Lab_7_Regression_Part_2

September 17, 2022

#**LAB 7 : Regression Part 2**

In this Lab we will look into the shortcomings of Linear Regression and see how those problems can be solved using Logistic Regression. We will also explore Polynomian Regression

1. Polynomial Regression
2. Linear Regression on a specific pattern of data to observe shortcomings
3. Logistic Regression to solve those problems

[35]:
```
import numpy as np
import matplotlib.pyplot as plt
```

#Polynomial Regression

1. Generate data using relation $y = 0.25x^3 + 1.25x^2 - 3x - 3$
2. Corrupt y by adding random noise (uniformly sampled)
3. Fit the generated curve using different polynomial order. (Using matrix inversion and gradient descent)

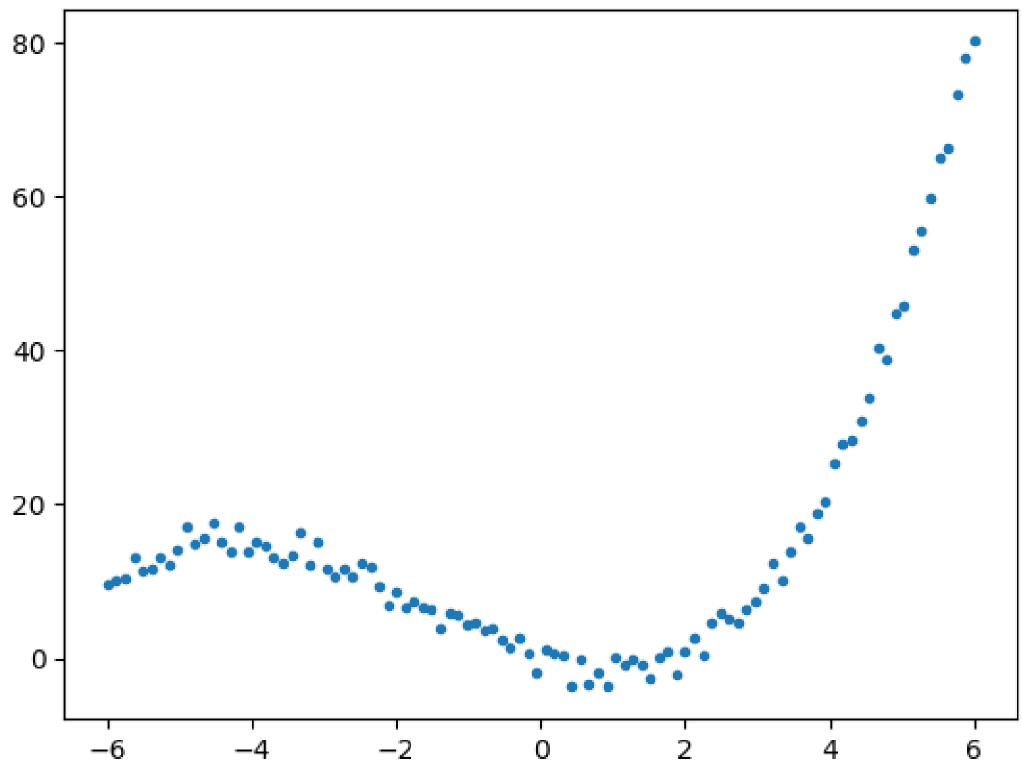
[76]:
```
## Use the Regression class defined in the previous lab
class regression:

  def __init__(self, name='reg'):
    self.name = name

  def grad_update(self,w_old,lr,y,x):
    w=w_old-(1/x.shape[1])*lr*(x @ ((x.T @ w_old)-y))
    return w

  def error(self,w,y,x):
    return np.mean(np.power((y-x.T @ w),2))

  def mat_inv(self,y,x_aug):
    return np.linalg.pinv((x_aug @ x_aug.T)) @ x_aug @ y

  def Regression_grad_des(self,x,y,lr):
    err=[]
    w_init = np.random.uniform(-1, 1, (x.shape[0],1))
    w_old=w_init
    w_pred=w_init
```

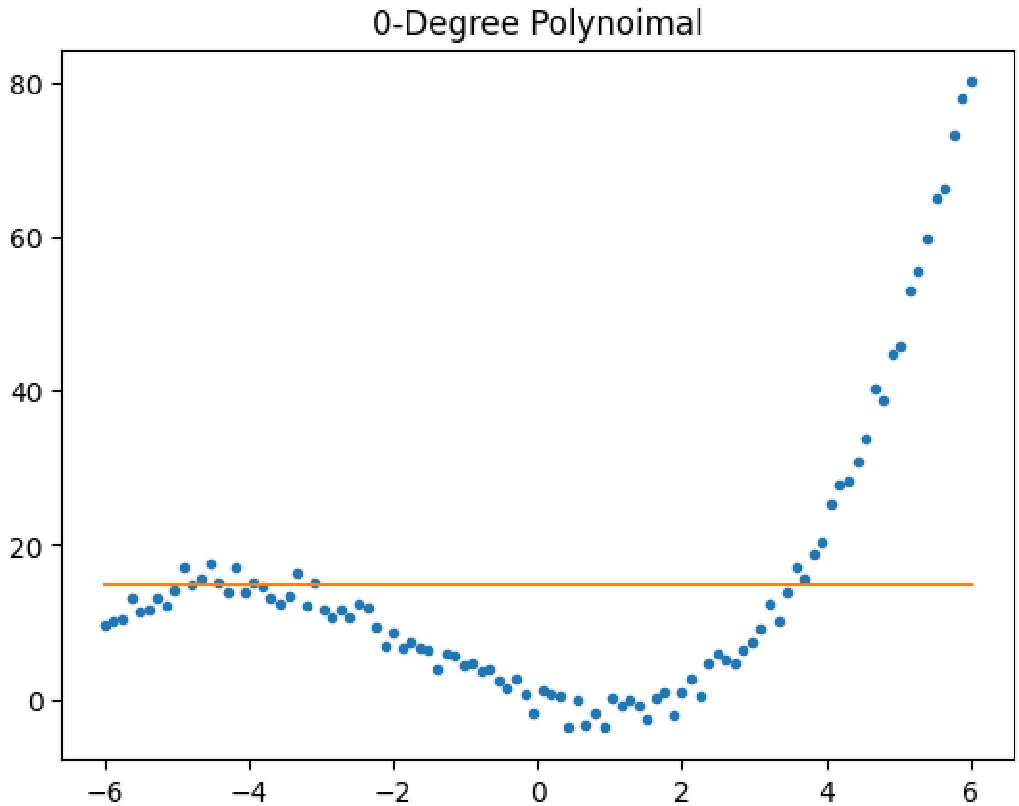
```
    for i in range(20000):
      w_old=w_pred
      w_pred=self.grad_update(w_old,lr,y,x)

      err.append(self.error(w_pred,y,x))
      dev=np.abs(self.error(w_pred,y,x)-self.error(w_old,y,x))

      if dev<=1e-4:
        break

    return w_pred,err
```

[55]:
```
## Data generation

x=np.linspace(-6,6,100)
x=x[np.newaxis,:]

w = np.array([[-3],[-3],[1.25],[0.25]]) ## Define Weights as per the given␣
 ↪equation

## Function to transform the data into polynomial

def data_transform(X,degree):
  X_new=[]
  for i in range(degree +1):
    X_new.append(X**i)
  X_new = np.concatenate(X_new)
  return X_new


X = data_transform(x,3)

y = X.T @ w

y = y+5*np.random.uniform(0,1,y.shape)

plt.plot(x.T,y,'.')

reg=regression()

# By computation

# Code for degree 0 polynomial fitting

degree = 0
X_1 = data_transform(x,degree)
w_mat=reg.mat_inv(y,X_1)
```

```
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('0-Degree Polynoimal')


# Write the code for degree 1 polynomial fitting
degree = 1
X_1 = data_transform(x,degree)
w_mat=reg.mat_inv(y,X_1)
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('1-Degree Polynoimal')
# Write the code for degree 2 polynomial fitting
degree = 2
X_1 = data_transform(x,degree)
w_mat=reg.mat_inv(y,X_1)
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('2-Degree Polynoimal')
# Write the code for degree 3 polynomial fitting
degree = 3
X_1 = data_transform(x,degree)
w_mat=reg.mat_inv(y,X_1)
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('3-Degree Polynoimal')
# Write the code for degree 4 polynomial fitting
degree = 4
X_1 = data_transform(x,degree)
w_mat=reg.mat_inv(y,X_1)
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('4-Degree Polynoimal')
```

[55]:
```
Text(0.5, 1.0, '4-Degree Polynoimal')
```


80
60
40
20
0
−6
−4
−2
0
2
4
6


0-Degree Polynoimal
80
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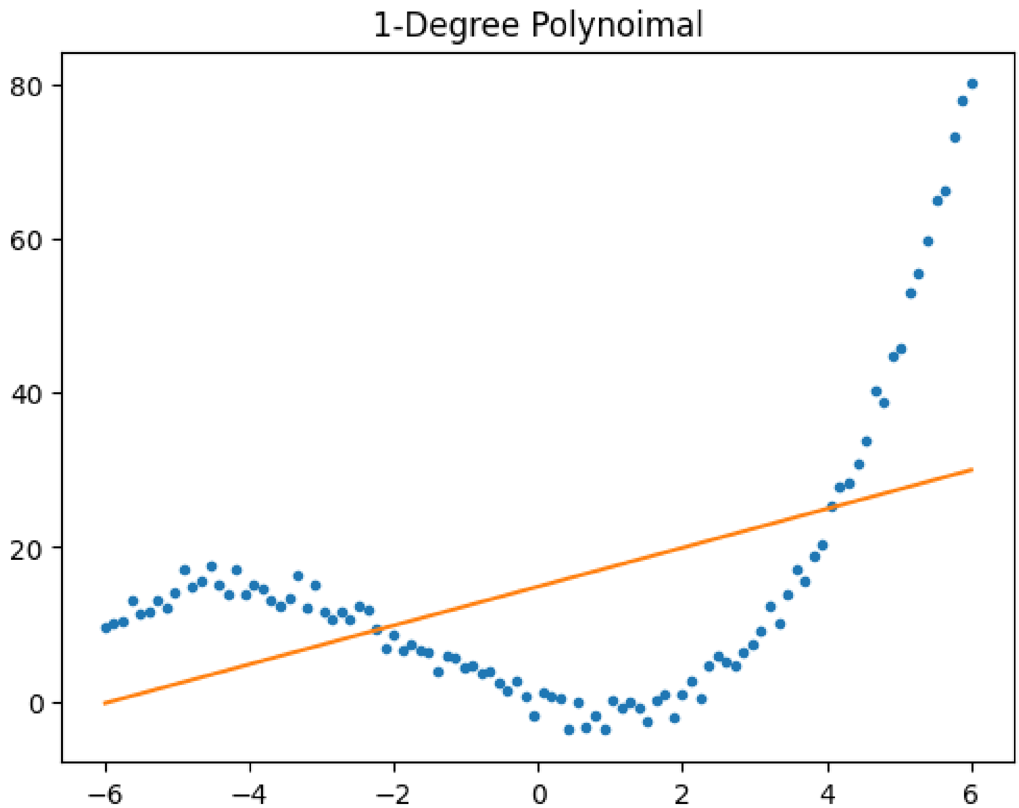
−6
−4
−2
0
2
4
6


1-Degree Polynoimal
80
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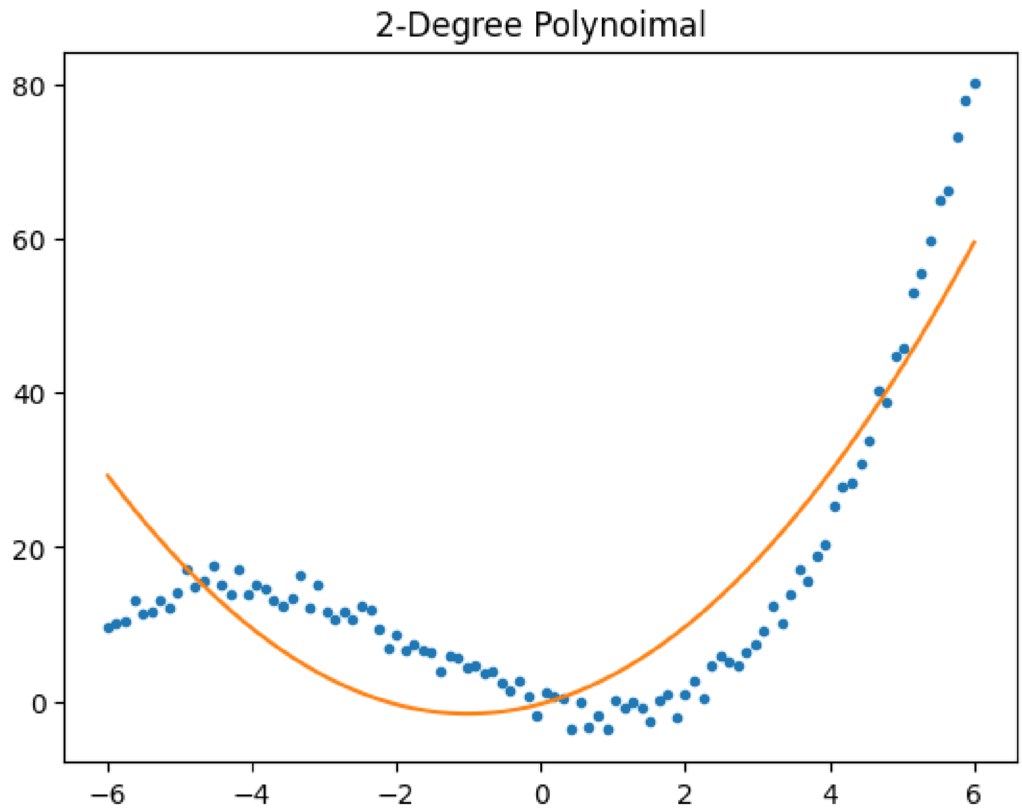
−4
−2
0
2
4
6


