In [2]:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, mean_squared_error
from tqdm import tqdm_notebook

from sklearn.preprocessing import OneHotEncoder
from sklearn.datasets import make_moons, make_circles
from sklearn.datasets import make_blobs # will be used to generate data which is not li
nearly separable.
```

Let us first test how our Sigmoid neuron works on a set of data.

In [3]:

```
class SigmoidNeuron:

  def __init__(self):
    self.w = None
    self.b = None

  def perceptron(self, x):
    return np.dot(x, self.w.T) + self.b

  def sigmoid(self, x):
    return 1.0/(1.0 + np.exp(-x))

# above two functions does the forward pass.

  def grad_w_mse(self, x, y):
    y_pred = self.sigmoid(self.perceptron(x))
    return (y_pred - y) * y_pred * (1 - y_pred) * x

  def grad_b_mse(self, x, y):
    y_pred = self.sigmoid(self.perceptron(x))
    return (y_pred - y) * y_pred * (1 - y_pred)

  def grad_w_ce(self, x, y):
    y_pred = self.sigmoid(self.perceptron(x))
    if y == 0:
      return y_pred * x
    elif y == 1:
      return -1 * (1 - y_pred) * x
    else:
      raise ValueError("y should be 0 or 1")

  def grad_b_ce(self, x, y):
    y_pred = self.sigmoid(self.perceptron(x))
    if y == 0:
      return y_pred
    elif y == 1:
      return -1 * (1 - y_pred)
    else:
      raise ValueError("y should be 0 or 1")

  def fit(self, X, Y, epochs=1, learning_rate=1, initialise=True, loss_fn="mse", displa
y_loss=False):

    # initialise w, b
    if initialise:
      self.w = np.random.randn(1, X.shape[1])
      self.b = 0

    if display_loss:
      loss = {}

    for i in tqdm_notebook(range(epochs), total=epochs, unit="epoch"):
      dw = 0
      db = 0
      for x, y in zip(X, Y):
        if loss_fn == "mse":
          dw += self.grad_w_mse(x, y)
          db += self.grad_b_mse(x, y)
        elif loss_fn == "ce":
```

```
          dw += self.grad_w_ce(x, y)
          db += self.grad_b_ce(x, y)

      m = X.shape[1]
      self.w -= learning_rate * dw/m  # we are here dividing by m because larger is the amount of data slower should be the learning rate we are normalising it.
      self.b -= learning_rate * db/m

      if display_loss:
        Y_pred = self.sigmoid(self.perceptron(X))
        if loss_fn == "mse":
          loss[i] = mean_squared_error(Y, Y_pred)
        elif loss_fn == "ce":
          loss[i] = log_loss(Y, Y_pred)

    if display_loss:
      plt.plot(loss.values())
      plt.xlabel('Epochs')
      if loss_fn == "mse":
        plt.ylabel('Mean Squared Error')
      elif loss_fn == "ce":
        plt.ylabel('Log Loss')
      plt.show()

  def predict(self, X):
    Y_pred = []
    for x in X:
      y_pred = self.sigmoid(self.perceptron(x))
      Y_pred.append(y_pred)
    return np.array(Y_pred)
```

Let us generate some non linearly separable data first.

In [13]:

```
data, labels = make_moons(n_samples=2000, random_state=0, noise=0.10)
print(data.shape, labels.shape)
```

```
(2000, 2) (2000,)
```

In [17]:

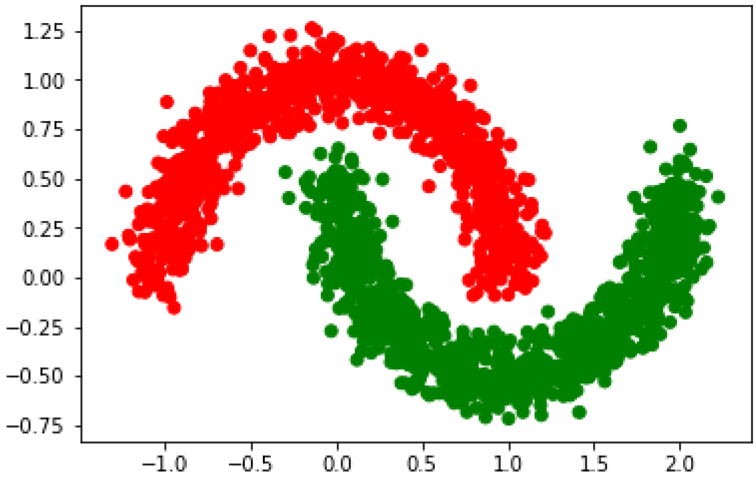
```
# number of classes we have
len(set(labels))
```

Out[17]:

```
2
```

In [14]:

```
my_cmap = matplotlib.colors.LinearSegmentedColormap.from_list("", ["red","blue","green"
])
np.random.seed(0)

plt.scatter(data[:,0], data[:,1], c=labels, cmap=my_cmap) # we have taken first two dim
ensions of our data only
plt.show()
```



In [18]:

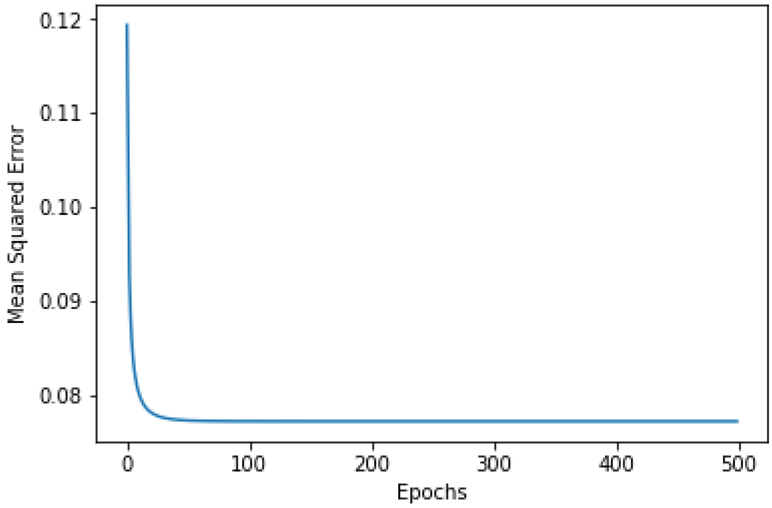
```
# train test split

X_train, X_test, Y_train, Y_test = train_test_split(data, labels, stratify=labels, rand
om_state=0) # validation set is similar to test set only.
print(X_train.shape, X_test.shape)
```

```
(1500, 2) (500, 2)
```

Performing Sigmoid neuron classification.

In [22]:

```
sn = SigmoidNeuron()
sn.fit(X_train, Y_train, epochs=500, learning_rate=0.05, display_loss=True)
```



In [24]:

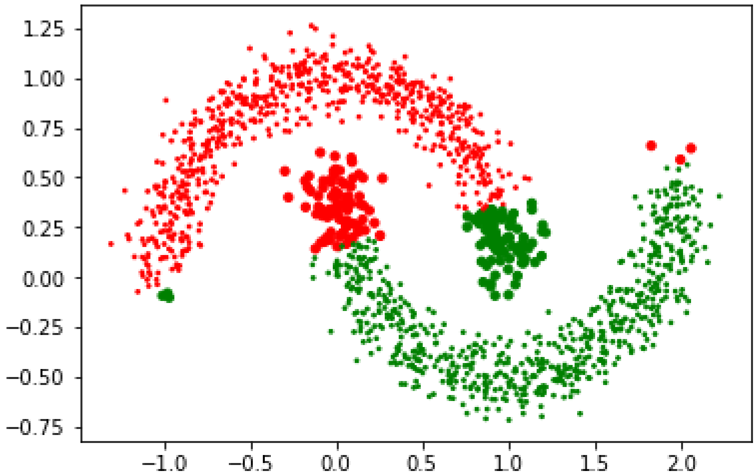
```
Y_pred_train = sn.predict(X_train)
Y_pred_binarised_train = (Y_pred_train >= 0.5).astype("int").ravel()
Y_pred_test = sn.predict(X_test)
Y_pred_binarised_test = (Y_pred_test >= 0.5).astype("int").ravel()
accuracy_train = accuracy_score(Y_pred_binarised_train, Y_train)
accuracy_test = accuracy_score(Y_pred_binarised_test, Y_test)

print("Training accuracy", round(accuracy_train, 2))
print("Test accuracy", round(accuracy_test, 2))
```

```
Training accuracy 0.89
Test accuracy 0.86
```

Plotting our training data points based on how they are classified

In [25]:

```
# Let us plot what model is predicting actually
# we are setting the size also in s for points and the point will be of large size if t
he point is not correctly predicted.
plt.scatter(X_train[:,0], X_train[:,1], c=Y_pred_binarised_train, cmap=my_cmap, s=15*(n
p.abs(Y_pred_binarised_train-Y_train)+.2))
plt.show()
```

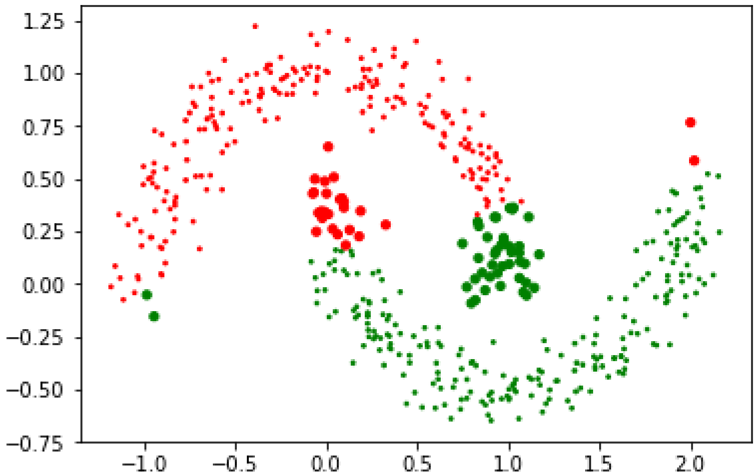


Points with larger size are not correctly classified.

Plotting our test data points based on how they are classified

In [26]:

```
# Let us plot what model is predicting actually
# we are setting the size also in s for points and the point will be of large size if t
he point is not correctly predicted.
plt.scatter(X_test[:,0], X_test[:,1], c=Y_pred_binarised_test, cmap=my_cmap, s=15*(np.a
bs(Y_pred_binarised_test-Y_test)+.2))
plt.show()
```



Now we are not satisfied with the accuracy we received for such a simple model hence now we will try Feed Forward neural network for our classification purpose.

Feed forward neural network

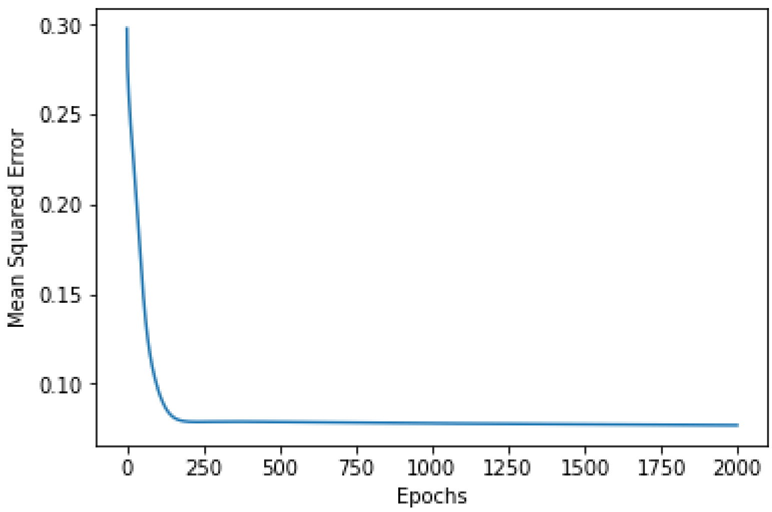
In [27]:

```
class FFSNNetwork:

  def __init__(self, n_inputs, hidden_sizes=[2]):  # hidden sizes is a list which conta
ins number of neurons in which layer
    self.nx = n_inputs
    self.ny = 1  # we are looking for binary classification
    self.nh = len(hidden_sizes)
    self.sizes = [self.nx] + hidden_sizes + [self.ny]

    self.W = {} # we will have matrix in dictionaries this refer to the matrix of W and
b
    self.B = {}
    for i in range(self.nh+1):
      self.W[i+1] = np.random.randn(self.sizes[i], self.sizes[i+1])
      self.B[i+1] = np.zeros((1, self.sizes[i+1]))

  def sigmoid(self, x):
    return 1.0/(1.0 + np.exp(-x))

  def forward_pass(self, x):
    self.A = {}
    self.H = {}
    self.H[0] = x.reshape(1, -1) # initial h is the input itself
    for i in range(self.nh+1):
      self.A[i+1] = np.matmul(self.H[i], self.W[i+1]) + self.B[i+1]
      self.H[i+1] = self.sigmoid(self.A[i+1])
    return self.H[self.nh+1]

  def grad_sigmoid(self, x):
    return x*(1-x)

  def grad(self, x, y):
    self.forward_pass(x)
    self.dW = {}
    self.dB = {}
    self.dH = {}
    self.dA = {}
    L = self.nh + 1
    self.dA[L] = (self.H[L] - y)
    for k in range(L, 0, -1):
      self.dW[k] = np.matmul(self.H[k-1].T, self.dA[k])
      self.dB[k] = self.dA[k]
      self.dH[k-1] = np.matmul(self.dA[k], self.W[k].T)
      self.dA[k-1] = np.multiply(self.dH[k-1], self.grad_sigmoid(self.H[k-1]))

  def fit(self, X, Y, epochs=1, learning_rate=1, initialise=True, display_loss=False):

    # initialise w, b
    if initialise:
      for i in range(self.nh+1):
        self.W[i+1] = np.random.randn(self.sizes[i], self.sizes[i+1])
        self.B[i+1] = np.zeros((1, self.sizes[i+1]))

    if display_loss:
      loss = {}

    for e in tqdm_notebook(range(epochs), total=epochs, unit="epoch"):
      dW = {}
      dB = {}
```

```
      for i in range(self.nh+1):
        dW[i+1] = np.zeros((self.sizes[i], self.sizes[i+1]))
        dB[i+1] = np.zeros((1, self.sizes[i+1]))
      for x, y in zip(X, Y):
        self.grad(x, y)
        for i in range(self.nh+1):
          dW[i+1] += self.dW[i+1]
          dB[i+1] += self.dB[i+1]

      m = X.shape[1]
      for i in range(self.nh+1):
        self.W[i+1] -= learning_rate * dW[i+1] / m
        self.B[i+1] -= learning_rate * dB[i+1] / m

      if display_loss:
        Y_pred = self.predict(X)
        loss[e] = mean_squared_error(Y_pred, Y)

    if display_loss:
      plt.plot(loss.values())
      plt.xlabel('Epochs')
      plt.ylabel('Mean Squared Error')
      plt.show()

  def predict(self, X):
    Y_pred = []
    for x in X:
      y_pred = self.forward_pass(x)
      Y_pred.append(y_pred)
    return np.array(Y_pred).squeeze()
```

In [32]:

