In [5]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs, make_moons
```

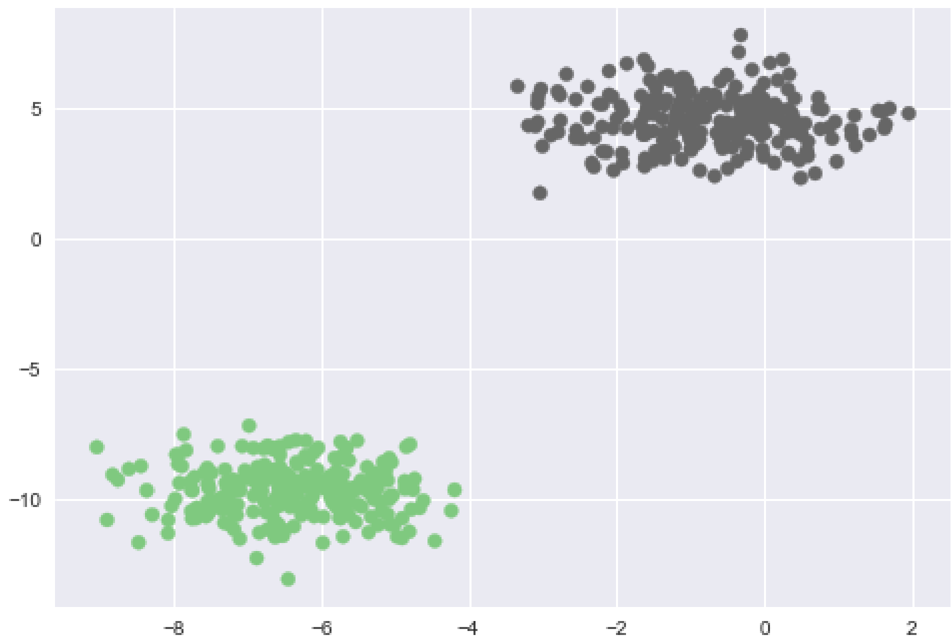
In [6]:

```
X,Y = make_blobs(n_samples=500,centers=2,n_features=2,random_state=11)
print(X.shape, Y.shape)
```

```
(500, 2) (500,)
```

In [7]:

```
plt.style.use('seaborn')
plt.scatter(X[:,0],X[:,1],c=Y,cmap=plt.cm.Accent)
plt.show()
```



Model and Helper Function

In [8]:

```
def sigmoid(z):
    return (1.0)/(1+np.exp(-z))
```

In [9]:

```
# Work for single value
print(sigmoid(4))

# Work for np array only
z = np.array([1,2,3,4,5])
print(sigmoid(z))
```

```
0.9820137900379085
[0.73105858 0.88079708 0.95257413 0.98201379 0.99330715]
```

Implement Perceptron Learning Algo

- Learn the weights
- Reduce the Loss
- Make the Predictions

In [10]:

```
def predict(X,weights):
    """X-> m*(n+1) matrix, W-> (n+1,) vector
       y = x0.theta0 + x1.theta1 + x2.theta2
       Pred => h(y) = sigmoid(y)
       # O/P - (m,) for I/P X - (m,n+1) and W - (n+1,)
       else for single example, it will be float value.
    """
    z = np.dot(X,weights)
    prediction = sigmoid(z)
    return prediction
```

In [11]:

```
def loss(X,Y,weights):
    """Binary Cross Entropy
       Loss Fn = Sum for all example m {( Yi.log(Yi_) + (1-Yi).log(1-Yi_) )}
       Yi = actual value of example Xi
       Yi_ = predicted value of example Xi
       we take mean of loss of examples by dividing total loss of all examples by tota
       np.mean() - gives mean directly
       # O/P - (m,) for I/P X - (m,n+1), Y- (m,) and W - (n+1,)
       else for single example, it will be float value.
    """
    Y_ = predict(X,weights)
    cost = np.mean(-Y*np.log(Y_) - (1-Y)*np.log(1-Y_))
    return cost
```

In [12]:

```
def update(X,Y,weights,learning_rate):
    """Perform weight update for 1 epoch
       # O/P - (n+1,) for I/P X - (m,n+1), Y- (m,), W - (n+1,) and learning_rate - con
       even for single example, it will be same (n+1,)
       Weight Update- d(Loss Fn)/dWj = (Y - Y_).Xj for jth weight
       we are taking -ve of update rule, i.e, Gradient Descent
    """
    Y_ = predict(X,weights)
    dw = np.dot(X.T,Y_ - Y) # (n+1,), but it contains sum of dw of all examples, so we
                            # of it by dividing it by total no of examples in i/p i.e,

    m = X.shape[0]
    weights = weights - learning_rate*dw/(float(m))
    return weights
```

In [13]:

