

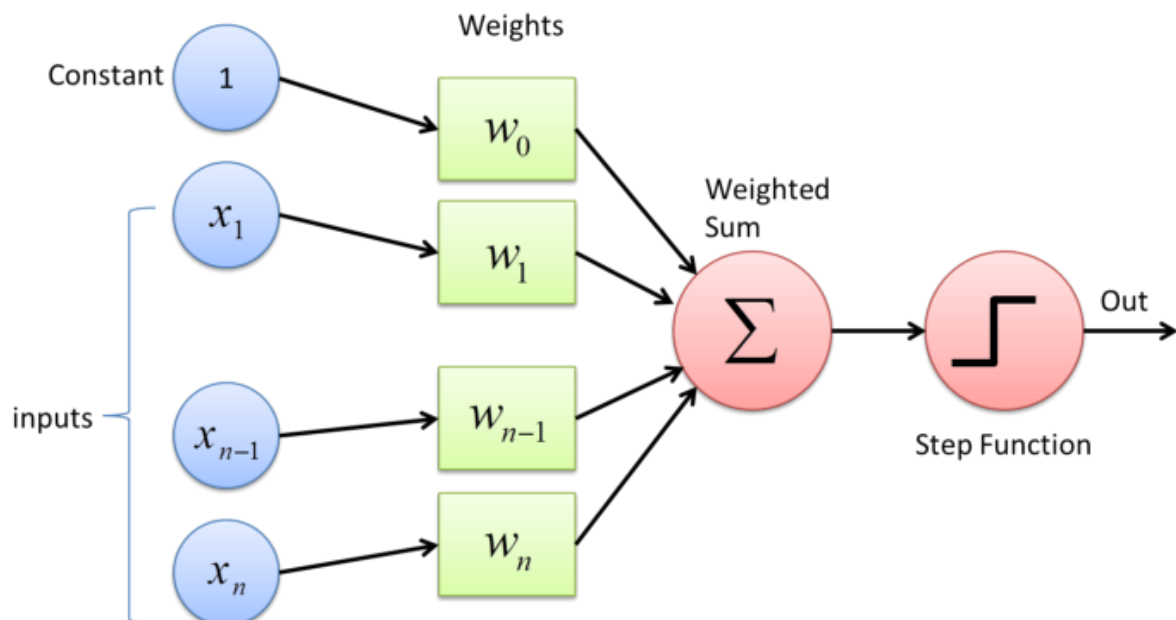
## **PART 1:**

What is Perceptron?:

Perceptron (artificial neuron) is considered one of the early version of modern neural networks

Its consists of a single-layer neural network and is used as a linear(binary) classifier in supervised classification. Perceptron is also considered an iterative algorithm.

- It consists of a vector of inputs(including the constant 1-for bias-)  $X$ .
- It consists of a vector of weights(including the bias)  $W$ .
  - Bias value allows us to move the activation function curve up or down.
- Weighted sum.
- It consists of an activation function to map the input to the desired output (binary output) e.g: (0,1).



### Applying the Algorithm by hand to some dataset:

Input	Output
[0.08,0.72]	-> 1
[0.1, 1]	-> 0
[0.26,0.58]	-> 1
[0.35,0.95]	-> 0
[0.45,0.15]	-> 1
[0.6,0.30]	-> 1
[0.7, 0.65]	-> 0
[0.92, 0.4]	-> 0