2-Degree Polynoimal
80
60
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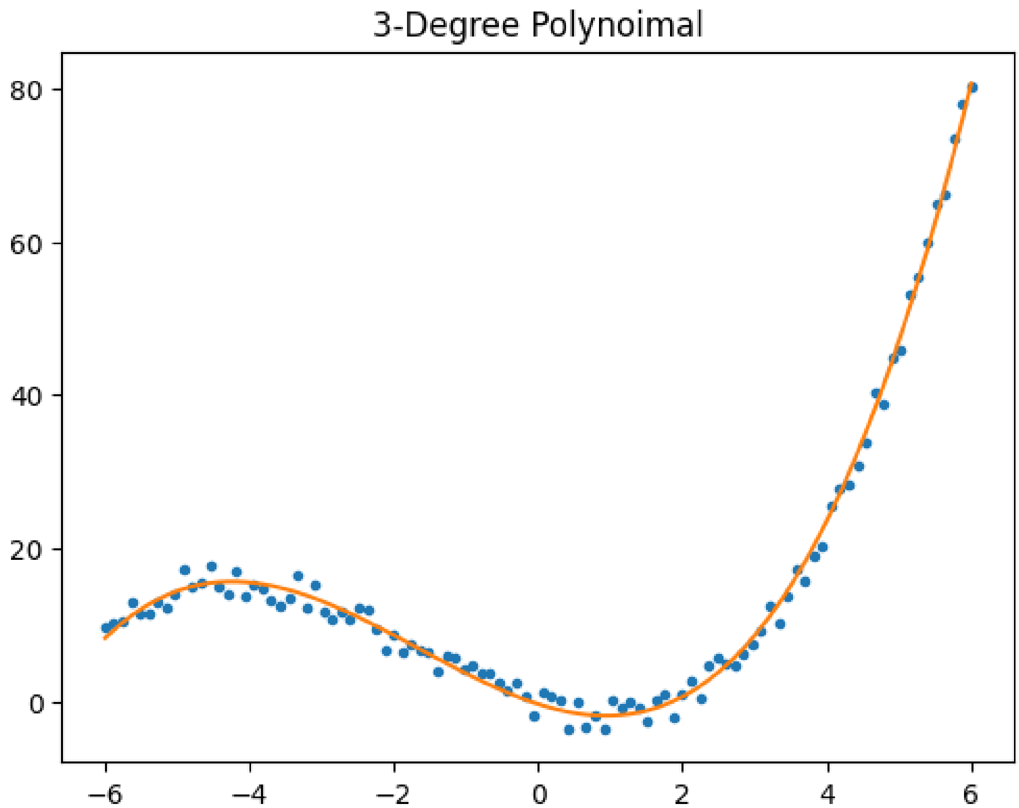
20
0
−6
−4
−2
0
2
4
6


3-Degree Polynoimal
80
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20
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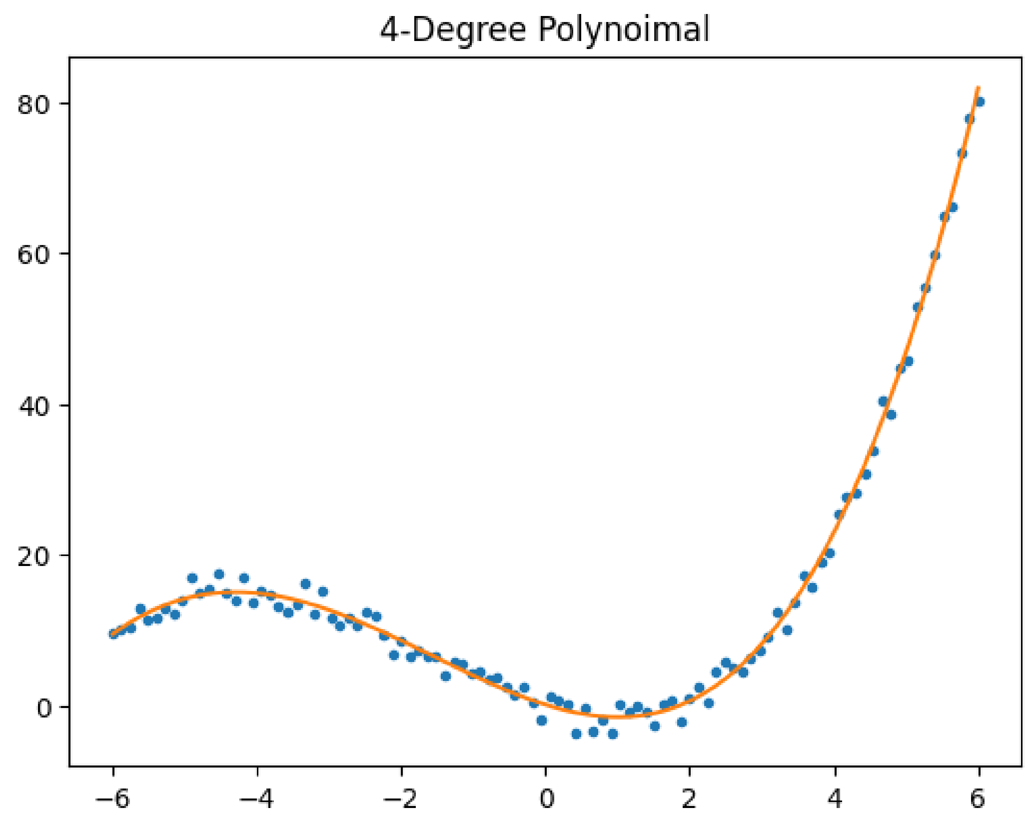
−6
−4
−2
0
2
4
6

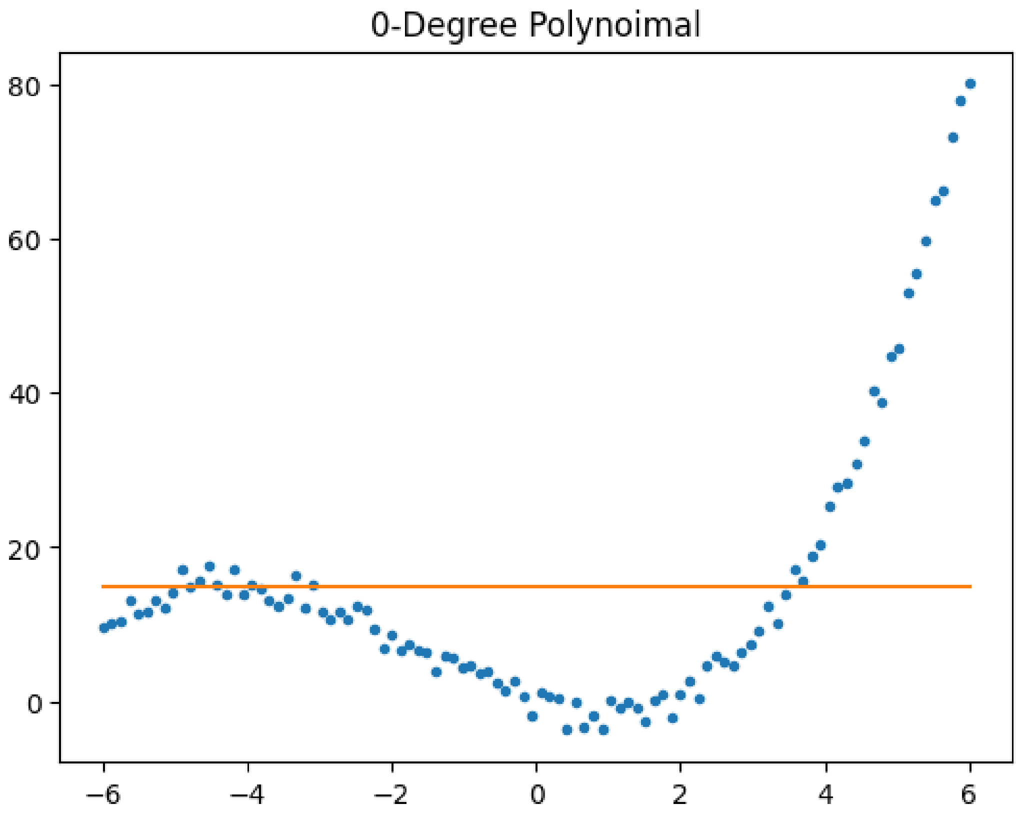


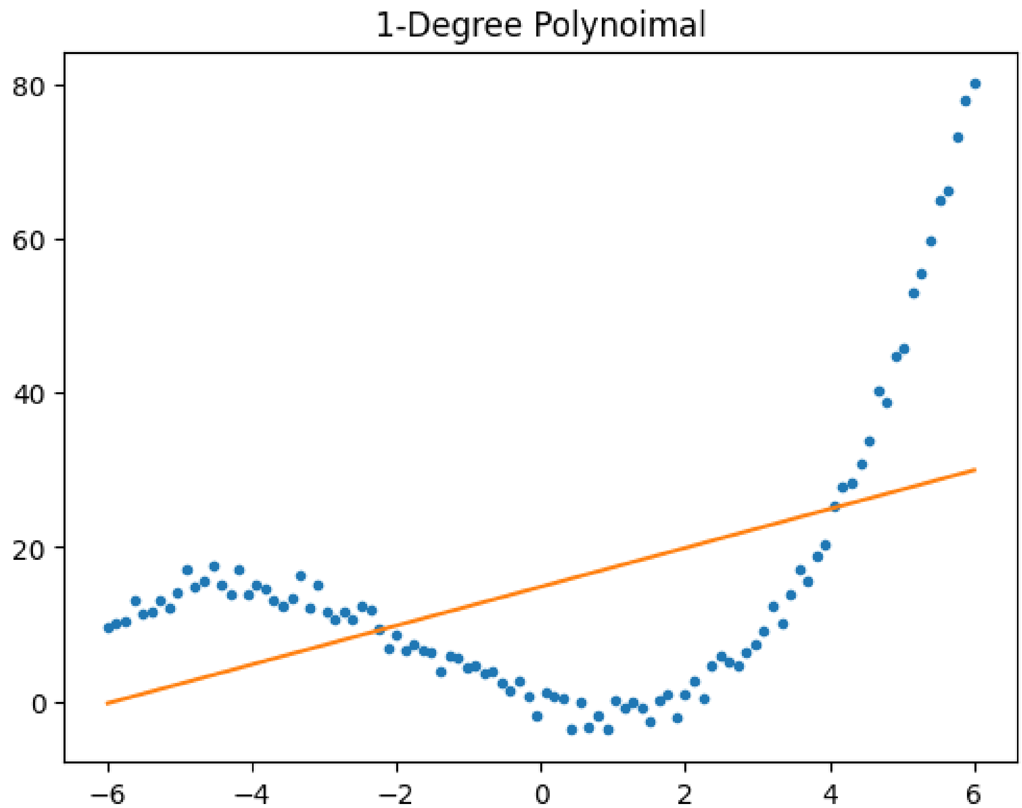
[79]:
```
# By Gradient Descent
x=np.linspace(-6,6,100)
x=x[np.newaxis,:]

degree = 0
X_0 = data_transform(x,degree)
w_mat, _=reg.Regression_grad_des(X_0,y, 0.1)
print(X_0.shape)
print(w_mat.shape)
y_pred=X_0.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('0-Degree Polynoimal')
## Write your code here
degree = 1
X_1 = data_transform(x,degree)
w_mat, _=reg.Regression_grad_des(X_1,y, 0.1)
y_pred=X_1.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
```

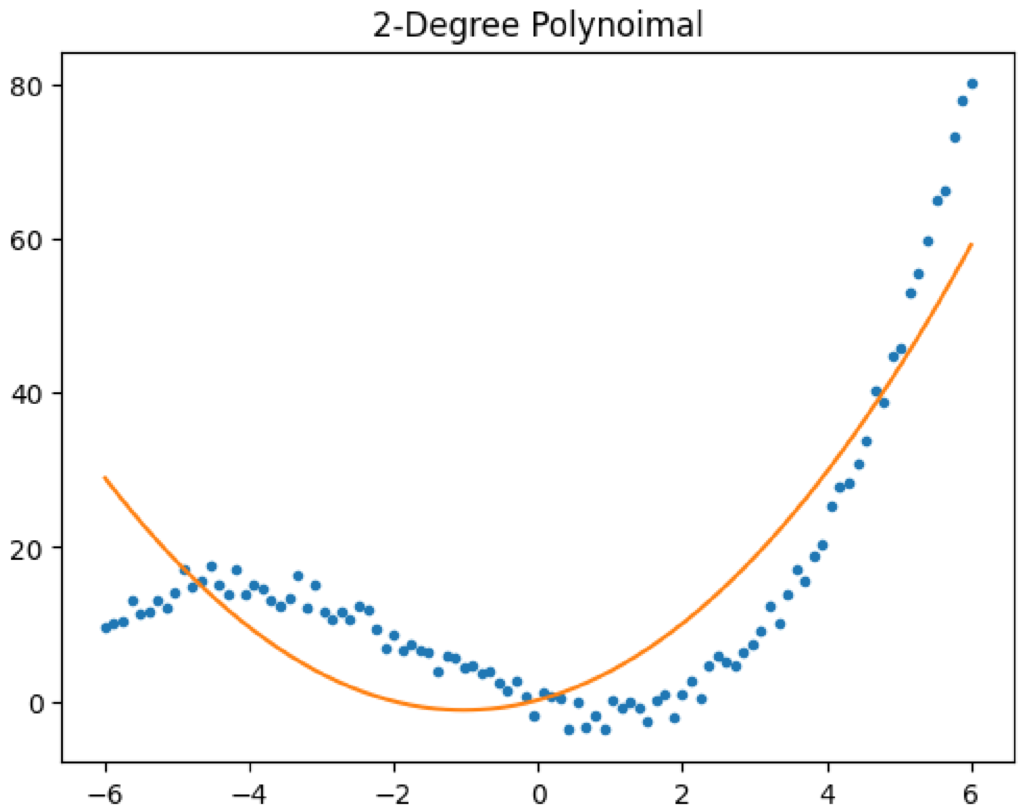
```
plt.plot(x.T,y_pred)
plt.title('1-Degree Polynoimal')


degree = 2
X_2 = data_transform(x,degree)
w_mat, _=reg.Regression_grad_des(X_2,y, 0.001)
y_pred=X_2.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('2-Degree Polynoimal')

degree = 3
X_3 = data_transform(x,degree)
w_mat, _=reg.Regression_grad_des(X_3,y, 0.0001)
y_pred=X_3.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('3-Degree Polynoimal')


degree = 4
X_4 = data_transform(x,degree)
w_mat, _=reg.Regression_grad_des(X_4,y, 0.000009)
y_pred=X_4.T @ w_mat
plt.figure()
plt.plot(x.T,y,'.')
plt.plot(x.T,y_pred)
plt.title('4-Degree Polynoimal')
```

```
(1, 100)
(1, 1)
```

