Introduction to Deep Learning

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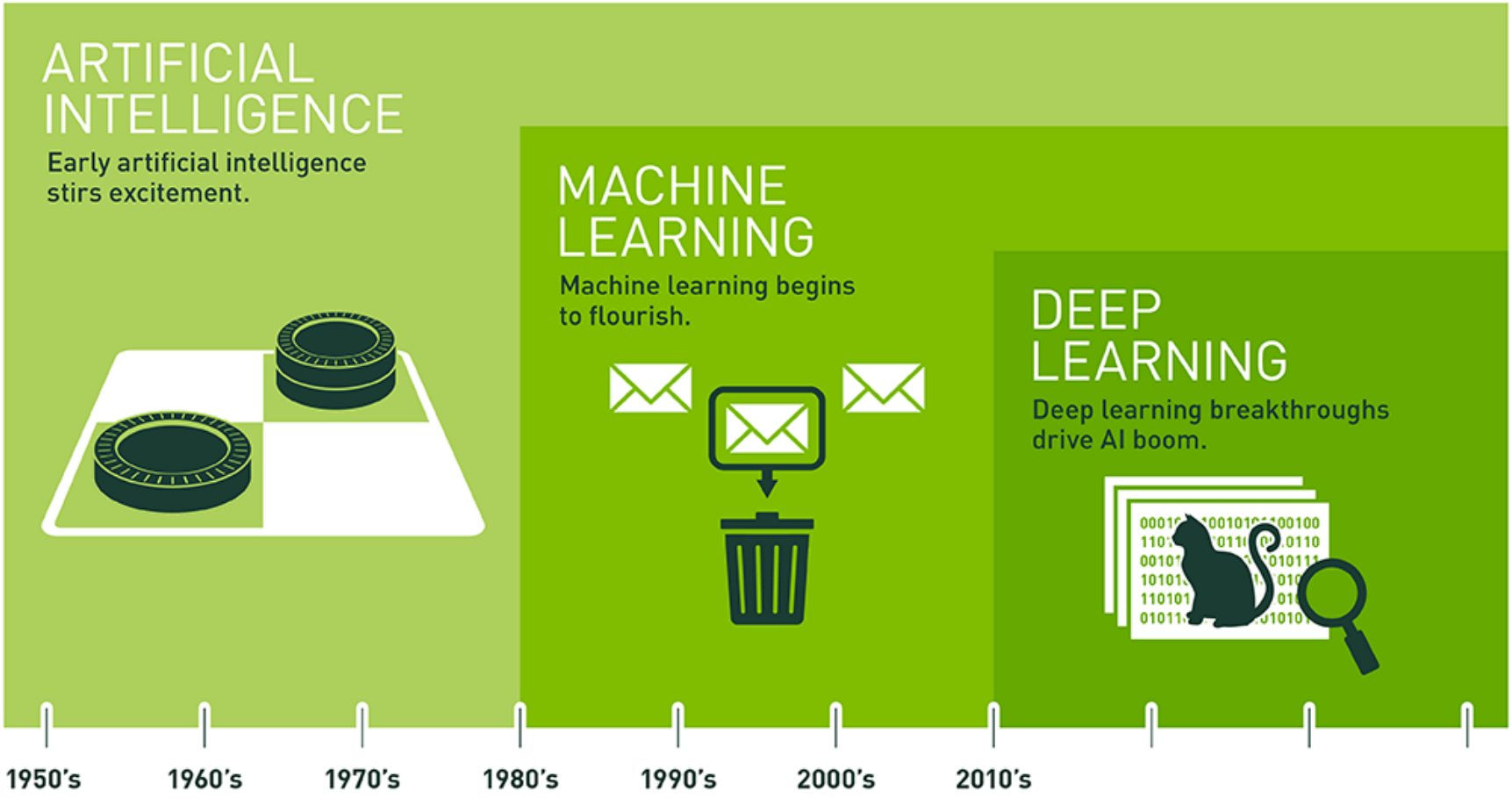
Part of slides referenced from
Nvidia, ***Deep Learning Institute (DLI) Teaching Kit***
Stanford, ***CS231n: Convolutional Neural Networks for Visual Recognition***
Martin Görner, ***Learn TensorFlow and deep learning, without a Ph.D***

Topics To Be Discussed

- **Fundamentals about Machine Learning**
  - What is ***Deep Learning***?
    - What is a (deep) neural network
    - How to train it
    - Deep Learning Frameworks
      - Tensorflow/Keras
      - PyTorch

- **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

AI, Machine Learning and Deep Learning



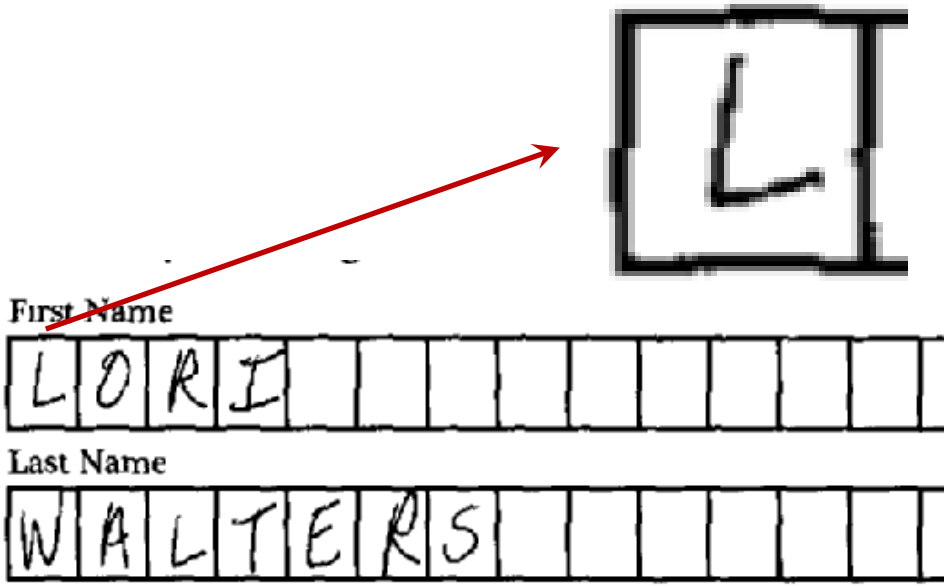
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

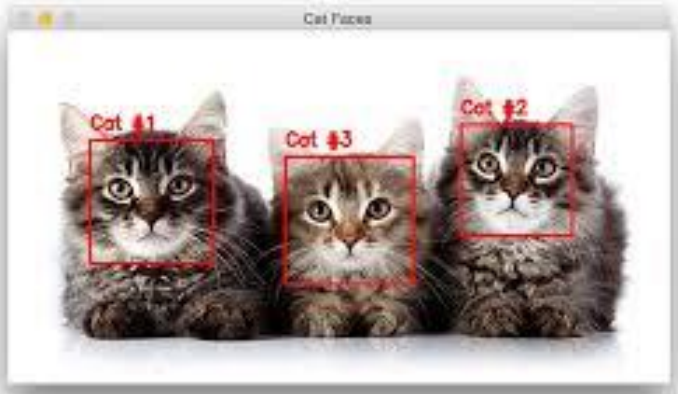
Applications of Machine Learning

- **Computer Vision (CV)**
  - Image Classification
    - label images with appropriate categories (e.g. Google Photos)
  - Handwriting Recognition
    - convert written letters into digital letters
- **Natural Language Processing (NLP)**
  - 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

Machine Learning

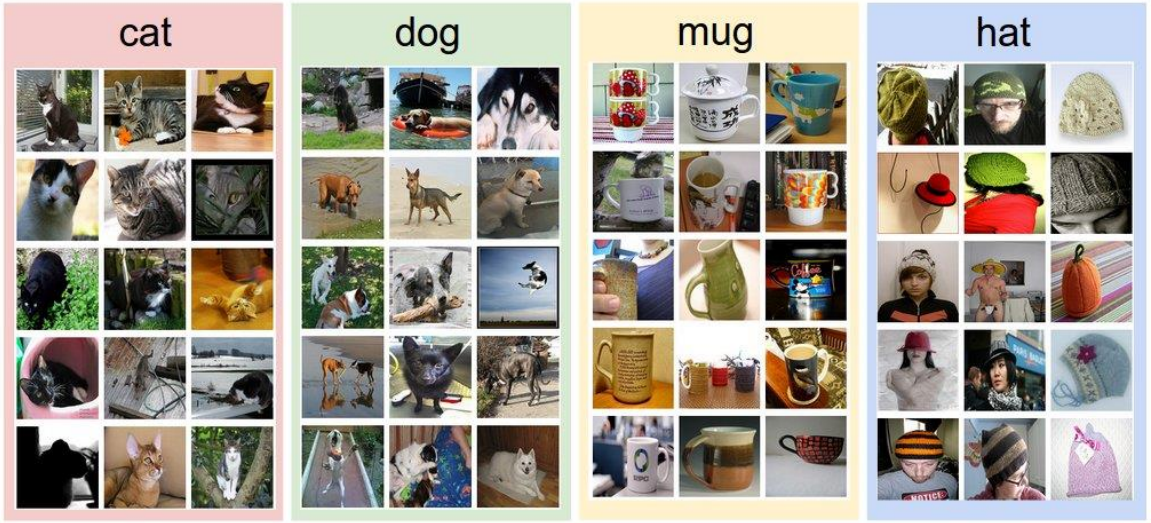
- **Machine Learning is the science of getting computers to learn, without being explicitly programmed.**
- **Examples are used to train computers to perform tasks that would be difficult to program**





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.**

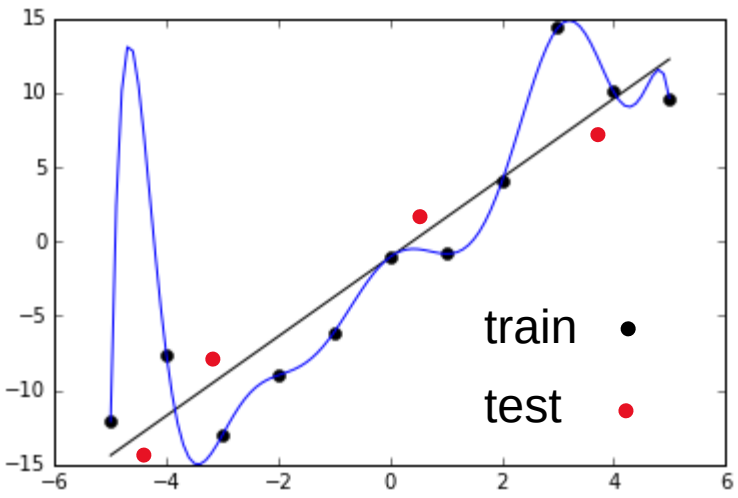


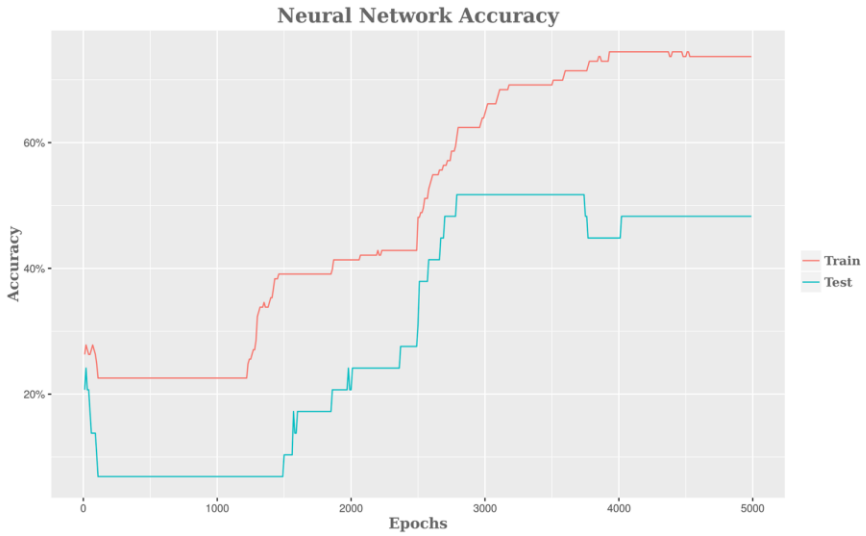
An example training set for four visual categories. In practice we may have thousands of categories and hundreds of thousands of images for each category. ***(From Stanford *CS231n*)**

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





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

Supervised Learning Algorithms

- **Linear Regression**
- **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.
- **Decision Trees**
- **Support Vector Machines**
- **K-Nearest Neighbor**

Machine Learning Frameworks

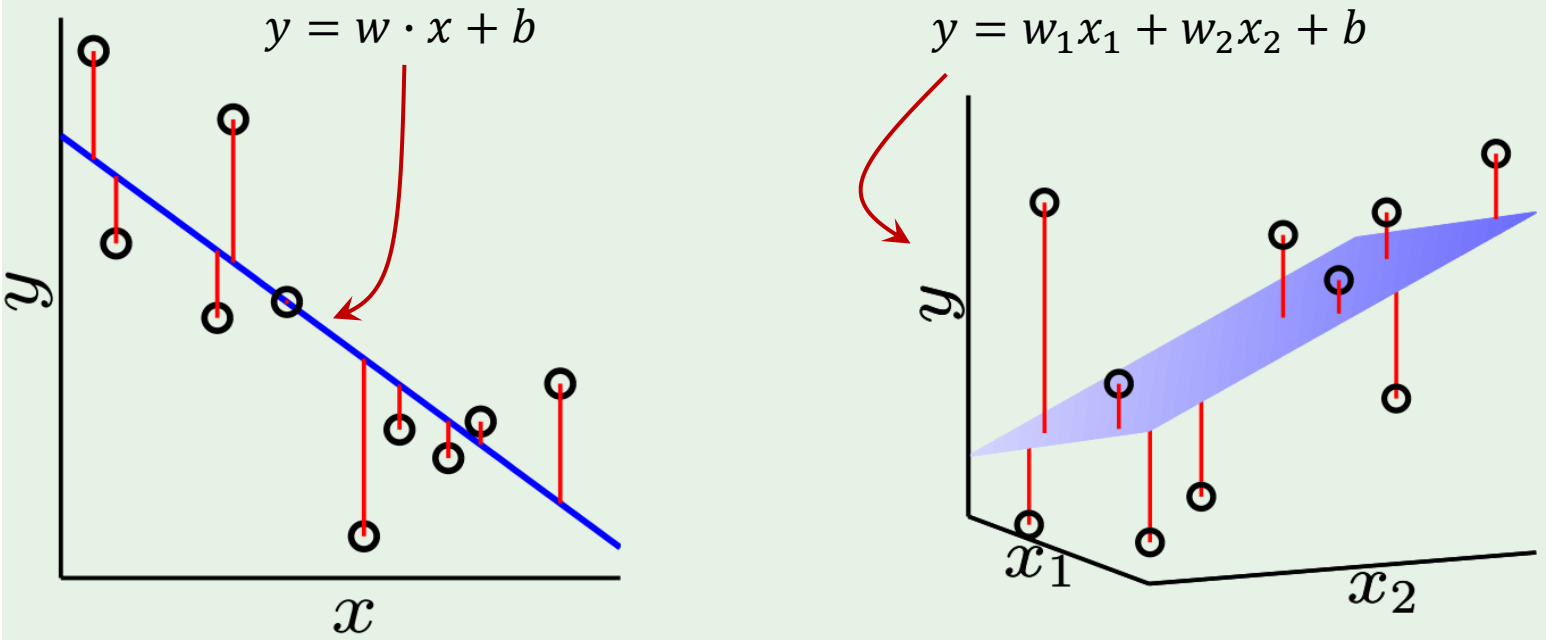
Tool	Uses	Language
Scikit-Learn	Classification, Regression, Clustering	Python
Spark MLlib	Classification, Regression, Clustering	Scala, R, Java
MXNet	Deep learning framework	Python, R, Julia, Scala, Go, Javascript and more
Caffe	Neural Networks	C++, Python
TensorFlow	Neural Networks	Python
PyTorch	Neural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

What is Deep Learning

Machine Learning and Deep Learning

Recall From The Least Square Method

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



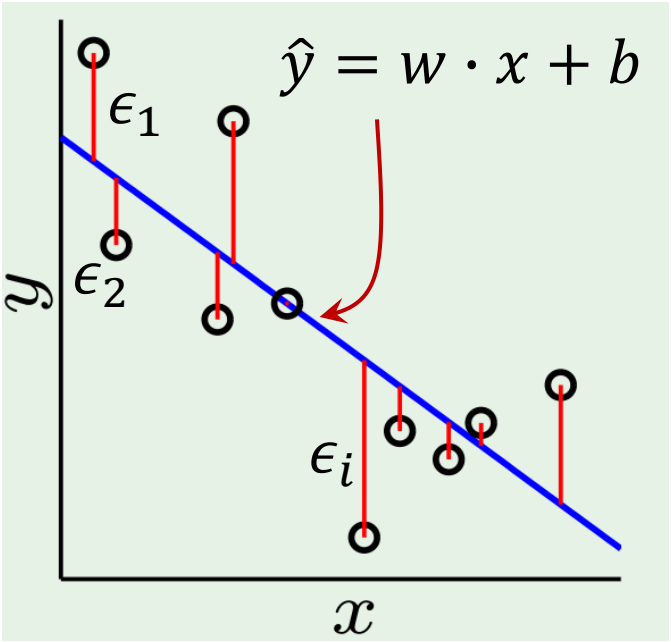
❖ from Yaser Abu-Mustafa “Learning From Data” Lecture 3

Recall Least Square Method - How to?