0 -> Red Class

1 -> Blue Class

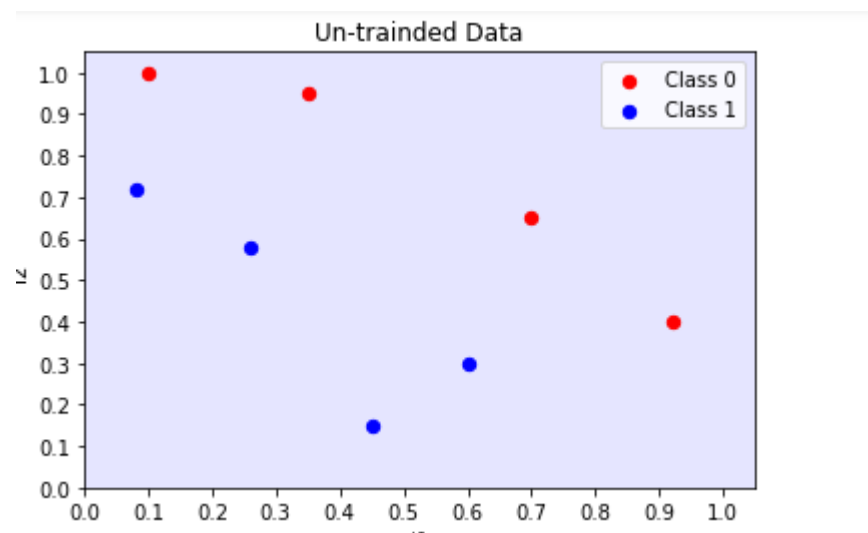
PS: We will add extra input for the input vector with value 1 (for bias)

Initial Weights:

[0, 0, 0]

Data before being classified, everything will be blue according to the initial weights and the activation function.

Activation function = 1 if weighted\_sum >= 0 else 0



So we calculate the new weights for each input

$W_{ij}' = W_{ij} + \text{learning rate} * (\text{Actual Output} - \text{Predicted Output}) * x_{ij}$ ,  $i$  = which weight for input,  $J$  = which input.

Delta\_Error

We will use learning rate = 0.2

Lower Lrate means need more epochs to train but will be more accurate than higher Lrate which needs fewer epochs but will give more incorrect results on the test

$$W_{11}' = 0 + 0.2 * (1 - 1) * 1 = 0$$

$$W_{21}' = 0 + 0.2 * 0 * 0.08 = 0$$

$$W_{21}' = 0 + 0.2 * 0 * 0.72 = 0$$

And so on

We do this for every input every epoch and we reach 100% accuracy.

When we apply this for the 2th input ([0.35,0.95] -> 0) in the first epoch

$$W_{12}' = 0 + 0.2 * -1 * 1 = -0.2$$

$$W_{22}' = 0 + 0.2 * -1 * 0.1 = -0.02$$

$$W_{32}' = 0 + 0.2 * -1 * 1 = -0.2$$

[ 0. 0.032 -0.084]  
 [ 0. 0.032 -0.084]  
 [ 0. 0.032 -0.084]  
 [ 0.2 0.152 -0.024]  
 [ 0. 0.012 -0.154]  
 [ 0. 0.012 -0.154]

In the 2ndEpoch, the weights will be:

[ 0. 0.012 -0.154]

And the accuracy will be 50% so we keep training

In the 3rd epoch:

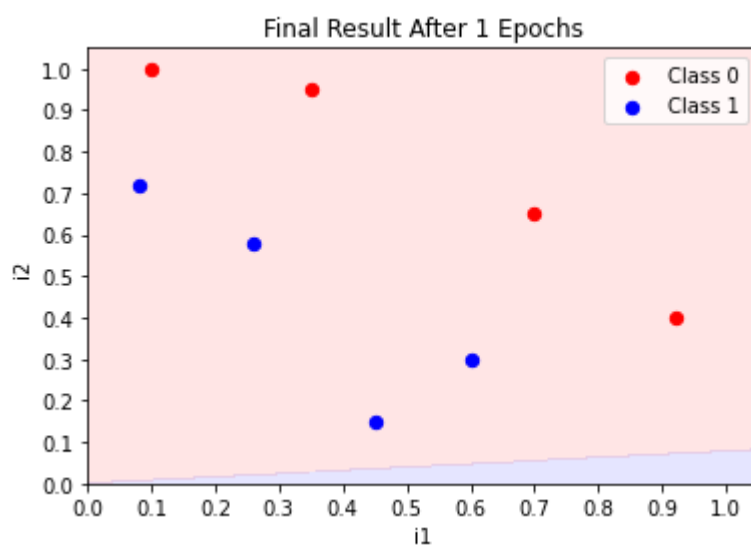
Weights: [ 0. -0.06 -0.384], Accuracy: 50%

