第 1 章

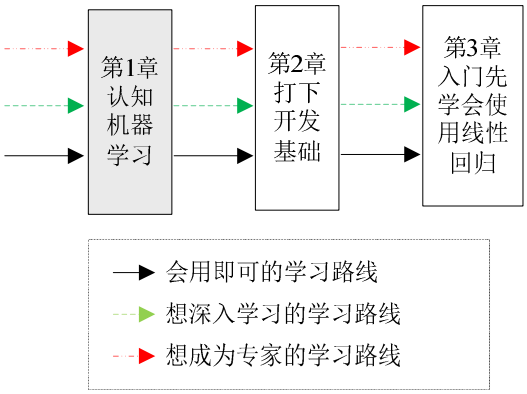


图 1-1　学习路线图

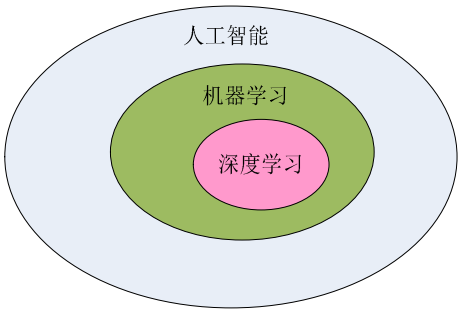


图 1-2　人工智能、机器学习、深度学习三者之间的关系

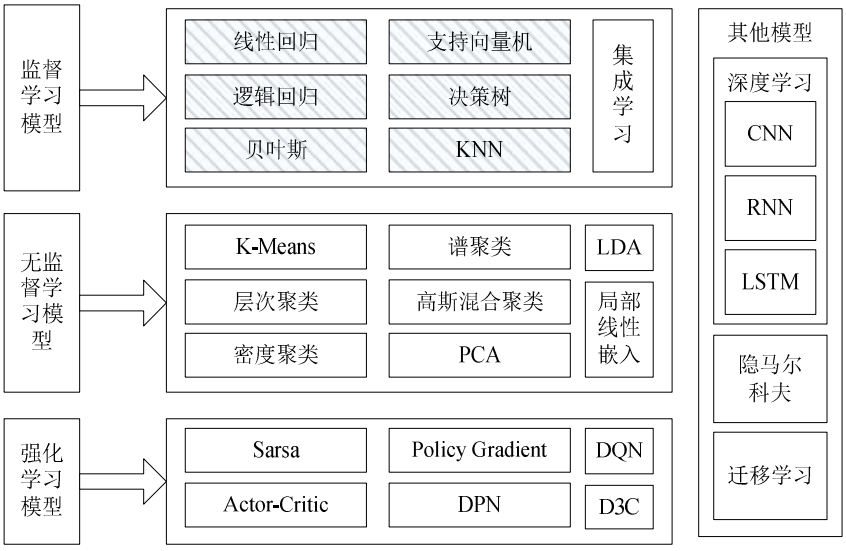


图 1-3　机器学习的模型

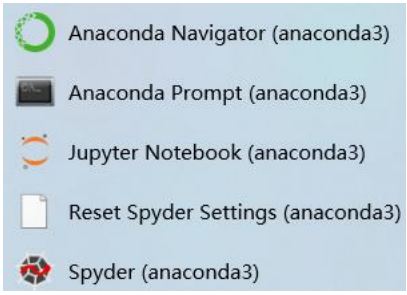


图 1-4　Anaconda 安装的 5 个工具

第 2 章

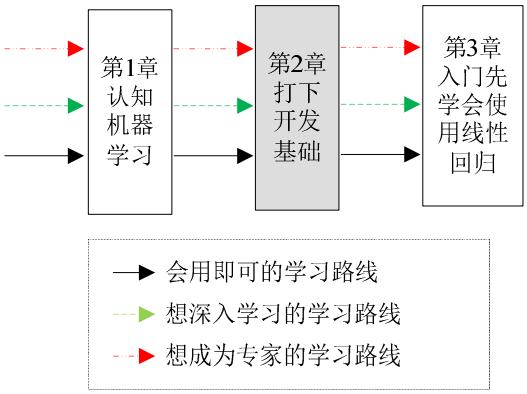


图 2-1　学习路线图

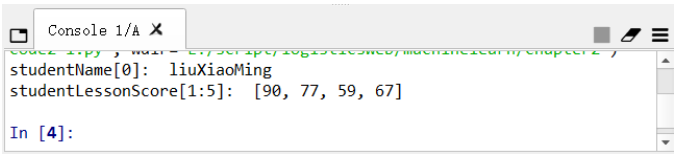


图 2-2　访问列表中的元素

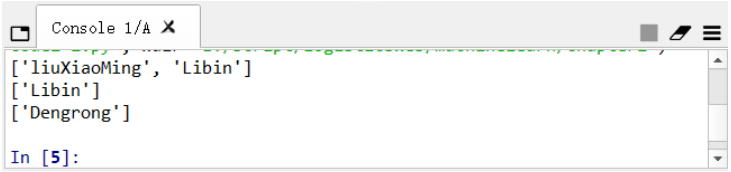


图 2-3　更新列表中的元素

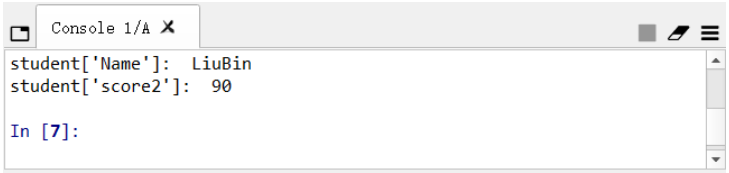


图 2-4　访问字典的值

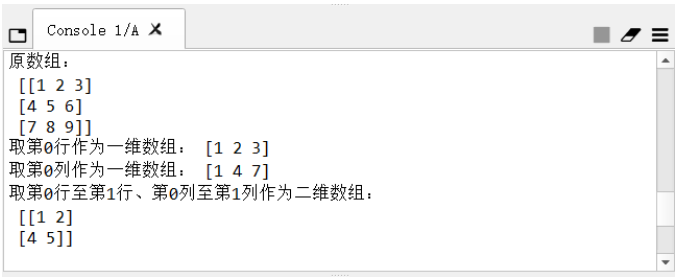


图 2-5　访问数组中的元素

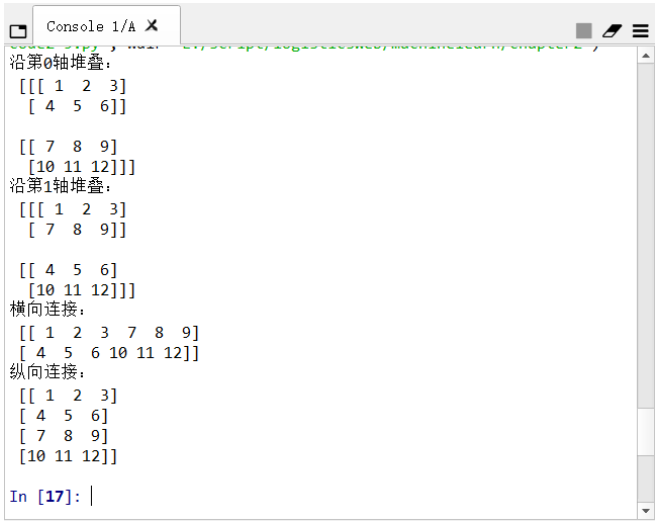


图 2-6　堆叠或连接数组

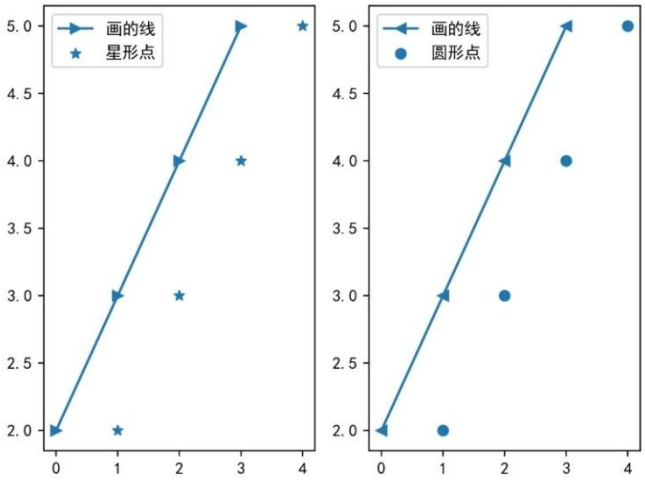


图 2-7　画一个含 2 个子图的图形

第 3 章

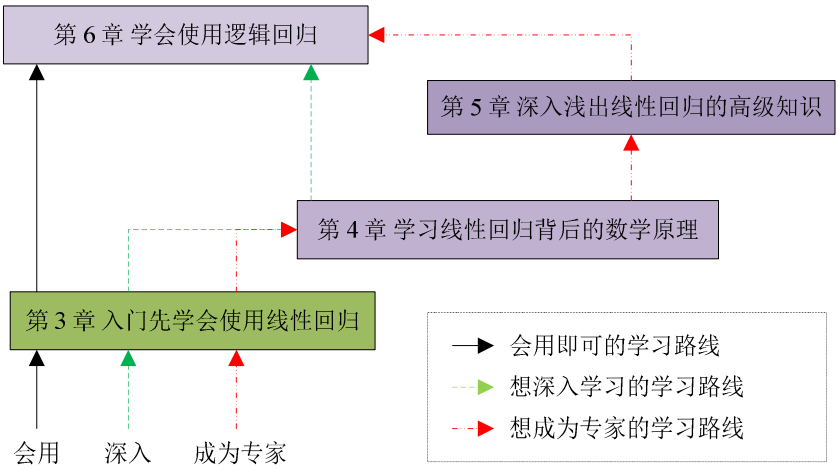


图 3-1　学习路线图

图 3-2　点到线的距离

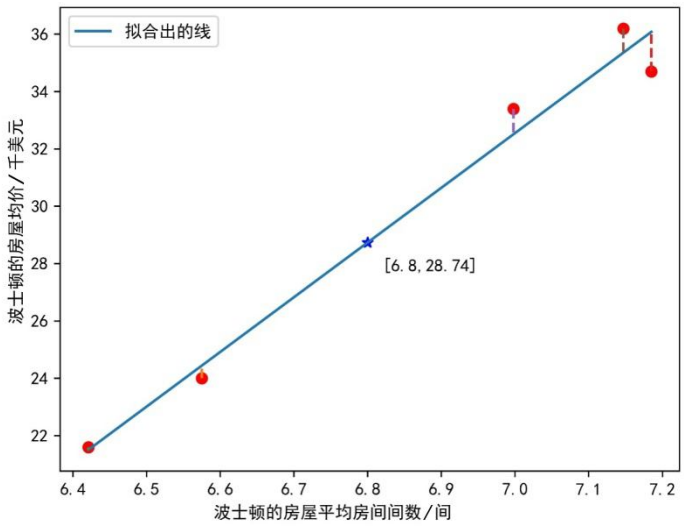


图 3-3　根据已知数据拟合出直线

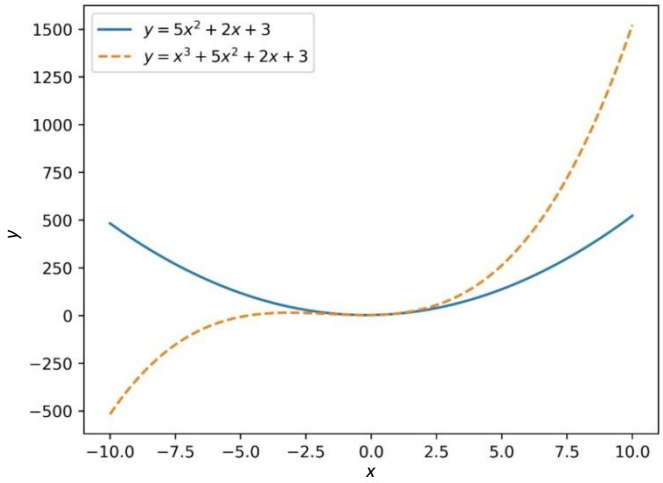


图 3-4　一元二次方程和一元三次方程的图形

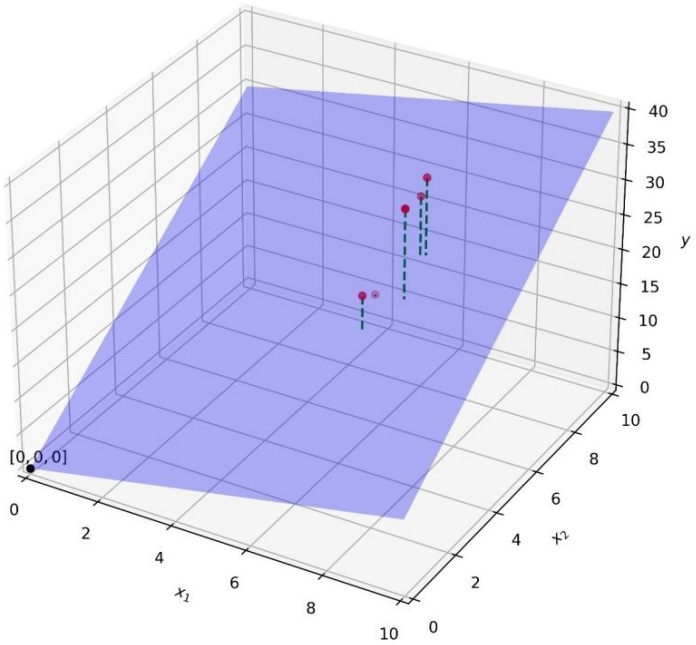


图 3-5　$y = x_1 + 3x_2$ 图形

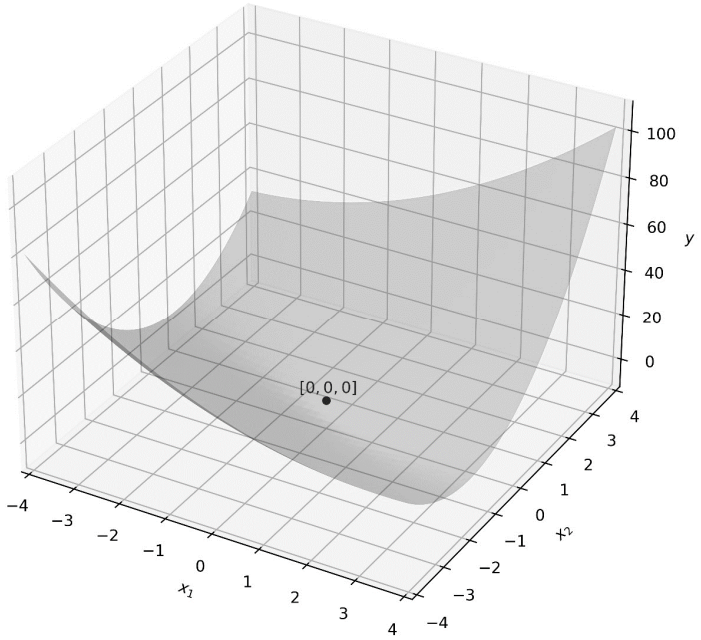


图 3-6　$y = x_1^2 + 2x_1x_2 + 3x_2^2 + x_1 + 2x_2 - 3$ 的图形

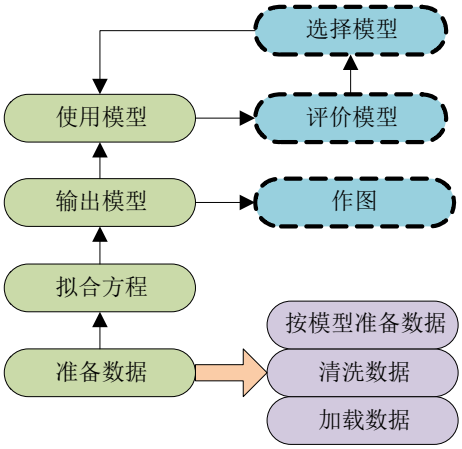


图 3-7　做线性回归的过程

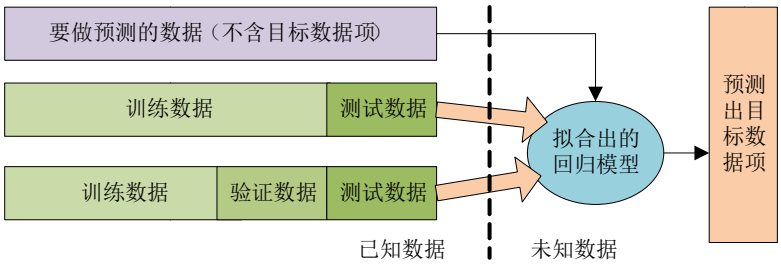


图 3-8　已知数据集的划分

```
Console 1/A
关键字： dict_keys(['data', 'target', 'feature_names', 'DESCR',
'filename'])
特征项： ['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD'
'TAX' 'PTRATIO'
 'B' 'LSTAT']
数据集的形状：(506, 13)
RM的前5条数据：         5
0  6.575
1  6.421
2  7.185
3  6.998
4  7.147
```

图 3-9　查看加载的波士顿房价数据集

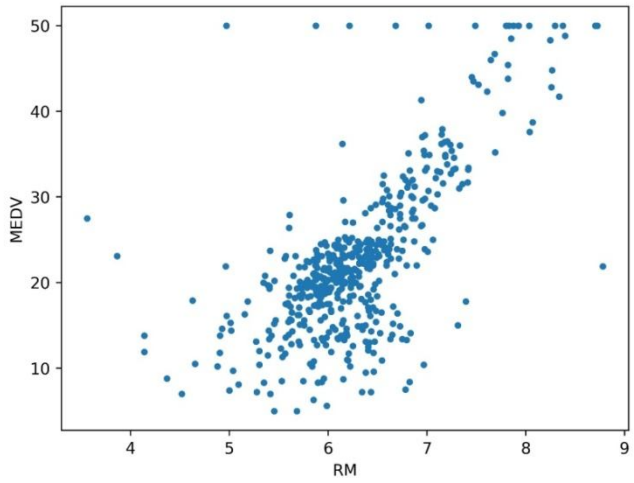


图 3-10　表达特征项 RM 与目标数据项 MEDV 关系的散点图

```
Console 1/A
(404, 1) (102, 1) (404, 1) (102, 1)

In [6]:
```

图 3-11　把波士顿房屋价格数据集划分成训练数据和测试数据的结果

```
Console 1/A
截距： [-33.22926501]
系数： [[8.8467407]]
线性方程： y=8.846740701403982x+(-33.229265012430446)

In [9]:
```

图 3-12　某次训练的输出结果

```
Console 1/A
预测结果：
 [[40.37152813]
 [24.04248004]
 [32.50438741]
 [28.80061326]
 [20.92446092]
 [18.59946401]
 [21.92475029]
 [13.67912171]
 [19.36545137]
 [14.03958634]
 [16.46371103]
```

图 3-13　一个预测的示例结果

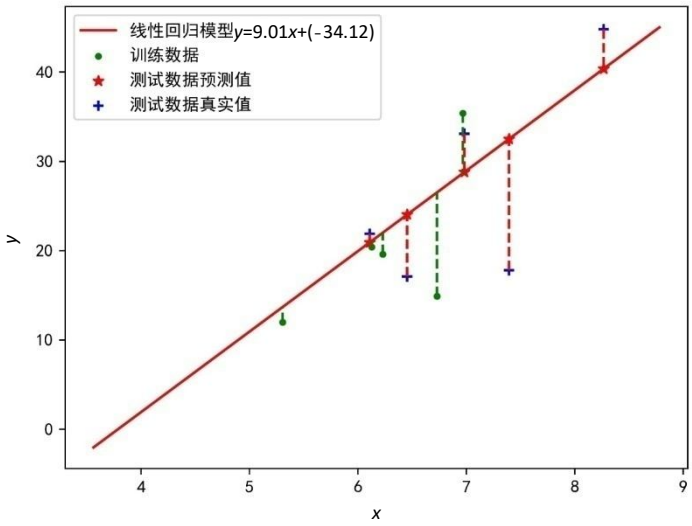


图 3-14　得到的线性回归模型

图 3-15　计算模型的 4 个评价指标的值

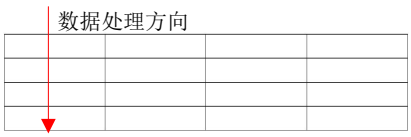


图 3-16　MinMaxScaler 的数据处理方向

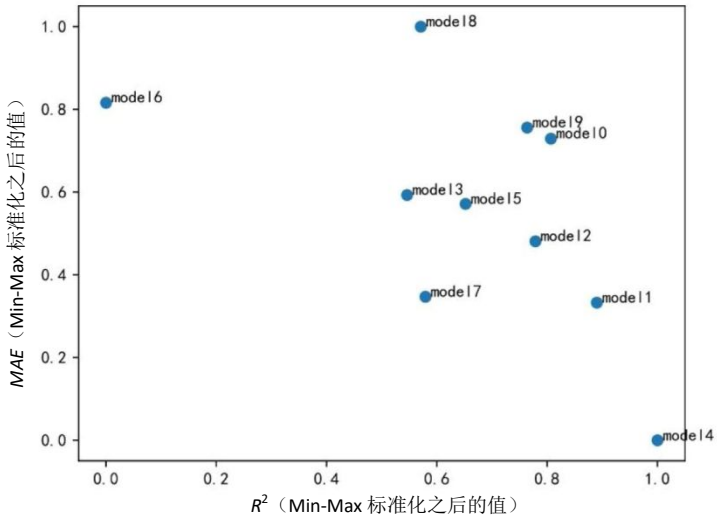


图 3-17　模型评价指标 R^2、*MAE* 的散点图

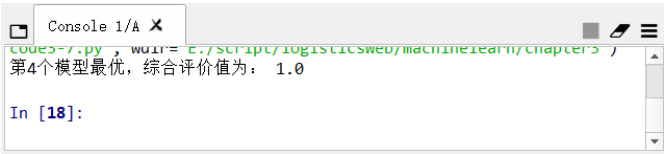


图 3-18　自动找到最优模型的结果

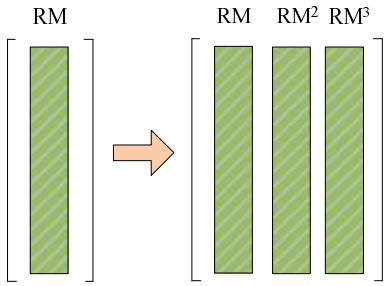


图 3-19　应模型要求数据集应做出的变化

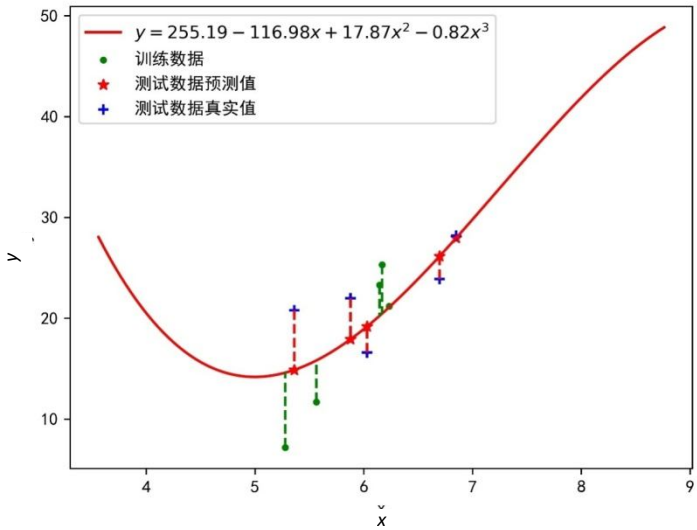


图 3-20　一元三次方程的图形

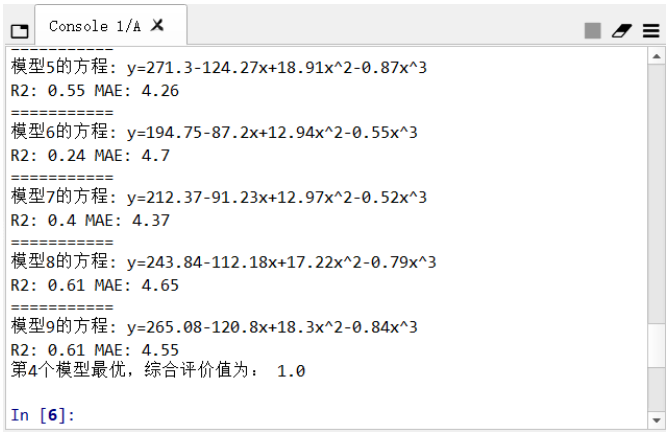


图 3-21　对 10 个一元三次方程的综合评价

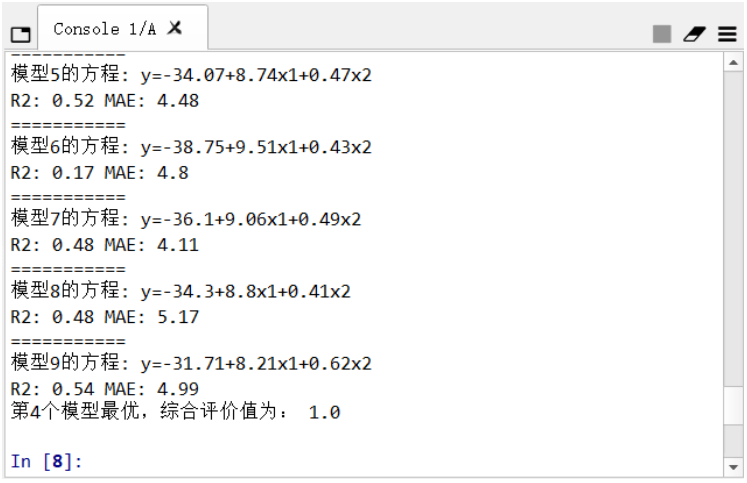


图 3-22　对 10 个二元一次方程的综合评价

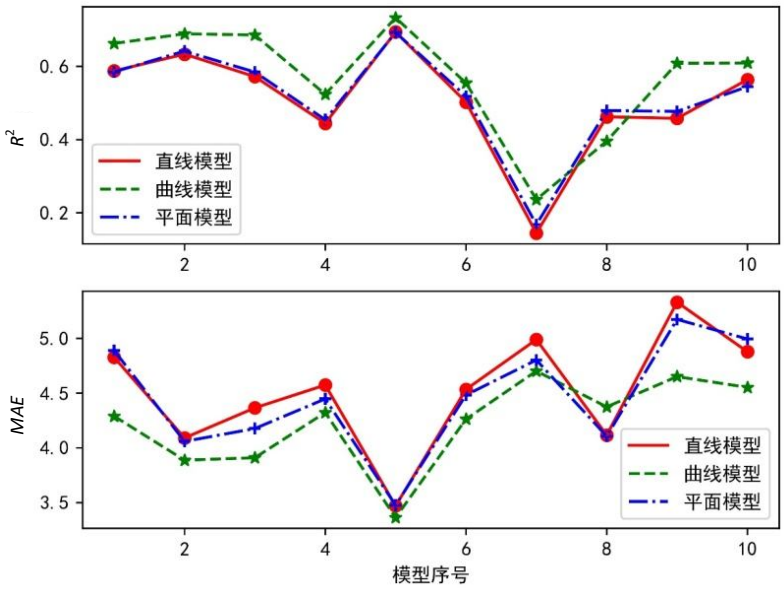


图 3-23　对比 3 种模型的评价指标

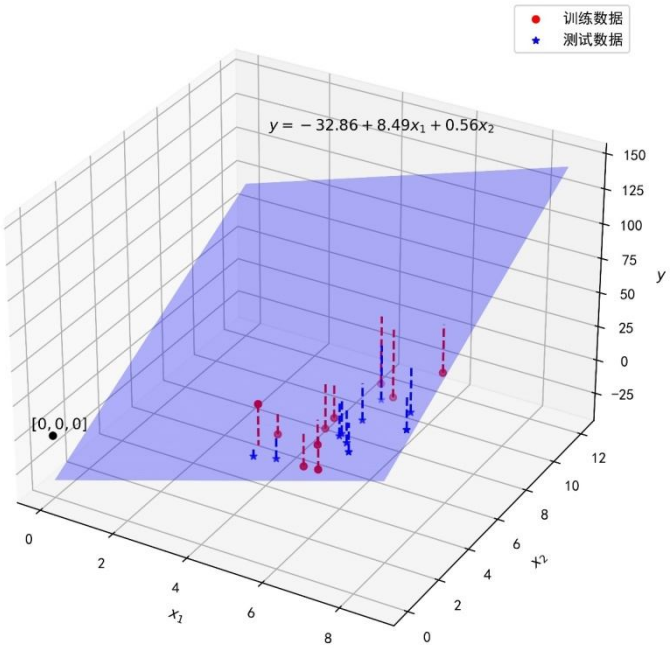


图 3-24　拟合出的平面

```
Console 1/A
模型7的方程:
y=182.77-68.56x1-11.67x2+3.81x1x2+7.98x1^2+0.07x2^2-0.14x1^2*x2-0.1
7x1*x2^2-0.23x1^3+0.04x2^3
R2: 0.43 MAE: 4.14
==========
模型8的方程:
y=223.17-99.36x1+2.26x2-0.24x1x2+14.54x1^2-0.1x2^2+0.13x1^2*x2-0.13
x1*x2^2-0.65x1^3+0.04x2^3
R2: 0.68 MAE: 3.98
==========
模型9的方程:
y=225.18-106.0x1+22.52x2-6.37x1x2+16.43x1^2-0.35x2^2+0.59x1^2*x2-0.
08x1*x2^2-0.8x1^3+0.04x2^3
R2: 0.58 MAE: 4.4
第4个模型最优，综合评价值为： 1.0

In [26]:
```

