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Intro-to-DCNN-2019-2-28.odp

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July 2018;
Feb. 8, 2022;
August 20, 2022

A Quick Look At the DCNN Archiecture

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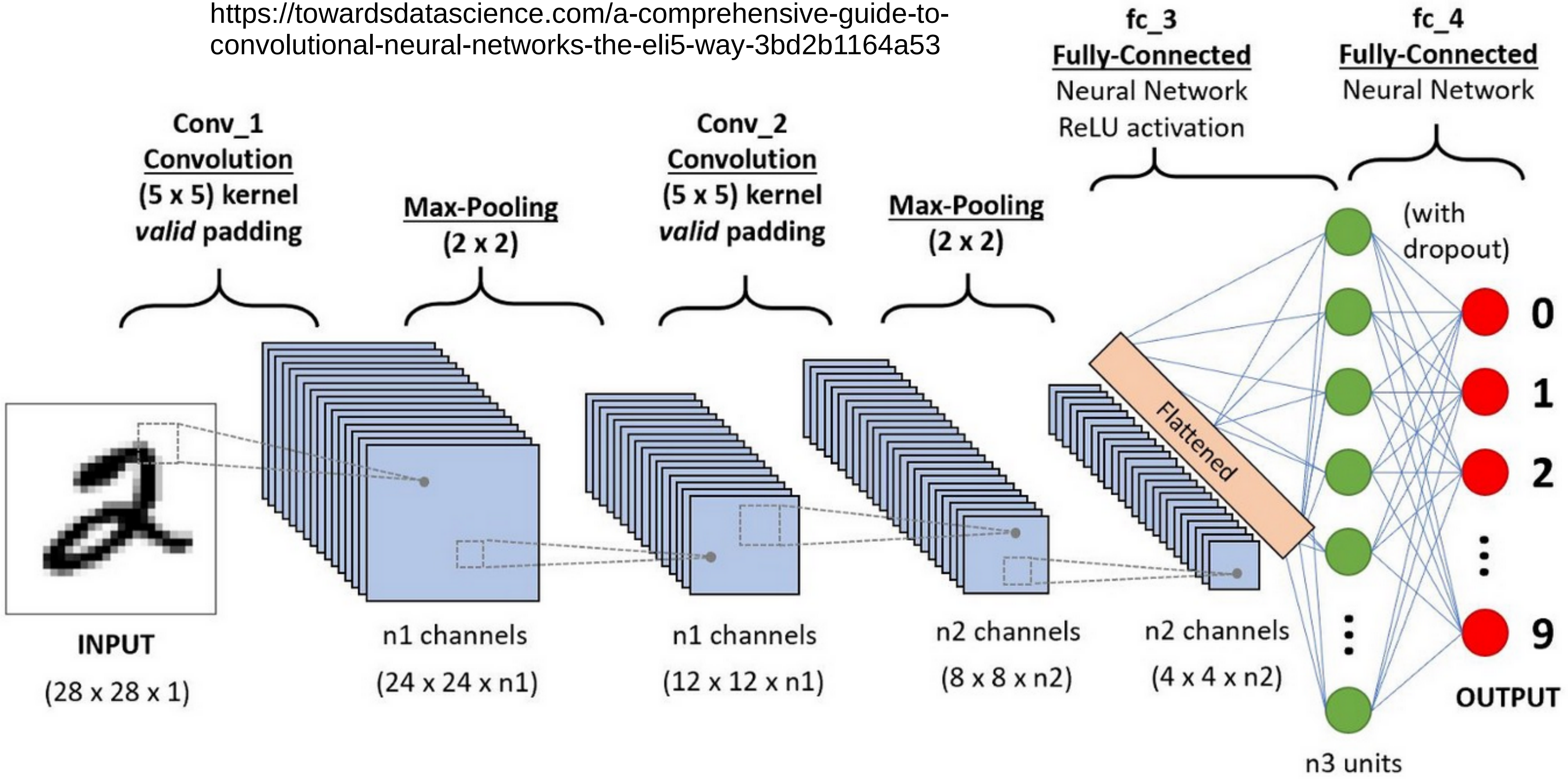
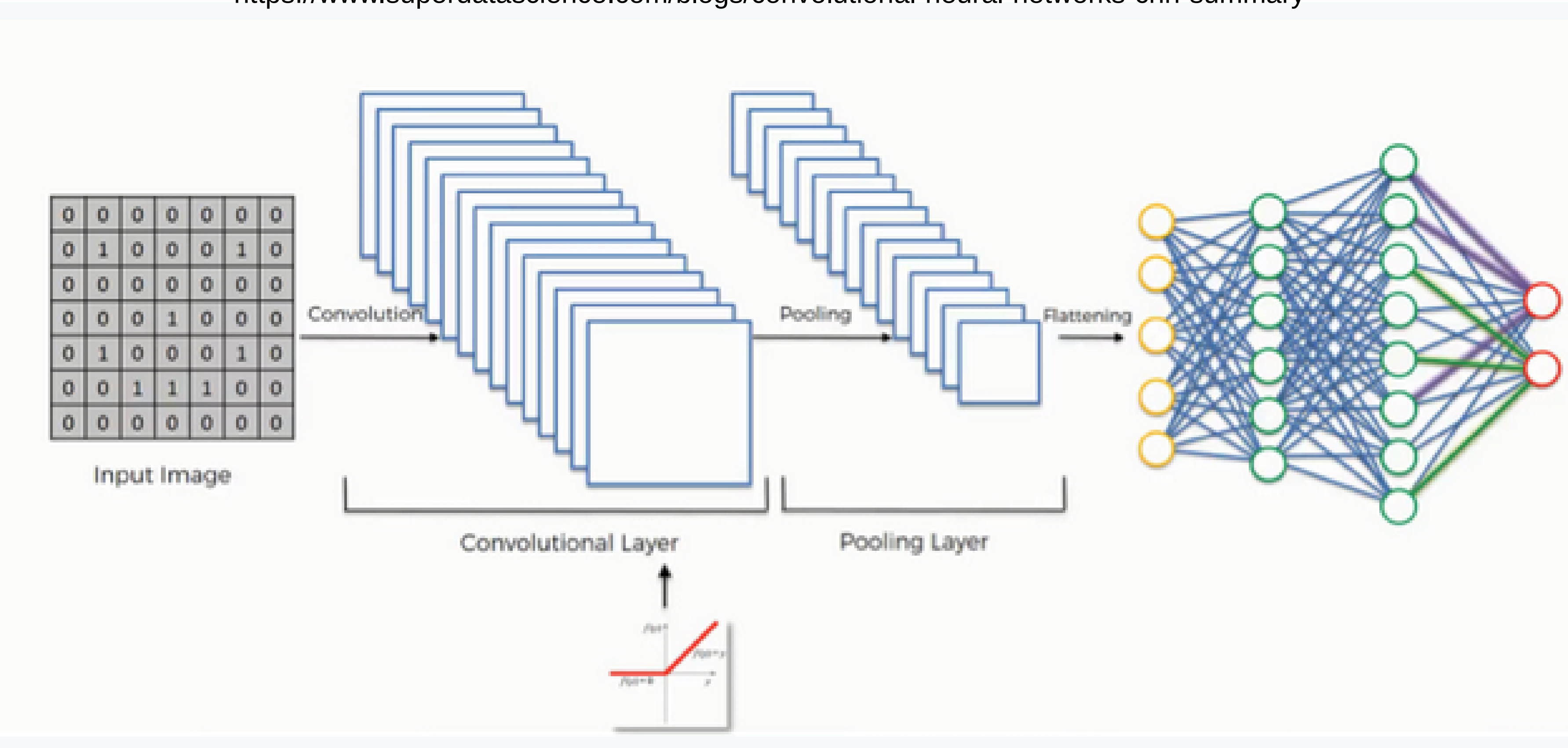
Illustration of A CNN for Digits Recognition