In the 4rd epoch:

Weights: [ 0. -0.184 -0.37 ], Accuracy: 50%

In the 5rd epoch:

Weights: [ 0.2 -0.168 -0.226], Accuracy: 100%

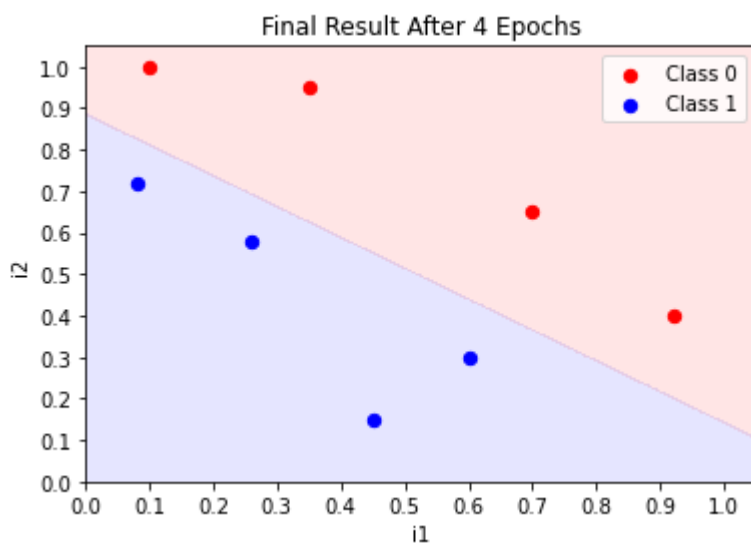


And so on

When we reach the 5th epoch the accuracy will be 100% (so it took 4 epochs to train)

And the final weights will be:

Final Weights: [ 0.2 -0.168 -0.226]



