# Perceptron from Scratch

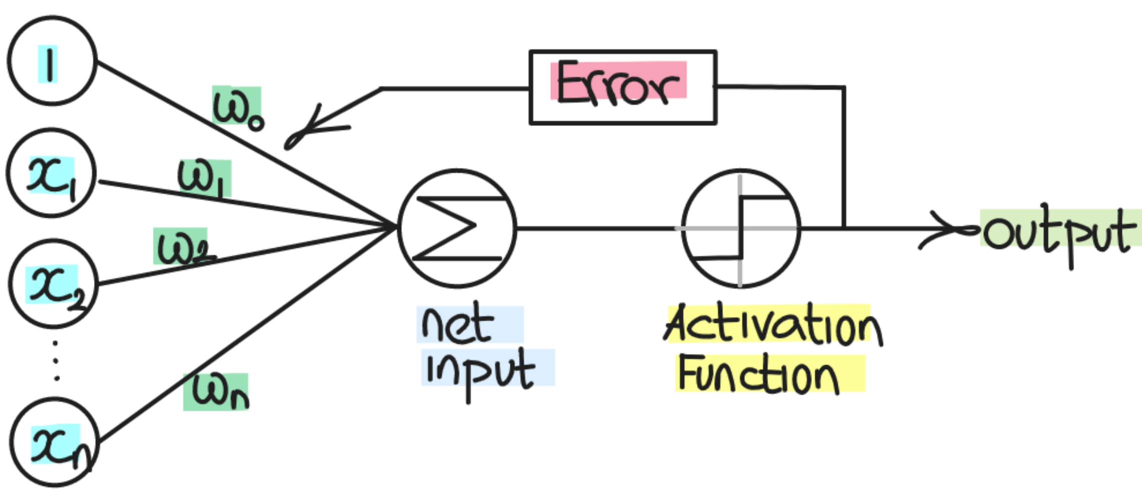
**Frank Rosenblatt's Perceptron or in short the 'Perceptron' is widely considered to be the very first neural model even though McCulloch Pitts neural model came around 13 years before it and the simple reason behind it is the fact that perceptron is the first neural model that is capable of learning.**

**Okay, so what do we mean by learning? Unlike McCulloch Pitts where the weights and biases had to be hand coded, perceptron can learn these weights and biases by looking at the data itself. Also McCulloch Pitts works only for binary inputs and outputs whereas perceptron works for any real number inputs and outputs.**

**Note that there are multiple versions of perceptron and even the McCulloch Pitts itself is sometimes referred to as perceptron. But what's shown below is the widely used definition of perceptron and it is considered to be the simplest learnable neural model and is considered to be the fundamental unit of all other complex neural networks.**

**Note: Perceptron can be used only on a strictly linearly separable binary class dataset**

## Architecture of Perceptron




In [1]:
```
# Loading the dependencies
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
from sklearn.datasets import make_blobs
```

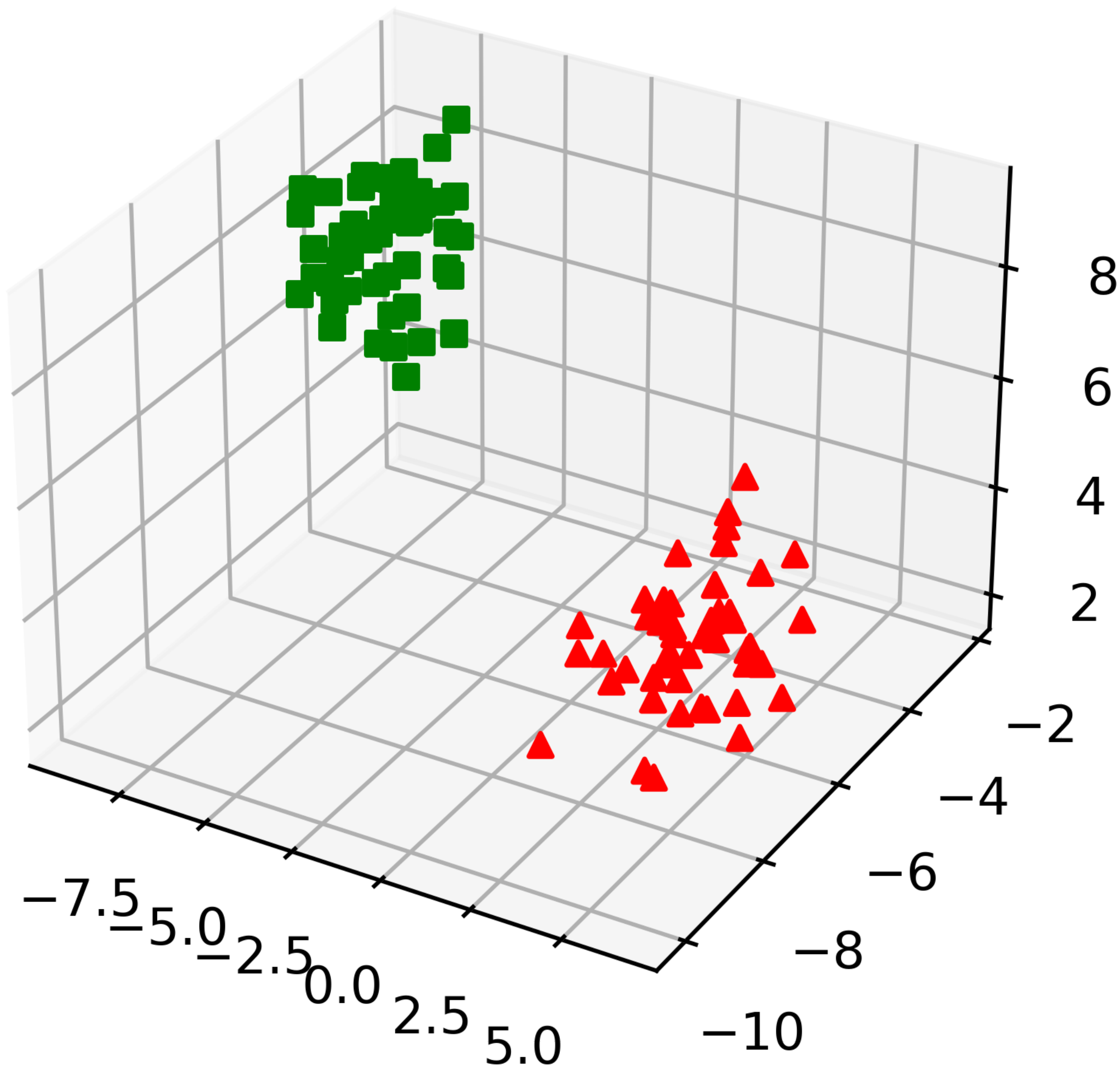
In [3]:
```
# Loading the data from scikit-learn
data,labels=make_blobs(n_features=3,n_samples=100, centers=2)
```

In [4]:
```
# converting the above data into a dataframe
df=pd.DataFrame(data, columns=['x1','x2','x3'])
df['labels']=labels
df.head()
```

Out[4]:

| | x1 | x2 | x3 | labels |
|---|---|---|---|---|
| **0** | 4.486062 | -5.677568 | 6.110462 | 0 |
| **1** | -6.675358 | -4.639986 | 8.439058 | 1 |
| **2** | -7.447927 | -5.142129 | 7.018258 | 1 |
| **3** | 2.001071 | -6.979936 | 3.300927 | 0 |
| **4** | -8.476516 | -5.480927 | 6.976501 | 1 |

In [5]:
```
# visualizing the above dataframe
fig = plt.figure(dpi=500)
ax = fig.gca(projection='3d')
ax.scatter(df.x1[df.labels==0],
           df.x2[df.labels==0],
           df.x3[df.labels==0],
           marker='^', color='red', alpha=1)
ax.scatter(df.x1[df.labels==1],
           df.x2[df.labels==1],
           df.x3[df.labels==1],
           marker='s', color='green', alpha=1);
```



In [6]:
```
def perceptron(X,y,eta,epochs):
    n,dim=X.shape # number of datapoints and dimension
    dim+=1

    b=np.ones([n,1]) # column for bias term
    X=X.values # attaching the above column to the X variable
    X=np.hstack([b,X])

    w=np.random.uniform(-10,10,dim) # randomly initializing weights

    for epoch in range(epochs): # running the algorithm for many epochs

        misclassified=0 # counting misclassified point
        for i in range(n):
            net_input=np.dot(w,X[i]) # finding the weighted sum of input vector

            if net_input>=0: # passing the above net input through step function
                y_hat=1
            else:
                y_hat=0

            if y[i]!=y_hat: # update weight when there's mislabelling
                w+=(eta*(y[i]-y_hat)*X[i])
                misclassified+=1 # increment misclassified point counter

        if misclassified==0: # early stop when perfect classification is done
            return w, epoch

    return w, epoch
```

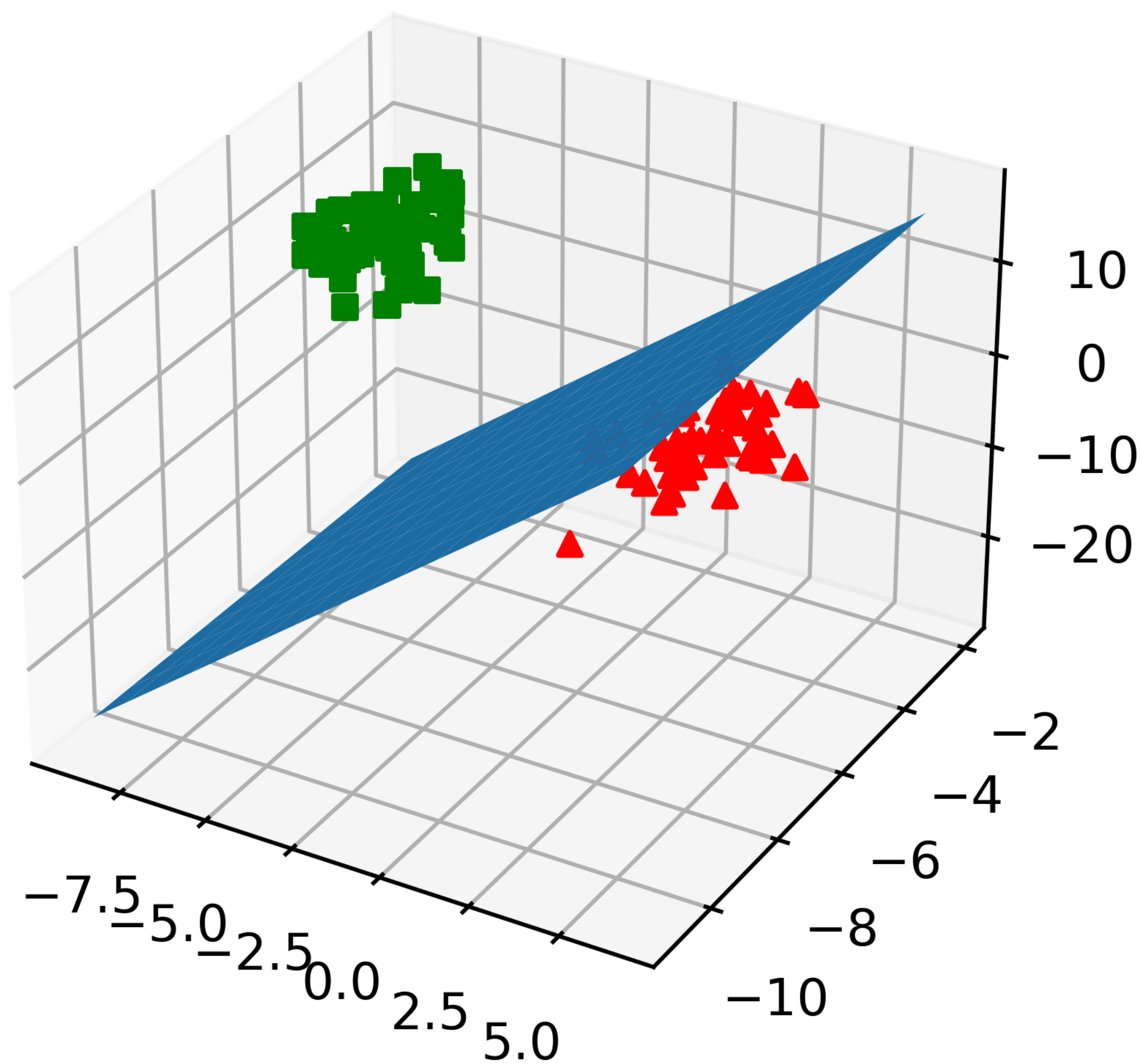
In [7]:
```
# segregating the predictor and target variable
X=df.drop('labels',axis=1)
y=df.labels
```

In [8]:
```
# fitting the perceptron on the above data
weight,epoch=perceptron(X,y,0.1,1000000)

print(f'The weight vector is {weight}\nThe perceptron classified in {epoch} epochs')
```

```
The weight vector is [ 5.28670879 -8.43150775  0.31535843  2.97025391]
The perceptron classified in 1 epochs
```

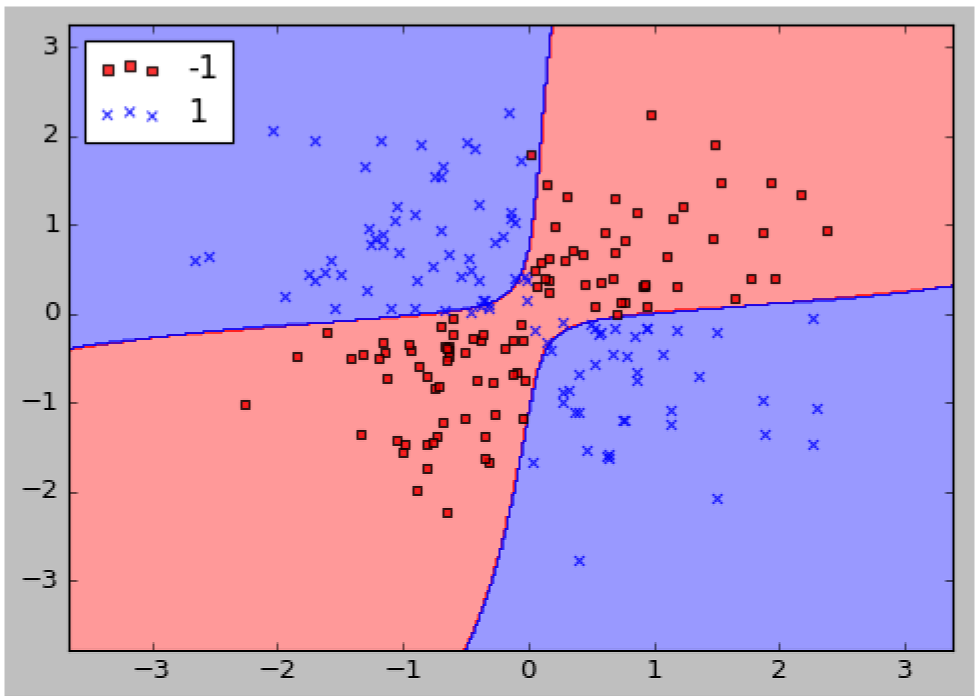
In [9]:
```
w0,w1,w2,w3=weight # capturing the bias and weights
```

In [10]:
```
# visualizing the above dataframe
fig = plt.figure(dpi=500)
plt.title('Segragated Classes')
ax = fig.gca(projection='3d')
ax.scatter(df.x1[df.labels==0],
           df.x2[df.labels==0],
           df.x3[df.labels==0],
           marker='^', color='red', alpha=1)
ax.scatter(df.x1[df.labels==1],
           df.x2[df.labels==1],
           df.x3[df.labels==1],
           marker='s', color='green', alpha=1)

x1=list(range(int(df.x1.min()-1),int(df.x1.max()+1)))
x2=list(range(int(df.x2.min()-1),int(df.x2.max()+1)))

x1, x2 = np.meshgrid(x1, x2)
eq = - (w0/w3) - (w1/w3) * x1 - (w2/w3) * x2
ax.plot_surface(x1, x2, eq);
```



## Limitations of Perceptron

**Perceptrons in its basic form with only one layer could not be used to solve XOR problem (as shown in the diagram below) which lead to the idea of Multilayer Perceptrons which could solve not just XOR but other wide range of problems as well.**




**Hope you found this notebook useful!**
**Lets connect**
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