Binary Classification based on Logistic Regression

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1 Binary Classification based on Logistic Regression

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```
In [302]: import matplotlib.pyplot as plt
          from random import *
          import numpy as np
```

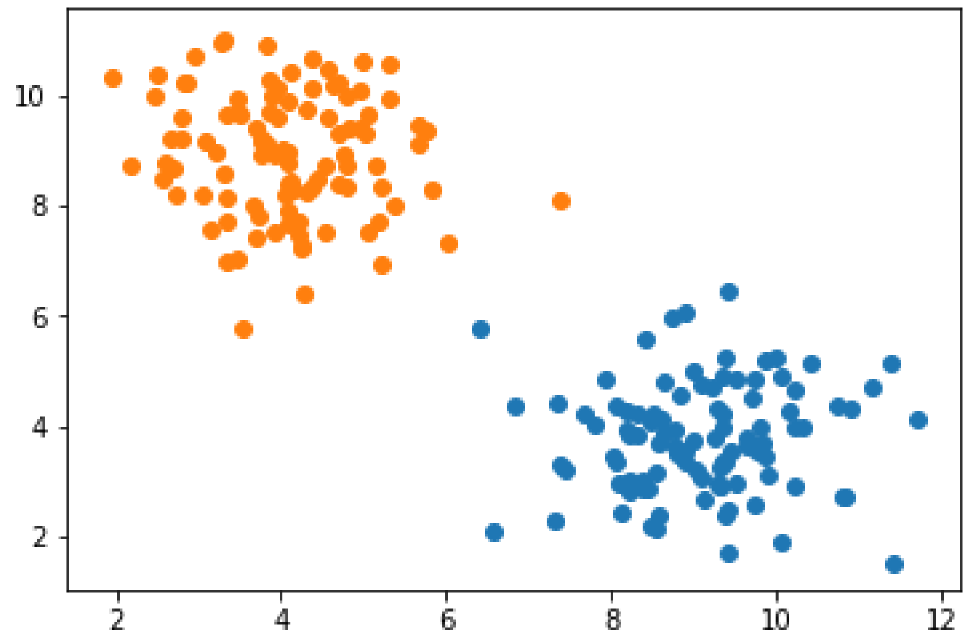
1.1 1. Plot two clusters of points for training dateset

- Generate two sets of separable random point clusters in R^2
- Let ${ x_i }_{i=1}^n $ be a set of points and $\{y_i\}_{i=1}^n$ be their corresponding labels Plot the point clusters in the training dataset using different colors depending on their labels

```
In [303]: s1=9
          t1=4
          s2=4
          t2=9
```

```
In [304]: x1_train=np.random.randn(100)
          y1_train=np.random.randn(100)
          x2_train=np.random.randn(100)
          y2_train=np.random.randn(100)
```

```
In [305]: xy0_train=np.column_stack([s1-x1_train,t1-y1_train])
          xy1_train=np.column_stack([s2-x2_train,t2-y2_train])
          one_arr=np.array([1.0]*100)
          xy0_train_plus1=np.column_stack([s1-x1_train,t1-y1_train,one_arr])
          xy1_train_plus1=np.column_stack([s2-x2_train,t2-y2_train,one_arr])
          plt.scatter(s1-x1_train,t1-y1_train)
          plt.scatter(s2-x2_train,t2-y2_train)
          plt.show()
```



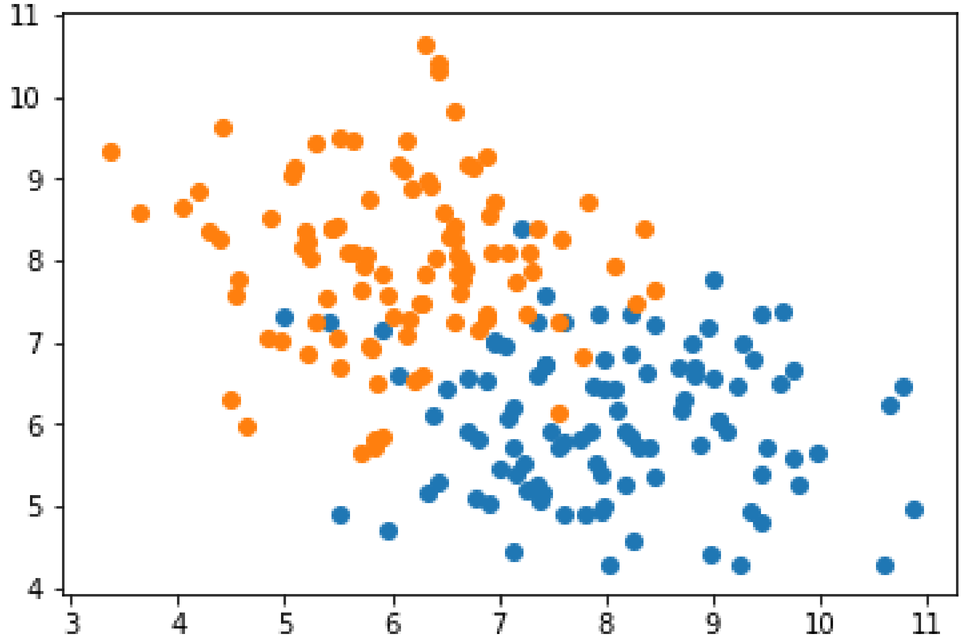
1.2 2. Plot two clusters of points for testing dataset

- Generate two sets of separable random point clusters in R^2 for a testing dataset using the same centroid and the standard deviation of random generator as the training dataset
- Plot the point clusters in the testing dataset using different colors depending on their labels (different colors from the training dataset)

In [381]:
```
s1_test=8
t1_test=6
s2_test=6
t2_test=8
```

In [382]:
```
x1_test=np.random.randn(100)
y1_test=np.random.randn(100)
x2_test=np.random.randn(100)
y2_test=np.random.randn(100)
```

In [391]:
```
xy0_test=np.column_stack([s1_test-x1_test,t1_test-y1_test])
xy1_test=np.column_stack([s2_test-x2_test,t2_test-y2_test])
xy0_test_plus1=np.column_stack([s1_test-x1_test,t1_test-y1_test,one_arr])
xy1_test_plus1=np.column_stack([s2_test-x2_test,t2_test-y2_test,one_arr])
plt.scatter(s1_test-x1_test,t1_test-y1_test)
plt.scatter(s2_test-x2_test,t2_test-y2_test)
plt.show()
```



1.3 3. Plot the learning curves

- Apply the gradient descent algorithm
- Plot the training loss at every iteration
- Plot the testing loss at every iteration
- Plot the training accuracy at every iteration
- Plot the testing accuracy at every iteration

In [392]:
```
label0=0
label1=1

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


def f_z(x,y):
    z=ux+vy+b
    return z


def h_func(xy,u,v,b):
    h=np.zeros(100)

    for i in range(len(xy)):
        z=u*xy[i][0]+v*xy[i][1]+b
        h[i]=sigmoid(z)
```

```
    return h


def cross_entropy(h,label):

    if(h==0 ):
        ln=10000.0
        f= -(label*ln+(1-label)*(np.log(1-h)))

    elif(h==1):
        ln=10000.0
        f= -(label*np.log(h)+(1-label)*ln)

    else:
        f= -(label*np.log(h)+(1-label)*(np.log(1-h)))

    return f


def cross_entropy_total(h_label0,h_label1,label0,label1):
    total=0
    for i in range(len(h_label0)):
        total+=cross_entropy(h_label0[i],label0)
    for i in range(len(h_label1)):
        total+=cross_entropy(h_label1[i],label1)

    return total/200




def partial_differential_of_total_cross_entropy(label0,label1,h_label0,h_label1,xy0,x
    L=0

    for i in range(100):
        L+=(-(label0*(1-h_label0[i])*xy0[i]-(1-label0)*(h_label0[i])*xy0[i]))
    for i in range(100):
        L+=(-(label1*(1-h_label1[i])*xy1[i]-(1-label0)*(h_label1[i])*xy1[i]))

    L=L/200

    return L



def gradient_descent_algorithms(label0,label1,h_label0,h_label1,xy0,xy1):
    learning_rate = 0.01
```

```
    u=0
    v=0
    b=0
    i=0
    total_new=0
    total=cross_entropy_total(h_label0,h_label1,label0,label1)
    iteration=0
    total_loss=np.zeros(1000)

    while abs(total_new-total)>0.00001:
        total=total_new
        u = u - learning_rate* partial_differential_of_total_cross_entropy(label0,lal
        v = v - learning_rate* partial_differential_of_total_cross_entropy(label0,lal
        b = b - learning_rate* partial_differential_of_total_cross_entropy(label0,lal
        h_label0=h_func(xy0_train,u,v,b)
        h_label1=h_func(xy1_train,v,v,b)
        total_new=cross_entropy_total(h_label0,h_label1,label0,label1)
        total_loss[i]=total_new
        iteration+=1
        i+=1

    return total_loss,iteration
```

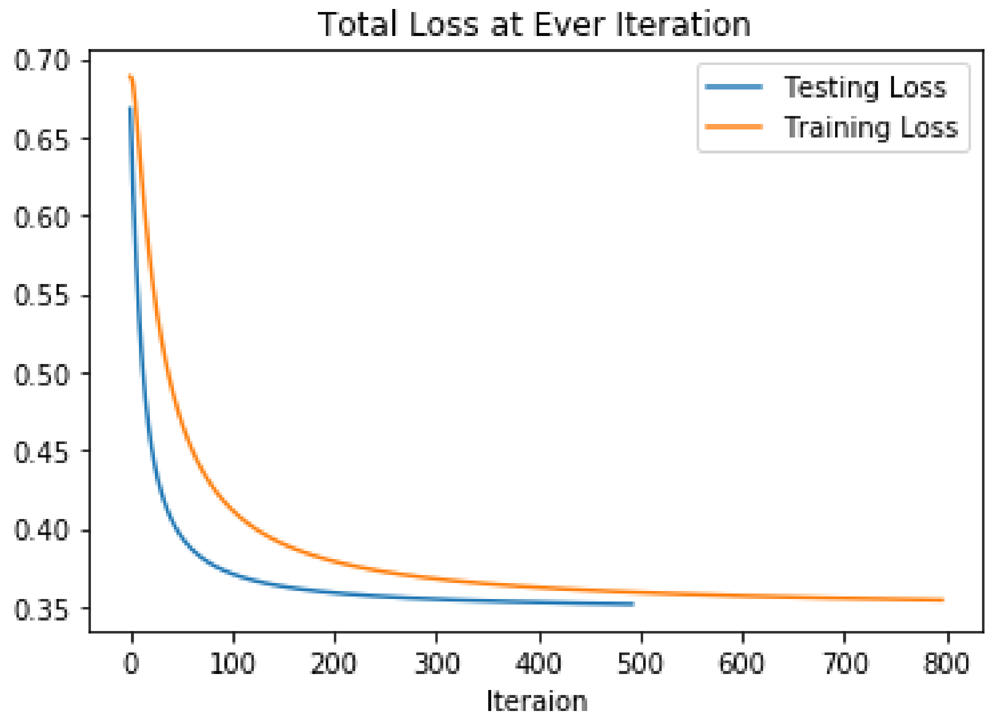
In [393]:
```
h_label0_training=h_func(xy0_train,0,0,0)
h_label1_training=h_func(xy1_train,0,0,0)
training_total_loss,training_iteration= gradient_descent_algorithms(label0,label1,h_l
                                                                    h_label1_trainin
```

In [394]:
```
h_label0_testing=h_func(xy0_test,0,0,0)
h_label1_testing=h_func(xy1_test,0,0,0)
testing_total_loss,testing_iteration= gradient_descent_algorithms(label0,label1,h_lal
                                                                  h_label1_testing,xy
```

In [401]:
```
print(testing_iteration)
print(training_iteration)
plt.plot(training_total_loss[:493],label='Testing Loss')
plt.plot(testing_total_loss[:797],label='Training Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Ever Iteration")
plt.xlabel("Iteraion")
```

```
797
493
```

Out[401]:
```
Text(0.5, 0, 'Iteraion')
```



Total Loss at Ever Iteration
Testing Loss
Training Loss
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0
100
200
300
400
500
600
700
800
Iteraion


```
In [ ]:
```