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53



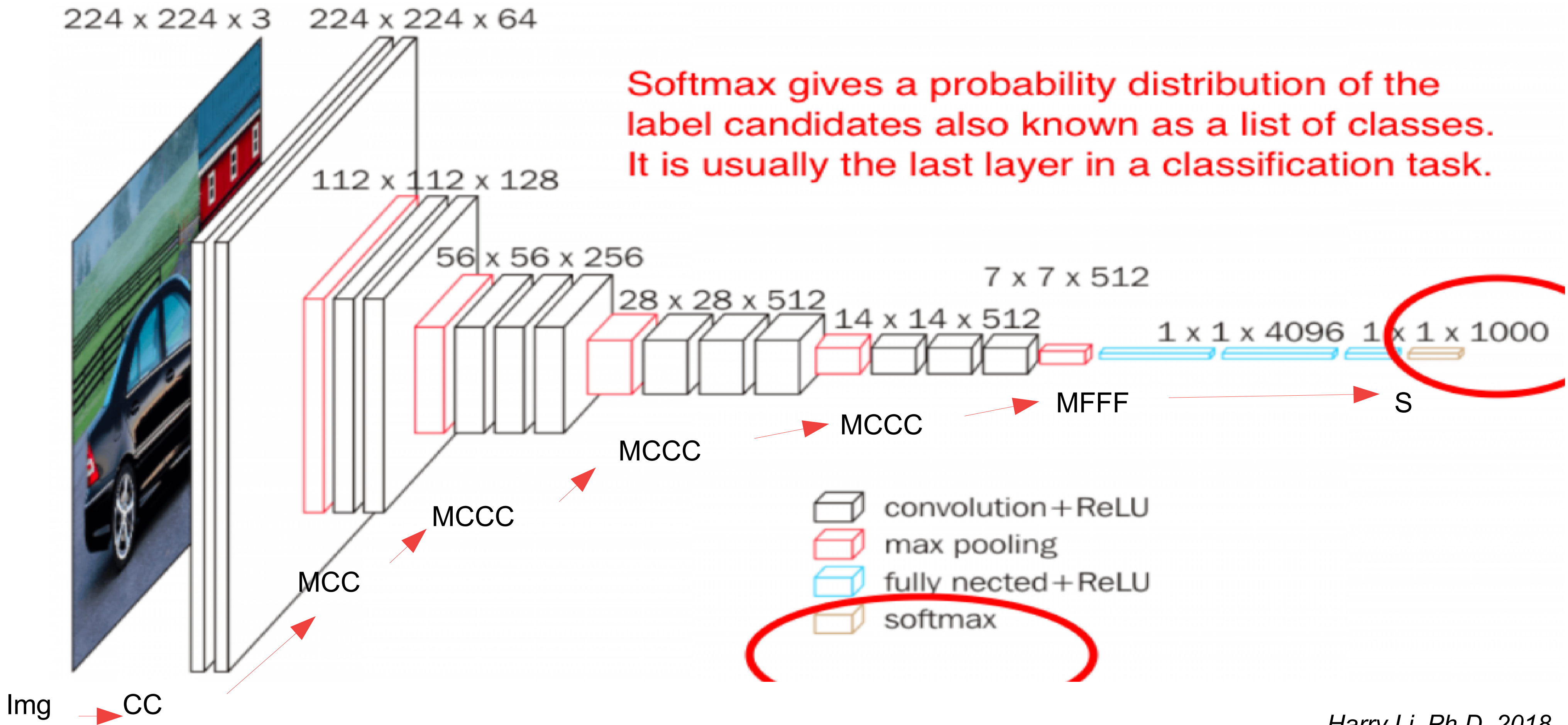
Convolution Neural Networks

https://www.superdatascience.com/blogs/convolutional-neural-networks-cnn-summary



Architecture Example VGG16

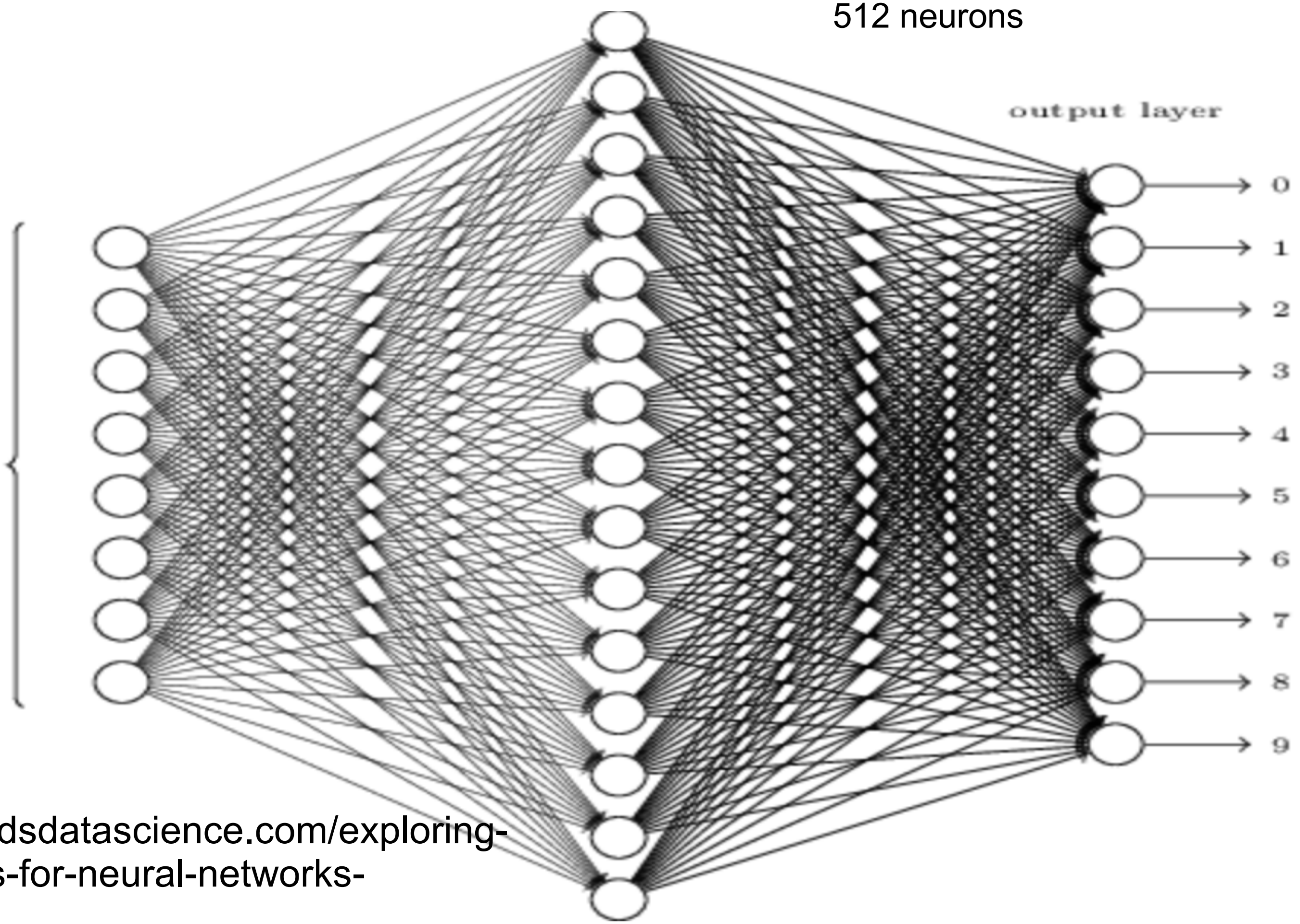
https://medium.com/data-science-bootcamp/understand-the-softmax-function-in-minutes-f3a59641e86d