```
def train(X,Y,learning_rate=0.8,maxEpochs=100):

    # Modify the input to handle the bias term
    ones = np.ones((X.shape[0],1))
    X = np.hstack((ones,X))

    # Init Weights
    weights = np.zeros(X.shape[1]) # n+1 entries

    for epoch in range(maxEpochs):
        # Iterate over all epochs and make update
        weights = update(X,Y,weights,learning_rate)

        if epoch%10==0:
            l = loss(X,Y,weights)
            print("Epoch %d Loss %.4f"%(epoch,l))


    return weights
```

In [14]:

```
weights = train(X,Y, maxEpochs=1000)
```

```
Epoch 0 Loss 0.0005
Epoch 10 Loss 0.0004
Epoch 20 Loss 0.0004
Epoch 30 Loss 0.0004
Epoch 40 Loss 0.0004
Epoch 50 Loss 0.0004
Epoch 60 Loss 0.0004
Epoch 70 Loss 0.0004
Epoch 80 Loss 0.0003
Epoch 90 Loss 0.0003
Epoch 100 Loss 0.0003
Epoch 110 Loss 0.0003
Epoch 120 Loss 0.0003
Epoch 130 Loss 0.0003
Epoch 140 Loss 0.0003
Epoch 150 Loss 0.0003
Epoch 160 Loss 0.0003
Epoch 170 Loss 0.0003
Epoch 180 Loss 0.0003
Epoch 190 Loss 0.0003
Epoch 200 Loss 0.0002
Epoch 210 Loss 0.0002
Epoch 220 Loss 0.0002
Epoch 230 Loss 0.0002
Epoch 240 Loss 0.0002
Epoch 250 Loss 0.0002
Epoch 260 Loss 0.0002
Epoch 270 Loss 0.0002
Epoch 280 Loss 0.0002
Epoch 290 Loss 0.0002
Epoch 300 Loss 0.0002
Epoch 310 Loss 0.0002
Epoch 320 Loss 0.0002
Epoch 330 Loss 0.0002
Epoch 340 Loss 0.0002
Epoch 350 Loss 0.0002
Epoch 360 Loss 0.0002
Epoch 370 Loss 0.0002
Epoch 380 Loss 0.0002
Epoch 390 Loss 0.0002
Epoch 400 Loss 0.0002
Epoch 410 Loss 0.0002
Epoch 420 Loss 0.0002
Epoch 430 Loss 0.0002
Epoch 440 Loss 0.0002
Epoch 450 Loss 0.0002
Epoch 460 Loss 0.0002
Epoch 470 Loss 0.0002
Epoch 480 Loss 0.0002
Epoch 490 Loss 0.0001
Epoch 500 Loss 0.0001
Epoch 510 Loss 0.0001
Epoch 520 Loss 0.0001
Epoch 530 Loss 0.0001
Epoch 540 Loss 0.0001
Epoch 550 Loss 0.0001
```

