Experiment No. 1 - Implement simple logic network using Mc-Culloch Pitts (MP) neuron model

Mc-Culloch Pitts (MP) neuron

The fundamental block of deep learning is artificial neuron i.e. it takes a weighted aggregate of inputs, applies a function and gives an output. The very first step towards the artificial neuron was taken by Warren McCulloch and Walter Pitts in 1943 inspired by neurobiology, created a model known as McCulloch-Pitts Neuron. [2]

- **Data** - Binary Input
- **Task** - Classification Binary Output (0 or 1)
- **Mathematical Model** - MP Neuron
- **Loss Function** - Mean Squared Error
- **Learning Algorithm** - Bruce Force
- **Model Evaluation** - Accuracy

Algorithm

1. Import Library
2. Load the data
3. Train Test Split
4. Binarisation of data
5. MP Neuron Model
6. Training the Model
7. Testing the Model

1. Import Library

In [1]:
```
import sklearn.datasets
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import Image
```

2. Load the data

In [2]:
```
breast_cancer = sklearn.datasets.load_breast_cancer()

#Converting the data to Pandas dataframe

data = pd.DataFrame(breast_cancer.data, columns = breast_cancer.featur
e_names)
data['class']=breast_cancer.target
print(data.head())
```

```
   mean radius  mean texture  mean perimeter  mean area  mean smoothne
ss  \
0        17.99         10.38          122.80     1001.0          0.118
40
1        20.57         17.77          132.90     1326.0          0.084
74
2        19.69         21.25          130.00     1203.0          0.109
60
3        11.42         20.38           77.58      386.1          0.142
50
4        20.29         14.34          135.10     1297.0          0.100
30

   mean compactness  mean concavity  mean concave points  mean symmetr
y  \
0           0.27760          0.3001              0.14710          0.241
9
1           0.07864          0.0869              0.07017          0.181
2
2           0.15990          0.1974              0.12790          0.206
9
3           0.28390          0.2414              0.10520          0.259
7
4           0.13280          0.1980              0.10430          0.180
9

   mean fractal dimension  ...  worst texture  worst perimeter  worst
area  \
0                 0.07871  ...          17.33           184.60      20
19.0
1                 0.05667  ...          23.41           158.80      19
56.0
2                 0.05999  ...          25.53           152.50      17
09.0
3                 0.09744  ...          26.50            98.87       5
67.7
4                 0.05883  ...          16.67           152.20      15
75.0

   worst smoothness  worst compactness  worst concavity  worst concave
points  \
0            0.1622             0.6656           0.7119
0.2654
1            0.1238             0.1866           0.2416
0.1860
2            0.1444             0.4245           0.4504
0.2430
3            0.2098             0.8663           0.6869
0.2575
4            0.1374             0.2050           0.4000
0.1625

   worst symmetry  worst fractal dimension  class
0          0.4601                  0.11890      0
1          0.2750                  0.08902      0
2          0.3613                  0.08758      0
3          0.6638                  0.17300      0
4          0.2364                  0.07678      0

[5 rows x 31 columns]
```

In [3]:
```
print(breast_cancer.target_names)
print(data['class'].value_counts())

print(data.groupby('class').describe())
```

```
['malignant' 'benign']
1    357
0    212
Name: class, dtype: int64
      mean radius
\
            count       mean       std     min     25%     50%    75%
max
class
0           212.0  17.462830  3.203971  10.950  15.075  17.325  19.59
28.11
1           357.0  12.146524  1.780512   6.981  11.080  12.200  13.37
17.85

      mean texture             ... worst symmetry           \
             count       mean  ...            75%     max
class                          ...
0            212.0  21.604906  ...       0.359225  0.6638
1            357.0  17.914762  ...       0.298300  0.4228

      worst fractal dimension
\
                        count      mean       std      min       25%
50%
class
0                       212.0  0.091530  0.021553  0.05504  0.076302
0.08760
1                       357.0  0.079442  0.013804  0.05521  0.070090
0.07712


            75%     max
class
0      0.102625  0.2075
1      0.085410  0.1486

[2 rows x 240 columns]
```

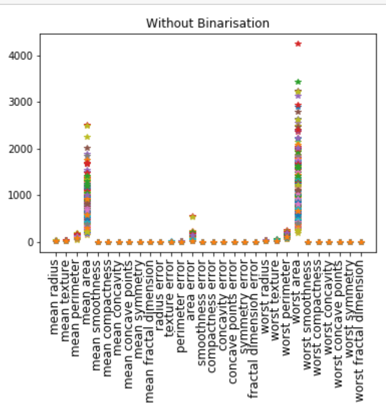
3. Train Test Split

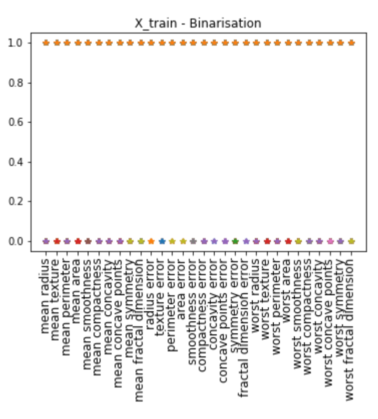
In [4]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

X = data.drop('class', axis = 1)
Y = data['class']