- **Calculate the sum of square of errors (residual)**

$$E = \sum \epsilon_i^2 = \sum (y_i - \hat{y}_i)^2$$

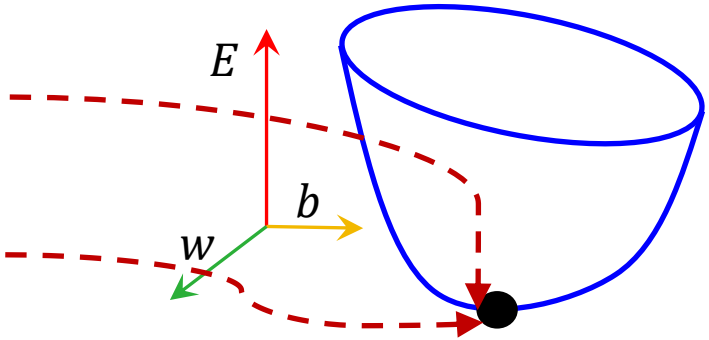
$$= \sum \left(y_i - (wx_i + b)\right)^2$$



- **Minimize the error function**
  - How to minimize the error function?

$$\frac{\partial E}{\partial w} = 0$$

$$\frac{\partial E}{\partial b} = 0$$



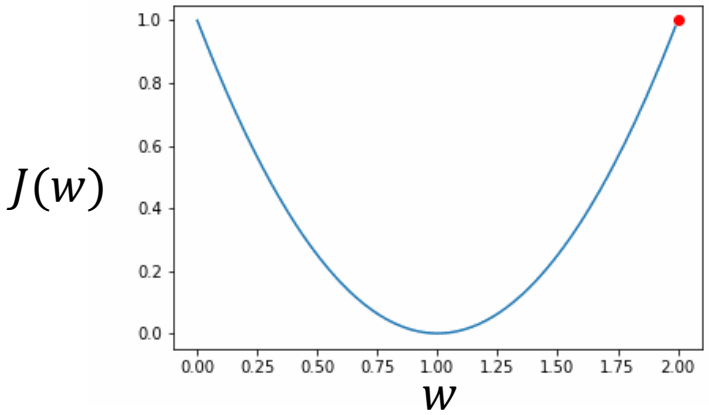
  - We will then get the expression of w and b

$$w = w(x_i, y_i)$$

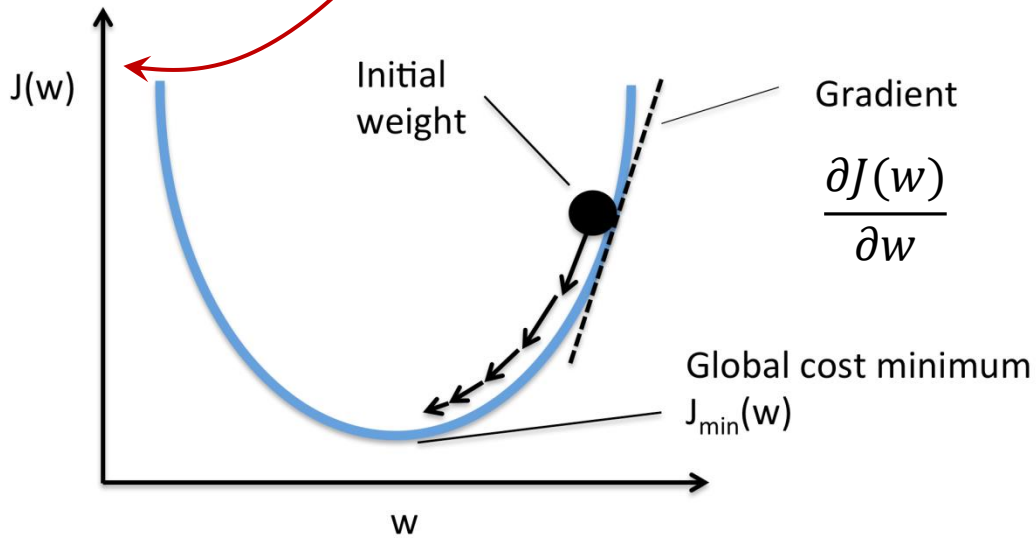
$$b = b(x_i, y_i)$$

To The Machine Learning Language

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

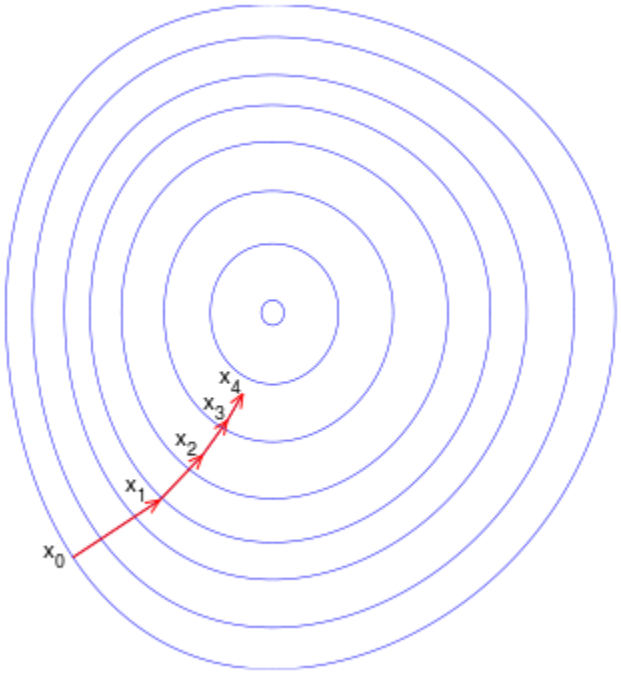


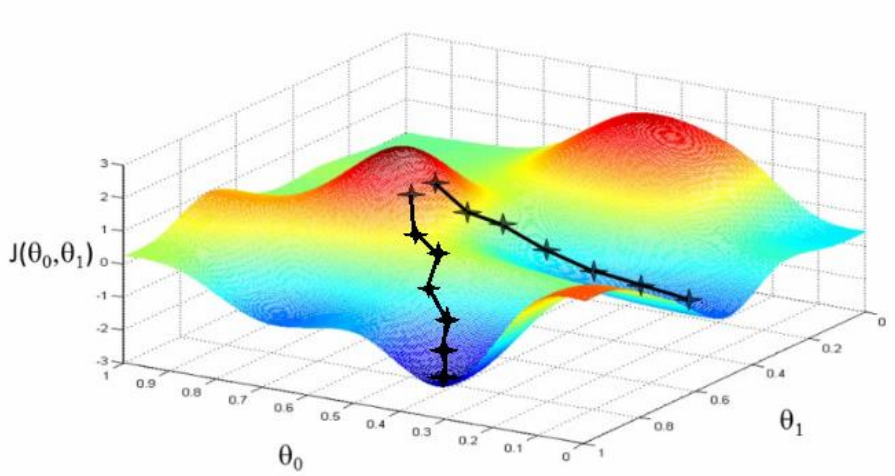
- **Define the cost function of your problem**
- **Find the set of weights that minimizes the cost function (loss)**



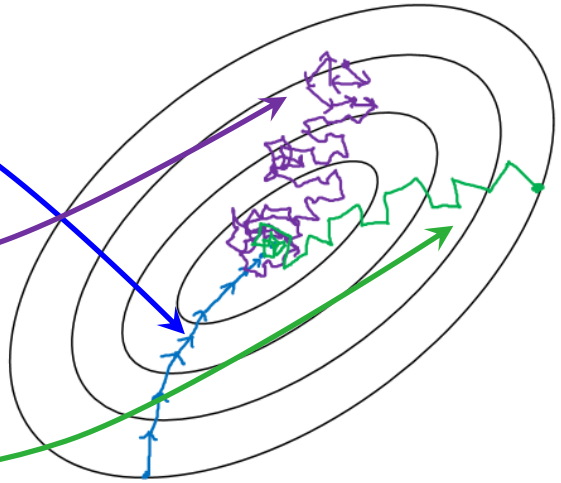
Theory: Gradient Descent

- **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.**





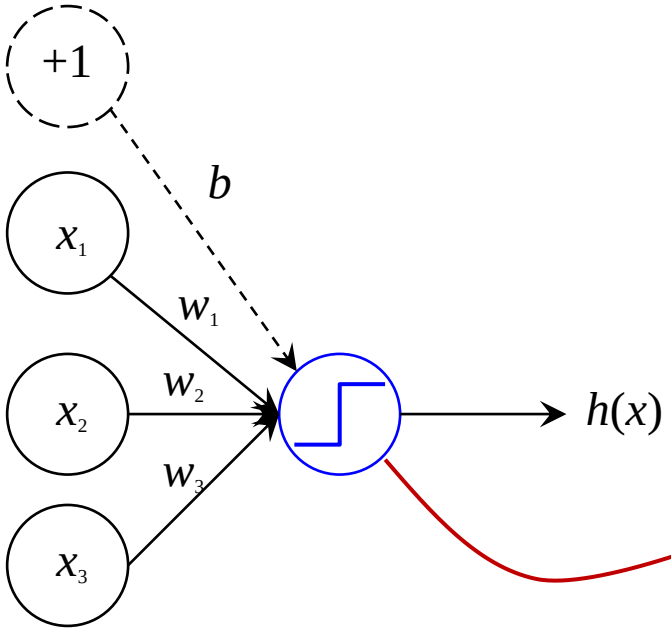
Mini-batch Gradient Descent



- **Batch gradient descent:**
  - Use all examples in each iteration
- **Stochastic gradient descent:**
  - Use one example in each iteration
- **Mini-batch gradient descent**
  - Splits the training dataset into small batches (size *b*) that are used to calculate model error and update model coefficients.
- **In the neural network terminology:**
  - one ***epoch*** consists of one full training cycle on the training set.
  - Using all your batches once is 1 ***epoch***. If you have 10 epochs it mean that you will use all your data 10 times (split in batches).

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

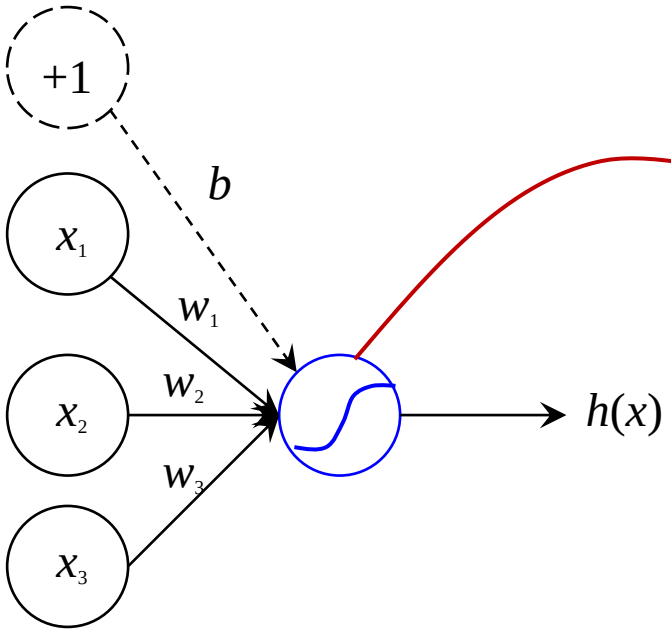
$$\mathbf{x}=\begin{bmatrix}x_1\\x_2\\x_3\end{bmatrix} \quad \mathbf{w}=\begin{bmatrix}w_1\\w_2\\w_3\end{bmatrix}$$

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

Hypothesis (Prediction: y)

Perceptron To Neuron

- **Replace the sign to sigmoid**



Activation function:

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

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

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

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

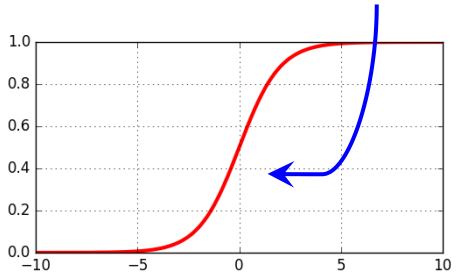
$$z = \mathbf{w}^T\mathbf{x} + b$$

$$y = h(x) = \sigma(z)$$

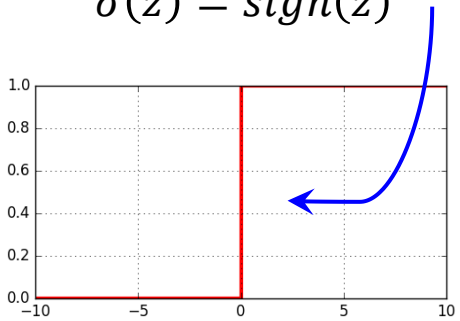
Sigmoid Neurons

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

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

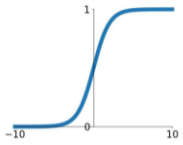


$$\sigma(z) = sign(z)$$

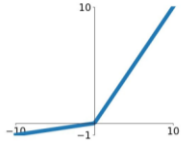


- **There are many other activation functions. (We will touch later.)**

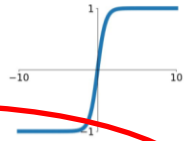
Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



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

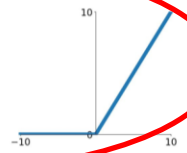


tanh
$\tanh(x)$



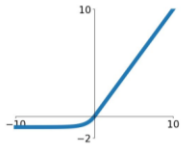
Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ReLU
$\max(0, x)$



