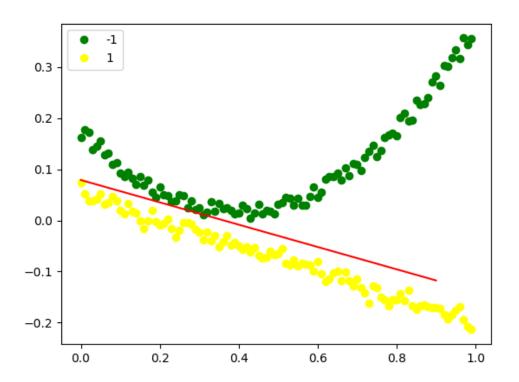
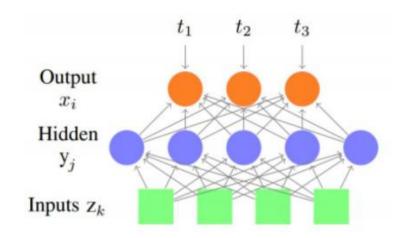
As we can see, the classification is good.



The python code is:

```
import numpy as np
import matplotlib.pyplot as plt
def load_data():
     import scipy.io
     Dataset_MATLAB = scipy.io.loadmat('data3.mat')
     Data = Dataset_MATLAB['data']
    X_Data = [Data[i][:-1] for i in range(len(Data))]
     Y_Data = [Data[i][-1] for i in range(len(Data))]
     return X_Data,Y_Data
def perceptron(X, Y, eta):
    w=np.ones((X.shape[1],1))
     X=np.matrix(X)
    Y=np.matrix(Y).T
     b=1
     round = 0
     all_correct=False
     while True:
```

```
Errors = 0
          for i in range(X.shape[0]):
               XX = X[i]
               YY = Y[i]
               if
                      ((w.T*XX.T+b).getA()[0][0]
                                                     <0
                                                             and
                                                                      YY.getA()[0][0]
                                                                                          >0)
                                                                                                   or
((w.T*XX.T+b).getA()[0][0] >0 and YY.getA()[0][0] <0):
                    w+=eta*(XX.T*YY)
                    b+=eta*YY
                    Errors += 1
          if Errors == 0:
               break
          round += 1
          print(round, Errors)
     return w, b
def draw(w, b, X, Y):
     x_points = np.arange(0, 1, 0.1)
    y_points = np.array([-(w[0]*i+b)/w[1] for i in x_points]).flatten()
    x_0 = []
    x_1 = []
     for i in range(X.shape[0]):
          if Y[i] == -1:
               x_0.append(X[i])
          else:
               x_1.append(X[i])
     x_0 = np.array(x_0)
     x_1 = np.array(x_1)
     plt.plot(x_0[:, 0], x_0[:, 1], 'o', color='green', label='-1')
     plt.plot(x_1[:, 0], x_1[:, 1], 'o', color='yellow', label='1')
     plt.plot(x_points, y_points, '-', color='red')
     plt.legend()
     plt.show()
if __name__ == "__main__":
    X_Data, Y_Data = load_data()
    X = np.array(X_Data)
    Y = np.array(Y_Data)
     w,b=perceptron(X, Y, 0.01)
     draw(w, b, X, Y)
```



$$\begin{aligned} &E = -\sum_{i} (t_{i} \log(x_{i}) + (1-t_{i}) \log(1-x_{i})) \\ &x_{i} = \frac{1}{1+e^{-s_{i}}} \\ &\frac{\partial E}{\partial \omega_{ji}} = \frac{1}{N} \sum_{i} \left(\frac{\partial E_{i}^{n}}{\partial x_{i}^{n}} \right) \left(\frac{\partial x_{i}^{n}}{\partial \omega_{ji}} \right) = \frac{1}{N} \sum_{i} \left(\frac{\partial E_{i}^{n}}{\partial x_{i}^{n}} \right) \left(\frac{\partial x_{i}^{n}}{\partial s_{i}^{n}} \right) \left(\frac{\partial s_{i}^{n}}{\partial \omega_{ji}} \right) \\ &\frac{\partial E_{i}}{\partial x_{i}} = \frac{\partial \left(-(t_{i} \log(x_{i}) + (1-t_{i}) \log(1-x_{i})) \right)}{\partial x_{i}} = -\frac{t_{i}}{x_{i}} - ((1-t_{i}) \cdot \frac{1}{1-x_{i}} \cdot (-1)) = -\frac{t_{i}}{x_{i}} + \frac{1-t_{i}}{1-x_{i}} \\ &\frac{\partial x_{i}}{\partial s_{i}} = \frac{\partial \frac{1}{1+e^{-s_{i}}}}{\partial s_{i}} = \frac{\partial \frac{e^{s_{i}}}{1+e^{s_{i}}}}{\partial s_{i}} = \frac{(e^{s_{i}}) \cdot (1+e^{s_{i}}) - e^{s_{i}} \cdot (1+e^{s_{i}})^{2}}{(1+e^{s_{i}})^{2}} = \frac{e^{s_{i}}}{(1+e^{s_{i}})^{2}} = \frac{1}{1+e^{s_{i}}} \cdot \frac{1}{1+e^{s_{i}}} = x_{i} \cdot (1-x_{i}) \\ s_{i} = \sum_{j} y_{j} \omega_{ji} \\ &\frac{\partial s_{i}}{\partial \omega_{ji}} = y_{i} \\ &\frac{\partial E_{i}}{\partial \omega_{ji}} = \frac{\partial E_{i}}{\partial x_{i}} \cdot \frac{\partial s_{i}}{\partial s_{i}} \cdot \frac{\partial s_{i}}{\partial s_{i}} = \left(-\frac{t_{i}}{x_{i}} + \frac{1-t_{i}}{1-x_{i}} \right) \cdot x_{i} \cdot (1-x_{i}) \cdot y_{i} = (x_{i}-t_{i}) \cdot y_{i} \\ &y_{j} = \frac{1}{1+e^{-p_{j}}}, \ p_{j} = \sum_{k} z_{k} m_{kj} \\ &\frac{\partial E}{\partial m_{i}} = -\sum_{i} \left(\frac{t_{i}}{x_{i}} - \frac{1-t_{i}}{1-x_{i}} \right) \cdot \frac{\partial s_{i}}{\partial s_{i}} \cdot \frac{\partial s_{j}}{\partial s_{i}} \cdot \frac{\partial s_{j}}{\partial s_{i}} \cdot \frac{\partial s_{j}}{\partial s_{i}} = -\sum_{i} (x_{i}-t_{i}) \cdot y_{j} \cdot (1-y_{j}) \cdot \omega_{ji} \cdot z_{k} \end{aligned}$$

$$\begin{split} E &= -\sum_{i} t_{i} \log(x_{i}) \\ x_{i} &= \frac{e^{s_{i}}}{\sum_{c} e^{c}} \\ y_{j} &= \frac{1}{1 + e^{-p_{j}}} \\ s_{i} &= \sum_{j} y_{j} \omega_{ji} \\ p_{j} &= \sum_{k} z_{k} m_{kj} \\ \frac{\partial x_{i}}{\partial s_{i}} &= x_{i} (1 - x_{i}) \quad i = j \\ \frac{\partial x_{i}}{\partial \omega_{ji}} &= -x_{i} x_{j} \quad i \neq j \\ \frac{\partial E}{\partial \omega_{ji}} &= -\sum_{n \neq i} \frac{t_{n}}{x_{n}} \cdot \frac{\partial x_{n}}{\partial s_{i}} \cdot \frac{\partial s_{i}}{\partial \omega_{ji}} - \frac{t_{i}}{x_{i}} \cdot \frac{\partial x_{i}}{\partial s_{i}} \cdot \frac{\partial s_{i}}{\partial \omega_{ji}} \\ &= -\sum_{n \neq i} \frac{t_{n}}{x_{n}} \cdot (-x_{n} x_{i}) \cdot y_{j} - \frac{t_{i}}{x_{i}} \cdot x_{i} (1 - x_{i}) \cdot y_{j} \\ &= (\sum_{n \neq i} t_{n} x_{i} - t_{i} (1 - x_{i})) \cdot y_{j} \\ \frac{\partial E}{\partial m_{kj}} &= -\sum_{n} \frac{\partial E}{\partial x_{n}} \cdot \sum_{i} \frac{\partial x_{n}}{\partial s_{i}} \cdot \frac{\partial s_{i}}{\partial y_{j}} \cdot \frac{\partial y_{j}}{\partial p_{j}} \cdot \frac{\partial p_{j}}{\partial m_{kj}} \\ &= \sum_{n} \frac{t_{n}}{x_{n}} \sum_{i} \frac{\partial x_{n}}{\partial s_{i}} \cdot \frac{\partial s_{i}}{\partial y_{j}} \cdot \frac{\partial y_{j}}{\partial p_{j}} \cdot \frac{\partial p_{j}}{\partial m_{kj}} \\ &= \sum_{n} \frac{t_{n}}{x_{n}} \cdot (x_{n} (1 - x_{n}) \omega_{jn} + \sum_{i \neq n} (-x_{n} x_{i}) \omega_{ji}) \cdot y_{j} (1 - y_{j}) z_{k} \\ &= \sum_{n} t_{n} \cdot ((1 - x_{n}) \omega_{jn} - \sum_{i \neq n} x_{i} \omega_{ji}) \cdot y_{j} (1 - y_{j}) z_{k} \end{split}$$

$$H = -\sum_{k=1}^{N} p_k \log p_k$$

$$Set \ f(p) = \sum_{k=1}^{N} p_k \log p_k, \text{ where } G(p) = \sum_{k=1}^{N} p_k - 1 = 0$$

$$L(p) = f(p) - \lambda G(p) = \sum_{k=1}^{N} p_k \log p_k - \lambda (\sum_{k=1}^{N} p_k - 1)$$

$$\begin{cases} \frac{\partial L(p)}{\partial p} \Rightarrow \log p_k + 1 - \lambda = 0 \\ G(p) = 0 \Rightarrow \sum_{k=1}^{N} p_k = 1 \end{cases}$$

$$So \text{ we can get } \begin{cases} \lambda = 1 - \log N \\ L(p_0) = f(p_0) = \log N \end{cases}$$

The VC dimension of axis-aligned square is 3. We can see that when there are only three points, whether all three points are collinear or not, there will always be an axis-aligned square that can meet the condition. But If there are four points, the situation shown in the figure will appear, and no square meets the condition. Therefore the VC dimension of axis-aligned square is 3.