# after error add random_state=1
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.
1, stratify = Y)

print(X_train.shape, X_test.shape)

print(Y_train.mean())
print(Y_test.mean())
```

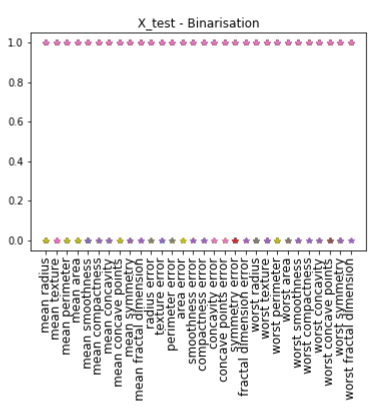
```
(512, 30) (57, 30)
0.626953125
0.631578947368421
```

4. Binarisation of data

In [5]:
```
plt.plot(X_train.T,'*')
plt.xticks(rotation = 'vertical', fontsize = 'large')
plt.title('Without Binarisation')
plt.show()

#converting the input features to a binary format
X_binarised_train = X_train.apply(pd.cut, bins=2, labels=[1,0])
X_binarised_test = X_test.apply(pd.cut, bins=2, labels=[1,0])

plt.plot(X_binarised_train.T,'*')
plt.xticks(rotation = 'vertical', fontsize = 'large')
plt.title('X_train - Binarisation')
plt.show()

plt.plot(X_binarised_test.T,"*")
plt.xticks(rotation = 'vertical',fontsize = 'large')
plt.title('X_test - Binarisation')
plt.show()

# convert to np array
X_binarised_test = X_binarised_test.values
X_binarised_train = X_binarised_train.values
```







5. MP Neuron Model

In [6]:
```
class MPNeuron:

    def __init__(self):
        self.b = None

    def model(self, x):
        return(sum(x) >= self.b)

    def predict(self, X):
        Y = []
        for x in X:
            result = self.model(x)
            Y.append(result)
        return np.array(Y)

    def fit(self, X, Y):
        accuracy = {}

        for b in range(X.shape[1]+1):
            self.b = b
            Y_pred = self.predict(X)
            accuracy[b] = accuracy_score(Y_pred, Y)

        best_b = max(accuracy, key = accuracy.get)
        self.b = best_b

        print('Optimal value of b is', best_b)
        print('Highest accuracy is', accuracy[best_b])
```

6. Training the Model

In [7]:
```
#Calling the class MPNeuron
mp_neuron = MPNeuron()

#Fitting the model
mp_neuron.fit(X_binarised_train, Y_train)
```

```
Optimal value of b is 28
Highest accuracy is 0.85546875
```

7. Testing the Model

In [8]:
```
#testing the model on the test data.
Y_test_pred = mp_neuron.predict(X_binarised_test)
accuracy_test = accuracy_score(Y_test_pred, Y_test)

#print the accuracy of the test data
print(accuracy_test)
```

```
0.8070175438596491
```

Questions

1. Explain Mc – Culloch Pitts Neuron architecture with neat figure.

Ans:-

In [9]:
```
Image(filename="img/architecture.png")
```

Out[9]:

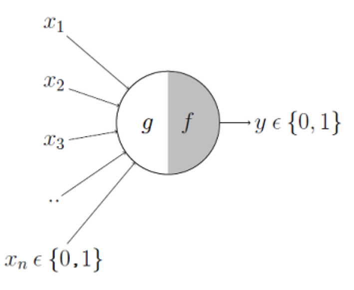


Fig. 1. Architecture of MP Neuron[3]

$$y = \sum_{i=1}^{n} x_i \geq b$$

where x is input or features,
b is threshold,
and, y is output

In MP Neuron we just do sum of input and through training we find the best threshold point. Input and output values are binary.

2. Realize AND-NOT function using MP neuron model.

Ans:-

AND function

A	B	Y
0	0	0
0	1	0
1	0	0
1	1	1

$$y = \begin{cases} 0 & \text{if } \sum x < 1 \\ 1 & \text{if } \sum x \geq 1 \end{cases}$$

NOT function

A	Y
0	1
1	0

$$y = \begin{cases} 0 & \text{if } x = 1 \\ 1 & \text{if } x = 0 \end{cases}$$

3. Draw structure of biological neuron and explain it.

Ans:-

In [10]:
```
Image(filename="img/biological_neuron.png")
```

Out[10]:

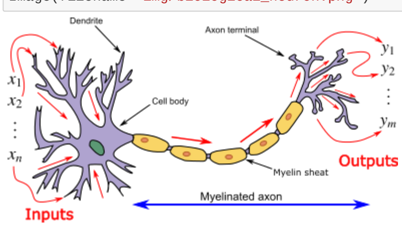


Fig. 2. Biological Neuron

- **Dendrite:** Receives signals from other neurons
- **Soma:** Sums all the incoming signals
- **Axon:** When a particular amount of input is received, then the cell fires. It transmits signal through axon to other cells

4. Realize NAND function using MP neuron model.

Ans:-

NAND function

A	B	Y
0	0	1
0	1	1
1	0	1
1	1	0

$$y = \begin{cases} 0 & \text{if } \sum x = 2 \\ 1 & \text{if } \sum x < 2 \end{cases}$$

5. State advantages & applications of MP neuron model.

Ans:-

Advantages

1. Simple
2. Low Size
3. Plays with 0 and 1

Applications

1. Logic Gates
2. LBW
3. Breast Cancer

References

[1] https://github.com/hitanshu-mehta/predicting-type-of-breast-cancer/blob/master/MP_neuron.ipynb

[2] https://hackernoon.com/mcculloch-pitts-neuron-deep-learning-building-blocks-7928f4e0504d

[3] https://towardsdatascience.com/mcculloch-pitts-model-5fdf65ac5dd1

Author Name:- Hemant Ghuge
LinkedIn:- https://www.linkedin.com/in/hemantghuge/
GitHub:- https://github.com/HemantGorakshGhuge