Dense Layer

512 neurons

768 input
(28x28)



From: https://towardsdatascience.com/exploring-activation-functions-for-neural-networks-73498da59b02

Step 1 Understand the Architecture (MNIST Convnet)

model.summary

```
>>> model.summary()
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                36928
_________________________________________________________________
dense_2 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
```

Notation, Block Diagram and Math Formulation of a Single Neuron

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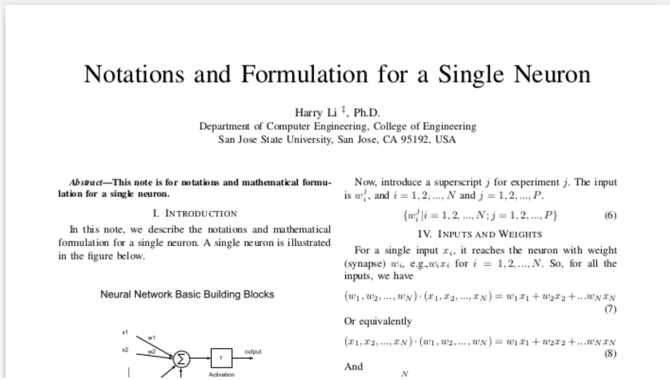
1. block diagram of a single neuron → 2. Notation for each component → 3. Transfer function and activation function → 4. Loss function (objective function)

Ref:



Notations and Formulation for a Single Neuron

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Abstract—**This note is for notations and mathematical formulation for a single neuron.**

I. Introduction

In this note, we describe the notations and mathematical formulation for a single neuron. A single neuron is illustrated in the figure below.

Neural Network Basic Building Blocks

Now, introduce a superscript j for experiment j. The input is w_i^j, and $i = 1, 2, ..., N$ and $j = 1, 2, ..., P$.

$$\{w_i^j | i = 1, 2, ..., N; j = 1, 2, ..., P\} \tag{6}$$

IV. Inputs and Weights

For a single input x_i, it reaches the neuron with weight (synapse) w_i, e.g.,$w_i x_i$ for $i = 1, 2, ..., N$. So, for all the inputs, we have

$$(w_1, w_2, ..., w_N) \cdot (x_1, x_2, ..., x_N) = w_1 x_1 + w_2 x_2 + ... w_N x_N \tag{7}$$

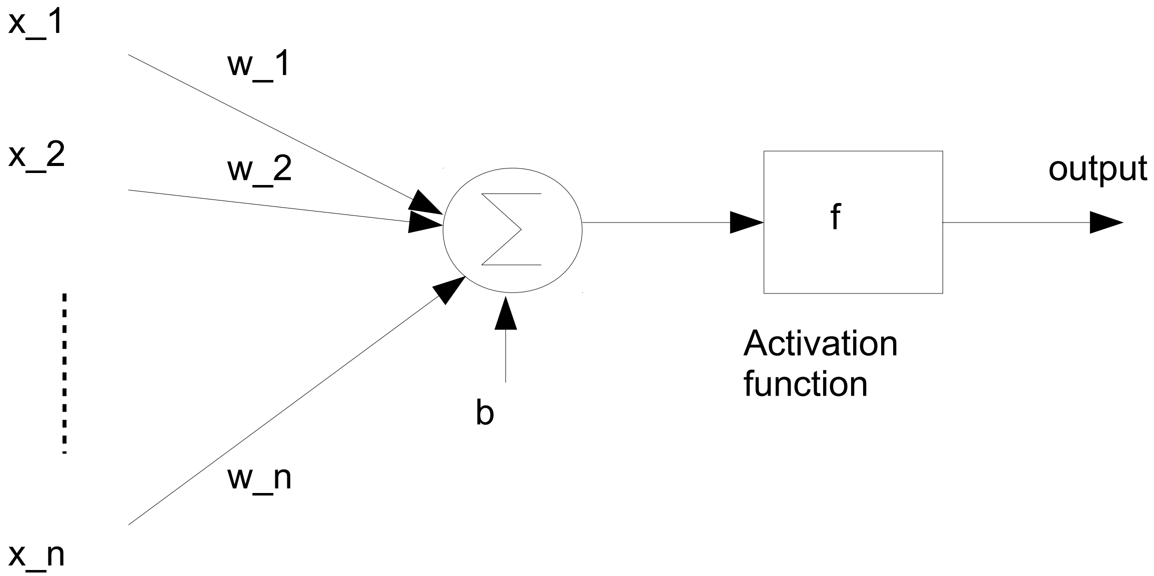
Or equivalently

$$(x_1, x_2, ..., x_N) \cdot (w_1, w_2, ..., w_N) = w_1 x_1 + w_2 x_2 + ... w_N x_N \tag{8}$$

And

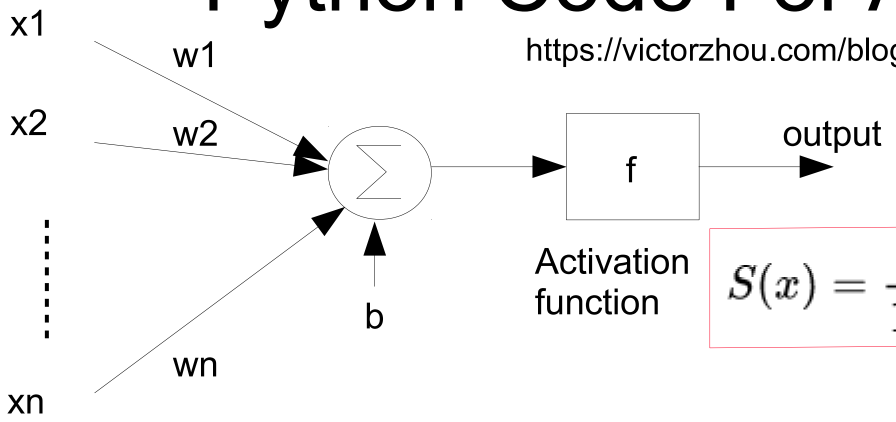
2022S-103a-notation-neuro-loss-function-2022-2-8.pdf

Neural Network Basic Building Block



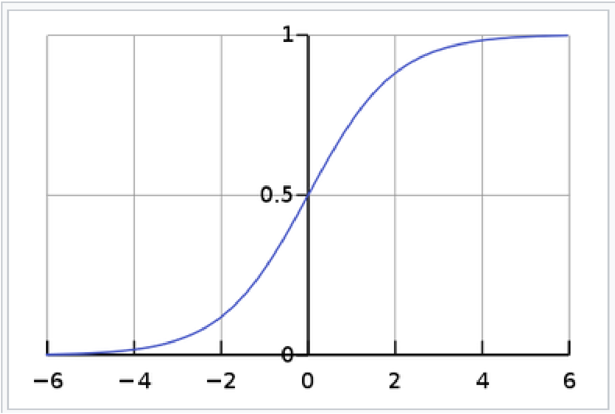
Python Code For A Single Neuron

https://victorzhou.com/blog/intro-to-neural-networks/



$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1} \qquad (1)$$

A sigmoid function is a mathematical function having a characteristic "S"-shaped curve



https://en.wikipedia.org/wiki/Sigmoid_function

Note: 1. define activation function

```
def sigmoid(x):
  # Our activation function: f(x) = 1 / (1 + e^(-x))
  return 1 / (1 + np.exp(-x))
```

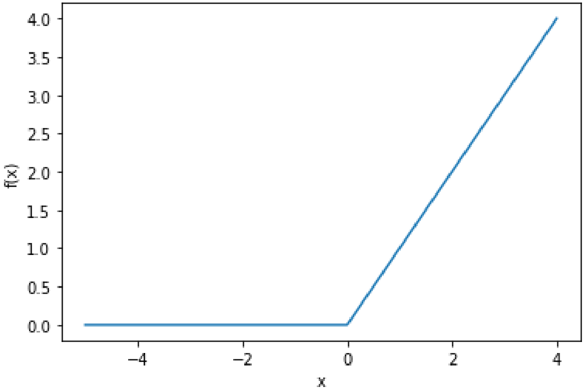
2. define a single neuron

```
class Neuron:
  def __init__(self, weights, bias):
    self.weights = weights
    self.bias = bias

  def feedforward(self, inputs):
    # Weight inputs, add bias, then use the activation function
    total = np.dot(self.weights, inputs) + self.bias
    return sigmoid(total)
```