**The code below represents the Perceptron algorithm for linear classification:**

```
In [8]: #12200116
#NOUVPAD SHA216
import numpy as np
from matplotlib import pyplot as plt

In [9]: #train the data by predicting the result and edit the weight each time
#until the accuracy is 100% or reaches the max. n_epochs
def Train_Data(inputs, outputs, weights, l_rate = 0.1, n_epoch=100):
    for epoch in range(1, n_epoch+1):
        if accuracy(inputs, outputs, weights) == 1:
            break;
        for i in range(inputs.shape[0]):
            delta_error = outputs[i] - predict(inputs[i], weights)
            for j in range(len(weights)):
                weights[j] = weights[j] + l_rate*delta_error*inputs[i][j]
        return epoch

In [10]: #predict the output based on the current weights
def predict(inputs, weights):
    weighted_sum = 0
    for i, v in zip(inputs, weights):
        weighted_sum += i*v
    return 1 if weighted_sum>= 0 else 0

In [11]: #check the accuracy.
def accuracy(inputs, outputs, weights):
    n_correct = 0
    for i in range(inputs.shape[0]):
        if predict(inputs[i], weights) == outputs[i]:
            n_correct += 1
    return n_correct/len(outputs)

In [12]: #This code wasn't written by me,
#I just edited some bits of code to suit my code
def plot(inputs, outputs, weights, title="Prediction Matrix"):
    fig, ax = plt.subplots()
    ax.set_title(title)
    ax.set_xlabel('1')
    ax.set_ylabel('1')

    map_min=0.0
    map_max=1.1
    y_res=0.001
    x_res=0.001
    ys=np.arange(map_min,map_max,y_res)
    xs=np.arange(map_min,map_max,x_res)
    zs=[]
    for cur_y in np.arange(map_min,map_max,y_res):
        for cur_x in np.arange(map_min,map_max,x_res):
            zs.append(predict([1.0,cur_x,cur_y],weights))
    xs,ys=np.meshgrid(xs,ys)
    zs=np.array(zs)
    zs = zs.reshape(xs.shape)
    cp=plt.contourf(xs,ys,zs,levels=[-1,-0.0001,0,1],colors=('b','r'),alpha=0.1)

    ci_data=[[],[]]
    c0_data=[[],[]]
    for i in range(len(outputs)):
        cur_i1 = inputs[i][1]
        cur_i2 = inputs[i][2]
        cur_y = outputs[i]
        if cur_y==1:
            ci_data[0].append(cur_i1)
            ci_data[1].append(cur_i2)
        else:
            c0_data[0].append(cur_i1)
            c0_data[1].append(cur_i2)

    plt.xticks(np.arange(0.0,1.1,0.1))
    plt.yticks(np.arange(0.0,1.1,0.1))
    plt.xlim(0,1.05)
    plt.ylim(0,1.05)

    c0s = plt.scatter(c0_data[0],c0_data[1],s=40.0,c='r',label='Class 0')
    cis = plt.scatter(ci_data[0],ci_data[1],s=40.0,c='b',label='Class 1')

    plt.legend(fontsize=10,loc=1)
    plt.show()
    return

In [13]: inputs = np.array([[0.00,0.72],
                             [0.1, 1],
                             [0.20,0.58],
                             [0.35,0.95],
                             [0.40,0.17],
                             [0.6,0.30],
                             [0.7, 0.67],
                             [0.92, 0.43]])
bias = np.ones((inputs.shape[0],1))
inputs = np.concatenate([bias,inputs ],axis=1) ## attaching the bias input

outputs = np.array([1, 0, 1, 0, 1, 1, 0, 0], dtype=float)

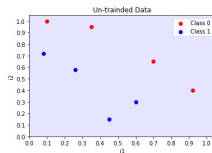
weights = np.random.randn(inputs.shape[1]) #I decided to make the weights random [0,1)
initial_weights = np.array(weights, copy=True)

plot(inputs, outputs, weights, "Un-trained Data")

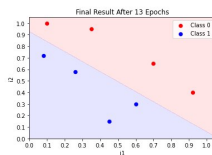
final_epoch = Train_Data(inputs, outputs, weights, 0.1,100)

print("Initial Weights : ",initial_weights,"Final Weights:", weights)

plot(inputs, outputs, weights, "Final Result After 10 Epochs"%final_epoch-1)
```



Initial Weights : [ 0.6802898 0.76758569 0.79523367]  
Final Weights: [ 0.18022898 -0.17449451 -0.20076033]



In [ ]:

# Applying the Algorithm By Handwriting

we choose random at first (we can also start with fixed values)

bias	$x_1$	$x_2$	<u>w-bias</u>	$w_1$	$w_2$	net	pre-y	actual-y
1	0	0	-0.2	0.1	0.2	-0.2	0	0
1	1	0	-0.2	0.1	0.2	-0.1	0	1
1	0	1						1
1	1	1						1

change  $w$  to  $w'$

we choose 0.2

$$w'_i = w_i + \text{learning-rate} \times (\text{Actual-y} - \text{pre-y}) \times x_i$$

$$w'_{\text{bias}} = -0.2 + 0.2 \times (1) \times 1 = 0$$

$$w'_1 = 0.1 + 0.2 \times 1 \times 1 = 0.3$$

$$w'_2 = 0.2 + 0.2 \times 1 \times 0 = 0.2$$

bias	$x_1$	$x_2$	w-bias	$w_1$	$w_2$	net	pre-y	actual-y
1	0	0	-0.2	0.1	0.2	-0.2	0	0
1	1	1	-0.2	0.1	0.2	0	0	1
1	0	1	0	0.3	0.2	0.2	1	1
1	1	1	0	0.3	0.2	0.5	1	1

So weights  
 $[0, 0.3, 0.2]$

we check it again

bias	$x_1$	$x_2$	w-bias	$w_1$	$w_2$	net	pre-y	actual-y
1	0	0	0	0.3	0.2	0	0	0
1	1	0	0	0.3	0.2	0.3	1	1
1	0	1	0	0.3	0.2	0.2	1	1
1	1	1	0	0.3	0.2	0.5	1	1

So no change happened

Final weights

$[0, 0.3, 0.2]$

## **PART 2:**

What is k-nearest neighbors(KNN)?:

It's an algorithm that can be considered as classification and regression, the output depends on the most common class of the K nearest neighbors.

