Scalable Deep Learning Using MXNet

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AWS Machine Learning

Why yet another deep networks tool?

- Caffe
- Torch
- Theano
- Tensorflow
- CNTK
- Keras
- Paddle
- Chainer
- SINGA
- DL4J

image credit - Banksy/wikipedia

Why yet another deep networks tool?

- **Frugality & resource efficiency**
  Engineered for cheap GPUs with smaller memory, slow networks
- **Speed**
  - Linear scaling with #machines and #GPUs
  - High efficiency on single machine, too (C++ backend)
- **Simplicity**
  Mix declarative and imperative code

frontend

backend

single implementation of backend system and common operators

performance guarantee regardless which frontend language is used

Imperative Programs

```python
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
print c
d = c + 1
```

Easy to tweak with python codes

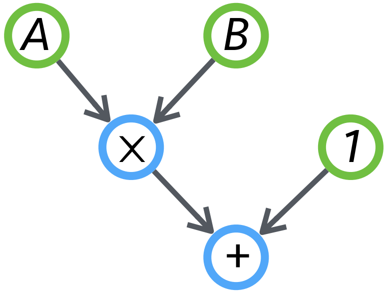
Pro

- Straightforward and flexible.
- Take advantage of language native features (loop, condition, debugger)

Con

- Hard to optimize

Declarative Programs




```
A = Variable('A')
B = Variable('B')
C = B * A
D = C + 1
f = compile(D)
d = f(A=np.ones(10),
      B=np.ones(10)*2)
```

C can share memory with *D*, because *C* is deleted later

Pro

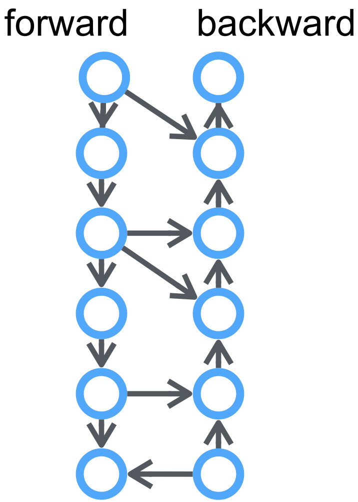
- More chances for optimization
- Cross different languages

Con

- Less flexible

Imperative vs. Declarative for Deep Learning

Computational Graph
of the Deep Architecture



Needs heavy optimization, fits **declarative** programs

Updates and Interactions with the graph

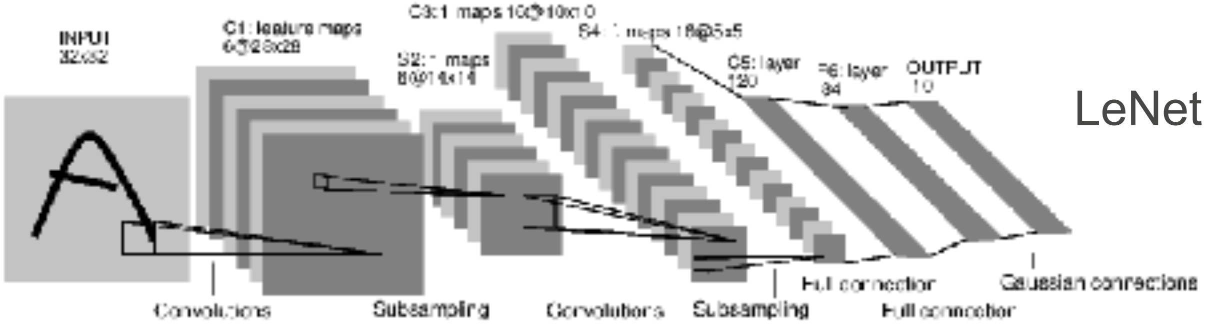
- Iteration loops
- Parameter update

$$w \leftarrow w - \eta \partial_w f(w)$$

- Beam search
- Feature extraction …

Needs mutation and more language native features, good for **imperative** programs

LeNet in R (using MXNet)