图 3-25　对 10 个二元三次方程的综合评价

```
##获得方程的特征项
dataBos=np.array(bos[[5,7]])
X=np.hstack((dataBos[:,0:1],\          ← x1
            dataBos[:,1:2],\           ← x2
            np.multiply(dataBos[:,0:1],dataBos[:,1:2]),\   ← x1x2
            np.power(dataBos[:,0:1],2),\   ← x1^2
            np.power(dataBos[:,1:2],2),\   ← x2^2
            np.multiply(np.power(dataBos[:,0:1],2),dataBos[:,1:2]),\   ← x1^2x2
            np.multiply(dataBos[:,0:1],np.power(dataBos[:,1:2],2)),\   ← x1x2^2
            np.power(dataBos[:,0:1],3),\   ← x1^3
            np.power(dataBos[:,1:2],3)\    ← x2^3
            ))
```

图 3-26　各个二维数组代数的特征项

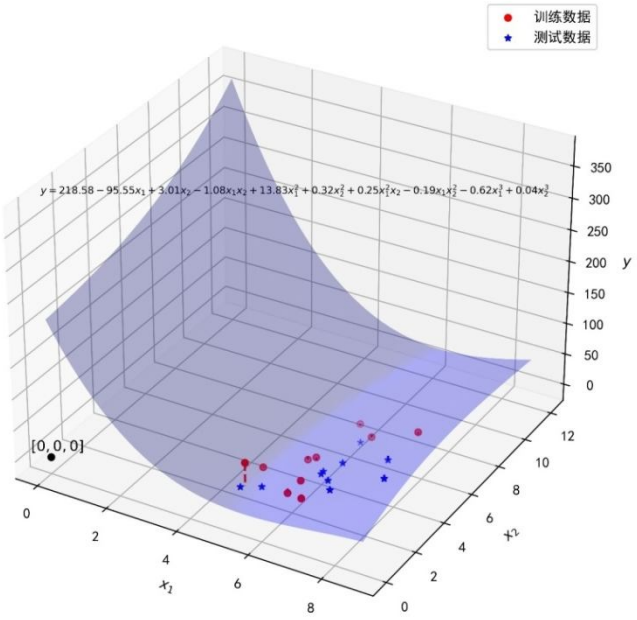


图 3-27　拟合出的曲面的图形

第 4 章

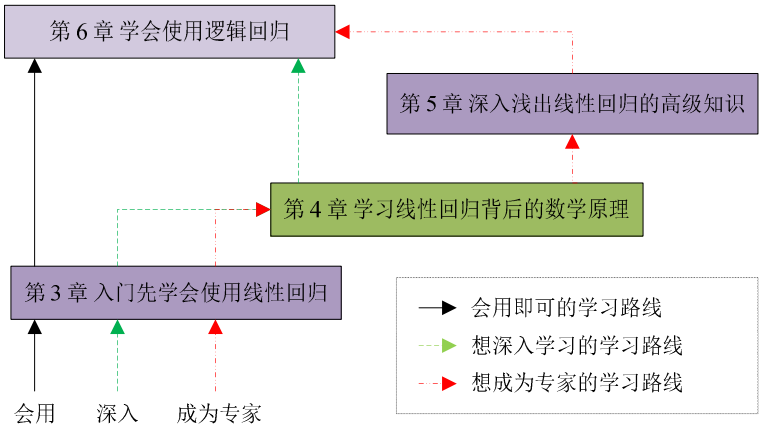


图 4-1　学习路线图

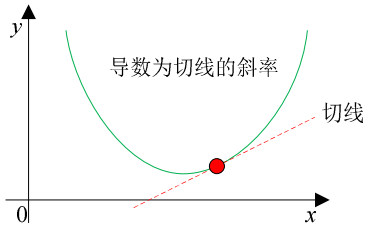


图 4-2　导数的几何意义

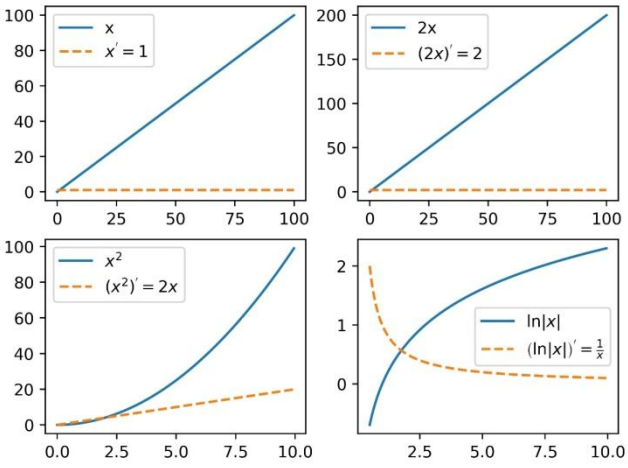
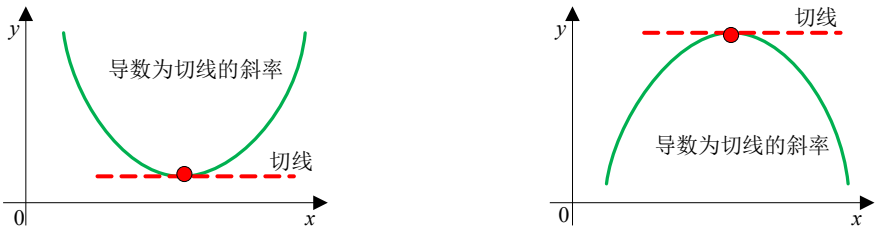


图 4-3　表 4-2 中第 1～4 个求导法则的示例



（a）　　（b）

图 4-4　函数在最大值、最小值处的导数

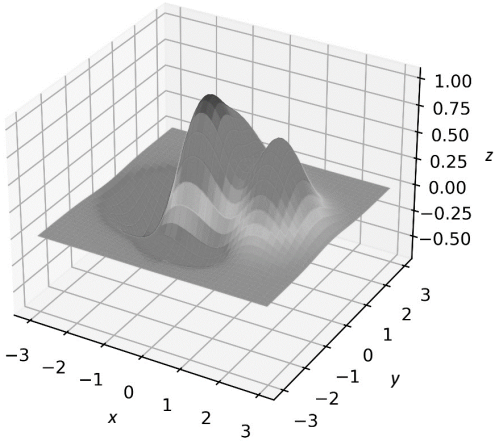


图 4-5　函数有多个极值的示例

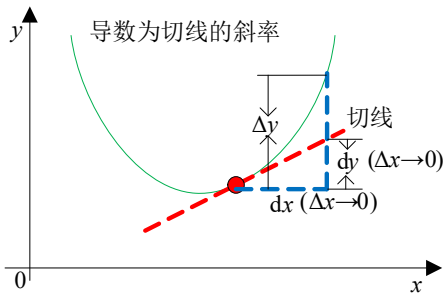


图 4-6　导数的含义示意图

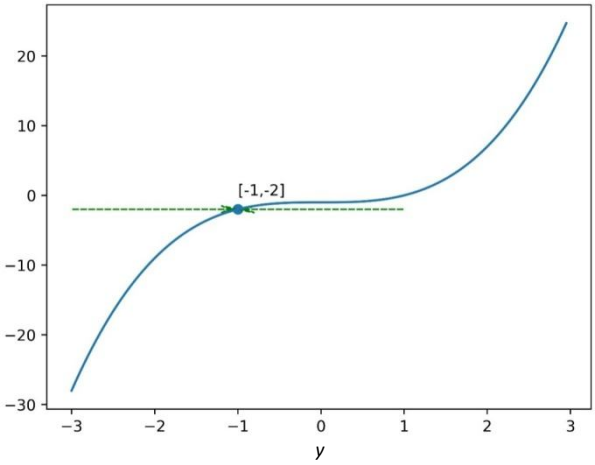


图 4-7　求 $\lim\limits_{x\to -1} x^3$

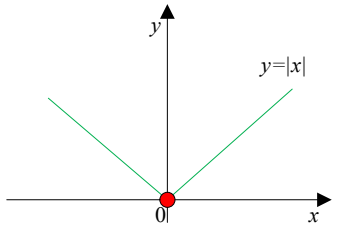


图 4-8　一个连续但不可导的函数示例

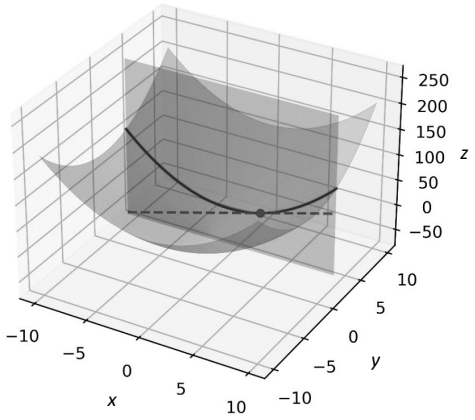


图 4-9　函数偏向x的导数

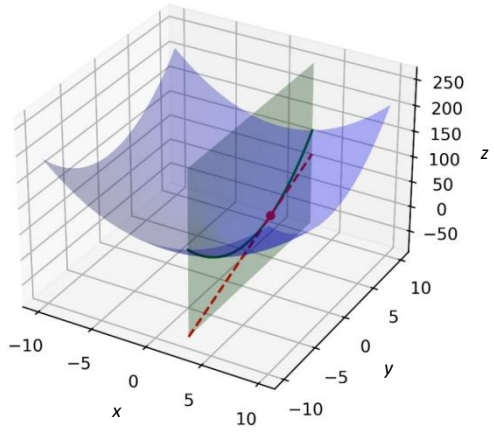


图 4-10　函数偏向y的导数

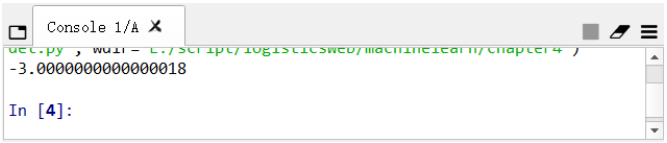
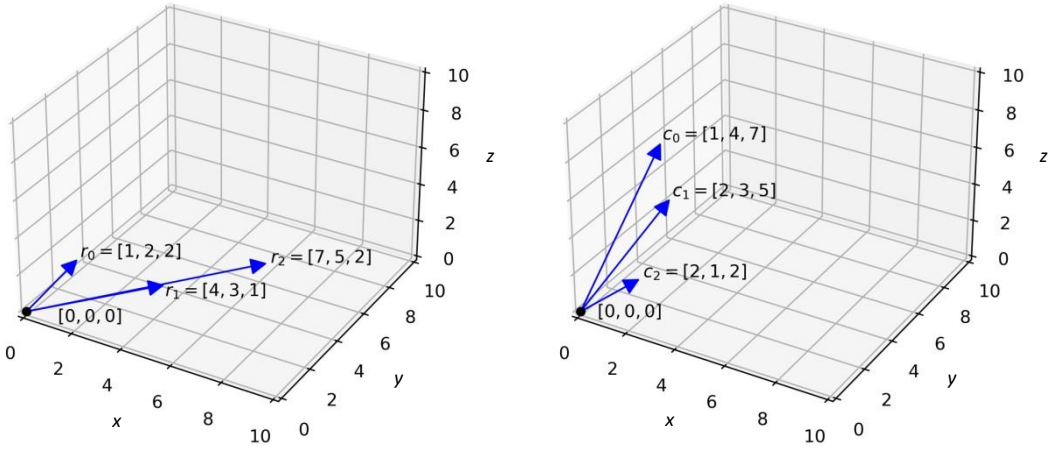


图 4-11　求行列式的值



（a）行向量　　（b）列向量

图 4-12　行列式的行向量与列向量

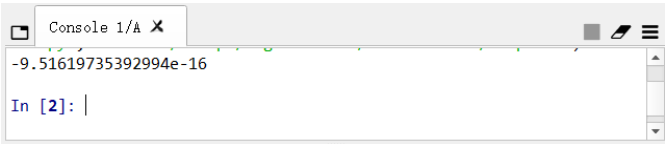


图 4-13　求解行列式的值

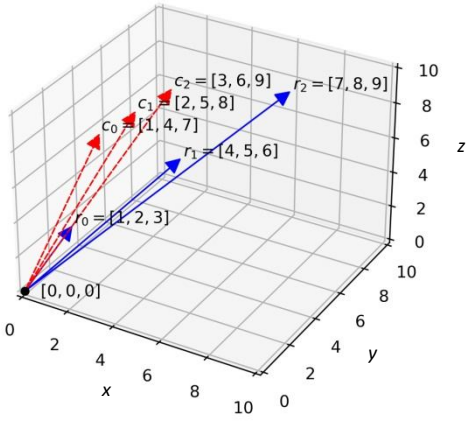
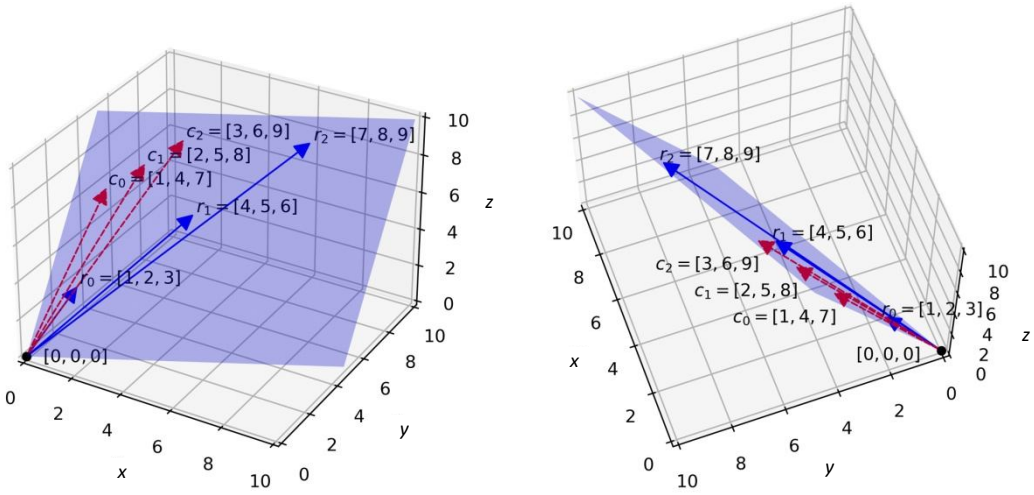


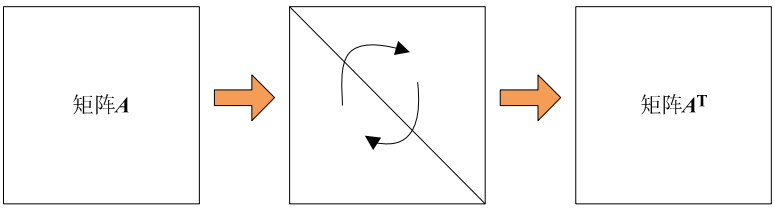
图 4-14　行列式的行向量和列向量

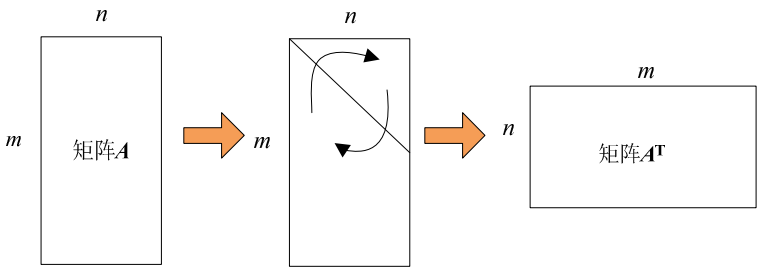


（a）未调视角时的图形　　（b）调整视角后的图形

图 4-15　行向量和列向量位于同一个平面

图 4-16　求矩阵的秩





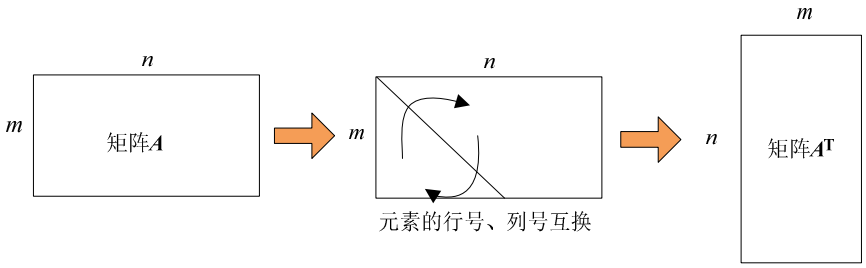


图 4-17　矩阵的转置

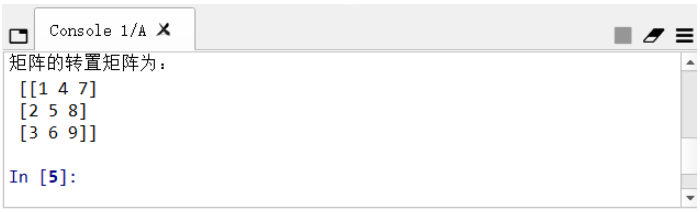


图 4-18　矩阵的转置运算结果

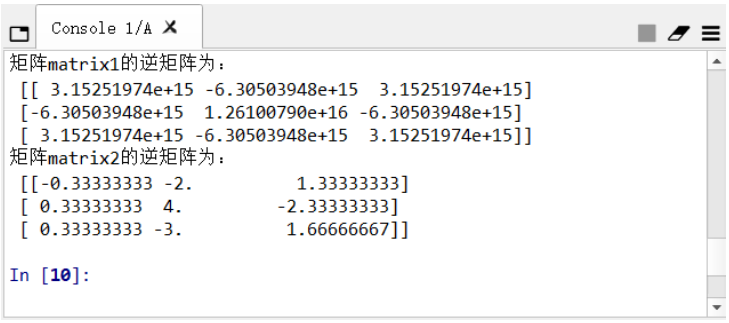


图 4-19　求矩阵的逆矩阵

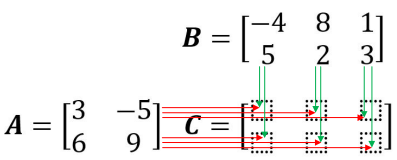


图 4-20　矩阵乘法的计算过程

图 4-21　矩阵乘法的计算结果

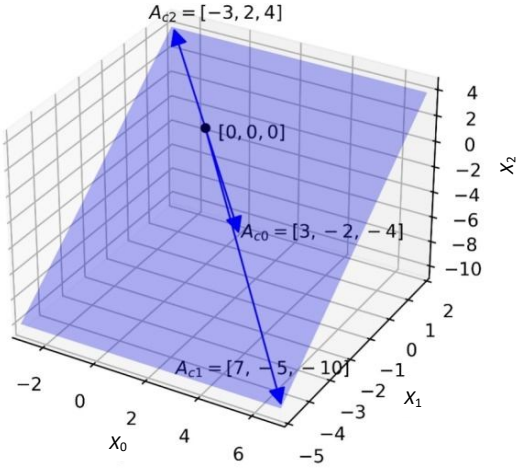


图 4-22　$\boldsymbol{R(A)} = 2$、$m = n = 3$时矩阵$\boldsymbol{A}$的列向量及列空间

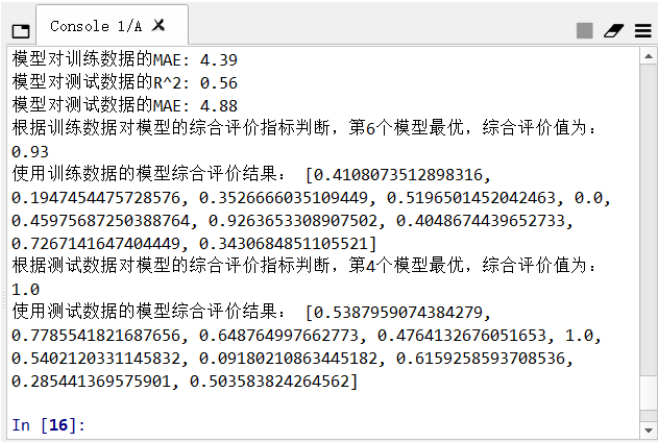


图 4-23　求解一元一次方程模型的参数

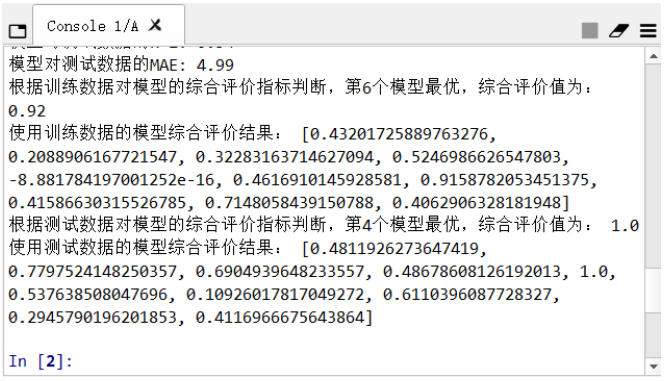


图 4-24　求解多元一次方程模型的参数

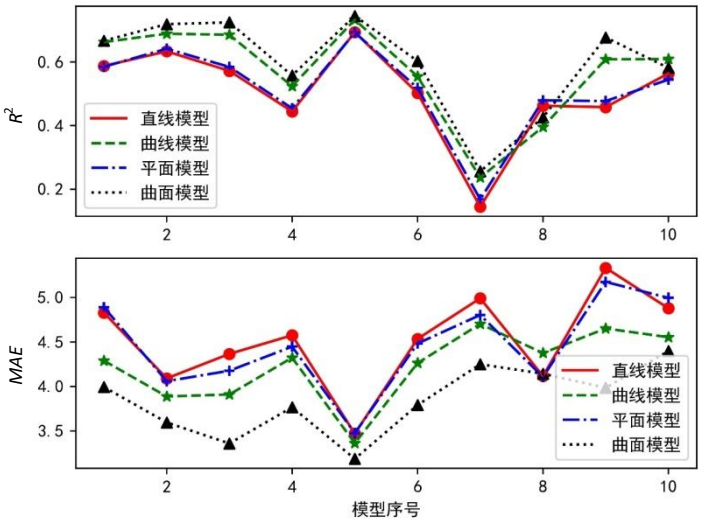


图 4-25　4 种模型的评价指标对比

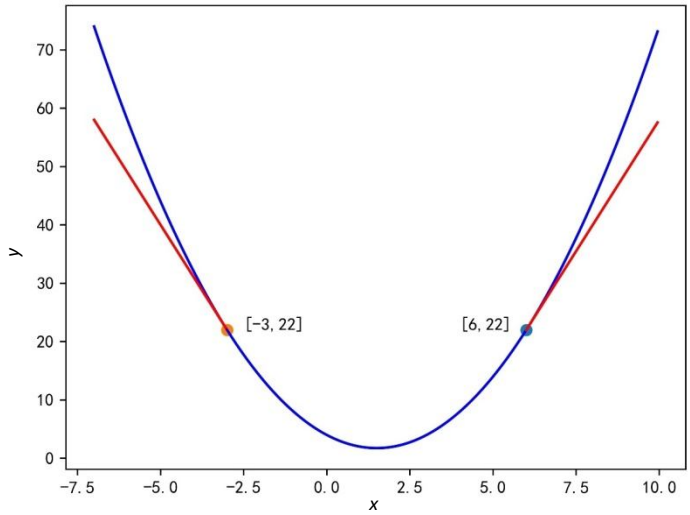
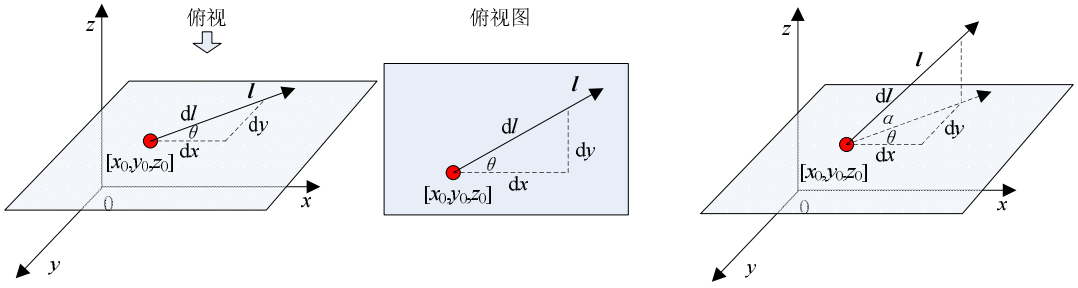


图 4-26　函数的梯度和切线



（a）　　（b）

图 4-27　方向导数图示

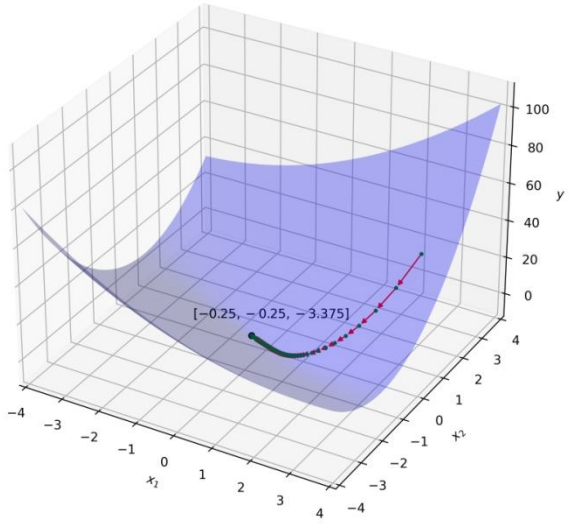


图 4-28　用梯度下降法求极小值

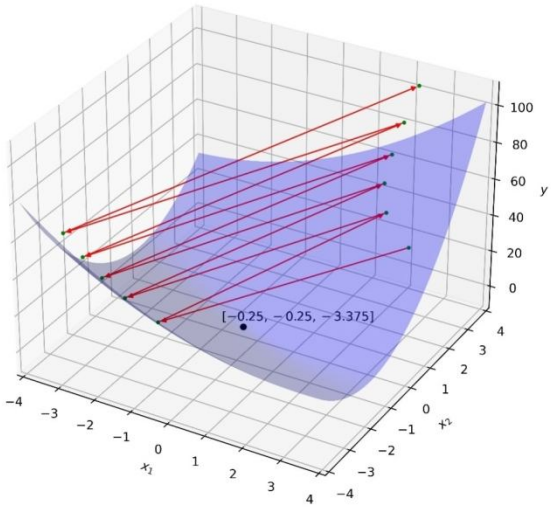


图 4-29　学习率过大时的情形

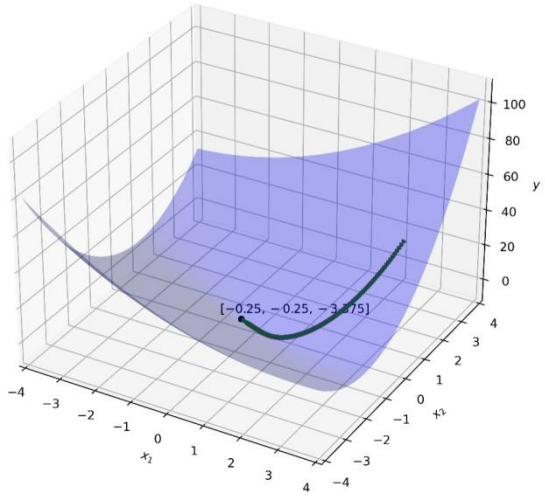


图 4-30　学习率过小时的情形

```
Console 1/A
Reloaded modules: common, common.common
起点时的梯度：  [11, 20]
在第219次迭代退出,此时梯度的模：
0.0009919175187914431
极小值：  [-0.24921779317965836,
-0.25032400067356625, -3.3749995800942543]

In [12]:
```