[79]:
```
Text(0.5, 1.0, '4-Degree Polynoimal')
```


0-Degree Polynoimal
80
60
40
20
0
−6
−4
−2
0
2
4
6


1-Degree Polynoimal
80
60
40
20
0
−6
−4
−2
0
2
4
6


2-Degree Polynoimal
80
60
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20
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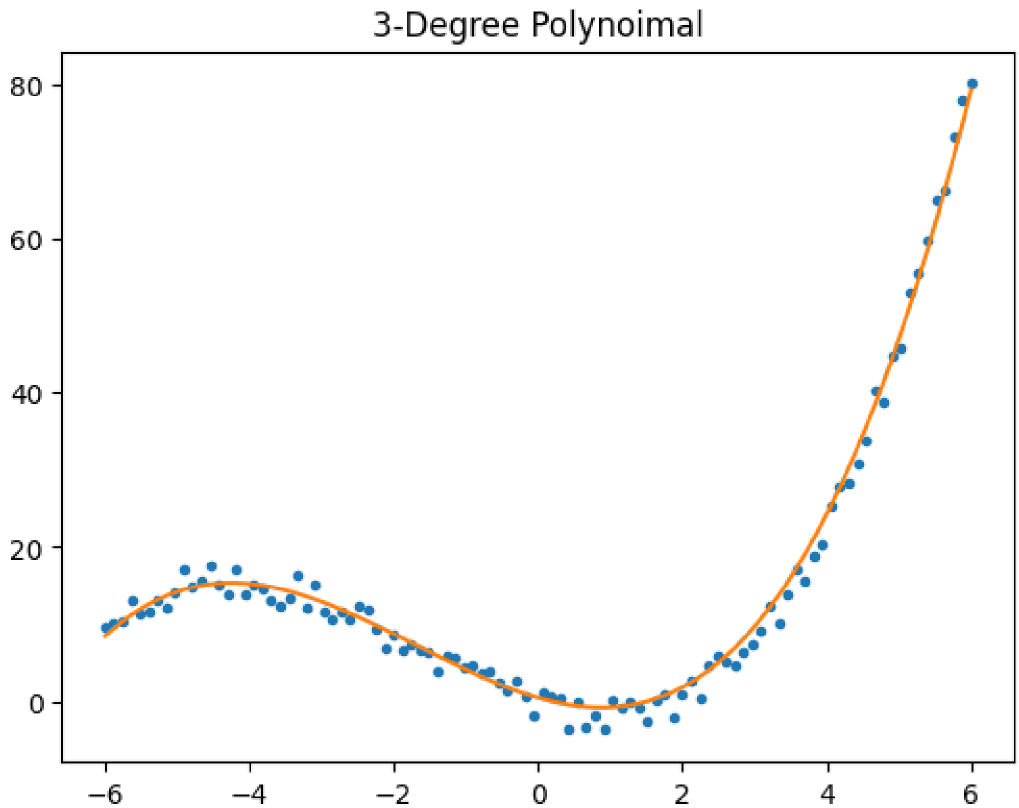
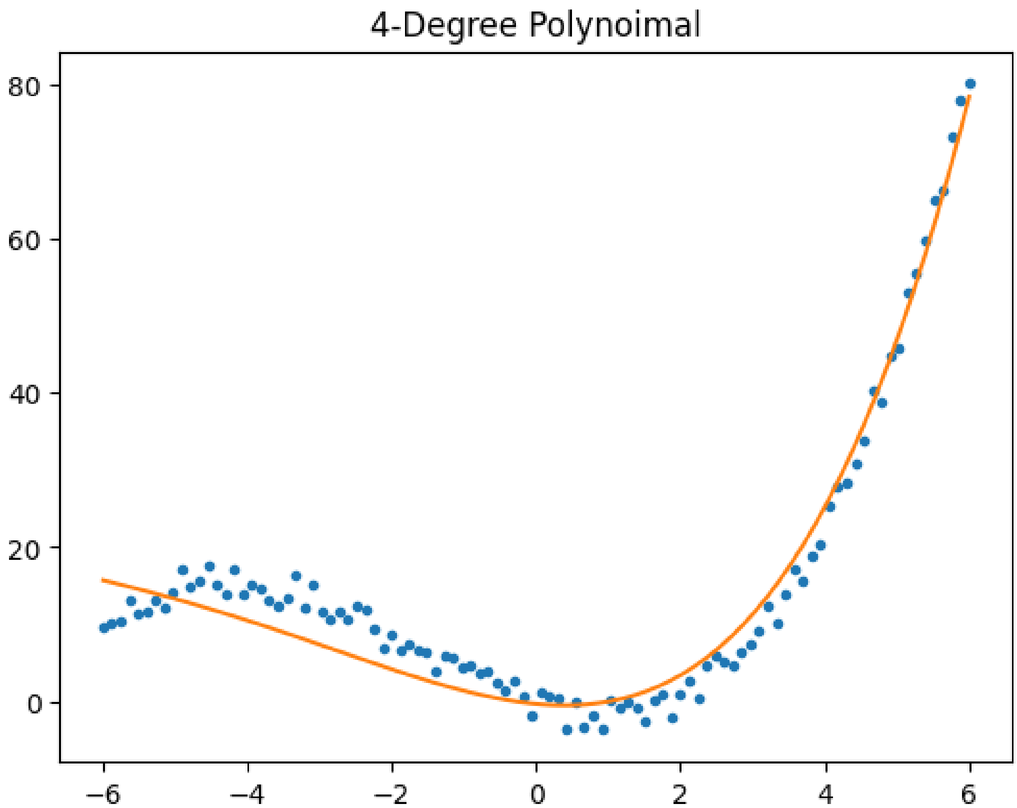
−6
−4
−2
0
2
4
6


3-Degree Polynoimal
80
60
40
20
0
−6
−4
−2
0
2
4
6



1 Linear Regression

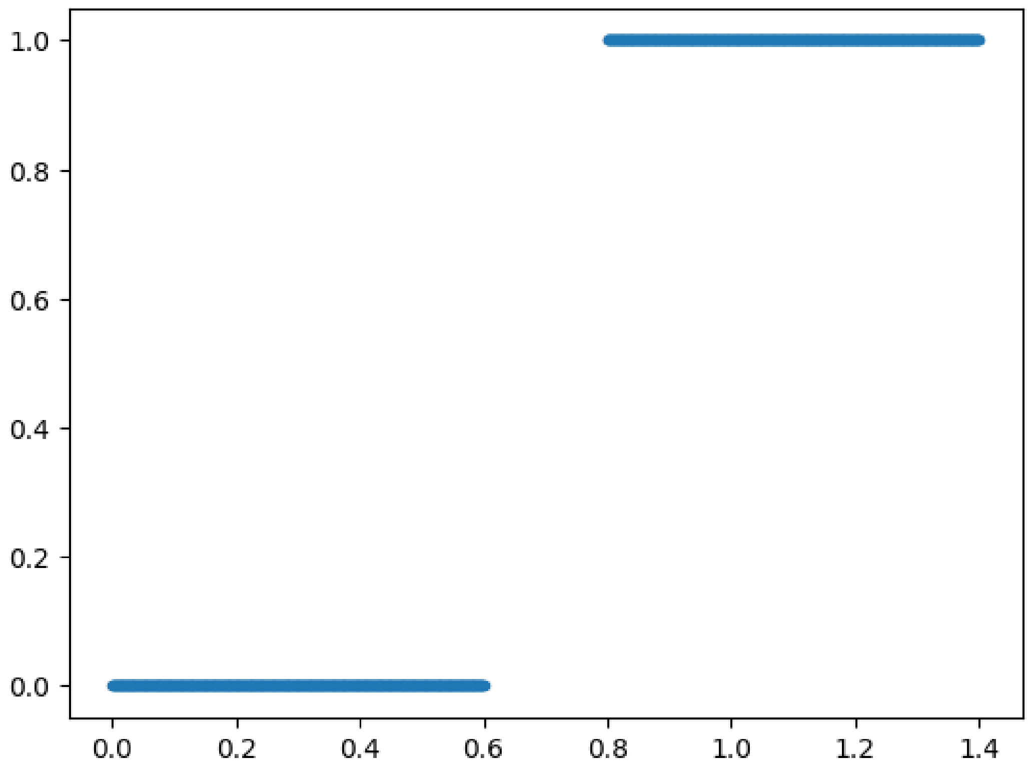
Generate the data as shown in the figure below

[84]:
```
## Write your code here
import numpy as np
import matplotlib.pyplot as plt

l1=np.linspace(0,0.6,500)
l2=np.linspace(0.8,1.4,500)
X=np.concatenate((l1,l2))

y1=np.zeros(l1.shape)
y2=np.ones(l2.shape)
Y=np.concatenate((y1,y2))

print(X.shape)

plt.figure()
plt.plot(X,Y,'.')
```

```
(1000,)
```

[84]:

```
[<matplotlib.lines.Line2D at 0x7ff088b93ee0>]
```



Use the Regression class defined in the previous lab to fit the curve

[85]:

```python
## Write your Code here
class regression:

  def __init__(self, name='reg'):
    self.name = name

  def grad_update(self,w_old,lr,y,x):
    w=w_old-(1/x.shape[1])*lr*(x @ ((x.T @ w_old)-y))
    return w

  def error(self,w,y,x):
    return np.mean(np.power((y-x.T @ w),2))

  def Regression_grad_des(self,x,y,lr):
    err=[]
    w_init = np.random.uniform(-1, 1, (x.shape[0],1))
    w_old=w_init
```

```
    w_pred=w_init
    for i in range(20000):
      w_old=w_pred
      w_pred=self.grad_update(w_old,lr,y,x)

      err.append(self.error(w_pred,y,x))
      dev=np.abs(self.error(w_pred,y,x)-self.error(w_old,y,x))

      if dev<=1e-4:
        break

    return w_pred,err
```

Augment the Data and generate optimal weights

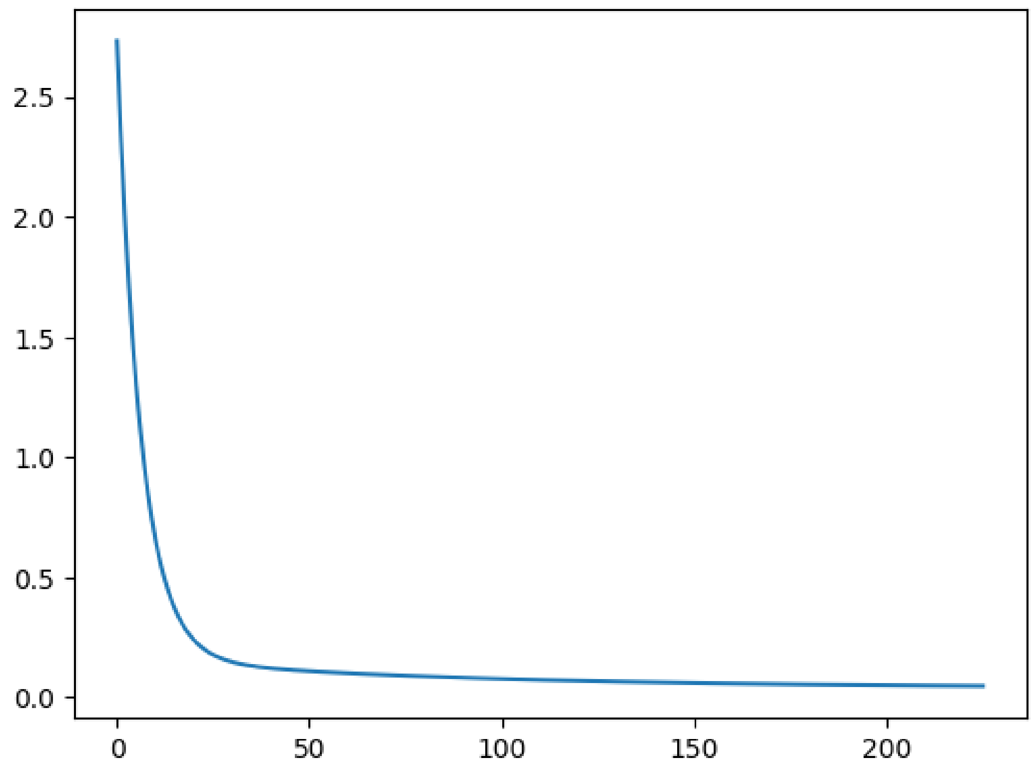
[87]:
```
## Write your Code here
_X = X[:, np.newaxis].T
x_ones = np.ones((1, _X.shape[1]))
x_aug = np.concatenate((x_ones, _X))
print(x_aug.shape)
y_new = Y[:, np.newaxis]

linreg = regression()
w, err = linreg.Regression_grad_des(x_aug, y_new, 0.05)
print(w)
```

```
(2, 1000)
[[-0.07585244]
 [ 0.85062802]]
```

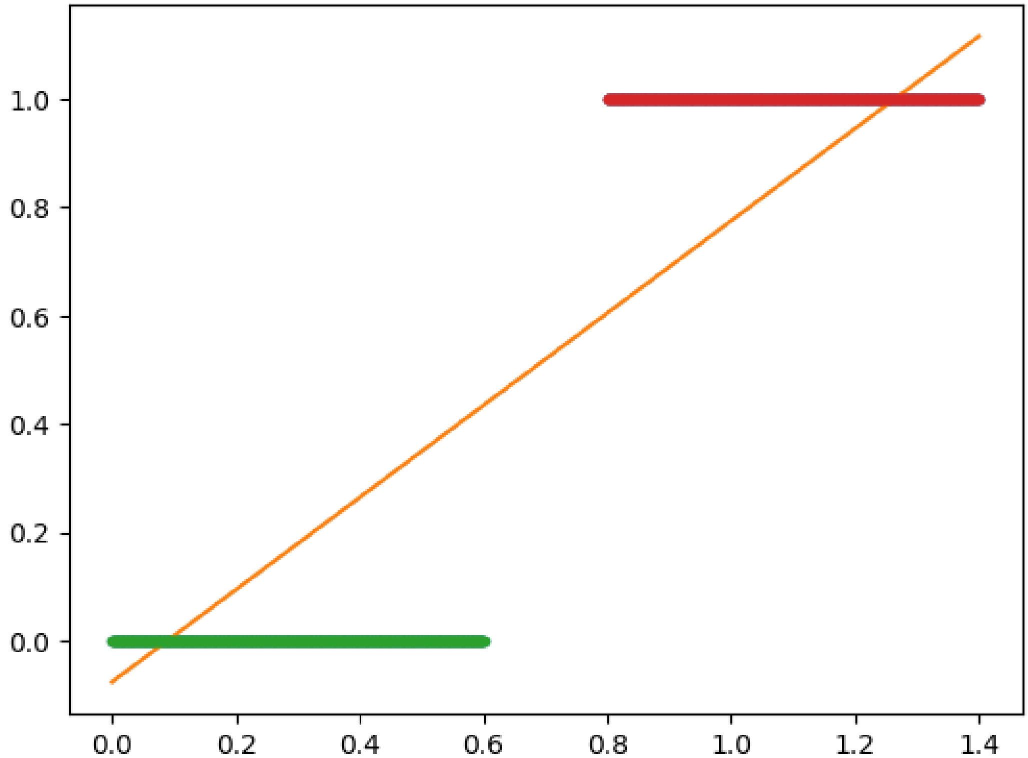
Using the optimal weights, fit the curve

[96]:
```
## Write your Code here
## Write your Code here
plt.figure()
plt.plot(err)
plt.show()

y_out = x_aug.T @ w

class_A = []
class_B = []

for i in range(len(X.T)):
    if y_out[i]>=0.5:
        class_A.append(X.T[i])
    else:
        class_B.append(X.T[i])
```

```
plt.figure()
plt.plot(X.T, Y,'.')
plt.plot(X.T, y_out)
plt.plot(class_B, np.zeros(len(class_B)), '.')
plt.plot(class_A, np.ones(len(class_A)), '.')
```



[96]: [<matplotlib.lines.Line2D at 0x7ff088857f40>]

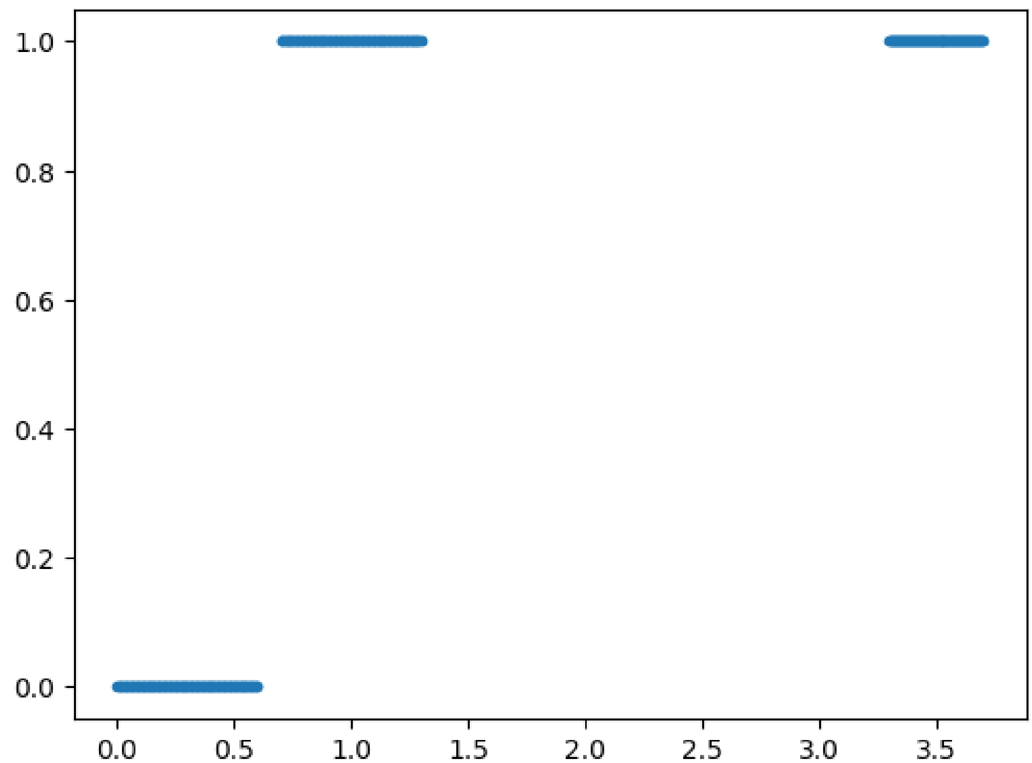


2 Drawback of Linear regression based Classificaton

Generate the Data as shown in the figure and follow the same steps as above to fit a curve using regression class

[97]:
```
## Write your code here
c1 = np.linspace(0,0.6,100)
c2 = np.linspace(0.7,1.3,100)
c3 = np.linspace(3.3,3.7,100)

y1 = np.zeros(c1.shape)
y2 = np.ones(c2.shape)
y3 = np.ones(c3.shape)

X = np.concatenate((c1,c2,c3))
Y = np.concatenate((y1,y2,y3))

plt.figure()
plt.plot(X.T, Y,'.')
```

[97]:
```
[<matplotlib.lines.Line2D at 0x7ff0887d86d0>]
```



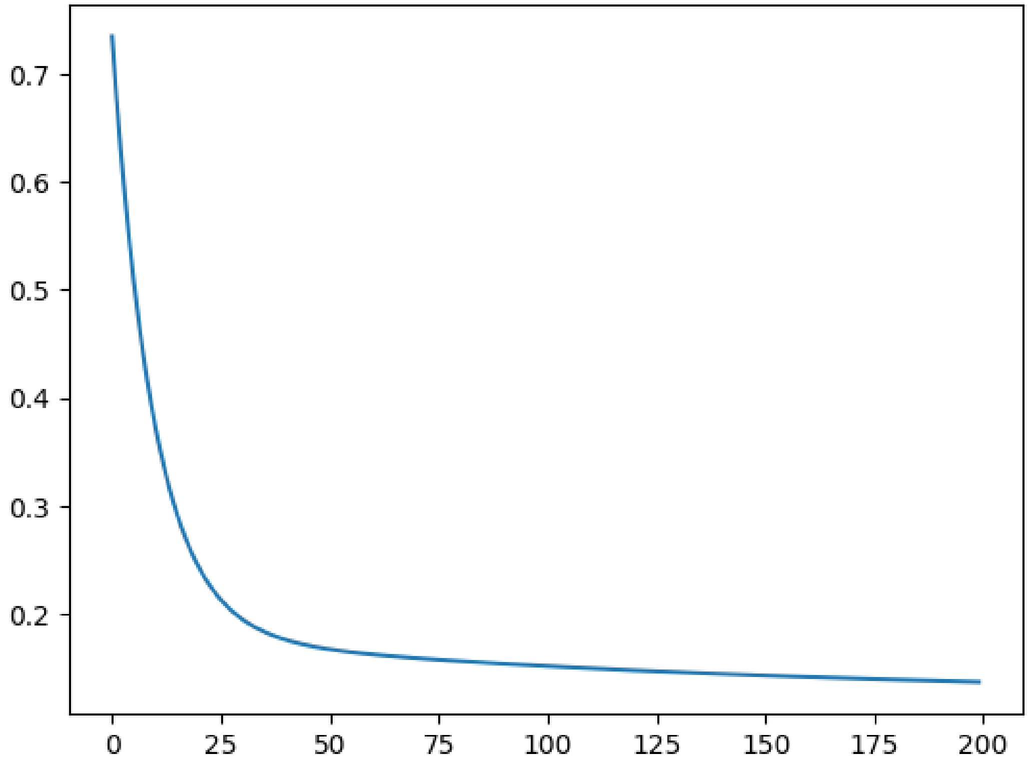
[102]:

```
## Write your code here

_X = X[:, np.newaxis].T
x_ones = np.ones((1, _X.shape[1]))
x_aug = np.concatenate((x_ones, _X))
y_new = Y[:, np.newaxis]


linreg = regression()
w, err = linreg.Regression_grad_des(x_aug, y_new, 0.01)

print(w)

plt.figure()
plt.plot(err)
```

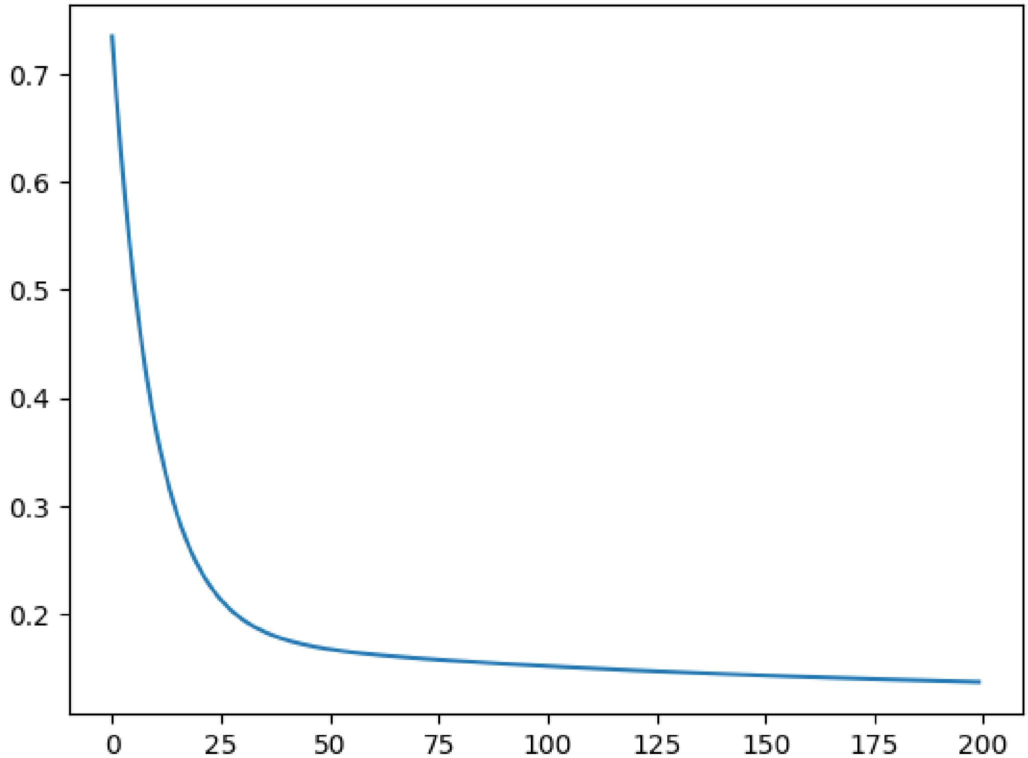
```
[[0.12923806]
 [0.29494205]]
```

[102]:

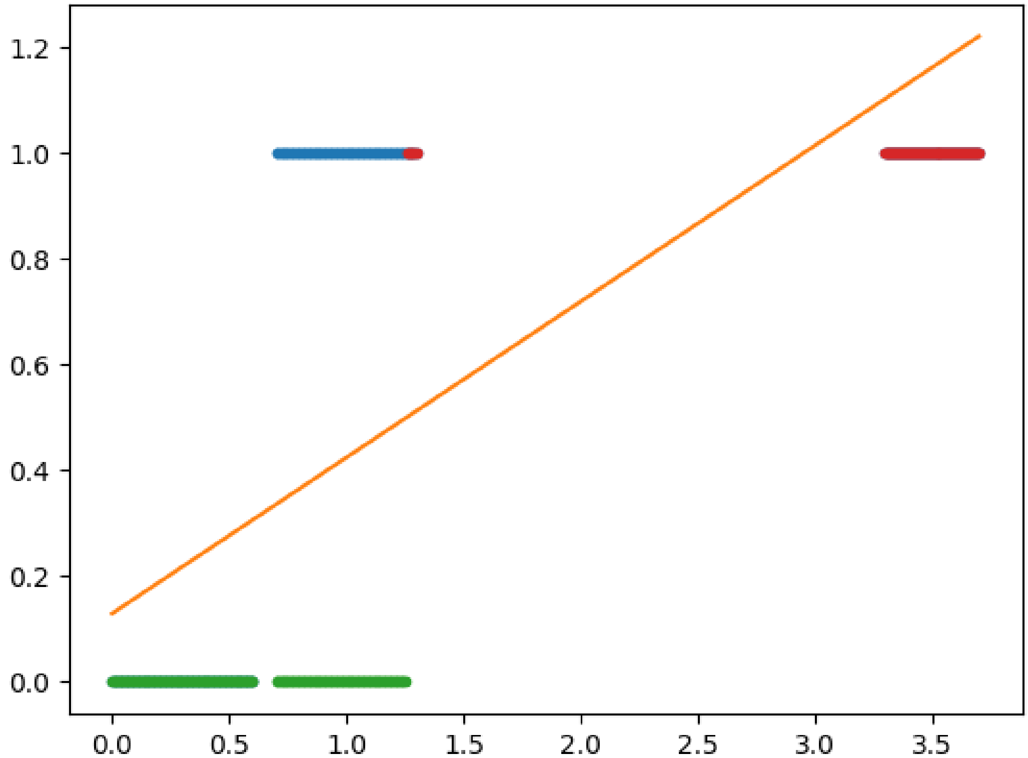
```
[<matplotlib.lines.Line2D at 0x7ff088691280>]
```



[103]:
```
plt.figure()
plt.plot(err)
plt.show()

y_out = x_aug.T @ w

class_A = []
class_B = []

for i in range(len(X.T)):
    if y_out[i]>=0.5:
        class_A.append(X.T[i])
    else:
        class_B.append(X.T[i])

plt.figure()
plt.plot(X.T, Y,'.')
plt.plot(X.T, y_out)
plt.plot(class_B, np.zeros(len(class_B)), '.')
plt.plot(class_A, np.ones(len(class_A)), '.')
```




```
[103]: [<matplotlib.lines.Line2D at 0x7ff0885e73a0>]
```