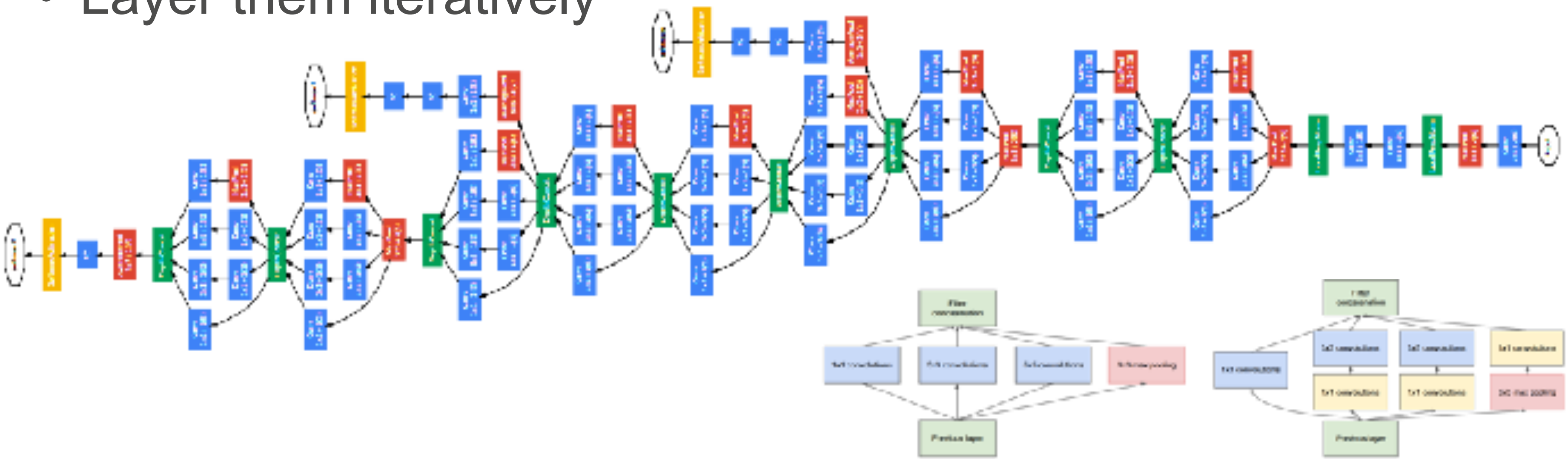


LeNet ~1995

```
get_symbol <- function(num_classes = 1000) {
  data <- mx.symbol.Variable('data')
  conv1 <- mx.symbol.Convolution(data = data, kernel = c(5, 5), num_filter = 20)
  tanh1 <- mx.symbol.Activation(data = conv1, act_type = "tanh")
  pool1 <- mx.symbol.Pooling(data = tanh1, pool_type = "max", kernel = c(2, 2), stride = c(2, 2))
  conv2 <- mx.symbol.Convolution(data = pool1, kernel = c(5, 5), num_filter = 50)
  tanh2 <- mx.symbol.Activation(data = conv2, act_type = "tanh")
  pool2 <- mx.symbol.Pooling(data = tanh2, pool_type = "max", kernel = c(2, 2), stride = c(2, 2))
  flatten <- mx.symbol.Flatten(data = pool2)
  fc1 <- mx.symbol.FullyConnected(data = flatten, num_hidden = 500)
  tanh3 <- mx.symbol.Activation(data = fc1, act_type = "tanh")
  fc2 <- mx.symbol.FullyConnected(data = tanh3, num_hidden = num_classes)
  lenet <- mx.symbol.SoftmaxOutput(data = fc2, name = 'softmax')
  return(lenet)
}
```

Fancy structures

- Compute different filters
- Compose one big vector from all of them
- Layer them iteratively