图 4-31　设置迭代出口时的运行结果

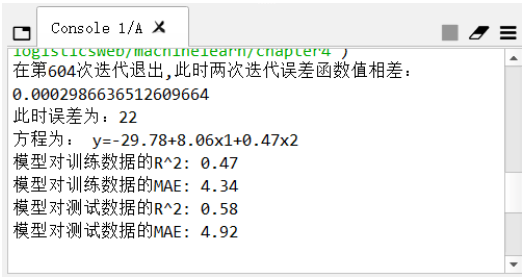


图 4-32　线性回归的梯度下降法程序运行的结果

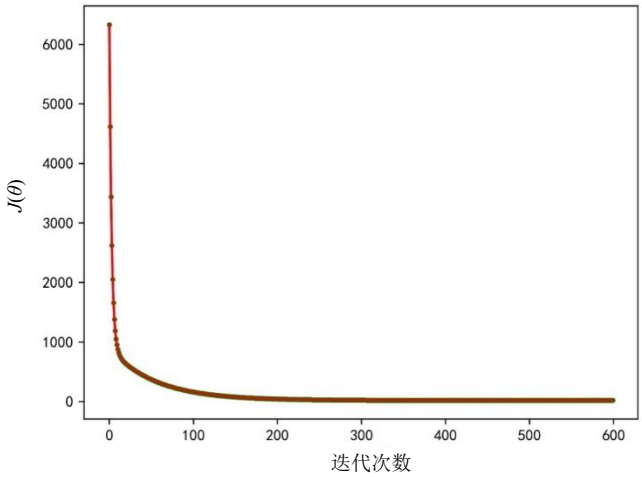


图 4-33　误差值变化的曲线

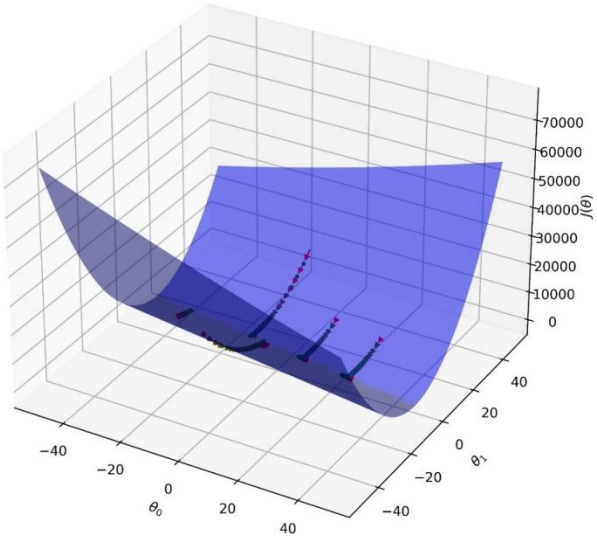


图 4-34　误差函数的图形

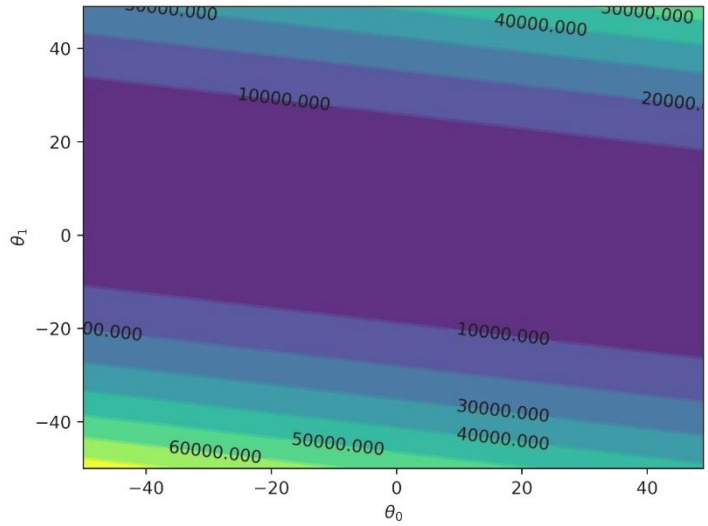


图 4-35　误差函数的等高线

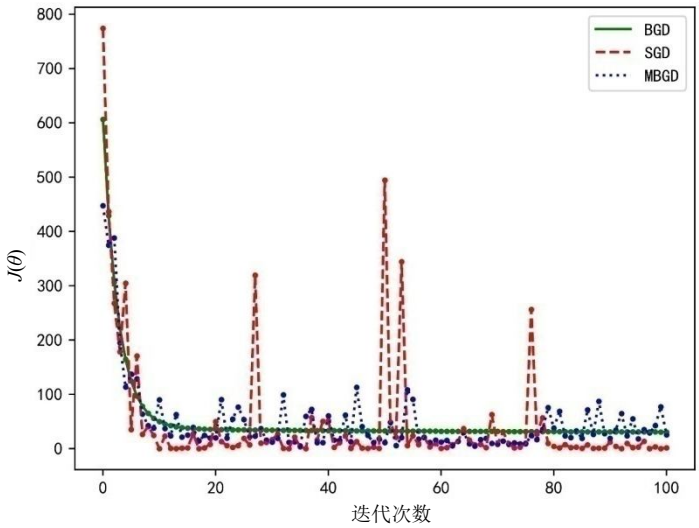


图 4-36　3 种梯度下降法误差下降过程的比较

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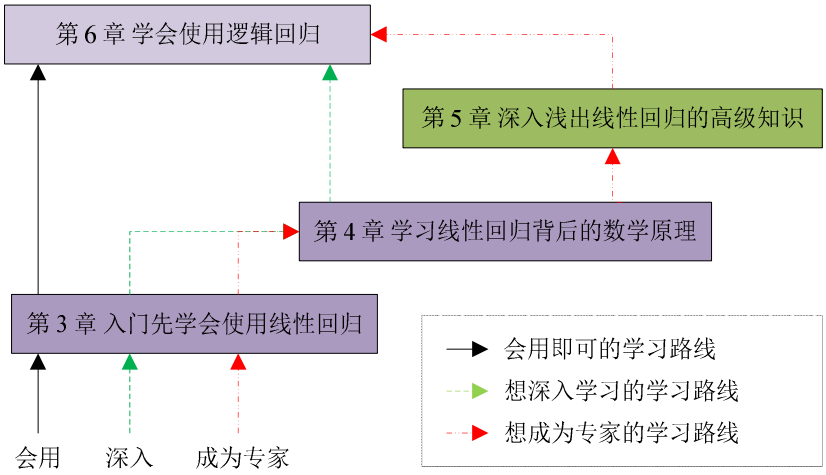
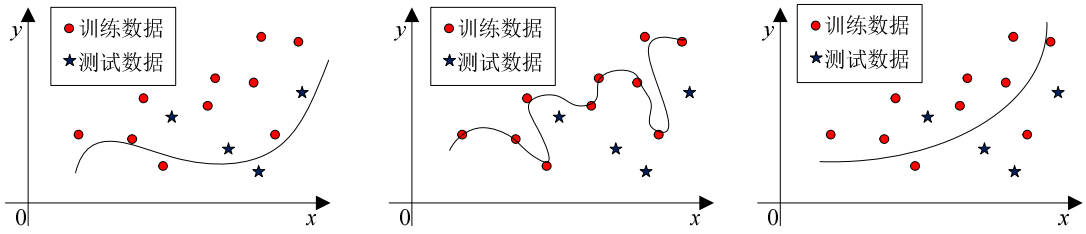


图 5-1　学习路线图



（a）欠拟合　　（b）过拟合　　（c）恰当拟合

图 5-2　对模型的 3 种定性评价

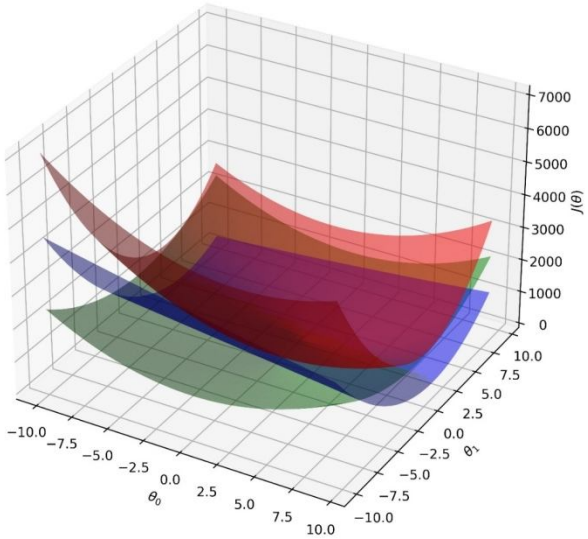
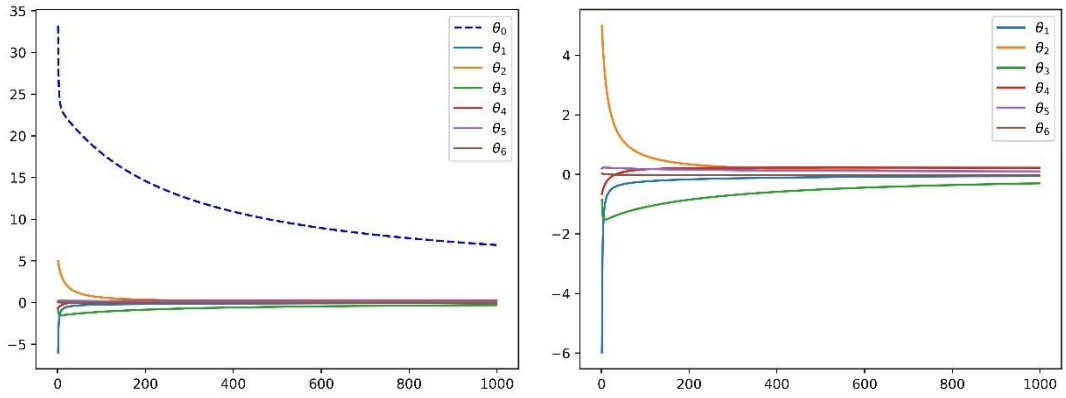


图 5-3　误差函数的图形



（a）带θ_0的岭迹图　　（b）不带θ_0的岭迹图

图 5-4　岭迹图

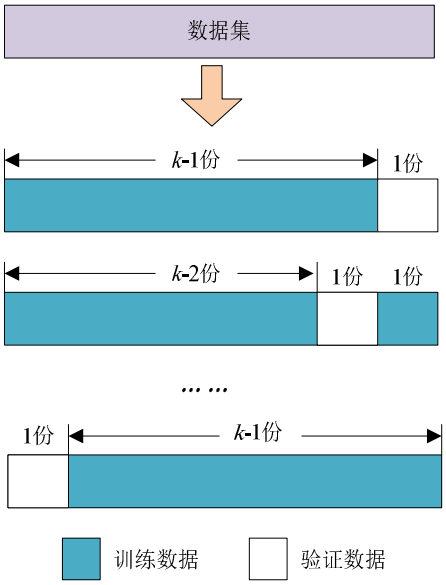


图 5-5　K-Fold 交叉验证法

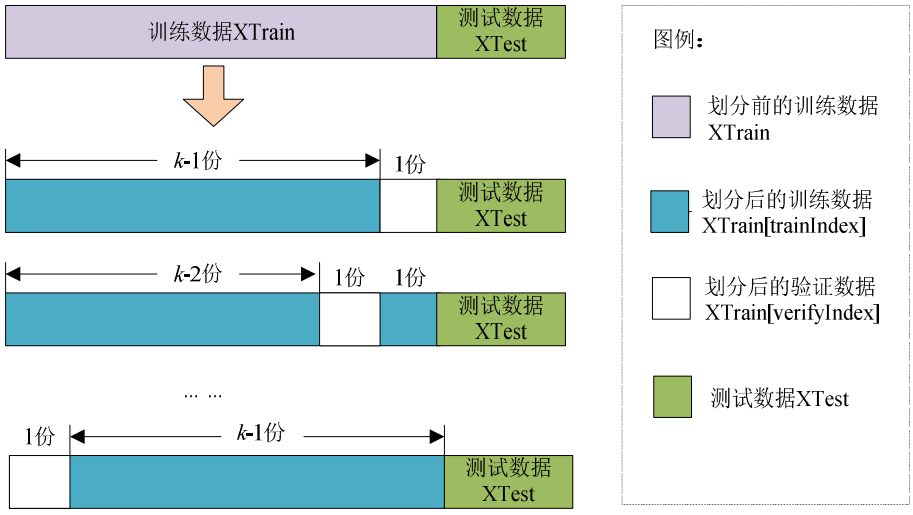


图 5-6　对训练数据使用 K-Fold 再做划分

```
Console 1/A
In [8]: runfile('E:/script/logisticsWeb/machinelearn/chapter5/
code5-2.py', wdir='E:/script/logisticsWeb/machinelearn/chapter5')
lambda: 0 。MAE: 4.372640307433445 ； R2: 0.40059917989644056
lambda: 1 。MAE: 4.375852660620379 ； R2: 0.4010367182805042
lambda: 2 。MAE: 4.379210867034098 ； R2: 0.4014369438586325
lambda: 3 。MAE: 4.3827459303625265 ； R2: 0.4018011238295614
lambda: 4 。MAE: 4.386252801397256 ； R2: 0.4021304804294747
lambda: 5 。MAE: 4.389722562421435 ； R2: 0.40242619271767255
lambda: 6 。MAE: 4.39324224519703 ； R2: 0.4026893982824086
lambda: 7 。MAE: 4.396929378779491 ； R2: 0.40292119487095535
lambda: 8 。MAE: 4.400675718075966 ； R2: 0.4031226419477038
lambda: 9 。MAE: 4.404475767324109 ； R2: 0.4032947621837045
根据综合评价指标判断，第5个lambda最优，lambda值为：5，综合评价值为：
0.57

In [9]:
```

图 5-7　运行源代码 5-2 后控制台的输出

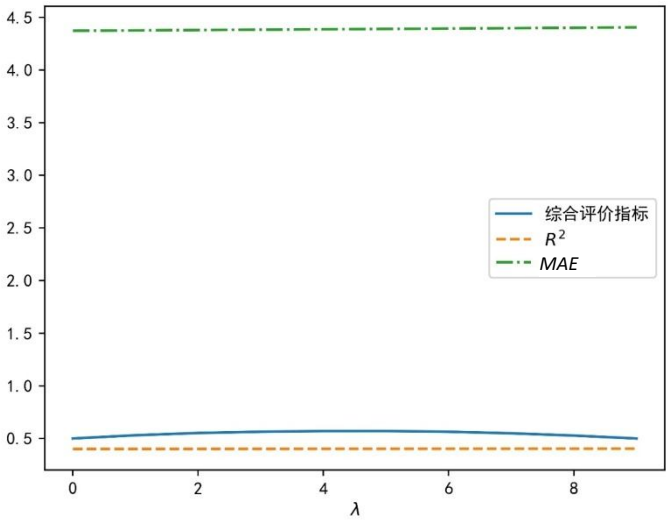


图 5-8　运行源代码 5-2 生成的图

```
Console 1/A
In [15]: runfile('E:/script/logisticsWeb/machinelearn/chapter5/
code5-3.py', wdir='E:/script/logisticsWeb/machinelearn/chapter5')
lambda: 0 。MAE: 6.135712059501724 ； R2: 0.04597718053265913
lambda: 1 。MAE: 5.986010731196492 ； R2: 0.10154666193714071
lambda: 2 。MAE: 5.26136543813031 ； R2: 0.22073251777952815
lambda: 3 。MAE: 6.000253420052512 ； R2: 0.0615676651687751
lambda: 4 。MAE: 6.000938796183889 ； R2: 0.08233079816862614
lambda: 5 。MAE: 5.533129758484052 ； R2: 0.1979647677017585
lambda: 6 。MAE: 5.801295264723441 ； R2: 0.14190780899920374
lambda: 7 。MAE: 5.085446104902408 ； R2: 0.29477994125635265
lambda: 8 。MAE: 6.101904005254979 ； R2: 0.002342576959671339
lambda: 9 。MAE: 5.89750275410145 ； R2: 0.10041807141975134
根据综合评价指标判断，第7个lambda最优，lambda值为：7，综合评价值为：
1.0

In [16]:
```

图 5-9　运行源代码 5-3 后控制台的输出

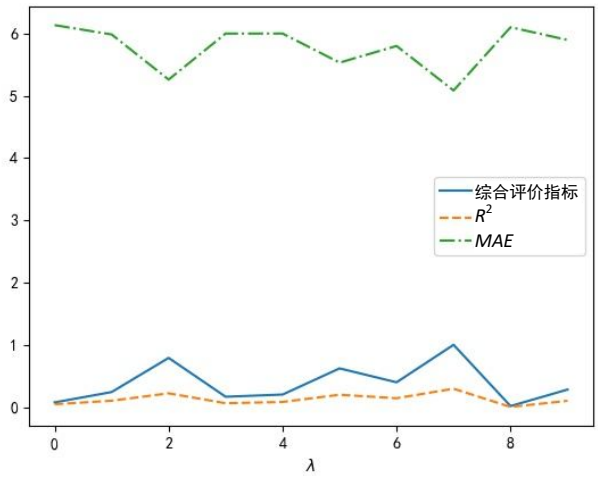


图 5-10　运行源代码 5-3 生成的图

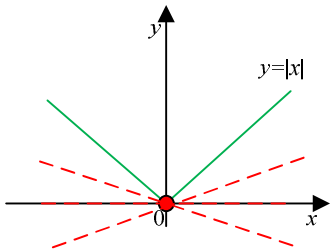
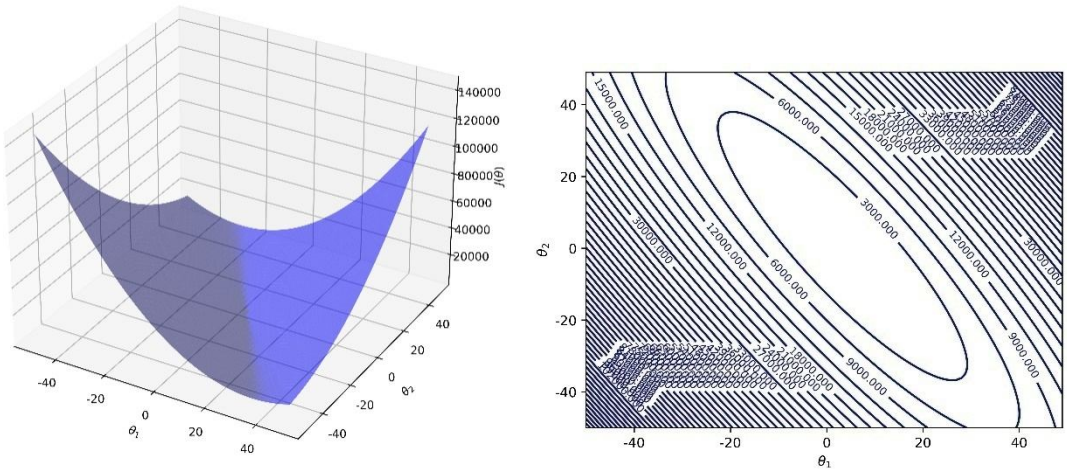
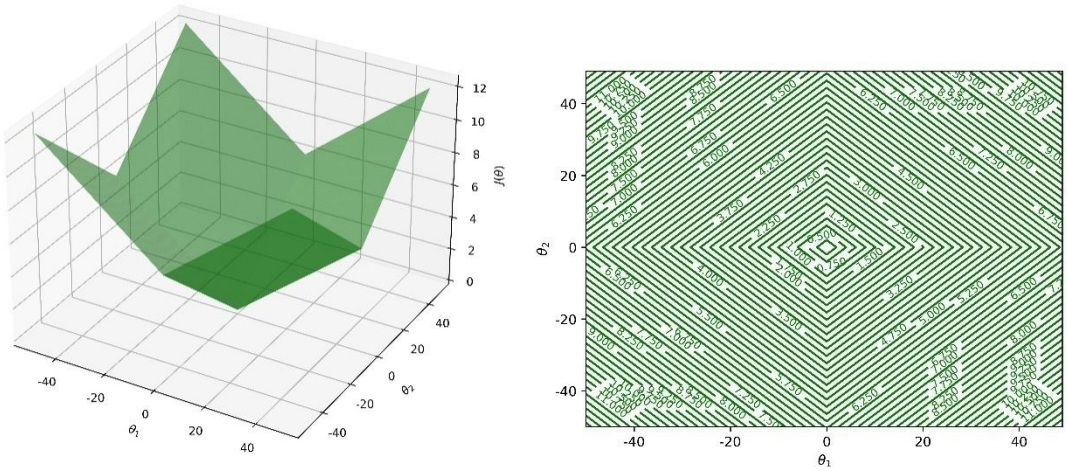


图 5-11　$y = |x|$的图形



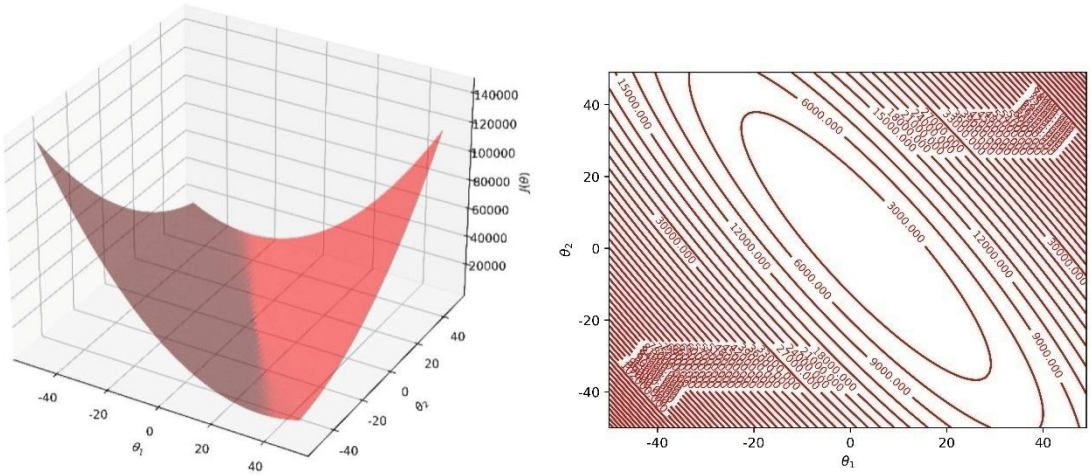
（a）3D 图　　（b）等高线图

图 5-12　Lasso 回归误差函数前半部分的图形



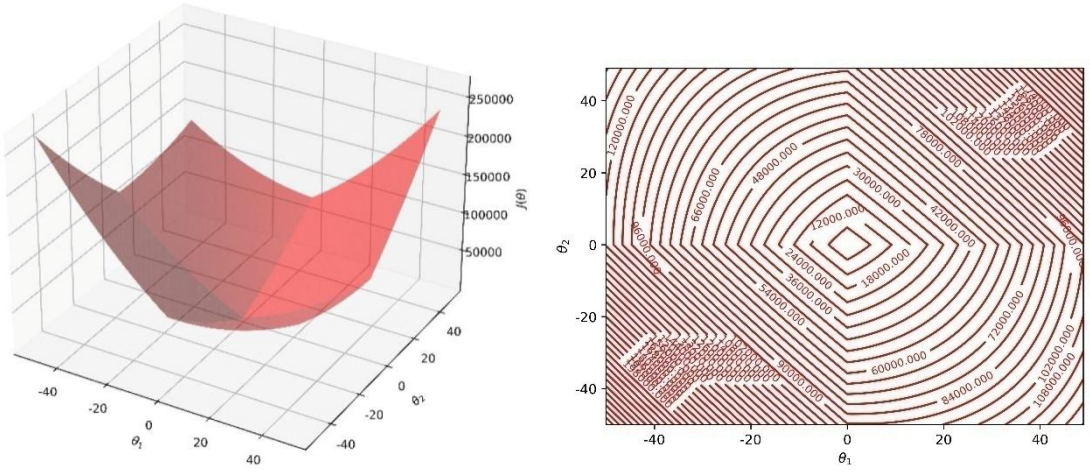
（a）3D 图　　（b）等高线图

图 5-13　Lasso 回归误差函数后半部分的图形（$\lambda = 100$）



（a）3D 图　　（b）等高线图

图 5-14　Lasso 回归误差函数的图形（$\lambda = 100$）



（a）3D 图　　（b）等高线图

图 5-15　Lasso 回归误差函数的图形（$\lambda = 1000000$）

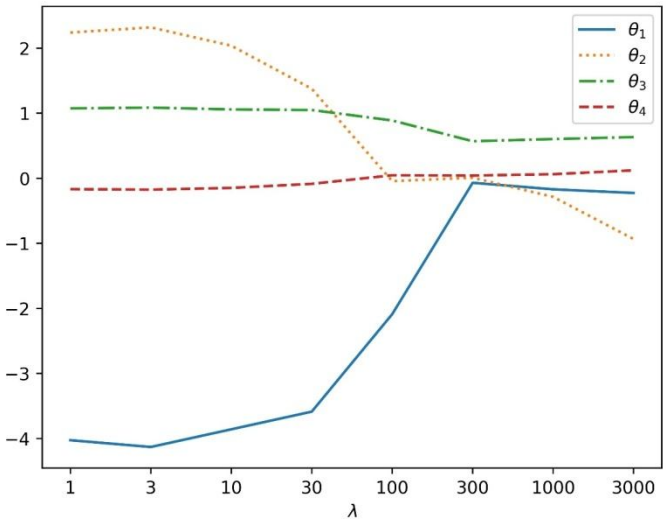


图 5-16　用坐标轴下降法做 Lasso 回归找到合适的λ值

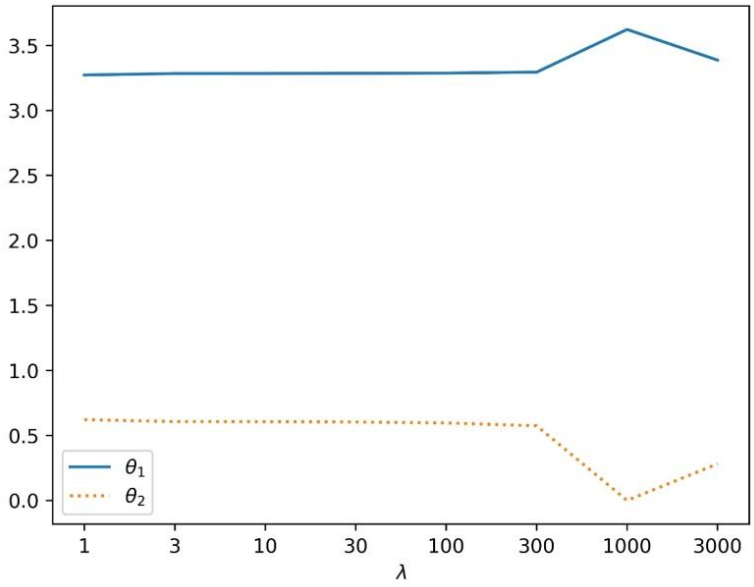


图 5-17　源代码 5-5 的运行结果

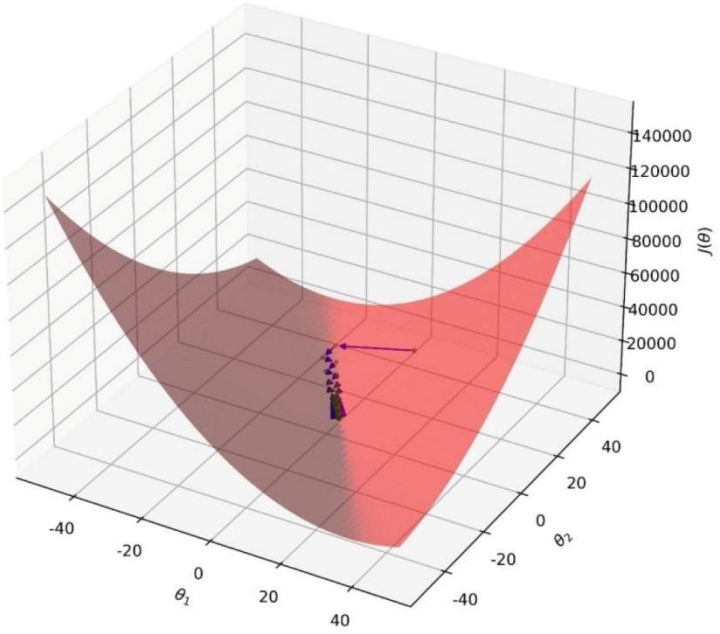


图 5-18　绘制带惩罚项的误差函数的图形及迭代的过程

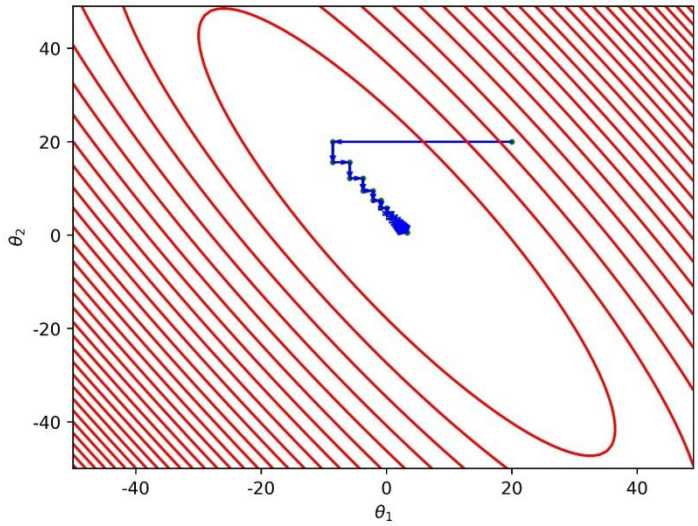


图 5-19　用等高线绘制带惩罚项的误差函数的图形及迭代的过程

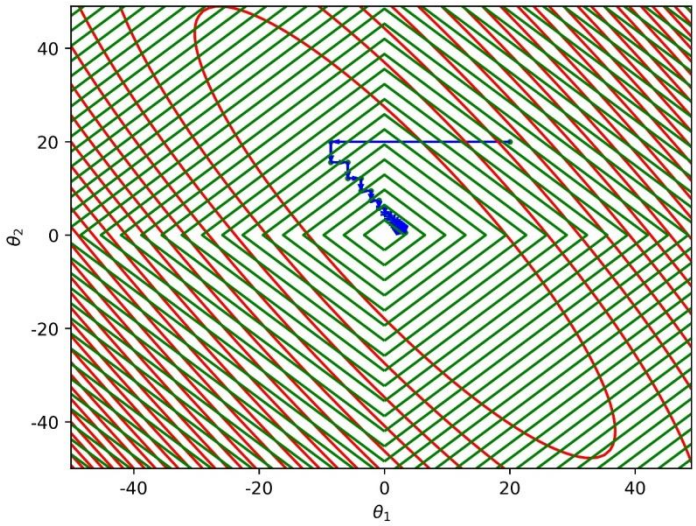


图 5-20　源代码 5-8 的运行结果

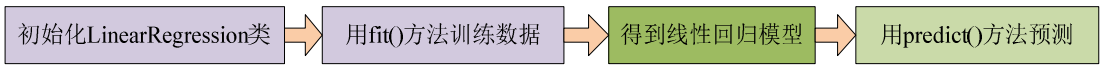


图 5-21　使用 LinearRegression 类的流程

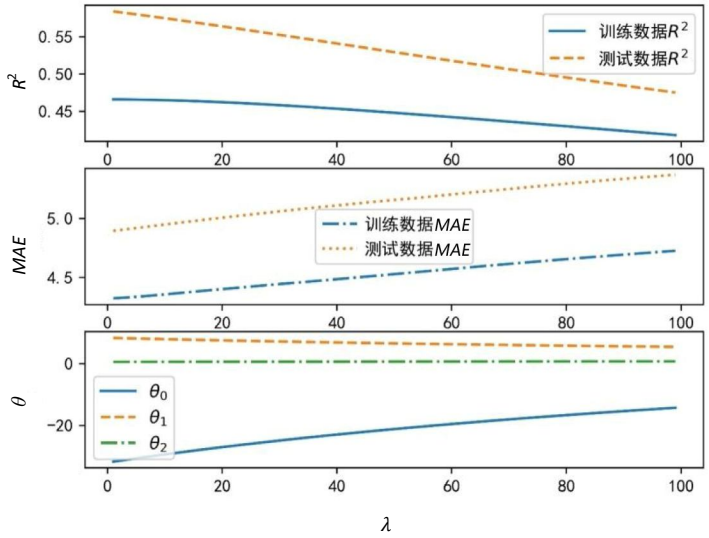


图 5-22　使用 Ridge 类看变换λ值后 ***MAE***、$\boldsymbol{R^2}$ 的变化情况

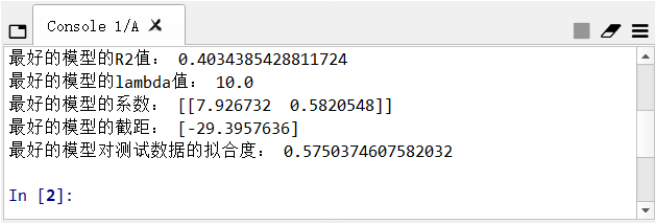


图 5-23　使用 RidgeCV 类寻找具有最好的拟合度的线性模型

```
Console 1/A
最好的模型的R2值： 0.4037645998814273
最好的模型的lambda值： 15
最好的模型的系数： [[7.72565556 0.5956479 ]]
最好的模型的截距： [-28.18726595]
最好的模型对测试数据的拟合度： 0.5696566167566552

In [3]:
```

图 5-24　寻找更好的λ值

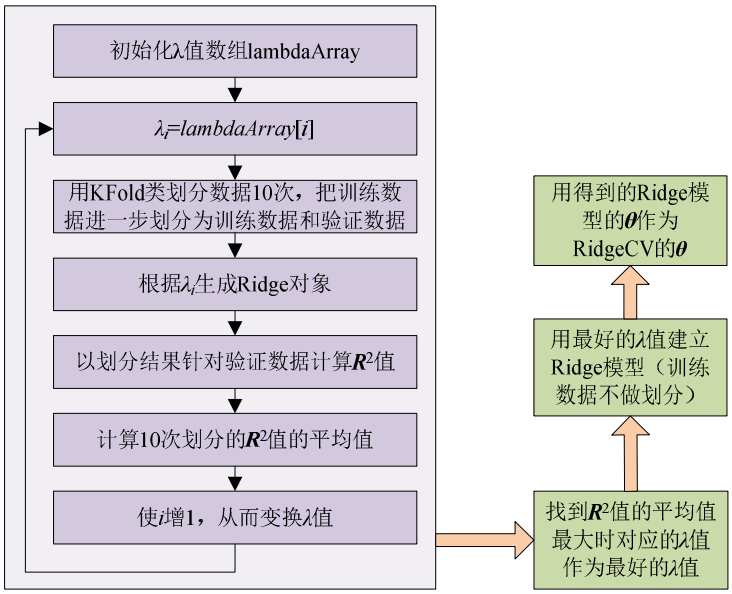


图 5-25　RidgeCV 构建最好的模型的过程

```
Console 1/A
最好的模型的R2值： 0.5596211916137239
最好的模型的lambda值： 0.01
最好的模型的系数： [-28.38150369   2.8497701    2.85426679
-0.2112797 ]
最好的模型的截距： 80.05875613092094
最好的模型对测试数据的拟合度： 0.6860025943775283

In [12]:
```

图 5-26　使用 LassoCV 类寻找具有最好的拟合度的线性模型

```
Console 1/A
======RidgeCV======
最好的模型的R2值： 0.4651415699201855
最好的模型的lambda值： 10.0
最好的模型的系数： [7.926732  0.5820548]
最好的模型的截距： -29.395763595061116
最好的模型对测试数据的拟合度： 0.5750374607582032
======LassoCV======
最好的模型的R2值： 0.46619175946061486
最好的模型的lambda值： 0.01
最好的模型的系数： [8.34177186 0.55143399]
最好的模型的截距： -31.880403588849905
最好的模型对测试数据的拟合度： 0.584712014498803
======ElasticNetCV======
最好的模型的R2值： 0.46609452248491035
最好的模型的l1_ratio值： 0.3
最好的模型的lambda值： 0.01
最好的模型的系数： [8.22826739 0.56076188]
最好的模型的截距： -31.20455718169214
最好的模型对测试数据的拟合度： 0.582249445910006

In [14]:
```

图 5-27　对比 RidgeCV、LassoCV、ElasticNetCV

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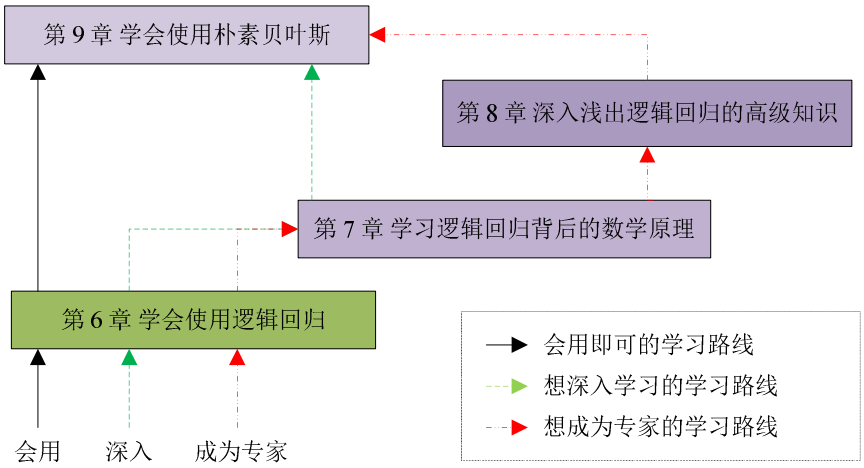

图 6-1　学习路线图

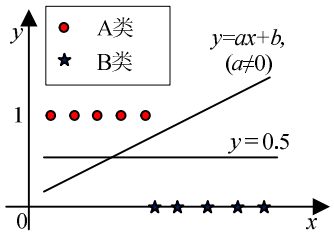

图 6-2　用线性模型来做二分法分类

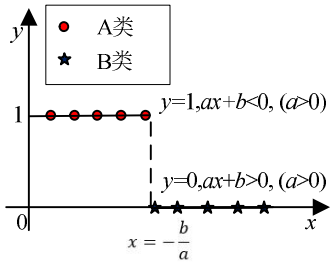

图 6-3　真正的分类函数的图示

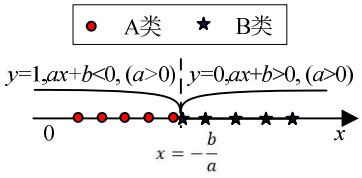

图 6-4　用一维来表示二分法分类

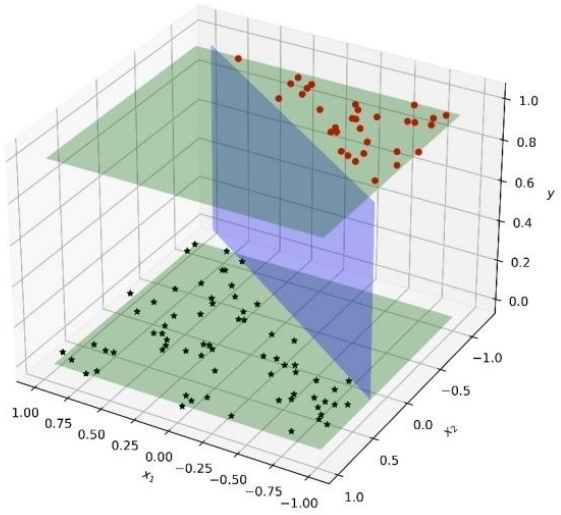

图 6-5　用三维空间表示分类函数

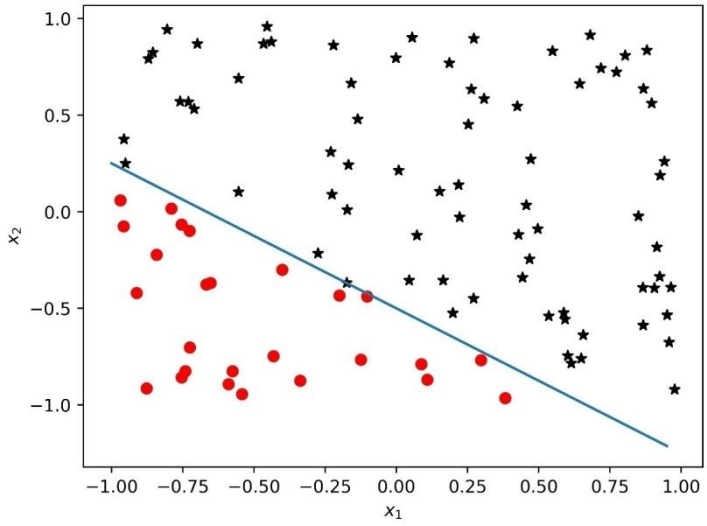

图 6-6　用二维空间表示分类函数

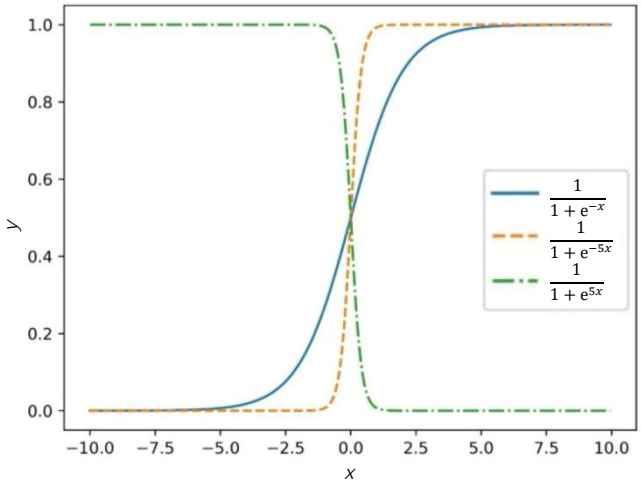

图 6-7　sigmoid 函数的图形

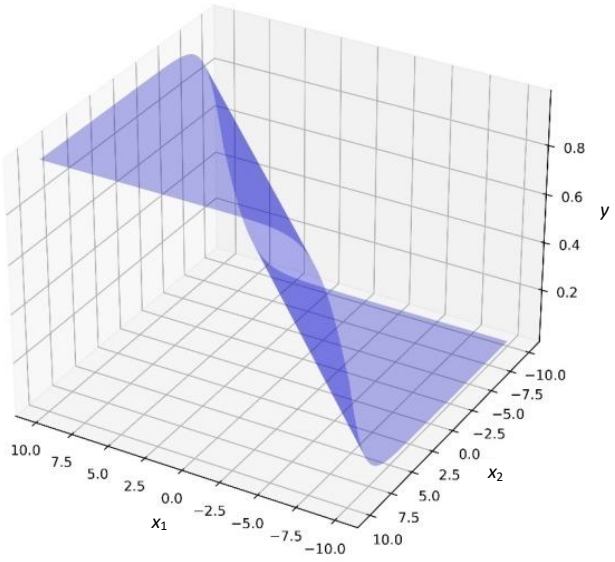

图 6-8　2 个自变量时的 sigmoid 函数的图形

```
Console 1/A
准确度： 0.9736842105263158
[[40  2]
 [ 1 71]]
              precision    recall  f1-score   support

          良性       0.98      0.95      0.96        42
          恶性       0.97      0.99      0.98        72

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114


In [26]:
```

图 6-9　用逻辑回归预测乳腺癌

```
Console 1/A
[1.24721913 1.63299316]

In [18]:
```

图 6-10　计算标准差

```
Console 1/A
[[ 0.26726124  0.        ]
 [ 1.06904497  1.22474487]
 [-1.33630621 -1.22474487]]

In [23]:
```

图 6-11　用 StandardScaler 类做标准化处理

```
Console 1/A
theta0: [0.22461276]
theta1~thetan: [[-0.42701394 -0.42526709 -0.41119274 -0.45572422
-0.19402935  0.31646816
  -0.78355203 -0.84208752  0.20837135  0.26411749 -1.11563016
0.08947472
  -0.64563517 -0.80305032 -0.19500456  0.89410936 -0.10036798
-0.45665969
   0.13148279  0.73144875 -1.08713277 -1.03171527 -0.94236607
-1.01526709
  -0.58196914  0.01760019 -0.90013199 -0.86259395 -0.78461151
-0.49674128]]

In [27]:
```

图 6-12　得到逻辑回归模型的参数

```
Console 1/A
[3.53596720e-03 9.96464033e-01]
[6.14468817e-06 9.99993855e-01]
[9.99997980e-01 2.01965088e-06]
[9.48142781e-01 5.18572189e-02]
[1.62551408e-05 9.99983745e-01]
[1.12361644e-01 8.87638356e-01]
[4.62090846e-04 9.99537909e-01]
[1.04170178e-03 9.98958298e-01]
[1.59571175e-02 9.84042883e-01]
[4.93634994e-04 9.99506365e-01]
[2.96028081e-05 9.99970397e-01]
[1.25402326e-01 8.74597674e-01]
[1.32728939e-02 9.86727106e-01]
[4.95932702e-03 9.95040673e-01]
[1.41560186e-05 9.99985844e-01]
[3.25315515e-04 9.99674684e-01]
[9.98227358e-01 1.77264212e-03]
[9.95467477e-01 4.53252303e-03]
[9.99668914e-01 3.31086308e-04]
[5.10052487e-01 4.89947513e-01]
[1.23813945e-01 8.76186055e-01]
[1.97578848e-04 9.99802421e-01]]

In [44]:
```

图 6-13　得到分类的可能性值

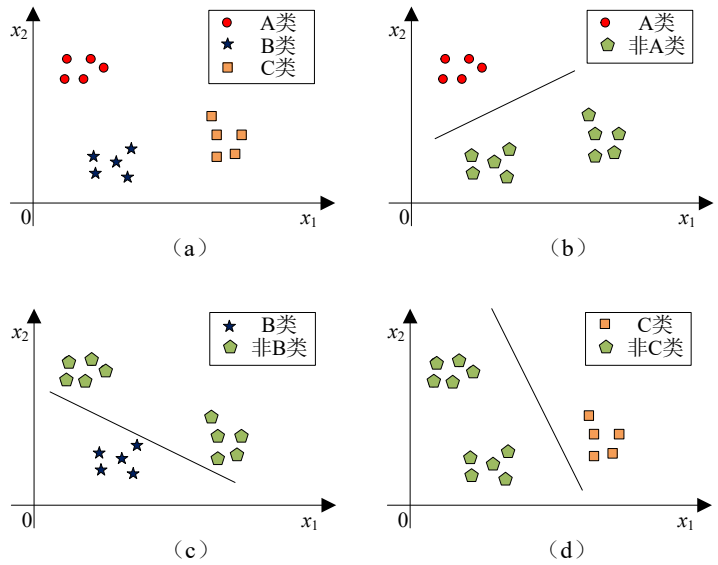

图 6-14　用 One-Vs-All 解决多分类问题

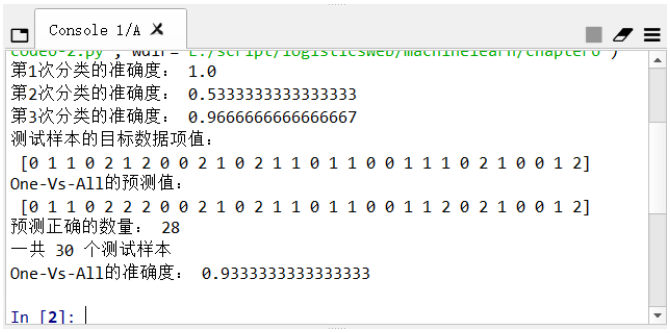

图 6-15　用 One-Vs-All 做鸢尾花分类

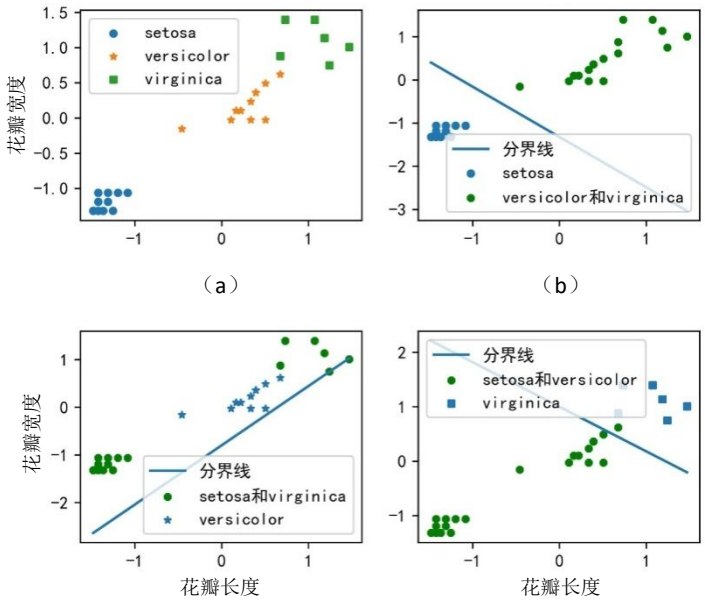

图 6-16　用 One-Vs-All 做鸢尾花分类的效果图

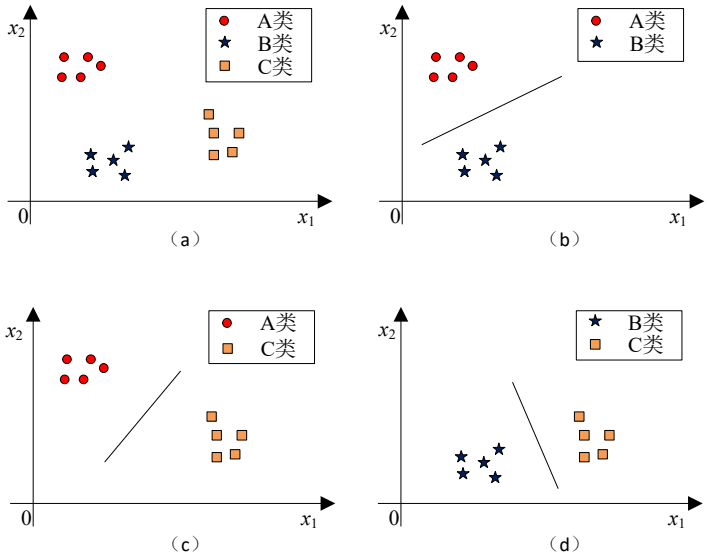

图 6-17　用 One-Vs-One 解决多分类问题

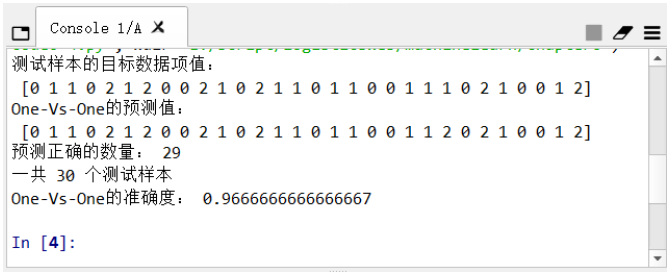

图 6-18　用 One-Vs-One 做鸢尾花分类

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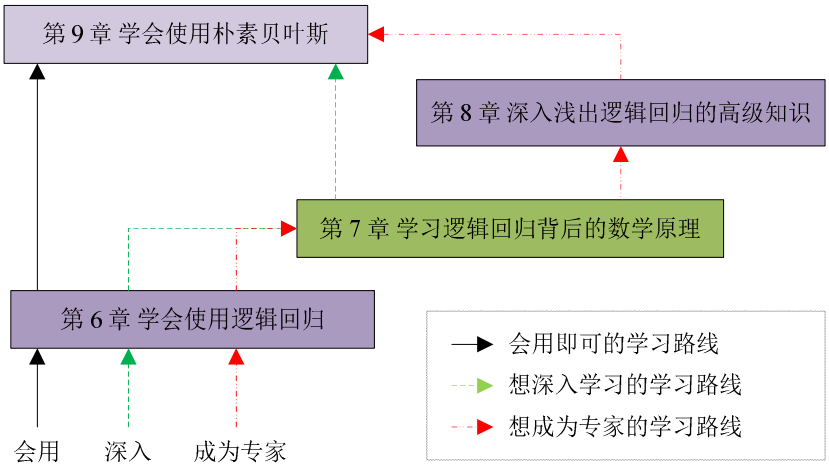
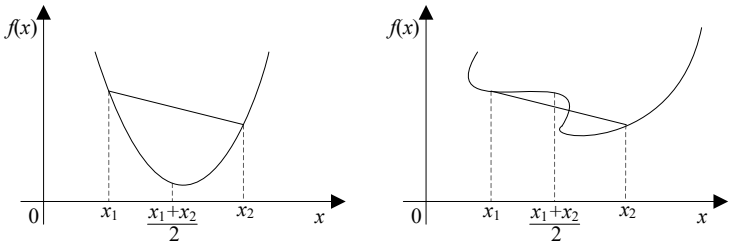


图 7-1　学习路线图



（a）　　（b）

图 7-2　凸函数和非凸函数

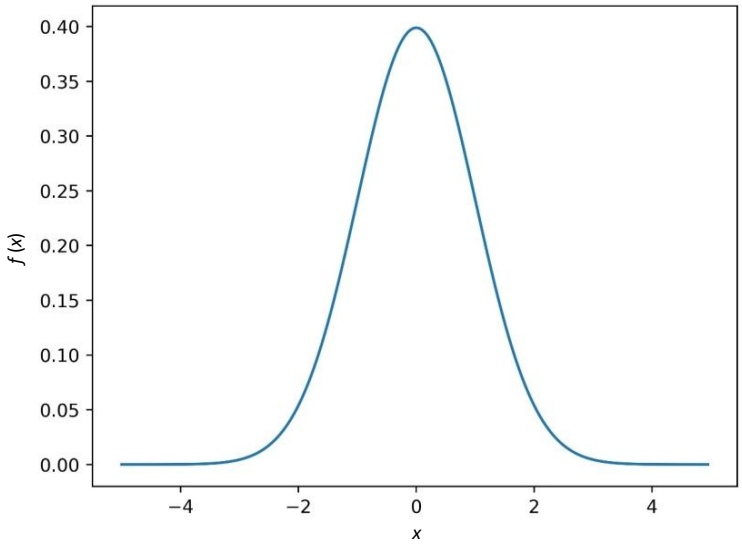


图 7-3　标准正态分布的图形

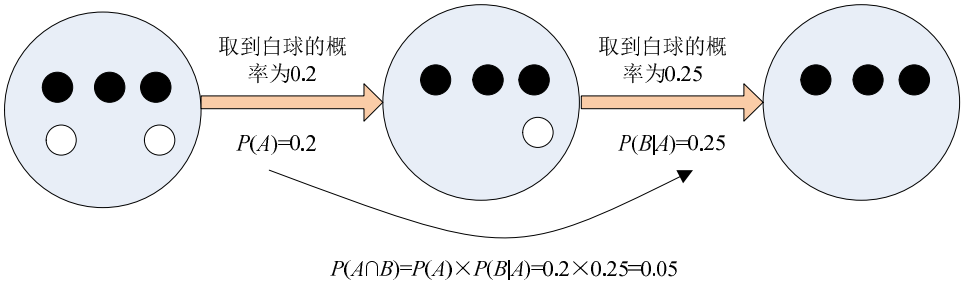


图 7-4　理解条件概率

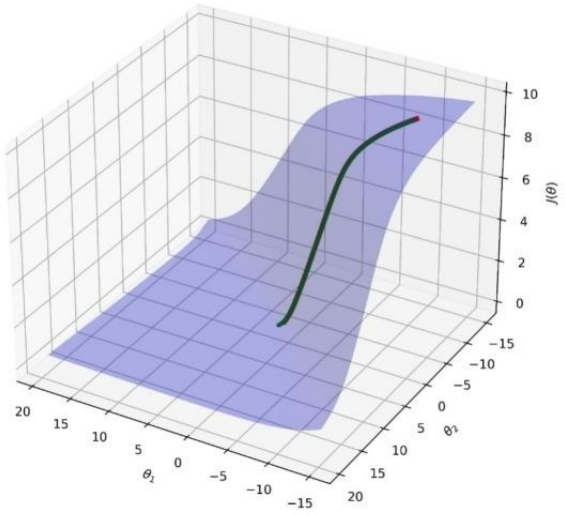


图 7-5　误差函数及梯度下降的过程

```
Console 1/A
第 517 次迭代,误差值为 0.29779521156906513 ，两次迭代差为
0.001038289476240073
第 518 次迭代,误差值为 0.2967713384721463 ，两次迭代差为
0.0010238730969188148
第 519 次迭代,误差值为 0.2957615883967735 ，两次迭代差为
0.001009750075372795
第 520 次迭代,误差值为 0.2947656756590386 ，两次迭代差为
0.0009959127377349164
参数值： [[0.92939968 0.61073482]]
真实值： [0 1 1 0 1 1 1 0 0 1 1 0 1 1 1 0 1 1 0 0 1 1 1 0 1 1 0 0 1
1]
预测值： [0 0 1 0 1 1 1 0 0 1 1 0 1 1 1 0 1 1 0 0 1 1 1 0 1 1 0 0 1
1]
              precision    recall  f1-score   support

      setosa       0.92      1.00      0.96        11
    非setosa       1.00      0.95      0.97        19

    accuracy                           0.97        30
   macro avg       0.96      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30


In [9]:
```

图 7-6　做鸢尾花分类的控制台输出

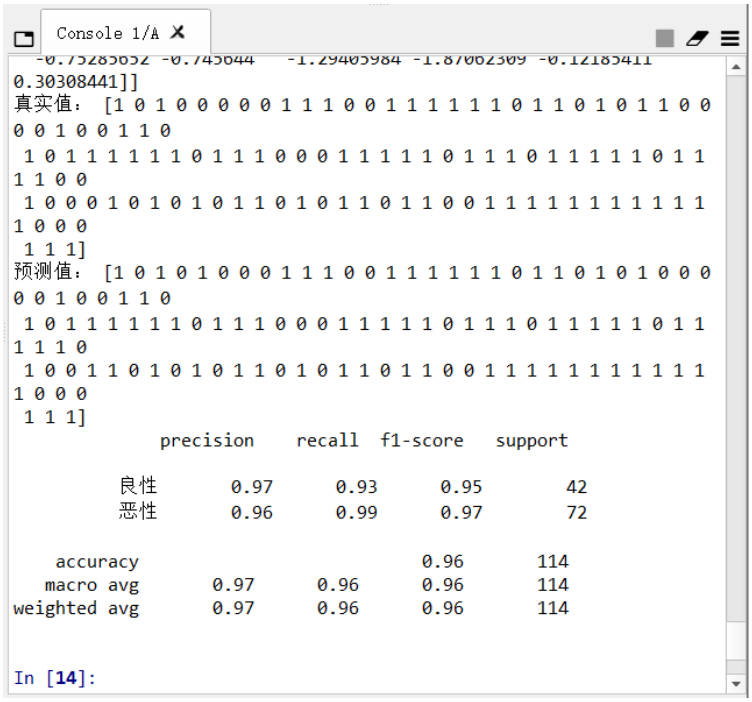


图 7-7　预测乳腺癌的控制台输出

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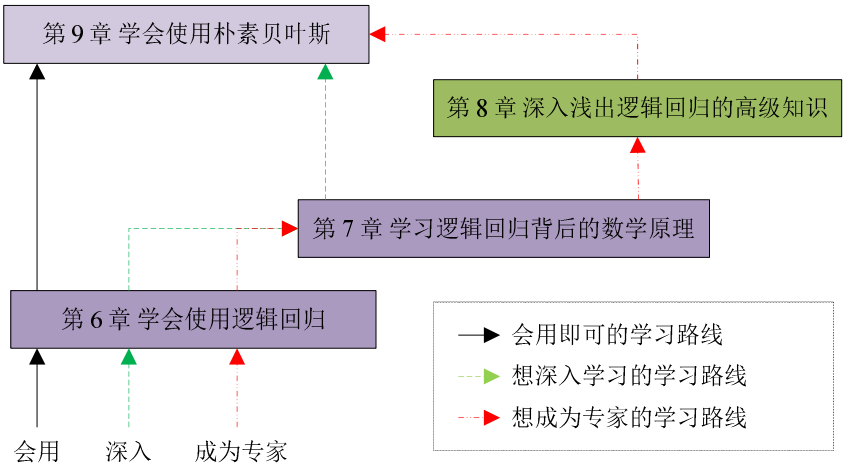

图 8-1　学习路线图

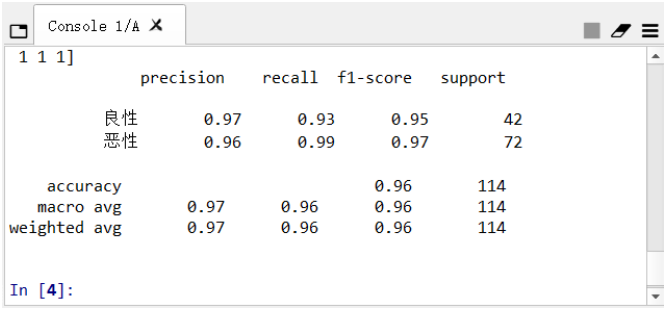

图 8-2　用逻辑回归的 L2 正则化预测乳腺癌

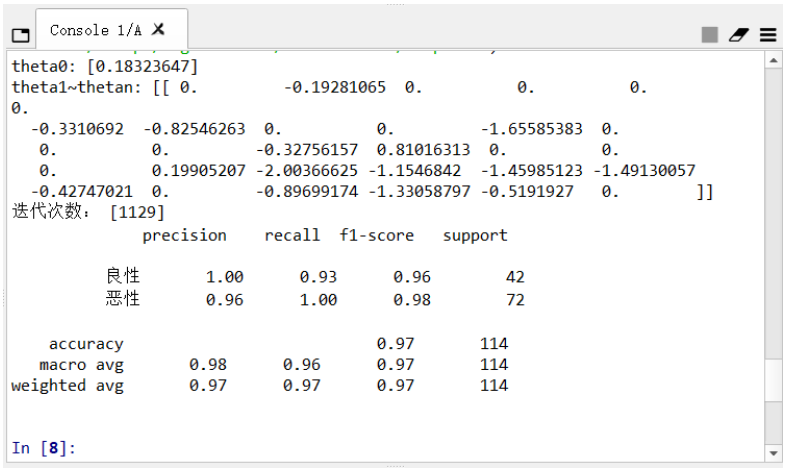

图 8-3　用逻辑回归的 L1 正则化来预测乳腺癌

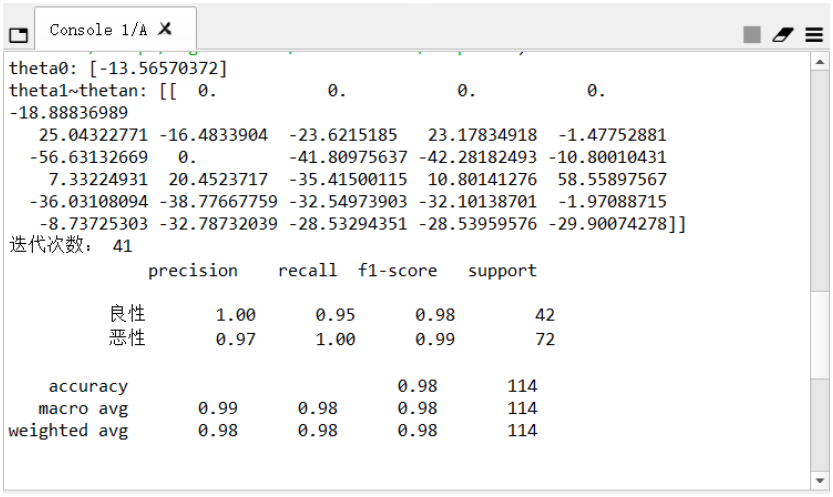

图 8-4　用 SGDClassifier 类的 L1 正则化来预测乳腺癌

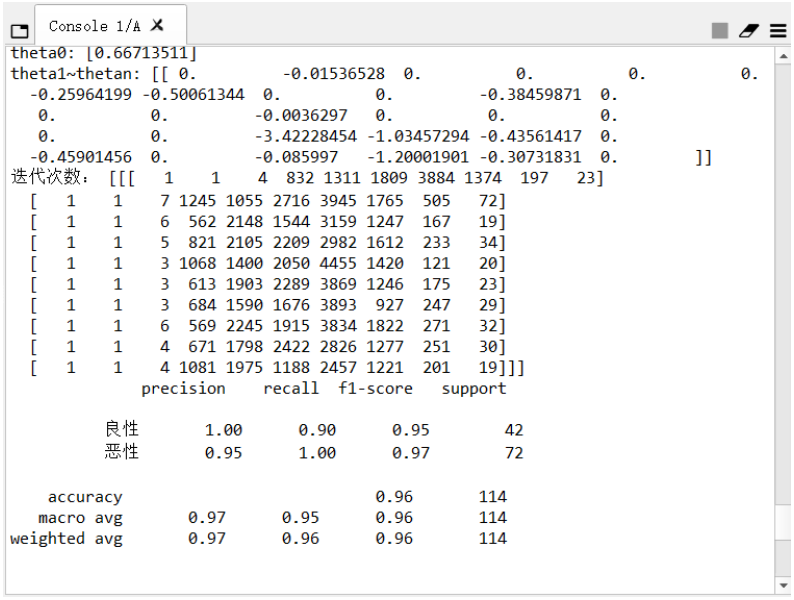

图 8-5　用 LogisticRegressionCV 类的 L1 正则化来预测乳腺癌

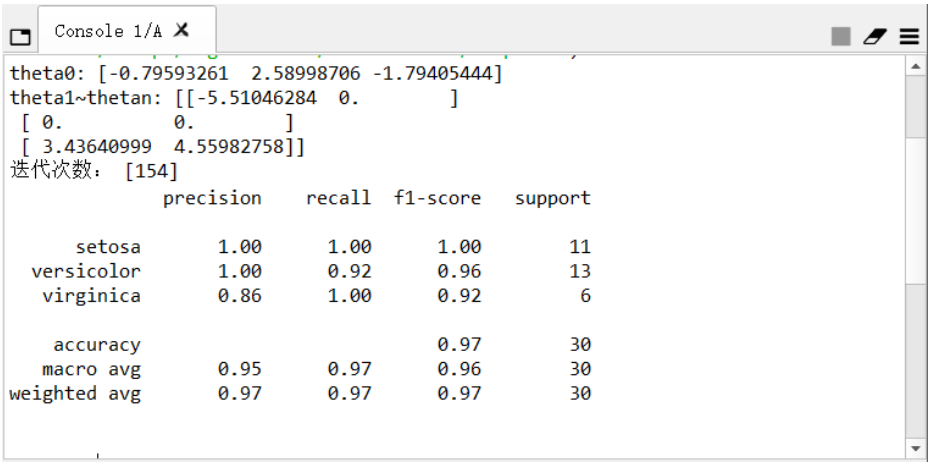

图 8-6　用 LogisticRegression 类对鸢尾花做三分类

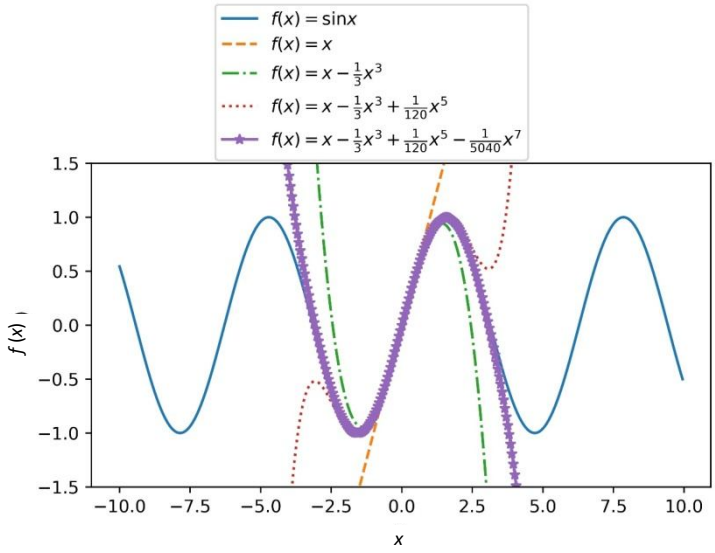

图 8-7　$f(x)=\sin x$的近似表达

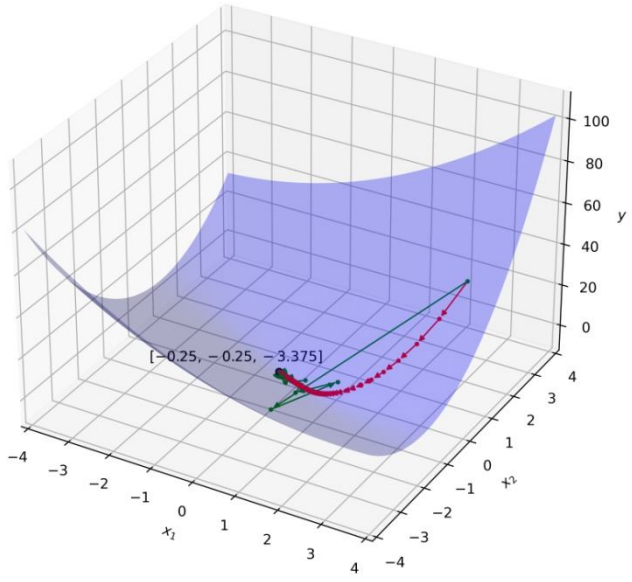

图 8-8　对比普通的梯度下降法和回溯法的下降过程

图 8-9　对比普通的梯度下降法和回溯法的结果

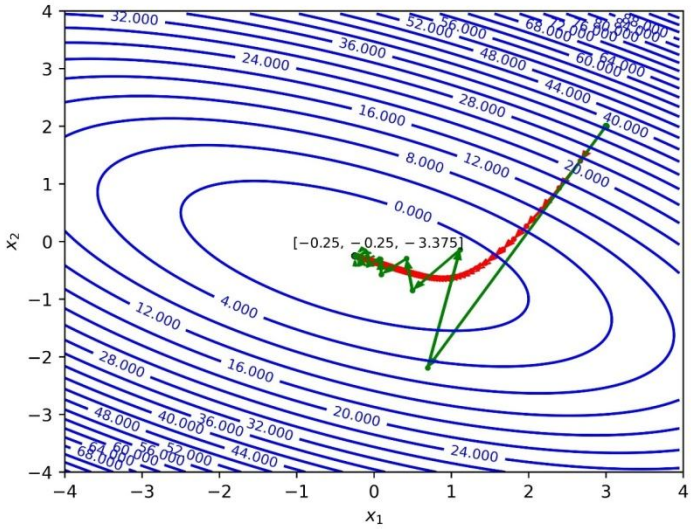

图 8-10　图 8-8 对应的二维图

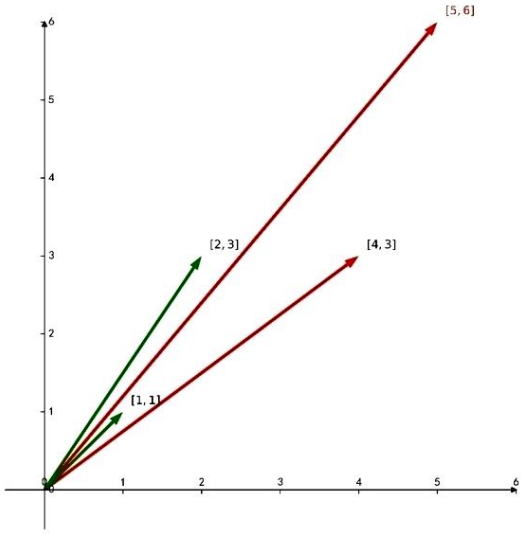

图 8-11　向量的图示

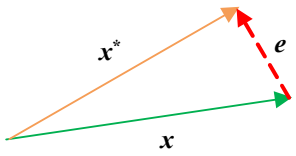

图 8-12　解与中间向量的误差

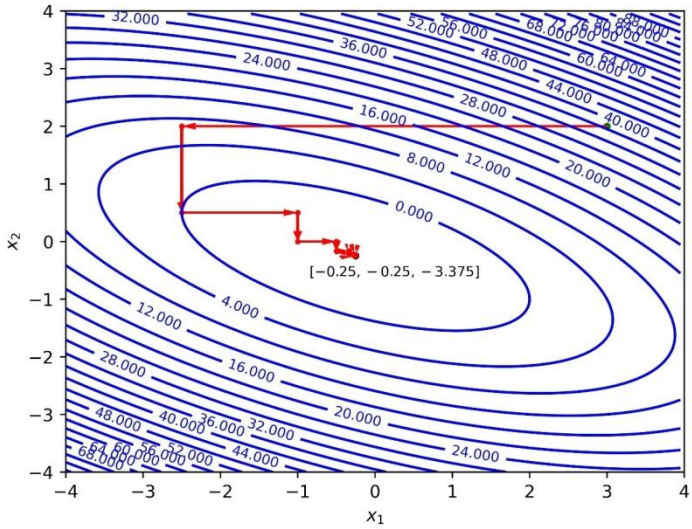

图 8-13　使用坐标下降法来求极小值

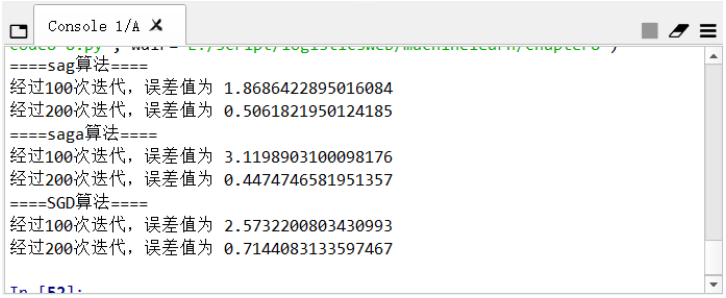

图 8-14　200 次迭代后控制台的输出

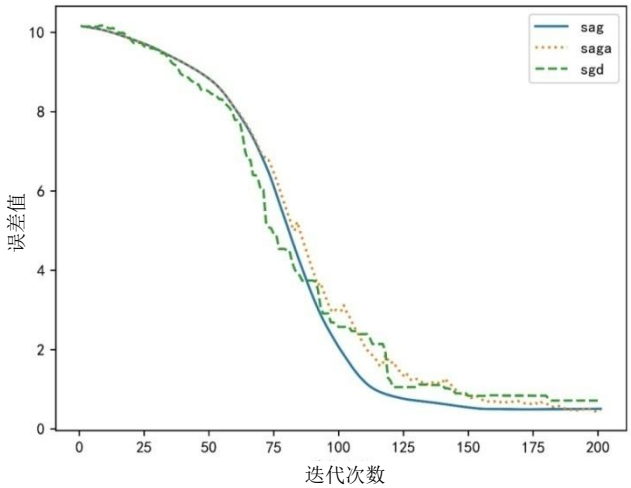

图 8-15　3 种算法的误差值变化曲线

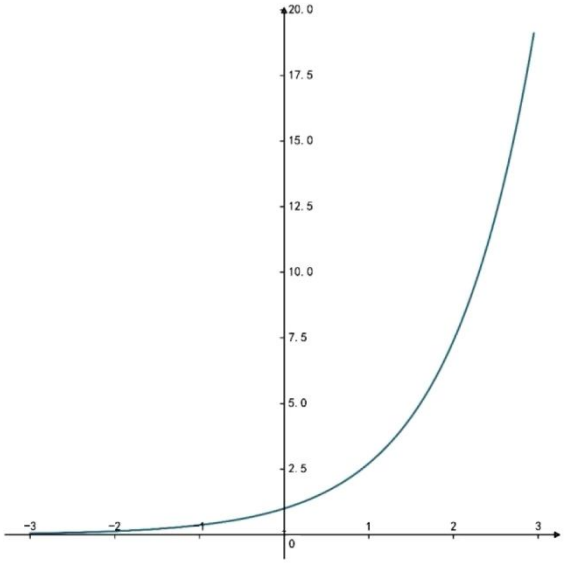

图 8-16　指数函数的图形

图 8-17　softmax 的计算效果

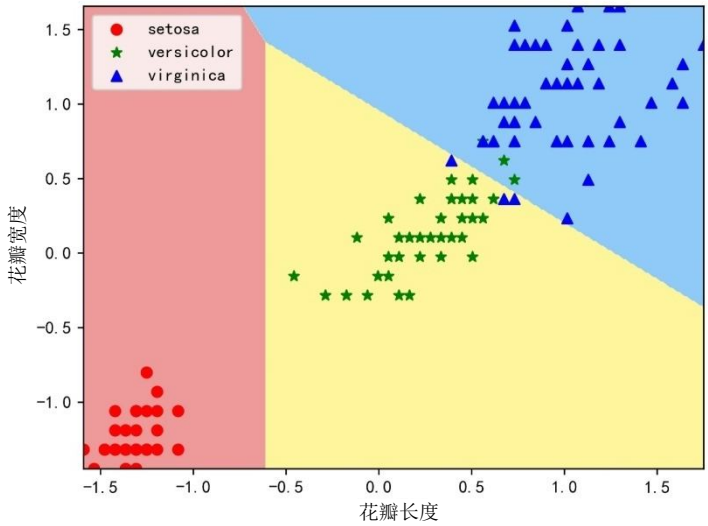

图 8-18　对鸢尾花做三分类的结果图示

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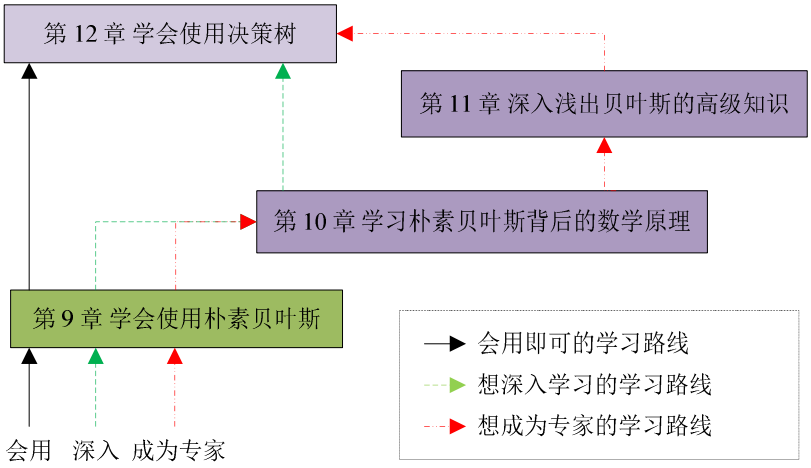

图 9-1　学习路线图

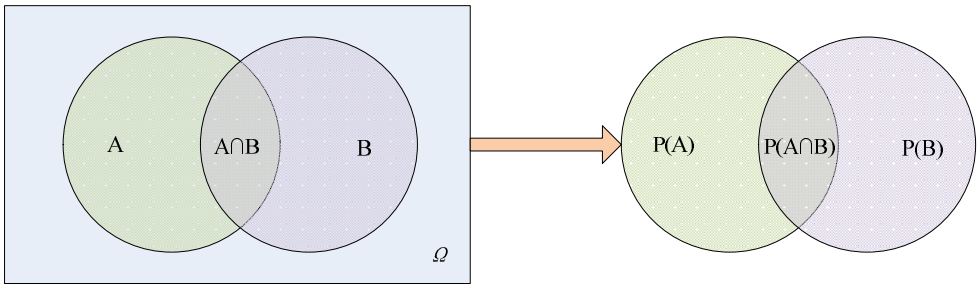

图 9-2　联合概率和条件概率

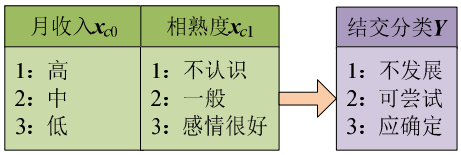

图 9-3　相亲的应用场景描述

```
Console 1/A
[3.08426338e-149 1.30779471e-001 8.69220529e-001]
[1.00000000e+000 1.83267245e-015 2.64881038e-022]
[1.24123122e-224 8.04117153e-005 9.99919588e-001]
[4.76778248e-082 9.99080297e-001 9.19702900e-004]
[1.00000000e+000 2.63115919e-016 6.04633949e-023]
[1.00000000e+000 1.53373081e-014 2.39137210e-021]
[5.86218548e-108 9.93960093e-001 6.03990658e-003]
[7.34237102e-162 6.95294528e-003 9.93047055e-001]]
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        11
  versicolor       1.00      0.92      0.96        13
   virginica       0.86      1.00      0.92         6

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30
```

图 9-4　使用 GuassianNB 类对鸢尾花做三分类

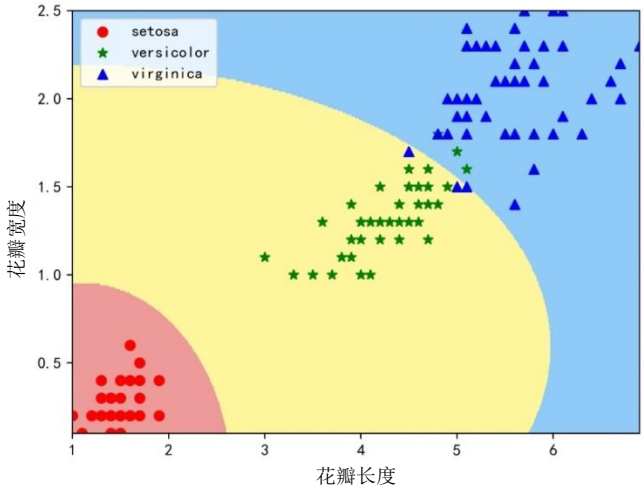

图 9-5　GuassianNB 类对鸢尾花做三分类的效果图

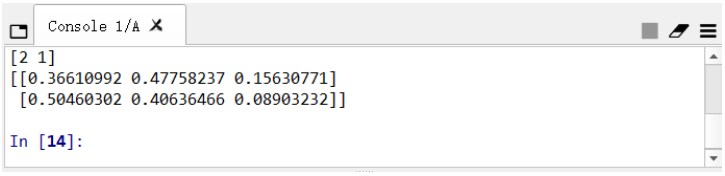

图 9-6　使用 MultinomialNB 类辅助某姑娘做相亲后的决策

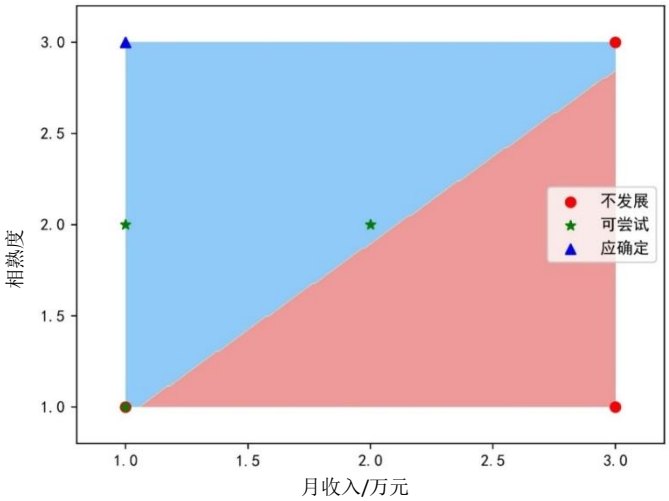

图 9-7　MultinomialNB 类辅助某姑娘做相亲后的决策效果图

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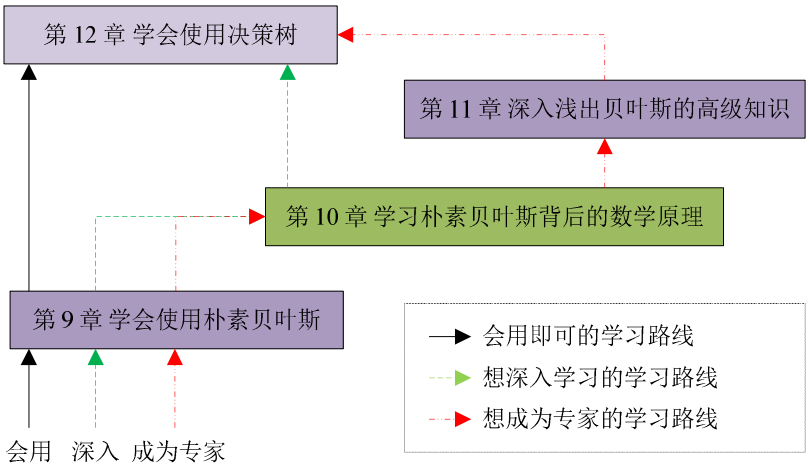

图 10-1　学习路线图

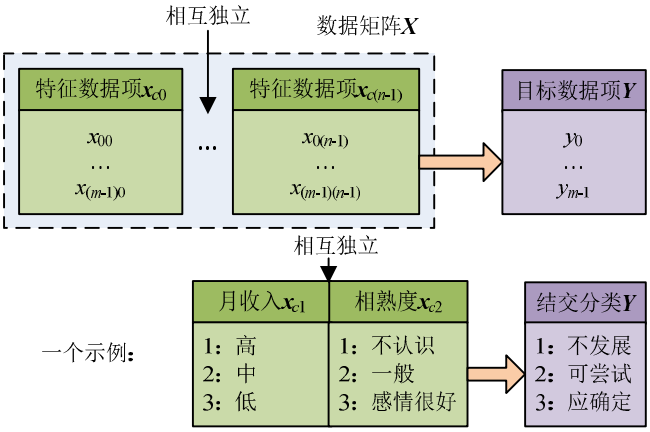

图 10-2　机器学习的应用场景

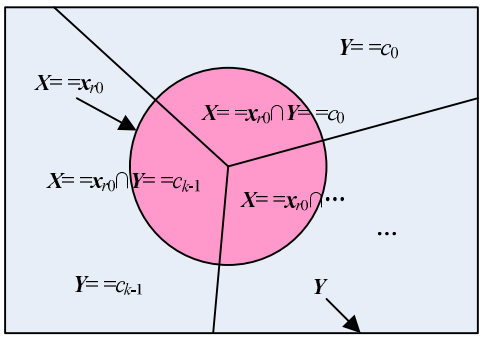

图 10-3　全概率公式的图示

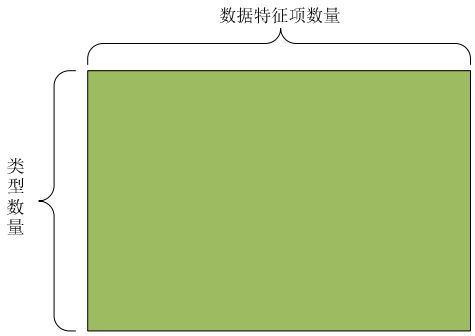

图 10-4　GuassianNB.theta_和 GuassianNB.sigma_的形状

```
Console 1/A
各个类别的先验概率： [0.325      0.30833333 0.36666667]
各个类别的训练样本数： [39. 37. 44.]
特征数据项在各个类别的平均值：
 [[1.46666667 0.23333333]
 [4.22972973 1.30540541]
 [5.53409091 2.02045455]]
特征数据项在各个类别的标准差：
 [[0.02529915 0.01094017]
 [0.21344047 0.03943024]
 [0.30315599 0.0788998 ]]
模型预测值： [[1.00000000e+00 6.31125192e-17 1.38220366e-23]]
计算出来的预测值： [1.00000000e+000 1.65954733e-190 1.87517920e-136]

In [17]:
```

图 10-5　用 GuassianNB 的属性来做朴素贝叶斯分类

```
Console 1/A
====高斯模型====
              precision    recall  f1-score   support

      非垃圾邮件       0.95      0.74      0.83       564
       垃圾邮件       0.69      0.94      0.80       357

    accuracy                           0.82       921
   macro avg       0.82      0.84      0.82       921
weighted avg       0.85      0.82      0.82       921

====多项式模型====
              precision    recall  f1-score   support

      非垃圾邮件       0.82      0.82      0.82       564
       垃圾邮件       0.72      0.71      0.71       357

    accuracy                           0.78       921
   macro avg       0.77      0.77      0.77       921
weighted avg       0.78      0.78      0.78       921

====伯努利模型====
              precision    recall  f1-score   support

      非垃圾邮件       0.89      0.94      0.92       564
       垃圾邮件       0.90      0.82      0.86       357

    accuracy                           0.89       921
   macro avg       0.90      0.88      0.89       921
weighted avg       0.89      0.89      0.89       921
```

图 10-6　用 3 种朴素贝叶斯模型区分垃圾邮件和非垃圾邮件

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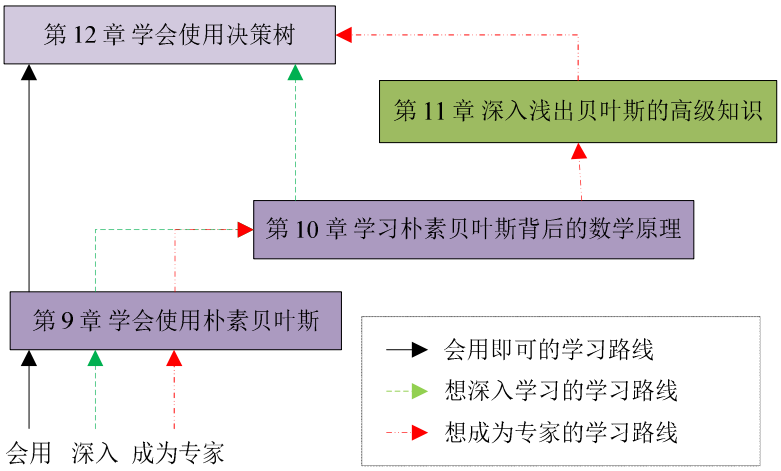


图 11-1　学习路线图

$$P(A,B) = P(A \cap B) = P(A) \times P(B)$$

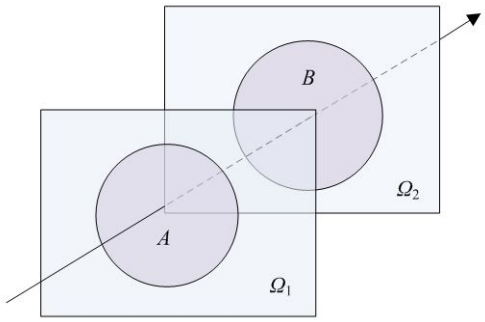
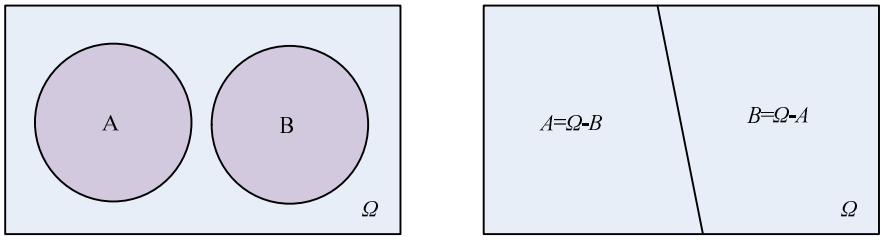


图 11-2　两个独立的事件



（a）　　（b）

图 11-3　两个互斥的事件

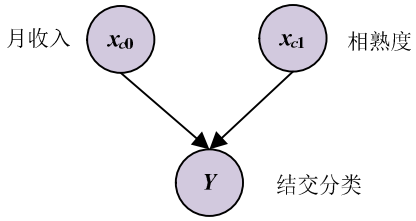


图 11-4　“某姑娘相亲后决定结交分类”的贝叶斯网络

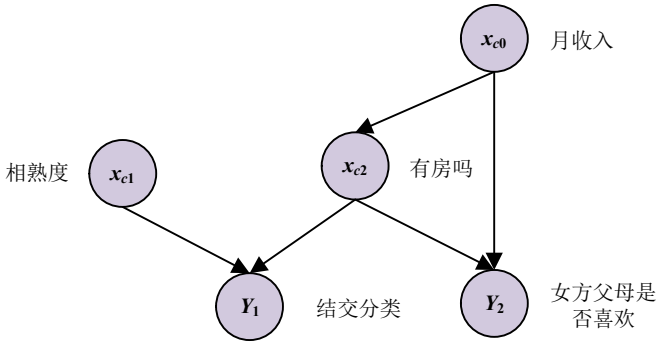


图 11-5　更复杂一点的贝叶斯网络

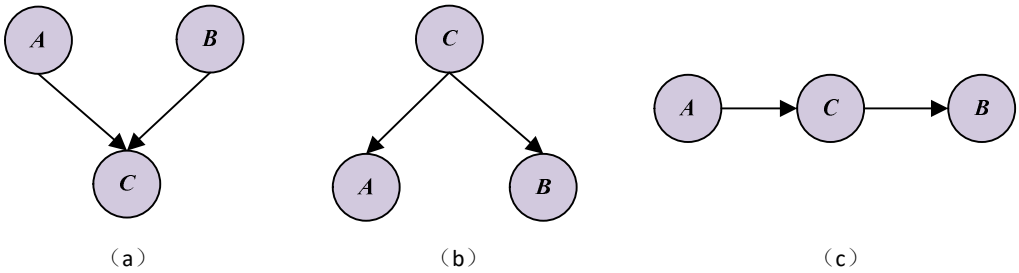


图 11-6　贝叶斯网络的 3 种基本结构

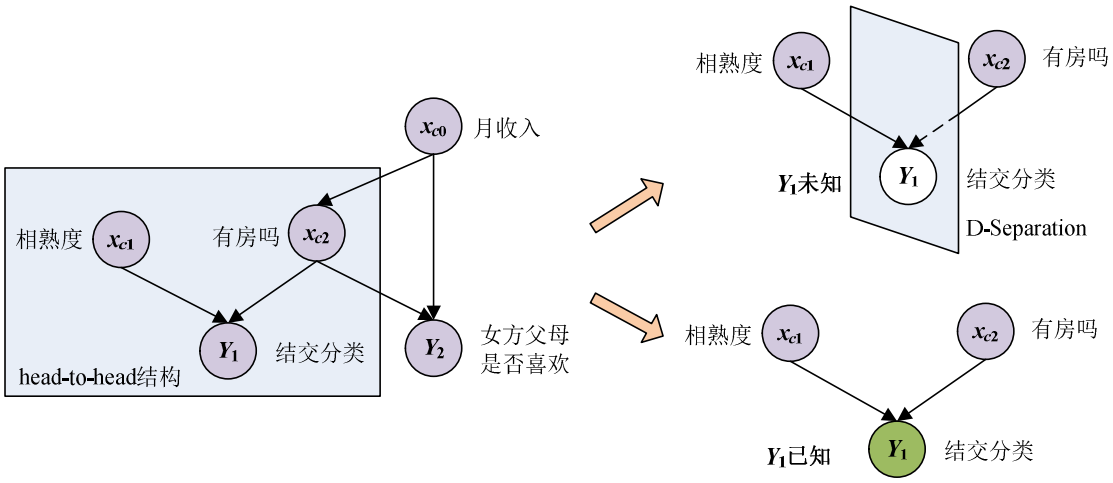


图 11-7　head-to-head 结构的示例

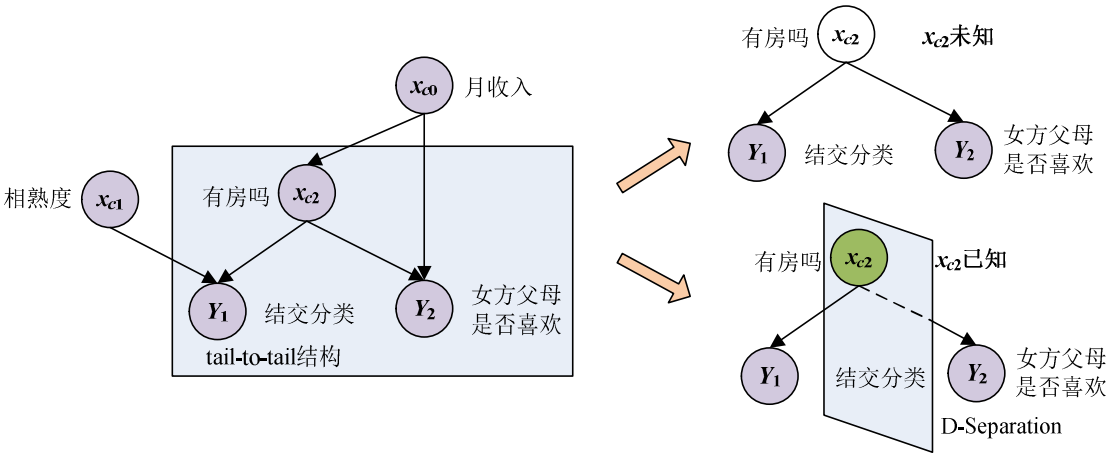


图 11-8　tail-to-tail 结构的示例

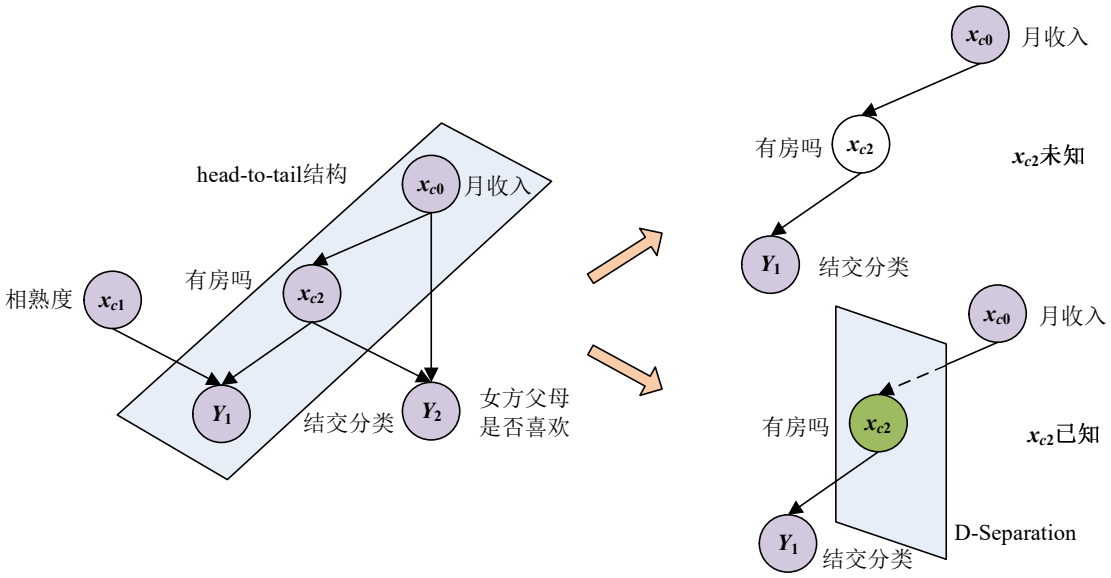


图 11-9　head-to-tail 结构的示例

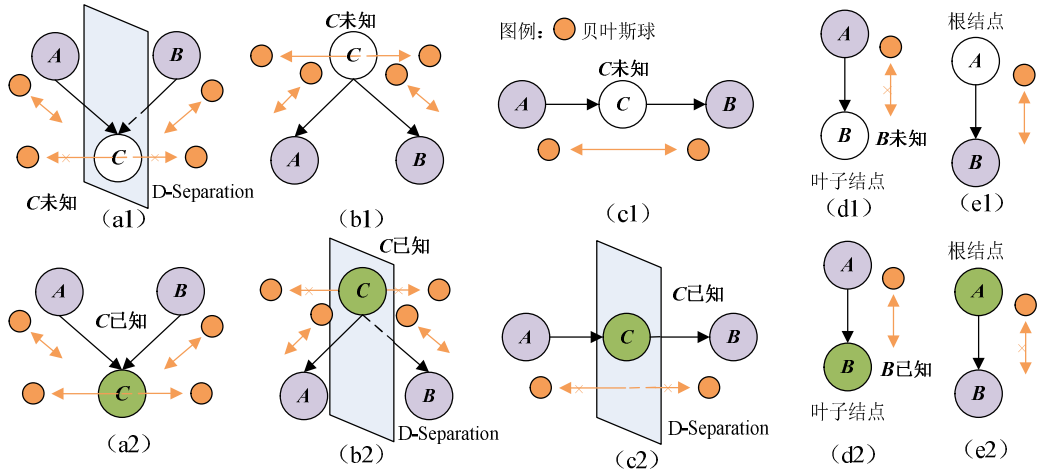


图 11-10　3 种基本结构对应的 6 条规则

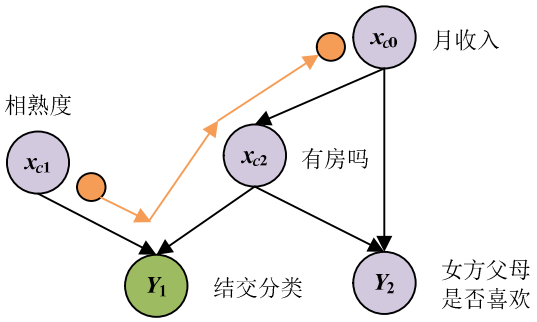


图 11-11　打贝叶斯球的过程

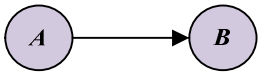


图 11-12　创建的简单的贝叶斯网络

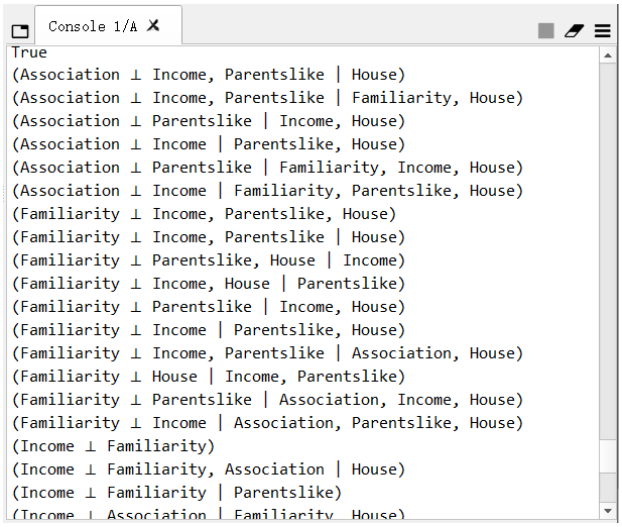


图 11-13　构建的贝叶斯网络的依赖关系

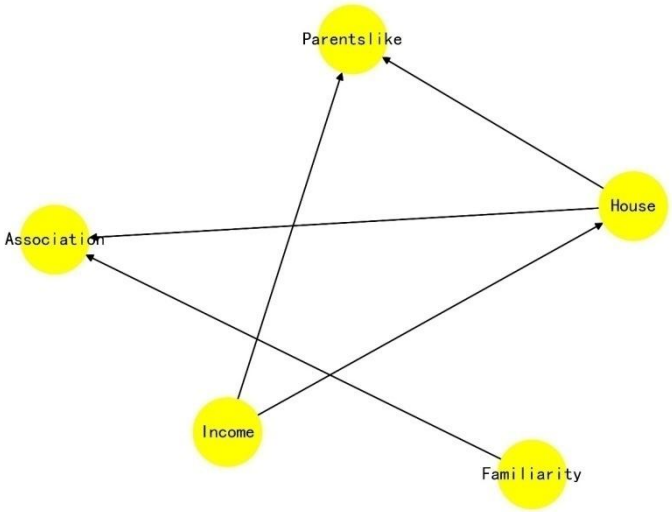


图 11-14　构建的贝叶斯网络的结构

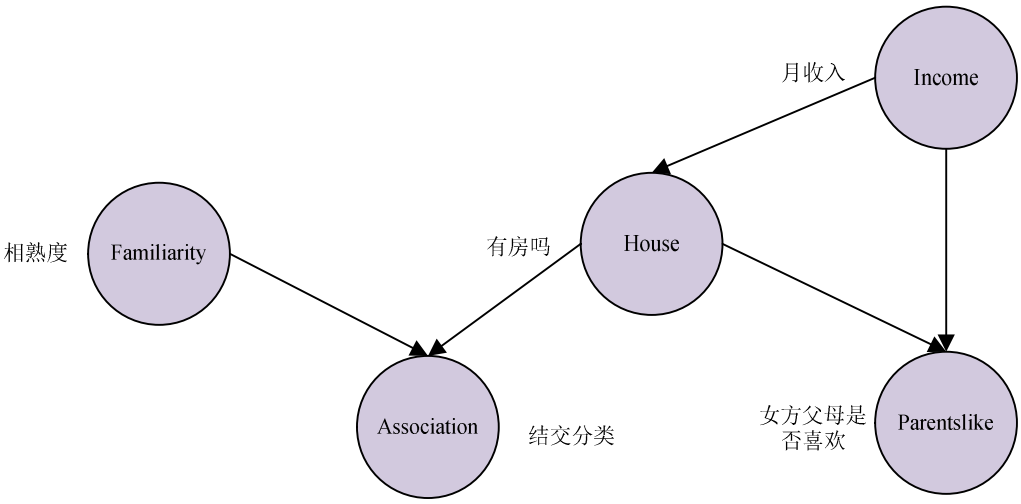


图 11-15　调整后等价的贝叶斯网络

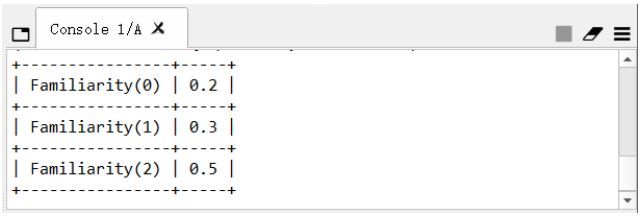


图 11-16　结点 Familiarity 的概率分布表

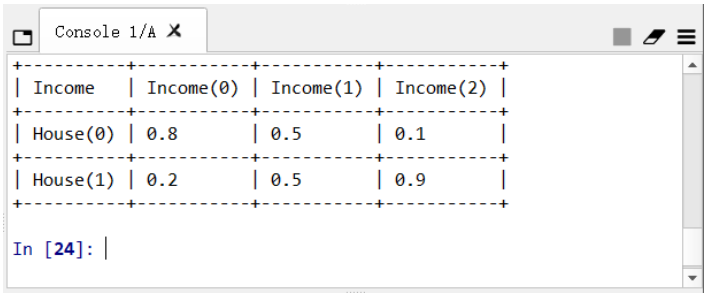


图 11-17　“House”结点的条件概率表

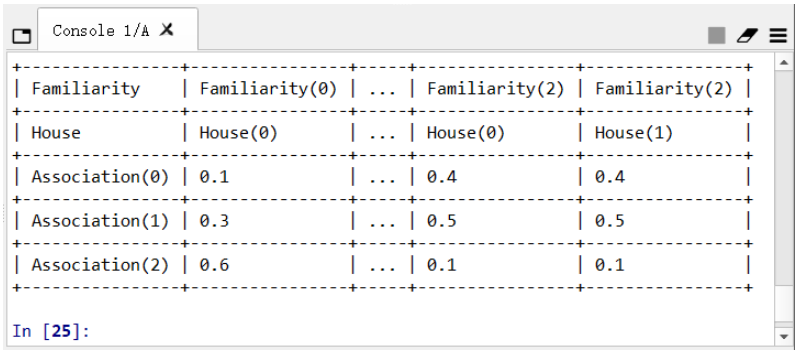


图 11-18　“Association”结点的条件概率表

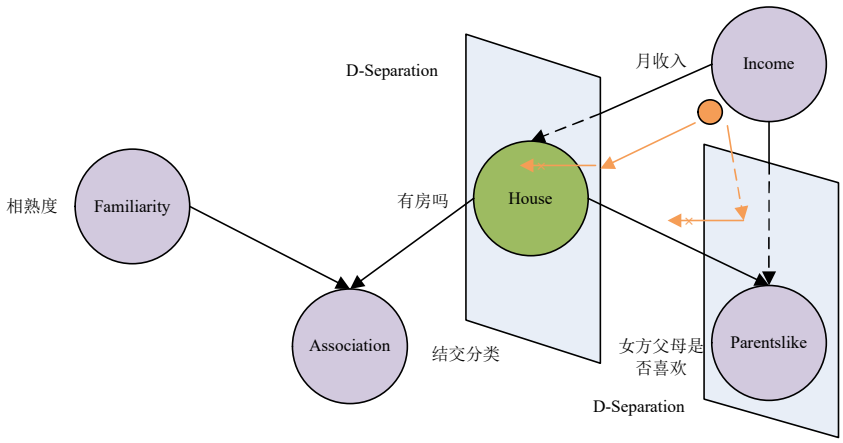


图 11-19　已知“House”事件时“Association”事件与“Income”事件的独立性

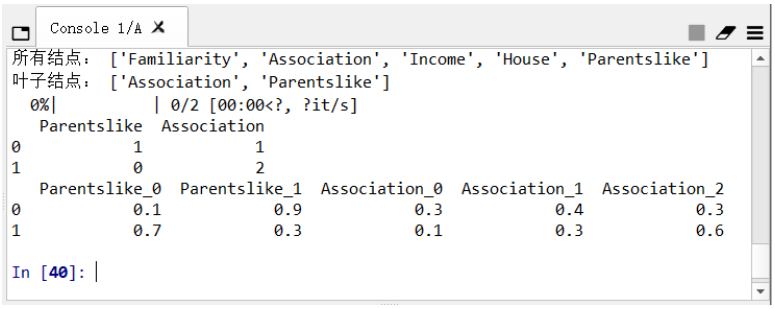


图 11-20　用贝叶斯网络预测的结果

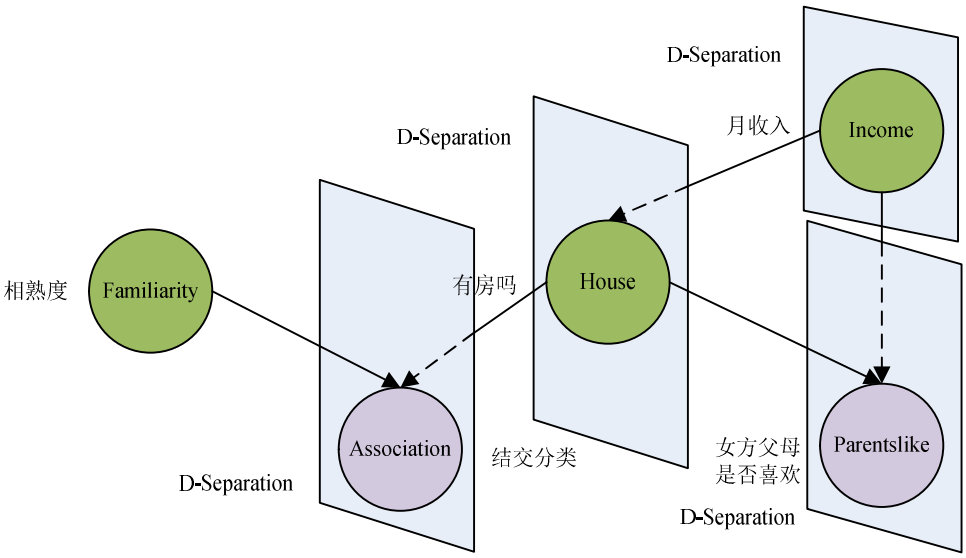


图 11-21　加上 D-Separation 的贝叶斯网络

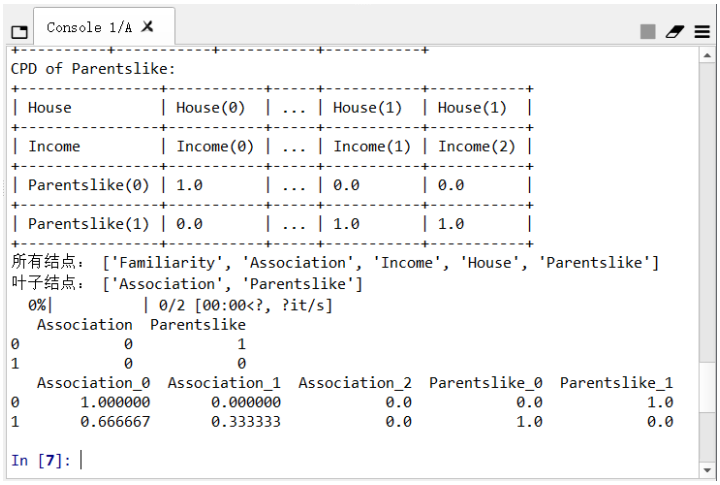


图 11-22　自动学习贝叶斯网络的参数

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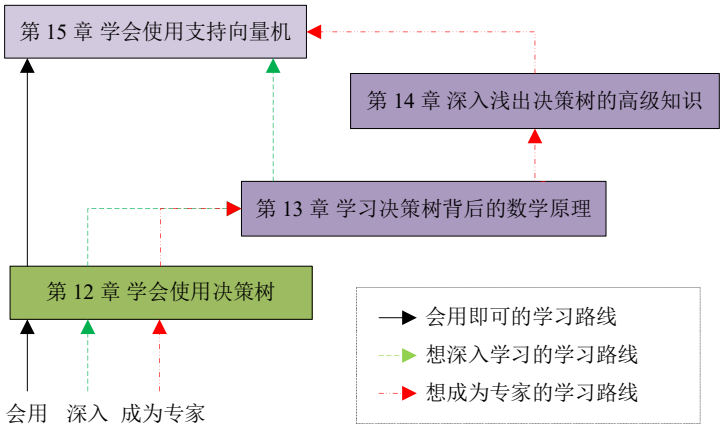
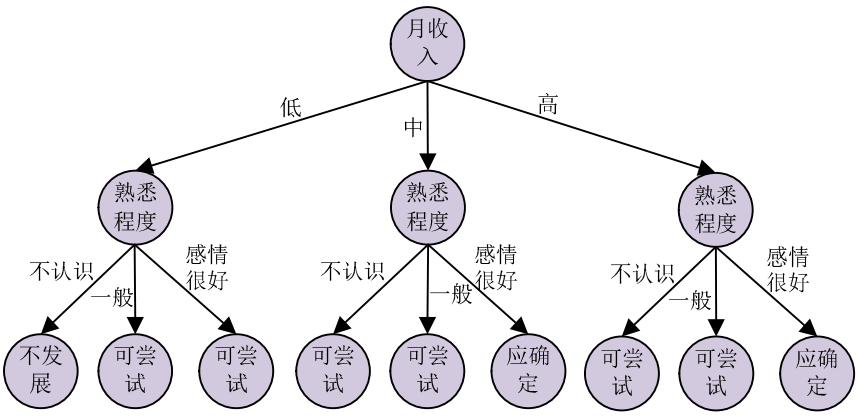
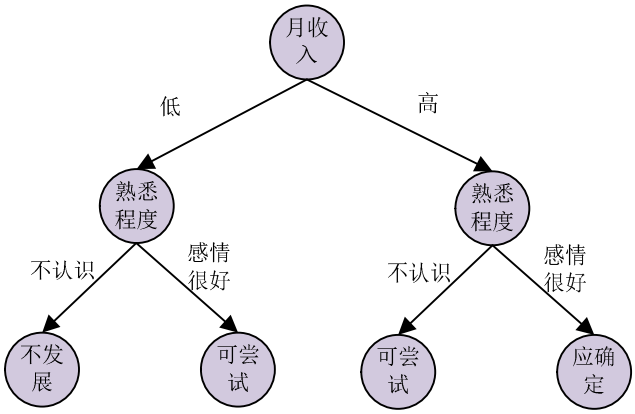


图 12-1　学习路线图



（a）多叉树



（b）二叉树

图 12-2　多叉树和二叉树

```
Console 1/A
[3 1]
[[0.  0.  1. ]
 [0.5 0.5 0. ]]

In [4]:
```

图 12-3　用决策树辅助某姑娘做相亲后的决策

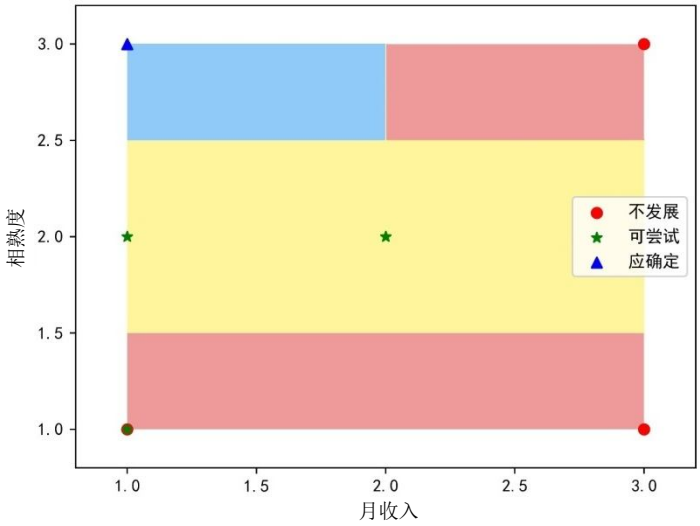


图 12-4　DecisionTreeClassifier 类辅助某姑娘做相亲后的决策效果图

```
Console 1/A
[0. 1. 0.]
[1. 0. 0.]
[1. 0. 0.]
[0. 1. 0.]
[0. 0. 1.]]
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        11
  versicolor       1.00      0.92      0.96        13
   virginica       0.86      1.00      0.92         6

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30


In [6]:
```

图 12-5　用决策树做鸢尾花分类

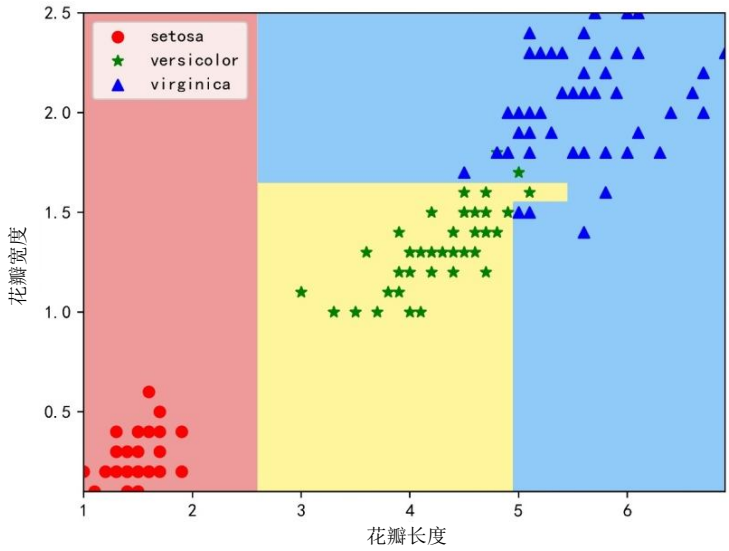


图 12-6　画出决策树对鸢尾花分类的分界线

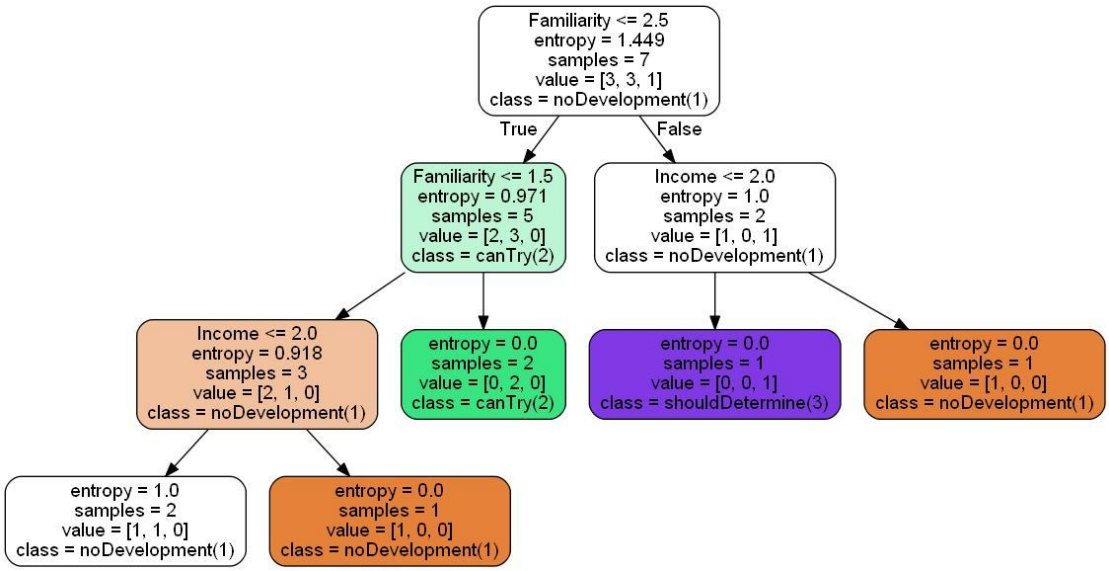


图 12-7　某姑娘相亲后决策的决策树

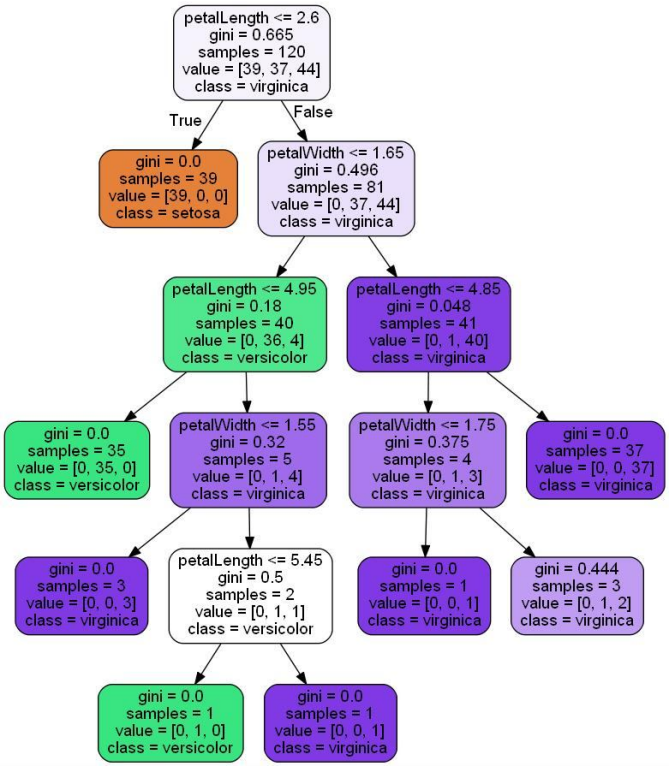


图 12-8　鸢尾花分类的决策树

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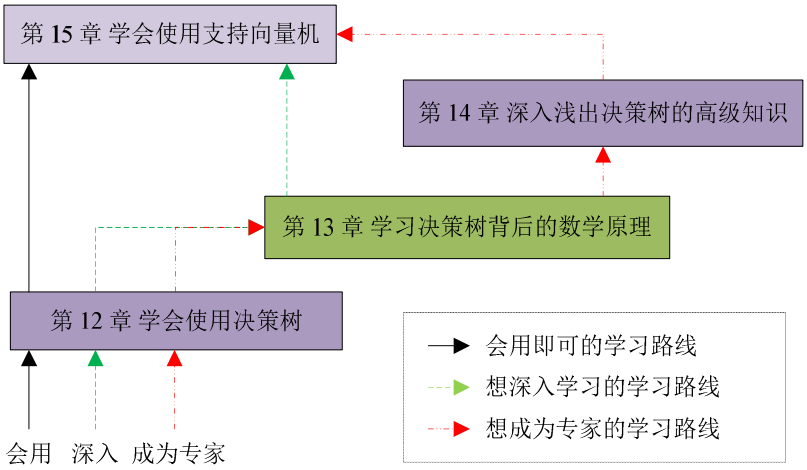


图 13-1　学习路线图

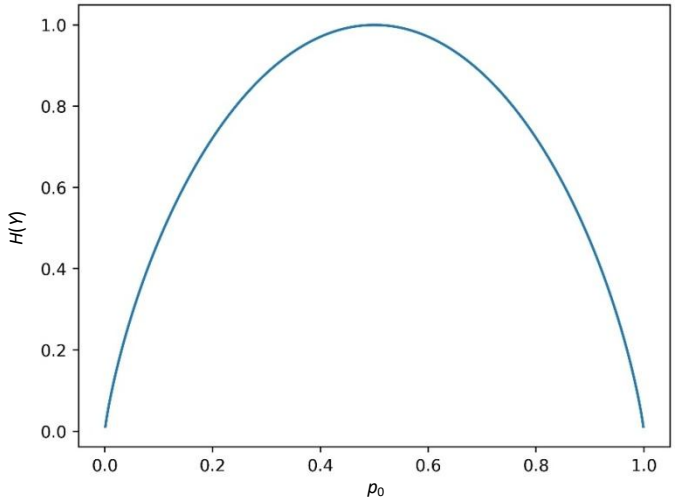


图 13-2　数据项只有 2 种取值时式（13-1）的图形

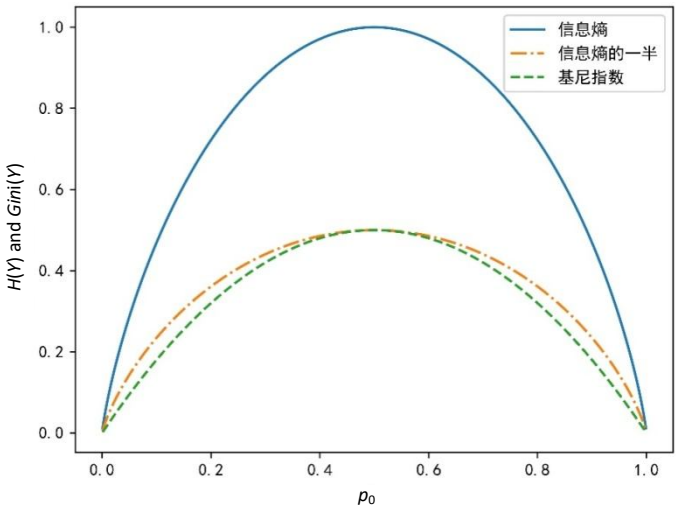


图 13-3　基尼指数的图形

训练数据集D	特征数据项x_{c0}	…	特征数据项$x_{c(n-1)}$	目标数据项Y
样本x_{r0}	x_{r0c0}	…	$x_{r0c(n-1)}$	y_0
…	…	…	…	…
样本$x_{r(m-1)}$	$x_{r(m-1)c0}$	…	$x_{r(m-1)c(n-1)}$	Y_{m-1}

目标数据项Y的取值有k种，这些取值的集合为$C=\{c_0, \cdots, c_{k-1}\}$

图 13-4　当前训练数据集的图示

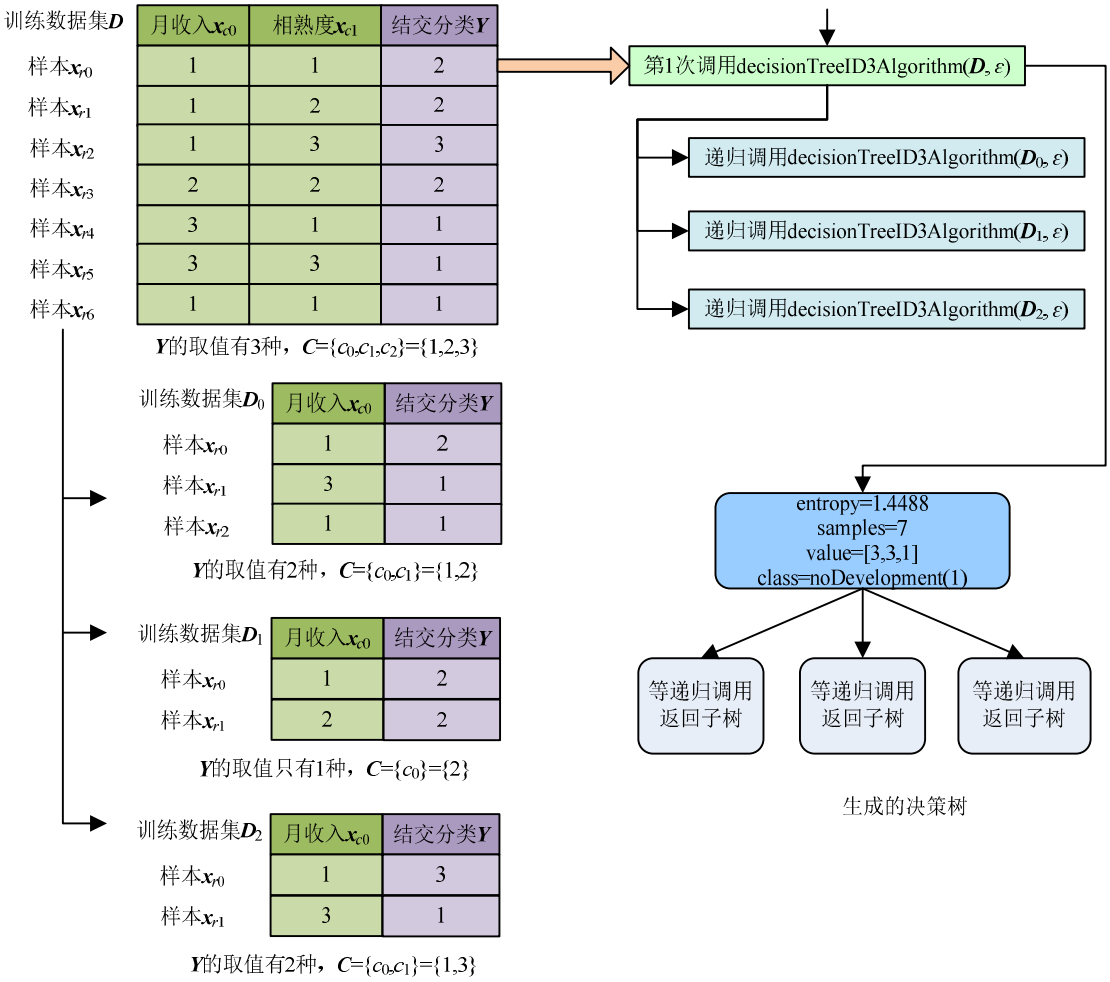


图 13-5　第 1 次调用 decisionTreeID3Algorithm(***D***, ε)

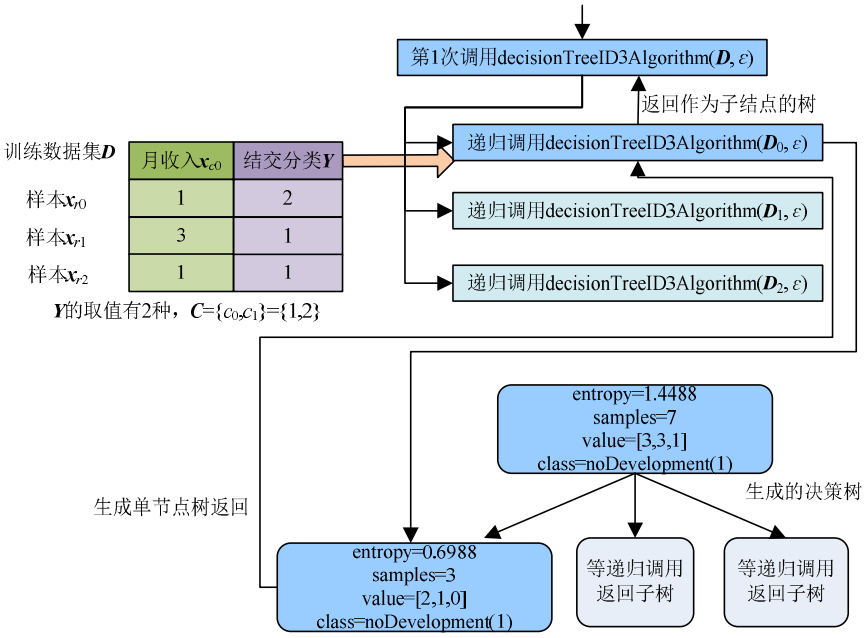


图 13-6　递归调用 decisionTreeID3Algorithm(D_0, ε)

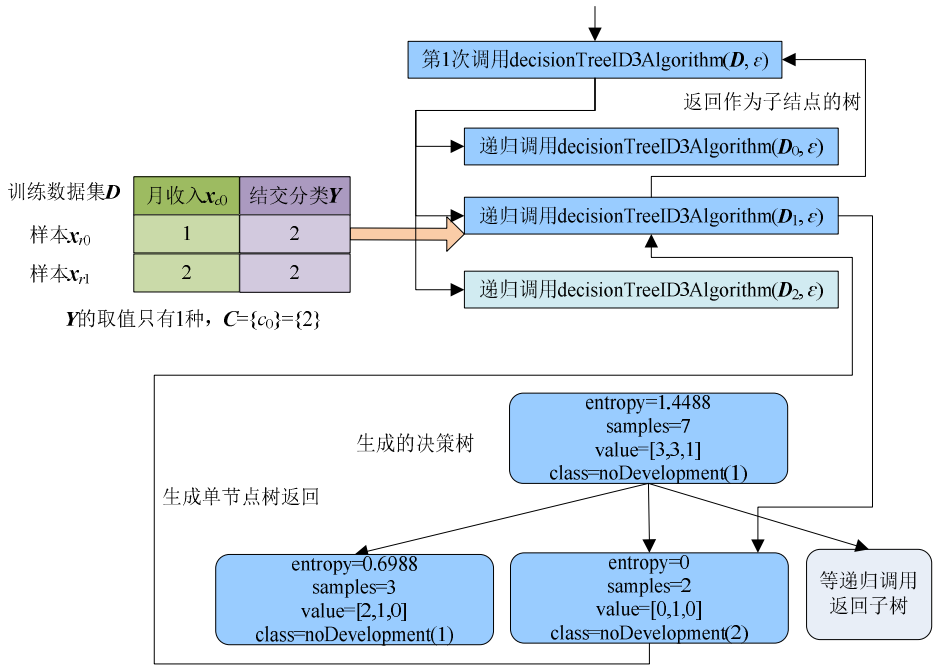


图 13-7　递归调用 decisionTreeID3Algorithm(D_1, ε)

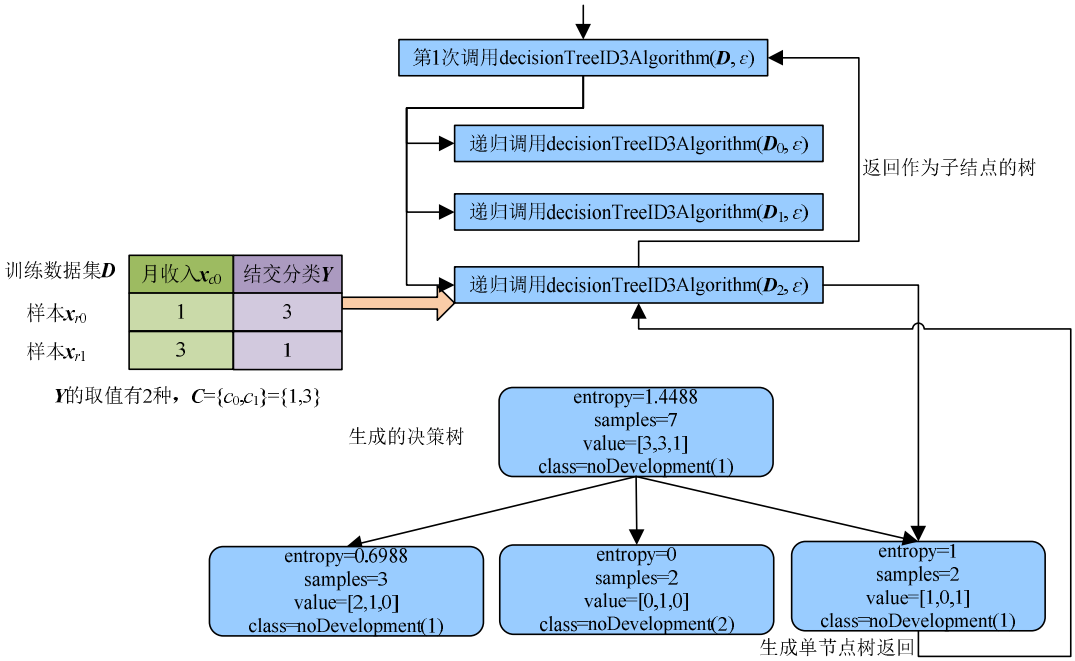


图 13-8　递归调用 decisionTreeID3Algorithm(D_2, ε)

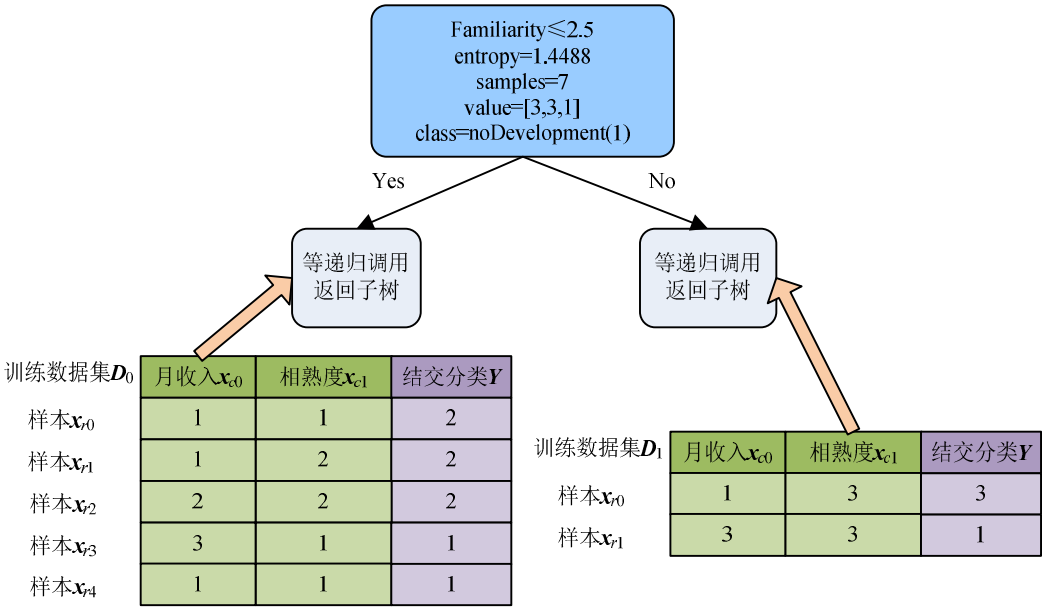
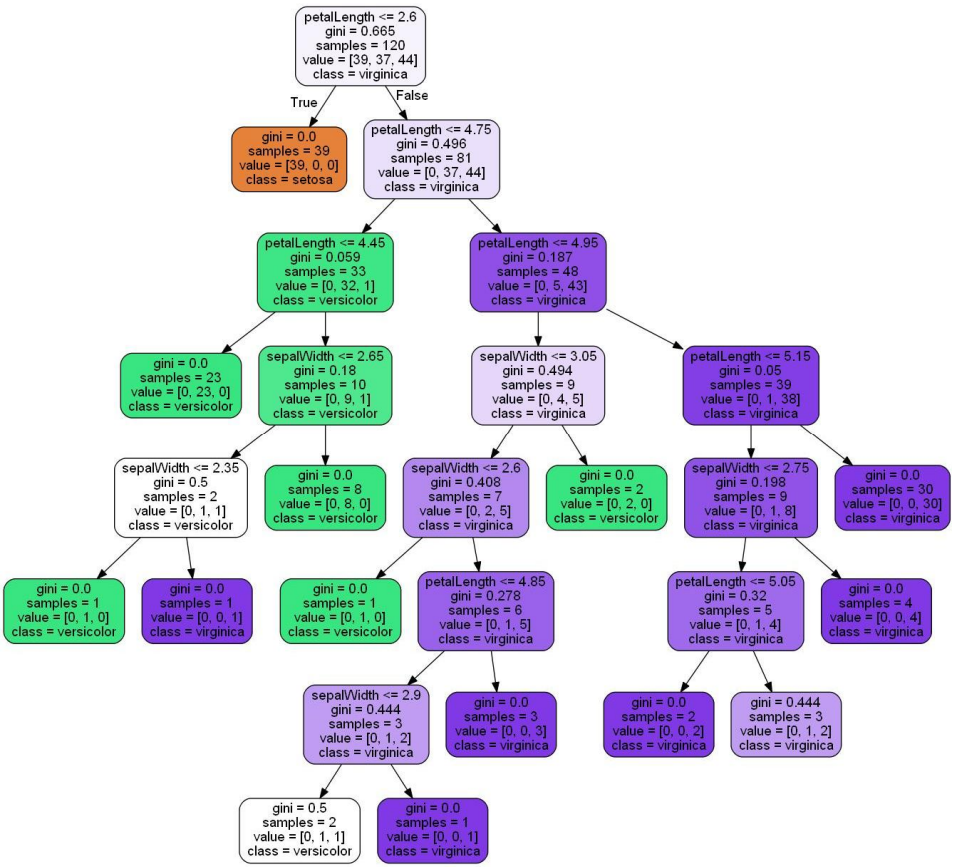
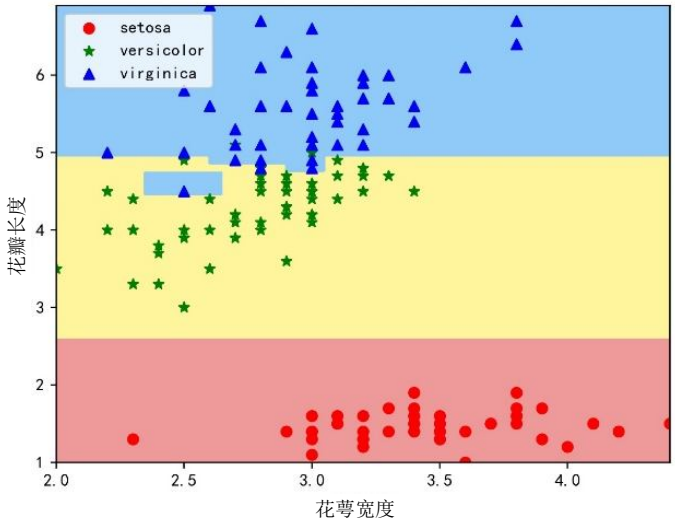