Reference: for further discussion on Sigmoid
https://deepai.org/machine-learning-glossary-and-terms/sigmoid-function

Reference: RELU activation



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Python Classes Example

https://www.tutorialspoint.com/python3/python_classes_objects.htm

```
Create a python class with keyword class, then the name of
the class, then : sign
```

```
class ClassName:
   'Optional class documentation string'
   class_suite
```

1. The class has a documentation string, which can be accessed via ClassName.__doc__.

```
class Employee:
   'Common base class for all employees'
   empCount = 0
   def __init__(self, name, salary):
      self.name = name
      self.salary = salary
      Employee.empCount += 1

   def displayCount(self):
     print ("Total Employee %d" % Employee.empCount)
   def displayEmployee(self):
      print ("Name : ", self.name,  ", Salary: ", self.salary)
```

2. class variable whose value is shared among all the instances of a in this class.

3. The first method __init__() is a special method, which is called class constructor or initialization method that Python calls when you create a new instance of this class.

4. You declare other class methods like normal functions with the exception that the first argument to each method is self. Python adds the self argument to the list for you; you do not need to include it when you call the methods.

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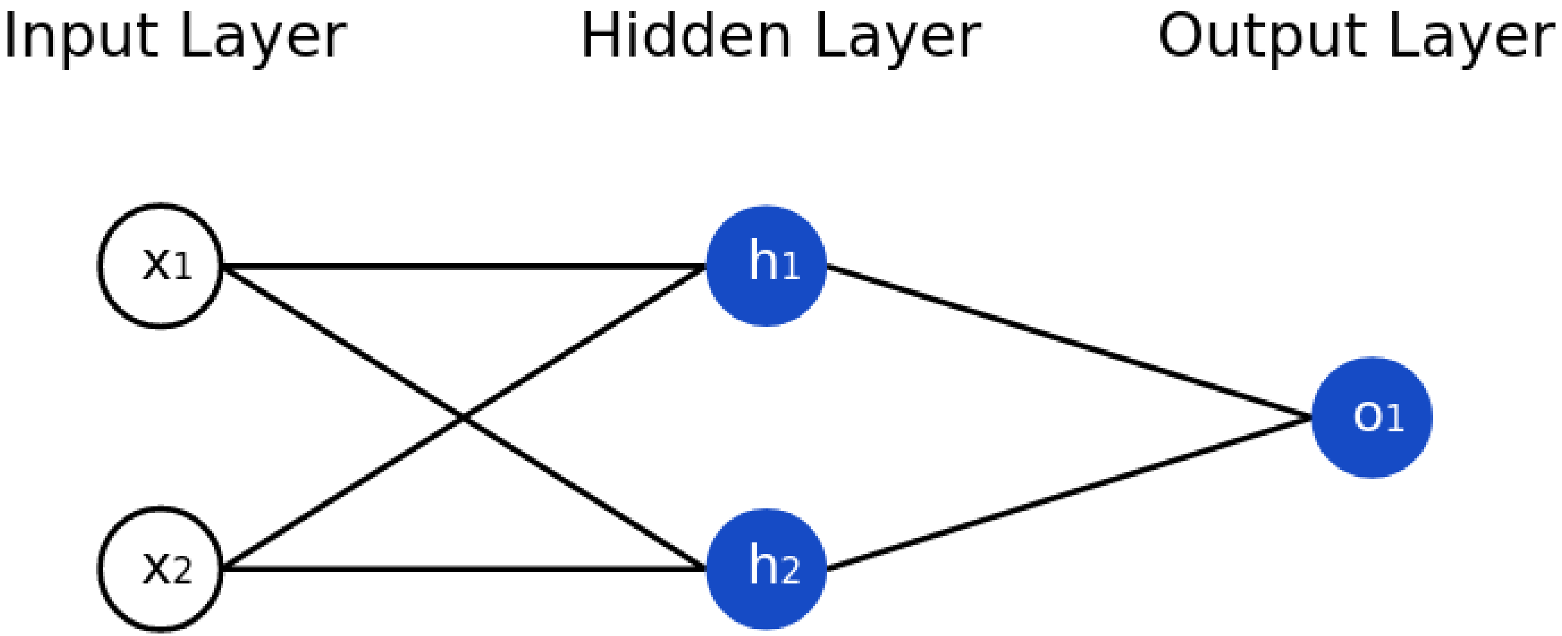
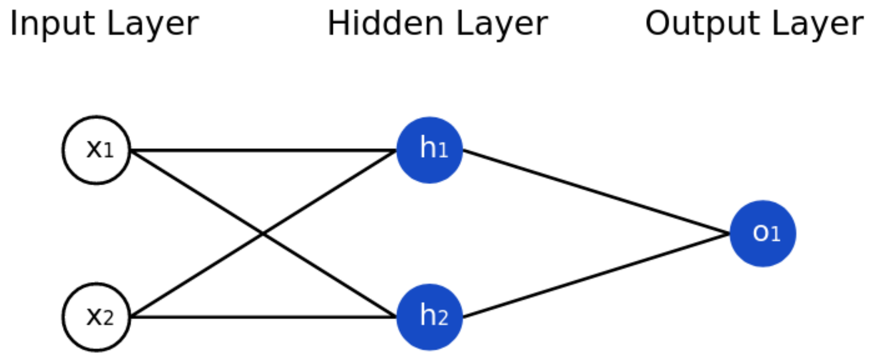
Feed Forward NN