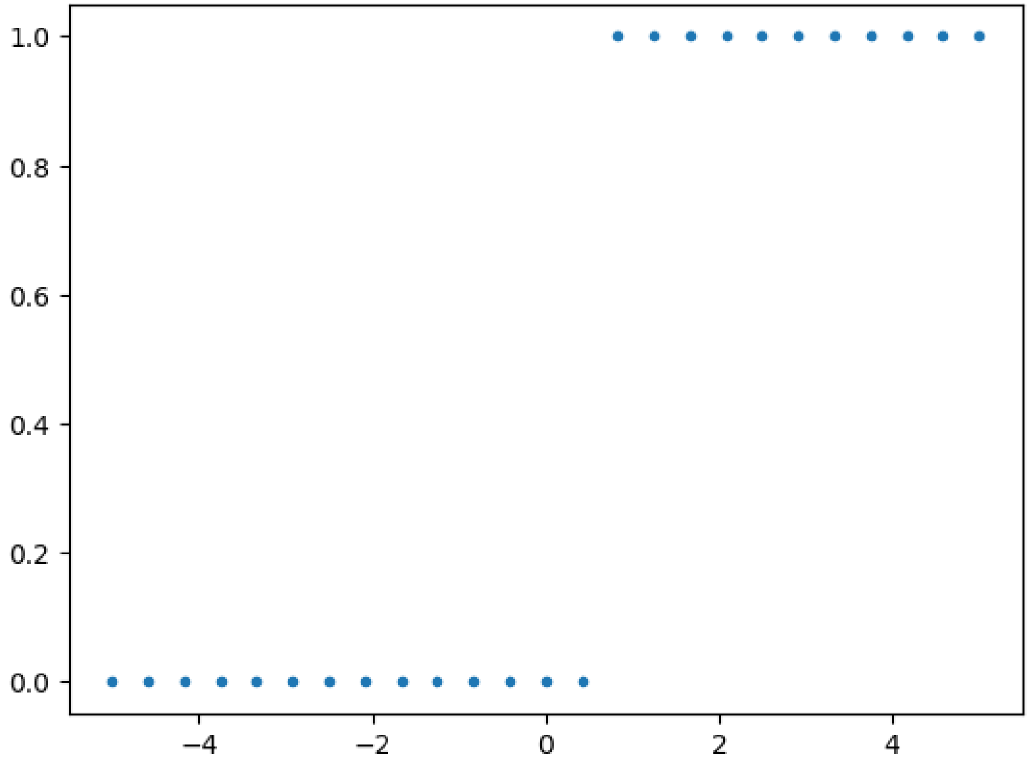


3 Logistic regression

Error Surface (Comparison between Logistic Loss and Mean Squared Error)

[109]:
```python
import numpy as np
import matplotlib.pyplot as plt


x=np.linspace(-5,5,25)
y=np.zeros(x.shape)
y[np.where(x>0.7314)]=1

plt.plot(x,y,'.')
```

[109]:
```
[<matplotlib.lines.Line2D at 0x7ff086ac19a0>]
```

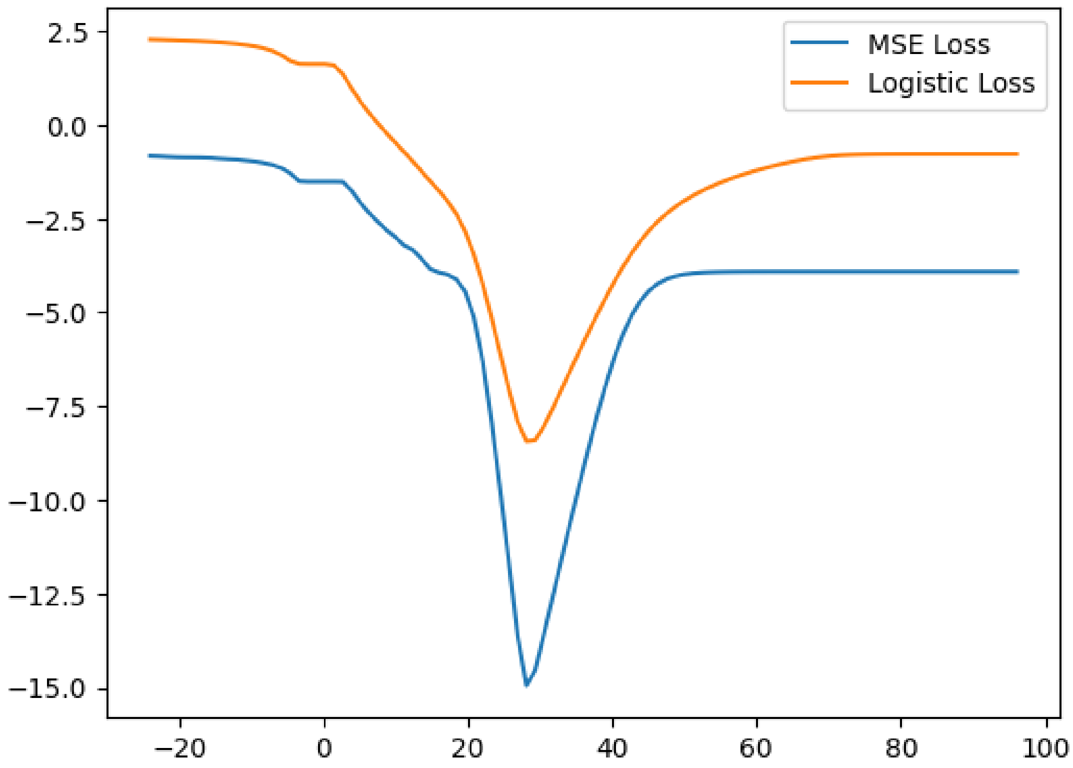


1. MSE=$\frac{1}{2N}\sum_{i=1}^{N}(y_i^p - y_i)^2$, where $y^p = \frac{1}{1+e^{-w^T x}}$
2. Logistic loss=$-\frac{1}{N}\sum_{i=1}^{N} y_i log(y_i^p) + (1-y_i)log(1-y_i^p)$

[112]:
```
# search space (only w1 is searched, where as w0 is fixed)
w1_in=10/(x[1]-x[0])
w0=-w1_in*0.7314
w1=np.linspace(-w1_in,4*w1_in,100)


cost_fn_mse=[]
cost_fn_logis=[]
for i in range(w1.shape[0]):
  z = w0 + w1[i]*x
  z_logistic = 1/(1 + np.exp(-z))

  MSE = np.sum((z_logistic - y)**2)/(2*x.shape[0])
  cost_fn_mse.append(MSE)

  LOG = -np.sum(y*np.log(z_logistic + 1e-5) + (1-y)*np.log(1-z_logistic+ 1e-5))/
 ↪(x.shape[0])
  cost_fn_logis.append(LOG)
```

[113]:
```
# Ploting of error surface
plt.figure()
plt.plot(w1,np.log(cost_fn_mse),label='MSE Loss')
plt.plot(w1,np.log(cost_fn_logis),label = 'Logistic Loss')
plt.legend()
```

[113]: <matplotlib.legend.Legend at 0x7ff086a99be0>



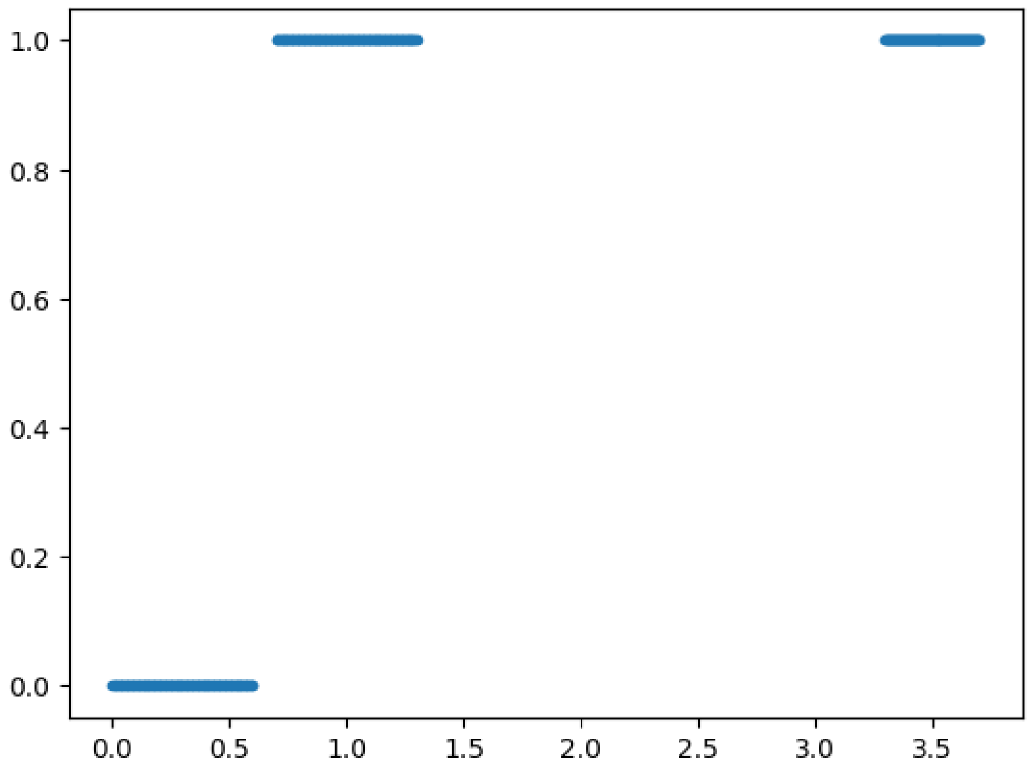
Solving the Outlier Issue

Generate the Data as shown in the figure

[114]:
```
## Write your Code here
c1 = np.linspace(0,0.6,100)
c2 = np.linspace(0.7,1.3,100)
c3 = np.linspace(3.3,3.7,100)

y1 = np.zeros(c1.shape)
y2 = np.ones(c2.shape)
y3 = np.ones(c3.shape)

X = np.concatenate((c1,c2,c3))
Y = np.concatenate((y1,y2,y3))
```

```
plt.figure()
plt.plot(X.T, Y,'.')
```

[114]: [<matplotlib.lines.Line2D at 0x7ff086a10c40>]



Define a Logistic Regression class

[115]:
```
class logis_regression:
  # Constructor
  def __init__(self, name='reg'):
    self.name = name  # Create an instance variable

  def logis(self,x,w_old):
    # write code here
    op = 1/(1 + np.exp(-(x.T @ w_old)))
    return op

  def grad_update(self,w_old,lr,y,x):
    # write code here
    w = w_old - (2*lr/x.shape[1])*(x @ ( (self.logis(x, w_old)-y )))
    return w
```

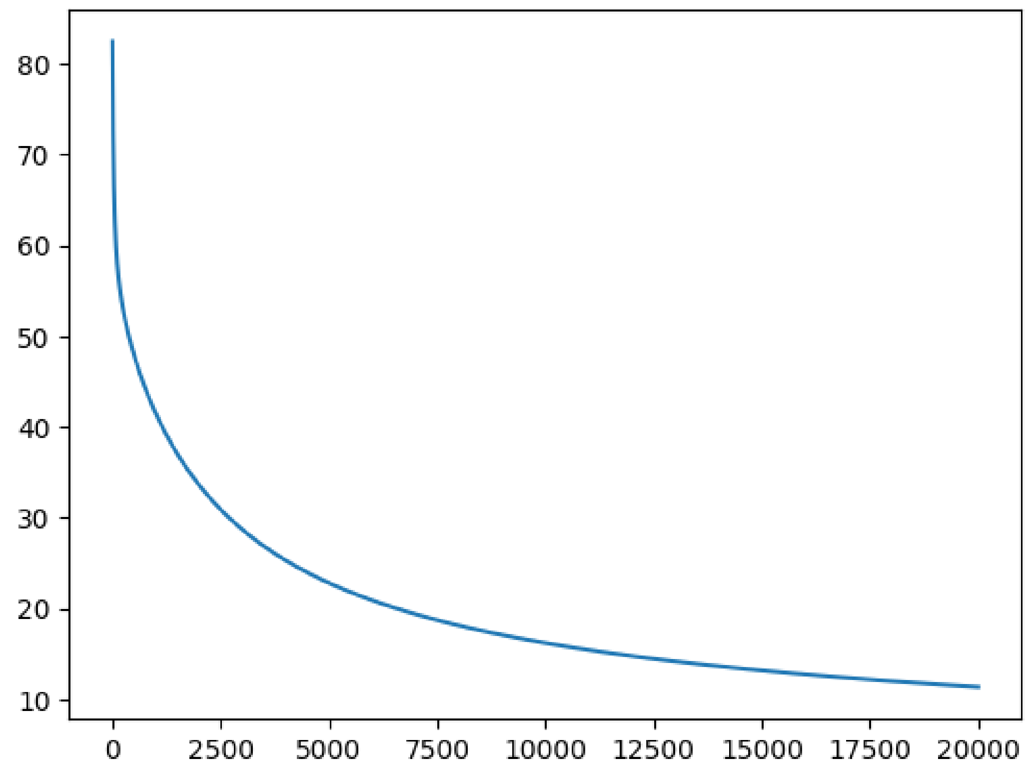
```python
  def error(self,w,y,x):

    LOG = self.logis(x,w)
    ret = -np.sum(y*np.log(LOG + 1e-5) + (1-y)*np.log(1-LOG+ 1e-5))/(x.shape[0])
    return ret

  def Regression_grad_des(self,x,y,lr):
    err=[]
    w_init = np.random.uniform(-1, 1, (x.shape[0],1))
    w_old=w_init
    w_pred=w_init
    for i in range(20000):
      w_old=w_pred
      w_pred=self.grad_update(w_old,lr,y,x)

      err.append(self.error(w_pred,y,x))
      dev=np.abs(self.error(w_pred,y,x)-self.error(w_old,y,x))

      if dev<=1e-4:
        break

    return w_pred,err
```

Augment the data and fit the curve by obtaining optimal weights (Using Gradient Descent)

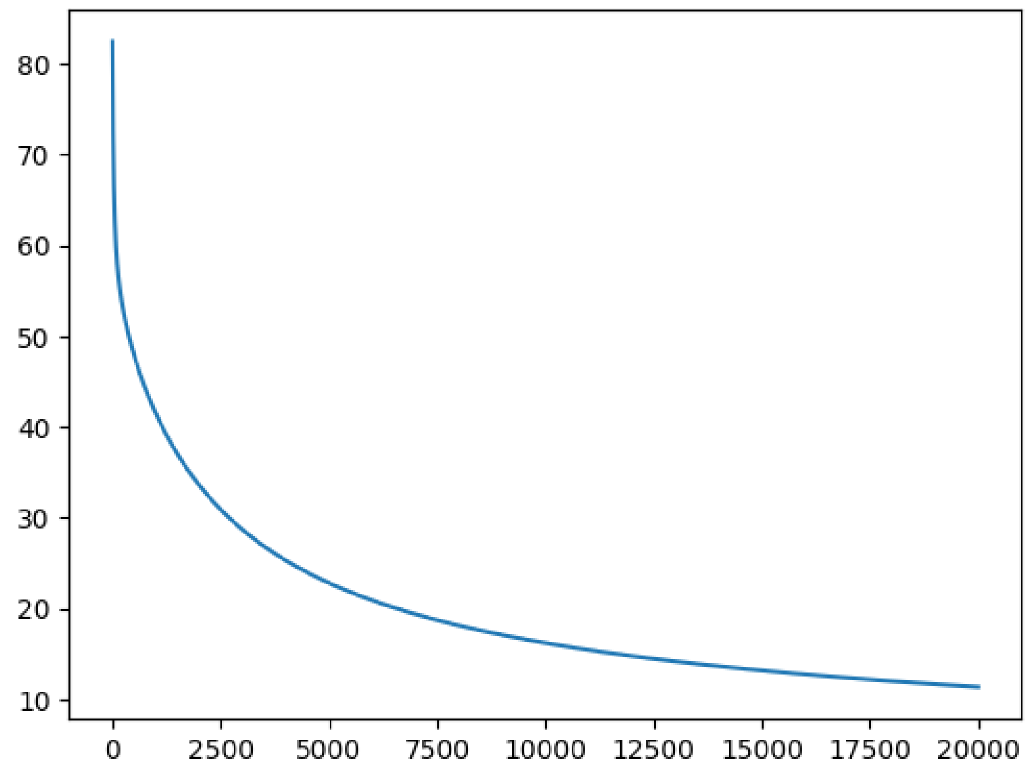
[116]:
```python
## Write your code here
_X = X[:, np.newaxis].T
x_ones = np.ones((1, _X.shape[1]))
x_aug = np.concatenate((x_ones, _X))
y_new = Y[:, np.newaxis]

linreg = logis_regression()
w, err = linreg.Regression_grad_des(x_aug, y_new, 0.01)

print(w)

plt.figure()
plt.plot(err)
```

```
[[-5.39035197]
 [ 8.45421495]]
```

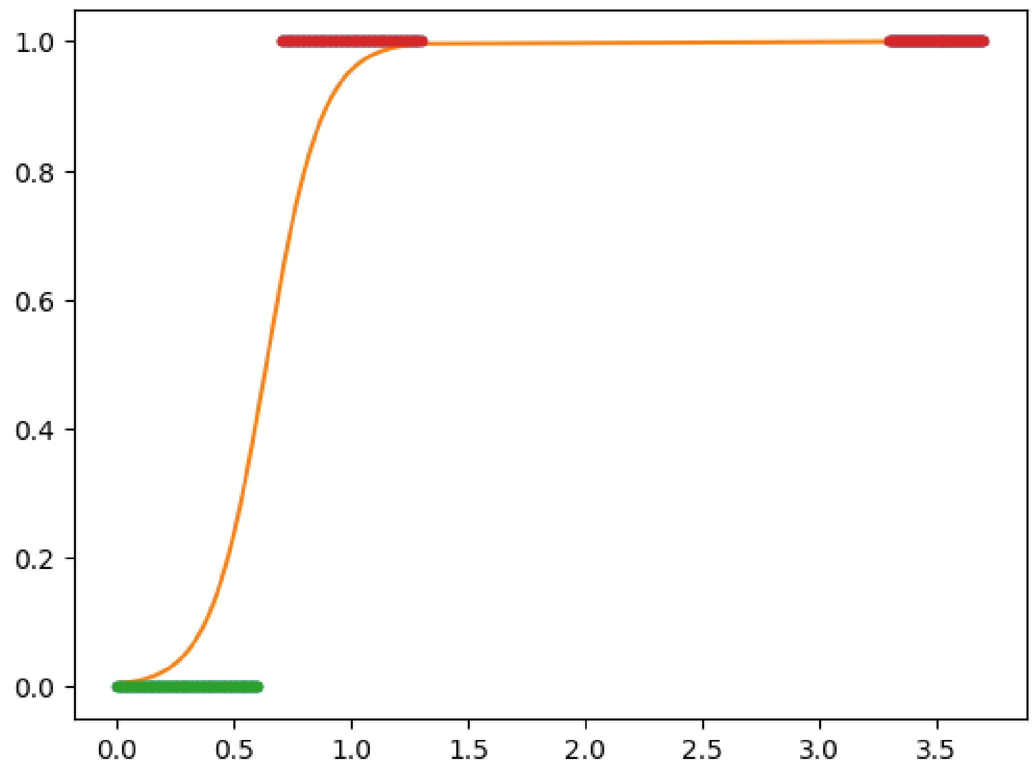
[116]:
```
[<matplotlib.lines.Line2D at 0x7ff0869266d0>]
```



[118]:
```
plt.figure()
plt.plot(err)
plt.show()

y_out = 1/(1 + np.exp(-(x_aug.T @ w)))

class_A = []
class_B = []

for i in range(len(X.T)):
    if y_out[i]>=0.5:
        class_A.append(X.T[i])
    else:
        class_B.append(X.T[i])

plt.figure()
plt.plot(X.T, Y,'.')
plt.plot(X.T, y_out)
plt.plot(class_B, np.zeros(len(class_B)), '.')
plt.plot(class_A, np.ones(len(class_A)), '.')
```



[118]: [<matplotlib.lines.Line2D at 0x7ff086762ca0>]

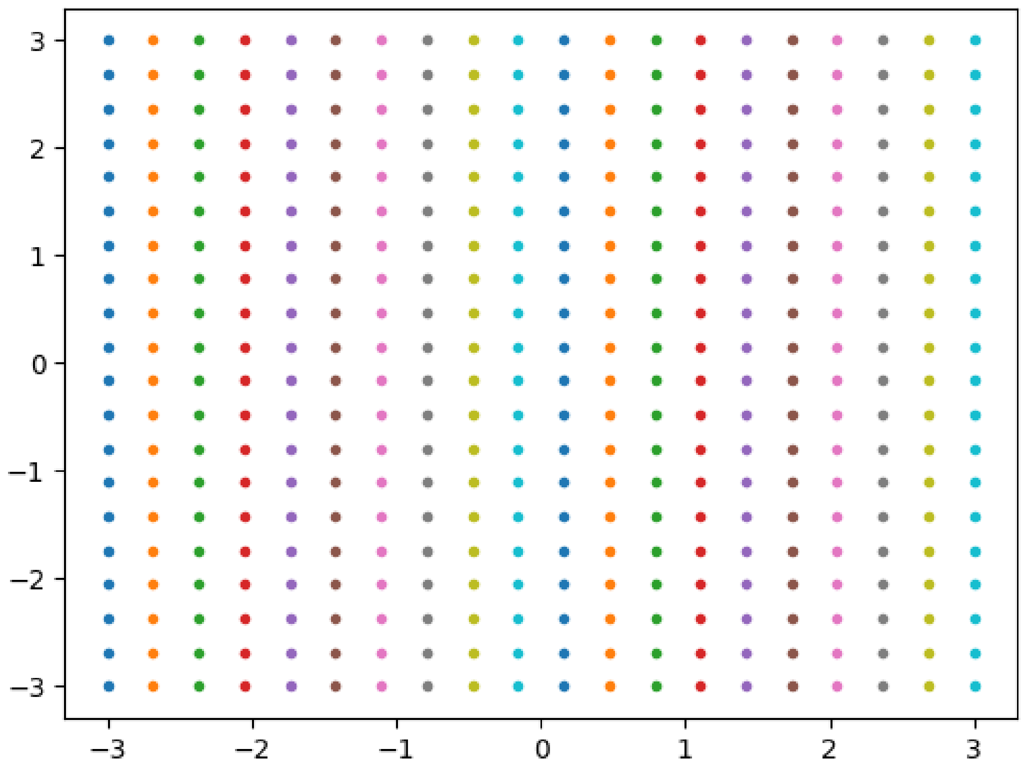


4 Classification of circularly separated data using logistic regression

[119]:
```
x1=np.linspace(-3,3,20)
x2=np.linspace(-3,3,20)

x11,x22=np.meshgrid(x1,x2)
plt.plot(x11,x22,'.')
```

[119]:
```
[<matplotlib.lines.Line2D at 0x7ff0866cabe0>,
 <matplotlib.lines.Line2D at 0x7ff0866cacd0>,
 <matplotlib.lines.Line2D at 0x7ff0866cadf0>,
 <matplotlib.lines.Line2D at 0x7ff0866caf10>,
 <matplotlib.lines.Line2D at 0x7ff0866d8070>,
 <matplotlib.lines.Line2D at 0x7ff0866d8190>,
 <matplotlib.lines.Line2D at 0x7ff0866d82b0>,
 <matplotlib.lines.Line2D at 0x7ff0866d83d0>,
 <matplotlib.lines.Line2D at 0x7ff0866d84f0>,
 <matplotlib.lines.Line2D at 0x7ff0866d8610>,
 <matplotlib.lines.Line2D at 0x7ff0866cac10>,
 <matplotlib.lines.Line2D at 0x7ff0866d8820>,
```

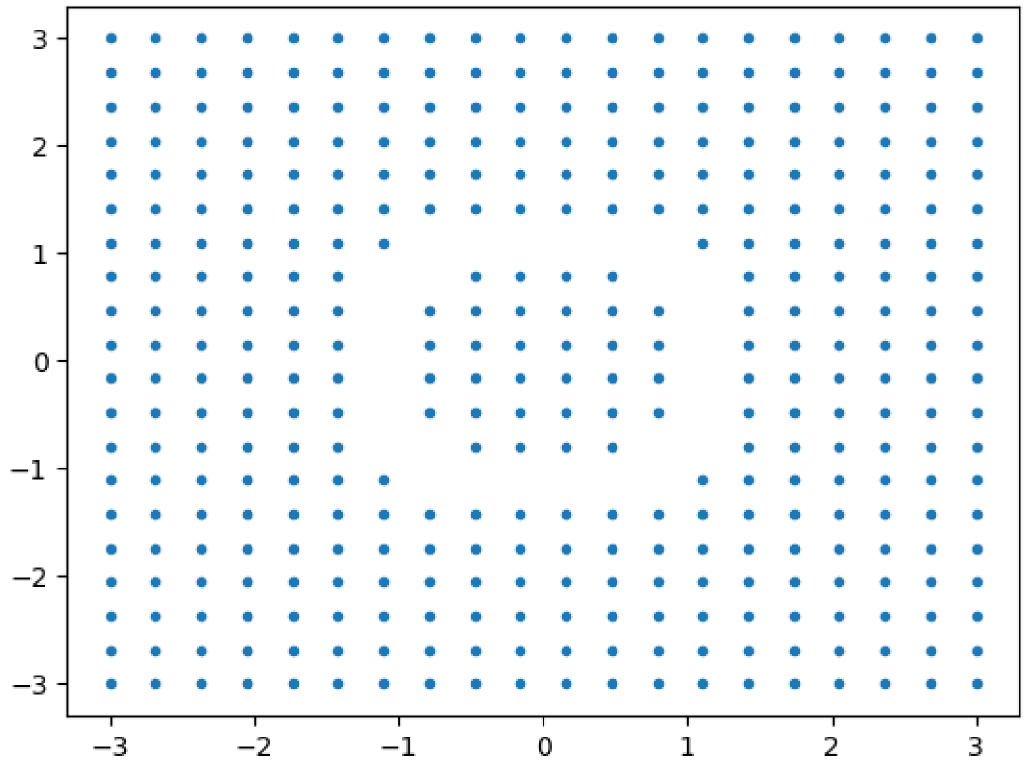
```
<matplotlib.lines.Line2D at 0x7ff0866d8940>,
<matplotlib.lines.Line2D at 0x7ff0866d8a60>,
<matplotlib.lines.Line2D at 0x7ff0866d8b80>,
<matplotlib.lines.Line2D at 0x7ff0866d8ca0>,
<matplotlib.lines.Line2D at 0x7ff0866d8dc0>,
<matplotlib.lines.Line2D at 0x7ff0866d8ee0>,
<matplotlib.lines.Line2D at 0x7ff0866de040>,
<matplotlib.lines.Line2D at 0x7ff0866de160>]
```



Using the above data generate circular data

[120]:
```
# Write code here
x1 = x11.flatten()
x1 = x1[:, np.newaxis]
x2 = x22.flatten()
x2 = x2[:, np.newaxis]
x = np.concatenate((x1, x2), axis=1)

inner_points = np.where((x[:,0]**2 + x[:,1]**2) <= 0.9)
outer_points = np.where((x[:,0]**2 + x[:,1]**2) >= 2.0)

x_inner = x[inner_points[0],:]
```

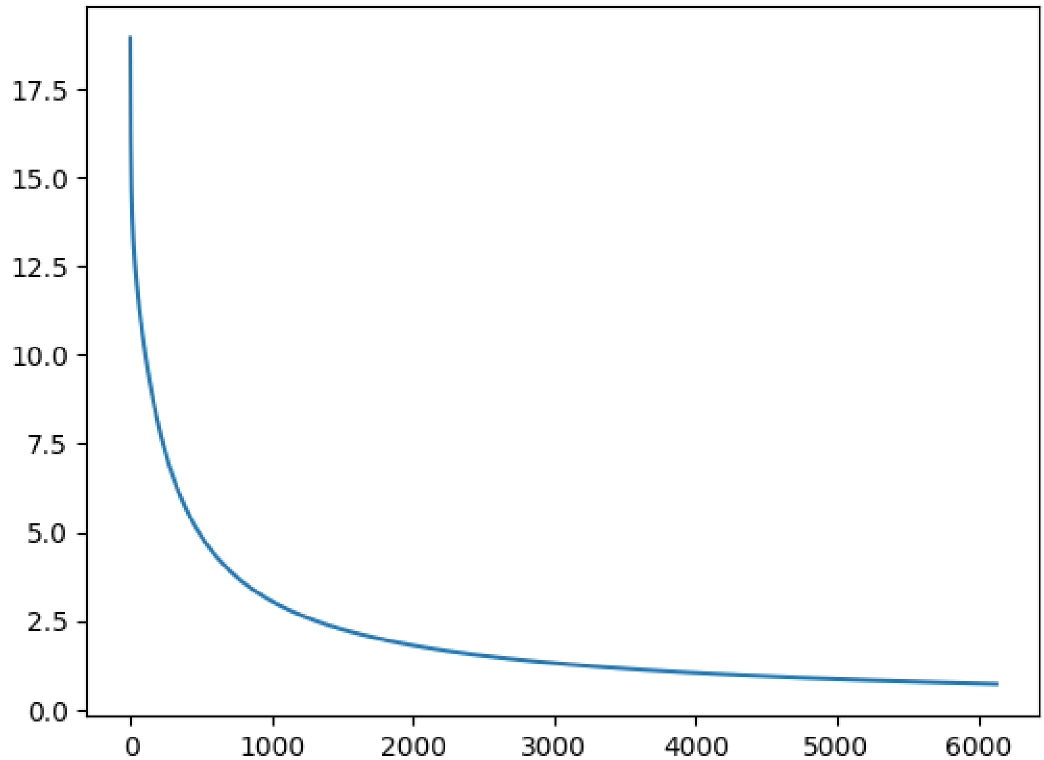
```
x_outer = x[outer_points[0],:]

X = np.concatenate((x_inner, x_outer))
plt.figure()
plt.plot(X[:,0], X[:,1], '.')
plt.show()
```



As in case of circularly separated data, the boundary is nonlinear, so squared feature is taken.