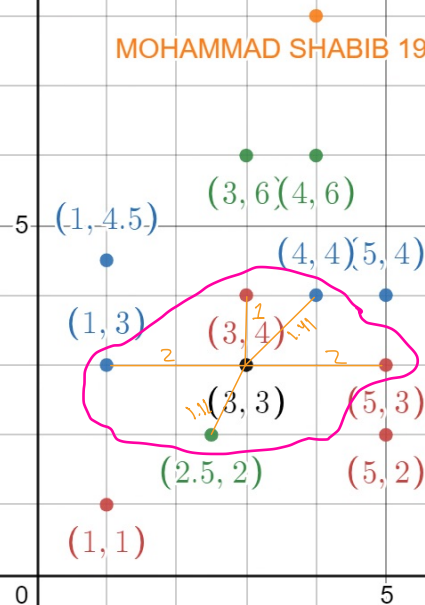
But for the weighted KNN algorithm distance plays a role, the more distance the neighbor has the less significance it has so (importance  $\sim 1/\text{distance}$ )

- Nearest Neighbor is considered a Lazy Algorithm because it doesn't learn a discriminative function from the training data but "memorizes" the training dataset.
- I implemented my code using the **weighted** k-nearest neighbor's algorithm.

# Weighted KNN

$$K = 5$$

MOHAMMAD SHABIB 19290116



Point	distance	weight ( $\frac{1}{d}$ )	
(3,4)	1	1	] 1.5
(5,3)	2	0.5	
(1,3)	2	0.5	} → 1.2
(4,4)	1.41	0.7	
(2.5,2)	1.11	0.9	} 0.9

So the point (3,3) will be classified as **red** but

if we used normal KNN

we would have had an issue since 2 classes have the same popularity, then we would have needed to change  $K$  to 6 or something else



```
In [99]: #19290116
#YOUNAMMAD_SHABIB
import numpy as np
import pandas as pd
from sklearn import datasets #this import is used for using the iris dataset
from sklearn.model_selection import train_test_split #this import is used to split the data into training and test
```

```
In [100]: #distance between two node
def euclidean_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2)**2))

#consider the weight of the node not just the popularity of the class
def weight_sum(k_weighted_labels):
    df = pd.DataFrame(k_weighted_labels, columns = ["label", "weight"])
    df = df.groupby(by=["label"]).sum()
    df.reset_index(inplace=True)
    df.sort_values(by=["weight"], ascending=False, inplace=True)
    return df["label"].iloc[0]
```

```
In [101]: def predictt_WKNN(x_test, x_train, y_train, k=3):
    y_predicted = np.array([], dtype=int)
    for test_item in x_test:
        distances = [euclidean_distance(test_item, x_t) for x_t in x_train]
        sorted_indices = np.argsort(distances)[:k]
        k_weighted_labels = [(y_train[i], 1/distances[i]) for i in sorted_indices]
        y_predicted = np.append(y_predicted, weight_sum(k_weighted_labels))
    return y_predicted
```

```
In [102]: x_test = np.array([[3,3],[1,4]])

x_train = np.array([
    [1,1],
    [5,3],
    [3,4],
    [5,2],
    [5,4],
    [1,4,5],
    [4,2],
    [1,3],
    [3,6],
    [4,0],
    [2,5,2]])

y_train = np.array([0,0,0,1,1,1,2,2,2])
#0 for red, 1 for blue, 2 for green
y_predicted = predictt_WKNN(x_test, x_train, y_train, k=5)
Colors = ["Red", "Blue", "Green"]
for i, result in enumerate(y_predicted):
    print("Point: (%0.1f,%0.1f) %s(x_test[1][0],x_test[1][1]), Result: %s"%Colors[result])

Point:(3.0,3.0) Result: Red
Point:(1.0,4.0) Result: Blue
```