Szegedy et al. arxiv.org/pdf/1409.4842v1.pdf

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```python
def get_symbol(num_classes=1000):
    data = mx.symbol.Variable(name="data")
    # stage 1
    conv1 = ConvFactory(data=data, num_filter=64, kernel=(7, 7), stride=(2, 2), pad=(3, 3), name='1')
    pool1 = mx.symbol.Pooling(data=conv1, kernel=(3, 3), stride=(2, 2), name='pool_1', pool_type='max')
    # stage 2
    conv2red = ConvFactory(data=pool1, num_filter=64, kernel=(1, 1), stride=(1, 1), name='2_red')
    conv2 = ConvFactory(data=conv2red, num_filter=192, kernel=(3, 3), stride=(1, 1), pad=(1, 1), name='2')
    pool2 = mx.symbol.Pooling(data=conv2, kernel=(3, 3), stride=(2, 2), name='pool_2', pool_type='max')
    # stage 3
    in3a = InceptionFactoryA(pool2, 64, 64, 64, 64, 96, "avg", 32, '3a')
    in3b = InceptionFactoryA(in3a, 64, 64, 96, 64, 96, "avg", 64, '3b')
    in3c = InceptionFactoryB(in3b, 128, 160, 64, 96, '3c')
    # stage 4
    in4a = InceptionFactoryA(in3c, 224, 64, 96, 96, 128, "avg", 128, '4a')
    in4b = InceptionFactoryA(in4a, 192, 96, 128, 96, 128, "avg", 128, '4b')
    in4c = InceptionFactoryA(in4b, 160, 128, 160, 128, 160, "avg", 128, '4c')
    in4d = InceptionFactoryA(in4c, 96, 128, 192, 160, 192, "avg", 128, '4d')
    in4e = InceptionFactoryB(in4d, 128, 192, 192, 256, '4e')
    # stage 5
    in5a = InceptionFactoryA(in4e, 352, 192, 320, 160, 224, "avg", 128, '5a')
    in5b = InceptionFactoryA(in5a, 352, 192, 320, 192, 224, "max", 128, '5b')
    # global avg pooling
    avg = mx.symbol.Pooling(data=in5b, kernel=(7, 7), stride=(1, 1), name="global_pool", pool_type='avg')
    # linear classifier
    flatten = mx.symbol.Flatten(data=avg, name='flatten')
    fc1 = mx.symbol.FullyConnected(data=flatten, num_hidden=num_classes, name='fc1')
    softmax = mx.symbol.SoftmaxOutput(data=fc1, name='softmax')
    return softmax
```

Bringing Caffe to MXNet

Caffe is widely used in computer vision

Call Caffe Operators in MXNet

```
import mxnet as mx
data = mx.symbol.Variable('data')
fc1  = mx.symbol.CaffeOp(data_0=data, num_weight=2, prototxt=
       "layer{type:\"InnerProduct\" inner_product_param{num_output: 128} }")
act1 = mx.symbol.CaffeOp(data_0=fc1, prototxt="layer{type:\"TanH\"}")
fc2  = mx.symbol.CaffeOp(data_0=act1, num_weight=2, prototxt=
       "layer{type:\"InnerProduct\" inner_product_param{num_output: 10}}")
mlp  = mx.symbol.SoftmaxOutput(data=fc3)
```

Bringing Torch to MXNet

Torch is a popular Lua framework for
both scientific computing and deep learning

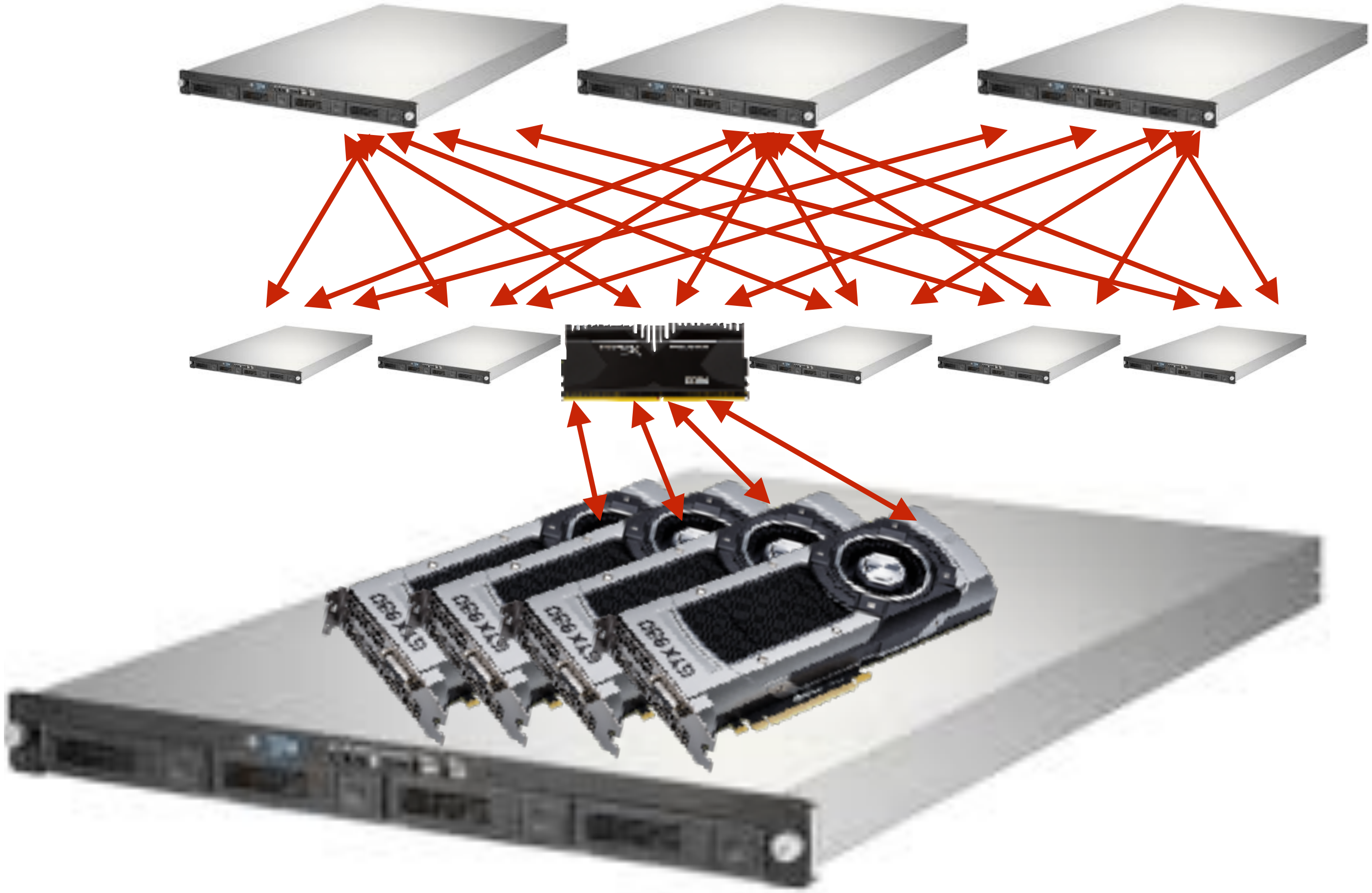
Tensor Computation

```
import mxnet as mx
x = mx.th.randn(2, 2, ctx=mx.gpu(0))
y = mx.th.abs(x)
print y.asnumpy()
```

Modules (Layers)

```
import mxnet as mx
data = mx.symbol.Variable('data')
fc   = mx.symbol.TorchModule(data_0=data, lua_string='nn.Linear(784, 128)',…
mlp  = mx.symbol.TorchModule(data_0=fc, lua_string='nn.LogSoftMax()',…
```

Distributed Deep Learning



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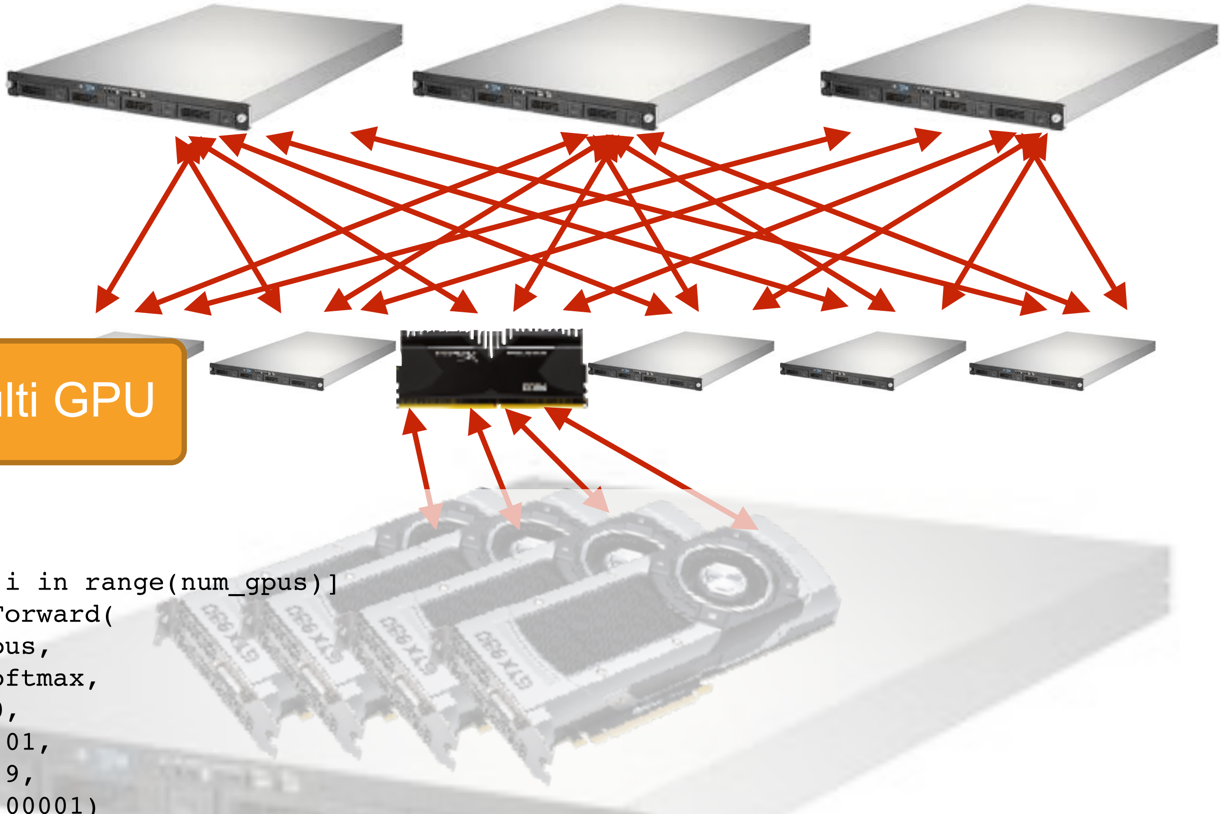
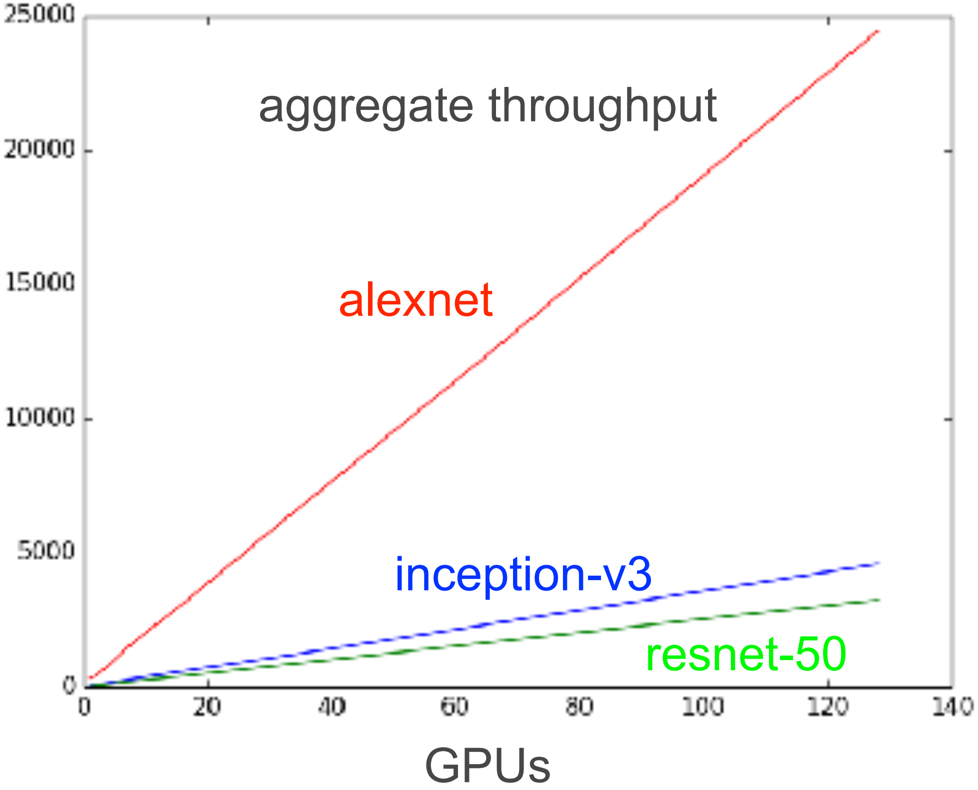
Distributed Deep Learning

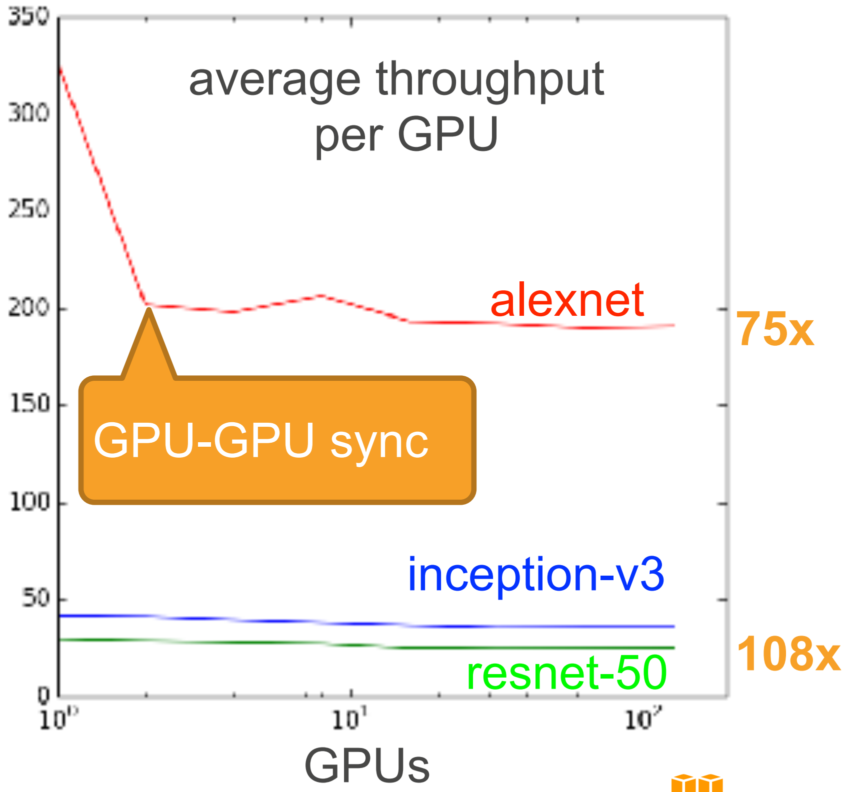


2 lines for multi GPU

```
## train
num_gpus = 4
gpus = [mx.gpu(i) for i in range(num_gpus)]
model = mx.model.FeedForward(
    ctx           = gpus,
    symbol        = softmax,
    num_round     = 20,
    learning_rate = 0.01,
    momentum      = 0.9,
    wd            = 0.00001)
model.fit(X = train, eval_data = val, batch_end_callback = mx.callback.Speedometer(batch_size=batch_size))
```

Scaling on p2.16xlarge





AMIs, Cloud Formation and DL Frameworks

- Amazon Machine Images (AMI)
- Deep Learning Frameworks
- Cloud Formation Templates

image credit - publicdomainpibtures

Amazon Machine Image for Deep Learning

http://bit.ly/deepami

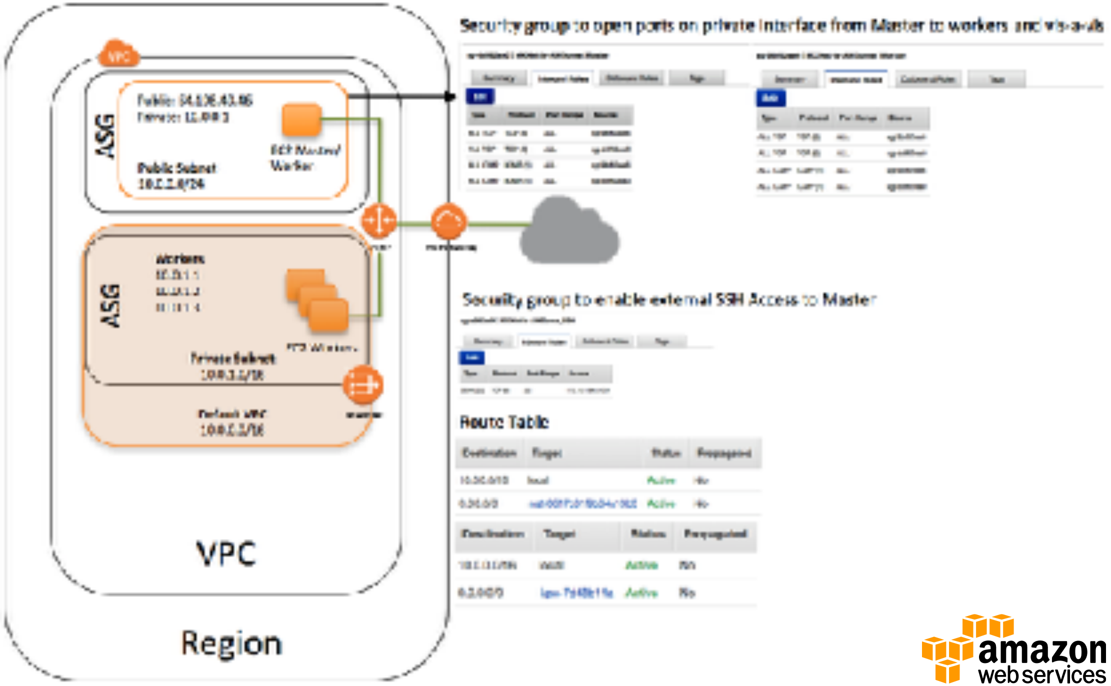
- Tool for data scientists and developers
- Setting up a DL system takes (install) time & skill
  - Keep packages up to date and compiled (MXNet, TensorFlow, Caffe, Torch, Theano, Keras)
  - Anaconda, Jupyter, Python 2 and 3
  - **NVIDIA** Drivers for G2 and P2 instances
  - **Intel MKL** Drivers for all other instances (C4, M4, …)

Getting started