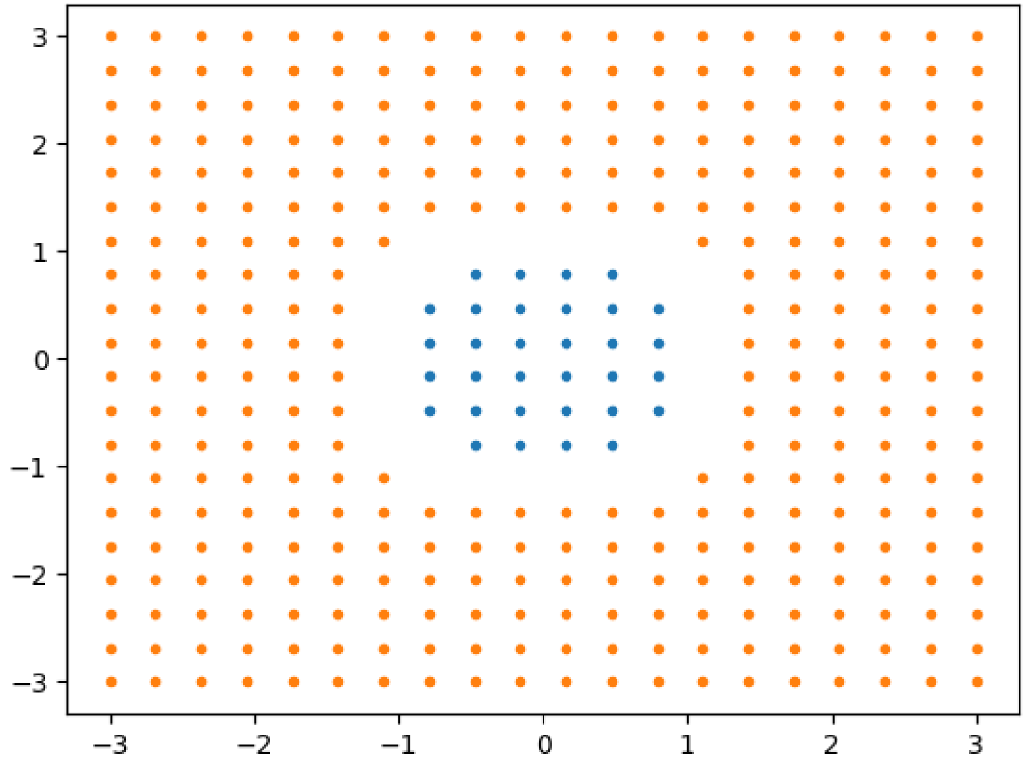
[121]:
```
# perform logistic regression
y_inner = np.zeros((x_inner.shape[0]))
y_outer = np.ones((x_outer.shape[0]))
Y = np.concatenate((y_inner, y_outer))
y_new = Y[:, np.newaxis]

x_sq = (X.T)**2
x_ones = np.ones((1, X.shape[0]))
x_aug = np.concatenate((x_ones, x_sq), axis=0)

reg = logis_regression()
w,err = reg.Regression_grad_des(x_aug, y_new, 0.1)
plt.figure()
```

```
plt.plot(err)
plt.show()
```



Plot classification using 0.5 as threshold

[124]:
```
#write code here
y_pred = reg.logis(x_aug,w)

inner, _ = np.where(y_pred < 0.5)
outer, _ = np.where(y_pred >= 0.5)

x_in_plt = X[inner,:]
x_out_plt = X[outer,:]

plt.figure()
plt.plot(x_in_plt[:,0], x_in_plt[:,1], '.')
plt.plot(x_out_plt[:,0], x_out_plt[:,1], '.')
plt.show()
```



5 Multiclass logistic regression

1. Generate 1D data with 3 classes

5.0.1 One vs rest classification

1. Lets take a polynomial of order 2 (by seeing the data distribution)

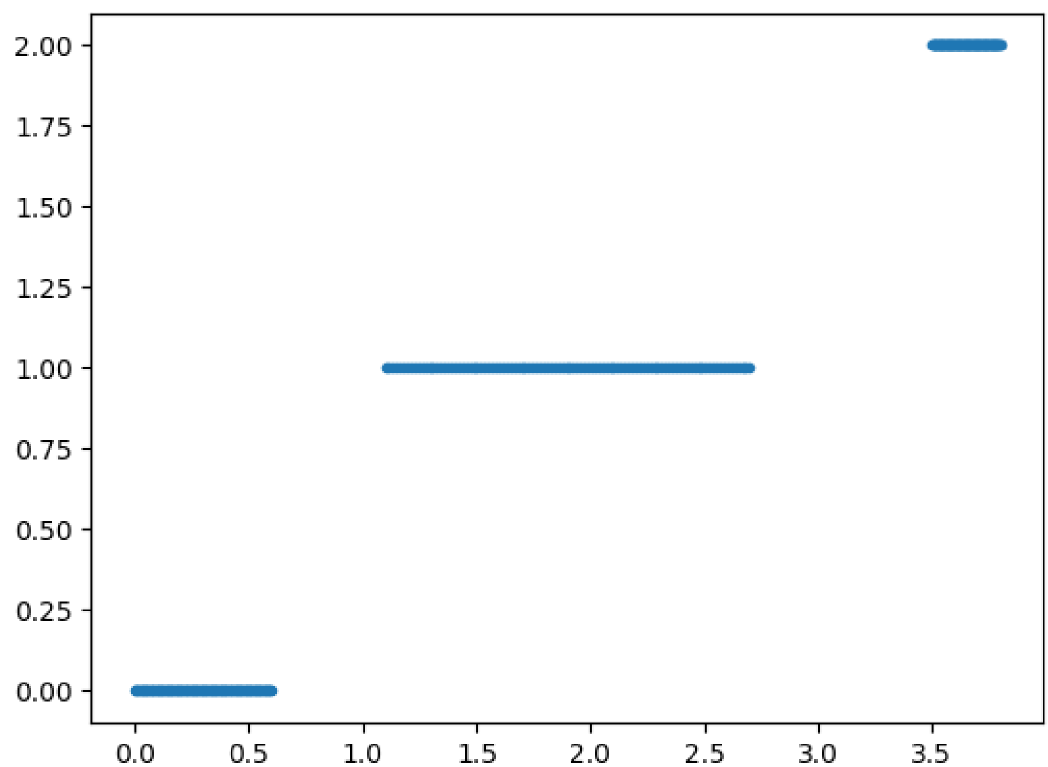
[125]:
```
## Write your code here

import numpy as np
import matplotlib.pyplot as plt

x1=np.linspace(0,0.6,100)
x2=np.linspace(1.1,2.7,100)
x3=np.linspace(3.5,3.8,100)

x=np.concatenate((x1,x2,x3))
print(x.shape)

y1=np.zeros(x1.shape)
y2=np.ones(x2.shape)
```

```
y3=np.tile([2],x3.shape)

y=np.concatenate((y1,y2,y3))

plt.figure()
plt.plot(x,y,'.')
```

```
(300,)
```

[125]:

```
[<matplotlib.lines.Line2D at 0x7ff0865b12b0>]
```



[126]:

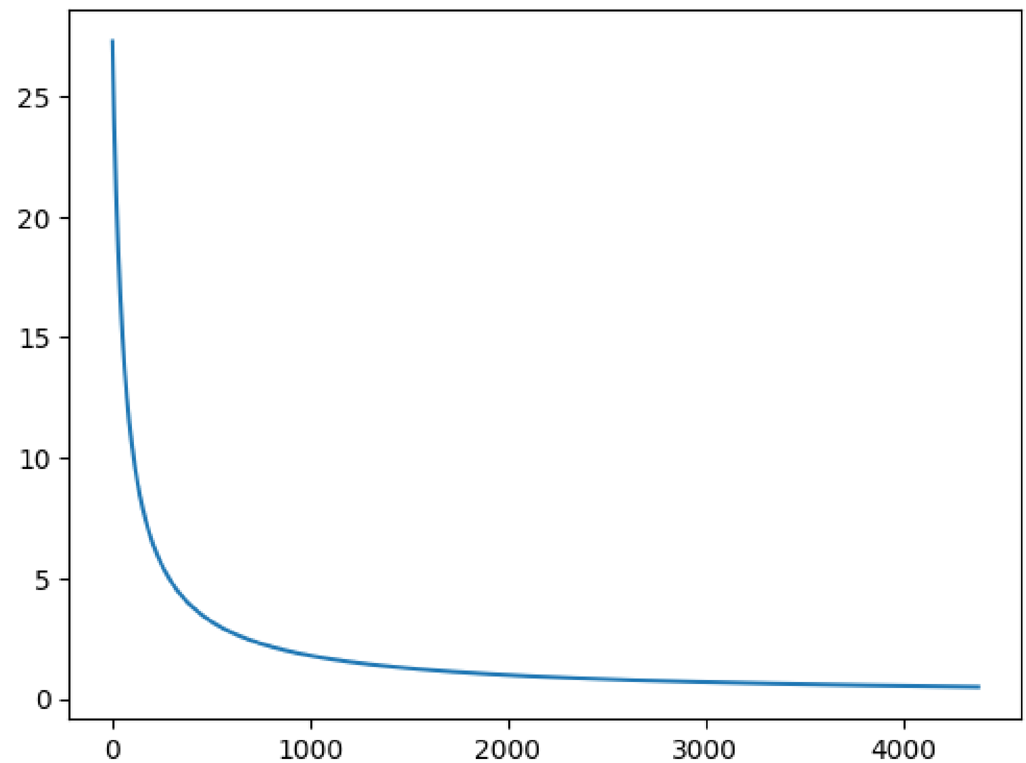
```
# def data_transform(X,degree):
#   X_new=[]
#   for i in range(degree +1):
#     # write code here to generate a polynomial

def data_transform(X,degree):
  X_new=[]
  for i in range(degree +1):
    X_new.append(X**i)
  X_new = np.concatenate(X_new)
  return X_new
```

```
x_aug=data_transform(x[np.newaxis,:],2)
```

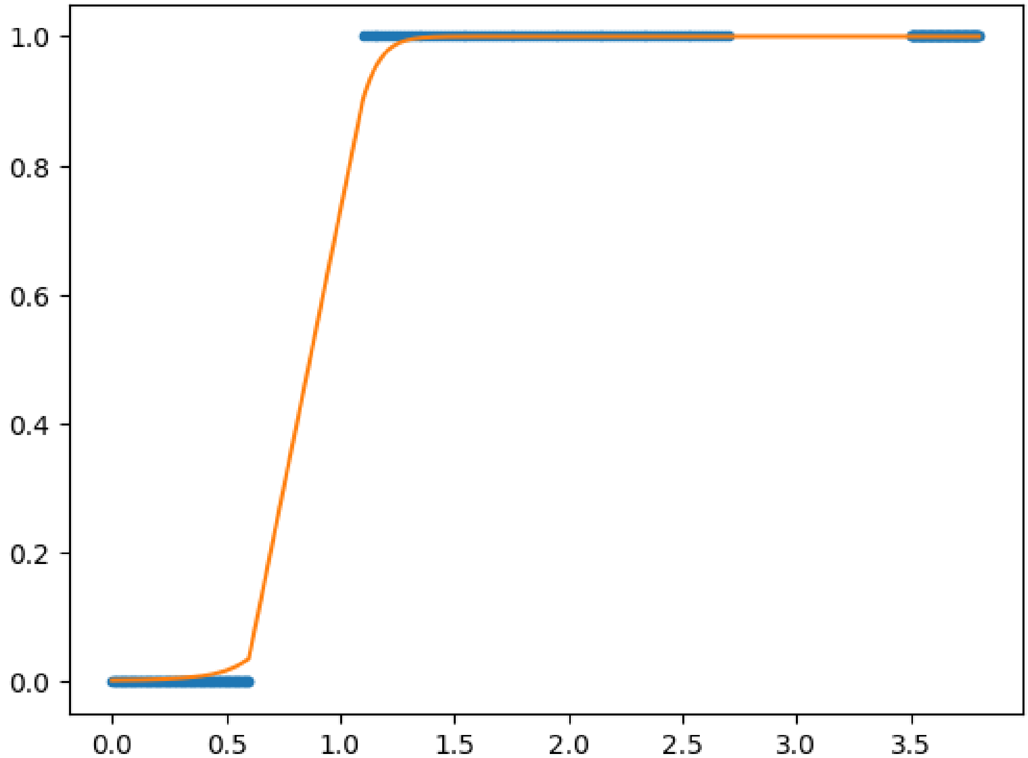
[127]:
```
# plot for classification
def plot_op(x,y_pred):

  ind0,_=np.where(y_pred<0.5)
  ind1,_=np.where(y_pred>=0.5)
  x0=x[ind0,:]
  x1=x[ind1,:]
  plt.plot(x0,np.zeros((x0).shape),'o',color='y')
  plt.plot(x1,np.ones((x1).shape),'x',color='r')
```

[136]:
```
def classify(y):
    ret = np.zeros(y.shape)
    for i in range(len(y)):
        if y[i] == 0:
            ret[i] = 0
        else:
            ret[i] = 1

    return ret

y_class = classify(y)
_y = y_class[:,np.newaxis]

reg = logis_regression()

w,err = reg.Regression_grad_des(x_aug, _y, 0.1)

print(w)

plt.figure()
plt.plot(err)
plt.show()

y0_pred = reg.logis(x_aug, w)

plt.figure()
plt.plot(x, _y, '.')
plt.plot(x, y0_pred[:,0])
```

```
[[-5.97256294]
 [ 0.96607156]
 [ 5.88665314]]
```



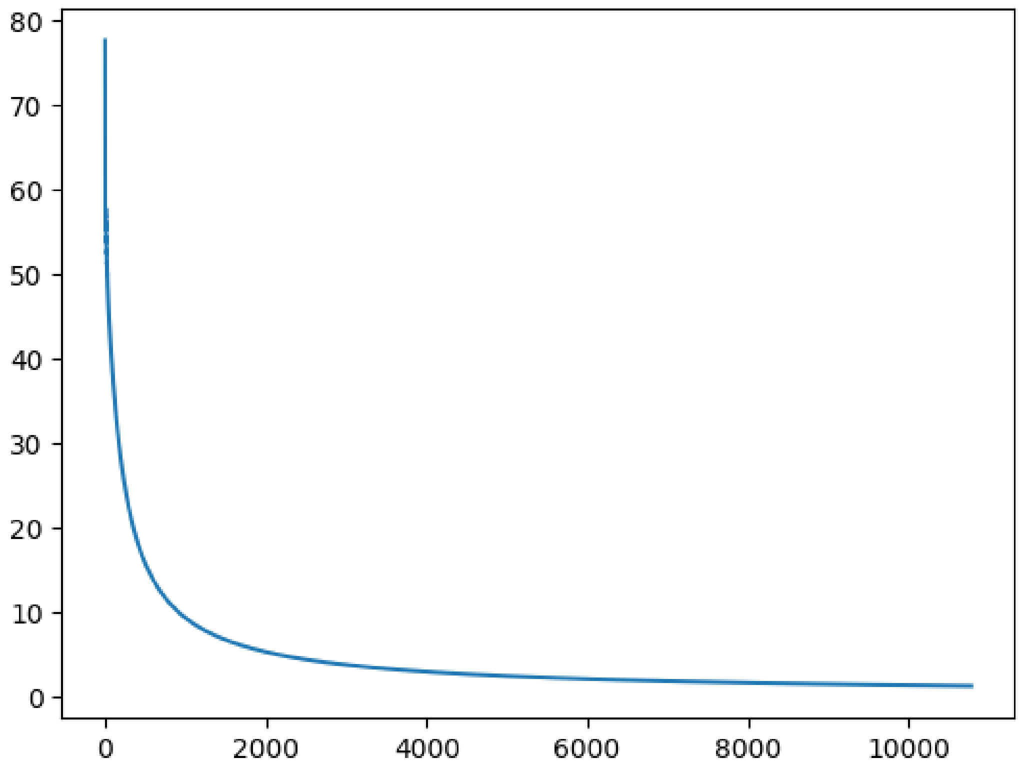
[136]: [<matplotlib.lines.Line2D at 0x7ff086389fa0>]



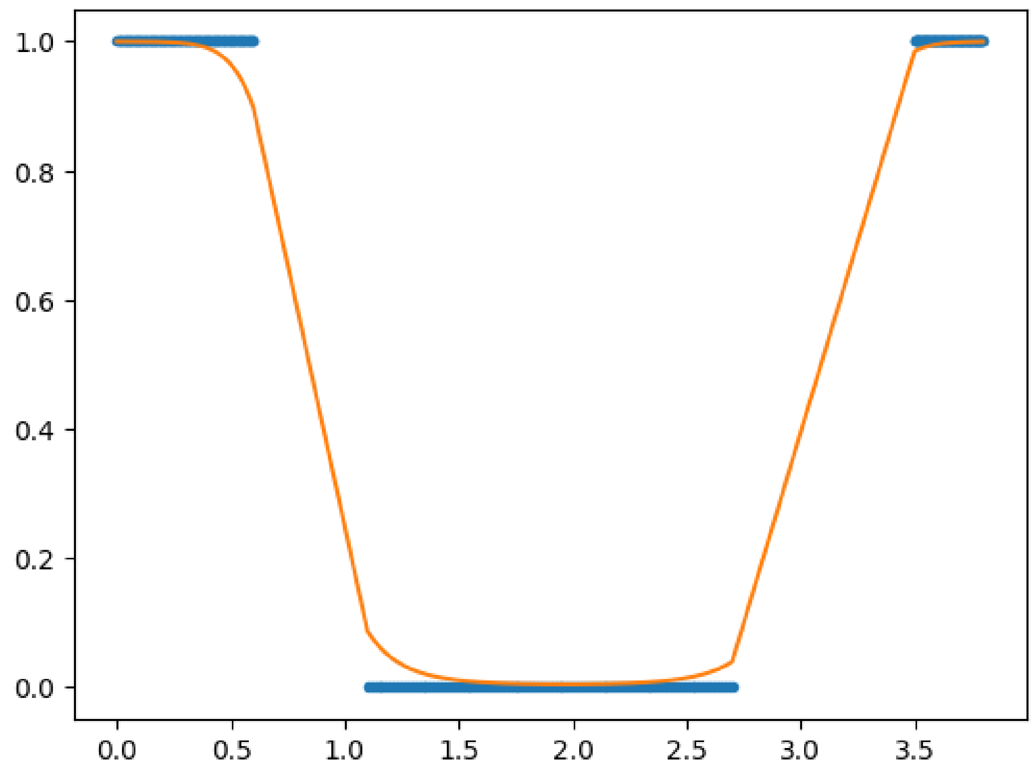
[137]:
```
# take class 1 as '0' and other to '1'
## Write your code here
def classify(y):
    ret = np.zeros(y.shape)
    for i in range(len(y)):
        if y[i] == 1:
            ret[i] = 0
        else:
            ret[i] = 1

    return ret

y_class = classify(y)
_y = y_class[:,np.newaxis]

reg = logis_regression()

w,err = reg.Regression_grad_des(x_aug, _y, 0.1)

print(w)

plt.figure()
```

```
plt.plot(err)
plt.show()

y1_pred = reg.logis(x_aug, w)

plt.figure()
plt.plot(x, _y, '.')
plt.plot(x, y1_pred[:,0])
```

```
[[ 10.22604314]
 [-15.87968348]
 [  4.04169751]]
```



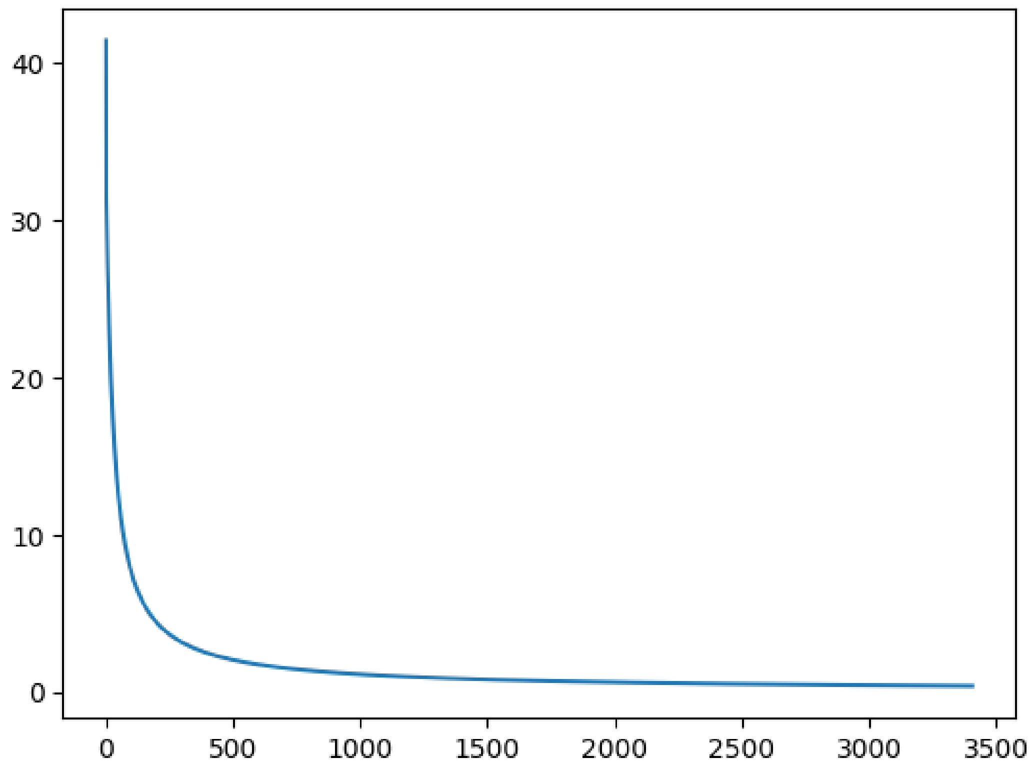
[137]: [<matplotlib.lines.Line2D at 0x7ff086285e80>]



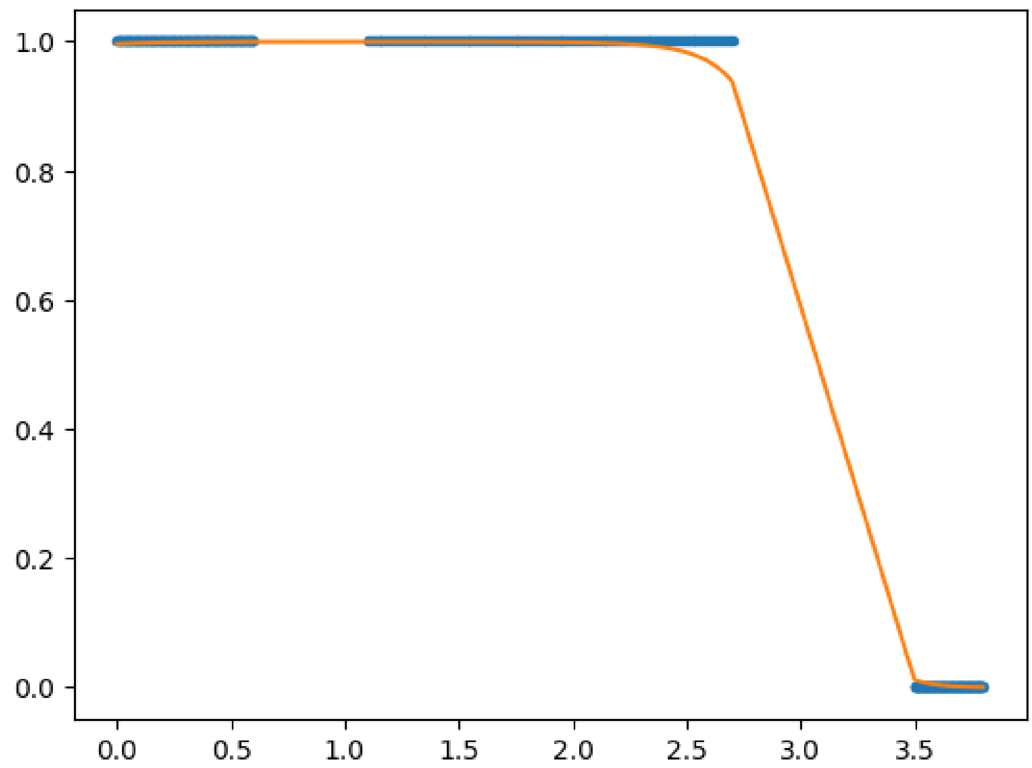
[138]:
```python
# Take class 2 as '0' and other to '1'
## Write your code here
def classify(y):
    ret = np.zeros(y.shape)
    for i in range(len(y)):
        if y[i] == 2:
            ret[i] = 0
        else:
            ret[i] = 1

    return ret

y_class = classify(y)
_y = y_class[:,np.newaxis]

reg = logis_regression()

w,err = reg.Regression_grad_des(x_aug, _y, 0.1)

print(w)

plt.figure()
```

```
plt.plot(err)
plt.show()

y2_pred = reg.logis(x_aug, w)

plt.figure()
plt.plot(x, _y, '.')
plt.plot(x, y2_pred[:,0])
```

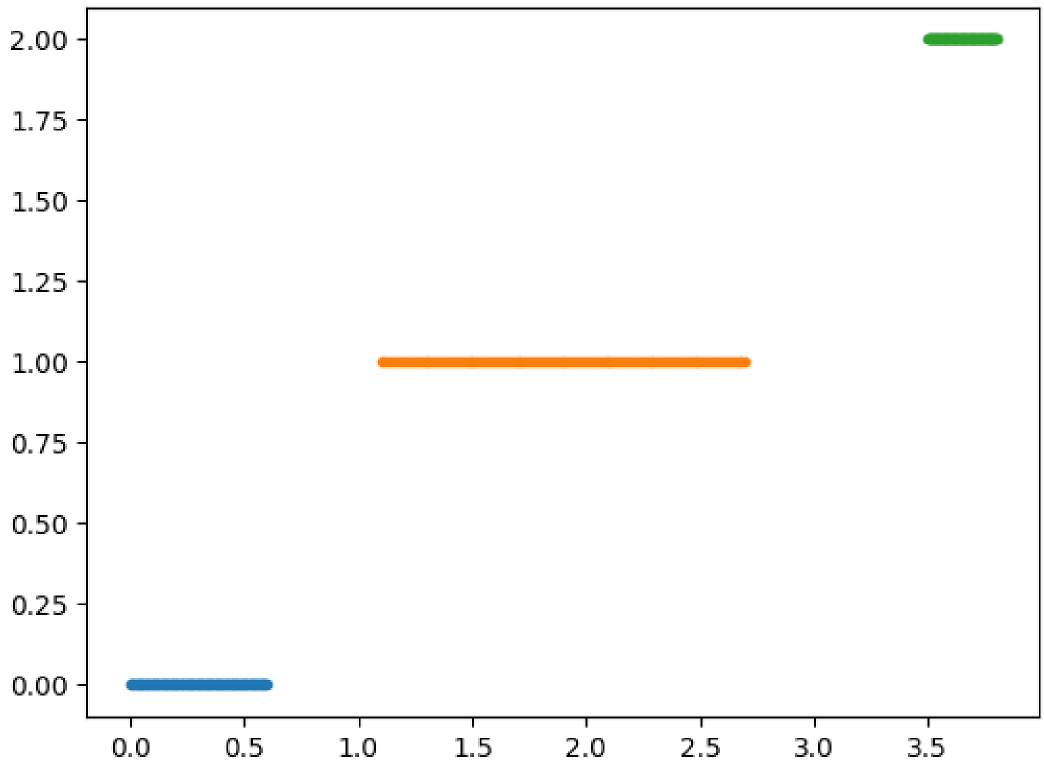
```
[[ 5.54298597]
 [ 5.05028712]
 [-2.25766734]]
```




```
[138]: [<matplotlib.lines.Line2D at 0x7ff08622d460>]
```



[140]:
```
# final classification
## Write your code here
class_0,_ = np.where(y0_pred < 0.5)
class_0 = x[class_0]

class_1,_ = np.where(y1_pred < 0.5)
class_1 = x[class_1]

class_2,_ = np.where(y2_pred < 0.5)
class_2 = x[class_2]

plt.figure()
plt.plot(class_0, np.zeros(class_0.shape), '.')
plt.plot(class_1, np.ones(class_1.shape), '.')
plt.plot(class_2, np.tile([2], class_2.shape), '.')
plt.show()
```


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5