In [ ]:

In [ ]:

## Weighted KNN:

$$k=5$$

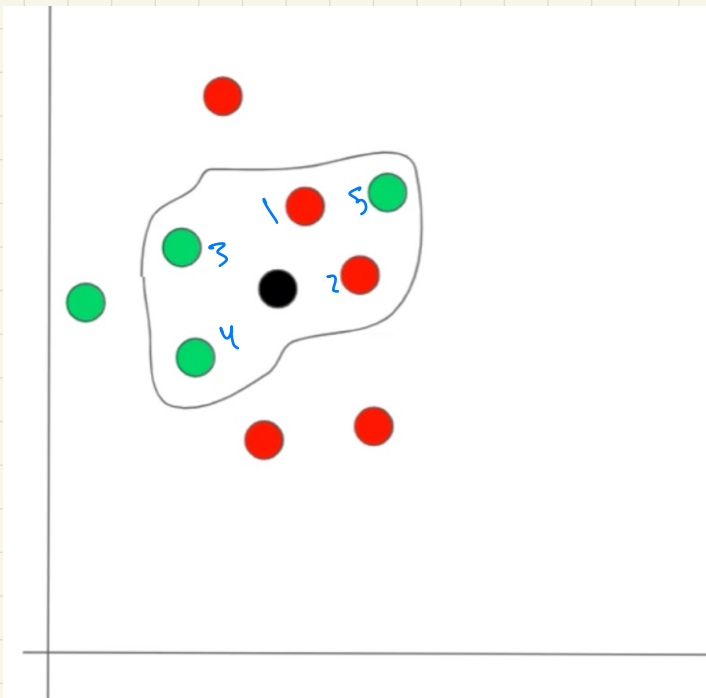
distance between the wanted point  
and point 1: 0.2      weight 5  
point 2: 0.5      2  
point 3: 0.7      1.4  
point 4: 1.2      0.8  
point 5: 1.5      0.6

we use function to give weights  
for each point (ex:  $\frac{1}{\text{distance}}$ )

weight of red points: 2  
weight of green points = 2.8

So the point to be  
classified will be red

But if it was normal KNN  
it would have been green  
(3 > 2)



```
In [1]: #19290116
#MONAMPIAD SHABIB
import numpy as np
import pandas as pd
from sklearn import datasets #this import is used for using the iris dataset
from sklearn.model_selection import train_test_split #this import is used to split the data into training and test
```

```
In [2]: #distance between two node
def euclidean_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2)**2))

#consider the weight of the node not just the popularity of the class
def weight_sum(k_weighted_labels):
    df = pd.DataFrame(k_weighted_labels, columns = ["label", "weight"])
    df = df.groupby(by=["label"]).sum()
    df.reset_index(inplace=True)
    df.sort_values(by=["weight"], ascending=False, inplace=True)
    return df["label"].iloc[0]
```

```
In [3]: def predictt_WKNN(x_test, x_train, y_train, k=3):
    y_predected = np.array([], dtype=int)
    for test_item in x_test:
        distances = [euclidean_distance(test_item, x_t) for x_t in x_train]
        sorted_indices = np.argsort(distances)[:k]
        k_weighted_labels = [(y_train[i], 1/distances[i]) for i in sorted_indices]
        y_predected = np.append(y_predected, weight_sum(k_weighted_labels))
    return y_predected
```

```
In [4]: def accuracy(y_true, y_pred):
    accuracy = np.sum(y_true == y_pred) / len(y_true)
    return accuracy
```

```
In [5]: iris = datasets.load_iris()
x, y = iris.data, iris.target
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1234)

y_predected = predictt_WKNN(x_test, x_train, y_train, k=3)
accuracy(y_test, y_predected)
```

Out[5]: 1.0

In [ ]: