二分类

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

获取数据

In [ ]:
```
def getData():
    data=pd.read_csv('ex2data1.txt',header=None)
    x=np.array(data.iloc[:,0:-1])
    x=np.insert(x,0,np.ones(x.shape[0]),axis=1)

    y=np.array(data.iloc[:,-1])

    theta=np.array([0,0,0])
    return x,y,theta
x,y,theta=getData()
```

激活函数

In [ ]:
```
def sigmoid(z):
    return 1/(1+np.exp(-z))
```

激活函数的导数

In [ ]:
```
def derivation_sigmoid(z):
    return sigmoid(z)*(1-sigmoid(z))
```

计算二分类计算

In [ ]:
```
def compute(x,theta):
    return sigmoid(x@theta)
```

代价函数

In [ ]:
```
def cost(x,y,theta):
    hx=compute(x,theta)
    j=(-y*np.log(hx)-(1-y)*np.log(1-hx)).sum()/x.shape[0]
    return j,hx
```

梯度下降

In [ ]:
```
def gradient_descent(hx,x,y):
    return np.sum((hx-y)[:,np.newaxis]*x,axis=0)
```

主函数，求解最小代价

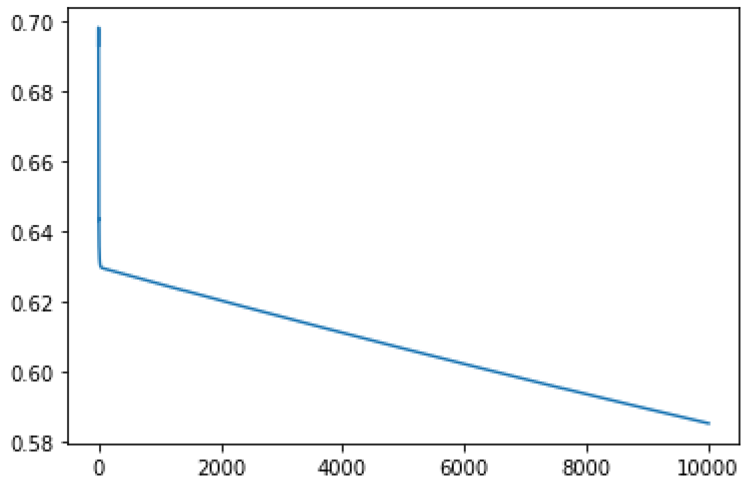
In [ ]:
```
def main(iterate,speed,x,y,theta):
    costs=[]
    for i in range(iterate):
        j,hx=cost(x,y,theta)
        costs.append(j)
        theta=theta-speed*gradient_descent(hx,x,y)
    plt.plot(costs)
    plt.show()
    return np.array(theta)
```

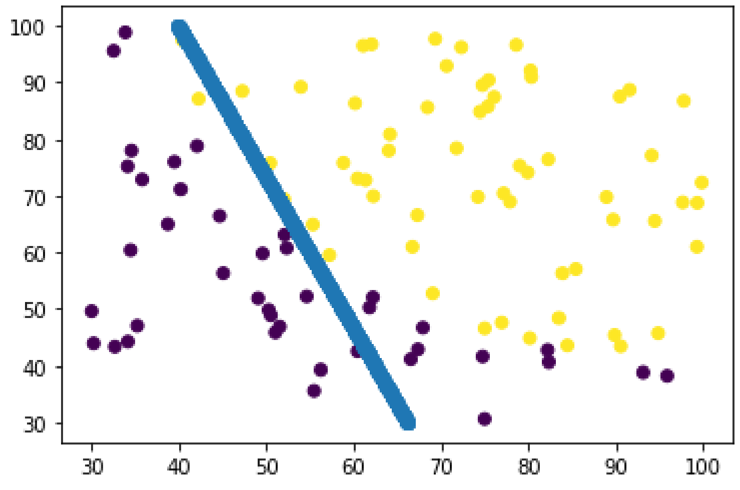
绘制边界

In [ ]:
```
def decision_boundaries(theta,range_min,range_max):
    plt.scatter(x[:,1],x[:,2],c=y)
    nums=np.linspace(range_min,range_max,1000)
    label_1=[]
    label_2=[]
    for i in range(len(nums)):
        for j in range(len(nums)):
            z=np.array([1,nums[i],nums[j]]).T@theta
            if(z>0.499 and z<0.501):
                label_1.append(nums[i])
                label_2.append(nums[j])
    plt.scatter(label_1,label_2)
    plt.show()
```

无特征缩放下降10000代

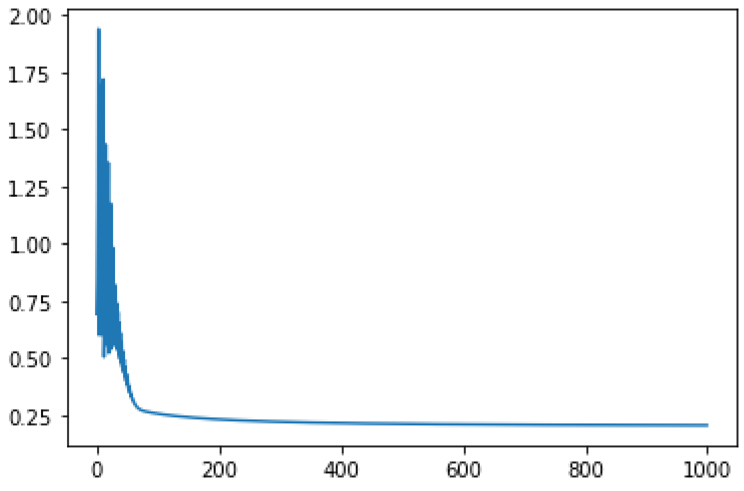
In [ ]:
```
#没有特征缩放的时候很慢，跑了1000000才近似拟合
x,y,theta=getData()
theta=main(10000,0.00001,x,y,theta)
theta
decision_boundaries(theta,30,100)
```

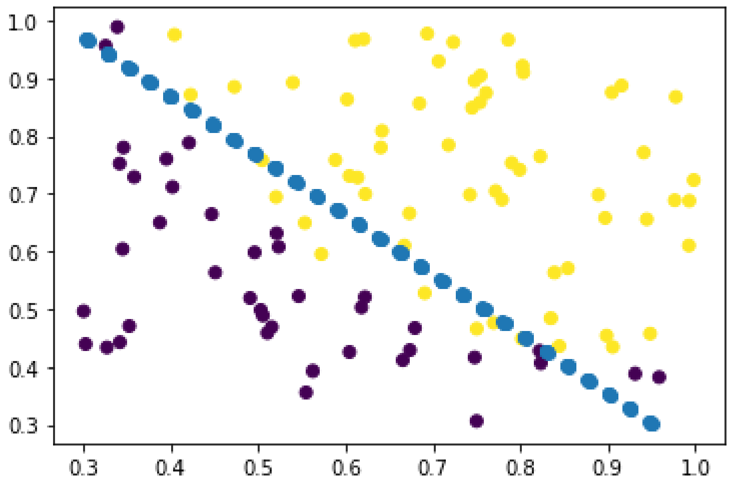




归一化后下降1000代

```
In [ ]: #归一化后，下降变快了
        x,y,theta=getData()
        x[:,1:]=x[:,1:]/100
        theta=main(1000,0.08,x,y,theta)
        decision_boundaries(theta,0.3,1)
```


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0
200
400
600
800
1000


1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0