```
Epoch 560 Loss 0.0001
Epoch 570 Loss 0.0001
Epoch 580 Loss 0.0001
Epoch 590 Loss 0.0001
Epoch 600 Loss 0.0001
Epoch 610 Loss 0.0001
Epoch 620 Loss 0.0001
Epoch 630 Loss 0.0001
Epoch 640 Loss 0.0001
Epoch 650 Loss 0.0001
Epoch 660 Loss 0.0001
Epoch 670 Loss 0.0001
Epoch 680 Loss 0.0001
Epoch 690 Loss 0.0001
Epoch 700 Loss 0.0001
Epoch 710 Loss 0.0001
Epoch 720 Loss 0.0001
Epoch 730 Loss 0.0001
Epoch 740 Loss 0.0001
Epoch 750 Loss 0.0001
Epoch 760 Loss 0.0001
Epoch 770 Loss 0.0001
Epoch 780 Loss 0.0001
Epoch 790 Loss 0.0001
Epoch 800 Loss 0.0001
Epoch 810 Loss 0.0001
Epoch 820 Loss 0.0001
Epoch 830 Loss 0.0001
Epoch 840 Loss 0.0001
Epoch 850 Loss 0.0001
Epoch 860 Loss 0.0001
Epoch 870 Loss 0.0001
Epoch 880 Loss 0.0001
Epoch 890 Loss 0.0001
Epoch 900 Loss 0.0001
Epoch 910 Loss 0.0001
Epoch 920 Loss 0.0001
Epoch 930 Loss 0.0001
Epoch 940 Loss 0.0001
Epoch 950 Loss 0.0001
Epoch 960 Loss 0.0001
Epoch 970 Loss 0.0001
Epoch 980 Loss 0.0001
Epoch 990 Loss 0.0001
```

In [15]:

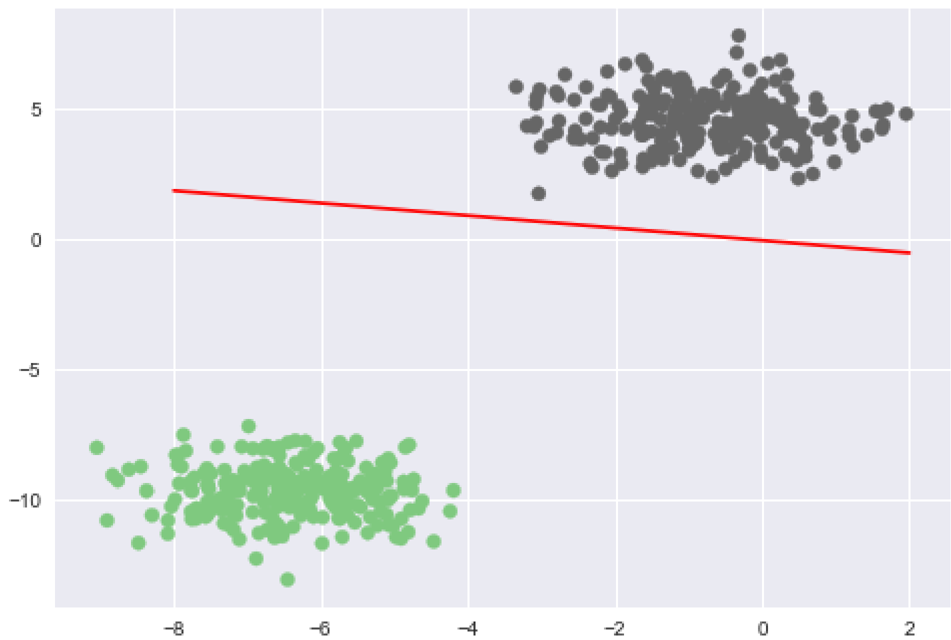
```
def getPredictions(X_Test,weights,labels=True):

        if X_Test.shape[1] != weights.shape[0]:
            ones = np.ones((X_Test.shape[0],1))
            X_Test = np.hstack((ones,X_Test))

        probs = predict(X_Test,weights)

        if not labels:
            return probs
        else:
            labels = np.zeros(probs.shape)
            labels[probs>=0.5] = 1
            return labels
```

In [16]:

```
x1 = np.linspace(-8,2,10)
x2 = -(weights[0] + weights[1]*x1)/weights[2]
```

In [17]:

```
plt.scatter(X[:,0],X[:,1],c=Y,cmap=plt.cm.Accent)
plt.plot(x1,x2,color='red')
plt.show()
```



In [18]:

```
# Find accuracy
Y_ = getPredictions(X,weights,labels=True)
training_accuracy = np.sum(Y_==Y)/Y.shape[0]
print(training_accuracy)
```

```
1.0
```

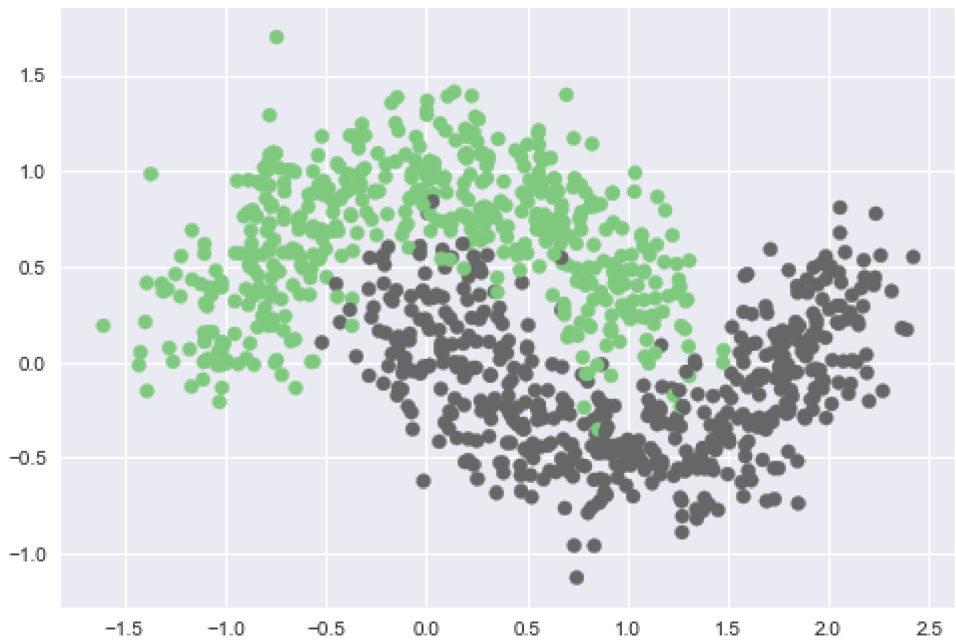
Generate Non Linear Data

In [19]:

