Deep Learning on OpenPower using PowerAI

Workshop at NCSA, UIUC

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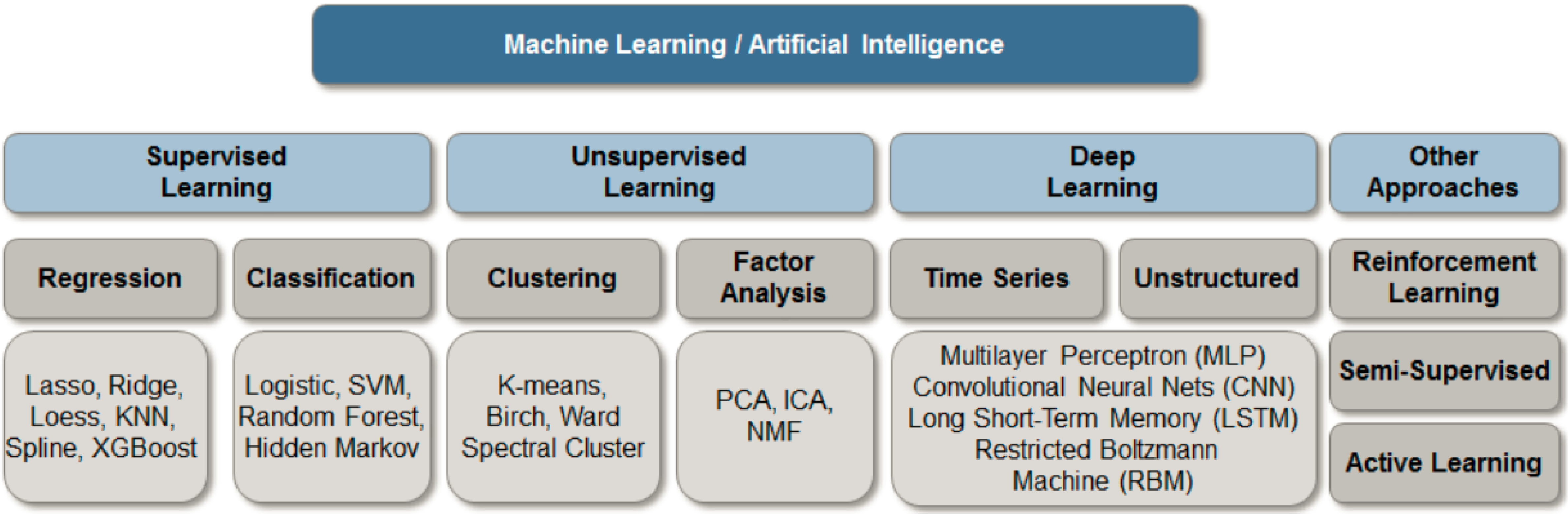
Agenda – AM Session (Machine Learning)

- 8.00 AM – 8.30 AM (slides 4-8)
  - Welcome
  - Overview of Machine Learning algorithms
  - Review of IBM Minsky, IBM PowerAI, and Nimbix
  - Workshop Objectives
- 8.30 AM – 9.30 AM (slides 9-12)
  - Introduction to Linear Regression
  - Introduction to the Structure of a Tensorflow Program
  - Hands-on Exercise on Linear Regression
    - Change Learning Rate, Number of Epochs, and Learning Algorithm
- 9.30 AM – 10.30 AM (slides 13-15)
  - Logistic Regression, Multinomial Logistic Regression/Softmax Regression
  - Lab – Multinomial Logistic Regression Using Tensorflow and MNIST
- 10.30 AM – 11.00 AM
  - Break
- 11.00 AM – 12.00 AM (slides 16-21)
  - Introduction to Fully Connected Neural Network
  - Lab – Fully Connected Neural Net Using Tensorflow

Agenda – PM Session (Deep Learning)

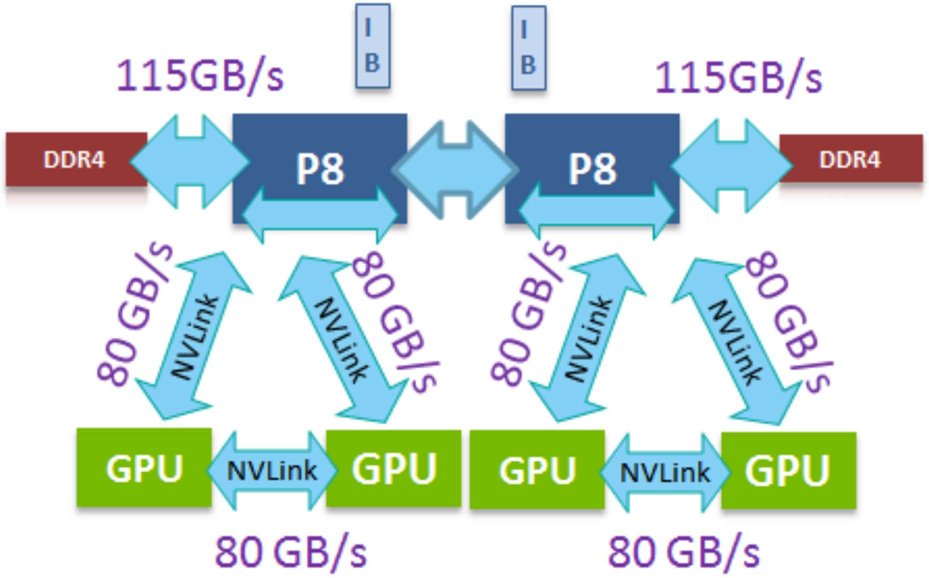
- 12.00 PM – 1.00 PM
  - Lunch
- 1.00 PM – 2.00 PM (slides 22-31)
  - Introduction to Deep Learning
  - Introduction to Convolutional Neural Networks
  - Lab – ImageNet Exercise Using Caffe
  - Lab – Transfer Learning Exercise Using Caffe
- 2.00 PM – 2.30 PM
  - Break
- 2.30 PM – 3.00 PM (slides 32 - 36)
  - Introduction to Recurrent Neural Networks
  - Lab – NLP Exercise Using Tensorflow
- 3.30 PM – 4.00 PM
  - NCSA Review of NCSA Deep Learning Environment, How to Access etc.

Classification of Machine Learning Techniques



Source JP Morgan QDS

POWER, NVLink and P100 Advantage




```
In [7]: # CPU mode
        net.forward()  # call once for allocation
        %timeit net.forward()

        1 loop, best of 3: 7.22 s per loop
```

That's a while, even for a batch size of 50 images. Let's switch to GPU mode.

```
In [8]: # GPU mode
        caffe.set_device(0)
        caffe.set_mode_gpu()
        net.forward()  # call once for allocation
        %timeit net.forward()

        10 loops, best of 3: 56.4 ms per loop
```

- Shorter training times
- Facilitates distributed deep learning and large model support in IBM PowerAI

PowerAI Platform

Deep Learning Frameworks

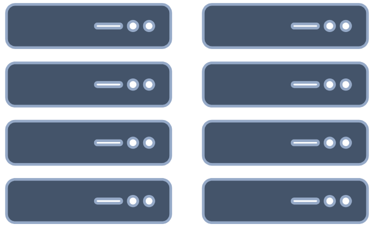
- Caffe
- NVCaffe
- IBMCaffe
- Torch
- TensorFlow
- Chainer
- Theano

Supporting Libraries

- OpenBLAS
- Bazel
- Distributed Frameworks
- NCCL
- DIGITS

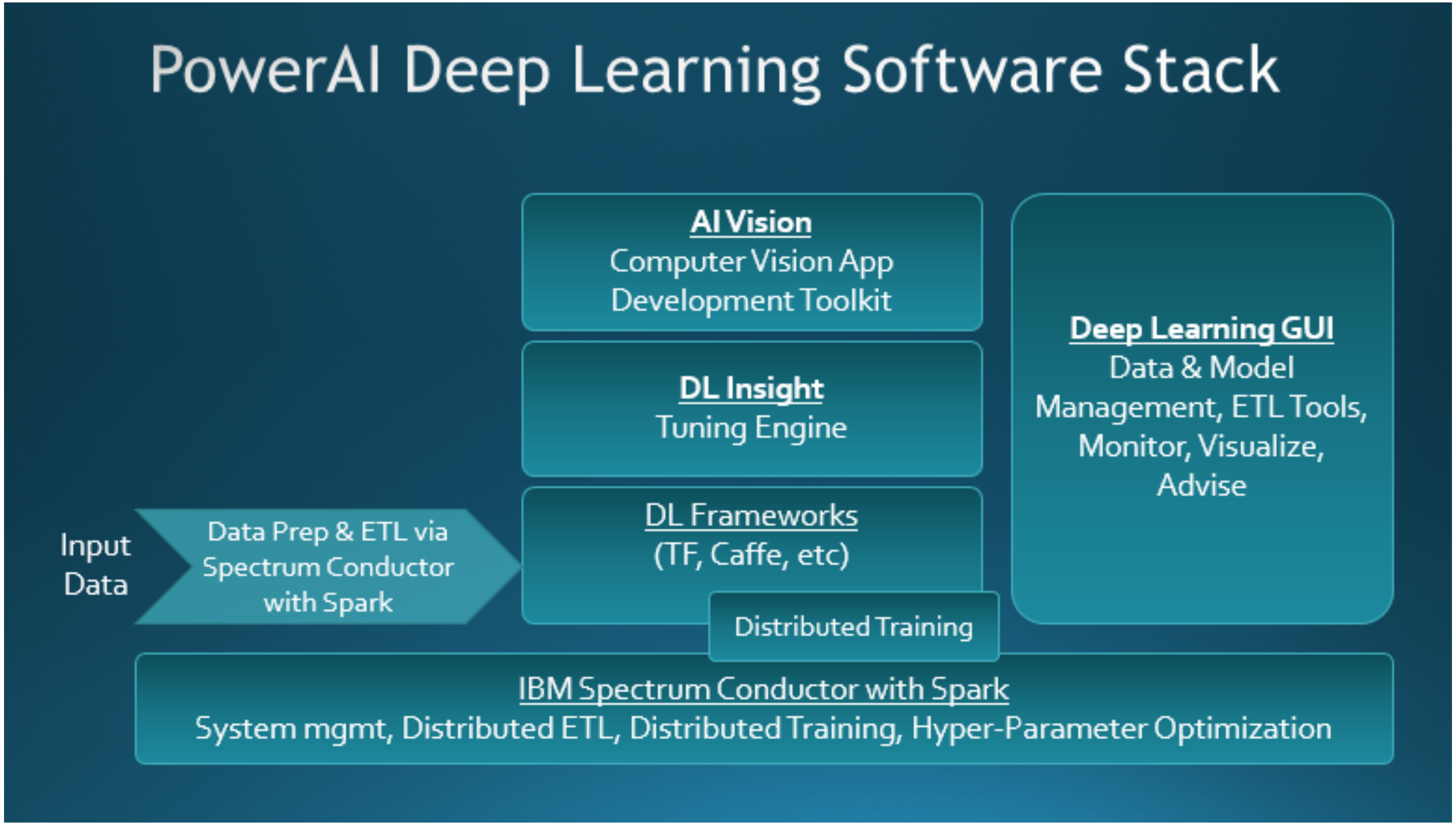
Accelerated Servers and Infrastructure for Scaling

Cluster of NVLink Servers



Spectrum Scale: High-Speed Parallel File System

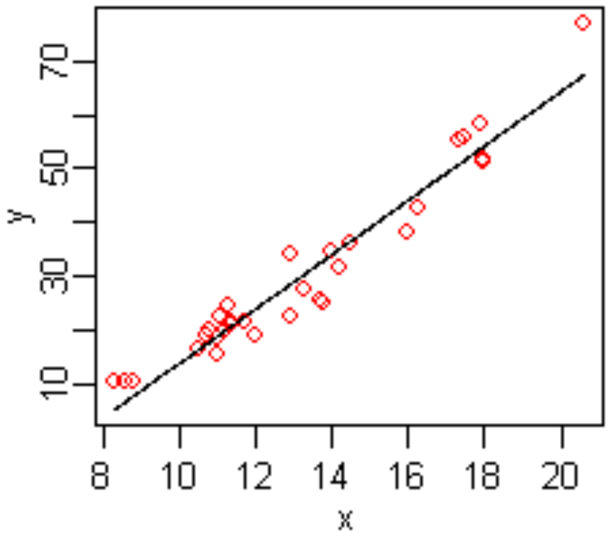
Scale to Cloud

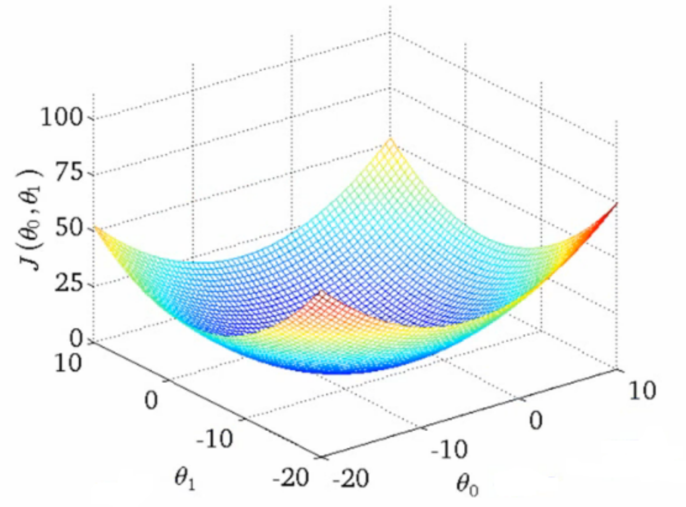

PowerAI Deep Learning Software Stack
AI Vision
Computer Vision App Development Toolkit
DL Insight
Tuning Engine
DL Frameworks
(TF, Caffe, etc)
Distributed Training
Deep Learning GUI
Data & Model Management, ETL Tools, Monitor, Visualize, Advise
Input Data
Data Prep & ETL via Spectrum Conductor with Spark
IBM Spectrum Conductor with Spark
System mgmt, Distributed ETL, Distributed Training, Hyper-Parameter Optimization

Objectives

- Introduce the foundations of deep learning
- Give an overview of state-of-the-art deep learning technologies
- Demonstrate the benefits of leveraging IBM deep learning technology offerings (Minsky and PowerAI) for research, teaching, and course projects
- Targeted audience include software developers, faculty, research scientists, postdocs, graduate/undergraduate students across various scientific disciplines

Linear Regression





Hypothesis: $h_\theta(x) = \theta_0 + \theta_1 x$

Parameters: θ_0, θ_1

Cost Function: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$

Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

Gradient descent algorithm

$\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$

repeat until convergence {

$$\theta_0 := \theta_0 - \alpha \boxed{\frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)}$$

$$\theta_1 := \theta_1 - \alpha \boxed{\frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) \cdot x^{(i)}}$$

}

update θ_0 and θ_1 simultaneously

$\frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$

$h_\theta(x) = \theta_0 + \theta_1 x$

Andrew Ng

Structure of a Tensorflow Program

Setup libraries

Define parameters to train

Hidden layer

Loss (true vs predicted)

Optimizer to minimize loss

Training data and labels

Initialize and start session to run

Repeat training

Output prediction accuracy

```
import numpy as np
import tensorflow as tf

# Model parameters
W = tf.Variable([.3], tf.float32)
b = tf.Variable([-.3], tf.float32)
# Model input and output
x = tf.placeholder(tf.float32)
linear_model = W * x + b
y = tf.placeholder(tf.float32)
# loss
loss = tf.reduce_sum(tf.square(linear_model - y)) # sum of the squares
# optimizer
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)
# training data
x_train = [1,2,3,4]
y_train = [0,-1,-2,-3]
# training loop
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init) # reset values to wrong
for i in range(1000):
  sess.run(train, {x:x_train, y:y_train})

# evaluate training accuracy
curr_W, curr_b, curr_loss  = sess.run([W, b, loss], {x:x_train, y:y_train})
print("W: %s b: %s loss: %s"%(curr_W, curr_b, curr_loss))
```

Build

Run

Ref: https://www.tensorflow.org/get_started/get_started

Jupyter Notebooks

jupyter linear_regression (autosaved)

Logout

File Edit View Insert Cell Kernel Help

Python 2

Code CellToolbar

In [1]:

```python
# A linear regression learning algorithm example using TensorFlow library.

# Author: Aymeric Damien
# Project: https://github.com/aymericdamien/TensorFlow-Examples/
```

In [6]:

```python
import tensorflow as tf
import numpy
import matplotlib.pyplot as plt
rng = numpy.random
```

In [17]:

```python
# Parameters
learning_rate = 0.01
training_epochs = 1000
display_step = 50
print "learning rate set to: ", learning_rate
print "# of epochs set to: ", training_epochs
print "display sampling set to: ", display_step
```

```
learning rate set to:  0.01
# of epochs set to:  1000
display sampling set to:  50
```

In [8]:

```python
# Training Data
train_X = numpy.asarray([3.3,4.4,5.5,6.71,6.93,4.168,9.779,6.182,7.59,2.167,
                         7.042,10.791,5.313,7.997,5.654,9.27,3.1])
train_Y = numpy.asarray([1.7,2.76,2.09,3.19,1.694,1.573,3.366,2.596,2.53,1.221,
                         2.827,3.465,1.65,2.904,2.42,2.94,1.3])
n_samples = train_X.shape[0]
```

In [9]:

```python
# tf Graph Input
X = tf.placeholder("float")
Y = tf.placeholder("float")

# Set model weights
W = tf.Variable(rng.randn(), name="weight")
b = tf.Variable(rng.randn(), name="bias")
```

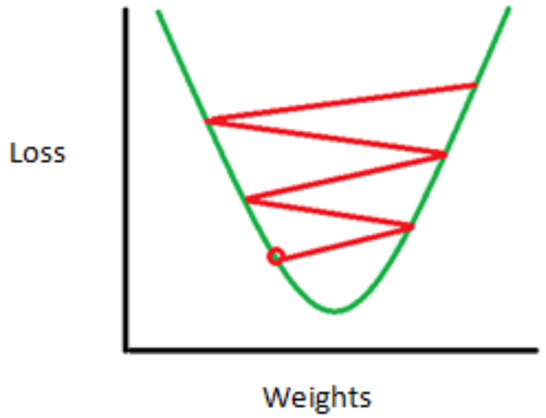
In [11]:

```python
# Construct a linear model
pred = tf.add(tf.multiply(X, W), b)
```

Linear Regression Exercise using Tensorflow

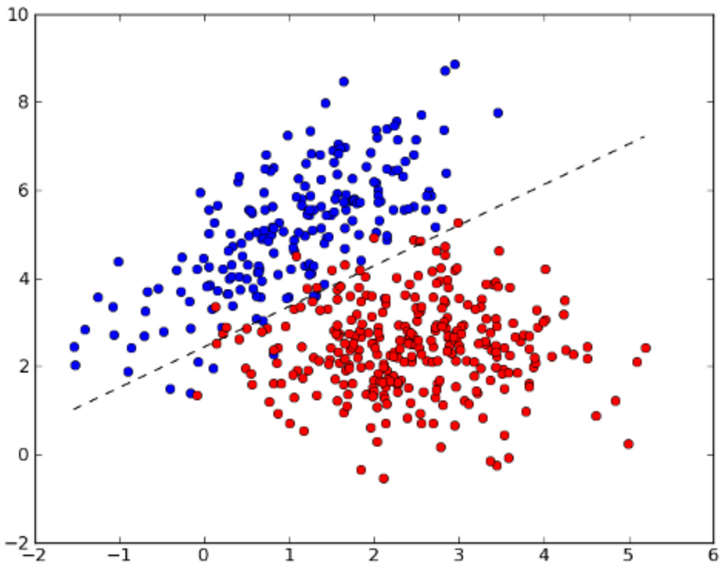
- https://github.com/aymericdamien/TensorFlow-Examples/blob/master/notebooks/2_BasicModels/linear_regression.ipynb
- Follow-up
  - Change learning rate with [0.001 0.003 0.01 0.03 0.1 0.3 1]
  - Change # of epochs with [500 1000 1500 2000 2500 3000]
  - Change learning algorithm with

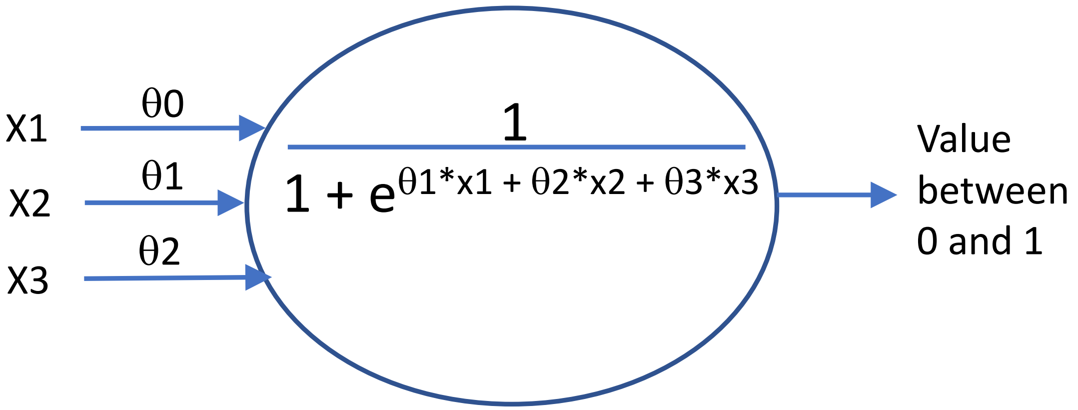
    [GradientDescentOptimizer MomentumOptimizer RMSPropOptimizer AdamOptimizer]



Consequence of a high learning rate where the jumps are too large and we are not able to minimize the loss.

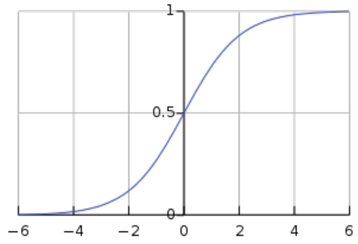
Classification (Logistic Regression)





Hypothesis:

$$\frac{1}{1 + e^{-(\theta_0 + \theta_1 * x_1 + \theta_2 * x_2)}}$$



Cost function:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}\log(h_\theta(x^{(i)})) + (1 - y^{(i)})\log(1 - h_\theta(x^{(i)}))]$$

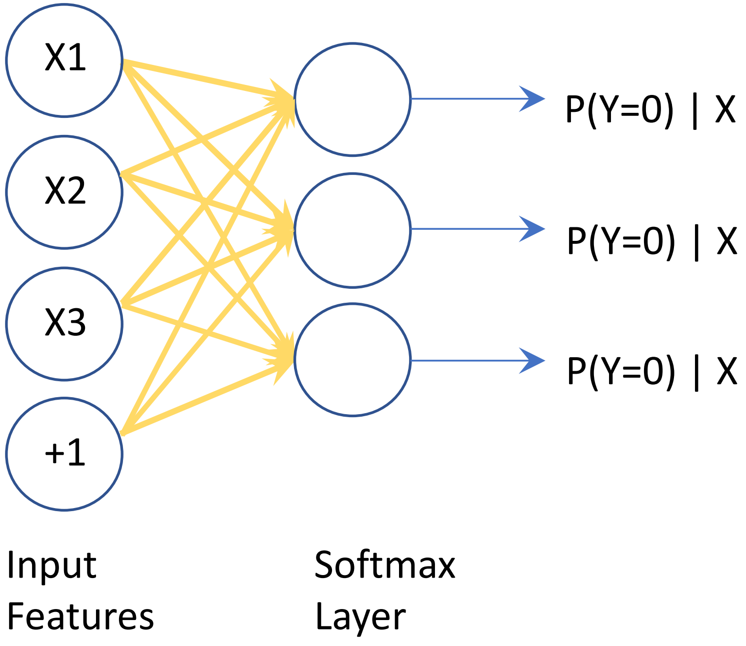
Gradient Descent Algorithm:

$$Repeat\ \{$$

$$\theta_j := \theta_j - \frac{\alpha}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$$

$$\}$$

Softmax Regression (Multinomial Logistic Regression)



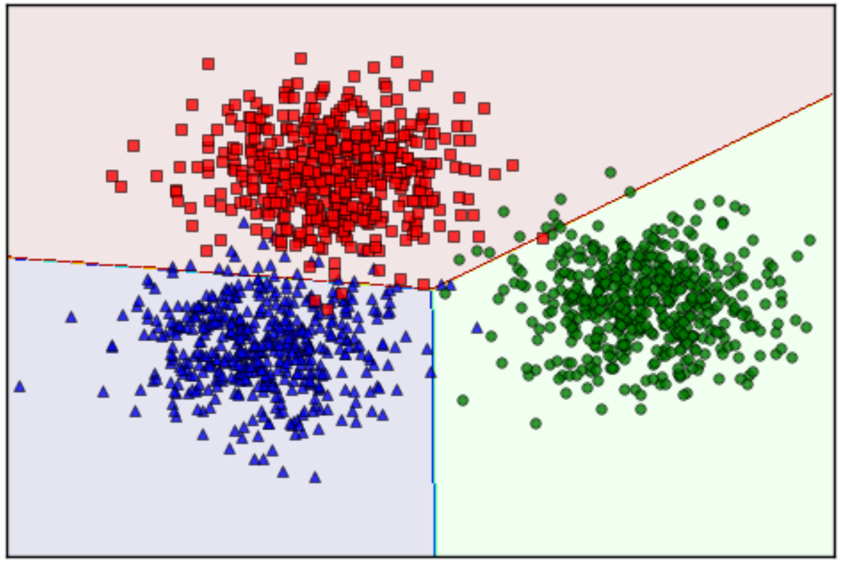
$$P(Y = i|x, W, b) = softmax_i(Wx + b)$$
$$= \frac{e^{W_i x + b_i}}{\sum_j e^{W_j x + b_j}}$$

$$J(\theta) = -\sum_i y_i ln(\hat{y}_i)$$

Ex:

Computed ($\hat{y}$)	Targets (y)
[0.3, 0.3, 0.4]	[0, 0, 1]

$$J(\theta) = -\sum_i^n [0 * ln(0.3) + 0 * ln(0.3) + 1 * ln(0.4)] = -ln(0.4)$$



Multinomial Logistic Regression using Tensorflow

- https://github.com/aymericdamien/TensorFlow-Examples/blob/master/notebooks/2_BasicModels/logistic_regression.ipynb
- Stochastic Gradient Descent used in previous exercise

    for epoch in 1 : num_epochs:

        for sample in 1:num_samples

            #Run the optimizer for sample

- Mini Batch Gradient Descent used in current exercise

    Initialize batch_size

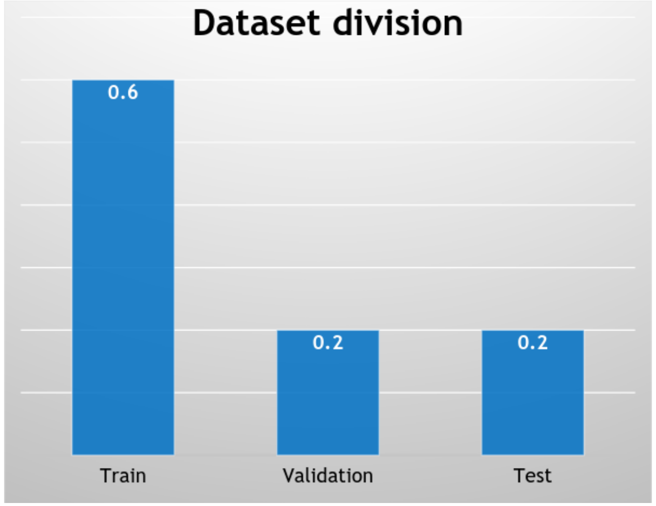
    num_batches = num_samples/batch_size

    for epoch in 1: num_epochs:

        for batch in 1:num_batches

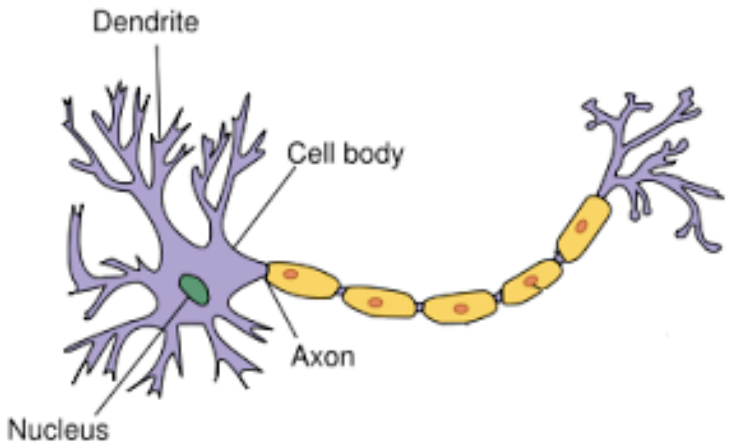
            #Run the optimizer for batch

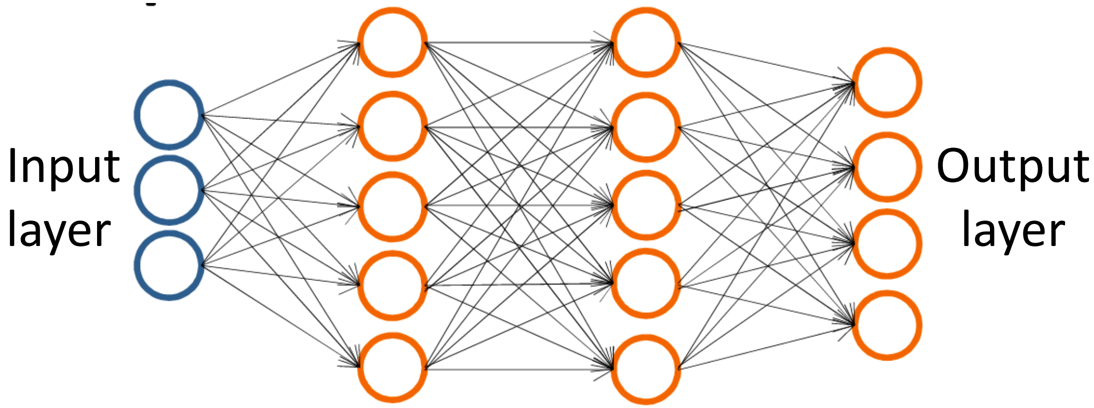
- Follow-up
- Change batch size in [25 50 100 200 400 800]
- Try with batch size 55000, i.e, batch gradient descent
- Try with batch size = 1, i.e, stochastic gradient descent
- Change number of epochs



- Training set:
    - bang on this data all you want
- Test set:
    - rarely (weekly), evaluate progress
- Validation set:
    - periodically during training, check

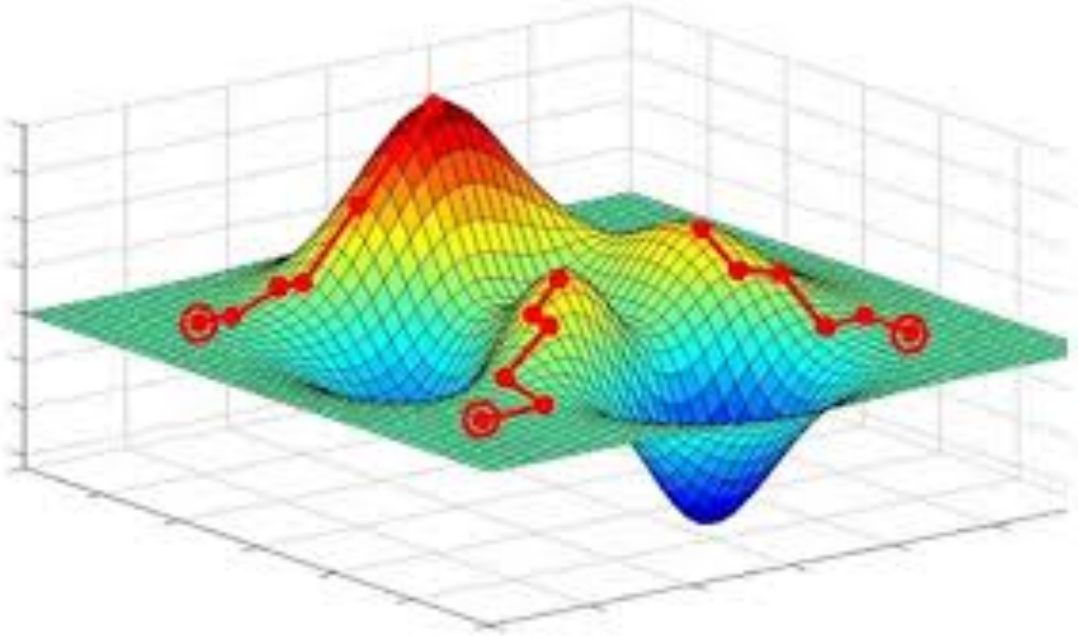
Artificial Neural Networks



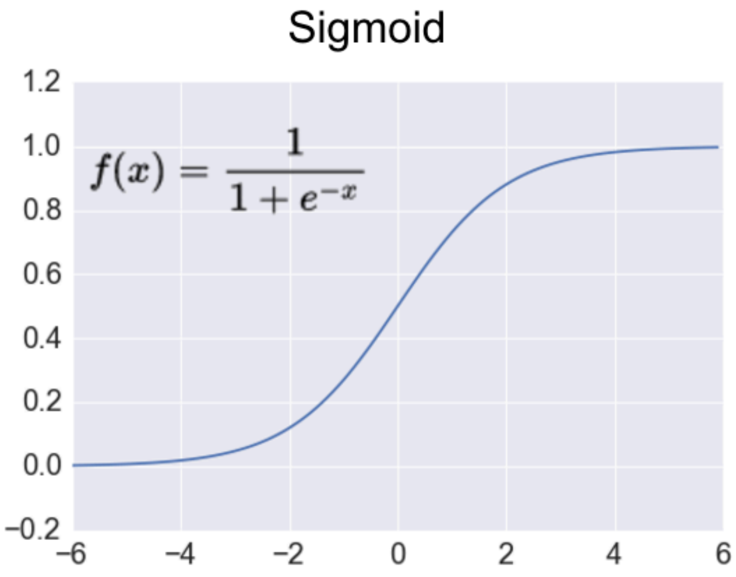


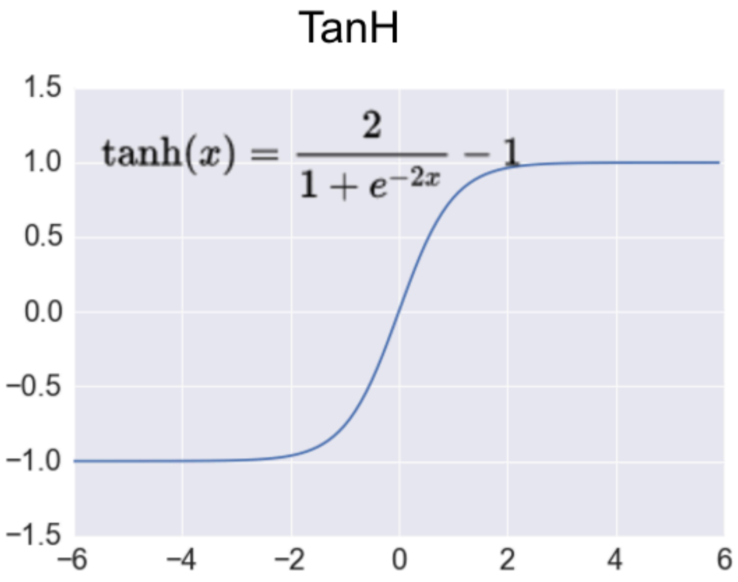
Cost Function:

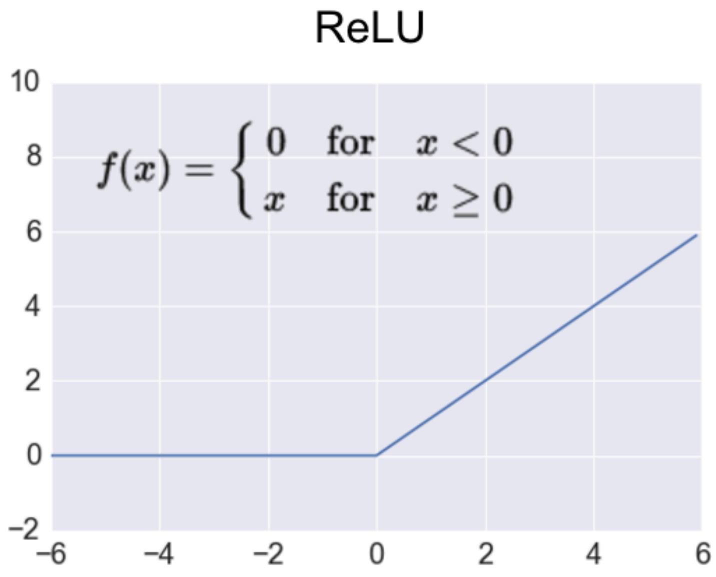
$$J(\Theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}\left[y_k^{(i)}\log((h_\Theta(x^{(i)}))_k) + (1-y_k^{(i)})\log(1-(h_\Theta(x^{(i)}))_k)\right]$$



Activation Functions







Forward Propagation and Back Propagation

Gradient Descent Iteration:

1. Forward Propagation (Calculate the cost using cost function)
2. Backward Propagation (Calculate partial derivatives of cost function w.r.t each parameter)

    Option 1: Numerical Derivatives

        Change the weight a little, calculate the change in cost function

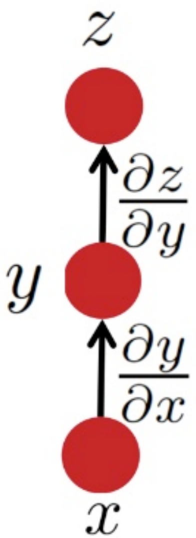
        Computationally intractable

    Option 2: Analytical Derivatives

        Use Chain rule and compute analytical derivatives

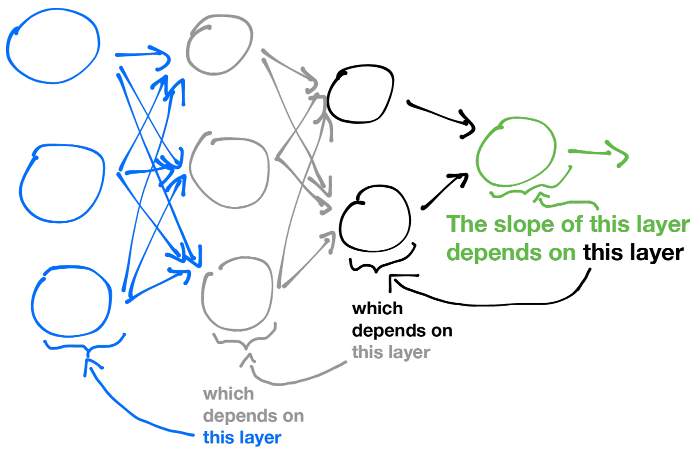
        Reasonable turnaround times, 1000s of times cheaper

Chain Rule:

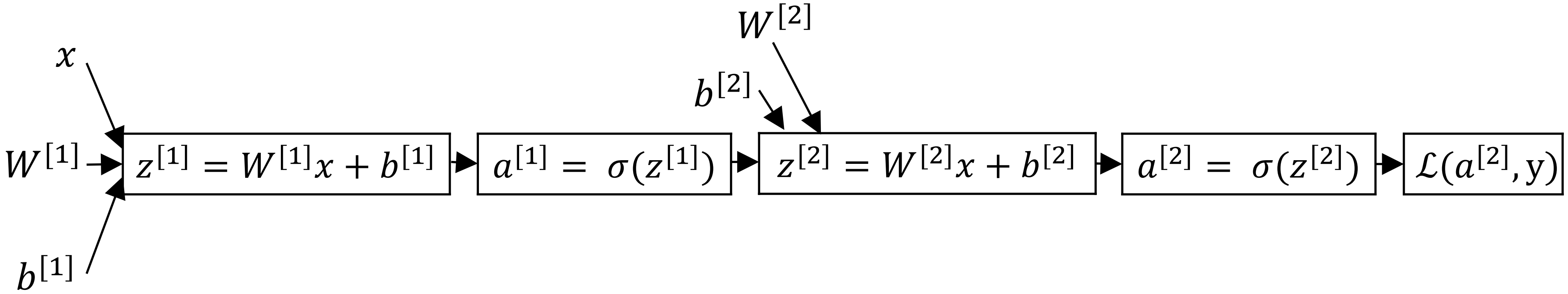


$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial y}\frac{\partial y}{\partial x}$$

Back Propagation:



Neural Network Gradients



$$dZ^{[2]} = A^{[2]} - Y$$

$$dW^{[2]} = \frac{1}{m} dZ^{[2]} {A^{[1]}}^T$$

$$db^{[2]} = \frac{1}{m} np.sum(dZ^{[2]}, axis = 1, keepdims = True)$$

$$dZ^{[1]} = W^{[2]T} dZ^{[2]} * g^{[1]\prime}(\mathrm{Z}^{[1]})$$

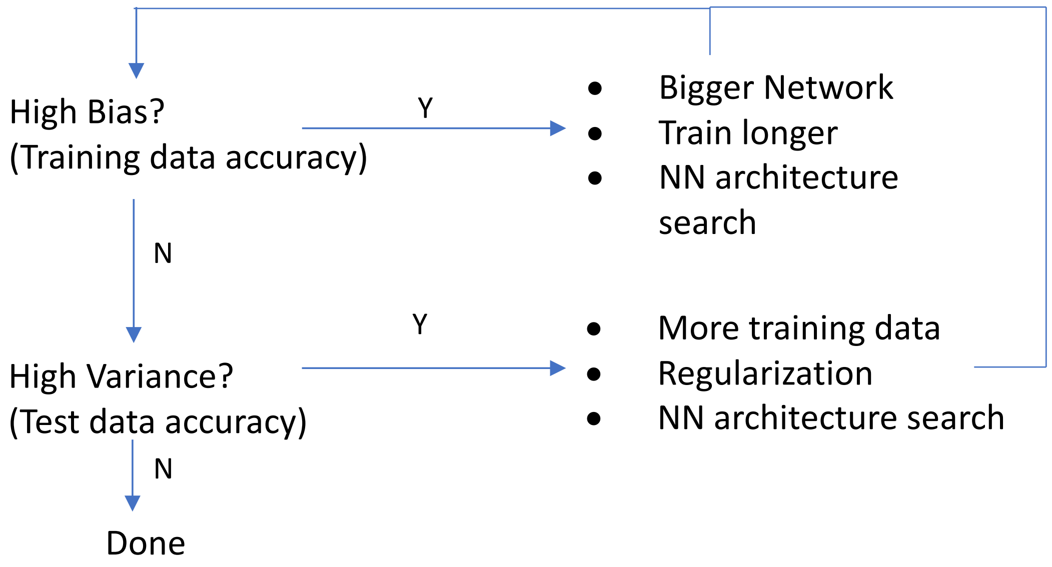
$$dW^{[1]} = \frac{1}{m} dZ^{[1]} X^T$$

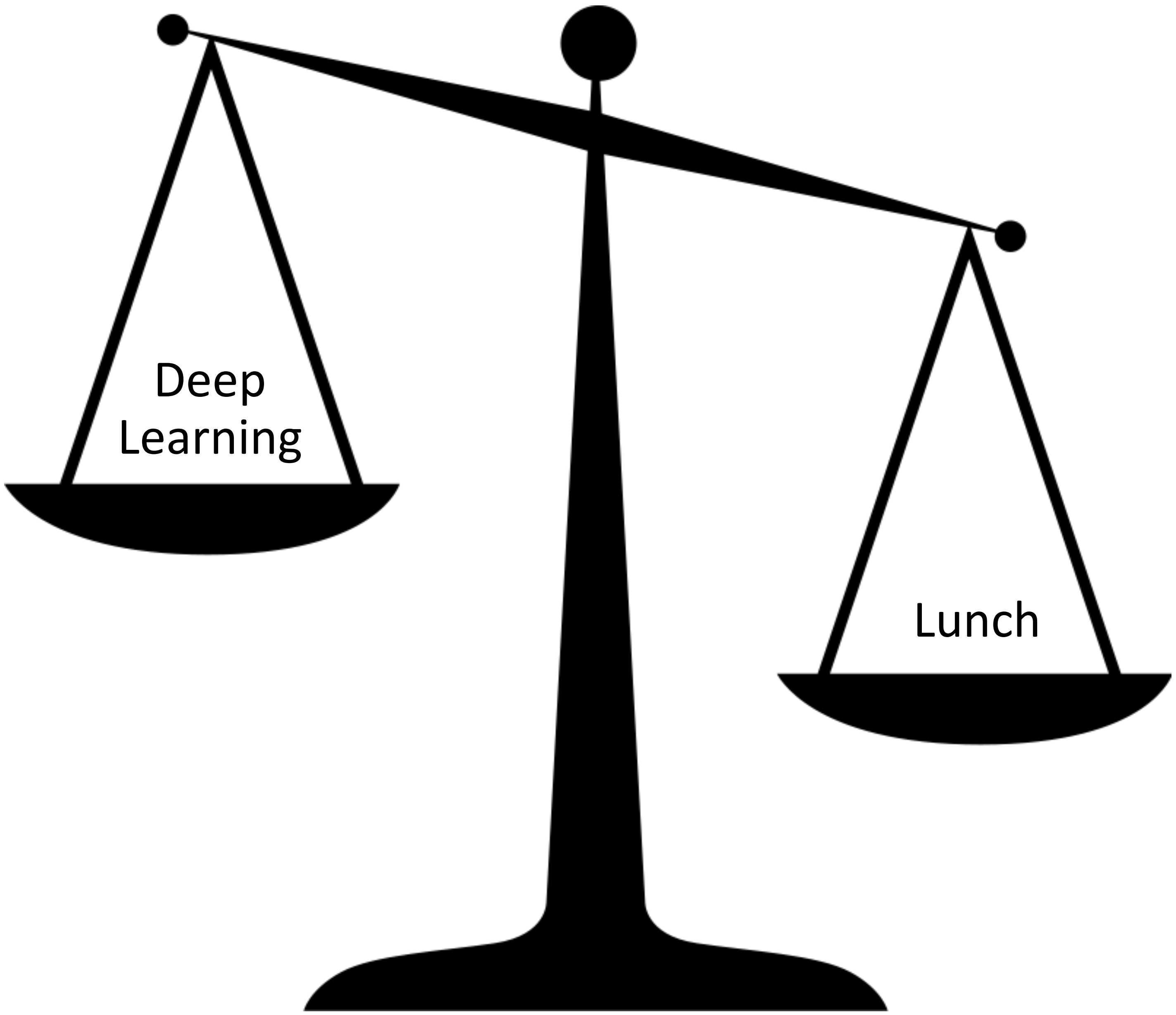
$$db^{[1]} = \frac{1}{m} np.sum(dZ^{[1]}, axis = 1, keepdims = True)$$

Fully Connected Neural Network using Tensorflow

- https://github.com/aymericdamien/TensorFlow-Examples/blob/master/notebooks/3_NeuralNetworks/neural_network_raw.ipynb
- Follow-up
- For the first 10 images in mnist.test.images
- Display Image
- Compute the prediction, then print the image and prediction by the model
- Change the number of neurons in hidden layers 1 and 2
- Change the activation function
- Change number of layers

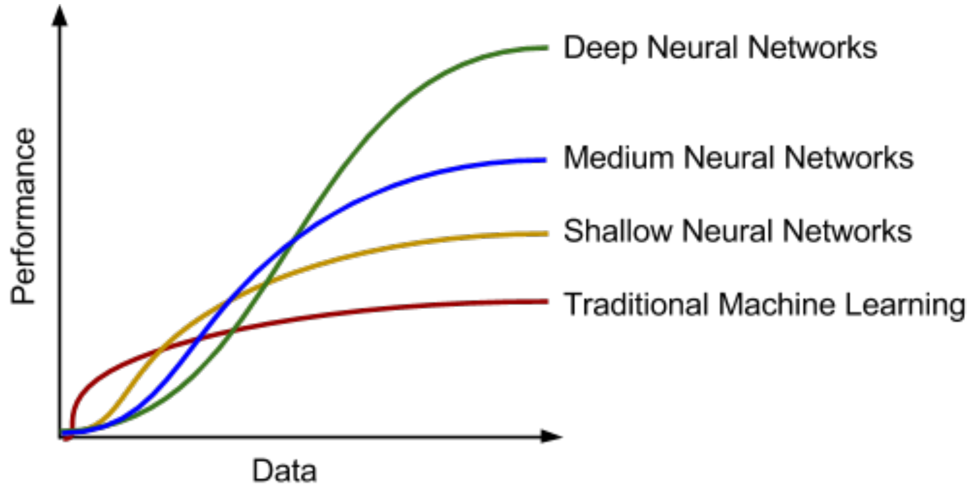
	High Bias (Underfitting)	High Variance (Overfitting)	High Bias & High Variance	Low Bias & Low Variance
Training Error	15%	5%	15%	5%
Testing Error	15%	15%	30%	5%



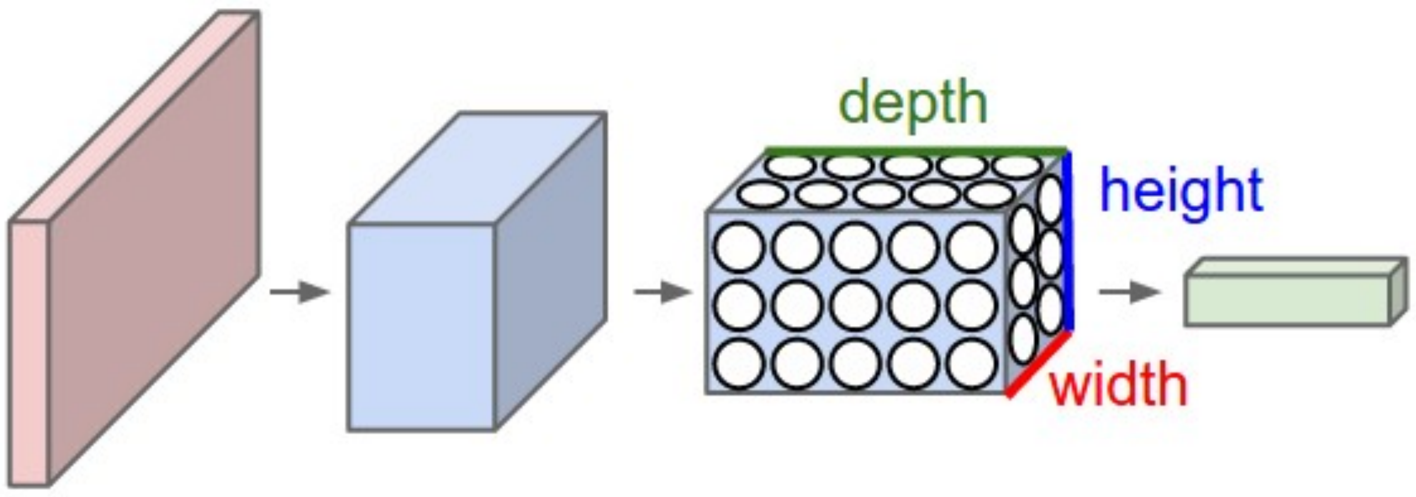

Deep
Learning
Lunch

Deep Learning

- Neural networks with lot more hidden layers (tens or hundreds)
- Types of Deep Neural Networks
  - Convolutional Neural Networks
  - Recurrent Neural Networks
  - Autoencoders
  - Restricted Boltzmann Machines
  - Generative Adversarial Networks
- Why now?
  - Data explosion
  - GPUs and other SIMD architectures
  - Some advancements in neural networks
- Nobody knows why it works but it works
- End-to-end Learning
  - No need for feature engineering



Convolutional Neural Networks

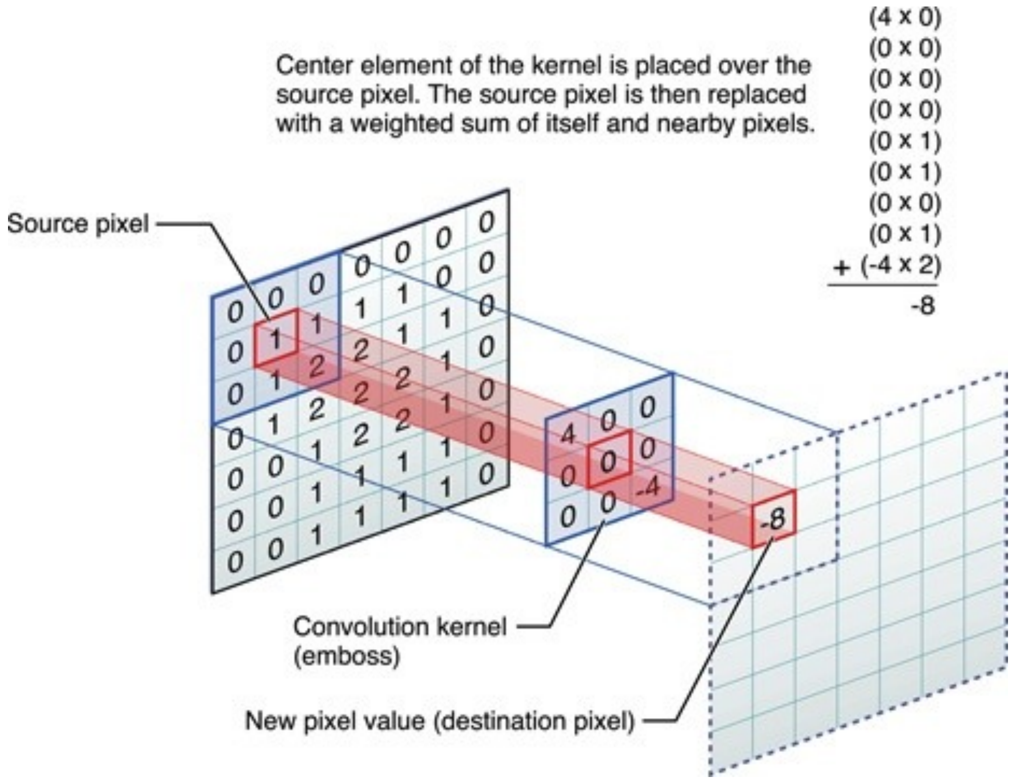


Types of Layers:

- Convolution Layer
- ReLU Layer
- Pooling Layer
- Dropout Layer
- Softmax Layer

http://cs231n.github.io/convolutional-networks/

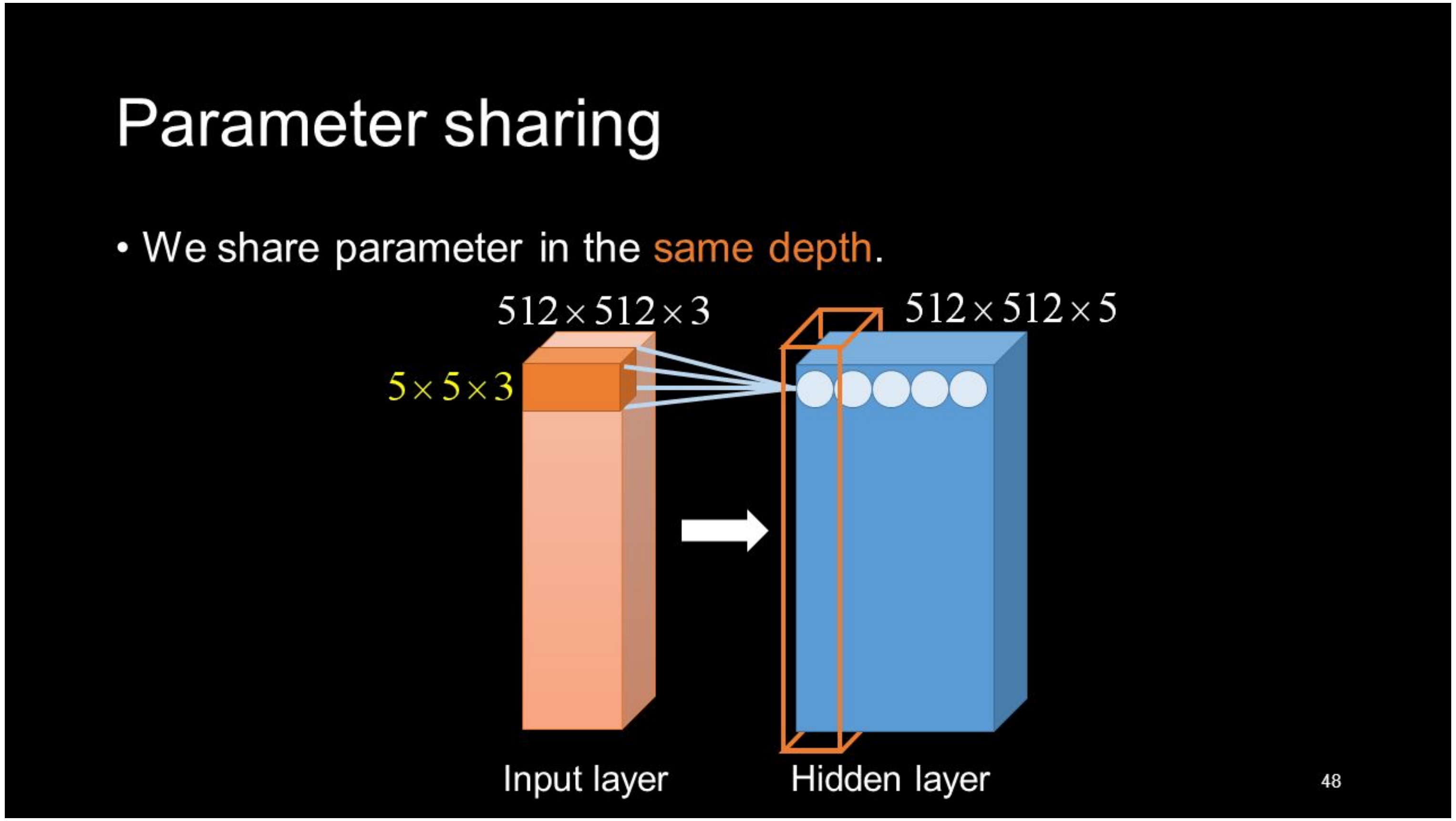
Convolution Operator in Convolutional Neural Networks



https://community.arm.com/graphics/b/blog/posts/when-parallelism-gets-tricky-accelerating-floyd-steinberg-on-the-mali-gpu

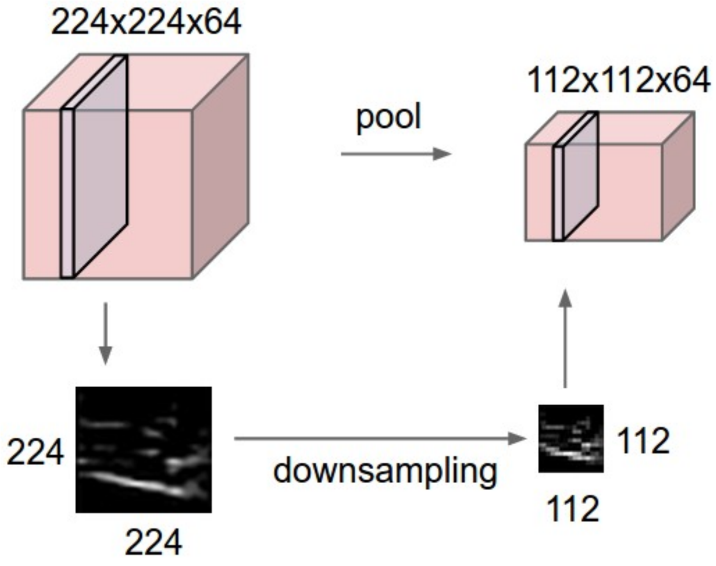
- CNN Hyper Parameters
  - Number of Filters (# of feature maps, depth of output layer)
  - Filter dimensions
  - Zero padding
  - Stride

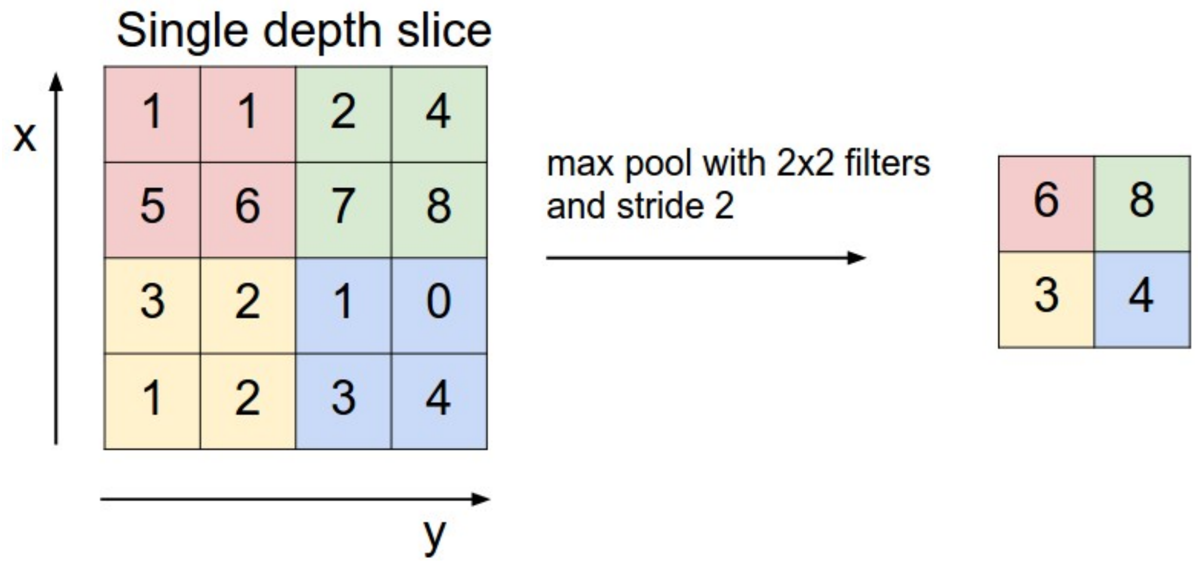
Parameter Sharing



- The kernel weights are shared across the image
- Reduces number of parameters
- Improves generalization capability of the model

Pooling in CNN

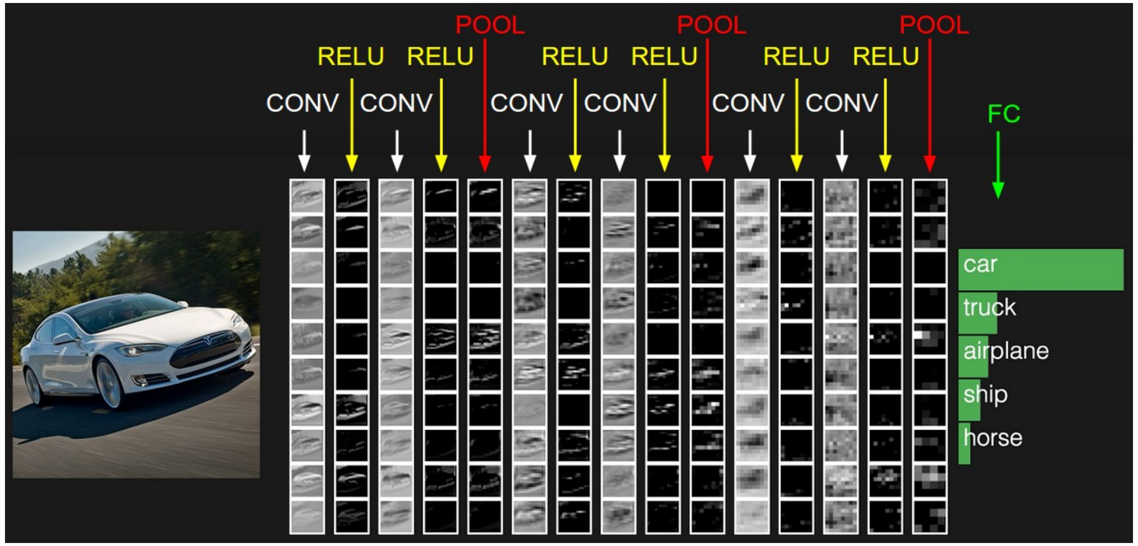




Convolutional Neural Networks

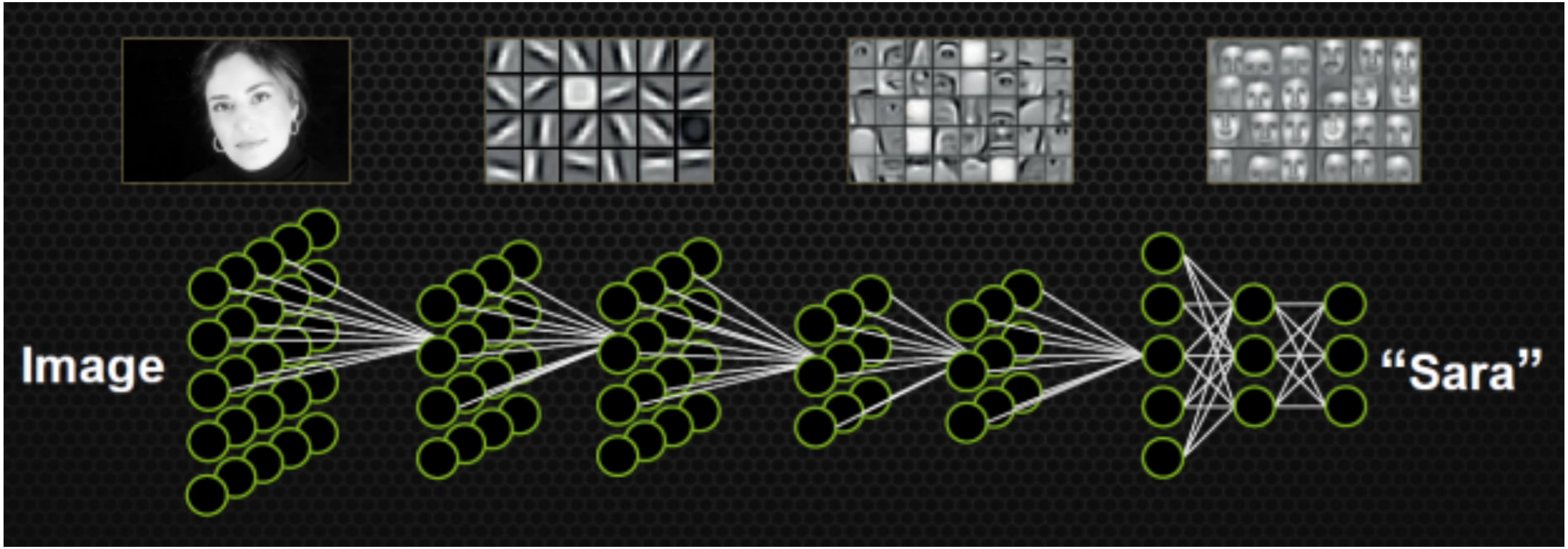
INPUT -> [[CONV -> RELU]*N -> POOL?]*M -> [FC -> RELU]*K -> FC

* Indicates repitition
POOL? – Optional pooling layer
M >= 0
N >= 0
K >= 0



https://community.arm.com/graphics/b/blog/posts/when-parallelism-gets-tricky-accelerating-floyd-steinberg-on-the-mali-gpu

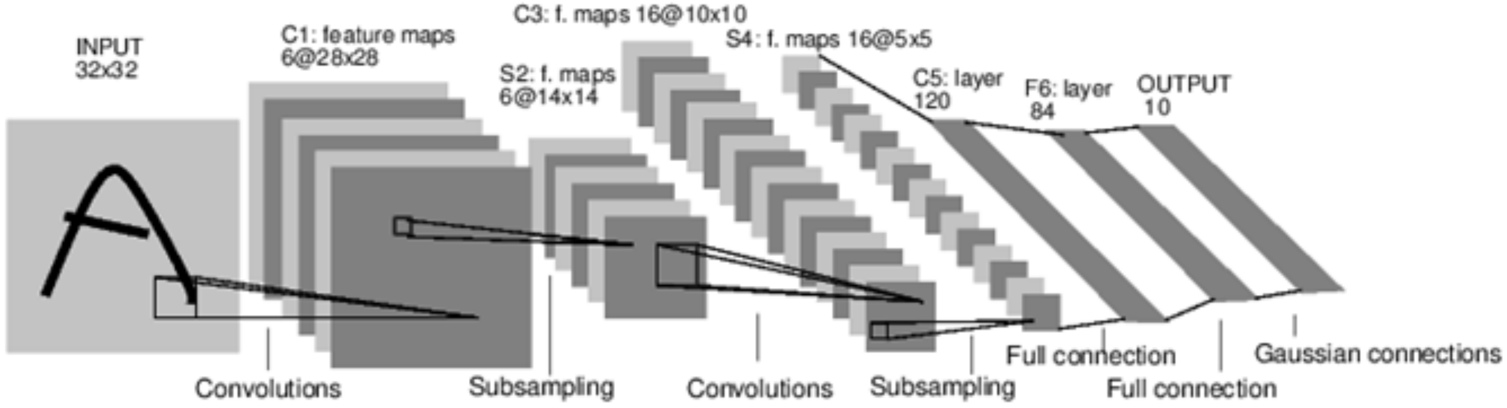
Features learned in CNN



https://devblogs.nvidia.com/parallelforall/accelerate-machine-learning-cudnn-deep-neural-network-library/

Some Popular CNNs

- LeNet (1990)
- AlexNet (2012)
- ZF net (2013)
- GoogLeNet (2014)
- VGGNet (2014)
- ResNet (2015)



A Full Convolutional Neural Network (LeNet)

Little Data (More hand engineering)

Lots of Data (Less hand engineering and simpler algorithms)

Object Detection

Image Recognition

Speech Recognition

Source Andrew Ng

AlexNet Exercise with IBM-Caffe

- /opt/DL/caffe-ibm/examples/00-classification.ipynb

Transfer Learning

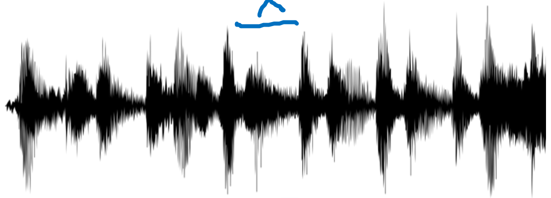
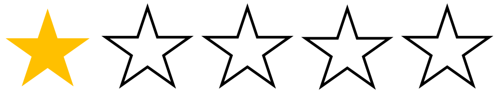
Transfer Learning Scenarios

- Fixed Feature Extractor
- Fine Tuning the ConvNet
  - Train entire or part of the network
- Caffe-Zoo

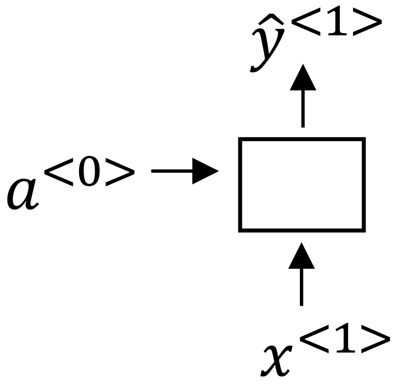
Transfer Learning Exercise Using Caffe

- /opt/DL/caffe-ibm/examples/02-fine-tuning.ipynb
- Follow-up
  - Try different images

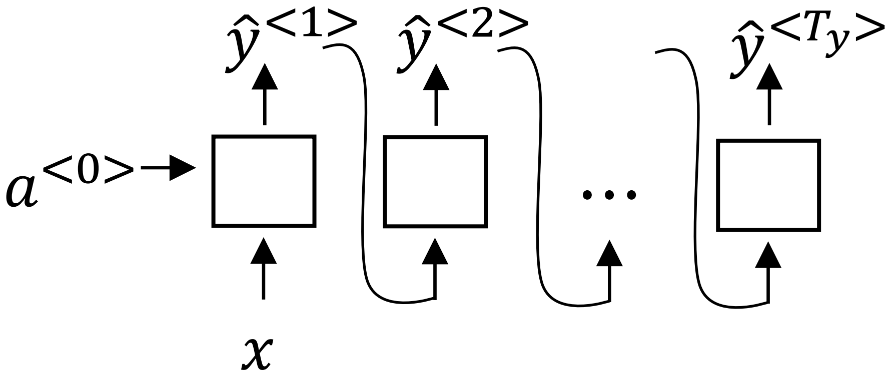
Applications of RNNs

	x		y
Speech recognition		→	"The quick brown fox jumped over the lazy dog."
Music generation	Ø	→	
Sentiment classification	"There is nothing to like in this movie."	→	
DNA sequence analysis	AGCCCCTGTGAGGAACTAG	→	AG**CCCCTGTGAGGAACT**AG
Machine translation	Voulez-vous chanter avec moi?	→	Do you want to sing with me?
Video activity recognition		→	Running
Name entity recognition	Yesterday, Harry Potter met Hermione Granger.	→	Yesterday, **Harry Potter** met **Hermione Granger**.

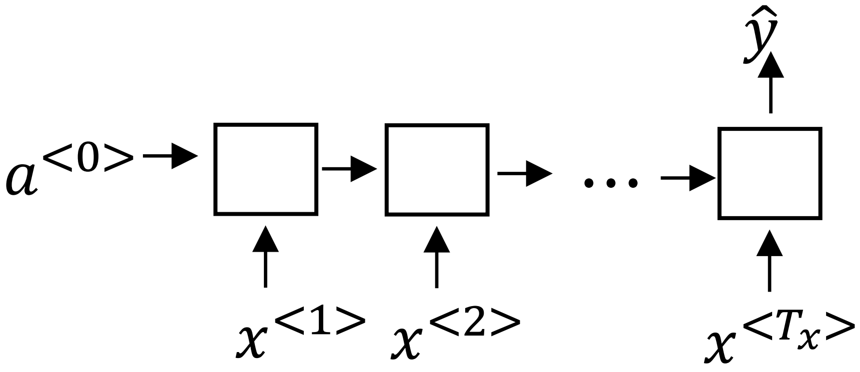
Summary of RNN types



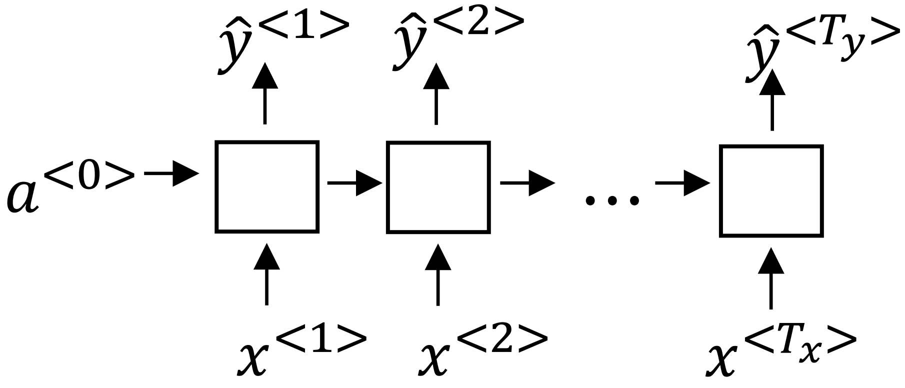
One to one



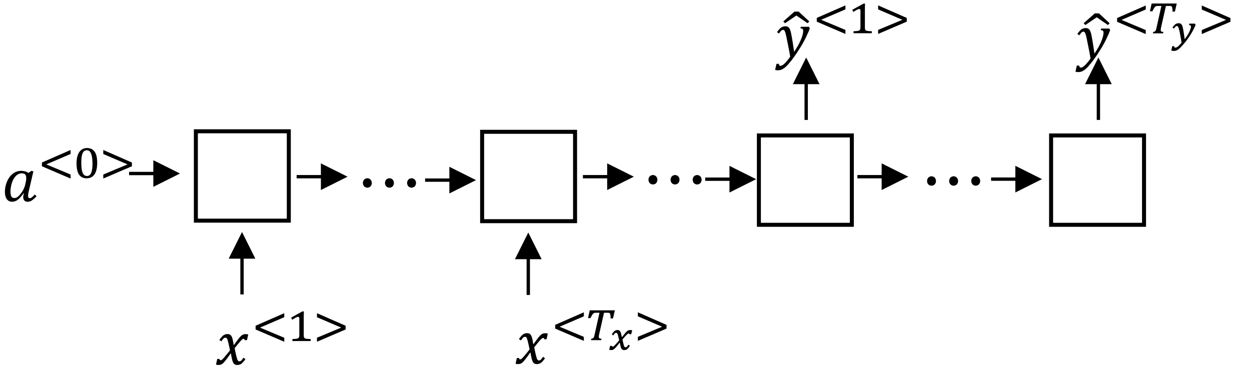
One to many



Many to one

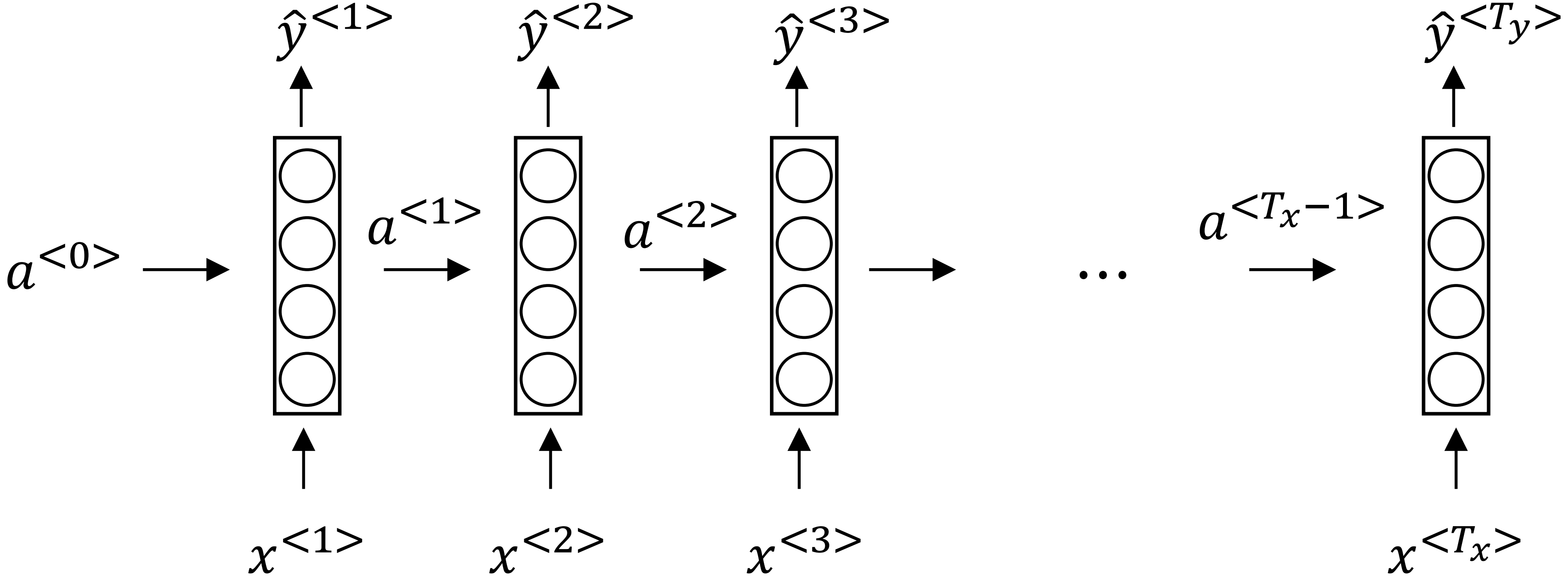


Many to many



Many to many

RNN Forward Propagation



RNN Parameters

$$a^{<t>} = g(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)$$

$$\hat{y}^{<t>} = g(W_{ya}a^{<t>} + b_y)$$

Recurrent Neural Networks

https://github.com/nfmcclure/tensorflow_cookbook/blob/master/09_Recurrent_Neural_Networks/03_Implementing_LSTM/03_implementing_lstm.ipynb

Thank You