Introduction to Deep Learning

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Part of slides referenced from
Nvidia, ***Deep Learning Institute (DLI) Teaching Kit***
Stanford, ***CS231n: Convolutional Neural Networks for Visual Recognition***
Martin Görner, ***Learn TensorFlow and deep learning, without a Ph.D***

Louisiana State University

Baton Rouge

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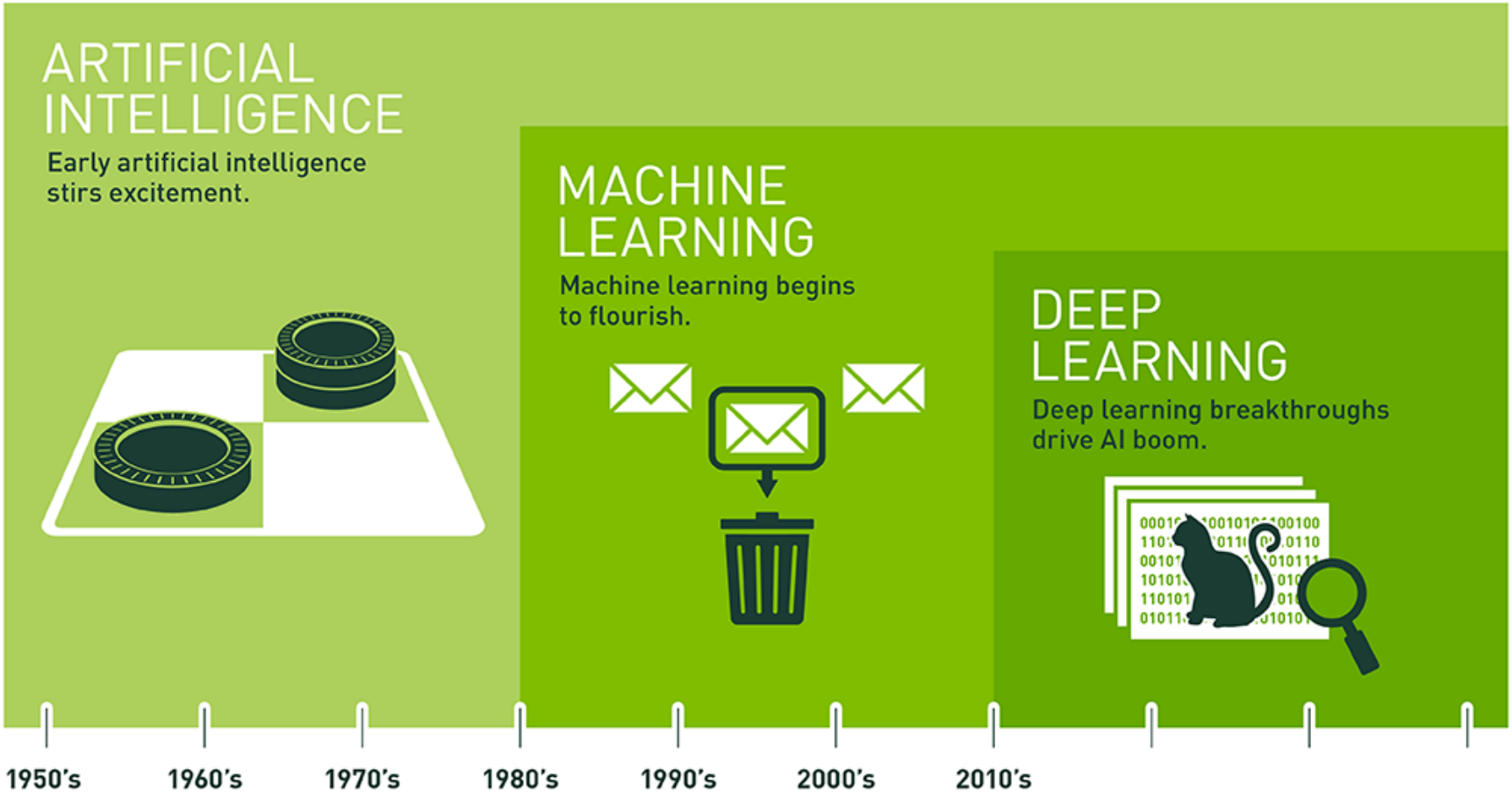
Topics To Be Discussed

- **Fundamentals about Machine Learning**
- **What is Deep Learning?**
  - What is a (deep) neural network
  - How to train it
- **Build a neural network model using Keras/TensorFlow**
  - MNIST example
    - Softmax classification
    - Cross-entropy cost function
    - A 5 layer deep neural network
    - Dropout
    - Convolutional networks
  - How to utilize HPC
    - Run batch jobs

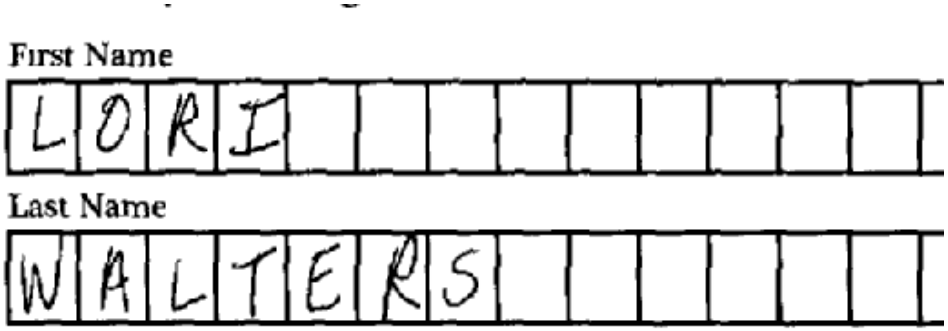
Machine Learning and Deep Learning

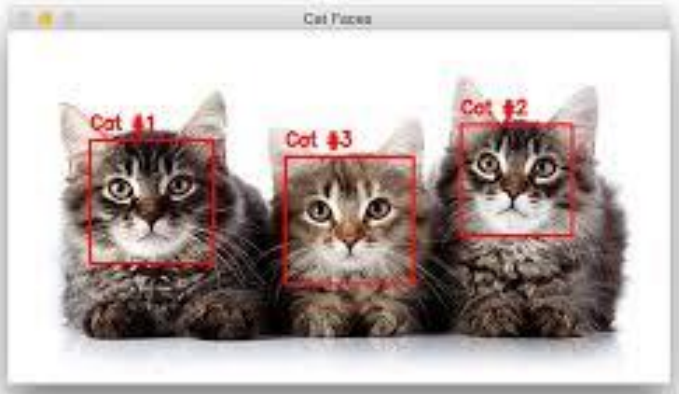


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Machine Learning

- **Machine Learning is the science of getting computers to learn, without being explicitly programmed.**
- **Examples are used to train computers to perform tasks that would be difficult to program**





Types of Machine Learning

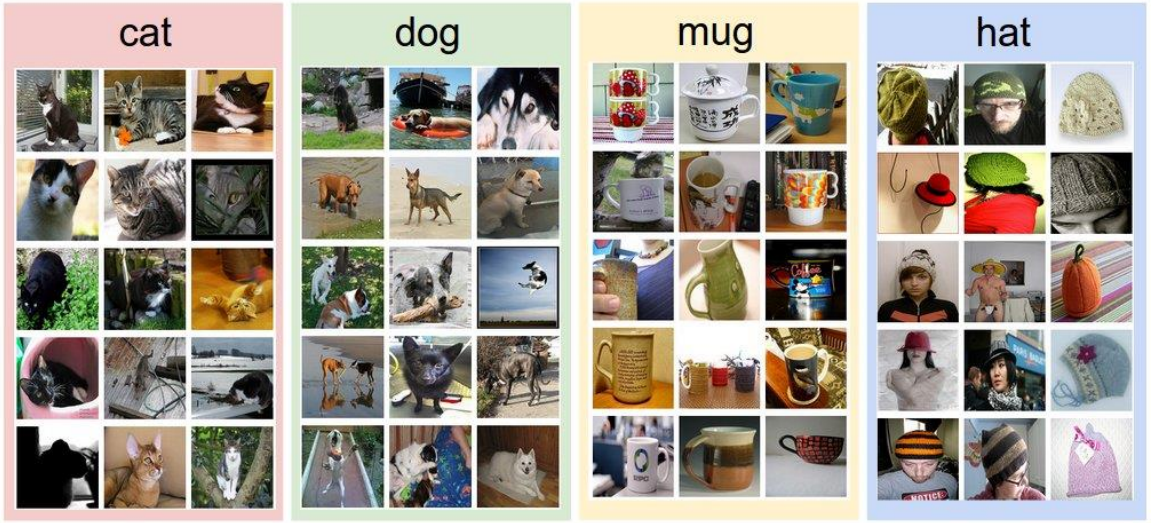
- **Supervised Learning**
  - Training data is labeled
  - Goal is correctly label new data
- **Unsupervised Learning**
  - Training data is unlabeled
  - Goal is to categorize the observations
- **Reinforcement Learning**
  - Training data is unlabeled
  - System receives feedback for its actions
  - Goal is to perform better actions

Applications of Machine Learning

- **Handwriting Recognition**
  - convert written letters into digital letters
- **Image Classification**
  - label images with appropriate categories (e.g. Google Photos)
- **Language Translation**
  - translate spoken and or written languages (e.g. Google Translate)
- **Speech Recognition**
  - convert voice snippets to text (e.g. Siri, Cortana, and Alexa)
- **Autonomous Driving**
  - enable cars to drive

Data-driven Approach

- **Instead of trying to specify what every one of the categories of interest look like directly in code, the approach that we will take is not unlike one you would take with a child:**
  - Provide the computer with many examples of each class
  - Develop learning algorithms that look at these examples and learn about the visual appearance of each class.
- **This approach is referred to as a data-driven approach.**

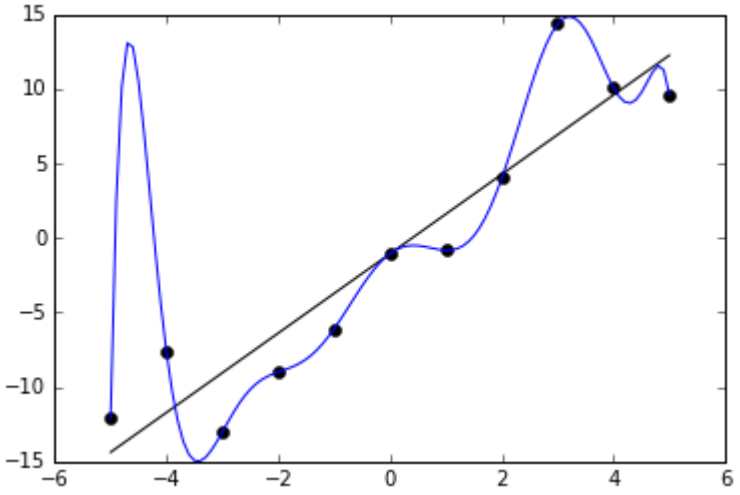


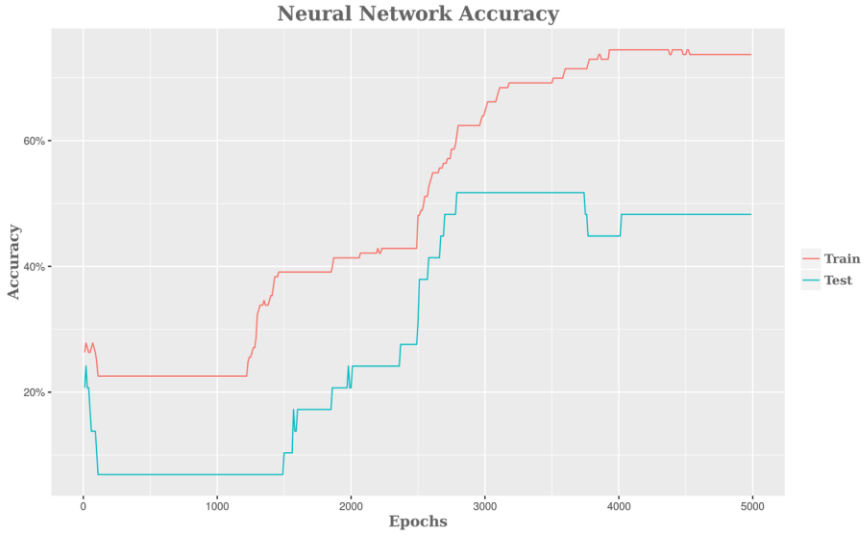
An example training set for four visual categories. In practice we may have thousands of categories and hundreds of thousands of images for each category. ***(From Stanford CS231n)**

Training and Test Data

- **Training Data**
  - data used to learn a model
- **Test Data**
  - data used to assess the accuracy of model

- **Overfitting**
  - Model performs well on training data but poorly on test data





Supervised Learning Algorithms

- **Linear Regression**
- **Decision Trees**
- **Support Vector Machines**
- **K-Nearest Neighbor**
- **Neural Networks**
  - Deep Learning is the branch of Machine Learning based on Deep Neural Networks (DNNs, i.e., neural networks composed of more than 1 hidden layer).
  - Convolutional Neural Networks (CNNs) are one of the most popular DNN architectures (so CNNs are part of Deep Learning), but by no means the only one.

Machine Learning Frameworks

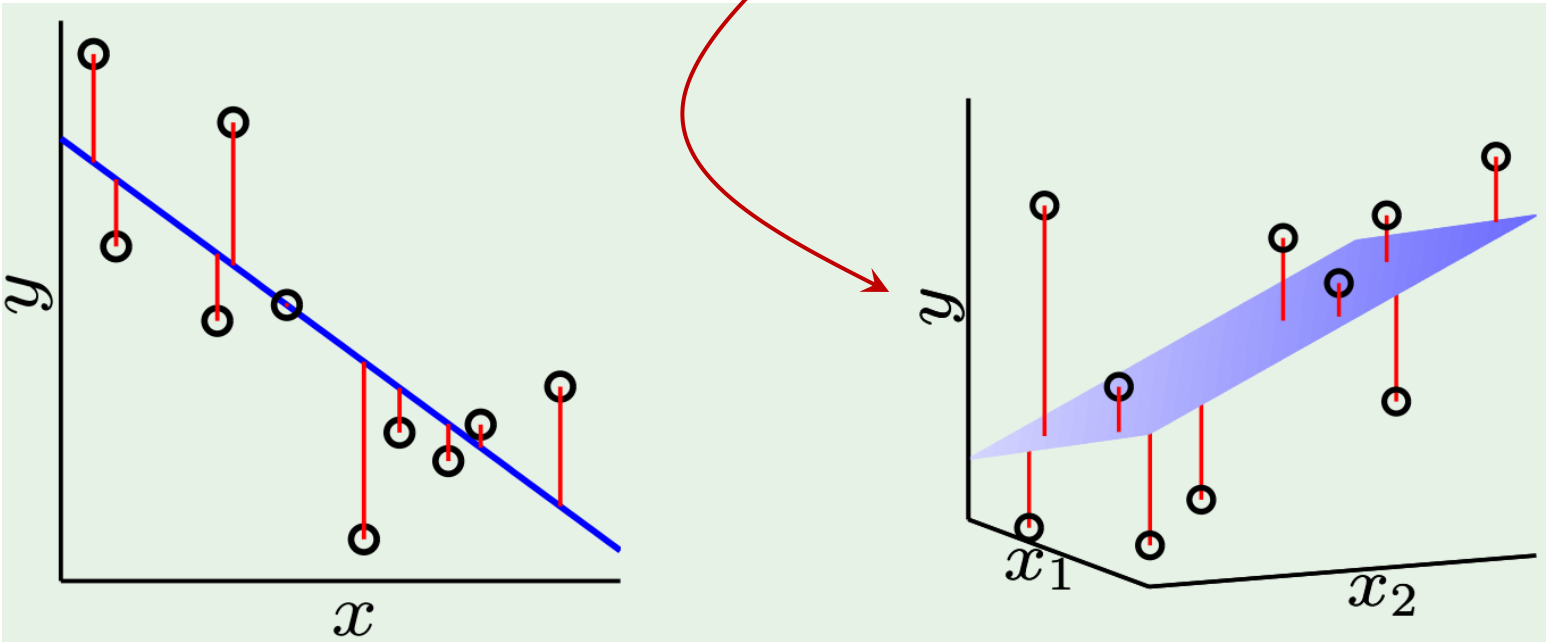
Tool	Uses	Language
Scikit-Learn	Classification, Regression, Clustering	Python
Spark MLlib	Classification, Regression, Clustering	Scala, R, Java
MXNet	Deep learning framework	Python, R, Julia, Scala, Go, Javascript and more
Caffe	Neural Networks	C++, Python
TensorFlow	Neural Networks	Python
PyTorch	Neural Networks	Python

What is Deep Learning

Machine Learning and Deep Learning

Understanding The Learning Process

- **Start from least square method...** $y = w_1 x_1 + w_2 x_2 + b$
- **Trying to find**
  - ***Parameters* (*w, b*)**: minimizes the sum of the squares of the errors
  - ***Errors***: distance between known data points and predictions

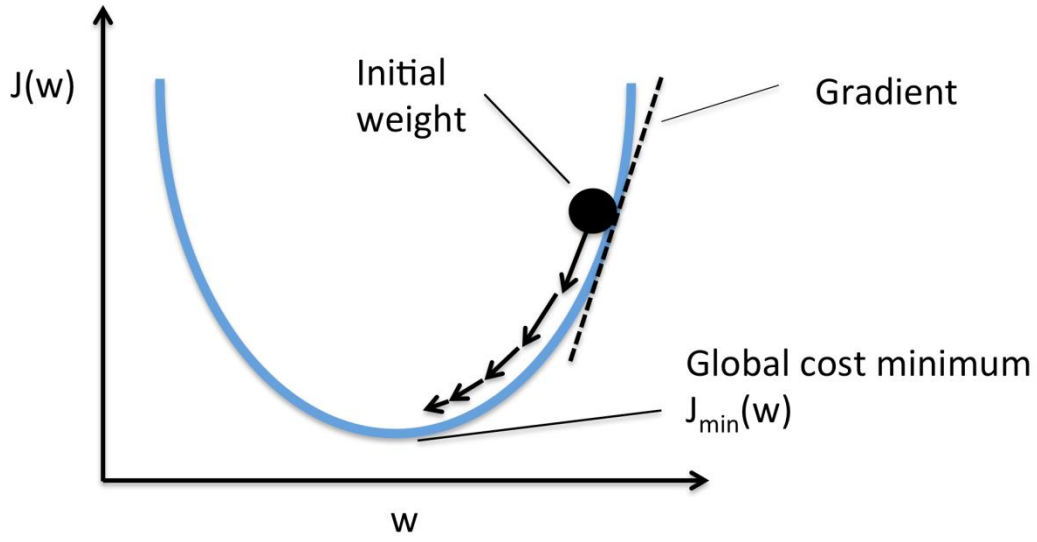


❖ from Yaser Abu-Mustafa “Learning From Data” Lecture 3

Recall From The Least Square Method

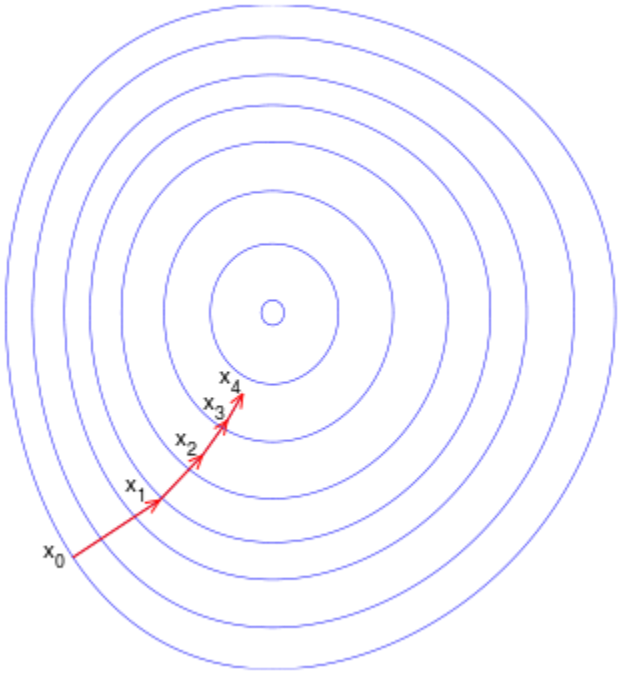
- **Error**
  - Cost Function (Loss): *J*(*w*), *C, L*
- **Parameters**
  - Weights and Biases: (*w, b*)

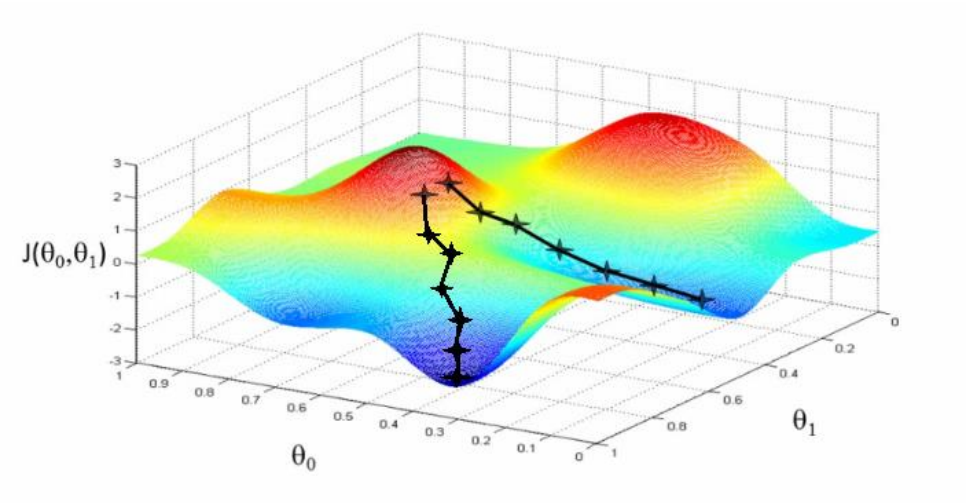
- **Define the cost function of your problem**
- **Find the set of weights that minimizes the cost function (loss)**



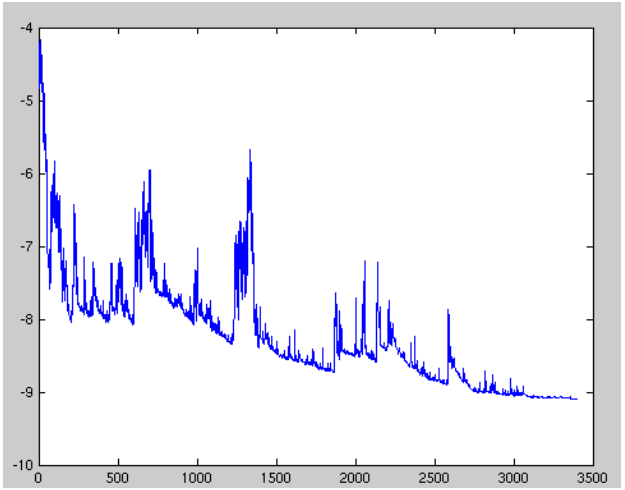
Theory: Gradient Descent

- **Gradient descent is a first-order iterative optimization algorithm. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient (or of the approximate gradient) of the function at the current point.**





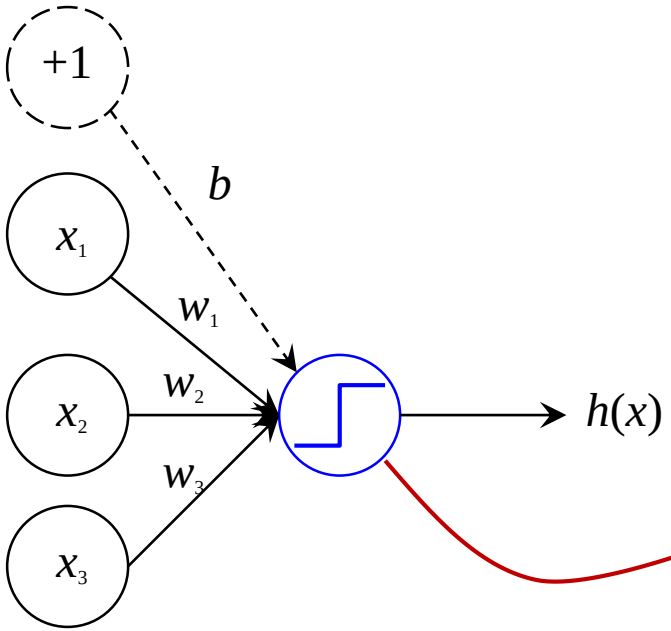
Mini-batch Gradient Descent



- **Batch gradient descent:**
  - Use all examples in each iteration
- **Stochastic gradient descent:**
  - Use one example in each iteration
- **Mini-batch gradient descent**
  - Use *b* examples in each iteration
- **In the neural network terminology:**
  - one ***EPOCH*** = one forward pass and one backward pass of all the training examples
  - batch size = the number of training examples in one forward/backward pass. The higher the batch size, the more memory space you'll need.
  - number of iterations = number of passes, each pass using [batch size] number of examples. To be clear, one pass = one forward pass + one backward pass (we do not count the forward pass and backward pass as two different passes).
  - ***Example:*** if you have 1000 training examples, and your batch size is 500, then it will take 2 iterations to complete 1 epoch.

What is a neural network?

- **Start from a perceptron**



x1	age	23
x2	gender	male
x3	annual salary	$30,000
b	threshold	some value

h(x)	Approve credit if: `h(x)>0`

Activation function:

$$\sigma(z)=sign(z)$$

Denote as: z

Feature vector: $\mathbf{x}$

$$\mathbf{x}=\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Weight vector: $\mathbf{w}$

$$\mathbf{w}=\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

$$h(x)=\text{sign}(w_1x_1+w_2x_2+w_3x_3+b)$$

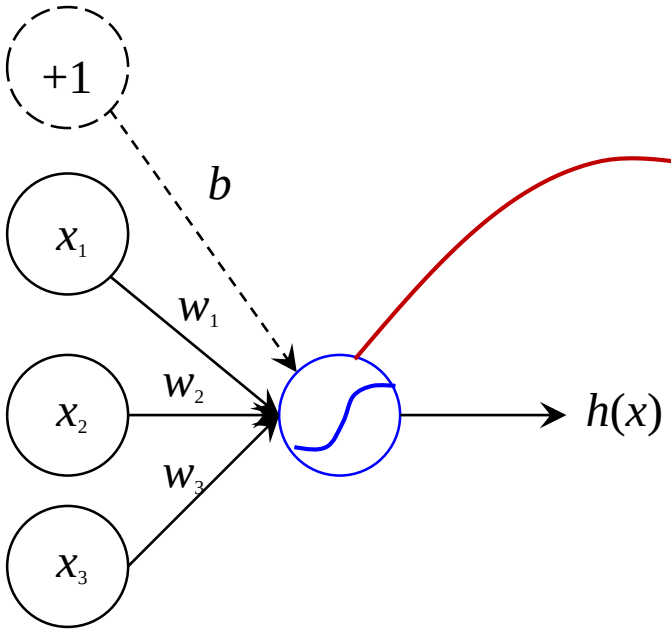
$$=\text{sign}\left(\sum_i w_i x_i+b\right)$$

$$=\text{sign}\left(\mathbf{w}^T\mathbf{x}+b\right)$$

Hypothesis (Prediction: y)

Perceptron To Neuron

- **Replace the sign to sigmoid**



Activation function:

$$\sigma(z)=sigmoid(z)$$

$$h(x)=\text{sigmoid}\left(w_1x_1+w_2x_2+w_3x_3+b\right)$$
$$=\text{sigmoid}\left(\sum_i w_ix_i+b\right)$$
$$=\text{sigmoid}\left(\mathbf{w}^T\mathbf{x}+b\right)$$

Feature vector: $\mathbf{x}$ Weight vector: $\mathbf{w}$

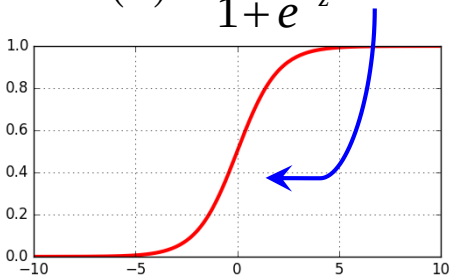
$$\mathbf{x}=\begin{bmatrix}x_1\\x_2\\x_3\end{bmatrix} \qquad \mathbf{w}=\begin{bmatrix}w_1\\w_2\\w_3\end{bmatrix}$$

$$z=\mathbf{w}^T\mathbf{x}+b$$
$$y=h(x)=\sigma(z)$$

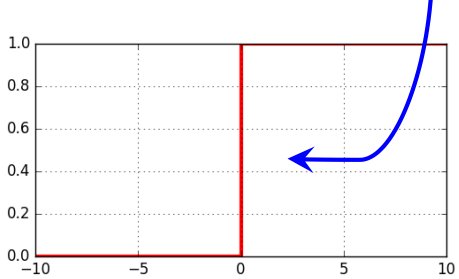
Sigmoid Neurons

- **Sigmoid activation Function**
  - In the field of Artificial Neural Networks, the sigmoid function is a type of activation function for artificial neurons.

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

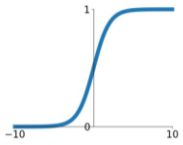


$$\sigma(z) = sign(z)$$

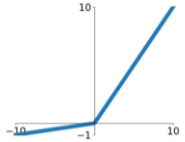


- **There are many other activation functions. (We will touch later.)**

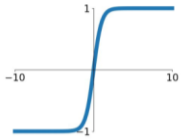
Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



Leaky ReLU
$\max(0.1x, x)$

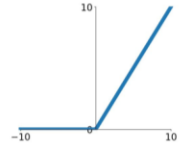


tanh
$\tanh(x)$

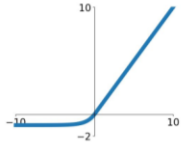


Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ReLU
$\max(0, x)$

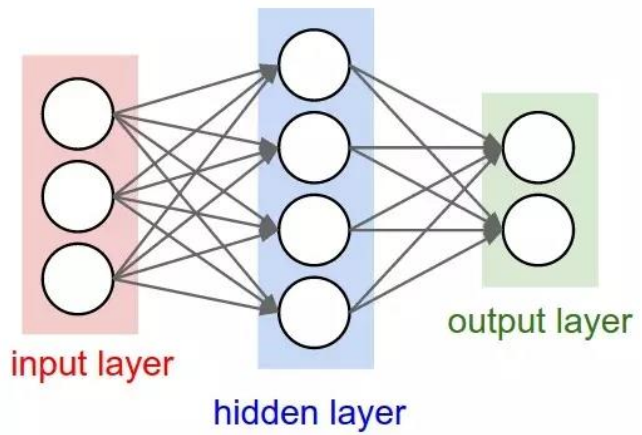


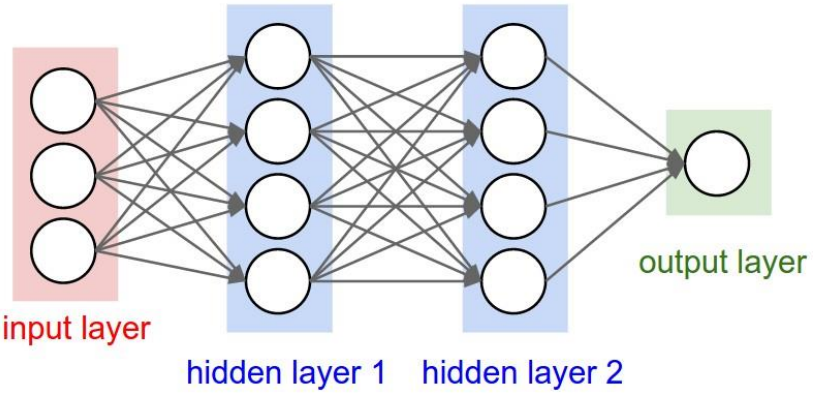
ELU
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



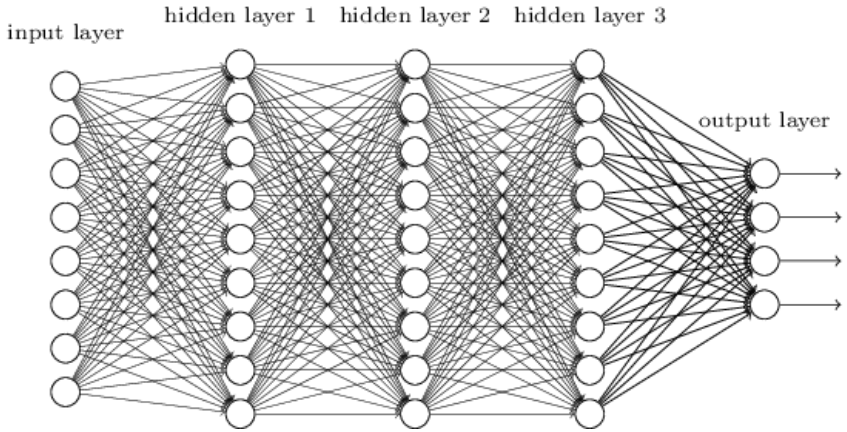
Network Of Neurons

- **A complex network of neurons could make quite subtle decisions**

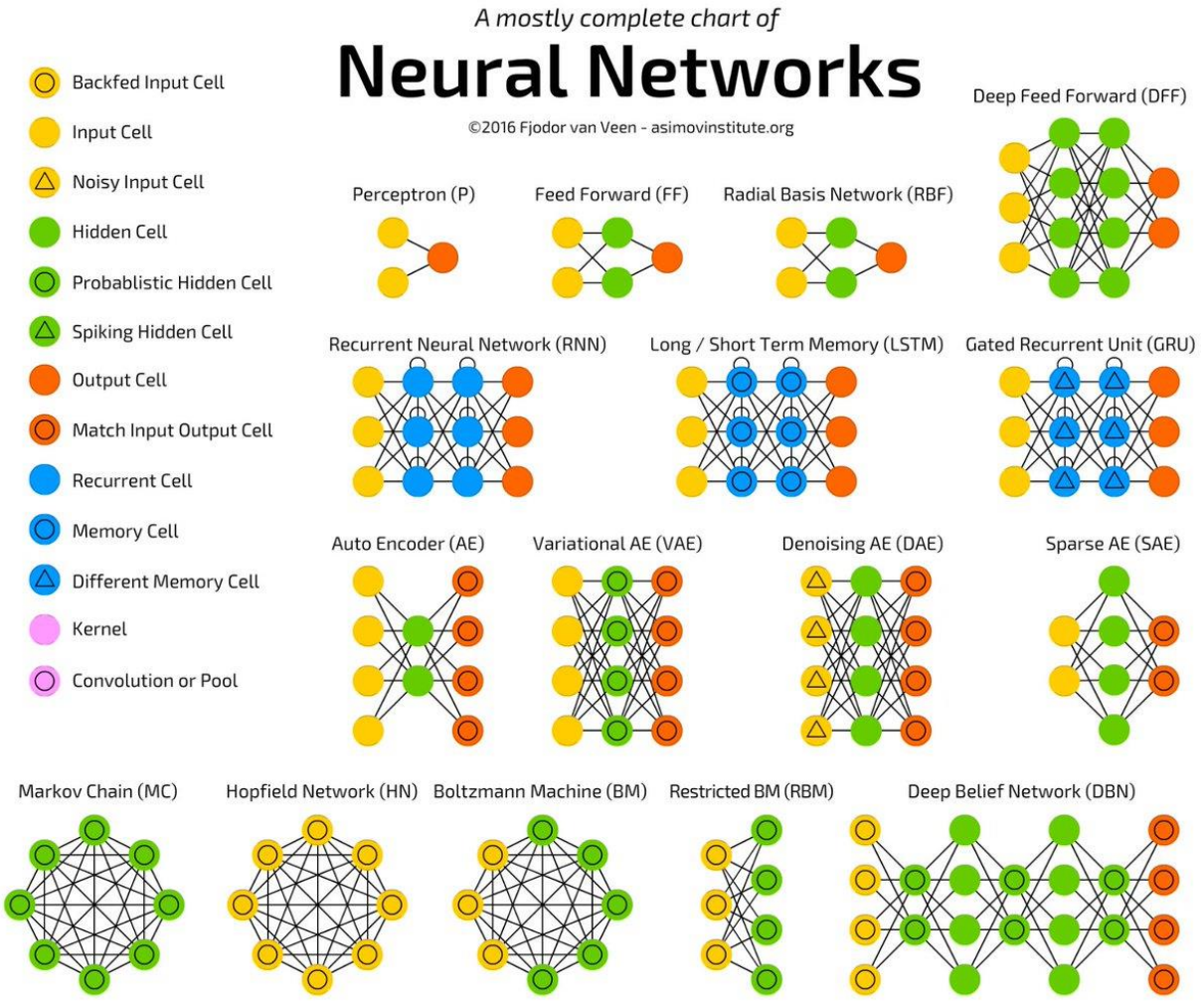




- **Deep Neuron Network: Number of hidden layers >1**



Types of Neural Networks



Ref: http://www.asimovinstitute.org/neural-network-zoo/

How to Train DNN?

- **Backward Propagation**
  - The backward propagation of errors or backpropagation, is a common method of training artificial neural networks and used in conjunction with an optimization method such as gradient descent.

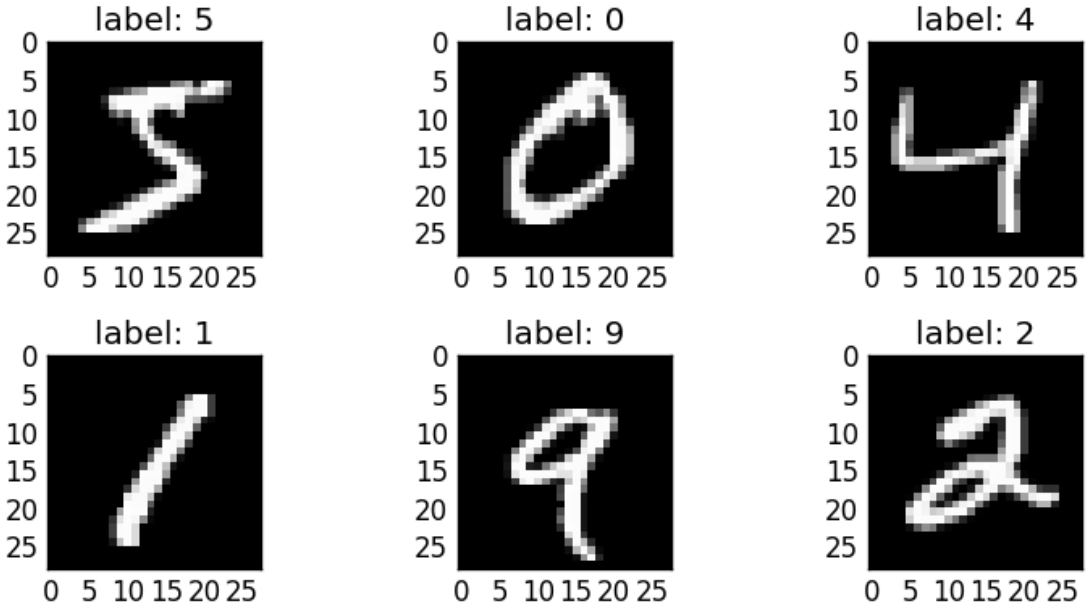
- **Deep Neural Networks are hard to train**
  - learning machines with lots of (typically in range of million) parameters
  - Unstable gradients issue
    - Vanishing gradient problem
    - Exploding gradient problem
  - Choice of network architecture and other hyper-parameters is also important.
  - Many factors can play a role in making deep networks hard to train
  - Understanding all those factors is still a subject of ongoing research

Deep Learning Example

Hello World of Deep Learning: Recognition of MNIST

Introducing the MNIST problem

- **MNIST (Mixed National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.**
- **It consists of images of handwritten digits like these:**



- **The MNIST database contains 60,000 training images and 10,000 testing images.**

Example Problem - MNIST

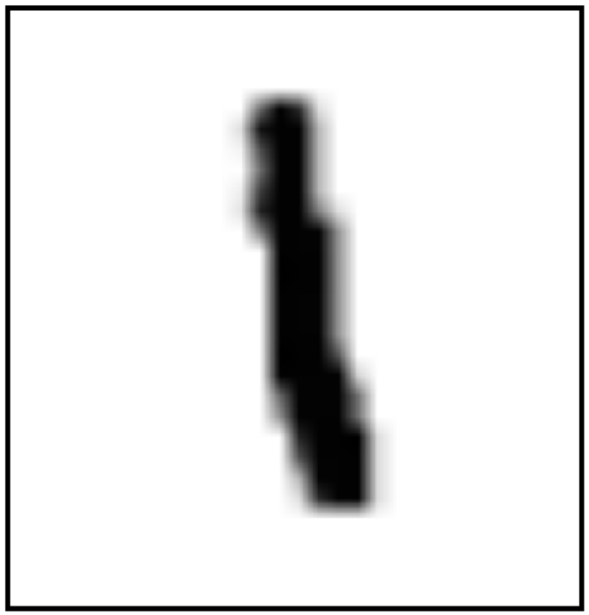
- **Recognizes handwritten digits.**
- **We uses the MNIST dataset, a collection of 60,000 labeled digits that has kept generations of PhDs busy for almost two decades. You will solve the problem with less than 100 lines of Python/Keras/TensorFlow code.**
- **We will gradually enhance the neural network to achieve above 99% accuracy by using the mentioned techniques.**

Steps for MNIST

- **Understand the MNIST data**
- **Softmax regression layer**
- **The cost function**

The MNIST Data

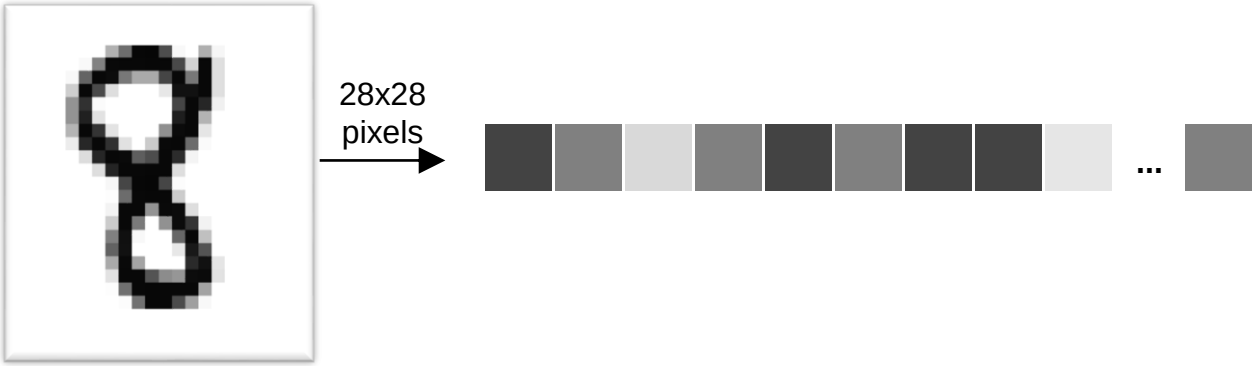
- **Every MNIST data point has two parts: an image of a handwritten digit and a corresponding label. We'll call the images "x" and the labels "y". Both the training set and test set contain images and their corresponding labels;**
- **Each image is 28 pixels by 28 pixels. We can interpret this as a big array of numbers:**



$$
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .6 & .8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .7 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .9 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .3 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

One Layer NN for MNIST Recognition

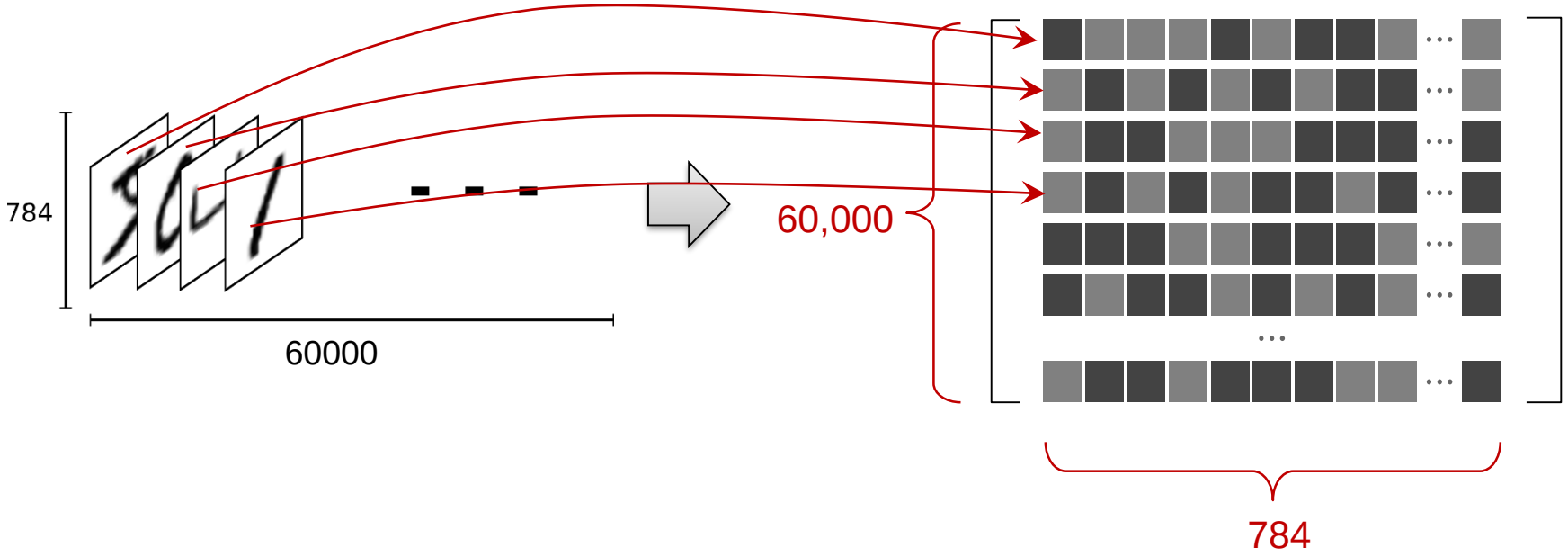
- **We will start with a very simple model, called Softmax Regression.**
- **We can flatten this array into a vector of 28x28 = 784 numbers. It doesn't matter how we flatten the array, as long as we're consistent between images.**
- **From this perspective, the MNIST images are just a bunch of points in a 784-dimensional vector space.**



❖ **What are we missing here?**

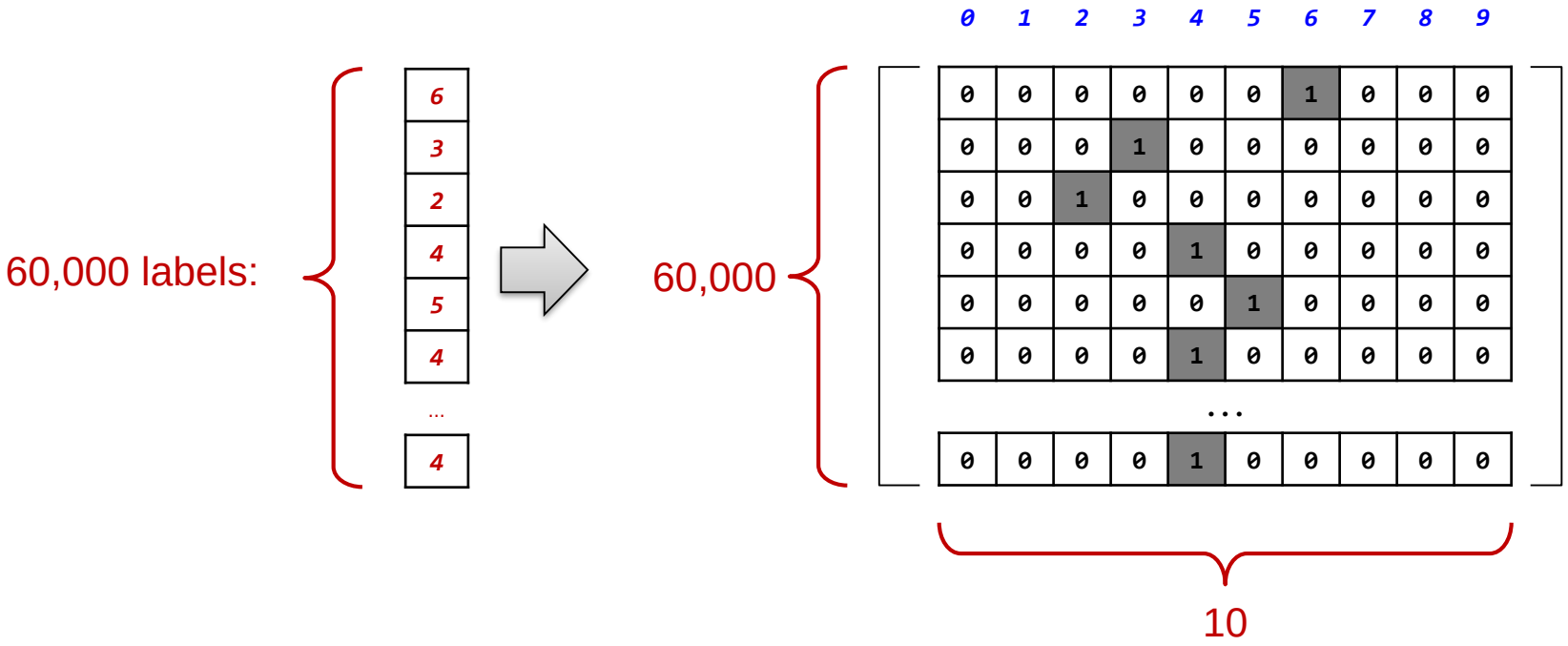
Result of the Flatten Operation

- The result is that the training images is a matrix (tensor) with a shape of `[60000, 784]`.
- The first dimension is an index into the list of images and the second dimension is the index for each pixel in each image.
- Each entry in the tensor is a pixel intensity between 0 and 1, for a particular pixel in a particular image.



One-hot Vector (One vs All)

- For the purposes of this tutorial, we label the y's as "one-hot vectors".
- A one-hot vector is a vector which is 0 in most dimensions, and 1 in a single dimension.
- How to label an "8"?
  - `[0,0,0,0,0,0,0,0,1,0]`
- What is the dimension of our y matrix (tensor)?



Softmax Regressions

- Every image in MNIST is of a handwritten digit between 0 and 9.
- So there are only ten possible things that a given image can be. We want to be able to look at an image and give the probabilities for it being each digit.
- For example, our model might look at a picture of an eight and be 80% sure it's an 8, but give a 6% chance to it being a 4 (because of the top loop) and a bit of probability to all the others because it isn't 100% sure.

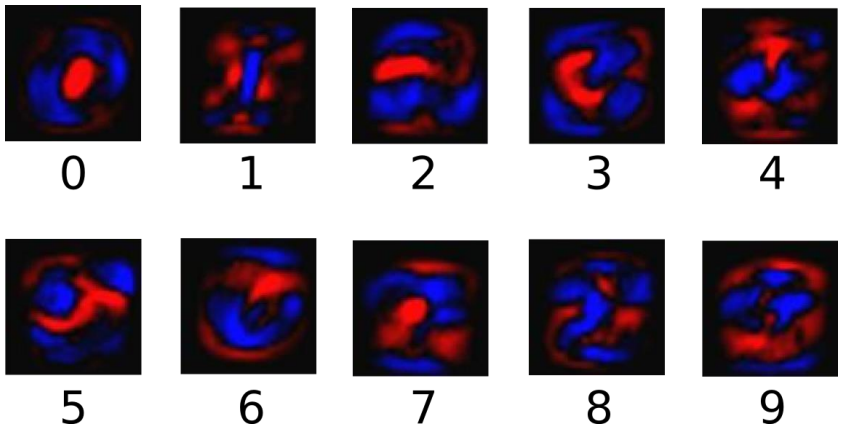
Softmax Regression

this is a "8"

0	1	2	3	4	5	6	7	8	9
0.04	0.02	0.01	0.01	0.06	0.03	0.01	0.01	0.80	0.01

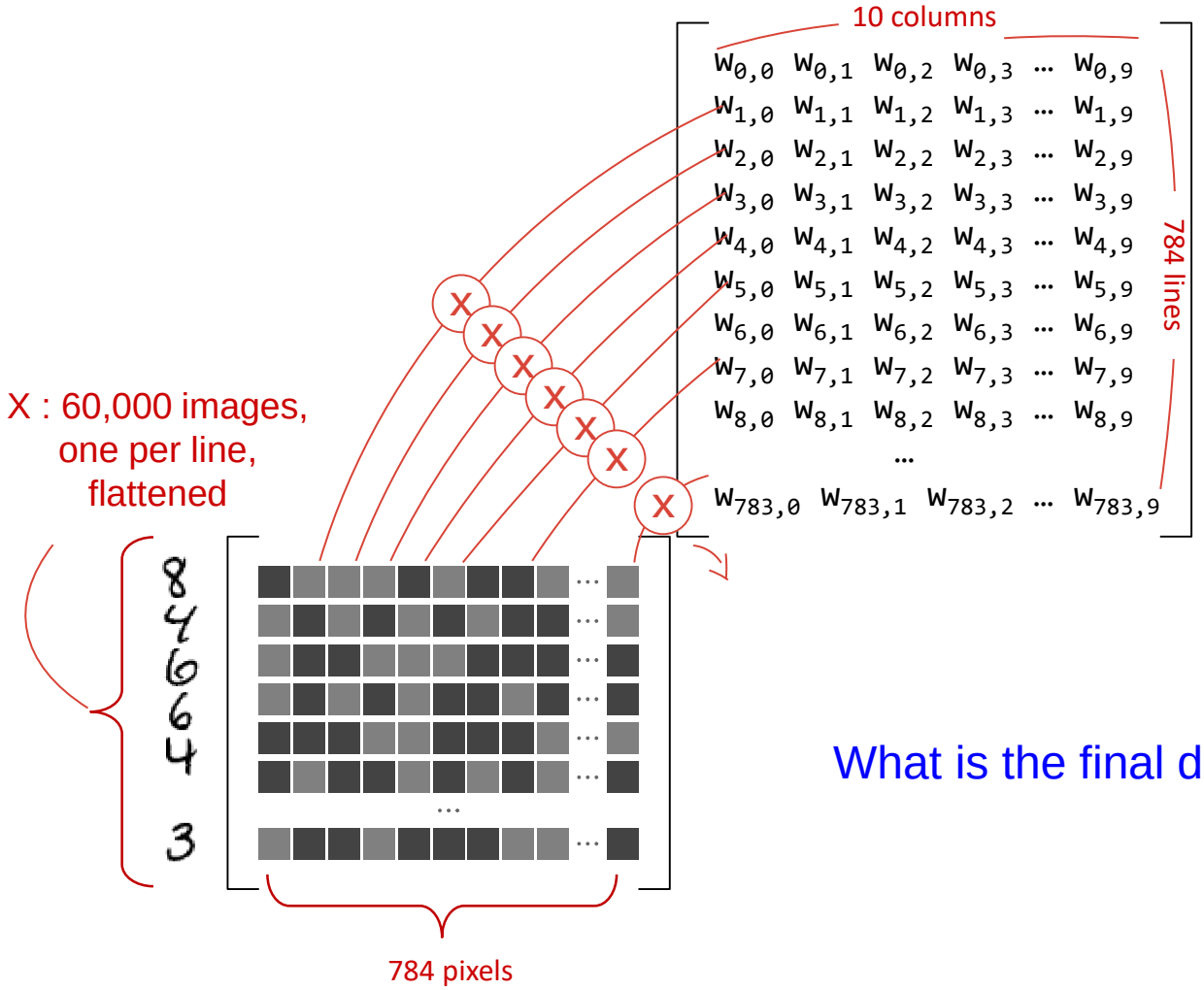
2 steps in softmax regression - Step 1

- **Step 1: Add up the evidence of our input being in certain classes.**
  - Do a weighted sum of the pixel intensities. The weight is negative if that pixel having a high intensity is evidence against the image being in that class, and positive if it is evidence in favor.



$$z_i = \sum_j W_{i,j} x_j + b_i$$

Matrix Representation of softmax layer



broadcast

$$Y = \text{softmax}(X \cdot W + b)$$

What is the final dimension for *X*W*?

2 steps in softmax regression - Step 2

- **Step 2: Convert the evidence tallies into our predicted probabilities y using the "softmax" function:**

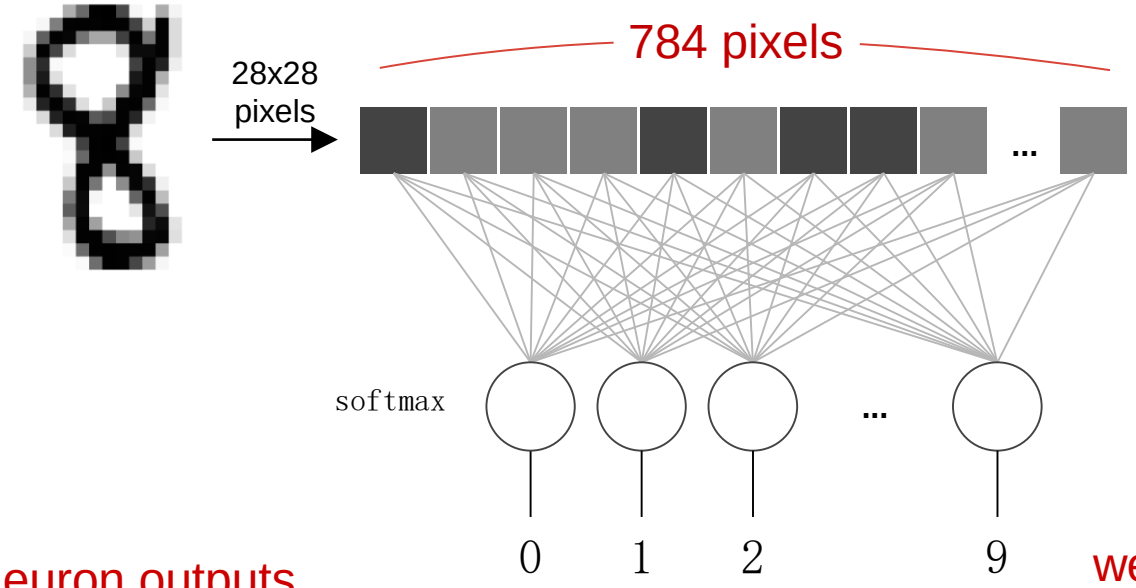
$$h(\mathbf{x}_i) = \text{softmax}(z_i) = \text{softmax}\left(\sum_j W_{i,j} x_j + b_i\right)$$

- **Here softmax is serving as an "activation" function, shaping the output of our linear function a probability distribution over 10 cases, defined as:**

$$\text{softmax}(z_i) = \text{normalize}(\exp(z)) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

The softmax layer

- **The output from the softmax layer is a set of probability distribution, positive numbers which sum up to 1.**



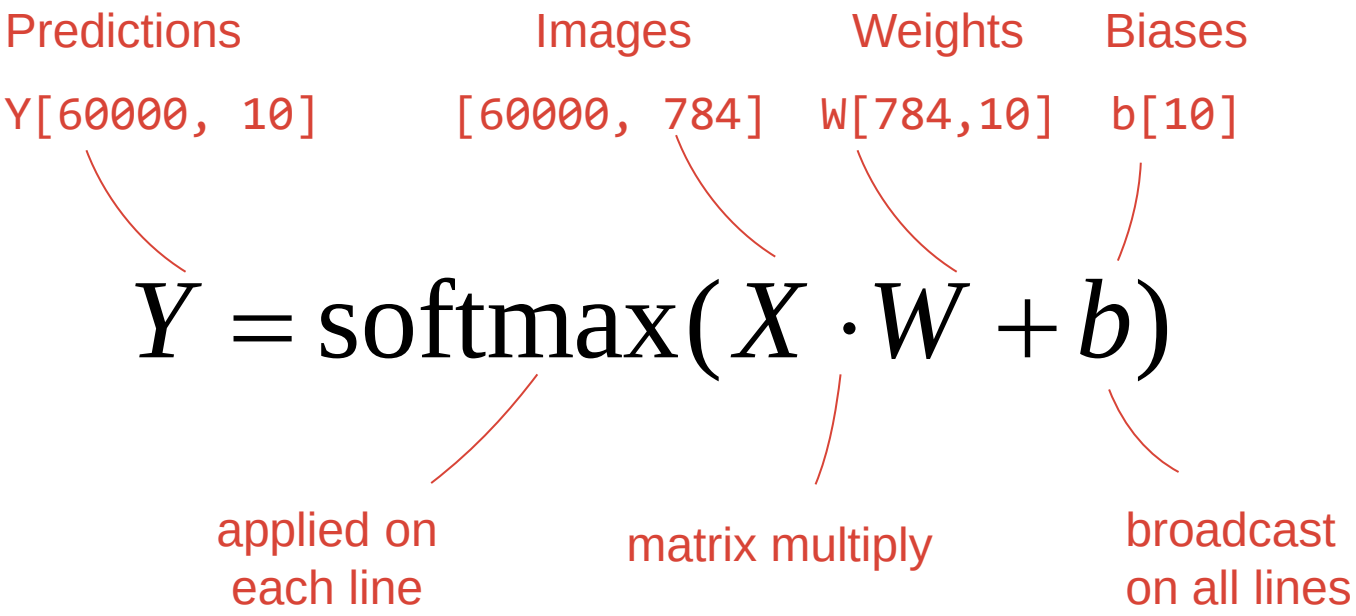
neuron outputs

weighted sum of all pixels + biases

$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

Softmax on a batch of images

- **More compact representation for "softmaxing" on all the images**



The Cross-Entropy Cost Function

- **For classification problems, the Cross-Entropy cost function works better than quadratic cost function.**
- **We define the cross-entropy cost function for the neural network by:**

0	0	0	0	0	0	1	0	0	0

"one-hot" encoded ground truth

Cross entropy

$$C = -\sum_i y_i' \cdot \log P\left(Y = y_i \mid X = x_i\right)$$

computed probabilities

this is a "6"

0.01	0.01	0.01	0.01	0.01	0.01	**0.90**	0.01	0.02	0.01
0	1	2	3	4	5	6	7	8	9

Short Summary

- **How MNIST data is organized**
  - X:
    - Flattened image pixels matrix
  - Y:
    - One-hot vector
- **Softmax regression layer**
  - Linear regression
  - Output probability for each category
- **Cost function**
  - Cross-entropy

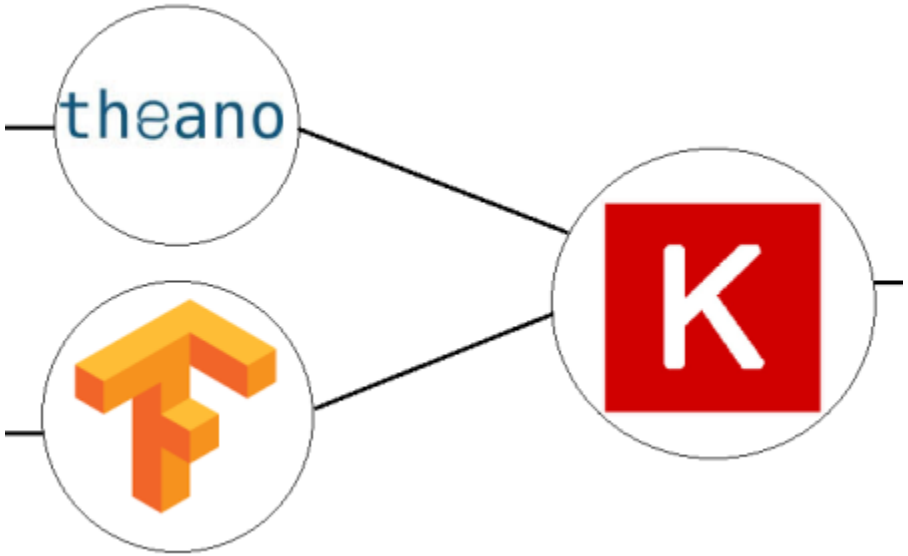
❖ **How to implement them?**

Deep Learning Example

Implementation in Keras/Tensorflow

Few Words about Keras, Tensorflow and Theano

- **Keras is a high-level neural networks library, written in Python and capable of running on top of either TensorFlow or Theano.**
- **TensorFlow is an open source software library for numerical computation using data flow graphs.**
- **Theano is a Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently.**



Introducing Keras

- **Keras is a high-level neural networks library,**
- **Written in Python and capable of running on top of either TensorFlow or Theano.**
- **It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research.**
- **See more at: https://github.com/fchollet/keras**

Typical Code Structure

- **Load the dataset (MNIST)**
- **Build the Neural Network/Machine Learning Model**
- **Train the model**

Software Environment

- **What you'll need**
  - Python 2 or 3 (Python 3 recommended)
  - TensorFlow/Keras
  - Matplotlib (Python visualization library)
- **On LONI QB2 the above modules are already setup for you, simply use:**

```
$ module load python/2.7.12-anaconda-tensorflow
```

OR

```
$ module load python/3.5.2-anaconda-tensorflow
```

Keras - Initialization

```
# import necessary modules
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D, MaxPooling2D
from keras.utils import np_utils
from keras import backend as K
```

Load The MNIST Dataset

```
# load the mnist dataset
import cPickle
import gzip
f = gzip.open('mnist.pkl.gz', 'rb')
# load the training and test dataset
# download https://s3.amazonaws.com/img-datasets/mnist.pkl.gz
# to use in this tutorial
X_train, y_train, X_test, y_test = cPickle.load(f)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

Output of the print line:

```
(60000, 28, 28) (60000,) (10000, 28, 28) (10000,)
```

Preprocessing the MNIST Dataset

Flatten 28x28 image to 1D

```
# Flatten the image to 1D
X_train = X_train.reshape(X_train.shape[0], img_rows*img_cols)
X_test = X_test.reshape(X_test.shape[0], img_rows*img_cols)
input_shape = (img_rows*img_cols,)
```

All grayscale values to 0.0-1.0

```
# convert all data to 0.0-1.0 float values
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
X_test /= 255
```

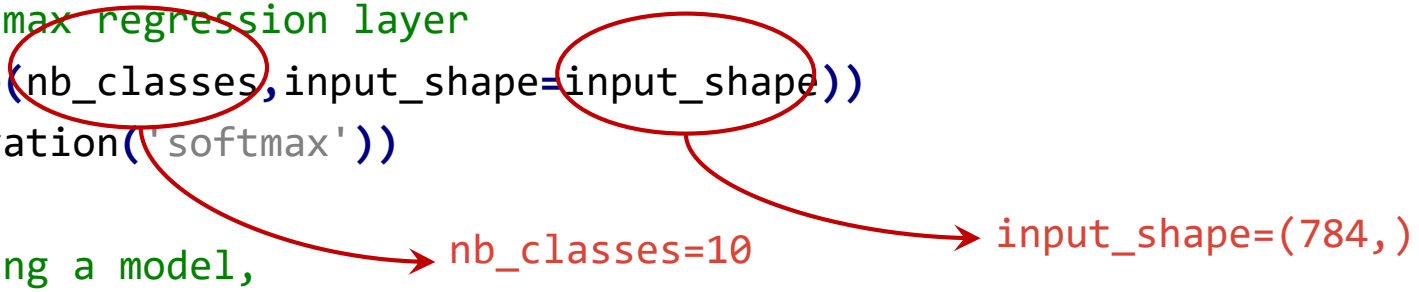
One-hot encoding

```
# convert class vectors to binary class matrices
Y_train = np_utils.to_categorical(y_train, nb_classes)
Y_test = np_utils.to_categorical(y_test, nb_classes)
```

Build The First softmax Layer

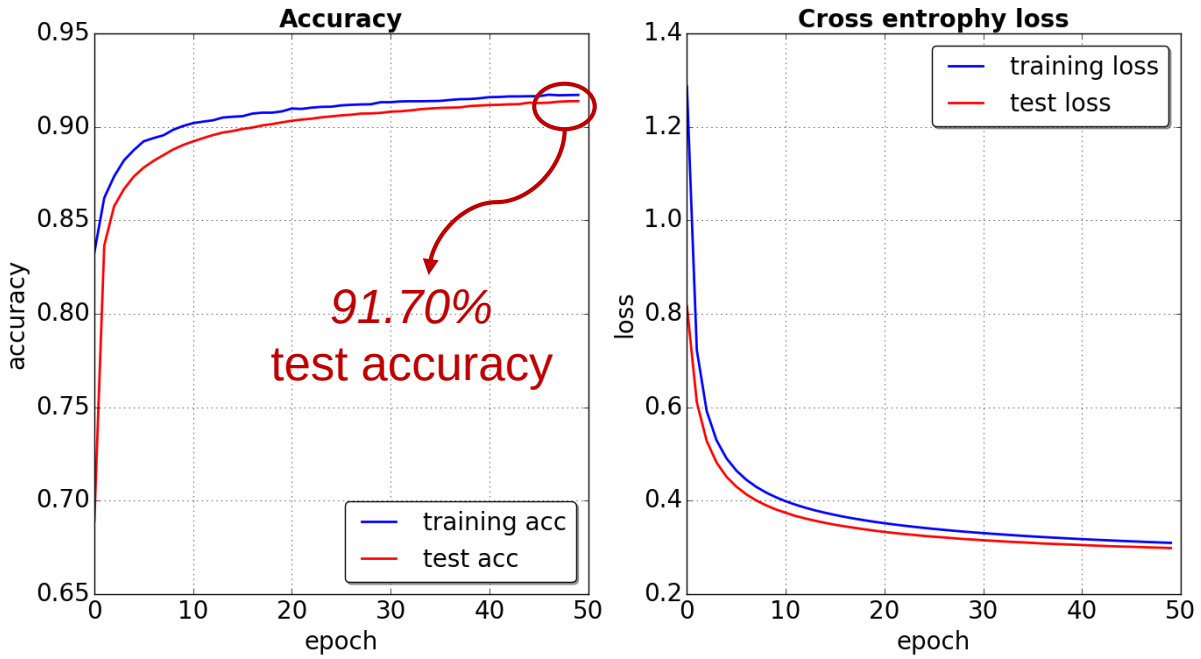
```
# The Sequential model is a linear stack of layers in Keras
model = Sequential()
#build the softmax regression layer
model.add(Dense(nb_classes,input_shape=input_shape))
model.add(Activation('softmax'))

