神经网络&深度学习 TENSORFLOW Google

11.4 实例：实现多元逻辑回归

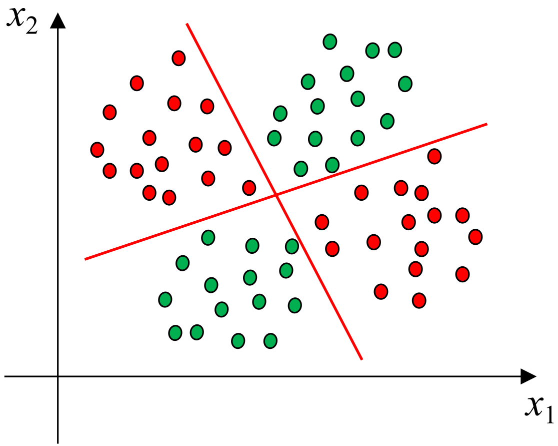
中国大学MOOC

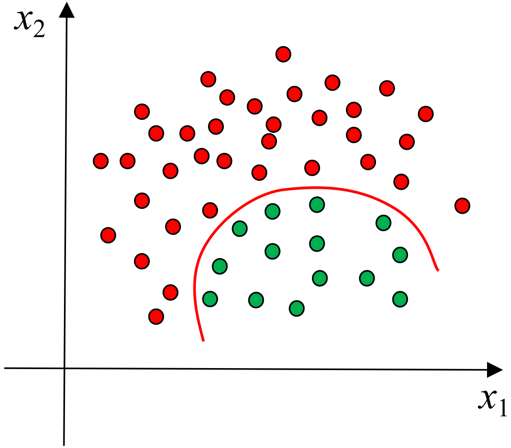
11.4.1 实现多元逻辑回归

中国大学MOOC

11.4.1 实现多元逻辑回归

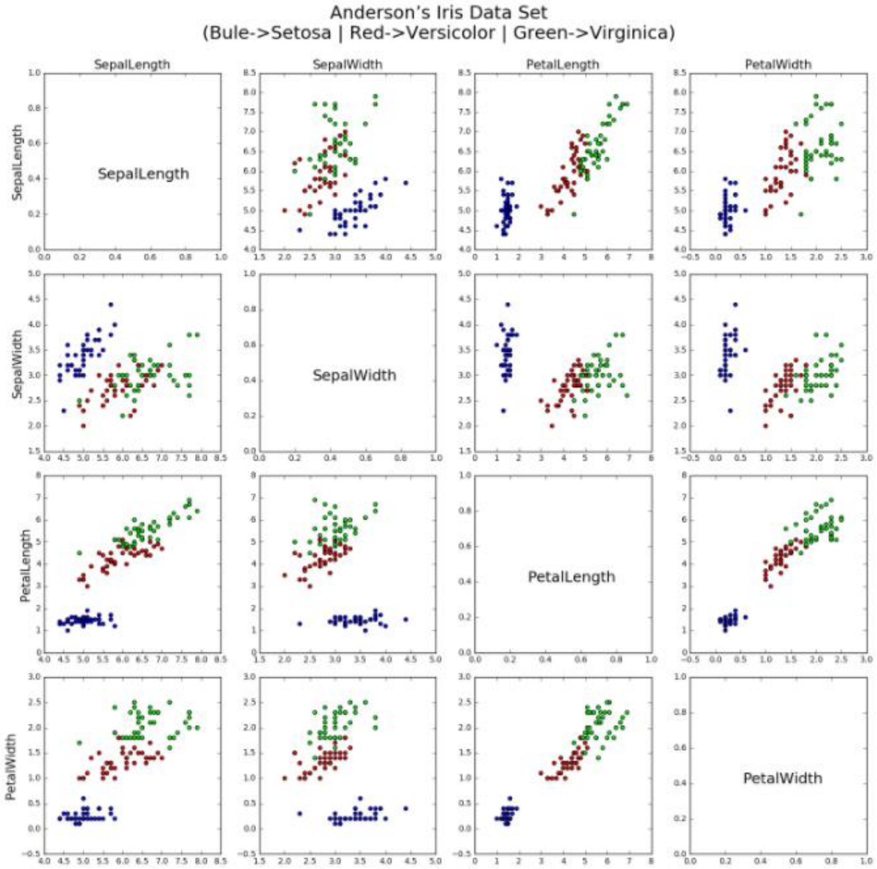
线性不可分





Iris数据集

- 150个样本
- 4个属性
  - 花萼长度（Sepal Length）
  - 花萼宽度（Sepal Width）
  - 花瓣长度（Petal Length）
  - 花瓣宽度（Petal Width）
- 1个标签
  - 山鸢尾（Setosa）
  - 变色鸢尾（Versicolour）
  - 维吉尼亚鸢尾（Virginica）



加载数据

```
In [1]: import tensorflow as tf
        print("TensorFlow version:",tf.__version__)

        TensorFlow version: 2.0.0

In [2]: import pandas as pd
        import numpy as np
        import matplotlib as mpl
        import matplotlib.pyplot as plt

In [3]: TRAIN_URL = "http://download.tensorflow.org/data/iris_training.csv"
        train_path = tf.keras.utils.get_file(TRAIN_URL.split('/')[-1], TRAIN_URL)

In [4]: df_iris = pd.read_csv(train_path, header=0)
```

处理数据

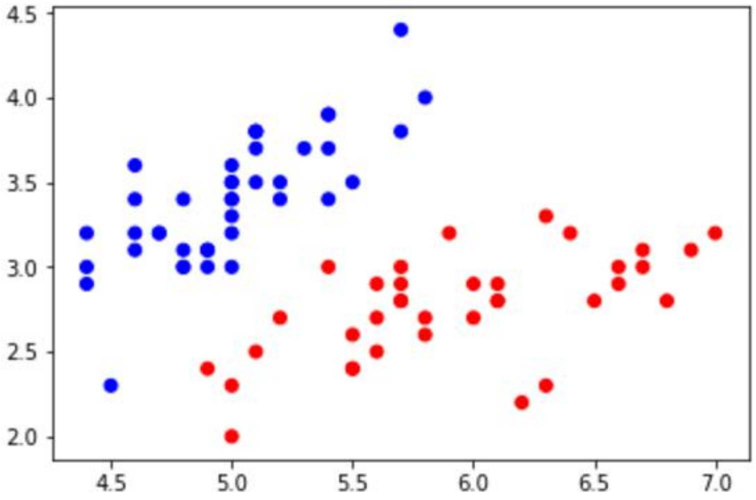
- 转化为NumPy数组
- 提取属性和标签
- 提取山鸢尾和变色鸢尾

```
In [5]: iris=np.array(df_iris)

In [6]: iris.shape

Out[6]: (120, 5)

In [7]: train_x=iris[:,0:2]
        train_y=iris[:,4]

In [8]: train_x.shape, train_y.shape

Out[8]: ((120, 2), (120,))

In [9]: x_train = train_x[train_y < 2]
        y_train = train_y[train_y < 2]

In [10]: x_train.shape, y_train.shape

Out[10]: ((78, 2), (78,))

In [11]: num=len(x_train)
```

