - Slow and expensive
- 3. Random Search ("Spray and pray")
  - Works better and faster than Grid Search
  - But... but... it's random!
- HPO: use Machine Learning
  - Training fewer models
  - Gaussian Process Regression and Bayesian Optimization
  - You can now resume from a previous tuning job



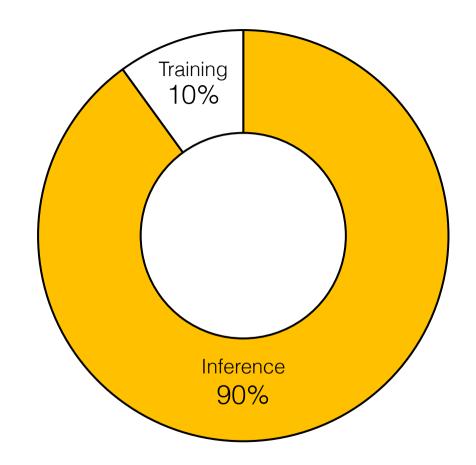
### Demo: HPO with Apache MXNet

https://github.com/awslabs/amazon-sagemaker-examples/tree/master/hyperparameter\_tuning/hpo\_mxn\_et\_mnist.ipynb

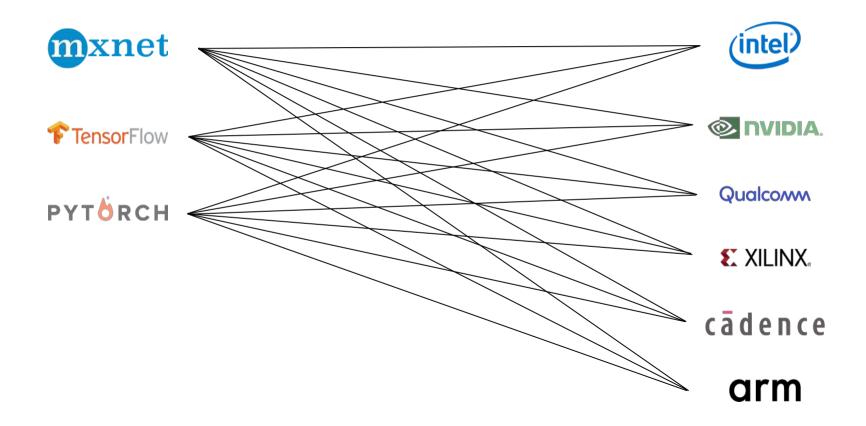
## Optimizing inference



Predictions drive complexity and cost in production



#### Model optimization is extremely complex



### Amazon Neo: compiling models

https://aws.amazon.com/blogs/aws/amazon-sagemaker-neo-train-your-machine-learning-models-once-run-them-anywhere/

- Train once, run anywhere
- Frameworks and algorithms
  - TensorFlow, Apache MXNet, PyTorch, ONNX, and XGBoost
- Hardware architectures
  - ARM, Intel, and NVIDIA starting today
  - Cadence, Qualcomm, and Xilinx hardware coming soon
- Amazon SageMaker Neo is open source, enabling hardware vendors to customize it for their processors and devices:

https://github.com/neo-ai/

# Compiling ResNet-50 for the Raspberry Pi

```
Configure the compilation job
  "RoleArn": $ROLE ARN,
  "InputConfia": {
   "S3Uri": "s3://jsimon-neo/model.tar.gz",
   "DataInputConfig": "{\"data\": [1, 3, 224, 224]}",
   "Framework": "MXNET"
 "OutputConfig": {
  "S30utputLocation": "s3://jsimon-neo/",
  "TargetDevice": "rasp3b"
 "StoppingCondition": {
 "MaxRuntimeInSeconds": 300
```

```
Compile the model

$ aws sagemaker create-compilation-job
--cli-input-json file://config.json
--compilation-job-name resnet50-mxnet-pi

$ aws s3 cp s3://jsimon-neo/model-
rasp3b.tar.gz .

$ gtar tfz model-rasp3b.tar.gz
compiled.params
compiled_model.json
compiled.so
```

```
Predict with the compiled model
from dlr import DLRModel
model = DLRModel('resnet50', input_shape,
output_shape, device)
out = model.run(input_data)
```

# Demo: compiling a pre-trained PyTorch model with Neo

https://github.com/awslabs/amazon-sagemaker-examples/blob/master/advanced\_functionality/pytorch\_torchvision\_neo.ipynb

#### Amazon Elastic Inference

https://aws.amazon.com/blogs/aws/amazon-elastic-inference-gpu-powered-deep-learning-inference-acceleration/



Lower inference costs up to 75%



Match capacity to demand



Available between 1 to 32 TFLOPS

Integrated with
Amazon EC2,
Amazon SageMaker,
and Amazon DL
AMIs

KEY
FEATURES
Support for TensorFlow,
Apache MXNet, and
ONNX
with PyTorch coming soon

Single and mixed-precision operations

## Demo: Elastic Inference with TensorFlow

https://github.com/awslabs/amazon-sagemaker-examples/blob/master/sagemaker-python-sdk/tensorflow iris dnn classifier using estimators/

Train & predict faster Save time **Save money** Save your sanity (no plumbing!)

## **Getting started**

https://ml.aws

https://aws.amazon.com/sagemaker

https://github.com/awslabs/amazon-sagemaker-examples

# Thank you!

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