```
X,Y = make_moons(n_samples=1000,shuffle=True,noise=0.2,random_state=True)
```

In [20]:

```
plt.style.use('seaborn')
plt.scatter(X[:,0],X[:,1],c=Y,cmap=plt.cm.Accent)
plt.show()
```



In [21]:

```
weights = train(X,Y, maxEpochs=1000)
```

```
Epoch 0 Loss 0.6234
Epoch 10 Loss 0.4134
Epoch 20 Loss 0.3672
Epoch 30 Loss 0.3457
Epoch 40 Loss 0.3327
Epoch 50 Loss 0.3239
Epoch 60 Loss 0.3175
Epoch 70 Loss 0.3128
Epoch 80 Loss 0.3091
Epoch 90 Loss 0.3063
Epoch 100 Loss 0.3041
Epoch 110 Loss 0.3023
Epoch 120 Loss 0.3009
Epoch 130 Loss 0.2997
Epoch 140 Loss 0.2988
Epoch 150 Loss 0.2980
Epoch 160 Loss 0.2973
Epoch 170 Loss 0.2968
Epoch 180 Loss 0.2963
Epoch 190 Loss 0.2959
Epoch 200 Loss 0.2956
Epoch 210 Loss 0.2953
Epoch 220 Loss 0.2951
Epoch 230 Loss 0.2949
Epoch 240 Loss 0.2947
Epoch 250 Loss 0.2946
Epoch 260 Loss 0.2944
Epoch 270 Loss 0.2943
Epoch 280 Loss 0.2942
Epoch 290 Loss 0.2941
Epoch 300 Loss 0.2941
Epoch 310 Loss 0.2940
Epoch 320 Loss 0.2940
Epoch 330 Loss 0.2939
Epoch 340 Loss 0.2939
Epoch 350 Loss 0.2938
Epoch 360 Loss 0.2938
Epoch 370 Loss 0.2938
Epoch 380 Loss 0.2938
Epoch 390 Loss 0.2937
Epoch 400 Loss 0.2937
Epoch 410 Loss 0.2937
Epoch 420 Loss 0.2937
Epoch 430 Loss 0.2937
Epoch 440 Loss 0.2937
Epoch 450 Loss 0.2937
Epoch 460 Loss 0.2936
Epoch 470 Loss 0.2936
Epoch 480 Loss 0.2936
Epoch 490 Loss 0.2936
Epoch 500 Loss 0.2936
Epoch 510 Loss 0.2936
Epoch 520 Loss 0.2936
Epoch 530 Loss 0.2936
Epoch 540 Loss 0.2936
Epoch 550 Loss 0.2936
```

```
Epoch 560 Loss 0.2936
Epoch 570 Loss 0.2936
Epoch 580 Loss 0.2936
Epoch 590 Loss 0.2936
Epoch 600 Loss 0.2936
Epoch 610 Loss 0.2936
Epoch 620 Loss 0.2936
Epoch 630 Loss 0.2936
Epoch 640 Loss 0.2936
Epoch 650 Loss 0.2936
Epoch 660 Loss 0.2936
Epoch 670 Loss 0.2936
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Epoch 770 Loss 0.2936
Epoch 780 Loss 0.2936
Epoch 790 Loss 0.2936
Epoch 800 Loss 0.2936
Epoch 810 Loss 0.2936
Epoch 820 Loss 0.2936
Epoch 830 Loss 0.2936
Epoch 840 Loss 0.2936
Epoch 850 Loss 0.2936
Epoch 860 Loss 0.2936
Epoch 870 Loss 0.2936
Epoch 880 Loss 0.2936
Epoch 890 Loss 0.2936
Epoch 900 Loss 0.2936
Epoch 910 Loss 0.2936
Epoch 920 Loss 0.2936
Epoch 930 Loss 0.2936
Epoch 940 Loss 0.2936
Epoch 950 Loss 0.2936
Epoch 960 Loss 0.2936
Epoch 970 Loss 0.2936
Epoch 980 Loss 0.2936
Epoch 990 Loss 0.2936
```

In [22]:

```
x1 = np.linspace(-2,2,10)
x2 = -(weights[0] + weights[1]*x1)/weights[2]
```

In [23]:

```
plt.scatter(X[:,0],X[:,1],c=Y,cmap=plt.cm.Accent)
plt.plot(x1,x2,color='red')
plt.show()
```

In [24]:

```
# Find accuracy
Y_ = getPredictions(X,weights,labels=True)
training_accuracy = np.sum(Y_==Y)/Y.shape[0]
print(training_accuracy)
```

```
0.869
```

In [ ]: