### concept of classification

```
In [3]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import warnings
   warnings.filterwarnings('ignore')

In [5]: x =np.array([0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0])

In [6]: y = np.round(x)

In [7]: y

Out[7]: array([0., 0., 0., 0., 0., 1., 1., 1., 1.])

In [8]: # and that is defined the concepts of classification
```

# Sigmoid curve

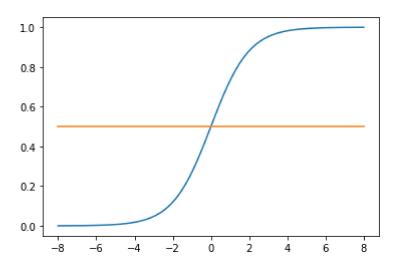
Sigmoid Function acts as an activation function in machine learning which is used to add non-linearity in a machine learning model, in simple words it decides which value to pass as output and what not to pass, there are mainly 7 types of Activation Functions which are used in machine learning and deep learning.

```
In [13]: data= pd.DataFrame({'Actual':x, 'pred':y})
In [15]: data
Out[15]:
               Actual pred
            0
                  0.1
                        0.0
            1
                  0.2
                        0.0
            2
                  0.3
                        0.0
            3
                        0.0
                  0.4
                  0.5
                        0.0
            5
                  0.6
                        1.0
            6
                  0.7
                        1.0
            7
                  8.0
                        1.0
            8
                  0.9
                        1.0
            9
                  1.0
                        1.0
```

```
In [28]: |outcome = 1/(1+np.exp(-data))|
In [29]:
         outcome
Out[29]:
               Actual
                         pred
             0.524979
                     0.500000
             0.549834
                     0.500000
            0.574443 0.500000
             0.598688
                     0.500000
             0.622459
                    0.500000
            0.645656 0.731059
             0.668188 0.731059
            0.689974 0.731059
             0.710950 0.731059
             0.731059 0.731059
         data1 = np.linspace(-8,8,1000)
In [30]:
In [31]:
         data1
Out[31]: array([-8.
                            , -7.98398398, -7.96796797, -7.95195195, -7.93593594,
                 -7.91991992, -7.9039039 , -7.88788789, -7.87187187, -7.85585586,
                 -7.83983984, -7.82382382, -7.80780781, -7.79179179, -7.77577578,
                 -7.75975976, -7.74374374, -7.72772773, -7.71171171, -7.6956957,
                 -7.67967968, -7.66366366, -7.64764765, -7.63163163, -7.61561562,
                 -7.5995996 , -7.58358358, -7.56756757, -7.55155155, -7.53553554,
                 -7.51951952, -7.5035035 , -7.48748749, -7.47147147, -7.45545546,
                 -7.43943944, -7.42342342, -7.40740741, -7.39139139, -7.37537538,
                 -7.35935936, -7.34334334, -7.32732733, -7.31131131, -7.2952953 ,
                 -7.27927928, -7.26326326, -7.24724725, -7.23123123, -7.21521522,
                 -7.1991992 , -7.18318318, -7.16716717, -7.15115115, -7.13513514,
                 -7.11911912, -7.1031031 , -7.08708709, -7.07107107, -7.05505506,
                 -7.03903904, -7.02302302, -7.00700701, -6.99099099, -6.97497497,
                 -6.95895896, -6.94294294, -6.92692693, -6.91091091, -6.89489489,
                 -6.87887888, -6.86286286, -6.84684685, -6.83083083, -6.81481481,
                 -6.7987988 , -6.78278278, -6.76676677, -6.75075075, -6.73473473,
                 -6.71871872, -6.7027027 , -6.68668669, -6.67067067, -6.65465465,
                 -6.63863864, -6.62262262, -6.60660661, -6.59059059, -6.57457457,
                 -6.55855856, -6.54254254, -6.52652653, -6.51051051, -6.49449449,
         outcome = 1/(1+np.exp(-data1))
In [35]:
```

```
In [36]:
         outcome
Out[36]: array([3.35350130e-04, 3.40762500e-04, 3.46262192e-04, 3.51850614e-04,
                3.57529197e-04, 3.63299395e-04, 3.69162683e-04, 3.75120564e-04,
                3.81174562e-04, 3.87326227e-04, 3.93577132e-04, 3.99928878e-04,
                4.06383089e-04, 4.12941419e-04, 4.19605544e-04, 4.26377170e-04,
                4.33258030e-04, 4.40249884e-04, 4.47354521e-04, 4.54573758e-04,
                4.61909443e-04, 4.69363453e-04, 4.76937693e-04, 4.84634101e-04,
                4.92454646e-04, 5.00401328e-04, 5.08476179e-04, 5.16681265e-04,
                5.25018684e-04, 5.33490567e-04, 5.42099082e-04, 5.50846429e-04,
                5.59734844e-04, 5.68766601e-04, 5.77944008e-04, 5.87269411e-04,
                5.96745194e-04, 6.06373779e-04, 6.16157627e-04, 6.26099239e-04,
                6.36201155e-04, 6.46465957e-04, 6.56896268e-04, 6.67494753e-04,
                6.78264119e-04, 6.89207119e-04, 7.00326548e-04, 7.11625245e-04,
                7.23106099e-04, 7.34772039e-04, 7.46626047e-04, 7.58671150e-04,
                7.70910422e-04, 7.83346990e-04, 7.95984029e-04, 8.08824765e-04,
                8.21872476e-04, 8.35130493e-04, 8.48602199e-04, 8.62291034e-04,
                8.76200490e-04, 8.90334117e-04, 9.04695521e-04, 9.19288366e-04,
                9.34116376e-04, 9.49183333e-04, 9.64493079e-04, 9.80049520e-04,
                9.95856623e-04, 1.01191842e-03, 1.02823900e-03, 1.04482253e-03,
                1.06167324e-03, 1.07879542e-03, 1.09619344e-03, 1.11387173e-03,
In [71]:
         plt.plot(data1,outcome)
         plt.plot([-8,8],[0.5,0.5
                          1)
```

#### Out[71]: [<matplotlib.lines.Line2D at 0x2a5ad128430>]



### **Confusion matrix**

confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data forwhich the true (actual) values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing

##Let's now define the most basic terms, which are whole numbers (not rates):

## true positives

(TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.true negatives (TN): We predicted no, and they don't have the disease.false positives (FP): We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")false negatives (FN): We predicted no, but they actually do have the disease. (Also known as a "Type II error.")

```
In [ ]:
 In [ ]:
In [39]:
         actual= [1,0,1,1,0,0,0,0,1,1]
         pred= [0,1,1,0,0,1,0,1,0,1]
In [42]: dataf = pd.DataFrame({'Actual':actual,'predicted':pred})
In [43]:
         dataf
Out[43]:
             Actual predicted
          0
                 1
                          0
                 0
                          1
          2
                 1
                          1
           3
                 1
                          0
                 0
                          0
          5
                 0
                          1
          6
                 0
                          0
                 0
                          1
          8
                          0
                          1
         from sklearn
                        import metrics
In [48]:
In [51]:
         from sklearn import metrics
In [53]: metrics.confusion_matrix(actual,pred)
Out[53]: array([[2, 3],
                 [3, 2]], dtype=int64)
In [54]: metrics.confusion_matrix(actual,pred)
Out[54]: array([[2, 3],
                 [3, 2]], dtype=int64)
```

```
In [58]: metrics.accuracy_score(actual,pred)*100
Out[58]: 40.0
In [60]: from sklearn import metrics
In [62]: metrics.confusion_matrix(actual,pred)
Out[62]: array([[2, 3],
                [3, 2]], dtype=int64)
In [63]: from sklearn import metrics
In [65]: metrics.confusion_matrix(actual,pred)
Out[65]: array([[2, 3],
                [3, 2]], dtype=int64)
In [66]: from sklearn import metrics
In [67]: metrics.confusion_matrix(actual,pred)
Out[67]: array([[2, 3],
                [3, 2]], dtype=int64)
In [70]: metrics.accuracy score(actual, pred)*100
Out[70]: 40.0
```