```
ffsnn = FFSNNetwork(2, [3,5])  # first layer will have 3 neurons and second layer will have 5 neurons
ffsnn.fit(X_train, Y_train, epochs=2000, learning_rate=.001, display_loss=True)
```



Above you can see that the loss has gone down slowly here because here we had a deeper neural network in which we have more parameters hence they take time.

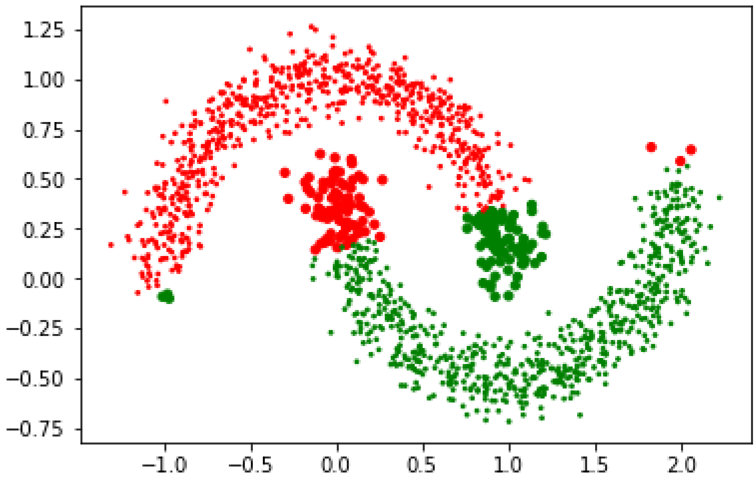
In [33]:

```
Y_pred_train = ffsnn.predict(X_train)
Y_pred_binarised_train = (Y_pred_train >= 0.5).astype("int").ravel()
Y_pred_test = ffsnn.predict(X_test)
Y_pred_binarised_test = (Y_pred_test >= 0.5).astype("int").ravel()
accuracy_train = accuracy_score(Y_pred_binarised_train, Y_train)
accuracy_test = accuracy_score(Y_pred_binarised_test, Y_test)

print("Training accuracy", round(accuracy_train, 2))
print("Test accuracy", round(accuracy_test, 2))
```

```
Training accuracy 0.89
Test accuracy 0.87
```

In [34]:

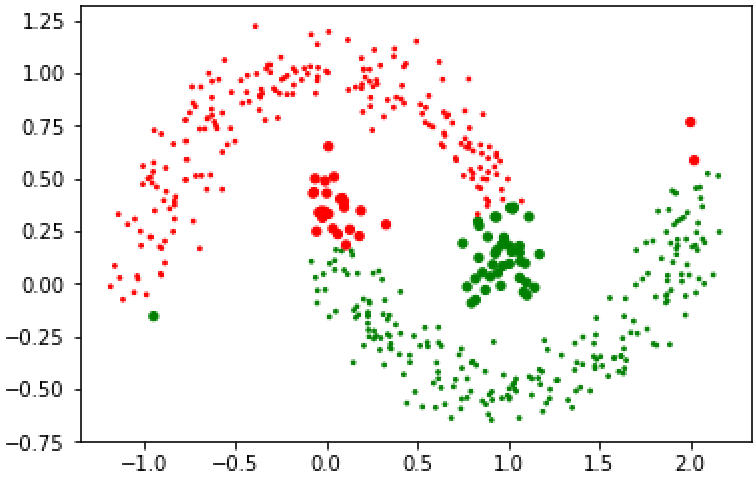
```
# let us plot what model is predicting actually
# we are setting the size also in s for points and the point will be of large size if t
he point is not correctly predicted.
plt.scatter(X_train[:,0], X_train[:,1], c=Y_pred_binarised_train, cmap=my_cmap, s=15*(n
p.abs(Y_pred_binarised_train-Y_train)+.2))
plt.show()
```



Test data predictions plotted

In [35]:

```
# let us plot what model is predicting actually
# we are setting the size also in s for points and the point will be of large size if t
he point is not correctly predicted.
plt.scatter(X_test[:,0], X_test[:,1], c=Y_pred_binarised_test, cmap=my_cmap, s=15*(np.a
bs(Y_pred_binarised_test-Y_test)+.2))
plt.show()
```



In [ ]:

```

```