# Before training a model,
# configure the learning process via the compile method.
# using the cross-entropy loss function (objective)
model.compile(loss='categorical_crossentropy',
              #using the stochastic gradient descent (SGD)
              optimizer='sgd',
              # using accuracy to judge the performance of your model
              metrics=['accuracy'])
# fit the model, the training process
h = model.fit(X_train, Y_train, batch_size=batch_size, nb_epoch=nb_epoch,
          verbose=1, validation_data=(X_test, Y_test))
```



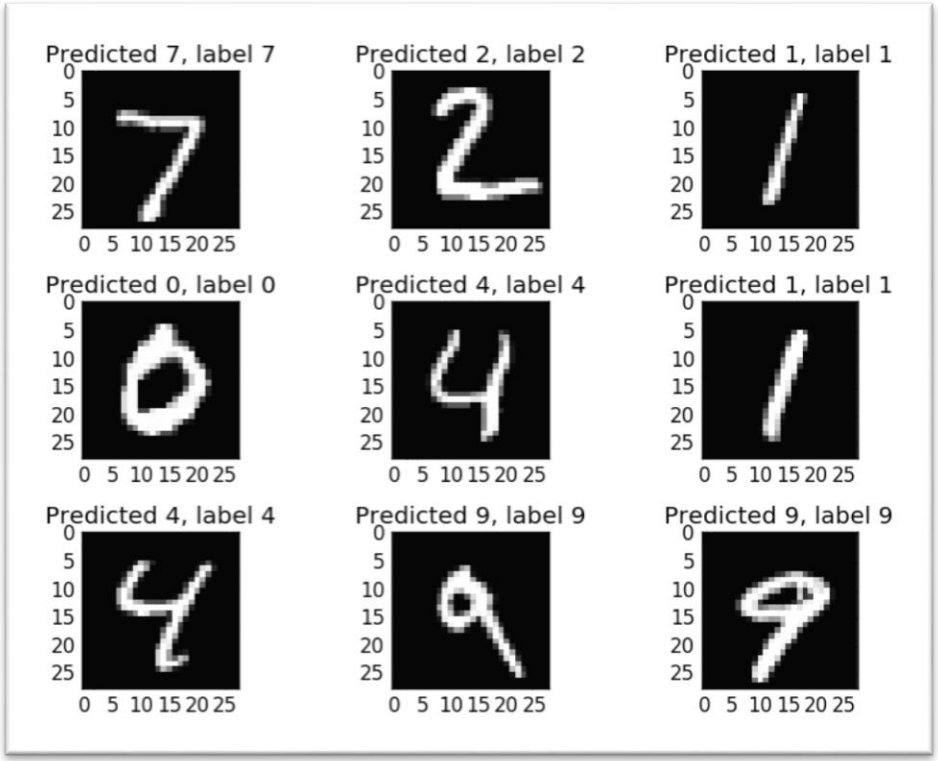
Results Of The First softmax Regression

- **Training accuracy vs Test accuracy, loss function**
- **We reach a test accuracy at *91.7%***

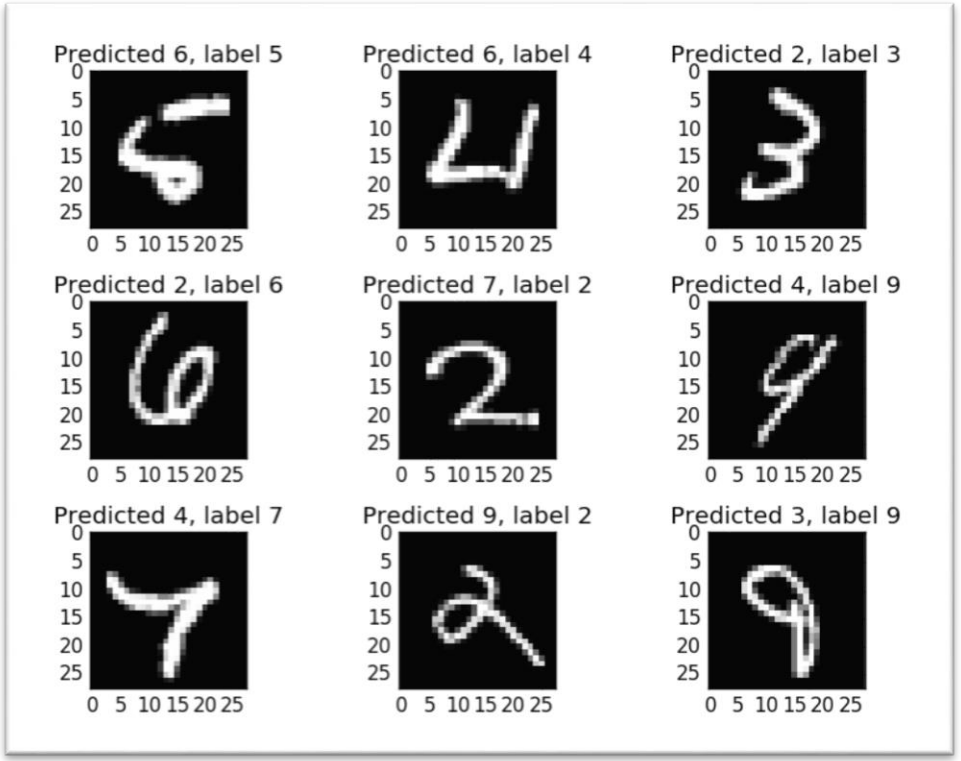


Review The Classified Results

Correctly classified

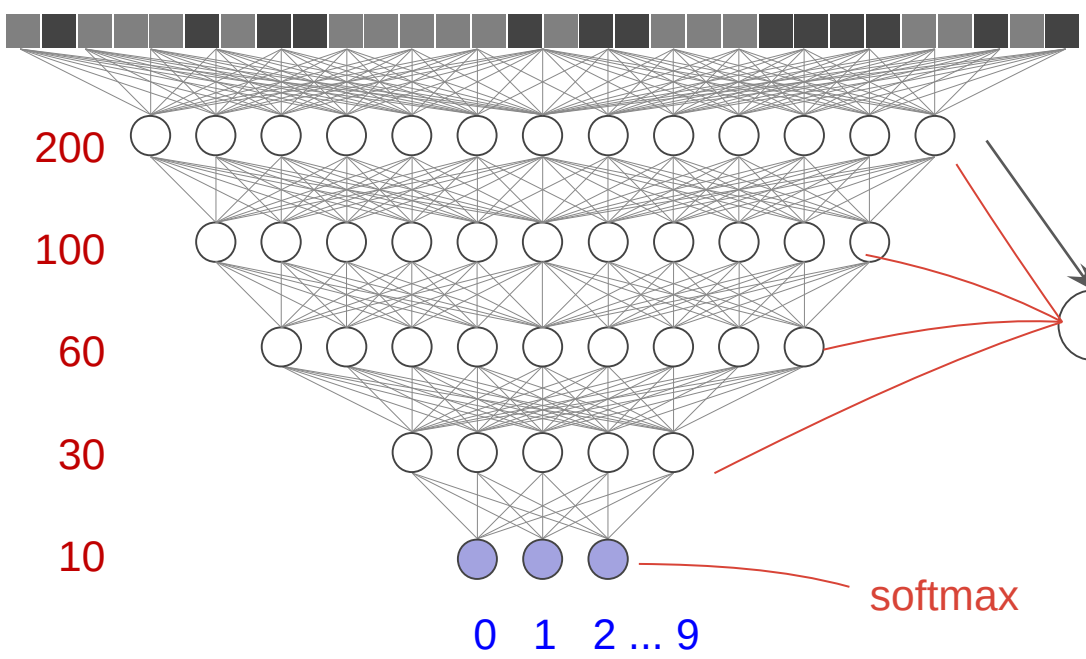


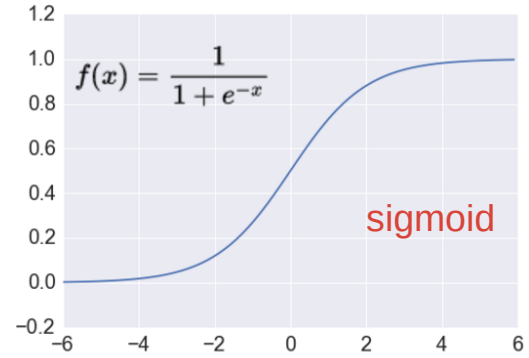
Incorrectly classified

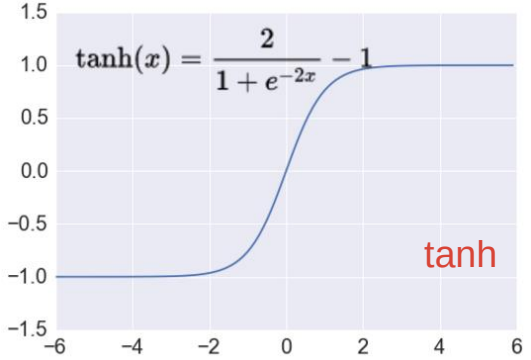


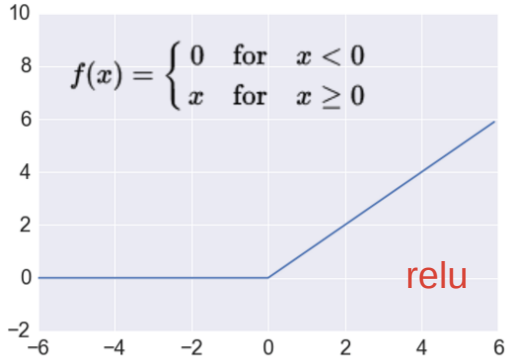
Adding More Layers?

- **Using a 5 fully connected layer model:**







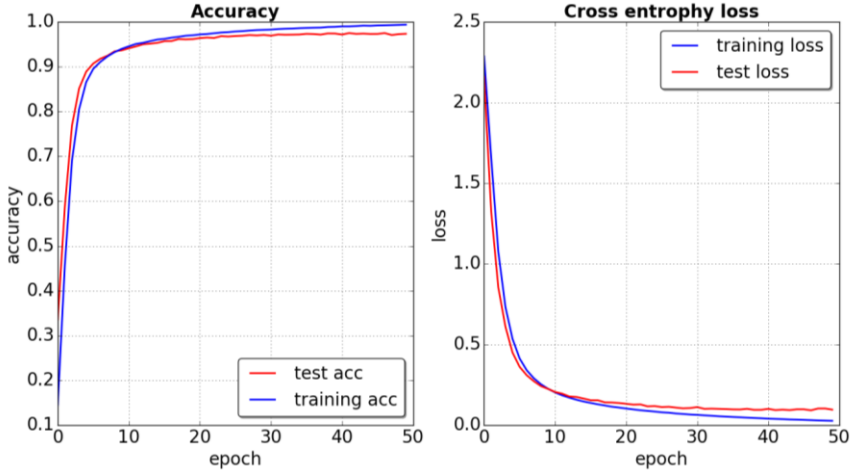


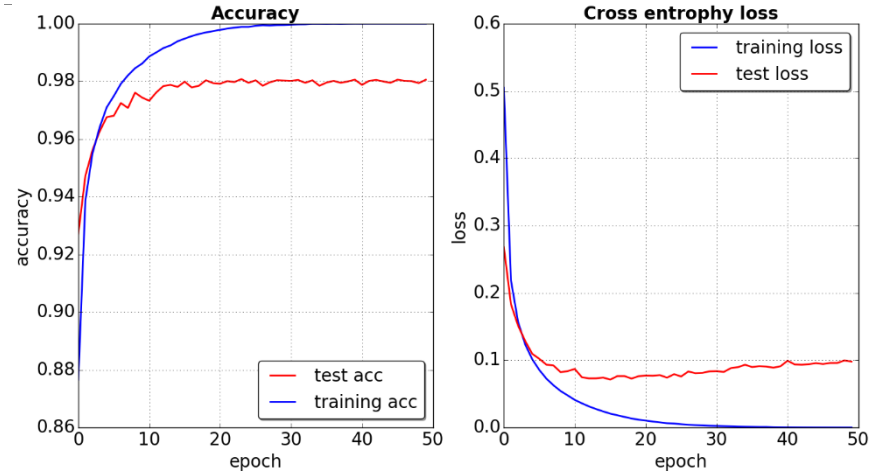
5 Layer Model In Keras

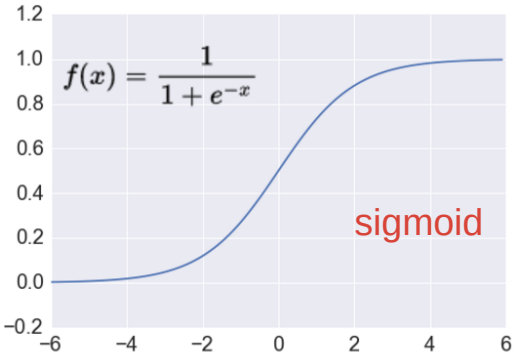
```
model = Sequential()
# try also tanh, sigmoid
act_func='relu'
model.add(Dense(200,activation=act_func,input_shape=input_shape))
model.add(Dense(100,activation=act_func))
model.add(Dense( 60,activation=act_func))
model.add(Dense( 30,activation=act_func))
model.add(Dense(nb_classes,activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='sgd',
              metrics=['accuracy'])
h = model.fit(X_train, Y_train, batch_size=batch_size,nb_epoch=nb_epoch,
          verbose=1, validation_data=(X_test, Y_test))
```

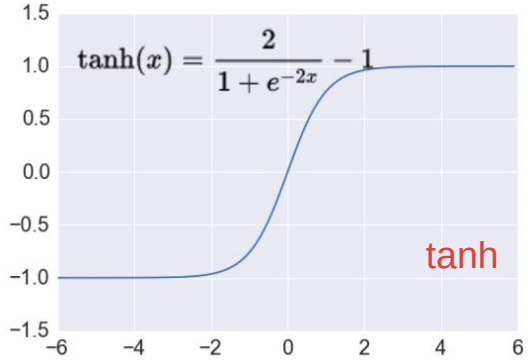
5 Layer Regression – Different Activation

- **Training accuracy vs Test accuracy, loss function**
- **We reach a Test accuracy at *97.35%* (*sigmoid*), *98.06%* (*tanh*)**







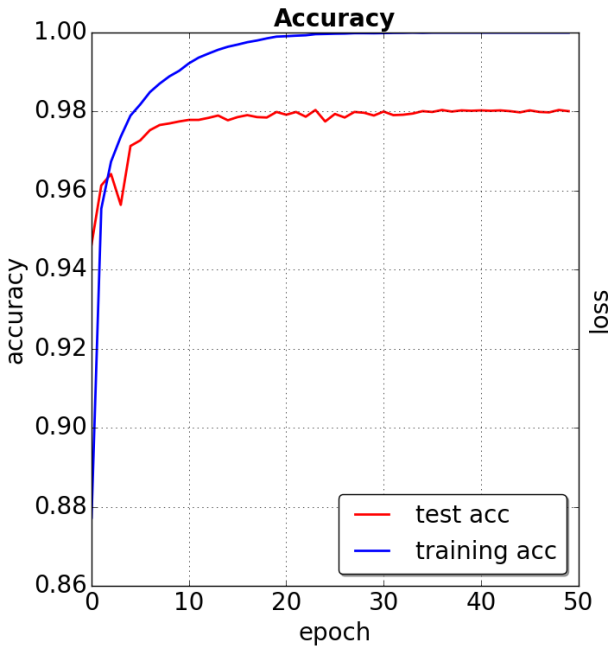


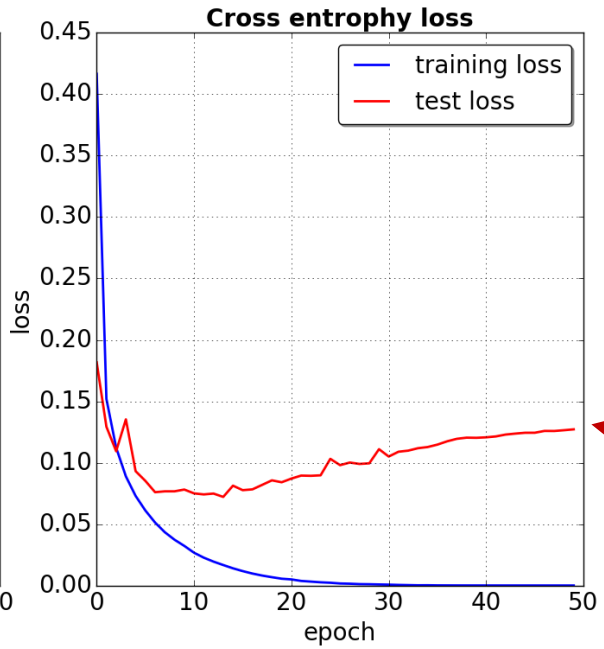
Rectified Linear Unit (ReLU) activation function

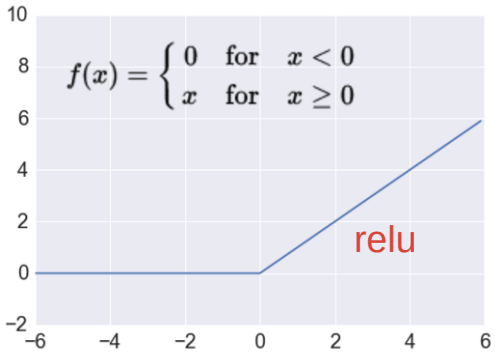
- **ReLU - The Rectified Linear Unit has become very popular in the last few years:**

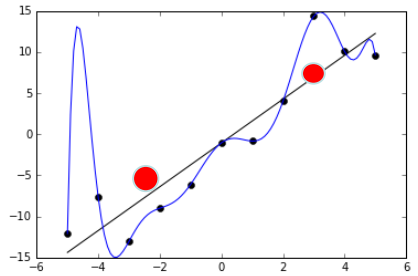
$$f(z) = \max(0, z)$$

- **We get a test accuracy of *98.07%* with ReLU**







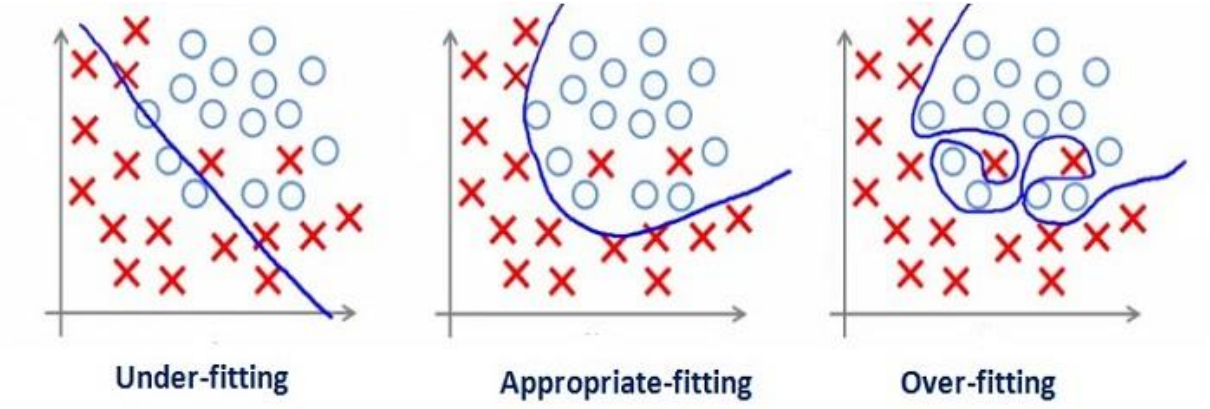


Overfitting

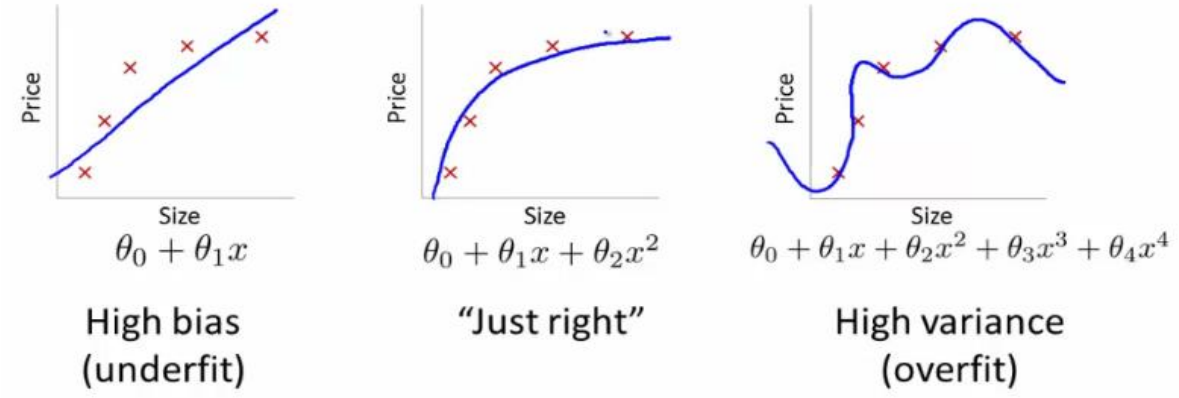
Overfitting

- **Overfitting occurs when a model is excessively complex, such as having too many parameters relative to the number of observations. A model that has been overfit has poor predictive performance, as it overreacts to minor fluctuations in the training data.**

Classification:

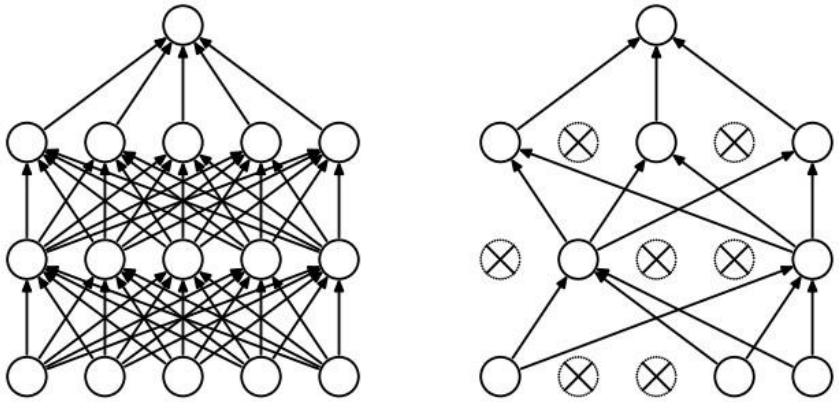


Regression:



Regularization - Dropout

- **Dropout is an extremely effective, simple and recently introduced regularization technique by Srivastava et al (2014).**



(a) Standard Neural Net (b) After applying dropout.

- **While training, dropout is implemented by only keeping a neuron active with some probability p (a hyperparameter), or setting it to zero otherwise.**
- **It is quite simple to apply dropout in Keras.**

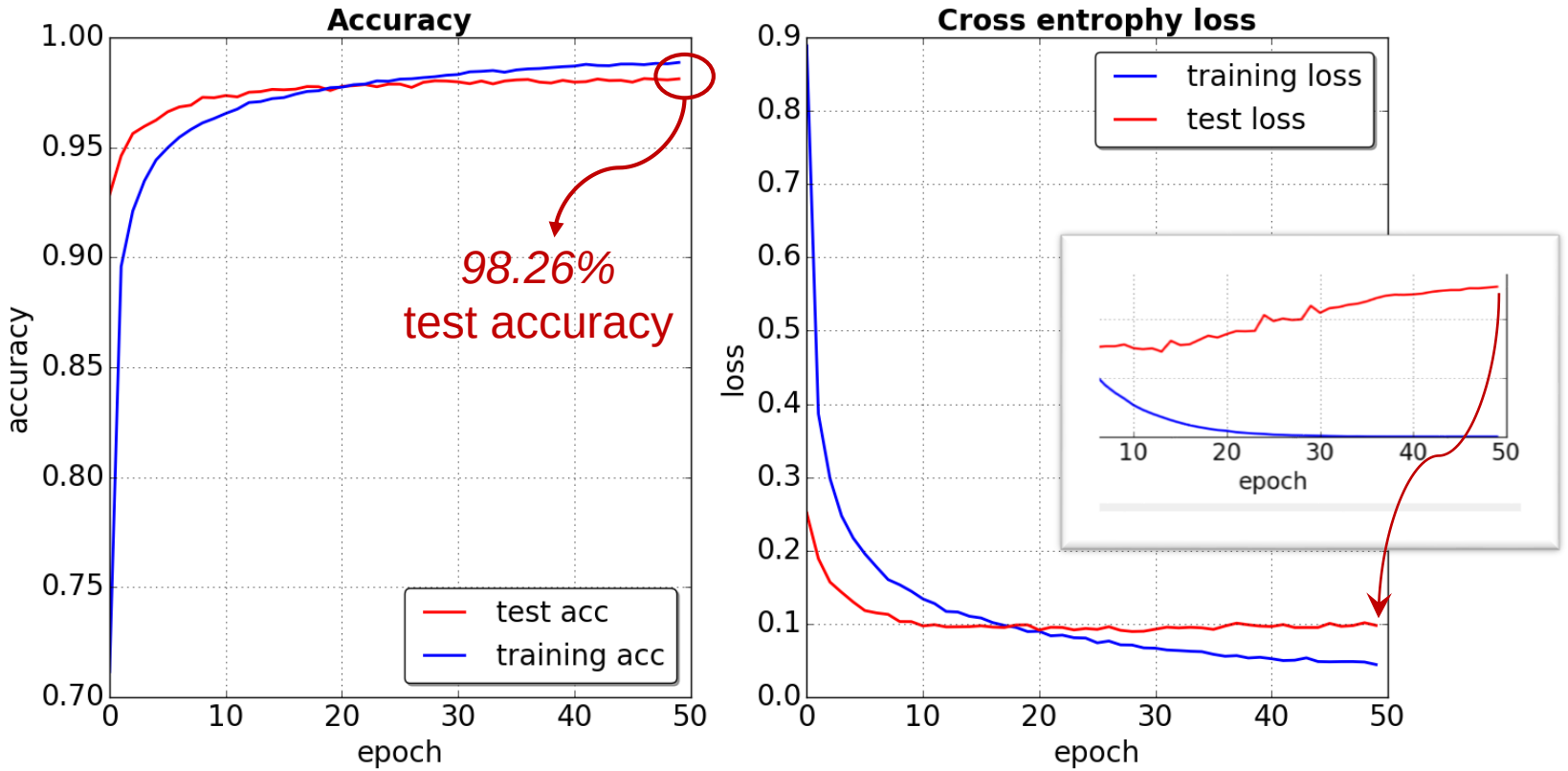
```
# apply a dropout rate 0.25 (drop 25% of the neurons)
model.add(Dropout(0.25))
```

Apply Dropout To The 5 Layer NN

```
model = Sequential()
act_func='relu'
p_dropout=0.25 # apply a dropout rate 25 %
model.add(Dense(200,activation=act_func,input_shape=input_shape))
model.add(Dropout(p_dropout))
model.add(Dense(100,activation=act_func))
model.add(Dropout(p_dropout))
model.add(Dense( 60,activation=act_func))
model.add(Dropout(p_dropout))
model.add(Dense( 30,activation=act_func))
model.add(Dropout(p_dropout))
model.add(Dense(nb_classes,activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='sgd',
              metrics=['accuracy'])
h = model.fit(X_train, Y_train, batch_size=batch_size,nb_epoch=nb_epoch,
          verbose=1, validation_data=(X_test, Y_test))
```

Results Using p_dropout=0.25

- **Resolve the overfitting issue**
- **Sustained *98.26%* accuracy**

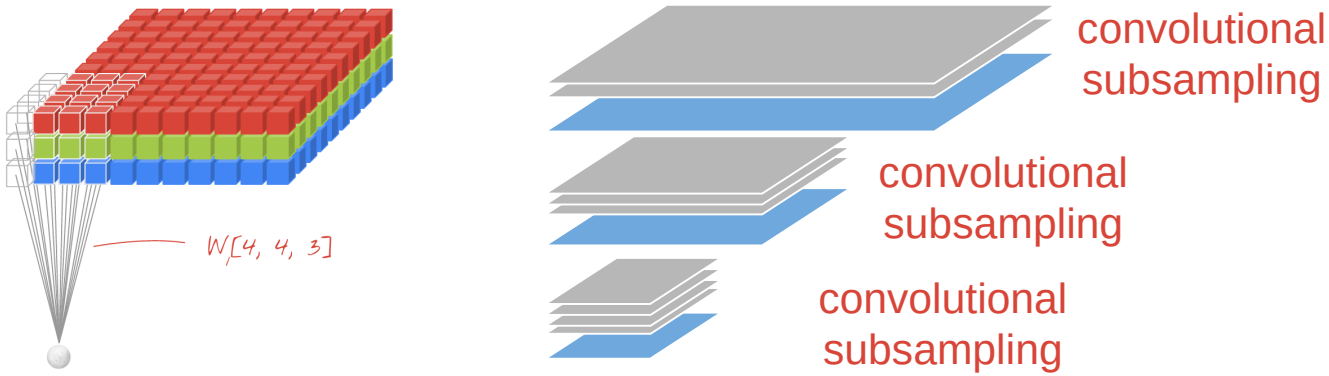


Why Using Fully Connected Layers?

- **Such a network architecture does not take into account the spatial structure of the images.**
  - For instance, it treats input pixels which are far apart and close together on exactly the same weight.
- **Spatial structure must instead be inferred from the training data.**

- **Is there an architecture which tries to take advantage of the spatial structure?**

Convolution Neuron Network (CNN)

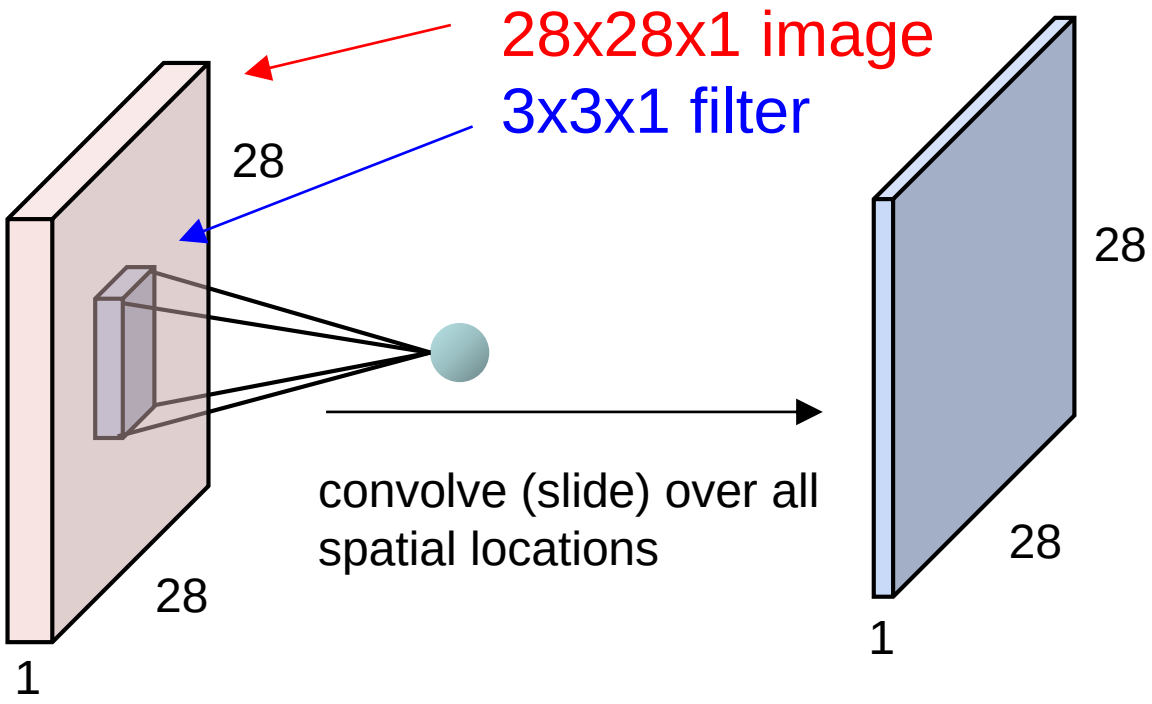


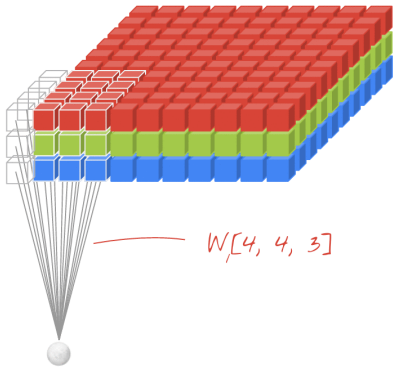
from Martin Görner Learn TensorFlow and deep learning, without a Ph.D

- **Deep convolutional network is one of the most widely used types of deep network.**
- **In a layer of a convolutional network, one "neuron" does a weighted sum of the pixels just above it, across a small region of the image only. It then acts normally by adding a bias and feeding the result through its activation function.**
- **The big difference is that each neuron reuses the same weights whereas in the fully-connected networks seen previously, each neuron had its own set of weights.**

activation map

How Does CNN Work?

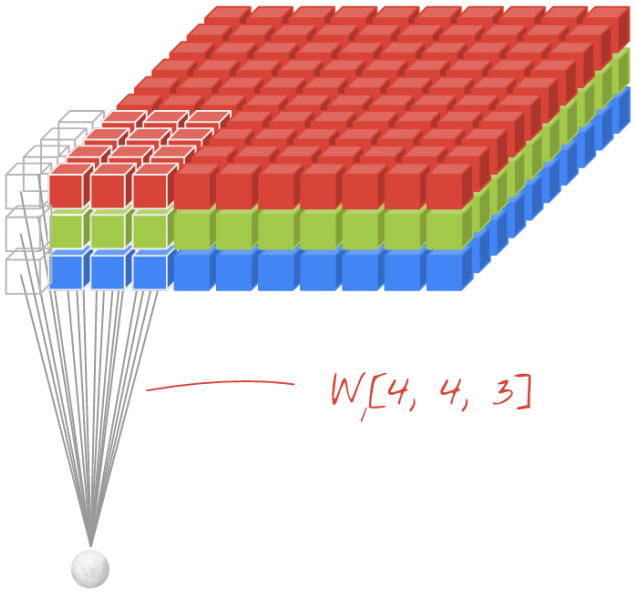


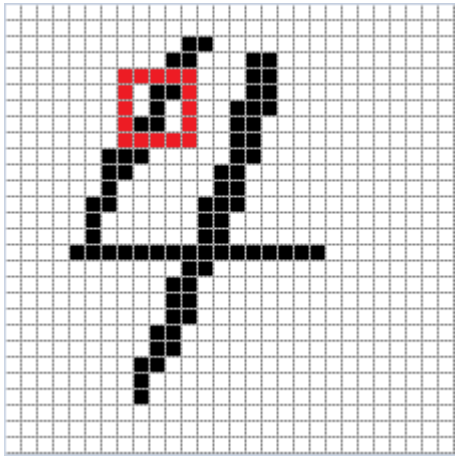


- **By sliding the patch of weights (filter) across the image in both directions (a convolution) you obtain as many output values as there were pixels in the image (some padding is necessary at the edges).**

Three basic ideas about CNN

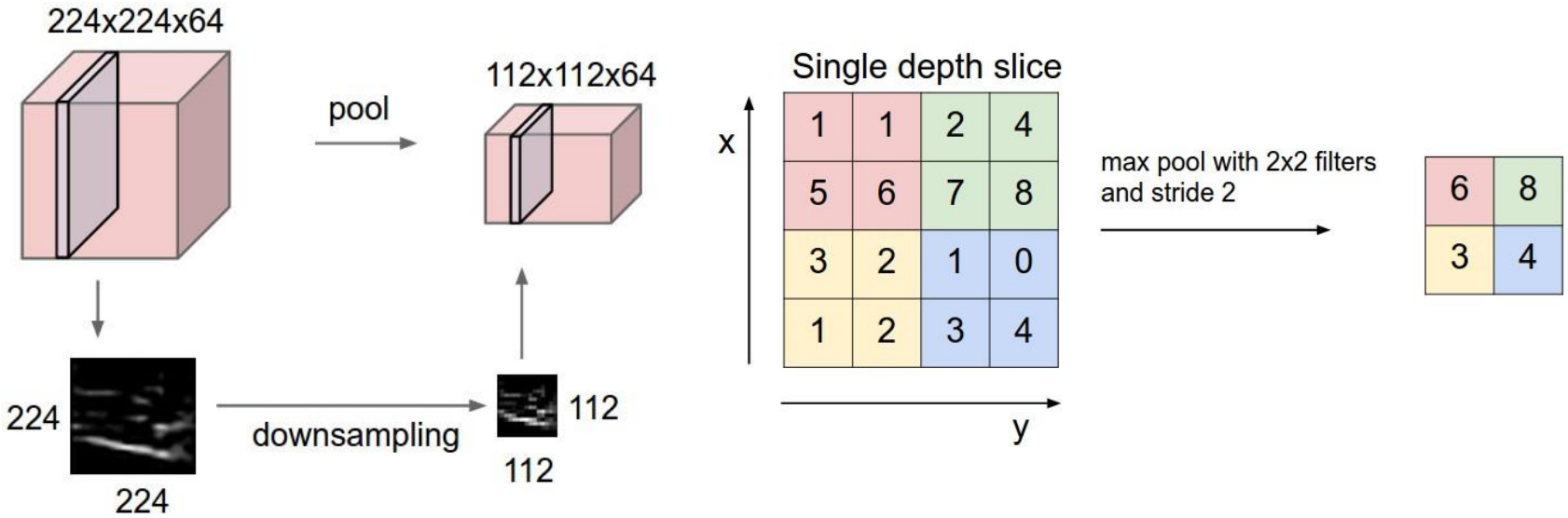
- **Local receptive fields**
- **Shared weights and biases:**
- **Pooling**



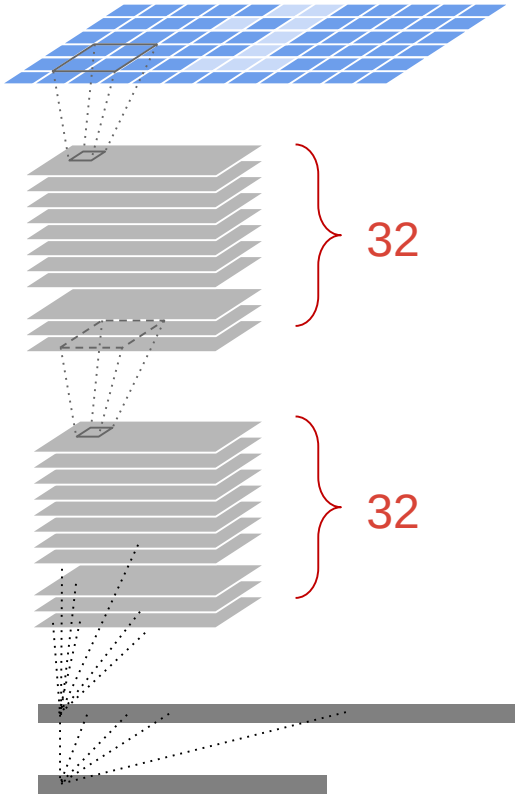


Pooling Layer

- **Convolutional neural networks also contain pooling layers. Pooling layers are usually used immediately after convolutional layers.**
- **What the pooling layers do is simplify the information in the output from the convolutional layer.**
- **We can think of max-pooling as a way for the network to ask whether a given feature is found anywhere in a region of the image. It then throws away the exact positional information.**



Convolutional Network With Fully Connected Layers



convolutional layer
32 output channels

convolutional layer
32 output channels

fully connected layer

softmax layer

Stacking And Chaining Convolutional Layers in Keras

```
model = Sequential()
# Adding the convulation layers
model.add(Convolution2D(nb_filters, kernel_size[0], kernel_size[1],
                        border_mode='valid',
                        input_shape=input_shape))
model.add(Activation('relu'))
model.add(Convolution2D(nb_filters, kernel_size[0], kernel_size[1]))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=pool_size))
model.add(Dropout(0.25))
# Fully connected layers
model.add(Flatten())
model.add(Dense(256,activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(nb_classes,activation('softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adadelta',
          metrics=['accuracy'])

h = model.fit(X_train, Y_train, batch_size=batch_size, nb_epoch=nb_epoch,
          verbose=1,callbacks=[history], validation_data=(X_test, Y_test))
```

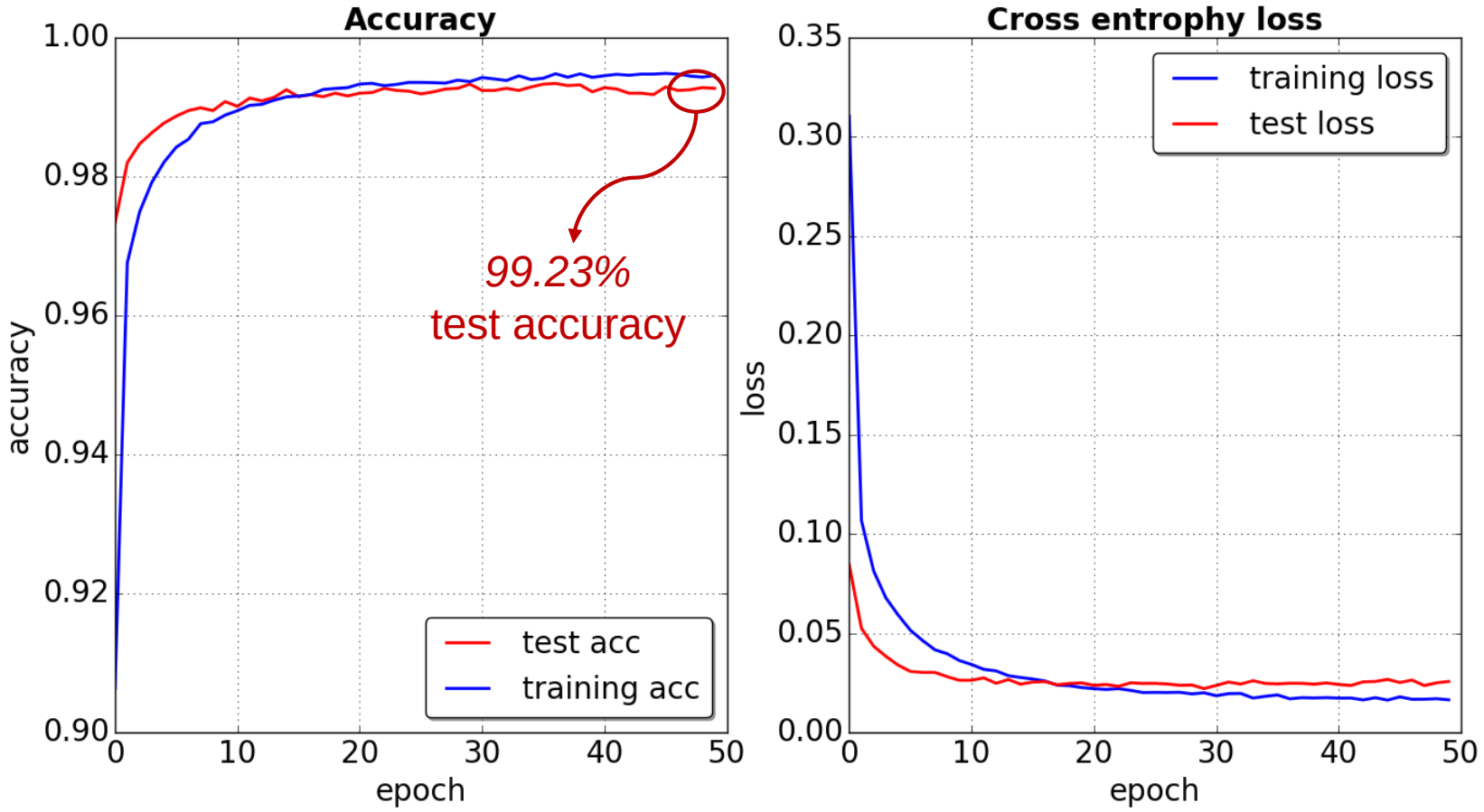
nb_filters=32

kernel_size=(3,3)

input_shape=(28,28)

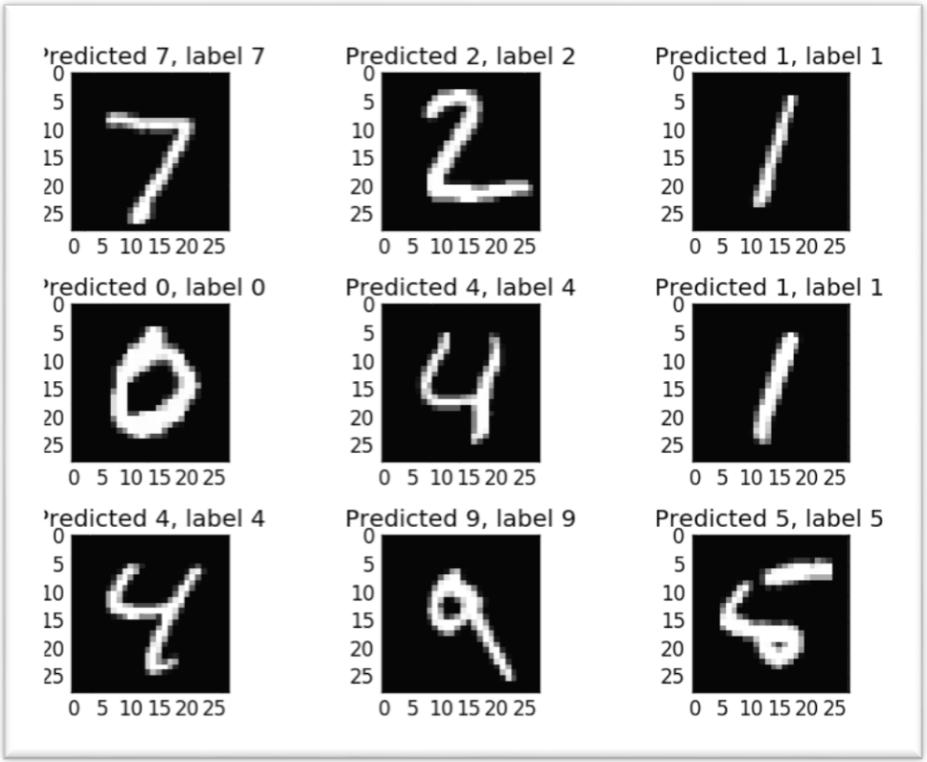
Challenging The 99% Testing Accuracy

- **By using the convolution layer and the fully connected layers, we reach a test accuracy of *99.23%***

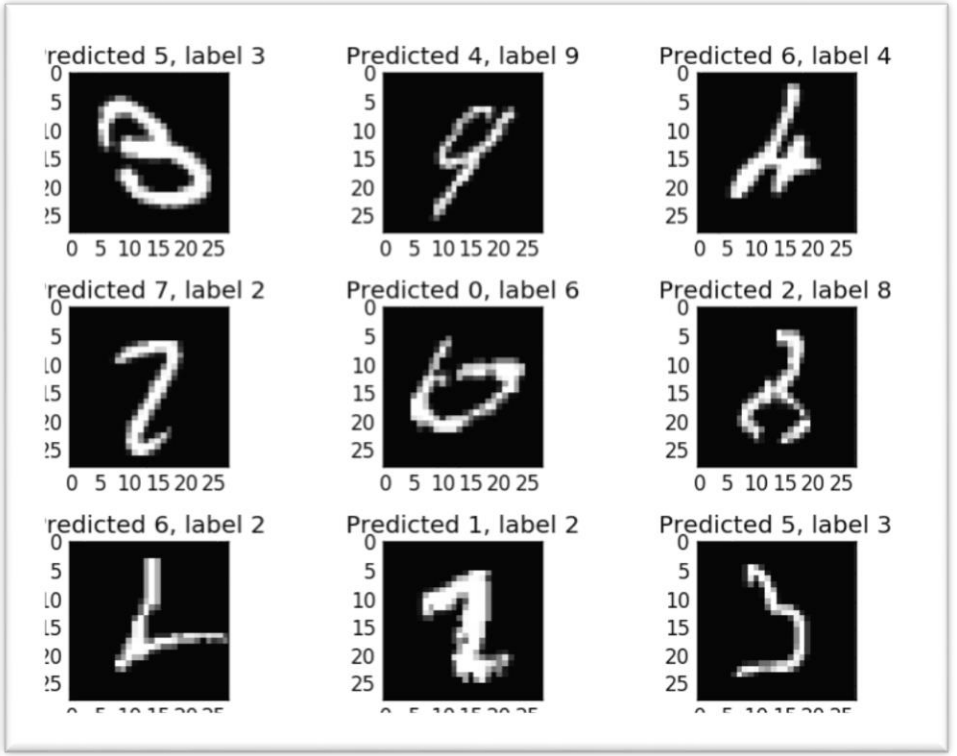


Review The Classified Results of CNN

Correctly classified

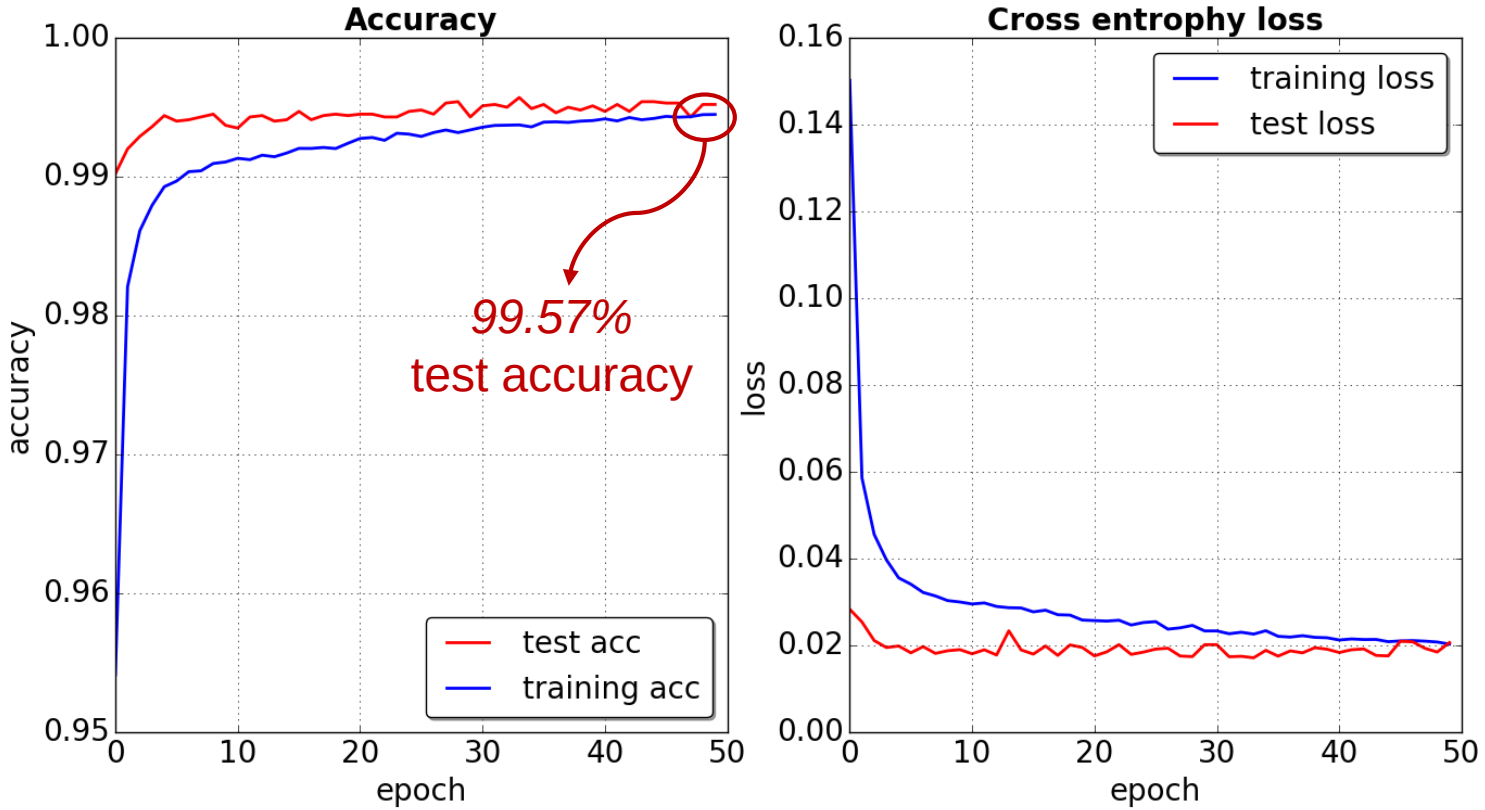


Incorrectly classified



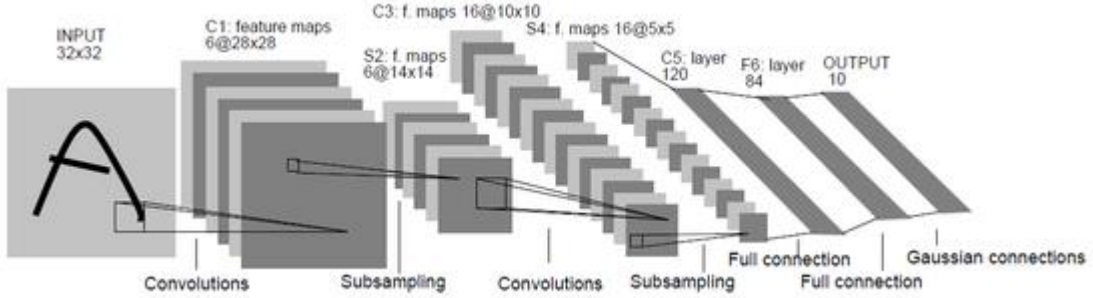
Feed More Data: Using Expanded Dataset

- **We can further increase the test accuracy by expanding the mnist.pkl.gz dataset, reaching a nearly *99.6%* test accuracy**

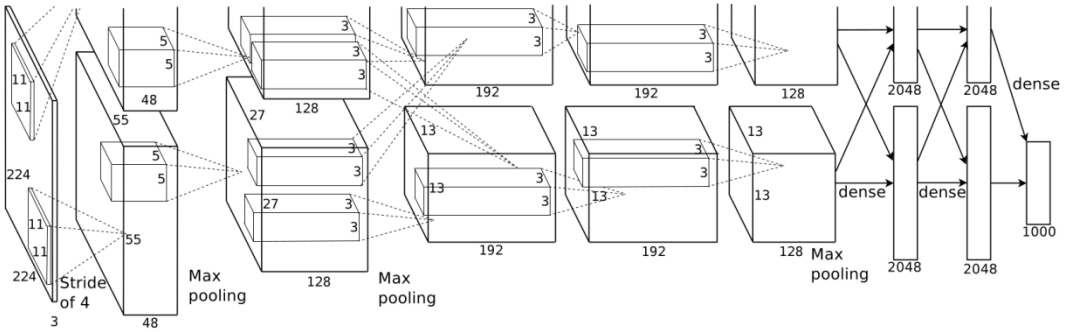


Examples of Convolution NN

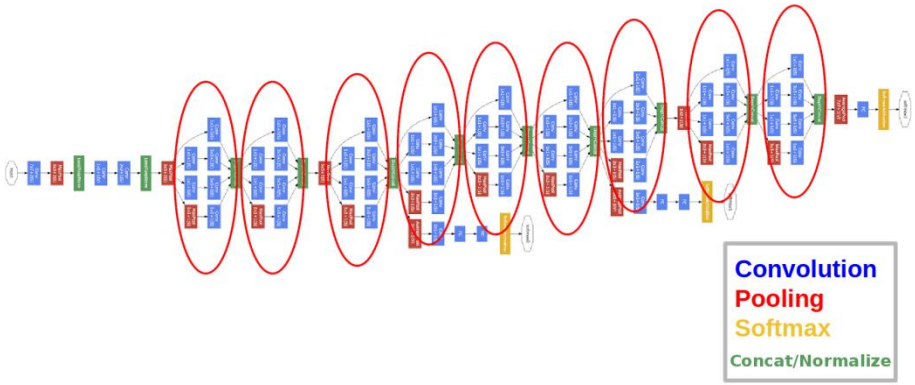
- **LeNet (1998)**



- **AlexNet (2012)**



- **GoogleLeNet (2014)**



Machine Learning Courses List

- **Machine Learning in Coursera**
  https://www.coursera.org/learn/machine-learning
- **Learning from Data (Caltech)**
  https://work.caltech.edu/telecourse.html
- **Convolutional Neural Networks for Visual Recognition**
  http://cs231n.github.io/
- **Deep Learning for Natural Language Processing**
  https://cs224d.stanford.edu/

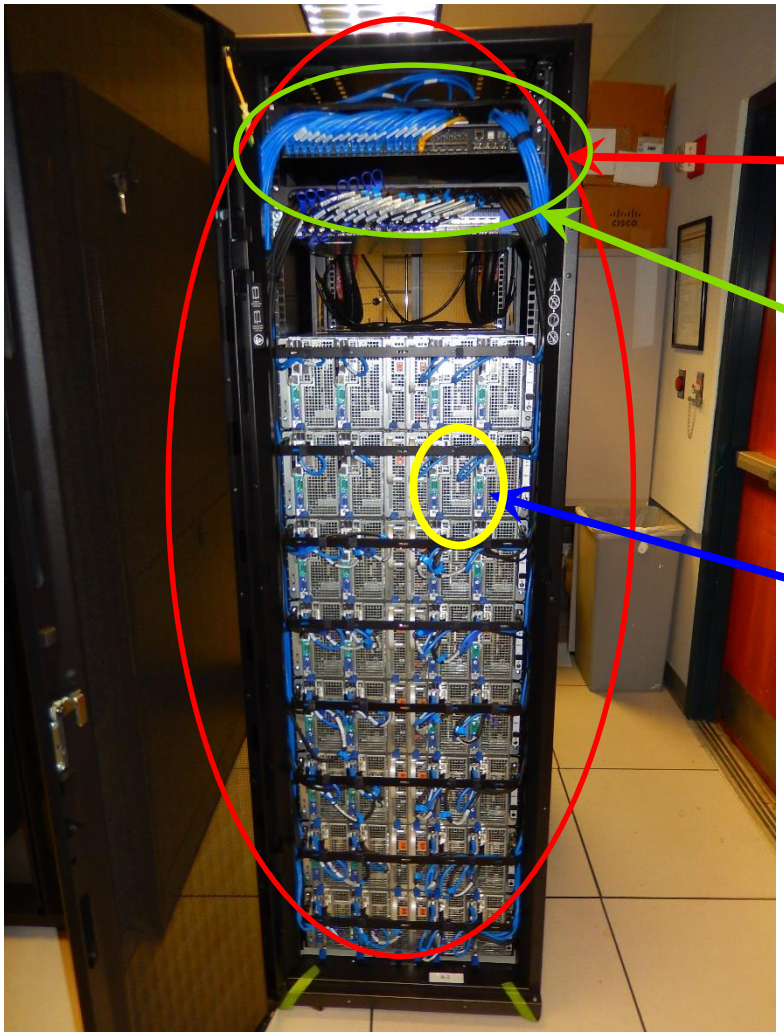
Deep Learning Examples on LONI QB2

Overview of LONI QB2

QB2 Hardware Specs

- **QB2 came on-line 5 Nov 2014.**
  - It is a 1.5 Petaflop peak performance cluster containing 504 compute nodes with
    - 960 NVIDIA Tesla K20x GPU's, and
    - Over 10,000 Intel Xeon processing cores. It achieved 1.052 PF during testing.
- **Ranked 46th on the November 2014 Top500 list.**
- **480 Compute Nodes, each with:**
  - Two 10-core 2.8 GHz E5-2680v2 Xeon processors.
  - 64 GB memory
  - 500 GB HDD
  - ***2 NVIDIA Tesla K20x GPU's***

Inside A QB Cluster Rack

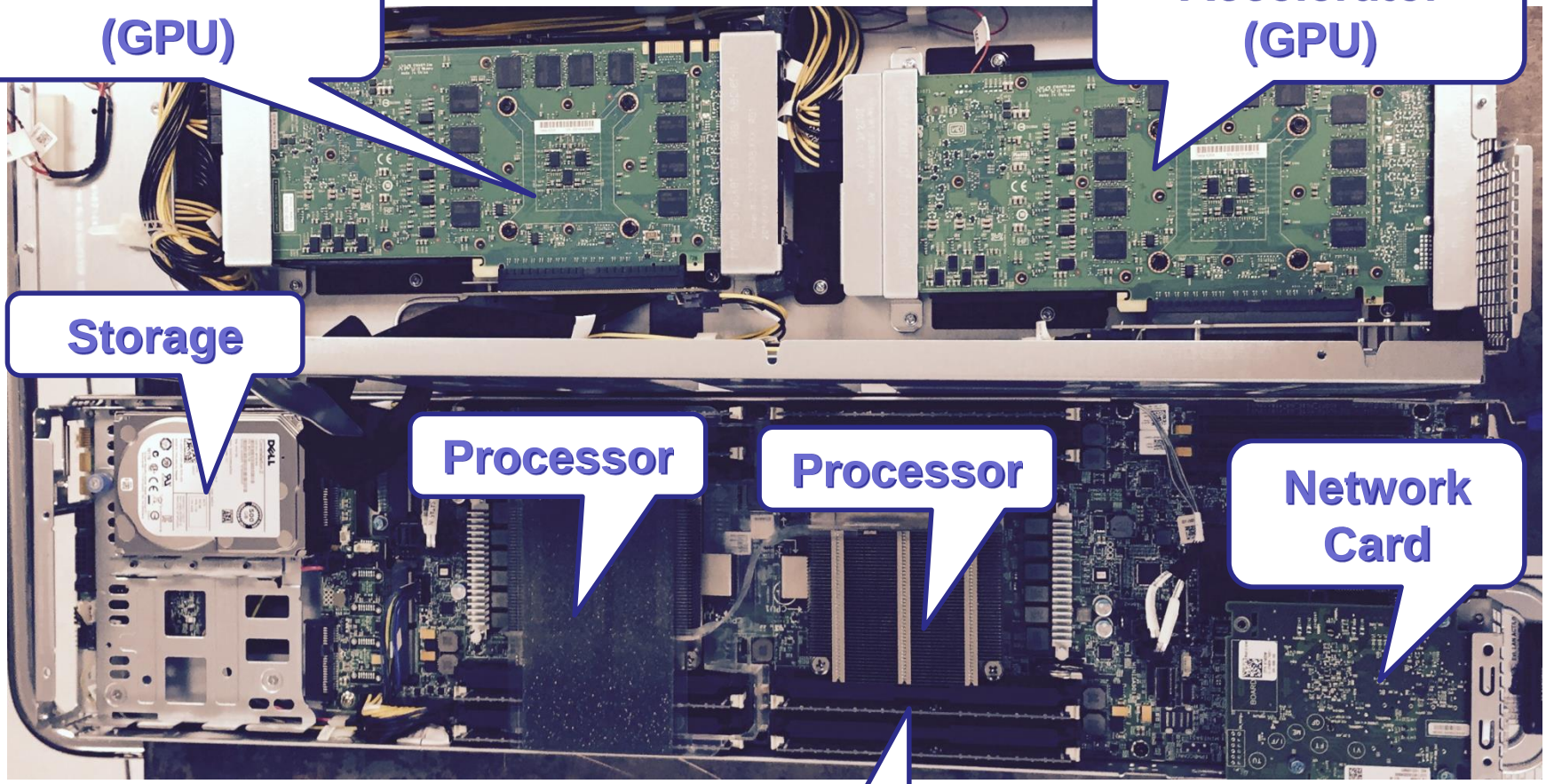


Rack

Infiniband Switch

Compute Node

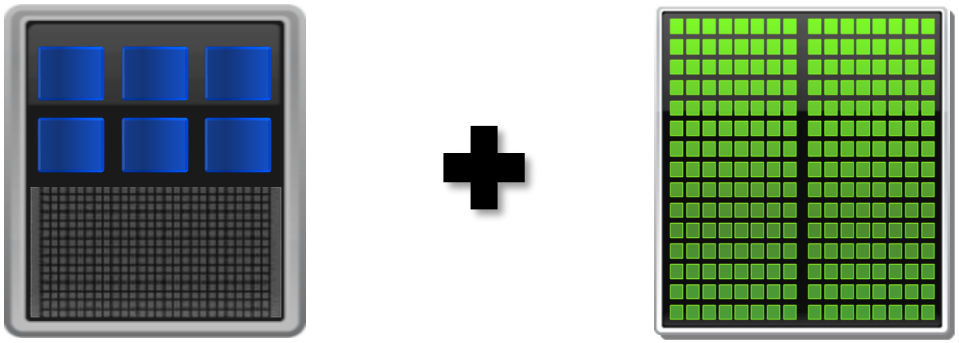
Inside A QB2 Dell C8000 Node



Add GPUs: Accelerate Science Applications

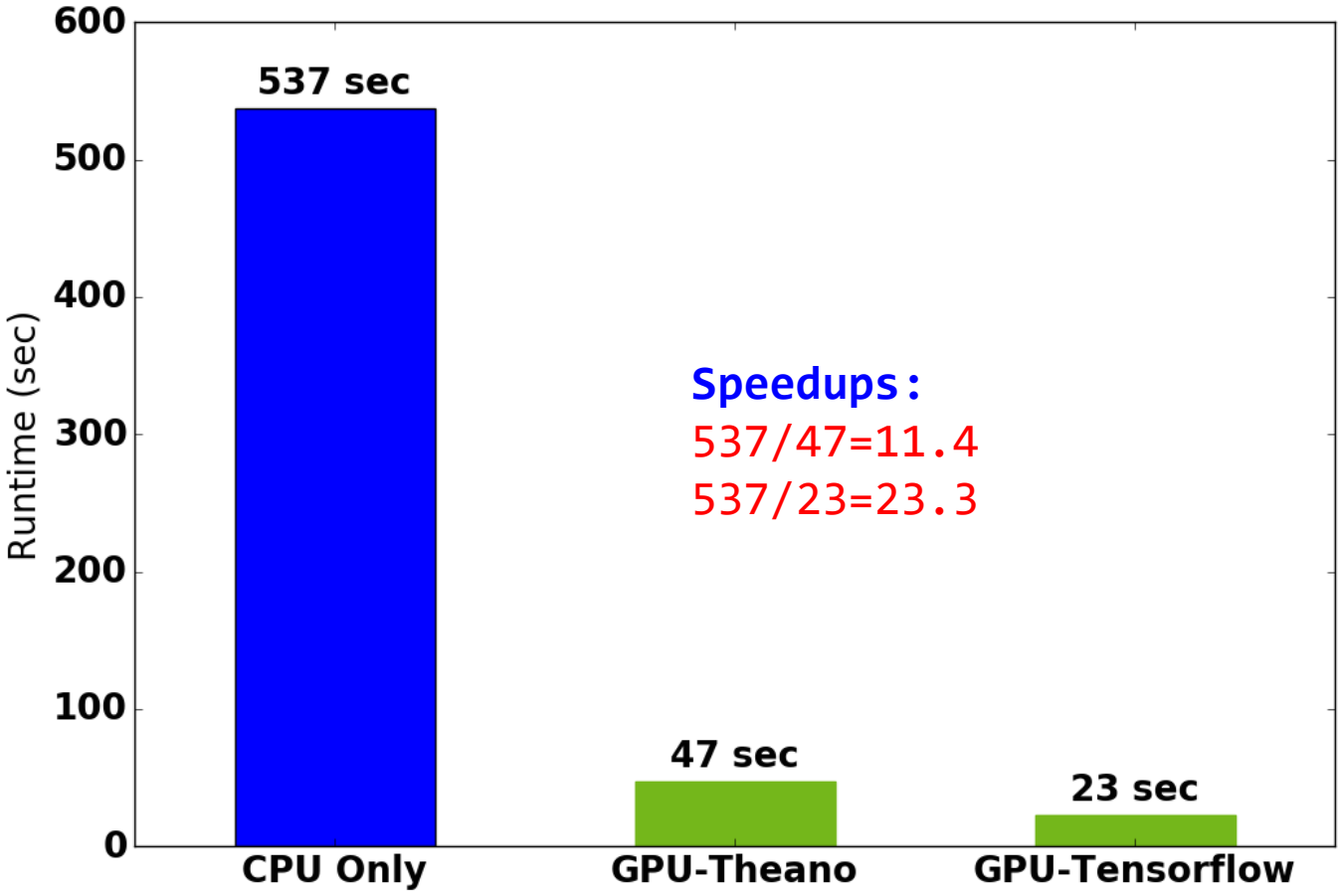
CPU

GPU



Performance Comparison CPU-GPU

- **Comparison of runtime for deep learning benchmark problem**
  - CIFAR10, 1 Epoch



Deep Learning Examples on LONI QB2

Submit and Monitor Your Jobs

Two Job Types

- **Interactive job**
  - Set up an interactive environment on compute nodes for users
    - Advantage: can run programs interactively
    - Disadvantage: must be present when the job starts
  - Purpose: testing and debugging, compiling
    - **Do not run on the head node!!!**
    - Try not to run interactive jobs with large core count, which is a waste of resources)
- **Batch job**
  - Executed without user intervention using a job script
    - Advantage: the system takes care of everything
    - Disadvantage: can only execute one sequence of commands which cannot changed after submission
  - Purpose: production run

PBS Script (MNIST) Tensorflow Backend

```
#!/bin/bash
#PBS -l nodes=1:ppn=20
#PBS -l walltime=72:00:00
#PBS -q workq
#PBS -N cnn.tf.gpu
#PBS -o cnn.tf.gpu.out
#PBS -e cnn.tf.gpu.err
#PBS -A loni_loniadmin1

cd $PBS_O_WORKDIR
# use the tensorflow backend
export KERAS_BACKEND=tensorflow
# use this python module key to access tensorflow, theano and keras
module load python/2.7.12-anaconda
python mnist_cnn.py
```

Tells the job scheduler how much resource you need.

How will you use the resources?

Steps to Submit Jobs

```
[fchen14@qb1 ml_tut]$ cd /project/fchen14/machine_learning/ml_tut
[fchen14@qb1 ml_tut]$ qsub sbm_cifar10_cnn_tensorflow.pbs
305669.qb3
[fchen14@qb1 ml_tut]$ qstat -u fchen14

qb3:
                                                                  Req'd  Req'd   Elap
Job ID               Username    Queue    Jobname          SessID NDS   TSK    Memory Time  S Time
-------------------- ----------- -------- ---------------- ------ ----- ------ ------ ----- - -----
305667.qb3           fchen14     workq    cnn.tf.gpu        25633     1     20    --  72:00 R   --
305669.qb3           fchen14     k40      cnn.tf.gpu          --      1     20    --  72:00 R   --
[fchen14@qb1 ml_tut]$ qshow 305669.qb3
PBS job: 305669.qb3, nodes: 1
Hostname  Days Load CPU U# (User:Process:VirtualMemory:Memory:Hours)
qb002       24 0.32 205  4 fchen14:python:166G:1.6G:0.1 fchen14:305669:103M:1M
PBS_job=305669.qb3 user=fchen14 allocation=loni_loniadmin1 queue=k40 total_load=0.32 cpu_hours=0.11
wall_hours=0.05 unused_nodes=0 total_nodes=1 ppn=20 avg_load=0.32 avg_cpu=205% avg_mem=1647mb
avg_vmem=170438mb top_proc=fchen14:python:qb002:166G:1.6G:0.1hr:205%
toppm=msun:python:qb002:169456M:1190M node_processes=4
```

Job Monitoring - Linux Clusters

- **Check details on your job using `qstat`**

```
$ qstat -n -u $USER   : For quick look at nodes assigned to you
$ qstat -f jobid      : For details on your job
$ qdel jobid          : To delete job
```

- **Check approximate start time using `showstart`**

```
$ showstart jobid
```

- **Check details of your job using `checkjob`**

```
$ checkjob jobid
```

- **Check health of your job using `qshow`**

```
$ qshow jobid
```

- **Dynamically monitor node status using `top`**
  - See next slides
- **Monitor GPU usage using `nvidia-smi`**
  - See next slides

- **Please pay close attention to the load and the memory consumed by your job!**

Using the "top" command

- **The top program provides a dynamic real-time view of a running system.**

```
[fchen14@qb1 ml_tut]$ ssh qb002
Last login: Mon Oct 17 22:50:16 2016 from qb1.loni.org
[fchen14@qb002 ~]$ top
top - 15:57:04 up 24 days,  5:38,  1 user,  load average: 0.44, 0.48, 0.57
Tasks: 606 total,   1 running, 605 sleeping,   0 stopped,   0 zombie
Cpu(s):  9.0%us,  0.8%sy,  0.0%ni, 90.2%id,  0.0%wa,  0.0%hi,  0.0%si,  0.0%st
Mem:  132064556k total,  9759836k used, 122304720k free,   177272k buffers
Swap: 134217720k total,        0k used, 134217720k free,  5023172k cached

  PID USER      PR  NI  VIRT  RES  SHR S %CPU %MEM    TIME+  COMMAND
21270 fchen14   20   0  166g 1.6g 237m S 203.6  1.3  16:42.05 python
22143 fchen14   20   0 26328 1764 1020 R  0.7  0.0   0:00.76 top
   83 root      20   0     0    0    0 S  0.3  0.0  16:47.34 events/0
   97 root      20   0     0    0    0 S  0.3  0.0   0:25.80 events/14
  294 root      39  19     0    0    0 S  0.3  0.0  59:45.52 kipmi0
    1 root      20   0 21432 1572 1256 S  0.0  0.0   0:01.50 init
    2 root      20   0     0    0    0 S  0.0  0.0   0:00.02 kthreadd
```

Monitor GPU Usage

- **Use nvidia-smi to monitor GPU usage:**

```
[fchen14@qb002 ~]$ nvidia-smi -l
Thu Nov  3 15:58:52 2016
+-----------------------------------------------------+
| NVIDIA-SMI 352.93     Driver Version: 352.93        |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla K40m          On   | 0000:03:00.0     Off |                    0 |
| N/A   34C    P0   104W / 235W |  11011MiB / 11519MiB |     77%      Default |
+-------------------------------+----------------------+----------------------+
|   1  Tesla K40m          On   | 0000:83:00.0     Off |                    0 |
| N/A   32C    P0    61W / 235W |  10950MiB / 11519MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID  Type  Process name                               Usage      |
|=============================================================================|
|    0     21270    C   python                                       10954MiB |
|    1     21270    C   python                                       10893MiB |
+-----------------------------------------------------------------------------+
```

Future Trainings

- **This is the last training for this semester**
  - Keep an eye on future HPC trainings at:
    - http://www.hpc.lsu.edu/training/tutorials.php#upcoming
- **Programming/Parallel Programming workshops in Summer**
- **Visit our webpage: www.hpc.lsu.edu**