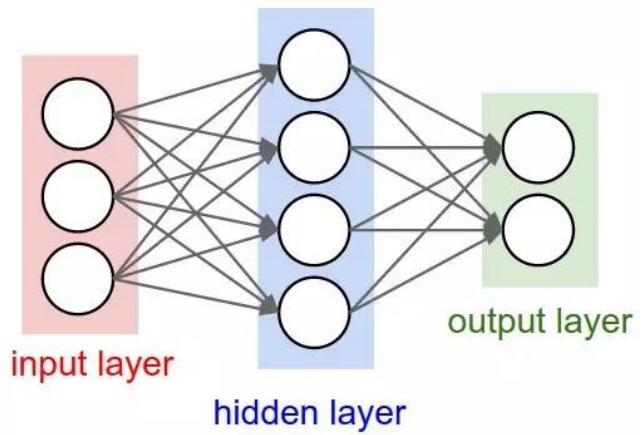
ELU

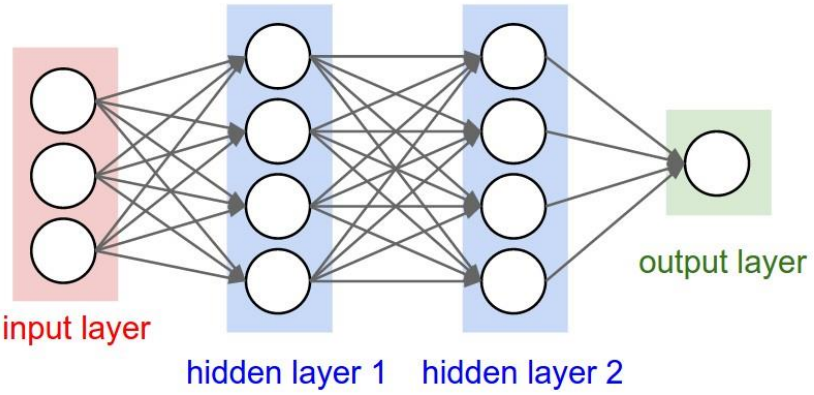
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



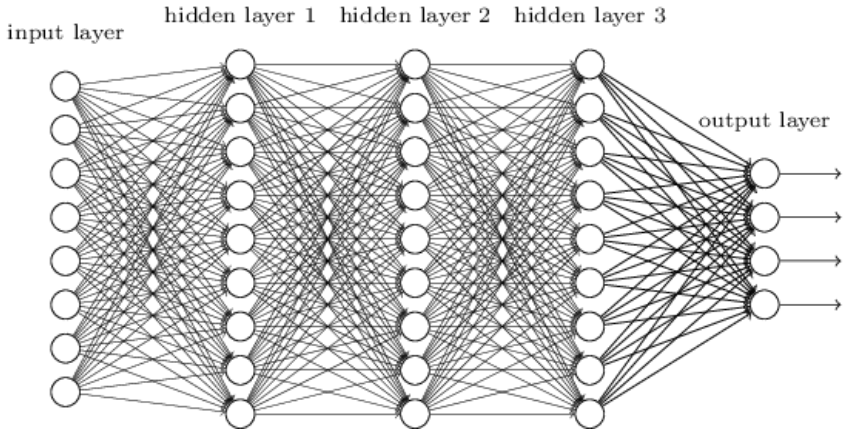
Network Of Neurons

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

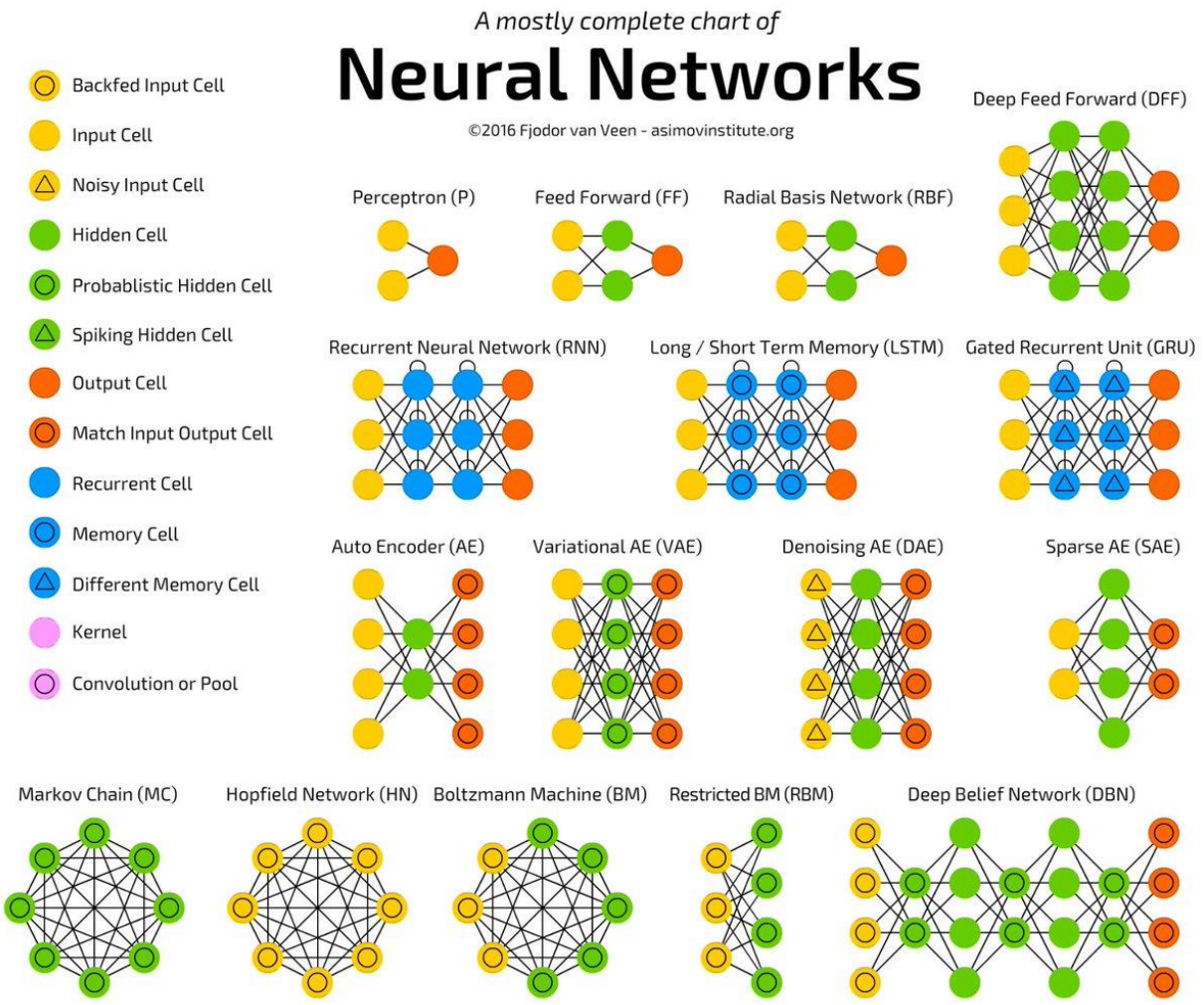




- **Deep Neuron Network: Number of hidden layers >1**



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.

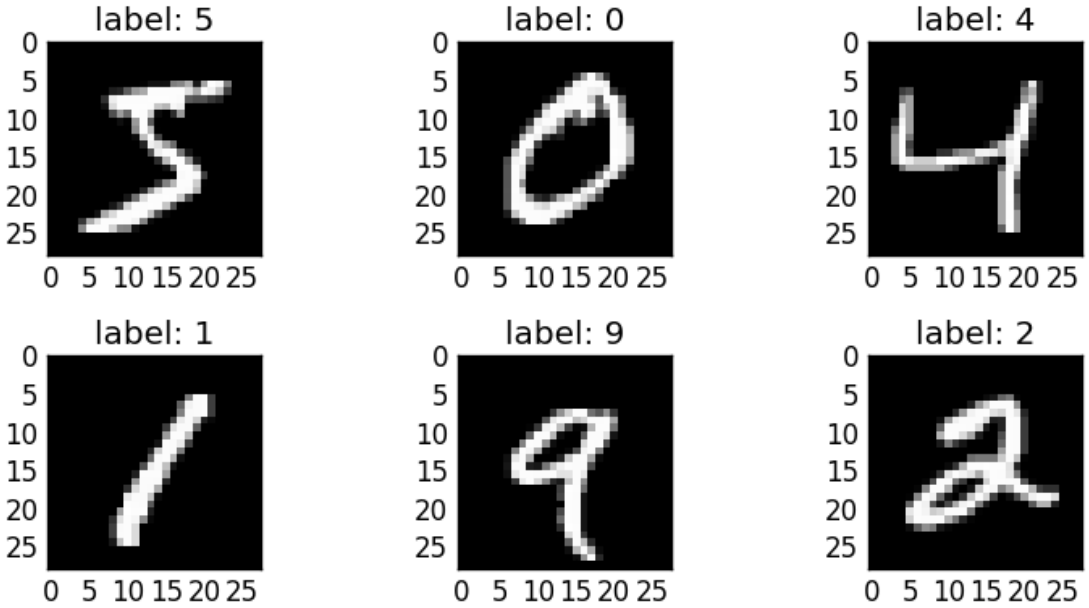
- **Deep Neural Networks are hard to train**
  - learning machines with lots of (typically in range of million) parameters
  - Unstable gradients issue
    - Vanishing gradient problem
    - Exploding gradient problem
  - Choice of network architecture and other hyper-parameters is also important.
  - 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

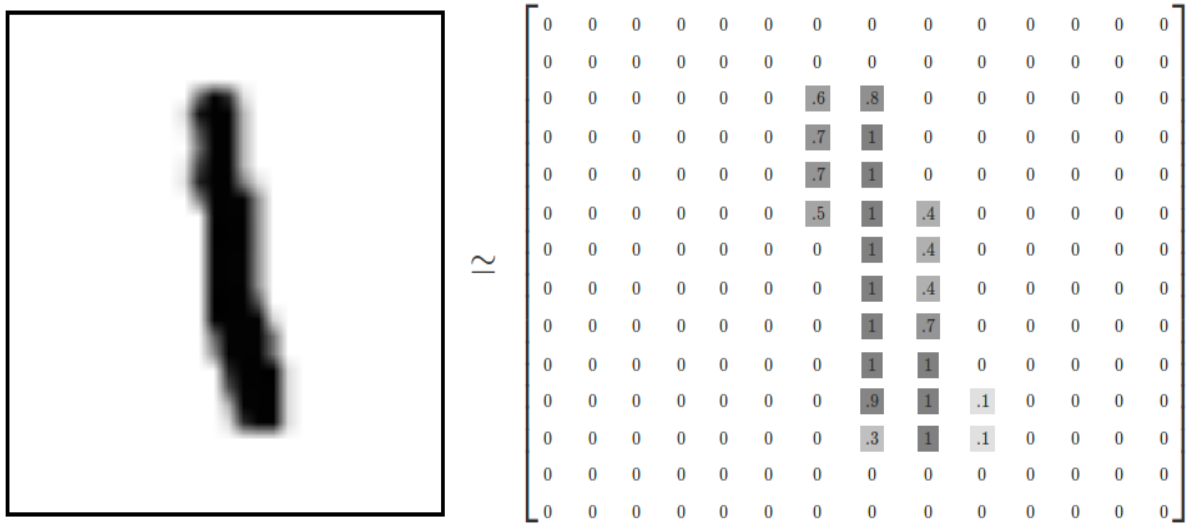
- **Recognizes handwritten digits.**
- **We uses the MNIST dataset, a collection of 60,000 labeled digits that has kept generations of PhDs busy for almost two decades. You will solve the problem with less than 100 lines of Python/Keras/TensorFlow code.**
- **We will gradually enhance the neural network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

Steps for MNIST

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

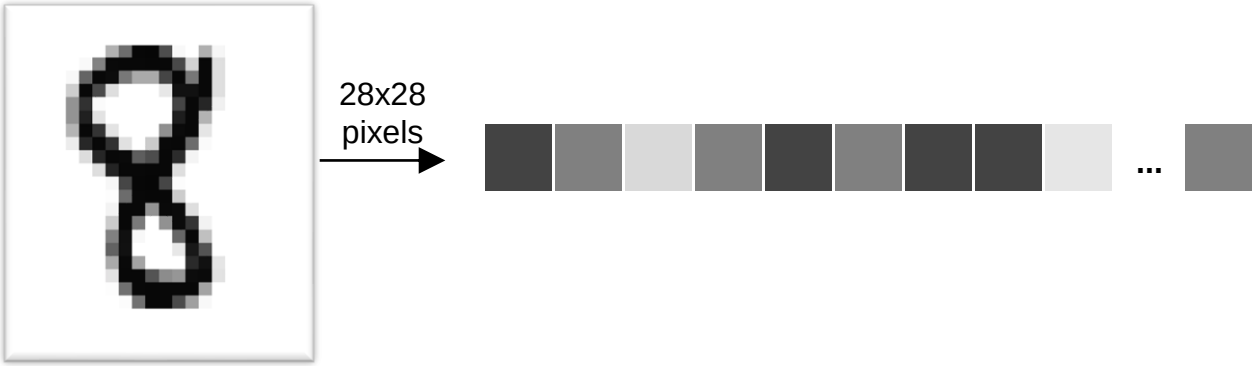
The MNIST Data

- **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;**
- **For each grayscale pixel value 0-255, we normalize it to 0-1;**
- **Each image is 28 pixels by 28 pixels. We can interpret this as a big array of numbers:**



One Layer NN for MNIST Recognition

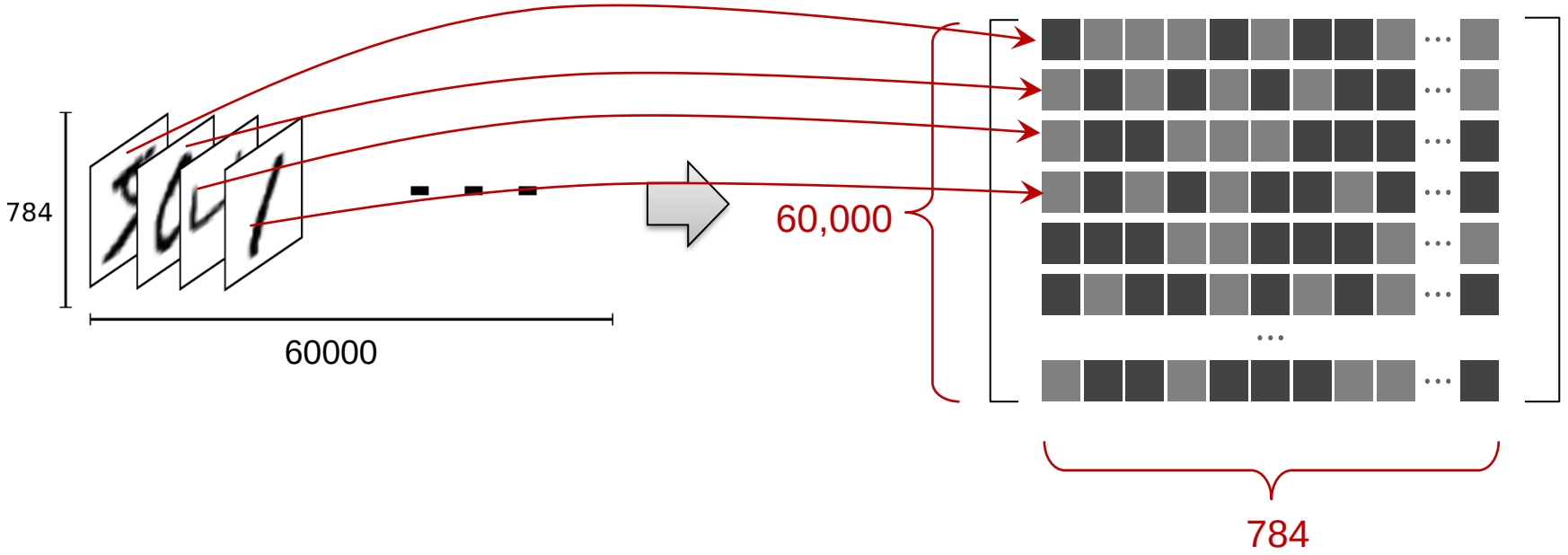
- **We will start with a very simple model, called Softmax Regression.**
- **We can flatten this array into a vector of 28x28 = 784 numbers. It doesn't matter how we flatten the array, as long as we're consistent between images.**
- **From this perspective, the MNIST images are just a bunch of points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