```
acbc32cf4de3:image-classification smola$ ssh ec2-user@54.210.246.140
Last login: Fri Nov 11 05:58:58 2016 from 72-21-196-69.amazon.com
=============================================================================
       __|  __|_  )
       _|  (     /   Deep Learning AMI for Amazon Linux
      ___|\___|___|

This is beta version of the Deep Learning AMI for Amazon Linux.

The README file for the AMI →→→→→→→→→→→→→→→→→→→→  /home/ec2-user/src/README.md
Tests for deep learning frameworks →→→→→→→→→→→→   /home/ec2-user/src/bin
=============================================================================

7 package(s) needed for security, out of 75 available
Run "sudo yum update" to apply all updates.
Amazon Linux version 2016.09 is available.
[ec2-user@ip-172-31-55-21 ~]$ cd src/
[ec2-user@ip-172-31-55-21 src]$ ls
anaconda2  bazel  caffe   cntk   keras  mxnet                 OpenBLAS  README.md   Theano
anaconda3  bin    caffe3  demos  logs   Nvidia_Cloud_EULA.pdf  opencv    tensorflow  torch
```

AWS CloudFormation Template for Deep Learning

http://bit.ly/deepcfn



AWS CloudFormation Components

- **VPC** in the customer account.
- The requested number of **worker instances** in an Auto Scaling group within the VPC. Workers are launched in a **private subnet**.
- **Master instance** in a separate Auto Scaling group that acts as a proxy to enable connectivity to the cluster via **SSH**.
- Two security groups that open ports on the **private subnet** for communication between the master and workers.
- **IAM role** that allows users to access and query Auto Scaling groups and the private IP addresses of the EC2 instances.
- **NAT gateway** used by instances within the VPC to talk to the outside.

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Roadmap

- **NNVM Migration** (complete)
- **Apache project** (proposal submitted)
- **Usability**
  - Documentation (installation, native documents, etc.)
  - Tutorials, examples
- **Platform** support
  (Linux, Windows, OS X, mobile …)
- **Language** bindings
  (Python, C++, R, Scala, Julia, JavaScript …)
- **Sparse** datatypes and **LSTM** performance improvements

We are hiring!

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