https://victorzhou.com/blog/intro-to-neural-networks/



Python Code for Feed Forward NN

https://victorzhou.com/blog/intro-to-neural-networks/




```
  def __init__(self):
    weights = np.array([0, 1])
    bias = 0

    # The Neuron class here is from the previous section
    self.h1 = Neuron(weights, bias)
    self.h2 = Neuron(weights, bias)
    self.o1 = Neuron(weights, bias)

  def feedforward(self, x):
    out_h1 = self.h1.feedforward(x)
    out_h2 = self.h2.feedforward(x)

    # The inputs for o1 are the outputs from h1 and h2
    out_o1 = self.o1.feedforward(np.array([out_h1, out_h2]))

    return out_o1

network = OurNeuralNetwork()
x = np.array([2, 3])
print(network.feedforward(x))
```

Data Set and Prepare for Training

https://victorzhou.com/blog/intro-to-neural-networks/

Example: Collecting data for training

Name	Weight (lb)	Height (in)	Gender
Alice	133	65	F
Bob	160	72	M
Charlie	152	70	M
Diana	120	60	F

→

Name	Weight (minus 135)	Height (minus 66)	Gender
Alice	-2	-1	1
Bob	25	6	0
Charlie	17	4	0
Diana	-15	-6	1

Note: to reduce the mean value of the data, so it will have balanced distribution for both positive and negative side, it is good for the activation function to handle

Signs	Mij	Mpq	Sign
V1	133	65	Stop
V2	160	72	Right
V3	152	70	Right
V4	120	60	Stop

Define Loss Function

https://victorzhou.com/blog/intro-to-neural-networks/

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

The Mean Square Error Function as a loss function, very often it is also defined as objective function, e.g., minimize the loss function becomes objective function, as shown below step by step.

$$\downarrow$$

$$y_{true} - y_{pred}$$

$$\downarrow$$

$$(y_{true} - y_{pred})^2$$

$$\downarrow$$

$$\sum_{i=1}^{n}(y_{true} - y_{pred})^2 \longrightarrow \text{Exp}\left[\sum_{i=1}^{n}(y_{true} - y_{pred})^2\right]$$

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Define Loss Function

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The Mean Square Error Function as a loss function, very often it is also defined as objective function, e.g., minimize the loss function becomes objective function, as shown below step by step.

```
import numpy as np
def mse_loss(y_true, y_pred):
  # y_true and y_pred are numpy arrays of the same length.
  return ((y_true - y_pred) ** 2).mean()
```

$$\downarrow$$

$$y_{true} - y_{pred}$$

$$\downarrow$$

$$(y_{true} - y_{pred})^2$$

$$\downarrow$$

$$\sum_{i=1}^{n}(y_{true} - y_{pred})^2 \longrightarrow \text{Exp}\left[\sum_{i=1}^{n}(y_{true} - y_{pred})^2\right]$$

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Compute Loss Function

https://victorzhou.com/blog/intro-to-neural-networks/

Example: Given the following y_{true} and y_{pred}, compute the MSE

Name	y_{true}	y_{pred}	(y_{true} - y_{pred})^2
Alice	1	0	1
Bob	0	0	0
Charlie	0	0	0
Diana	1	0	1

$$\text{MSE} = \frac{1}{4}(1 + 0 + 0 + 1) = \boxed{0.5}$$

```
import numpy as np
def mse_loss(y_true, y_pred):
  # y_true and y_pred are numpy arrays of the same length.
  return ((y_true - y_pred) ** 2).mean()
y_true = np.array([1, 0, 0, 1])
y_pred = np.array([0, 0, 0, 0])
print(mse_loss(y_true, y_pred)) # 0.5
```