处理数据

- 可视化样本

In [12]:
```
cm_pt = mpl.colors.ListedColormap(["blue", "red"])
plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)
plt.show()
```

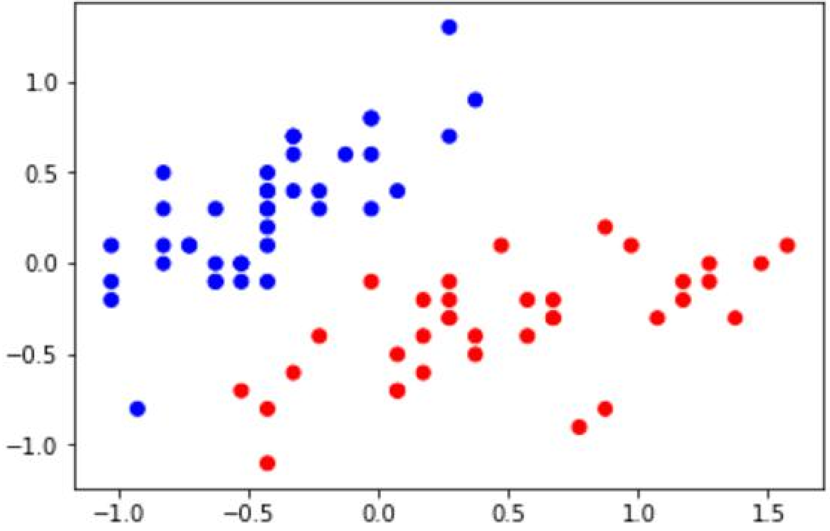


处理数据

- 属性中心化

```
In [13]: x_train=x_train-np.mean(x_train,axis=0)
```

```
In [14]: plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)
         plt.show()
```



处理数据

- 生成多元模型的属性矩阵和标签列向量

```
In [15]: x0_train = np.ones(num).reshape(-1,1)

In [16]: X =tf.cast(tf.concat((x0_train,x_train), axis = 1),tf.float32)
         Y= tf.cast(y_train.reshape(-1,1),tf.float32)

In [17]: X.shape, Y.shape

Out[17]: (TensorShape([78, 3]), TensorShape([78, 1]))
```

11.4.1 实现多元逻辑回归

■ 设置超参数

In [18]:
```
learn_rate=0.2
iter=120

display_step=30
```

■ 设置模型参数初始值

In [19]:
```
np.random.seed(612)
W=tf.Variable(np.random.randn(3,1),dtype=tf.float32)
```

训练模型

```
In [20]: ce=[]
acc=[]

for i in range(0, iter+1):
    with tf.GradientTape() as tape:
        PRED =1/(1+tf.exp(-tf.matmul(X,W)))
        Loss =-tf.reduce_mean(Y*tf.math.log(PRED)+(1-Y)*tf.math.log(1-PRED))

    accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.where(PRED.numpy()<0.5,0.,1.), Y),tf.float32))
    ce.append(Loss)
    acc.append(accuracy)

    dL_dW= tape.gradient(Loss,W)
    W.assign_sub(learn_rate*dL_dW)

    if i % display_step == 0:
        print("i: %i, Acc:%f, Loss: %f" % (i,accuracy,Loss))
```

```
i: 0, Acc:0.230769, Loss: 0.994269
i: 30, Acc:0.961538, Loss: 0.481892
i: 60, Acc:0.987179, Loss: 0.319128
i: 90, Acc:0.987179, Loss: 0.246626
i: 120, Acc:1.000000, Loss: 0.204982
```

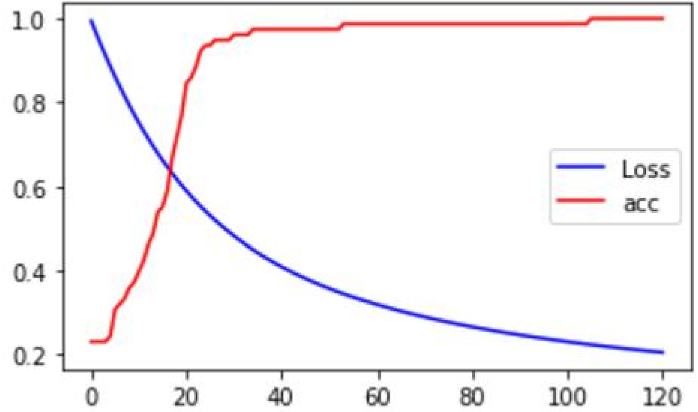
11.4.1 实现多元逻辑回归

可视化

- 绘制**损失**和**准确率**变化曲线

In [21]:

```
plt.figure(figsize=(5,3))
plt.plot(ce,color="blue",label="Loss")
plt.plot(acc,color="red",label="acc")
plt.legend()
plt.show()
```




```
i: 0,  Acc:0.230769,  Loss: 0.994269
i: 30,  Acc:0.961538,  Loss: 0.481892
i: 60,  Acc:0.987179,  Loss: 0.319128
i: 90,  Acc:0.987179,  Loss: 0.246626
i: 120,  Acc:1.000000,  Loss: 0.204982
```

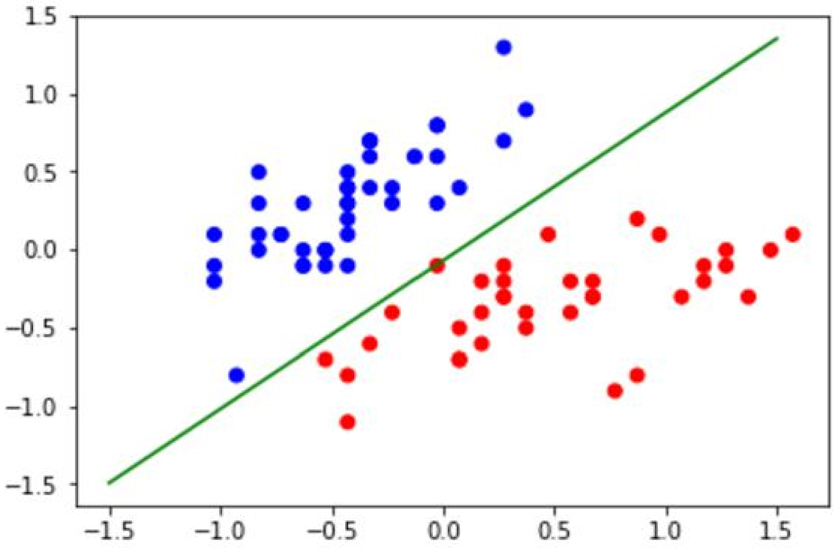
可视化

绘制决策边界

$$w_1x_1 + w_2x_2 + w_0 = 0$$

$$x2 = -\frac{w_1x_1 + w_0}{w_2}$$

```
In [22]: plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)
         x_=[-1.5,1.5]
         y_=-(W[1]*x_+W[0])/W[2]
         plt.plot(x_,y_,color="g")
         plt.show()
```