❖ **What are we missing here?**

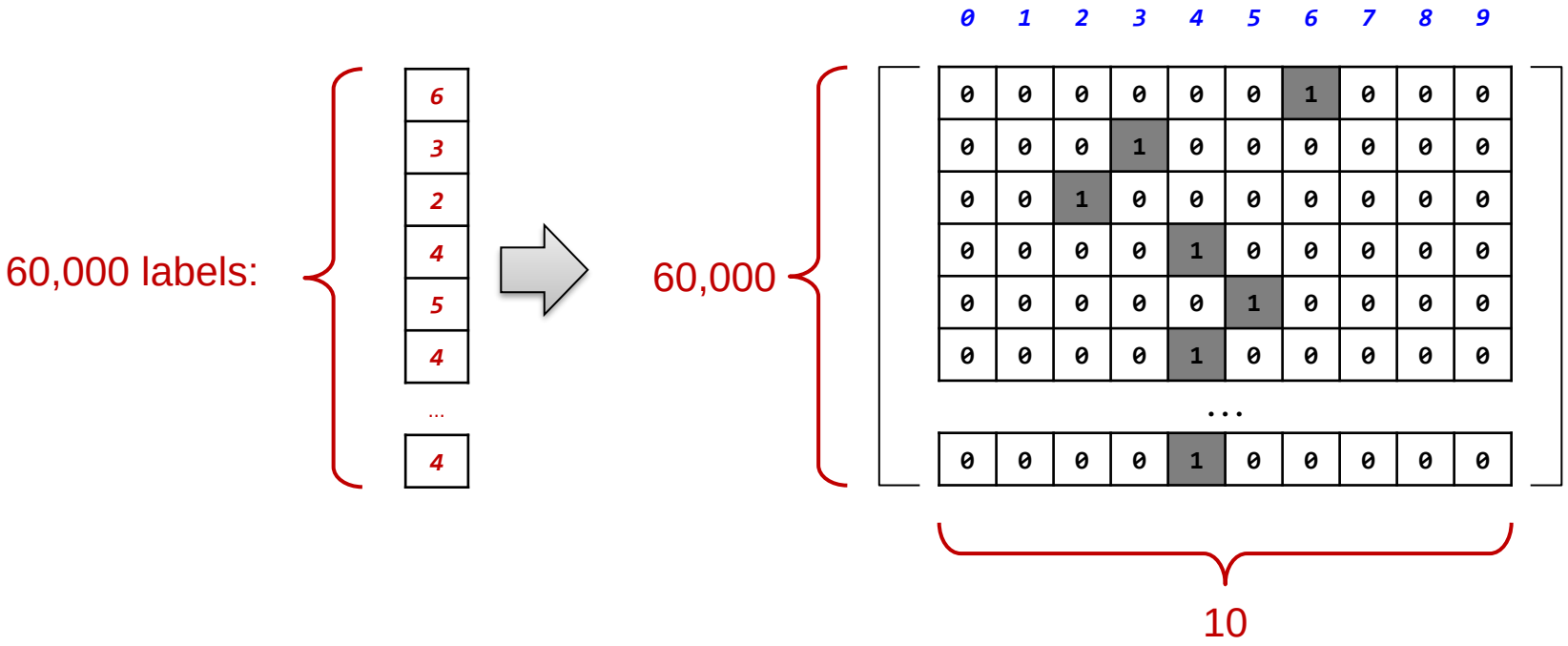
Result of the Flatten Operation

- **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.

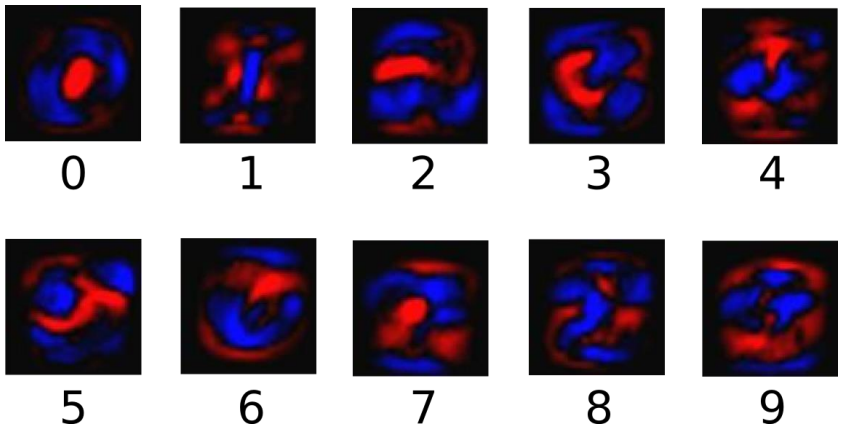
Softmax Regression

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

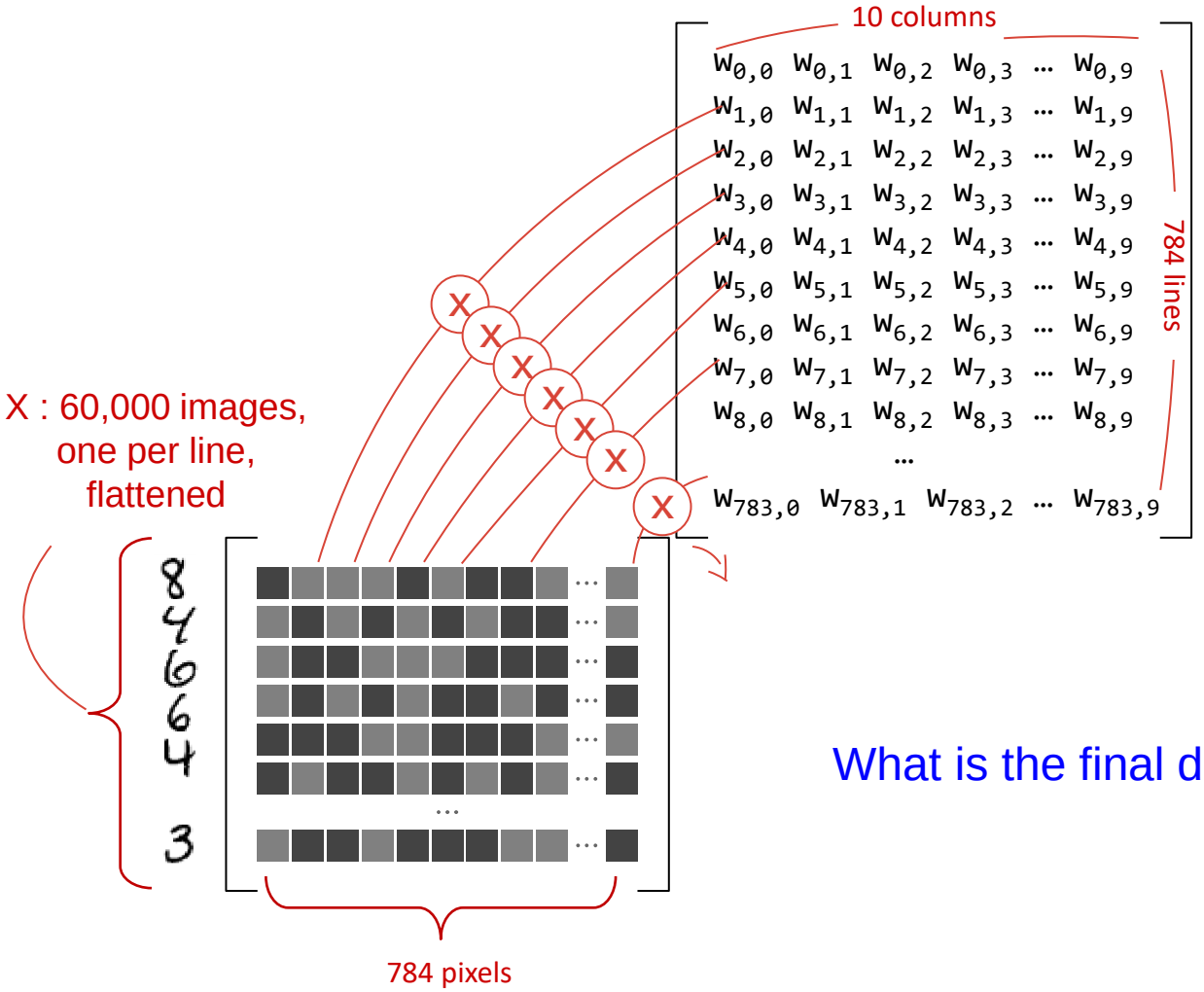
2 steps in softmax regression - Step 1

- **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:**

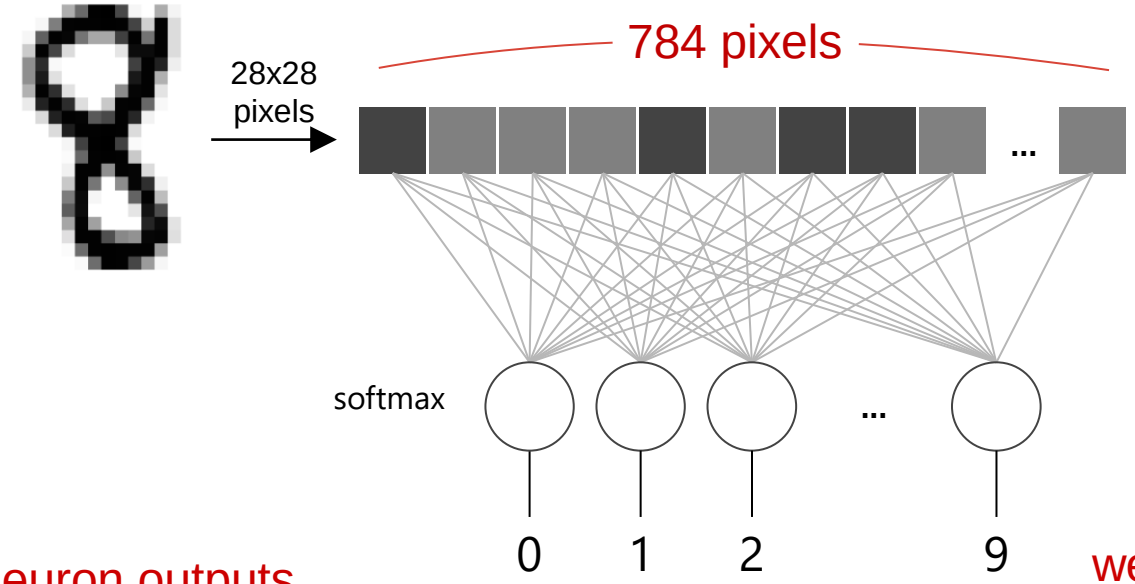
$$h(\mathbf{x}_i) = \text{softmax}(z_i) = \text{softmax}\left(\sum_j W_{i,j} x_j + b_i\right)$$

- **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**

Predictions `Y[60000, 10]` | Images `[60000, 784]` | Weights `W[784,10]` | Biases `b[10]`