Loss Function and Learning

https://victorzhou.com/blog/intro-to-neural-networks/

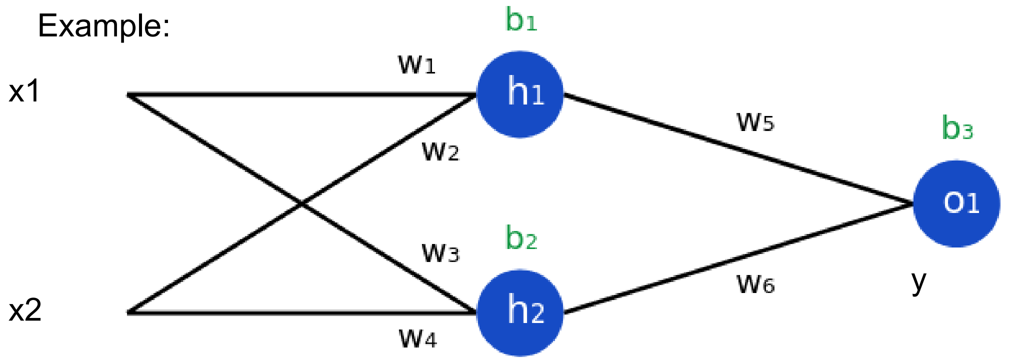
Loss function is a very important function to realize training, and to link the minimization of error to the NN weights.

Define a loss function as a function of NN parameters, e.g., weights and bias

$$L(w\_i , b\_j) = \sum_{i=1}^{n} (y_{true} - y_{pred})^2 \qquad (1)$$

Note y_{pred} is a function of NN parameters w_i, so it can be written as y_{pred} (w_i, b_j).

Example:



From the NN given in this example

We can write loss function with respect to the parameters as follows

L(w_i , b_j) , for I = 1,...,6 and for j = 1,2,3. So from Fig. 1 we have:

$$y_{pred} = o_1 = f(w_5 h_1 + w_6 h_2 + b_3) \qquad (2)$$

Where h1 can be written as

$$h_1 = f(w_1 x_1 + w_2 x_2 + b_1) \qquad (3)$$

Note: we will introduce more generalized notations from equations (1) to (3), for now we will stay with this notation

Remark 1: To minimize loss function with respect to the variables w and b according

Steepest Gradient Descent Algorithm

https://github.com/hualili/opencv/blob/master/deep-learning-2020S/20-2021S-4gradient-descent-final-2021-2-8.pdf

Lecture Note 1 on Gradient Descent

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***Abstract*—In this lecture note, we give a gradient descent example for its applications in Neural Networks (NN), e.g., the concept of the negative gradient -∇f follows the direction of steepest descent.**

I. Introduction

In this lecture note, we give a gradient descent example for Neural Networks (NN) applications. In particular, the basic concept of the negative gradient -∇f follows the direction of steepest descent of a given function f which can be an error function.

II. Partial Derivative vs. Gradient

Given a scalar-valued multivariable functions, e.g. the function with a multidimensional input $x_1, x_2, ..., x_n$, and a one-dimensional output as $y = f(x_1, x_2, ..., x_))$, where $f : R^n \rightarrow R$. The partial derivative of $f(x_1, x_2, ..., x_n)$ with respect to x_i for $i = 1, 2, ..., n$:

$$\frac{\partial f}{\partial x_i} = \lim_{\delta x \to 0} \frac{f(x_1, .., x_i + \delta x_i, .., x_n) - f(x_1, ..., x_i, ..., x_n)}{\delta x_i} \quad (1)$$

IV. Gredient Steepest Descent for Minimization

Now, let's define f as an error function, and we would like to minimize it. So we can try to change its inputs (x_1, x_2) by iteration steps:

$$(x_1^{k+1}, x_2^{k+1}) = (x_1^k, x_2^k) + (-\eta \nabla f) \quad (5)$$

which will reduce the function value f. To verify this, write f in terms of Taylar expansion as follows

$$f(x_1, x_2) \simeq f(a, b) + \frac{\partial f}{\partial x_1}(x_1 - a) + \frac{\partial f}{\partial x_2}(x_2 - b) \quad (6)$$

use simplified notation for the partial derivative f_{x_1} and f_{x_2}, we have

$$f(x_1, x_2) \simeq f(a, b) + f_{x_1}(a, b) * (x_1 - a) + f_{x_2}(a, b) * (x_2 - b) \quad (7)$$

we want to update (x_1^k, x_2^k) to (x_1^{k+1}, x_2^{k+1}) such that $f(x_1^{k+1}, x_2^{k+1}) < f(x_1^k, x_2^k)$. From equation (6), replace (x_1, x_2) by (x_1^{k+1}, x_2^{k+1}), and let $(x_1^k, x_2^k) = (a, b)$, so we have