可视化

- 在训练过程中绘制**决策边界**

In [19]:
```
np.random.seed(612)
W=tf.Variable(np.random.randn(3,1),dtype=tf.float32)
```

In [20]:
```
cm_pt = mpl.colors.ListedColormap(["blue", "red"])
```

In [21]:
```
x_=[-1.5,1.5]
y_=-(W[0]+W[1]*x_)/W[2]
```

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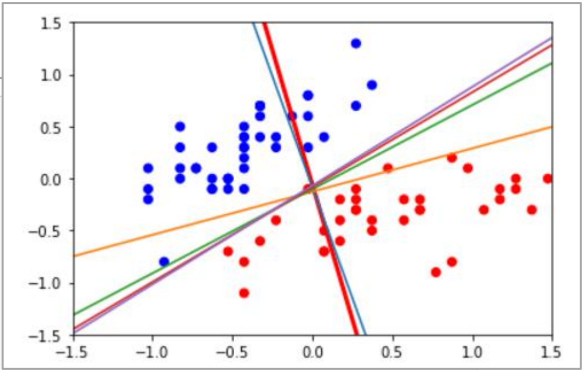
■ 训练模型

In [22]:
```
plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)
plt.plot(x_,y_,color="red",linewidth=3)
plt.xlim([-1.5,1.5])
plt.ylim([-1.5,1.5])

ce=[]
acc=[]
for i in range(0, iter+1):
    with tf.GradientTape() as tape:
        PRED =1/(1+tf.exp(-tf.matmul(X,W)))
        Loss =-tf.reduce_mean(Y*tf.math.log(PRED)+(1-Y)*tf.math.log(1-PRED))

    accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.where(PRED.numpy()<0.5,0.,1.), Y),tf.float32))
    ce.append(Loss)
    acc.append(accuracy)

    dL_dW= tape.gradient(Loss,W)
    W.assign_sub(learn_rate*dL_dW)

    if i % display_step == 0:
        print("i: %i, Acc:%f, Loss: %f" % (i,accuracy,Loss))
        y_=-(W[0]+W[1]*x_)/W[2]
        plt.plot(x_,y_)
```




```
i: 0, Acc:0.230769, Loss: 0.994269
i: 30, Acc:0.961538, Loss: 0.481892
i: 60, Acc:0.987179, Loss: 0.319128
i: 90, Acc:0.987179, Loss: 0.246626
i: 120, Acc:1.000000, Loss: 0.204982
```

使用测试集

加载数据集

```
In [1]: import tensorflow as tf
        print("TensorFlow version:",tf.__version__)

        TensorFlow version: 2.0.0

In [2]: import pandas as pd
        import numpy as np
        import matplotlib as mpl
        import matplotlib.pyplot as plt

In [3]: TRAIN_URL = "http://download.tensorflow.org/data/iris_training.csv"
        train_path = tf.keras.utils.get_file(TRAIN_URL.split('/')[-1], TRAIN_URL)

        TEST_URL = "http://download.tensorflow.org/data/iris_test.csv"
        test_path = tf.keras.utils.get_file(TEST_URL.split('/')[-1], TEST_URL)
```

数据处理

```
In [4]: df_iris_train = pd.read_csv(train_path, header=0)
        df_iris_test = pd.read_csv(test_path, header=0)

In [5]: iris_train=np.array(df_iris_train)
        iris_test=np.array(df_iris_test)

In [6]: iris_train.shape,iris_test.shape

Out[6]: ((120, 5), (30, 5))
```

数据处理

```
In [7]: train_x=iris_train[:,0:2]
        train_y=iris_train[:,4]

        test_x=iris_test[:,0:2]
        test_y=iris_test[:,4]

In [8]: train_x.shape,train_y.shape

Out[8]: ((120, 2), (120,))

In [9]: test_x.shape,test_y.shape

Out[9]: ((30, 2), (30,))
```

数据处理

In [10]:
```
x_train = train_x[train_y < 2]
y_train = train_y[train_y < 2]
```

In [11]:
```
x_train.shape, y_train.shape
```

Out[11]: ((78, 2), (78,))

In [12]:
```
x_test = test_x[test_y < 2]
y_test = test_y[test_y < 2]
```

In [13]:
```
x_test.shape, y_test.shape
```

Out[13]: ((22, 2), (22,))

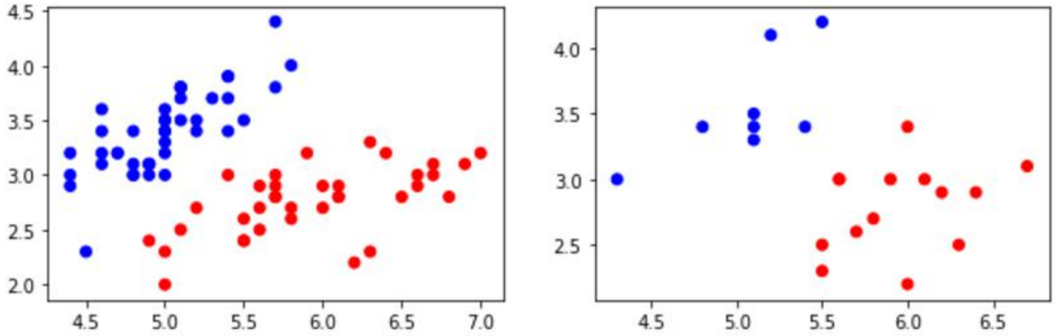
In [14]:
```
num_train=len(x_train)
num_test=len(x_test)
```

In [15]:
```
num_train,num_test
```

Out[15]: (78, 22)

11.4.1 实现多元逻辑回归

In [16]:
```
plt.figure(figsize=(10,3))
cm_pt = mpl.colors.ListedColormap(["blue", "red"])

plt.subplot(121)
plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)

plt.subplot(122)
plt.scatter(x_test[:,0],x_test[:,1],c=y_test,cmap=cm_pt)

plt.show()
```



数据处理——中心化

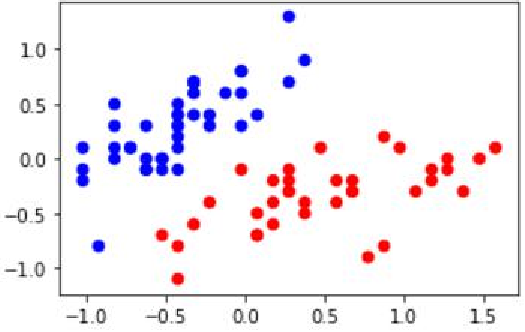
In [17]:
```
print(np.mean(x_train,axis=0))
print(np.mean(x_test,axis=0))
```

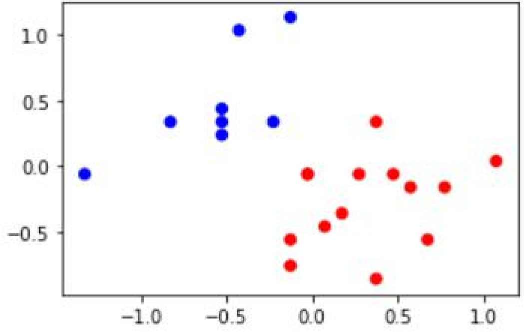
```
[5.42692308 3.1025641 ]
[5.62727273 3.06363636]
```

In [18]:
```
x_train=x_train-np.mean(x_train,axis=0)
x_test=x_test-np.mean(x_test,axis=0)
```

11.4.1 实现多元逻辑回归


```
In [19]: plt.figure(figsize=(10,3))

         plt.subplot(121)
         plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)

         plt.subplot(122)
         plt.scatter(x_test[:,0],x_test[:,1],c=y_test,cmap=cm_pt)

         plt.show()
```





11.4.1 实现多元逻辑回归


```
In [20]: x0_train = np.ones(num_train).reshape(-1,1)
         X_train = tf.cast(tf.concat((x0_train,x_train), axis = 1),dtype=tf.float32)
         Y_train = tf.cast(y_train.reshape(-1,1),dtype=tf.float32)

In [21]: X_train.shape, Y_train.shape

Out[21]: (TensorShape([78, 3]), TensorShape([78, 1]))

In [22]: x0_test = np.ones(num_test).reshape(-1,1)
         X_test =tf.cast(tf.concat((x0_test,x_test), axis = 1),dtype=tf.float32)
         Y_test = tf.cast(y_test.reshape(-1,1),dtype=tf.float32)

In [23]: X_test.shape, Y_test.shape

Out[23]: (TensorShape([22, 3]), TensorShape([22, 1]))
```

设置超参数、设置模型参数初识值

In [24]:
```
learn_rate=0.2
iter=120

display_step=30
```

In [25]:
```
np.random.seed(612)
W=tf.Variable(np.random.randn(3,1),dtype=tf.float32)
```

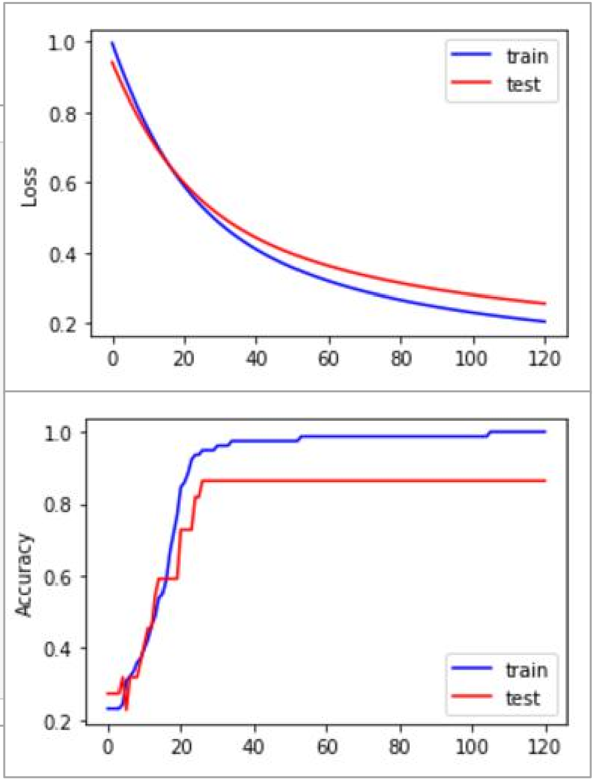
11.4.1 实现多元逻辑回归


```
In [26]: ce_train=[]
         ce_test=[]
         acc_train=[]
         acc_test=[]

         for i in range(0, iter+1):
             with tf.GradientTape() as tape:
                 PRED_train =1/(1+tf.exp(-tf.matmul(X_train,W)))
                 Loss_train =-tf.reduce_mean(Y_train*tf.math.log(PRED_train)+(1-Y_train)*tf.math.log(1-PRED_train))
                 PRED_test =1/(1+tf.exp(-tf.matmul(X_test,W)))
                 Loss_test =-tf.reduce_mean(Y_test*tf.math.log(PRED_test)+(1-Y_test)*tf.math.log(1-PRED_test))

             accuracy_train = tf.reduce_mean(tf.cast(tf.equal(tf.where(PRED_train.numpy()<0.5,0.,1.), Y_train),tf.float32))
             accuracy_test = tf.reduce_mean(tf.cast(tf.equal(tf.where(PRED_test.numpy()<0.5,0.,1.), Y_test),tf.float32))

             ce_train.append(Loss_train)
             ce_test.append(Loss_test)
             acc_train.append(accuracy_train)
             acc_test.append(accuracy_test)

             dL_dW= tape.gradient(Loss_train,W)
             W.assign_sub(learn_rate*dL_dW)

             if i % display_step == 0:
                 print("i: %i, TrainAcc:%f, TrainLoss: %f ,TestAcc:%f, TestLoss: %f" % (i,accuracy_train,Loss_train,accuracy_test,Loss_test))
```

```
i: 0, TrainAcc:0.230769, TrainLoss: 0.994269 ,TestAcc:0.272727, TestLoss: 0.939684
i: 30, TrainAcc:0.961538, TrainLoss: 0.481892 ,TestAcc:0.863636, TestLoss: 0.505456
i: 60, TrainAcc:0.987179, TrainLoss: 0.319128 ,TestAcc:0.863636, TestLoss: 0.362112
i: 90, TrainAcc:0.987179, TrainLoss: 0.246626 ,TestAcc:0.863636, TestLoss: 0.295611
i: 120, TrainAcc:1.000000, TrainLoss: 0.204982 ,TestAcc:0.863636, TestLoss: 0.256212
```

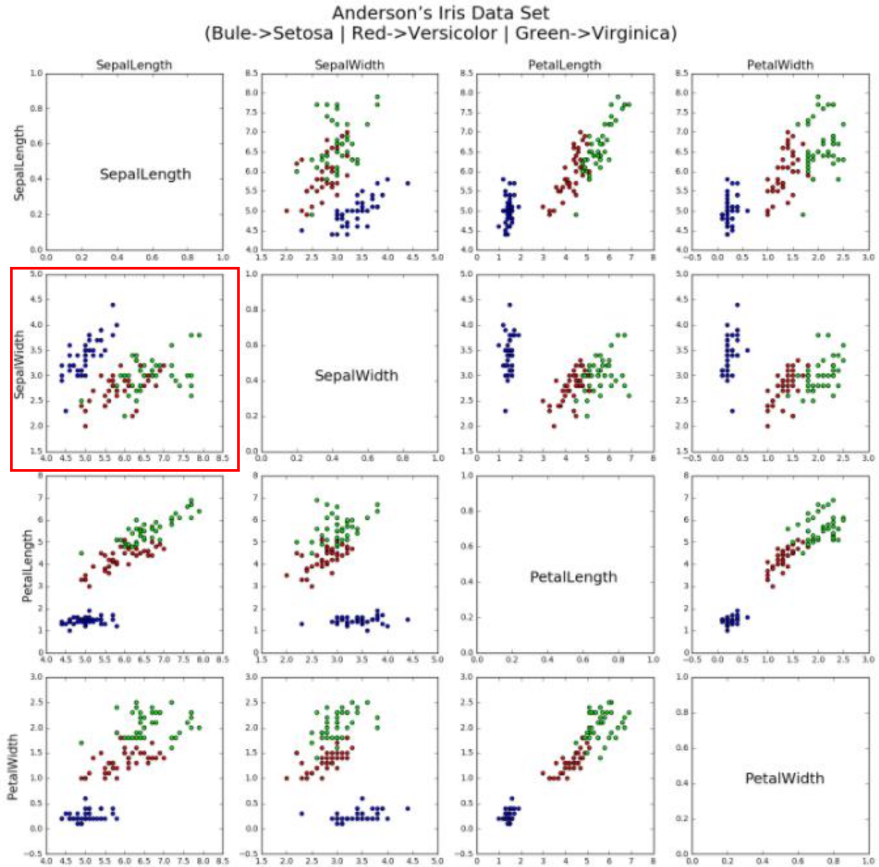
可视化

```
In [27]: plt.figure(figsize=(10,3))

         plt.subplot(121)
         plt.plot(ce_train,color="blue",label="train")
         plt.plot(ce_test,color="red",label="test")
         plt.ylabel("Loss")
         plt.legend()

         plt.subplot(122)
         plt.plot(acc_train,color="blue",label="train")
         plt.plot(acc_test,color="red",label="test")
         plt.ylabel("Accuracy")

         plt.legend()
         plt.show()
```

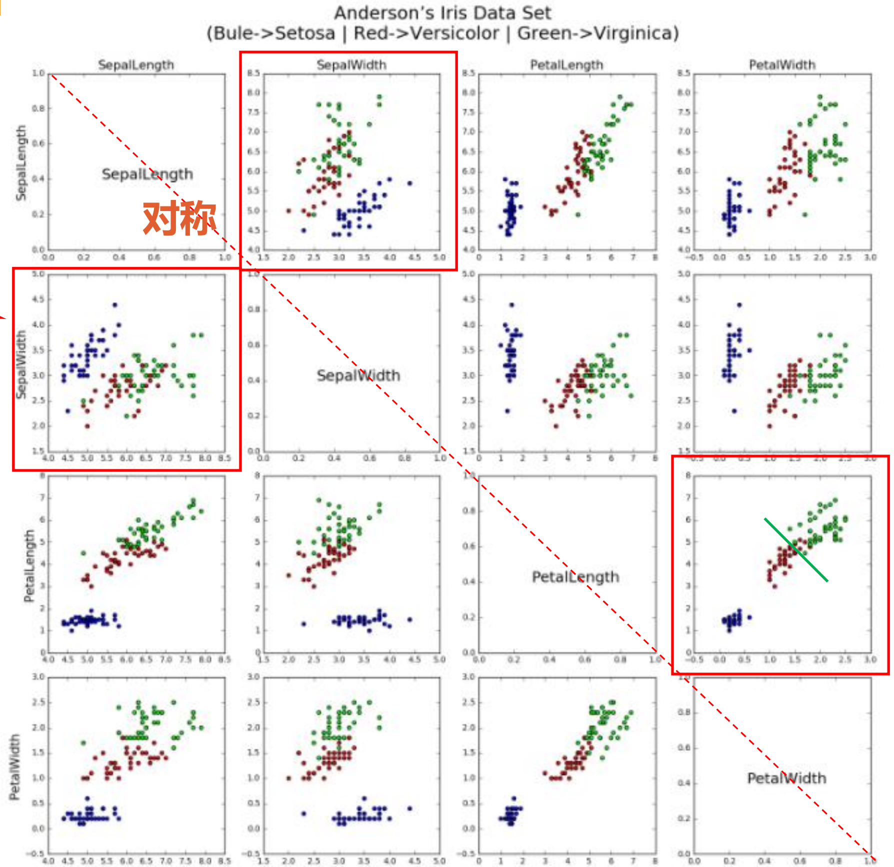


11.4 .1 实现多元逻辑回归

例程中的散点图



11.4.1 实现多元逻辑回归



例程中的散点图

11.4.2 绘制分类图

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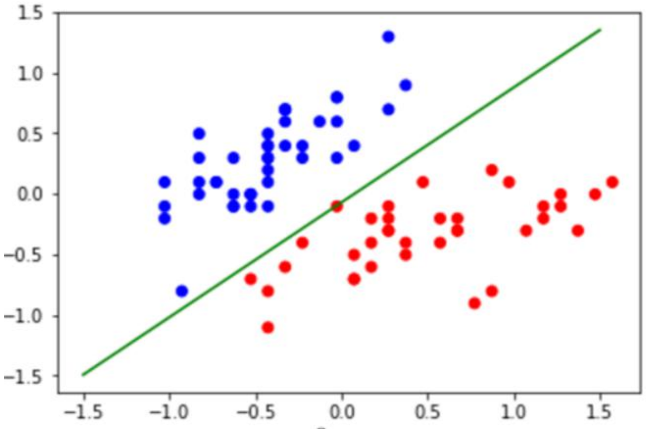
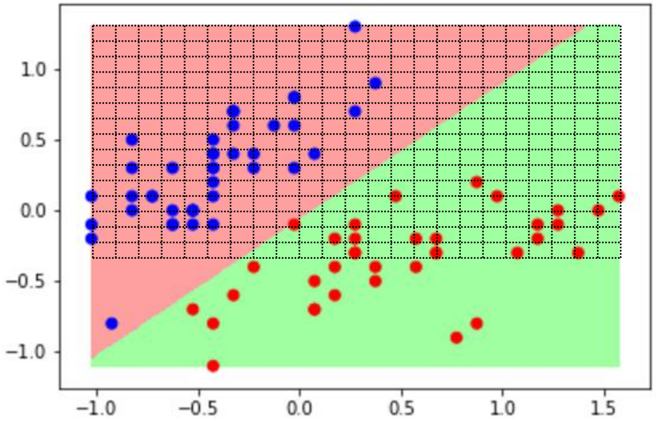
- **线性分类器**
- **决策边界**

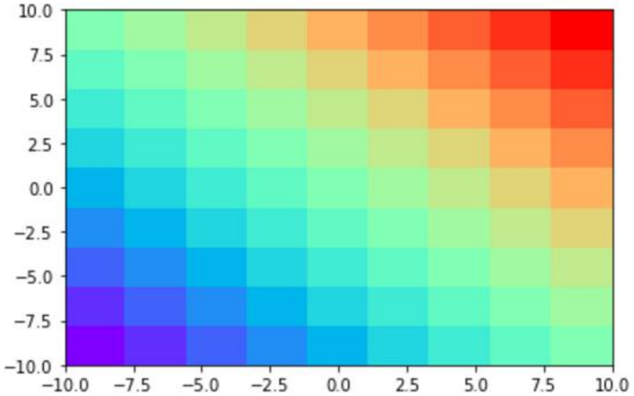

1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0
1.5

11.4.2 绘制分类图

生成网格坐标矩阵：np.meshgrid()

填充网格：plt.pcolomesh()



In [1]:
```python
import tensorflow as tf
print("TensorFlow version:",tf.__version__)
```

```
TensorFlow version: 2.0.0
```

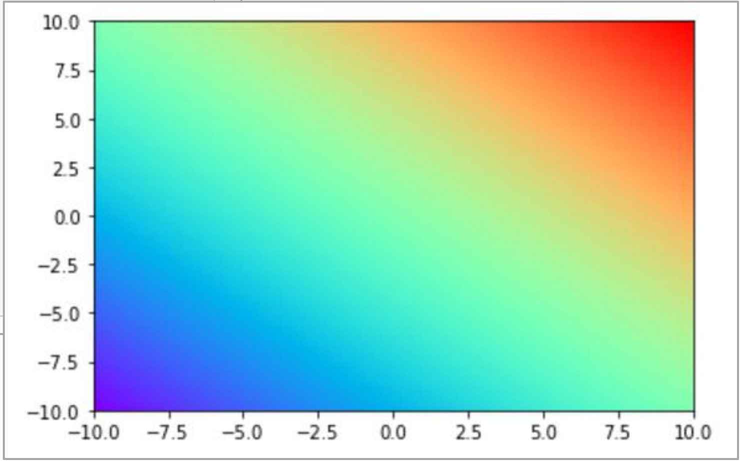
In [2]:
```python
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
```

In [3]:
```python
n = 10

x = np.linspace(-10,10,n)
y = np.linspace(-10,10,n)

X,Y = np.meshgrid(x,y)
Z = X+Y

plt.pcolormesh(X,Y,Z,cmap="rainbow")

plt.show()
```

meshgrid()详见9.6小节

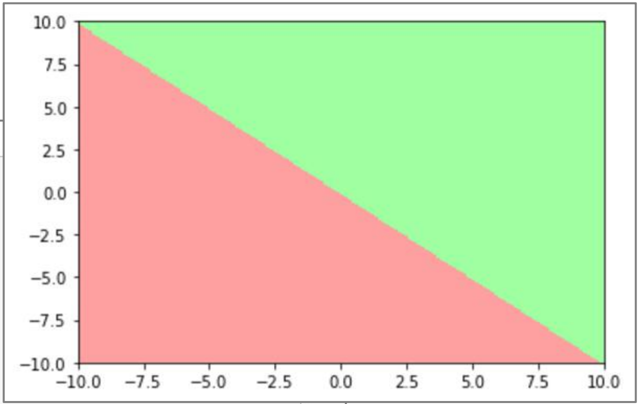
11.4.2 绘制分类图

In [4]:
```
n = 200

x = np.linspace(-10, 10, n)
y = np.linspace(-10, 10, n)

X, Y = np.meshgrid(x, y)
Z = X+Y

plt.pcolormesh(X, Y, Z, cmap="rainbow")

plt.show()
```



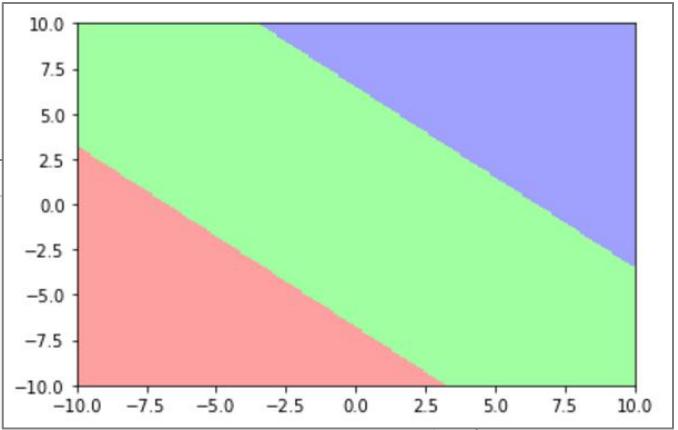
11.4.2 绘制分类图

```
In [5]: n = 200

        x = np.linspace(-10,10,n)
        y = np.linspace(-10,10,n)

        X,Y = np.meshgrid(x,y)
        Z = X+Y

        cm_bg = mpl.colors.ListedColormap(["#FFA0A0","#A0FFA0"])
        plt.pcolormesh(X,Y,Z,cmap=cm_bg)

        plt.show()
```



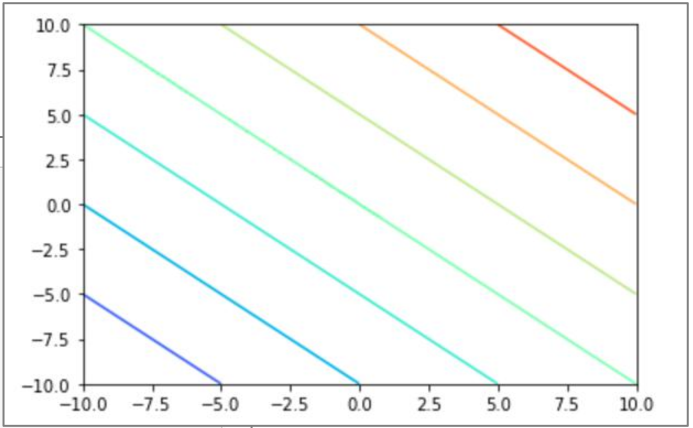
11.4.2 绘制分类图

```
In [6]: n = 200

        x = np.linspace(-10, 10, n)
        y = np.linspace(-10, 10, n)

        X, Y = np.meshgrid(x, y)
        Z = X+Y

        cm_bg = mpl.colors.ListedColormap(["#FFA0A0", "#A0FFA0", "#A0A0FF"])
        plt.pcolormesh(X, Y, Z, cmap=cm_bg)

        plt.show()
```



绘制轮廓线：plt.contour()

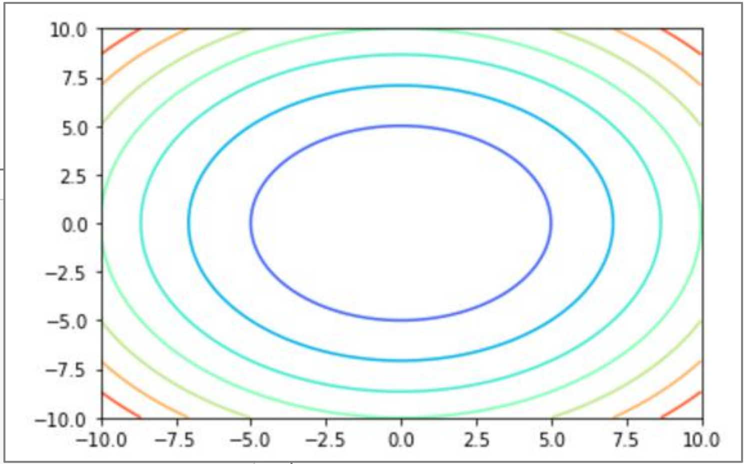
```
In [7]: n = 200

        x = np.linspace(-10, 10, n)
        y = np.linspace(-10, 10, n)

        X, Y = np.meshgrid(x, y)
        Z = X+Y

        plt.contour(X, Y, Z, cmap="rainbow")

        plt.show()
```



11.4.2 绘制分类图

绘制轮廓线：plt.contour()

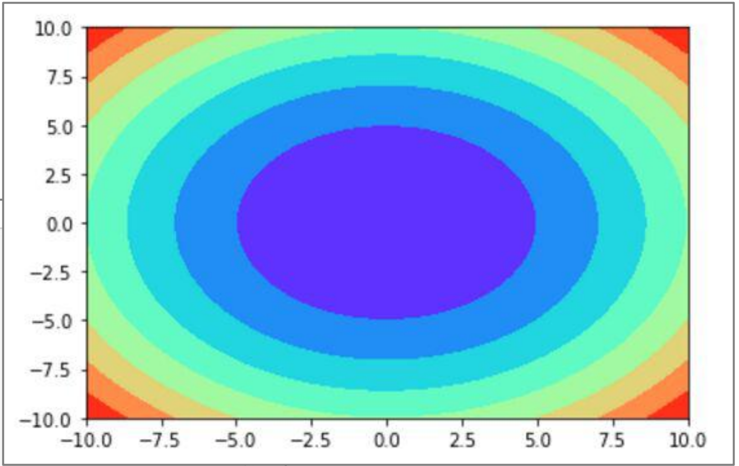
```
In [8]: n = 200

x = np.linspace(-10,10,n)
y = np.linspace(-10,10,n)

X,Y = np.meshgrid(x,y)
Z = X**2+Y**2

plt.contour(X,Y,Z,cmap="rainbow")

plt.show()
```



11.4.2 绘制分类图

填充分区：plt.contourf()

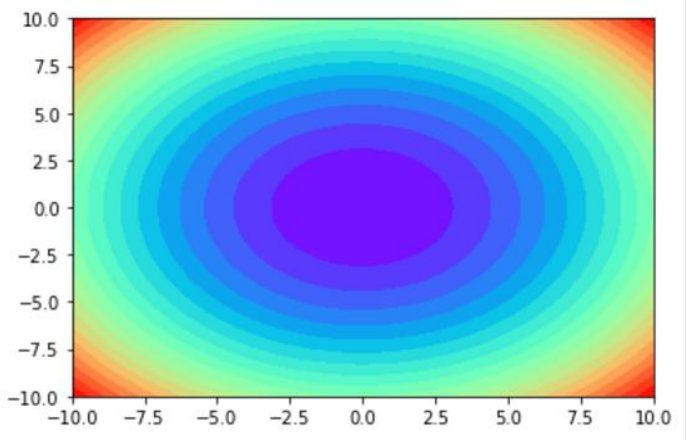
```
In [9]: n = 200

        x = np.linspace(-10, 10, n)
        y = np.linspace(-10, 10, n)

        X, Y = np.meshgrid(x, y)
        Z = X**2+Y**2

        plt.contourf(X, Y, Z, cmap="rainbow")

        plt.show()
```



11.4.2 绘制分类图

填充分区：plt.contourf()

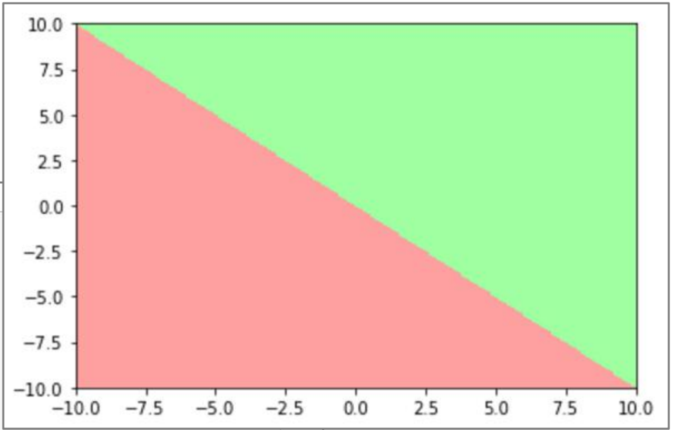
```
In [10]: n = 200

         x = np.linspace(-10, 10, n)
         y = np.linspace(-10, 10, n)

         X, Y = np.meshgrid(x, y)
         Z = X**2+Y**2

         plt.contourf(X, Y, Z, 20, cmap="rainbow")

         plt.show()
```



生成网格坐标矩阵：np.meshgrid()

绘制分类图：pcolormesh()/plt.contourf()

```
In [11]: n = 200

         x = np.linspace(-10,10,n)
         y = np.linspace(-10,10,n)

         X,Y = np.meshgrid(x,y)
         Z = X+Y

         cm_bg = mpl.colors.ListedColormap(["#FFA0A0","#A0FFA0"])
         Z=tf.where(Z<0,0,1)
         plt.pcolormesh(X,Y,Z,cmap=cm_bg)

         plt.show()
```

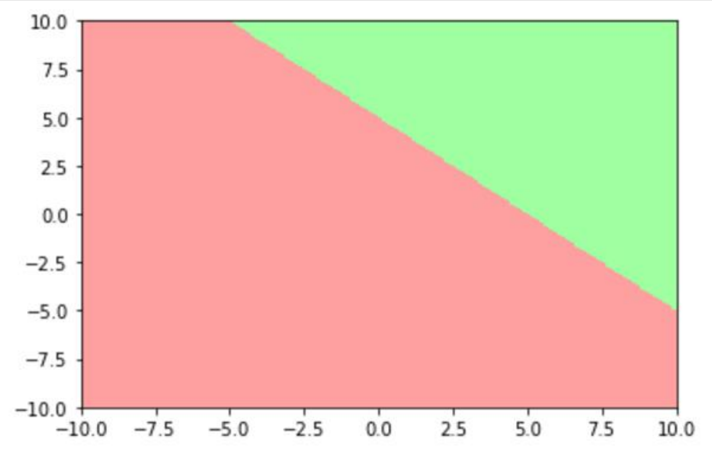


11.4.2 绘制分类图

生成网格坐标矩阵：np.meshgrid()

绘制分类图：pcolormesh()/plt.contourf()

In [12]:
```
n = 200

x = np.linspace(-10, 10, n)
y = np.linspace(-10, 10, n)

X, Y = np.meshgrid(x, y)
Z = X+Y

cm_bg = mpl.colors.ListedColormap(["#FFA0A0", "#A0FFA0"])
Z=tf.where(Z<5, 0, 1)
plt.pcolormesh(X, Y, Z, cmap=cm_bg)

plt.show()
```



11.4.2 绘制分类图

■ 根据鸢尾花分类模型，绘制分类图

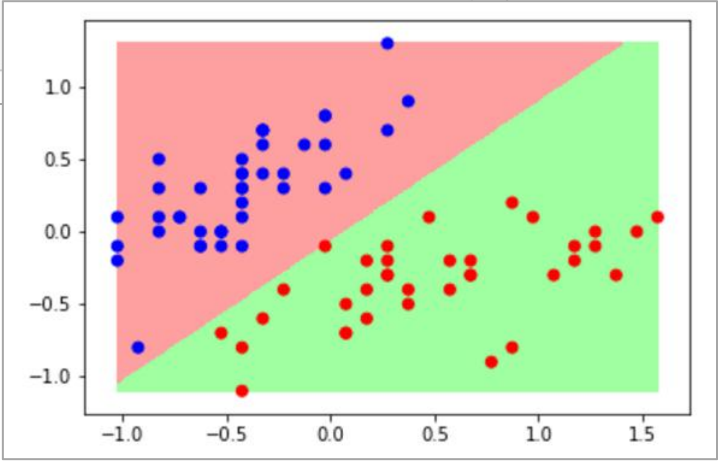
In [29]:
```
M=300
x1_min, x2_min = x_train.min(axis=0)
x1_max, x2_max = x_train.max(axis=0)
t1 = np.linspace(x1_min, x1_max, M)
t2 = np.linspace(x2_min, x2_max, M)
m1,m2 = np.meshgrid(t1, t2)
```

In [30]:
```
m0=np.ones(M*M)
X_mesh = tf.cast(np.stack((m0,m1.reshape(-1),m2.reshape(-1)), axis=1),dtype=tf.float32)
Y_mesh =tf.cast(1/(1+tf.exp(-tf.matmul(X_mesh,W))),dtype=tf.float32)
Y_mesh=tf.where(Y_mesh<0.5,0,1)
```

In [31]:
```
n=tf.reshape(Y_mesh,m1.shape)
```

11.4.2 绘制分类图

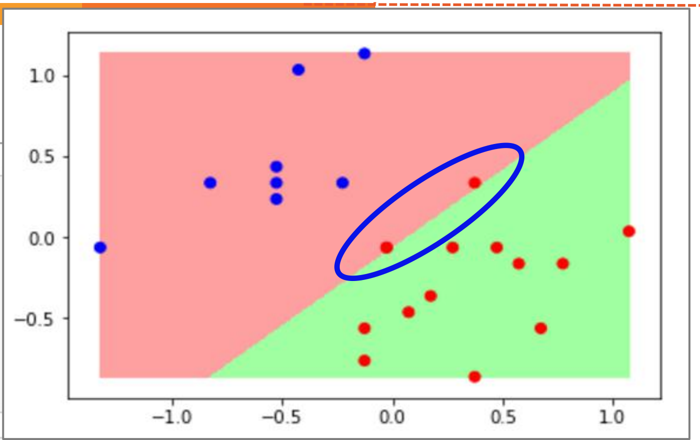

```
In [32]: cm_pt = mpl.colors.ListedColormap(["blue", "red"])
         cm_bg = mpl.colors.ListedColormap(["#FFA0A0","#A0FFA0"])

         plt.pcolormesh(m1, m2, n, cmap=cm_bg)
         plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap=cm_pt)

         plt.show()
```



11.4.2 绘制分类图

0.863636=19/22

```
In [33]: M=300
         x1_min, x2_min = x_test.min(axis=0)
         x1_max, x2_max = x_test.max(axis=0)
         t1 = np.linspace(x1_min, x1_max, M)
         t2 = np.linspace(x2_min, x2_max, M)
         m1,m2 = np.meshgrid(t1, t2)
```




```
In [34]: m0=np.ones(M*M)
         X_mesh = tf.cast(np.stack((m0,m1.reshape(-1),m2.reshape(-1)), axis=1),dtype=tf.float32)
         Y_mesh =tf.cast(1/(1+tf.exp(-tf.matmul(X_mesh,W))),dtype=tf.float32)
         Y_mesh=tf.where(Y_mesh<0.5,0,1)
```

```
In [35]: n=tf.reshape(Y_mesh,m1.shape)
```

```
In [36]: plt.pcolormesh(m1, m2, n, cmap=cm_bg)
         plt.scatter(x_test[:,0],x_test[:,1],c=y_test,cmap=cm_pt)
         plt.show()
```

13	5.5	2.5	4	1.3	1
14	5.6	2.8	4.9	2	2
15	5.5	4.2	1.4	0.2	0
16	5.5	2.3	4	1.3	1
17	5.6	3	4.1	1.3	1
18	5.6	3	4.5	1.5	1
19	5.7	2.6	3.5	1	1
20	5.8	2.7	3.9	1.2	1
21	5.7	2.5	5	2	2
22	5.9	3	4.2	1.5	1

11.4.2 绘制分类图

■ 分别绘制**训练集**和**测试集**的分类图