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

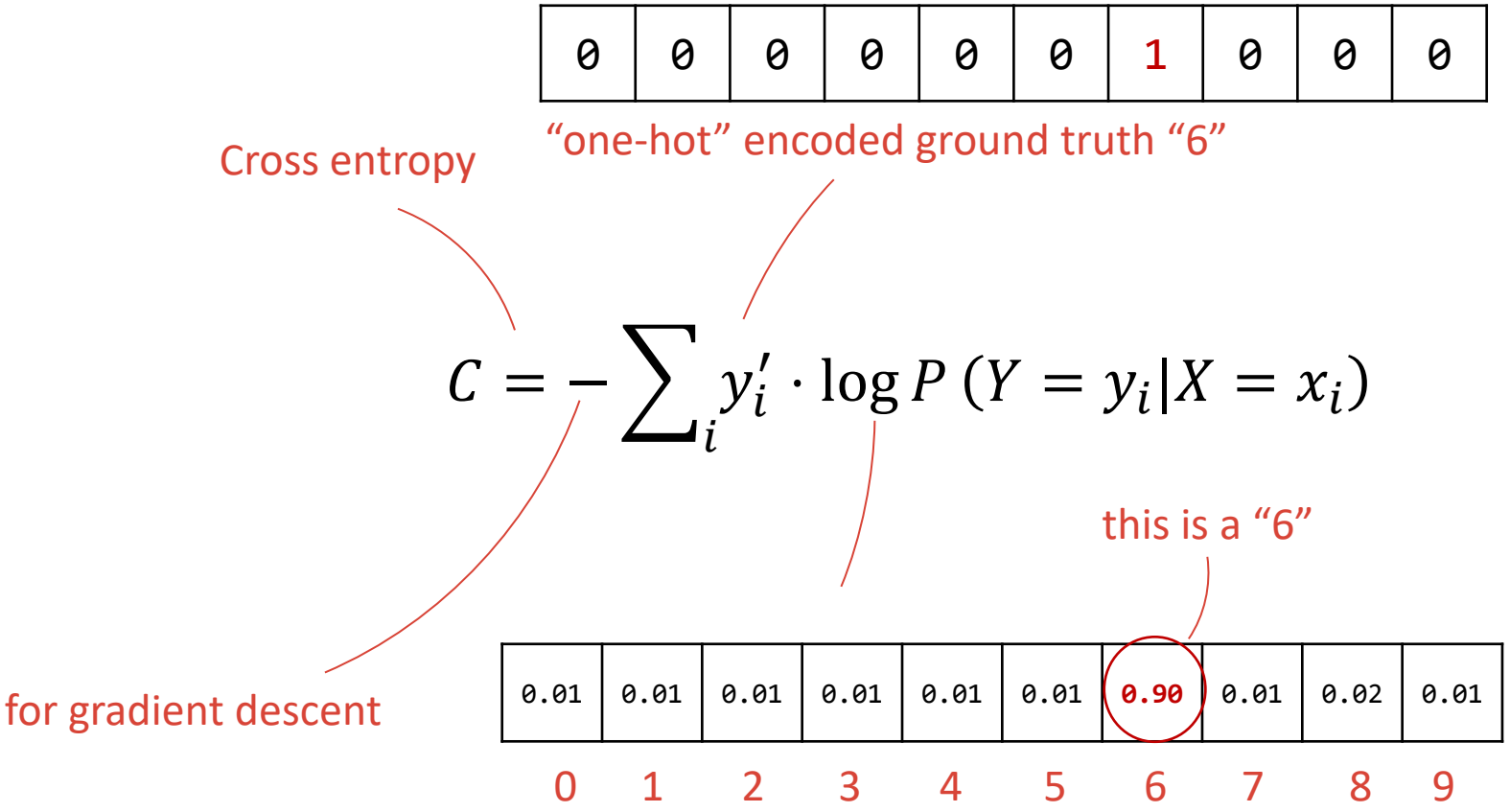
applied on each line

matrix multiply

broadcast on all lines

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:**



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

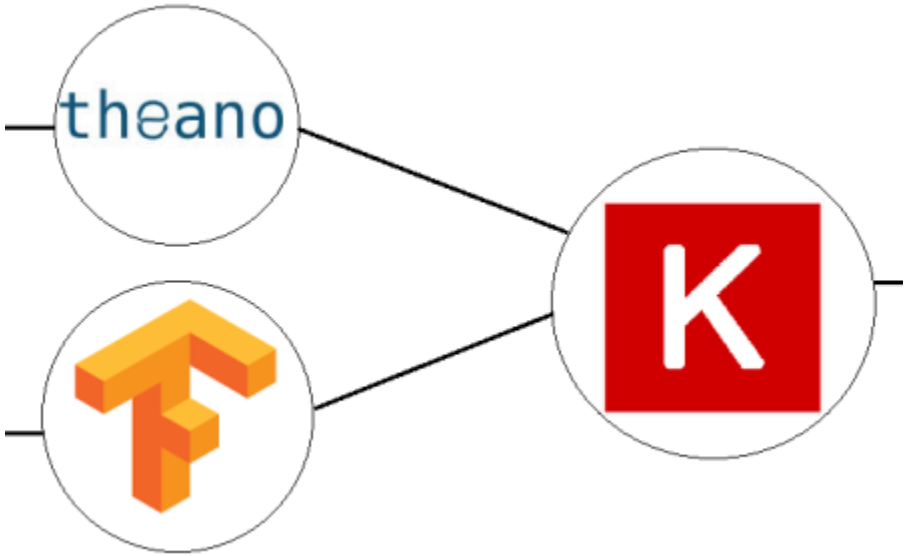
❖ **How to implement them?**

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**

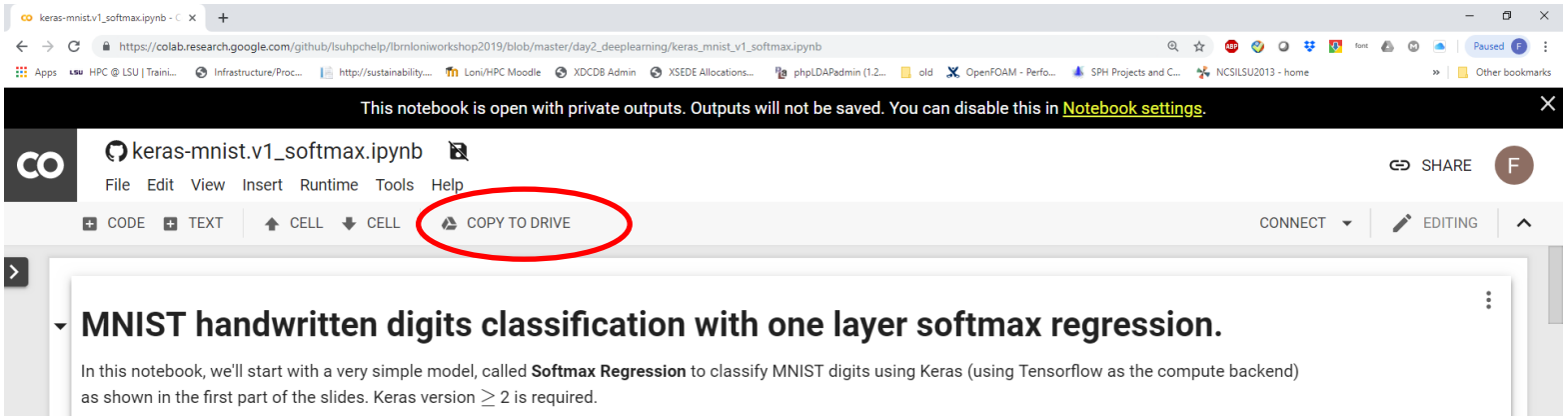
Software Environment

- **What you'll need**
  - Python 2 or 3 (Python 3 recommended)
  - TensorFlow and Keras
  - Matplotlib (Python visualization library)
- **We will use the Google Colaboratory**
  - Colaboratory is a research tool for machine learning education and research. It's a Jupyter notebook environment that requires no setup to use. You can refer to: https://research.google.com/colaboratory/faq.html for more information.
  - See next slide for starting the Colab notebook

Open Colab Notebook from Github

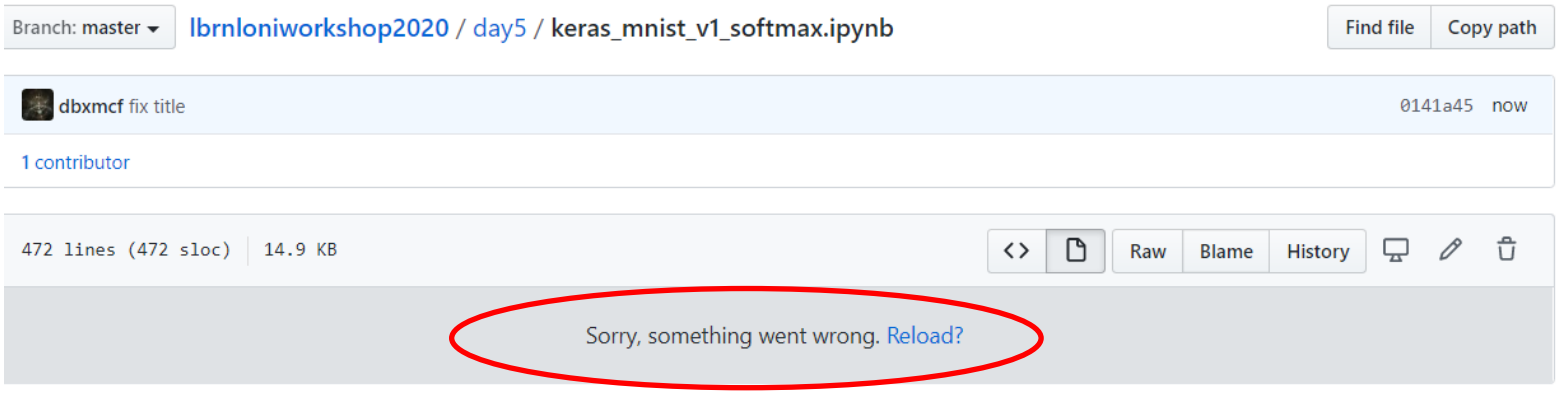
- **Open the below link:**
  - https://github.com/lsuhpchelp/lbrnloniworkshop2021/blob/main/day5/2021_keras_mnist_v1_softmax.ipynb
  - Or navigate yourself in the github repo:
    - https://github.com/lsuhpchelp/lbrnloniworkshop2021
  - Select "`day5 > 2021_keras_mnist_v1_softmax.ipynb`"
- **Click the "Open in Colab" link:**

- **After the Colab notebook is laid out, you need one more step, save the Colab notebook to your google drive by "COPY TO DRIVE", or you will be editing the notebook in "Playground" (read only) mode:**



Possible Bug of Github

- **In case of the "Something went wrong, try again later?"**



- **Copy and paste the github link from the browser URL box (https://github.com/lsuhpchelp/lbrnloniworkshop2020/blob/master/day5/keras_mnist_v1_softmax.ipynb) into the below the location to have it rendered: https://nbviewer.jupyter.org/**

Keras - Initialization

```
# import necessary modules
# The Sequential model is a linear stack of layers.
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 training and test dataset
# download https://s3.amazonaws.com/img-datasets/mnist.pkl.gz
# to use in this tutorial
from keras.datasets import mnist
(X_train, y_train), (X_test, y_test) = mnist.load_data()
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
```

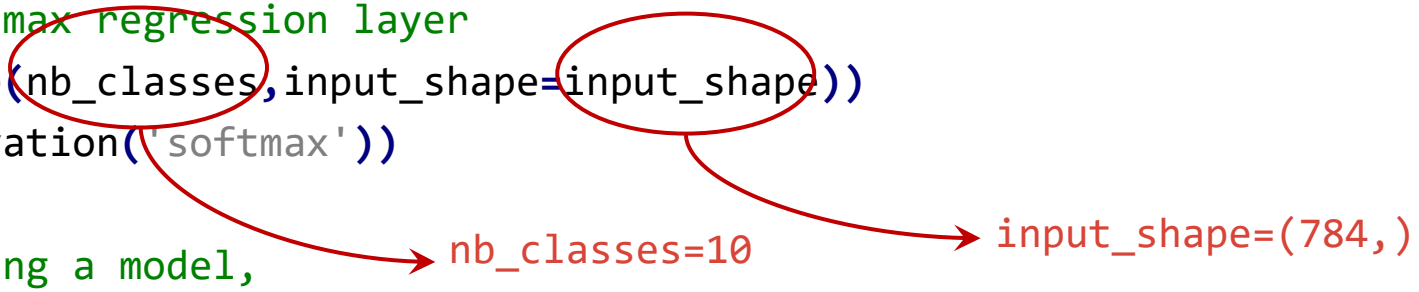
One-hot encoding

```
# 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

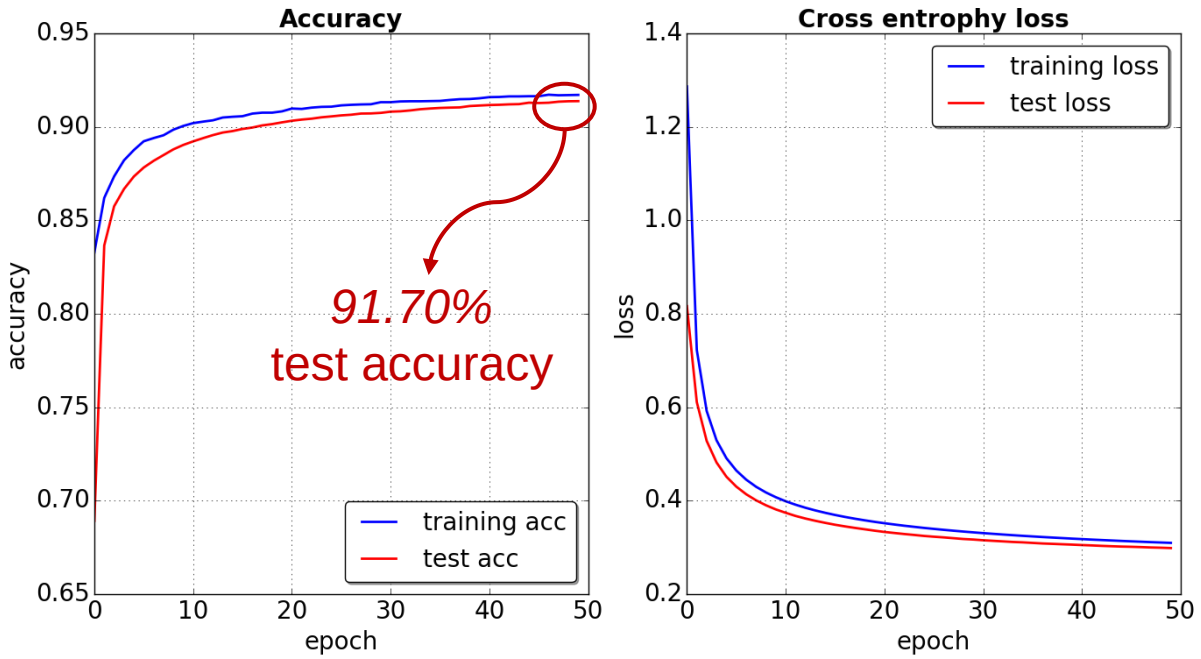
```
# The Sequential model is a linear stack of layers in Keras
model = Sequential()
#build the softmax regression layer
model.add(Dense(nb_classes,input_shape=input_shape))
model.add(Activation('softmax'))

# 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 one type of gradient descent method
              optimizer='rmsprop',
              # 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))
```



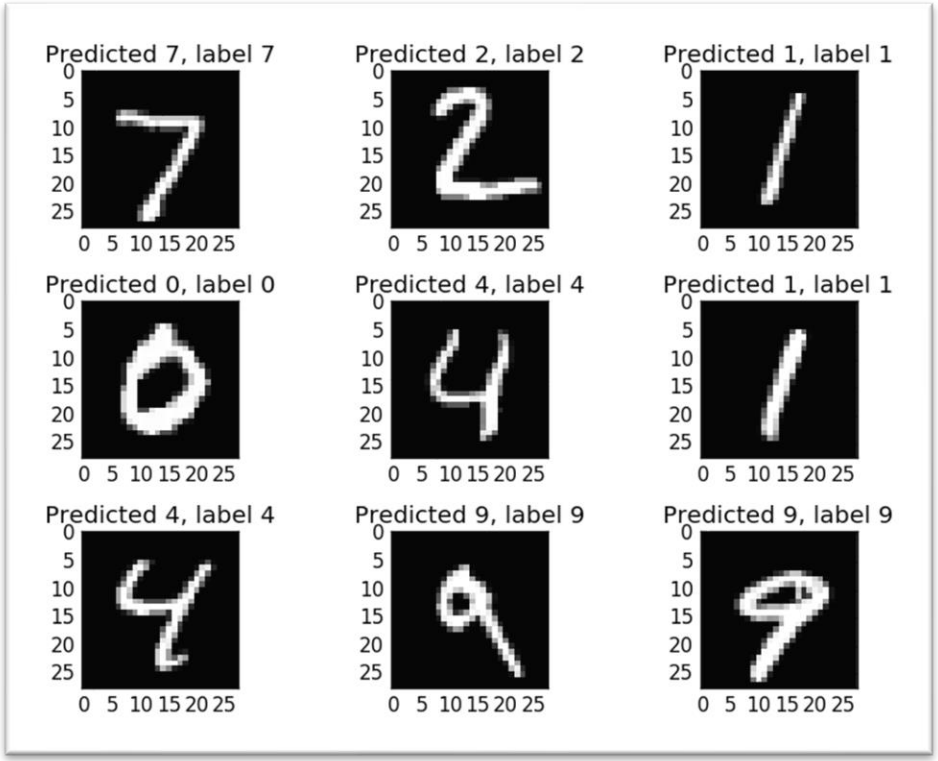
Results Of The First softmax Regression

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

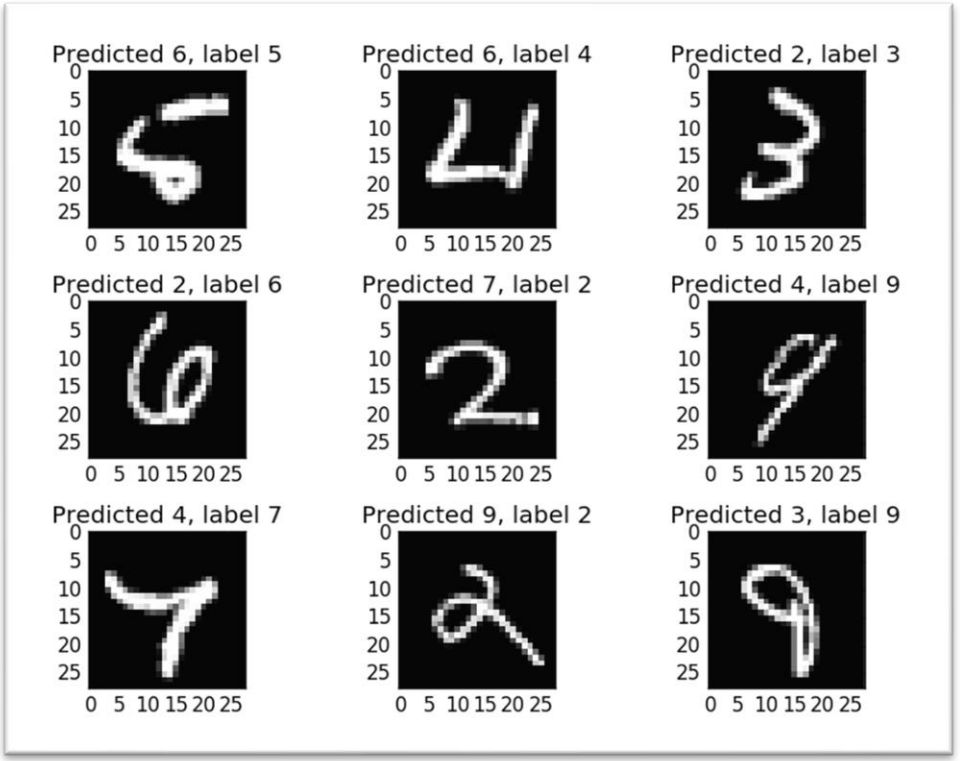


Review The Classified Results

Correctly classified

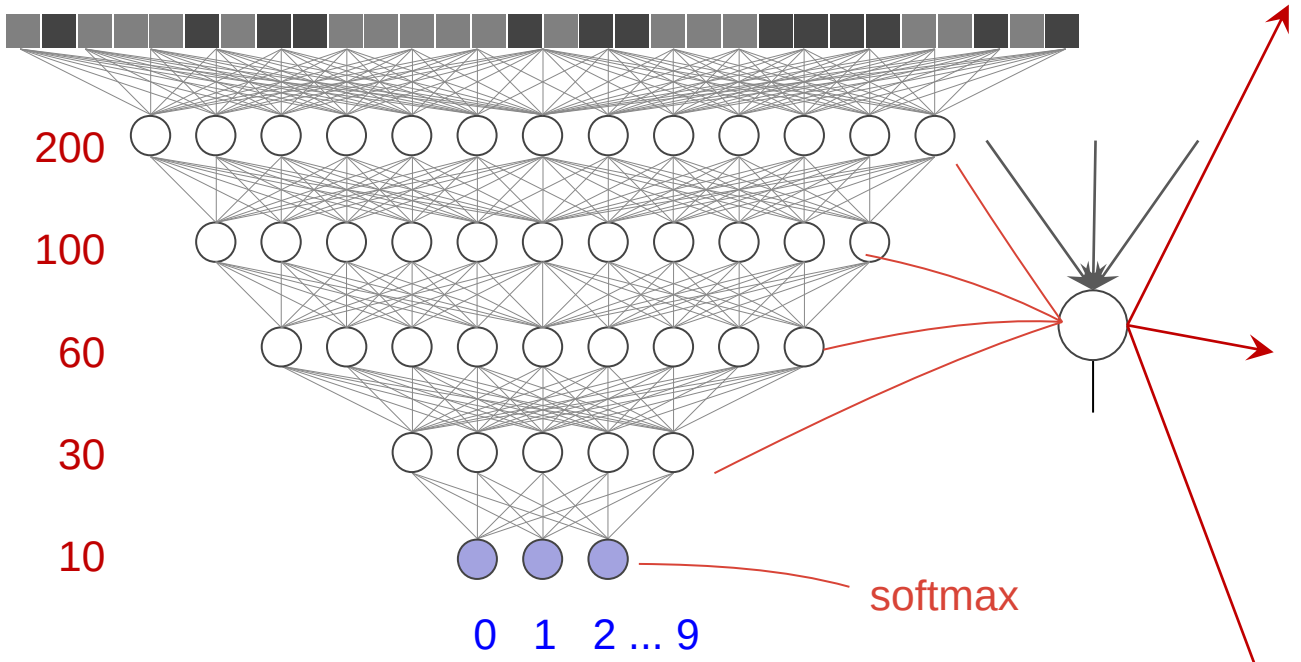


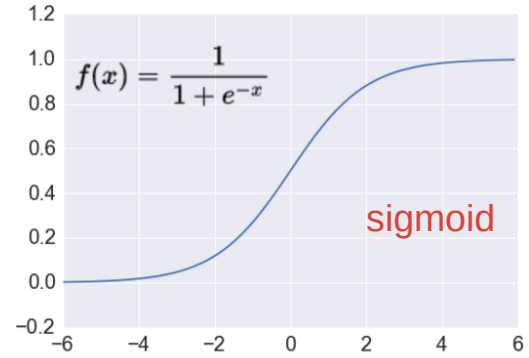
Incorrectly classified

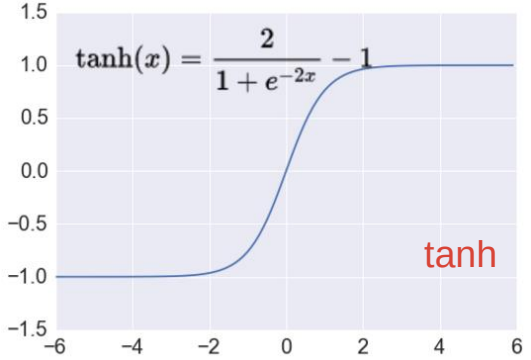


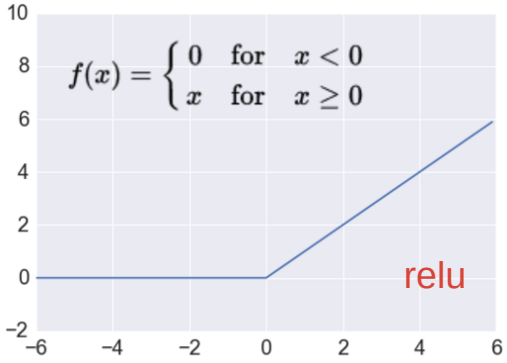
Adding More Layers?

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







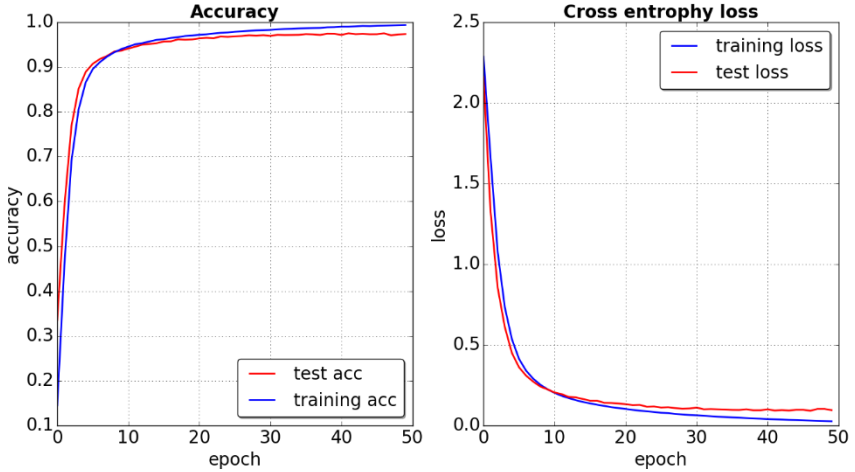


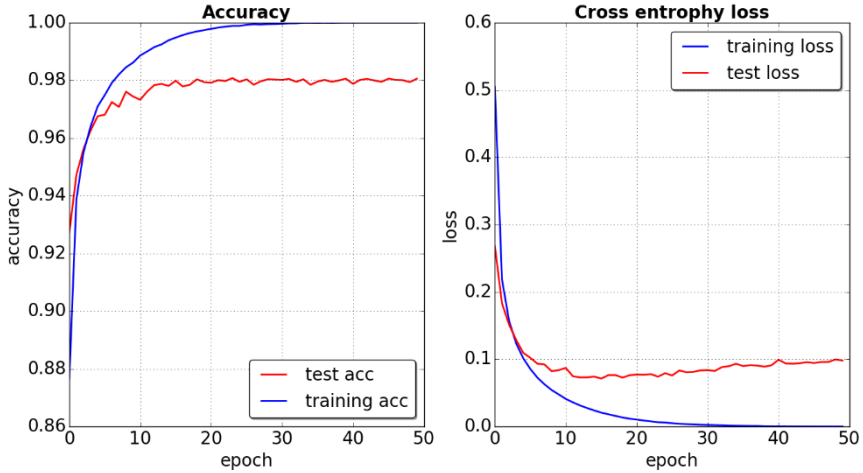
5 Layer Model In Keras

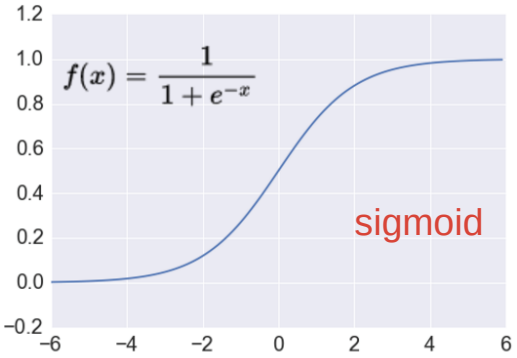
```
model = Sequential()
# try also tanh, sigmoid
act_func='relu'
model.add(Dense(200,activation=act_func,input_shape=input_shape))
model.add(Dense(100,activation=act_func))
model.add(Dense( 60,activation=act_func))
model.add(Dense( 30,activation=act_func))
model.add(Dense(nb_classes,activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='rmsprop',
              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))
```

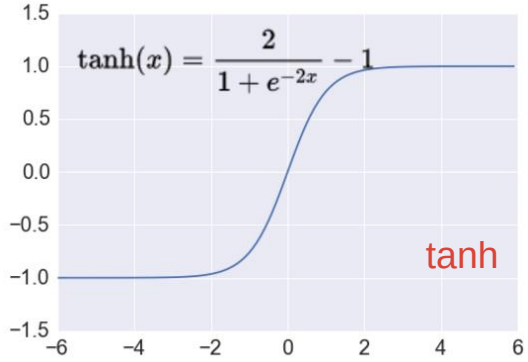
5 Layer Regression – Different Activation

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







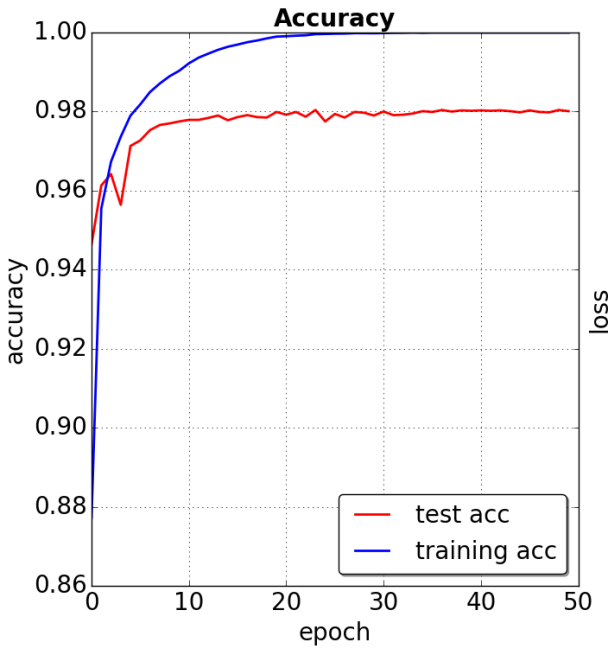


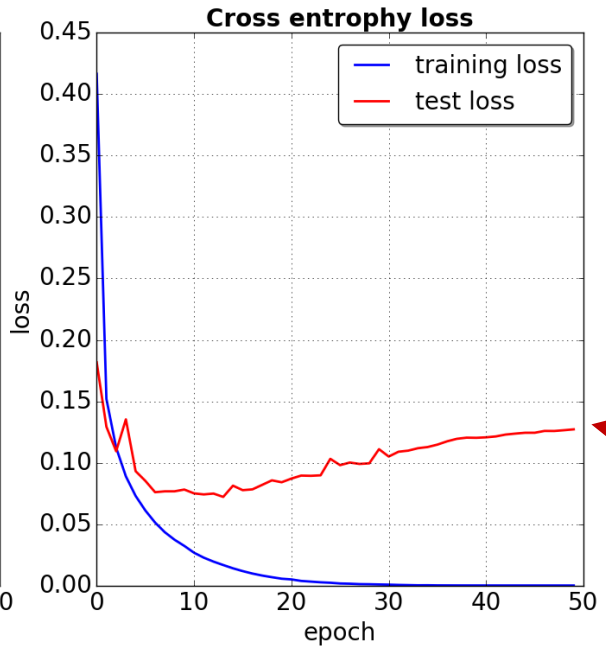
Rectified Linear Unit (ReLU) activation function

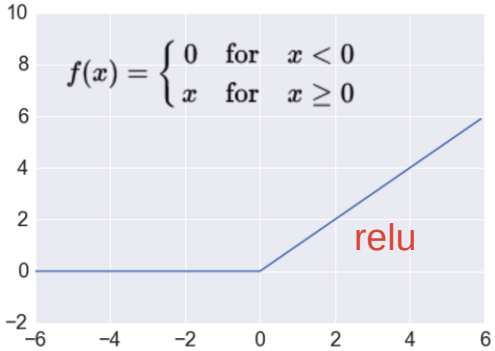
- **ReLU - The Rectified Linear Unit has become very popular in the last few years:**

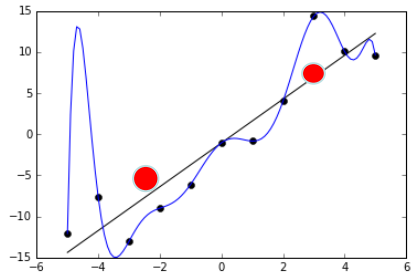
$$f(z) = \max(0, z)$$

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







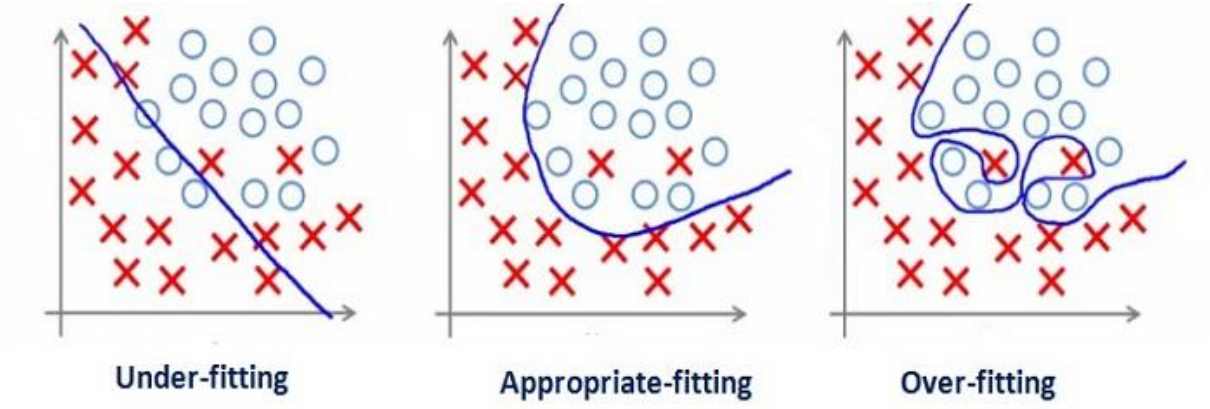


Overfitting

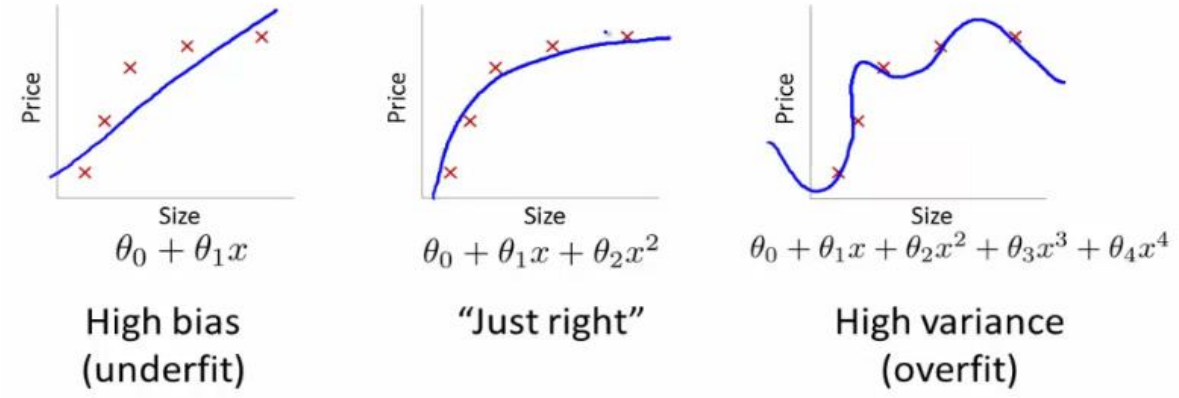
Overfitting

- **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:

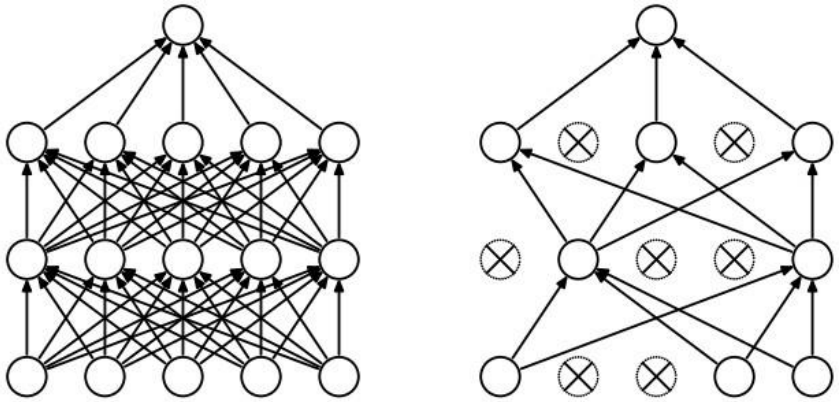


Regression:



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.**

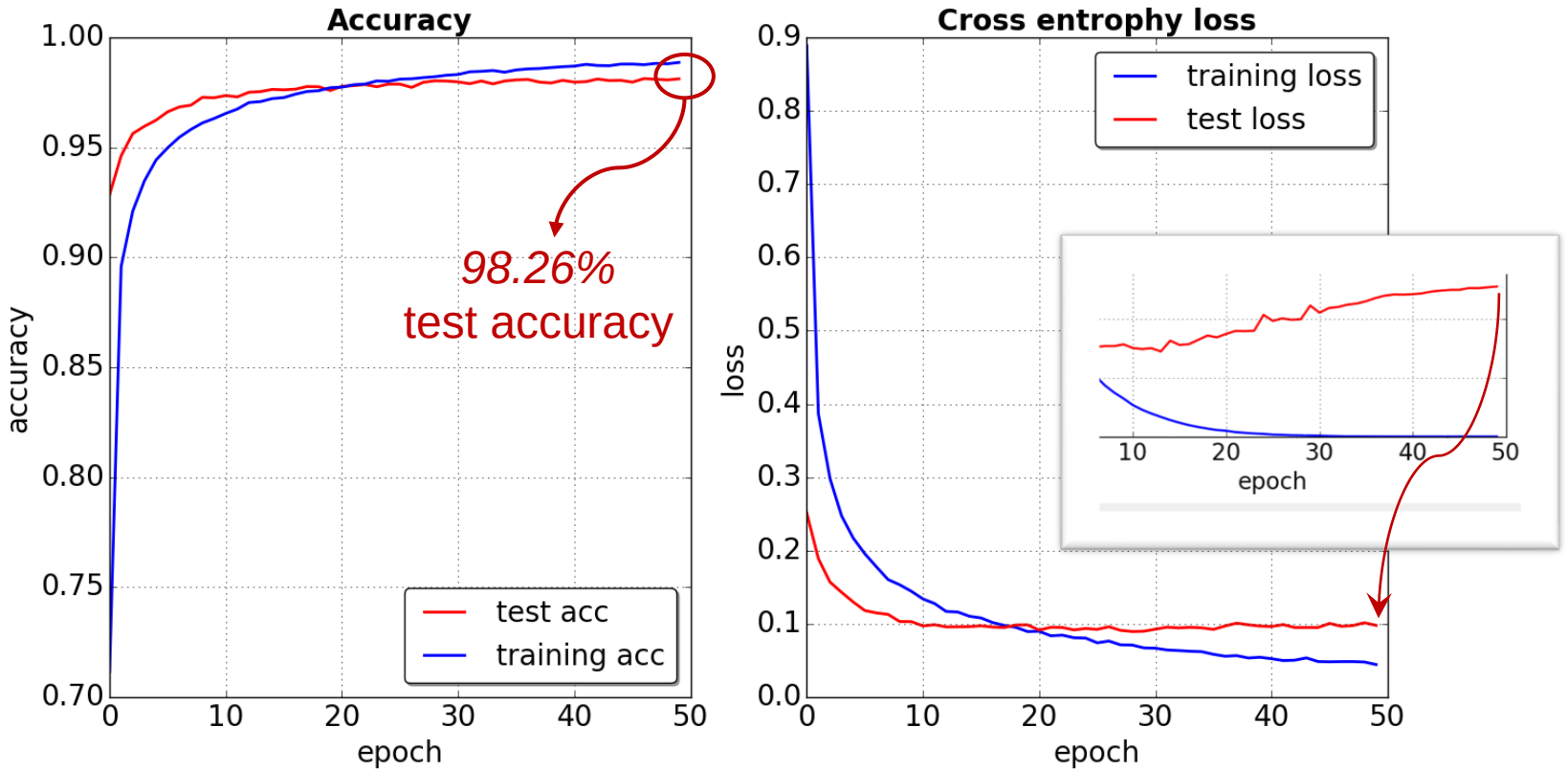
```
# apply a dropout rate 0.25 (drop 25% of the neurons)
model.add(Dropout(0.25))
```

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**

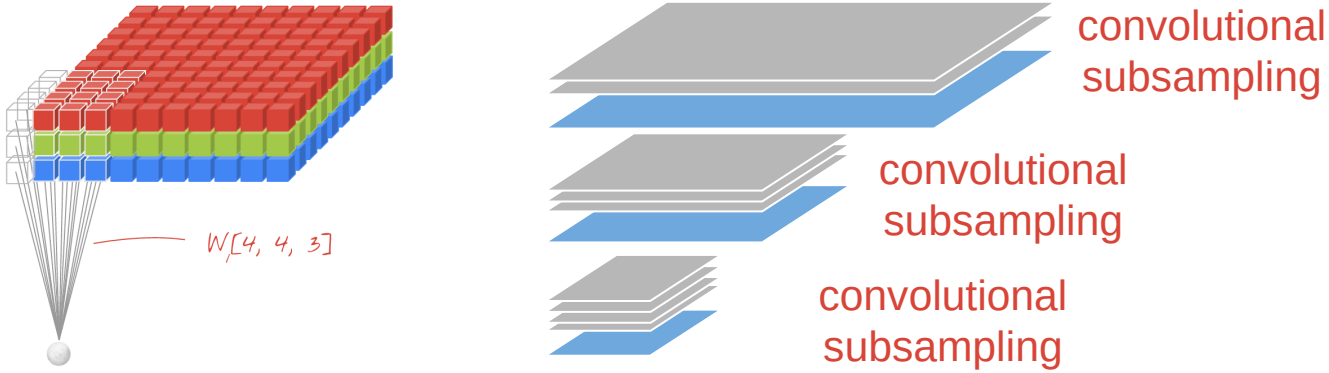


Why Using Fully Connected Layers?

- **Such a network architecture does not consider 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)

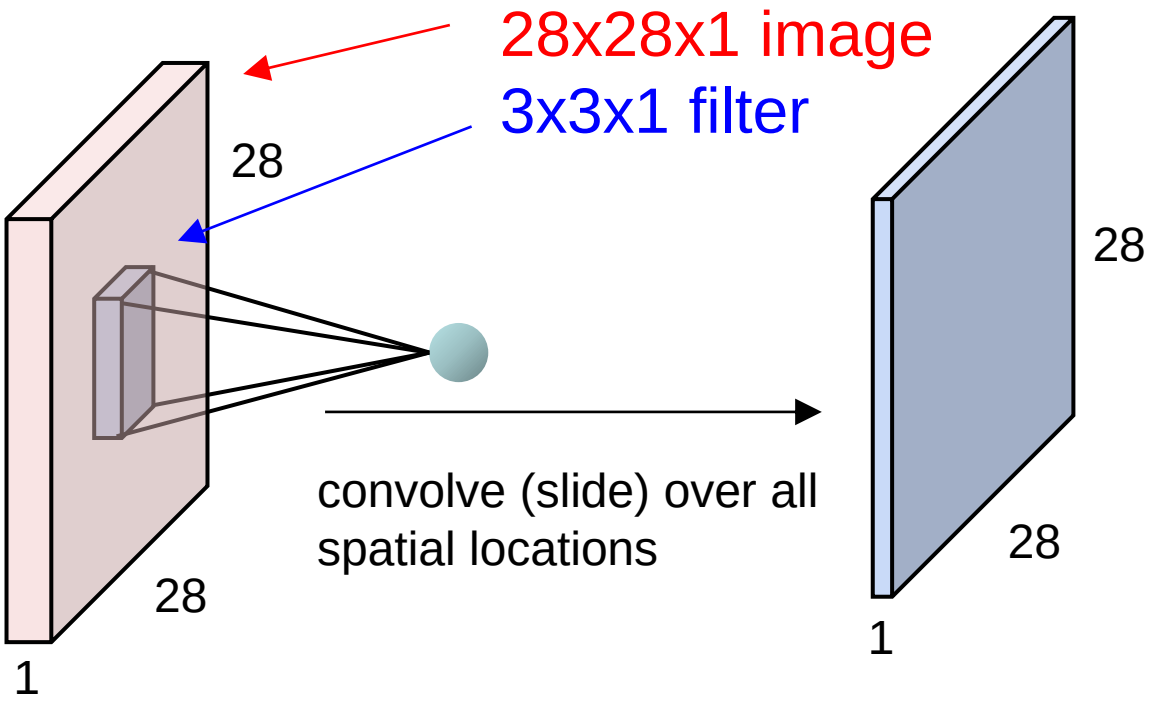


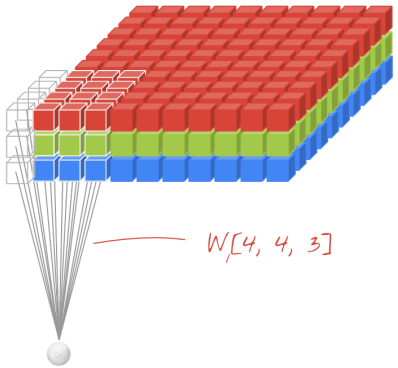
from Martin Görner Learn TensorFlow and deep learning, without a Ph.D

- **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?

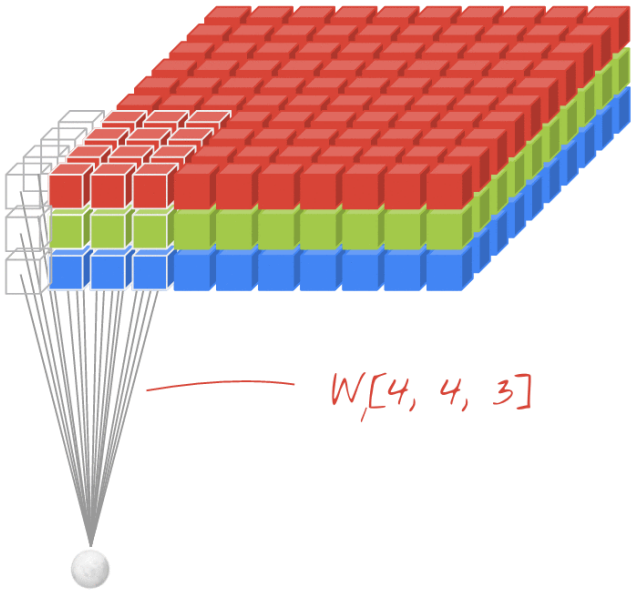


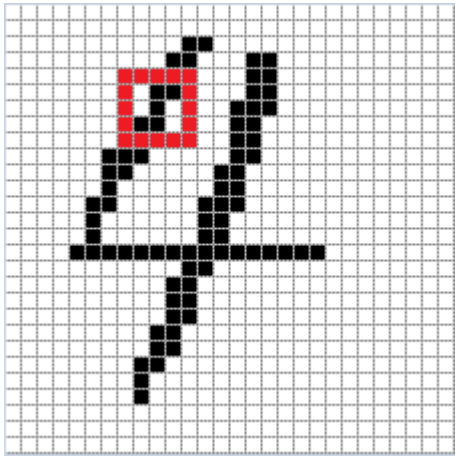


- **By sliding the patch of weights (filter) across the image in both directions (a convolution) you obtain as many output values as there were pixels in the image (some padding is necessary at the edges).**

Three basic ideas about CNN

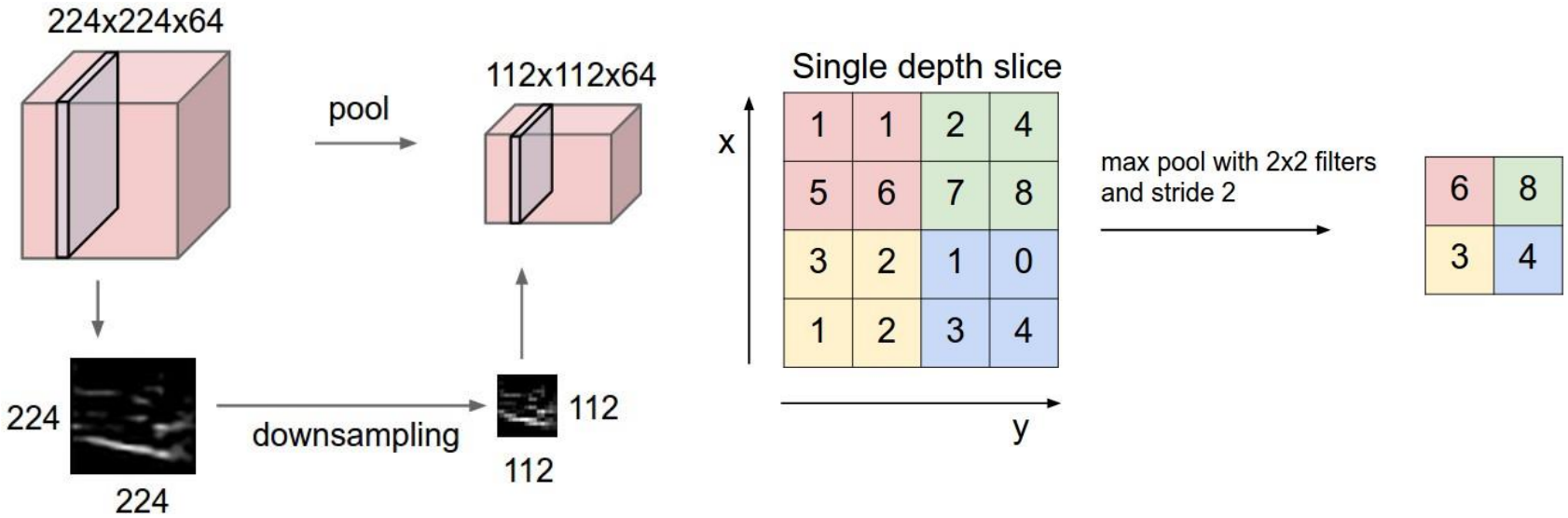
- **Local receptive fields**
- **Shared weights and biases:**
- **Pooling**



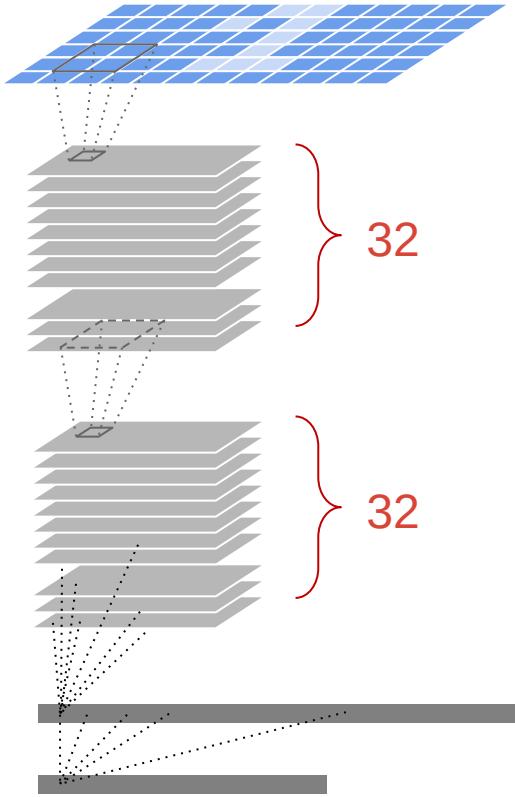


Pooling Layer

- **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



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))
```

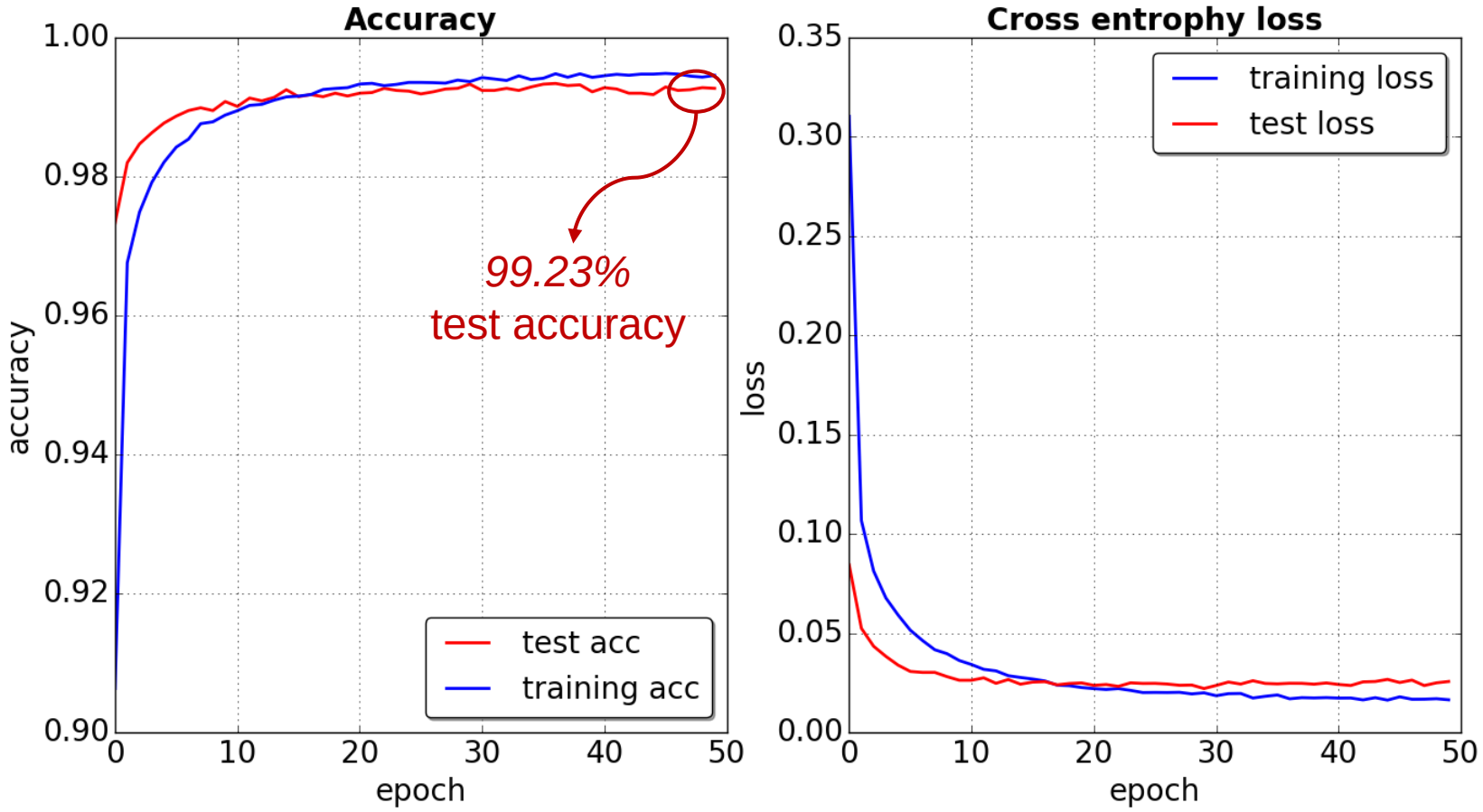
nb_filters=32

kernel_size=(3,3)

input_shape=(28,28)

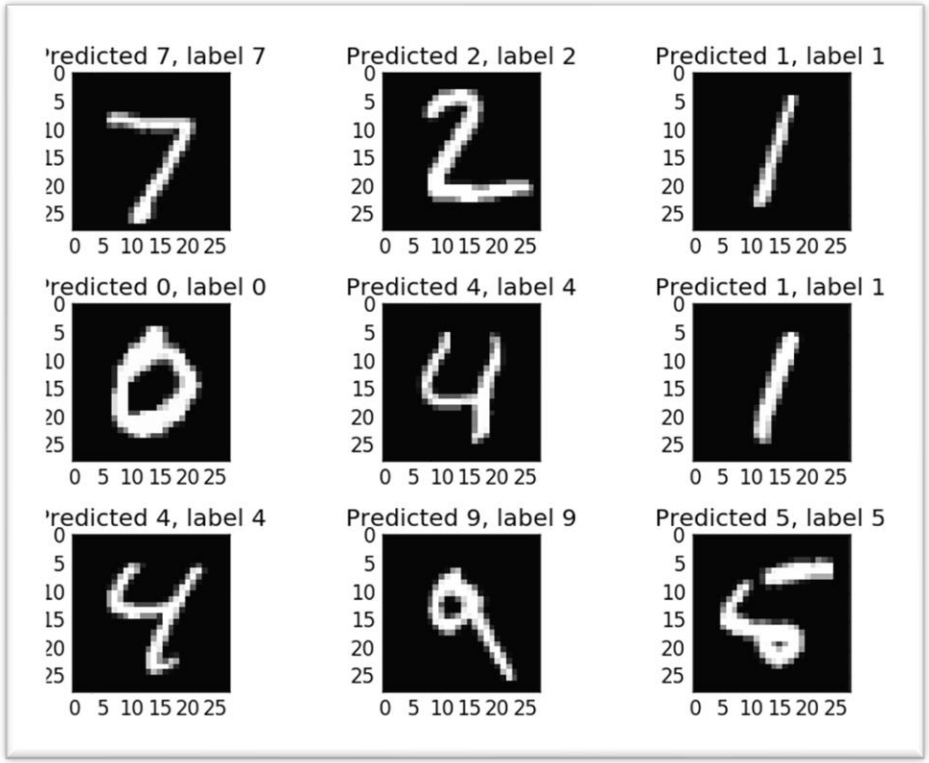
Challenging The 99% Testing Accuracy

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

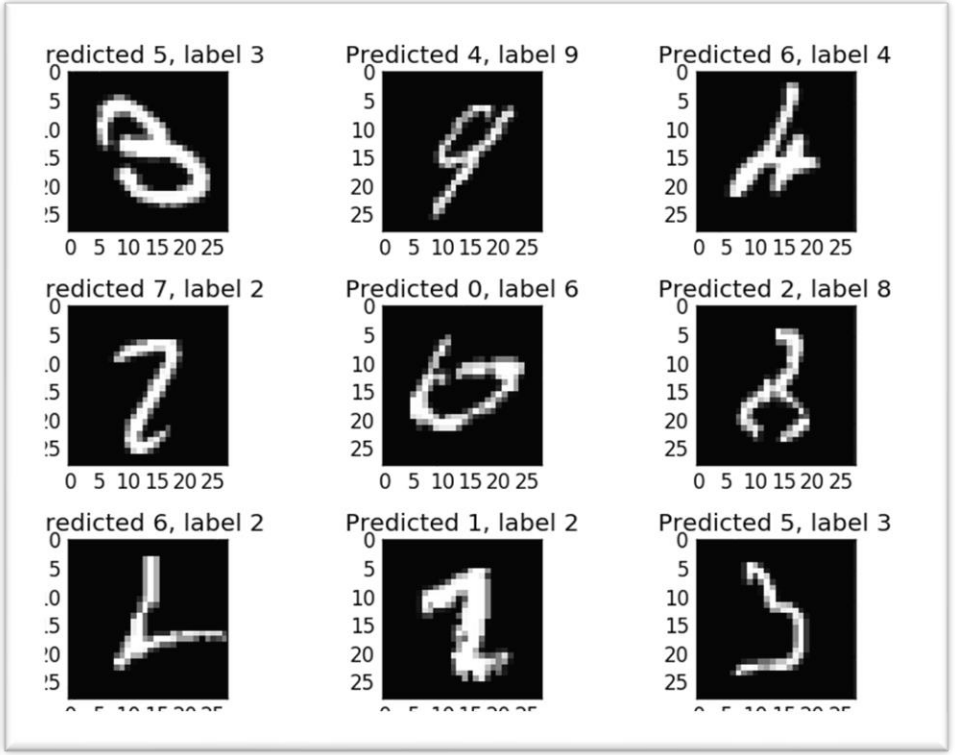


Review The Classified Results of CNN

Correctly classified

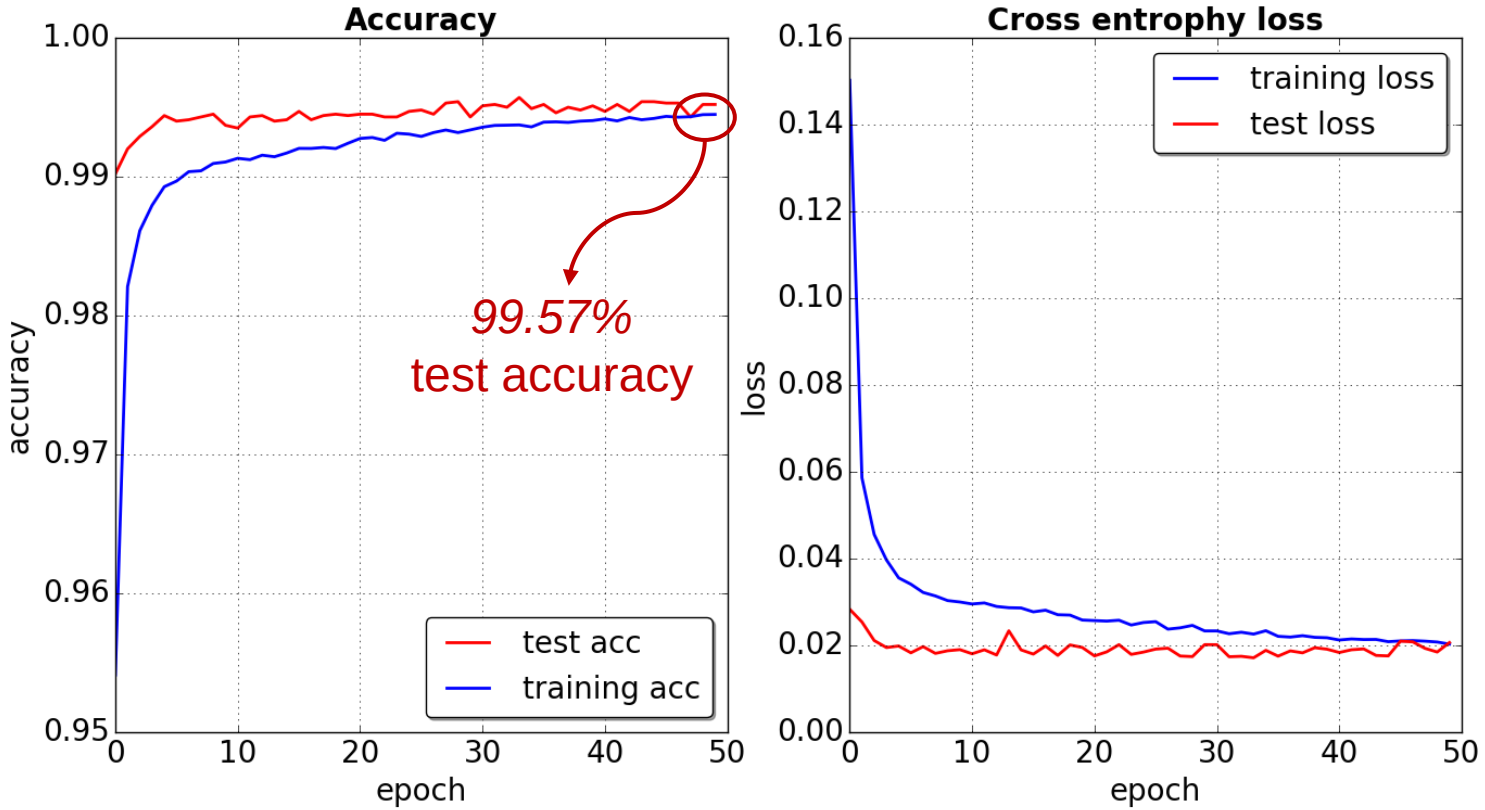


Incorrectly classified



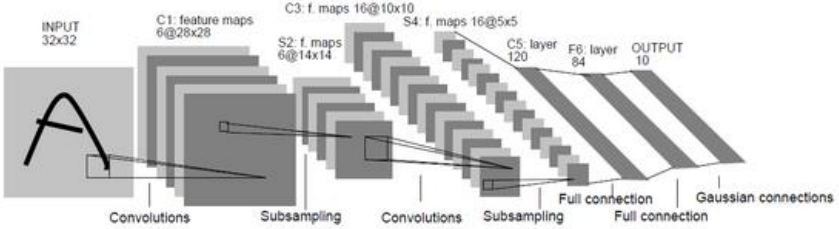
Feed More Data: Using Expanded Dataset

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

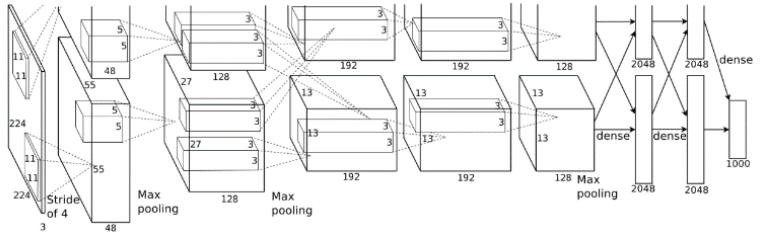


Examples of Convolution NN

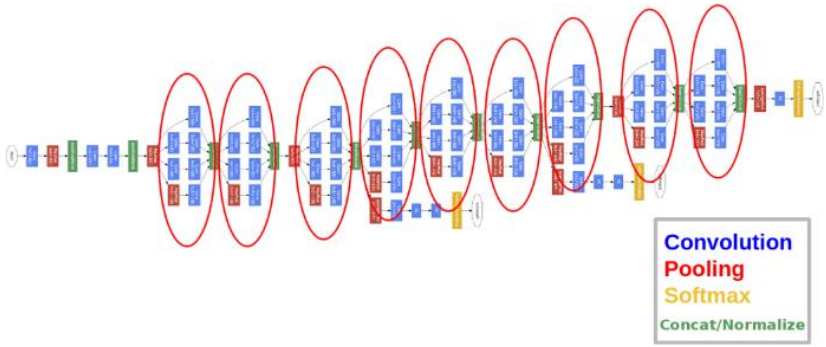
- **LeNet (1998)**



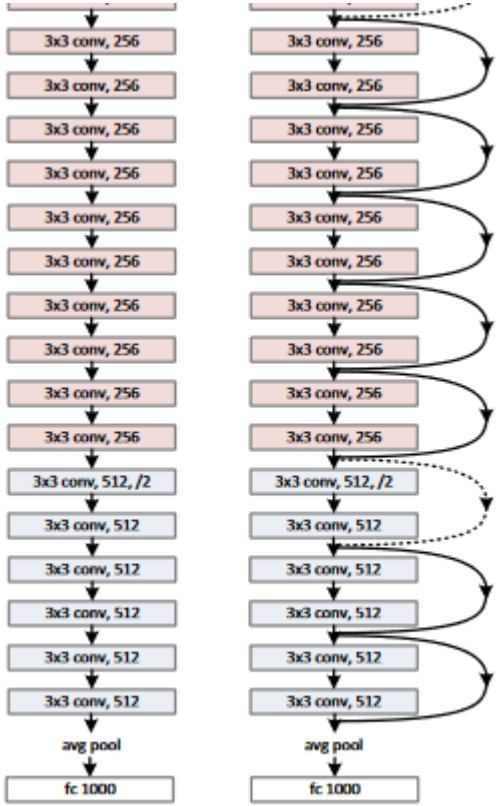
- **AlexNet (2012)**



- **GoogleLeNet (2014)**



- **ResNet (2015)**



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/