图 13-9　第 1 次分叉及切分方案

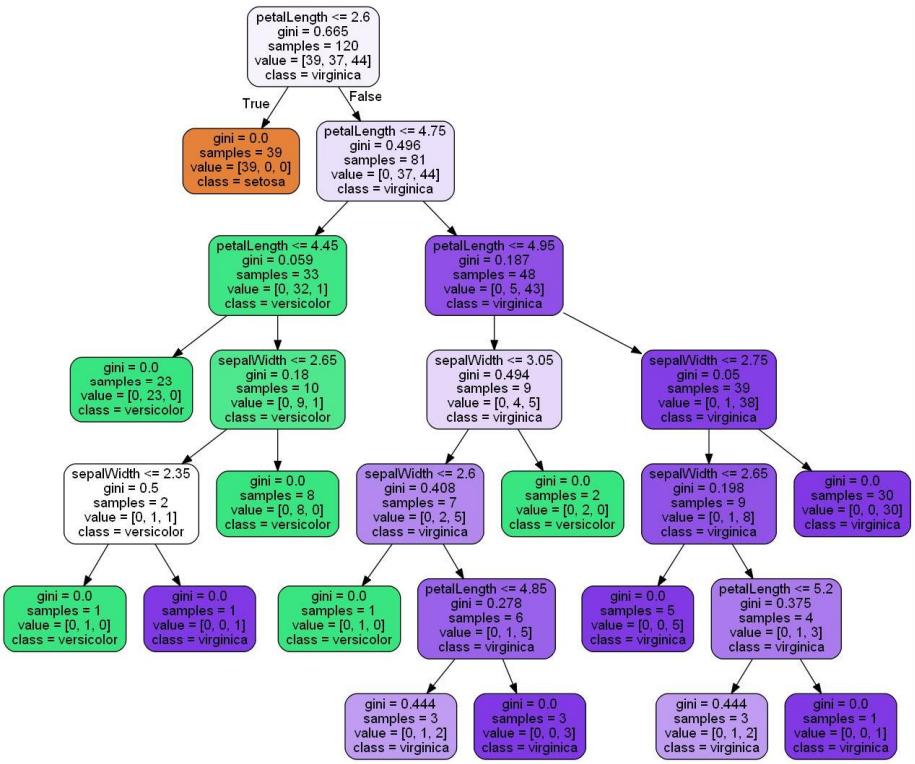


（a）不限制树的深度时的决策树

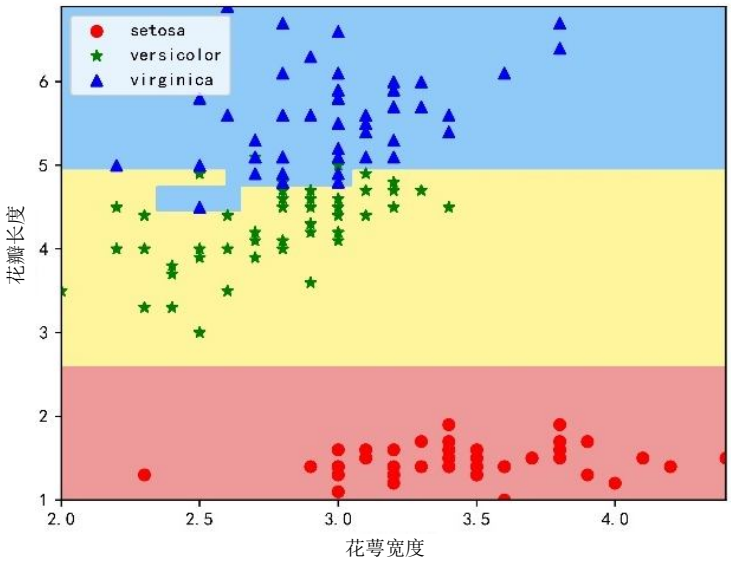


（b）不限制树的深度时的分类效果

图 13-10　鸢尾花分类的决策树及分类效果

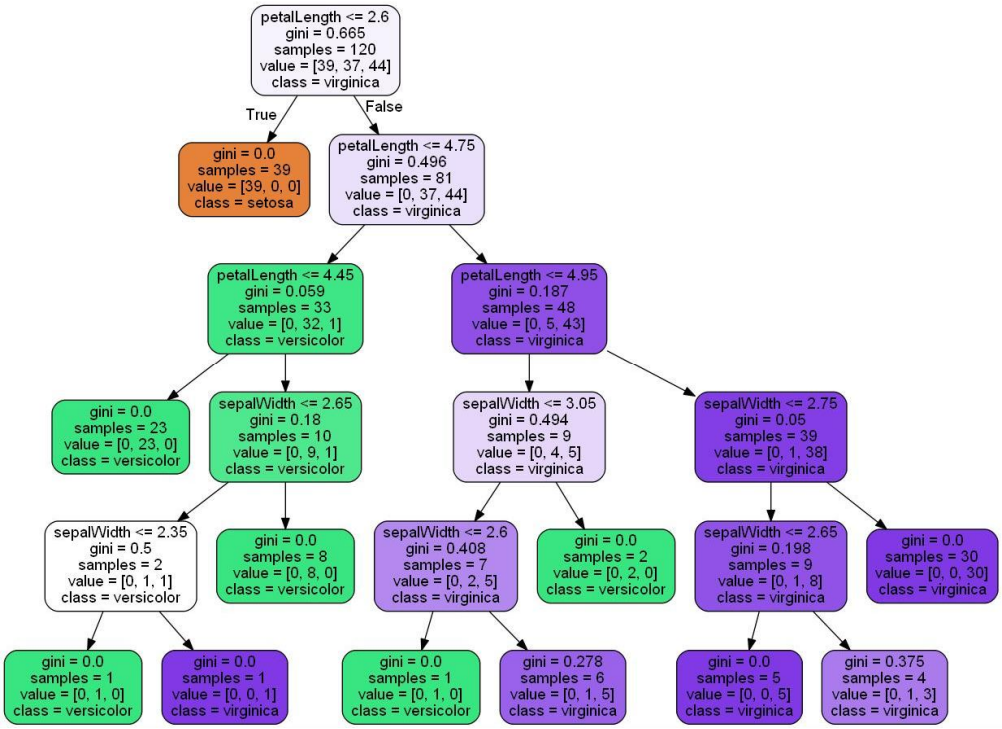


（c）树的深度最大为 6 时的决策树

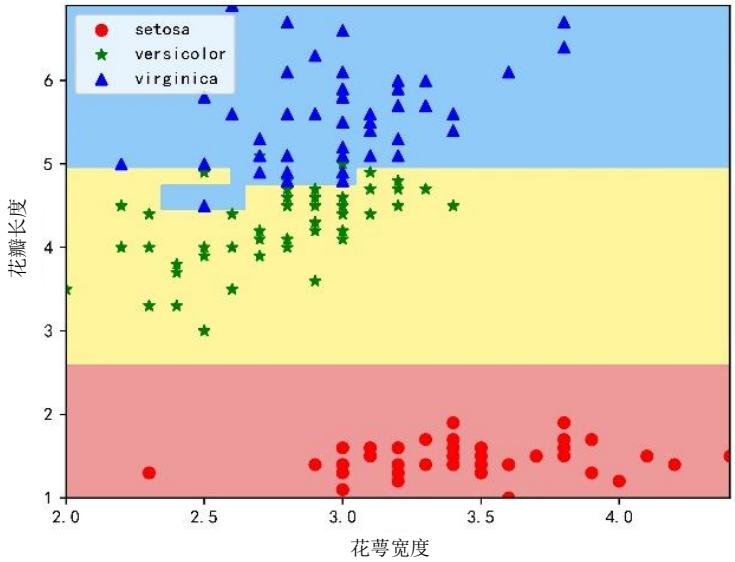


（d）树的深度最大为 6 时的分类效果

图 13-10　鸢尾花分类的决策树及分类效果（续图）

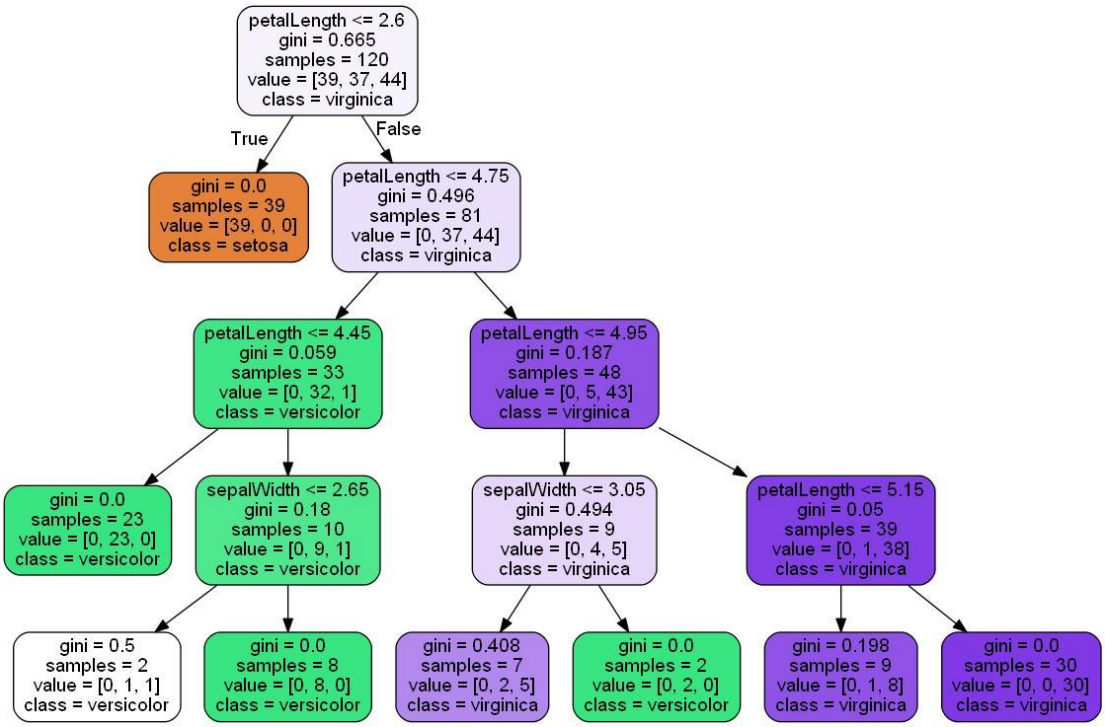


（e）树的深度最大为 5 时的决策树

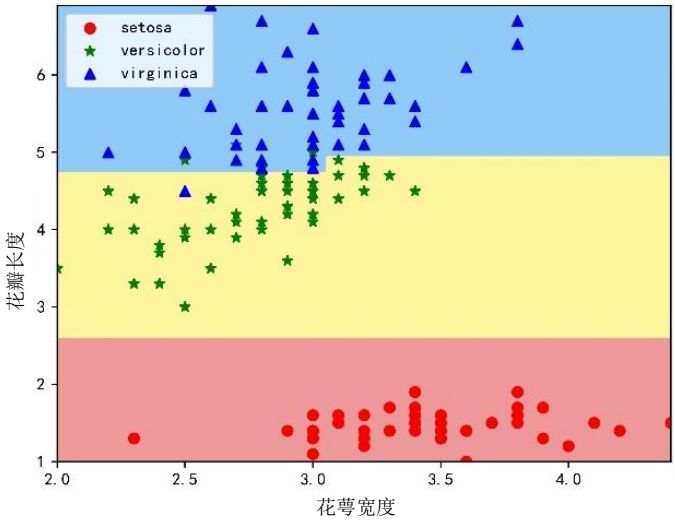


（f）树的深度最大为 5 时的分类效果

图 13-10　鸢尾花分类的决策树及分类效果（续图）

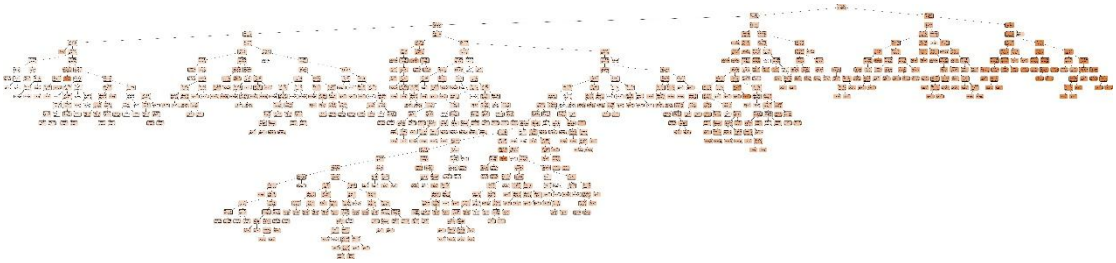


（g）树的深度最大为 4 时的决策树



（h）树的深度最大为 4 时的分类效果

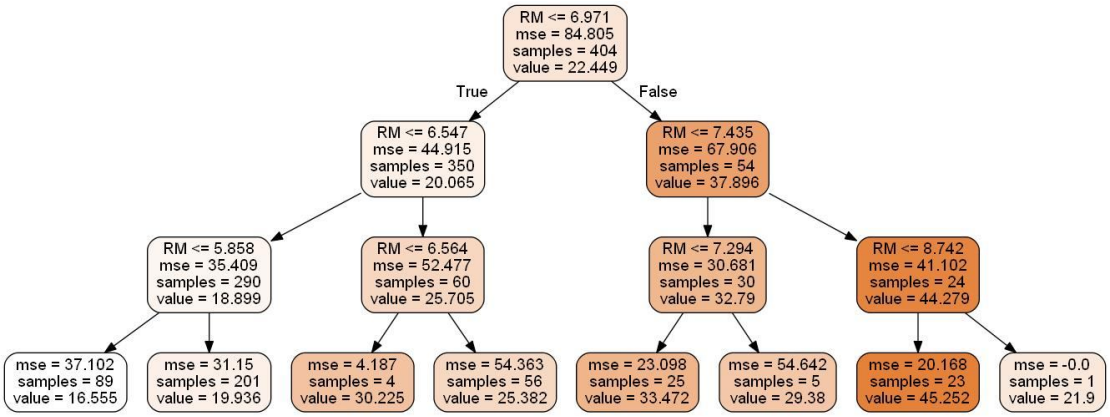
图 13-10　鸢尾花分类的决策树及分类效果（续图）



（a）不限制树的深度时的决策树

图 13-11　房价回归分析的决策树

（b）树的深度最大为 13 时的决策树



（c）树的深度最大为 3 时的决策树

图 13-11　房价回归分析的决策树（续图）

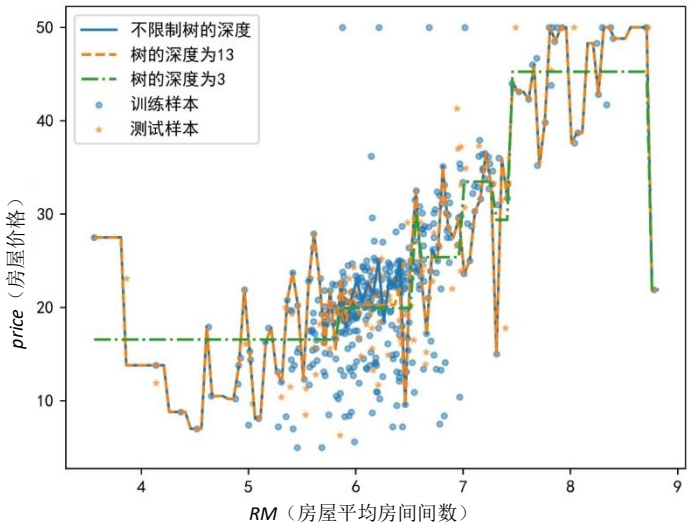


图 13-12　房价回归分析的决策树的拟合情况

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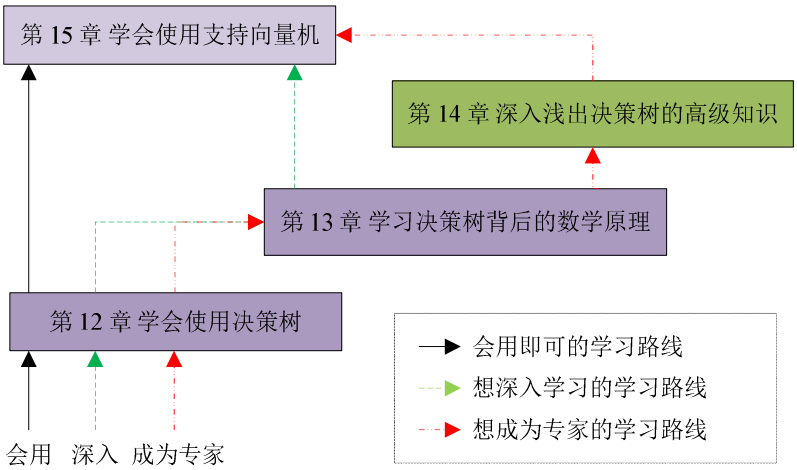


图 14-1　学习路线图

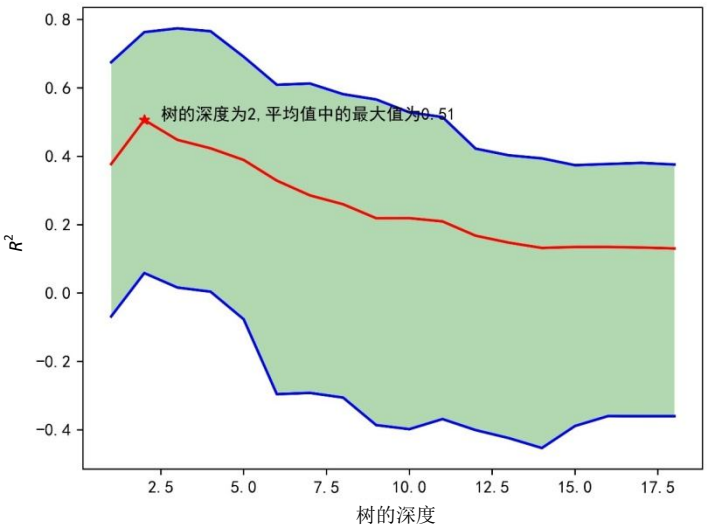


图 14-2　不同深度的决策树的 R^2

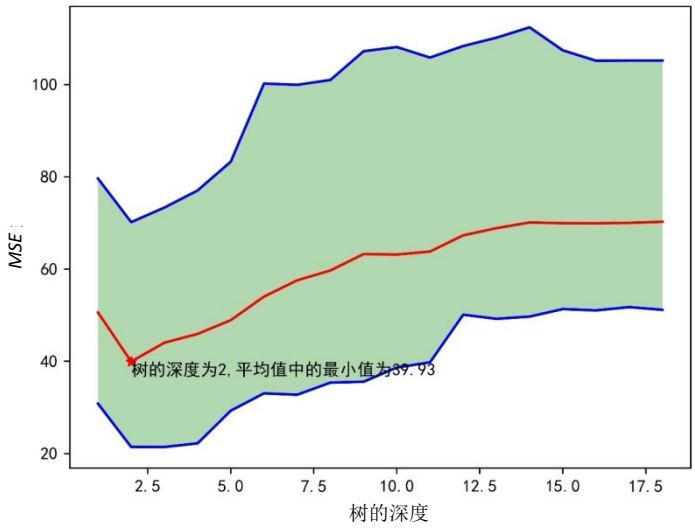


图 14-3　不同深度的决策树的 *MSE*

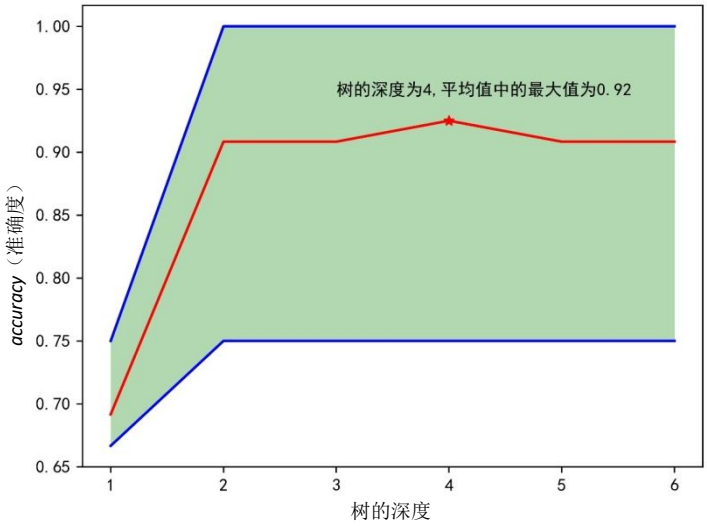


图 14-4　不同深度的决策树的准确度

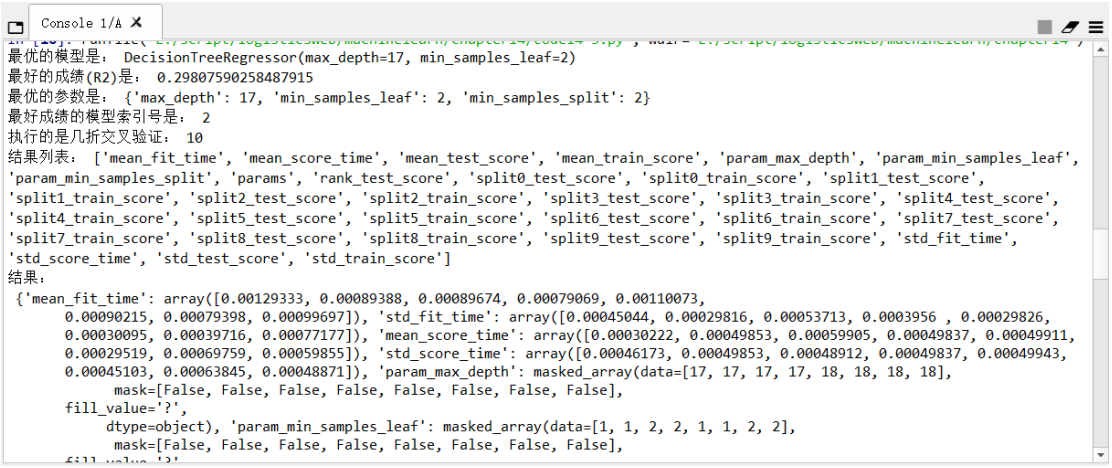


图 14-5　用 GridSearchCV 调节决策树模型的参数

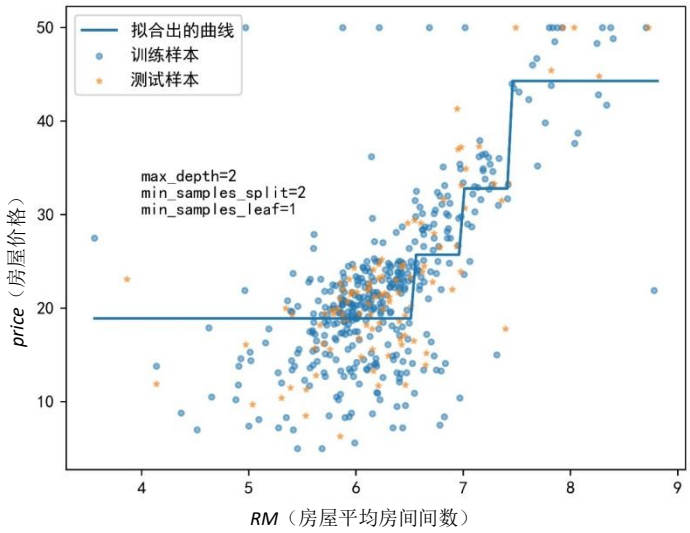


图 14-6　用 GridSearchCV 调节决策树模型的参数后得到的拟合曲线

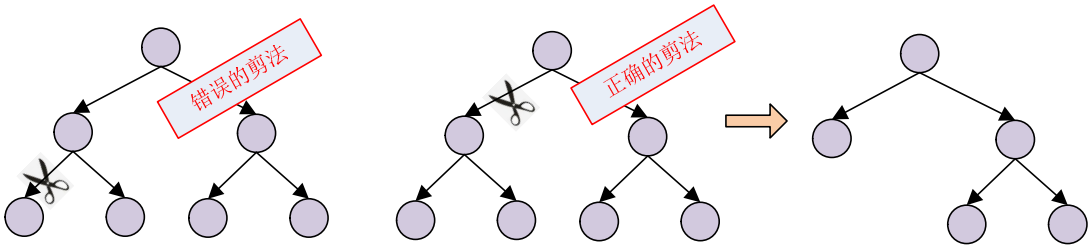


图 14-7　剪枝就是要把子树替换成叶子结点

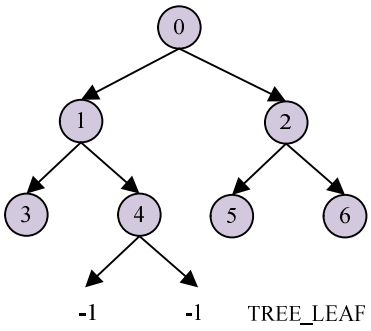


图 14-8　叶子结点的图示

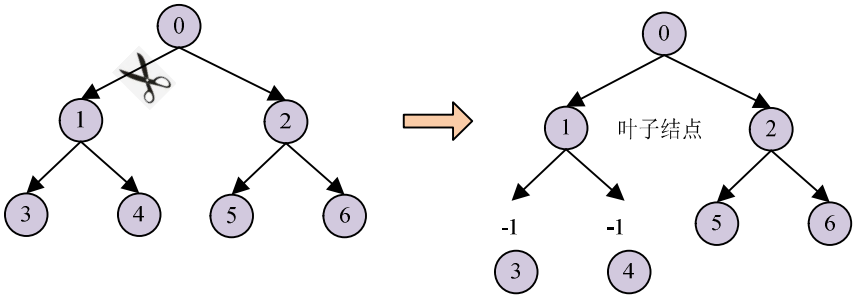


图 14-9　剪枝的做法

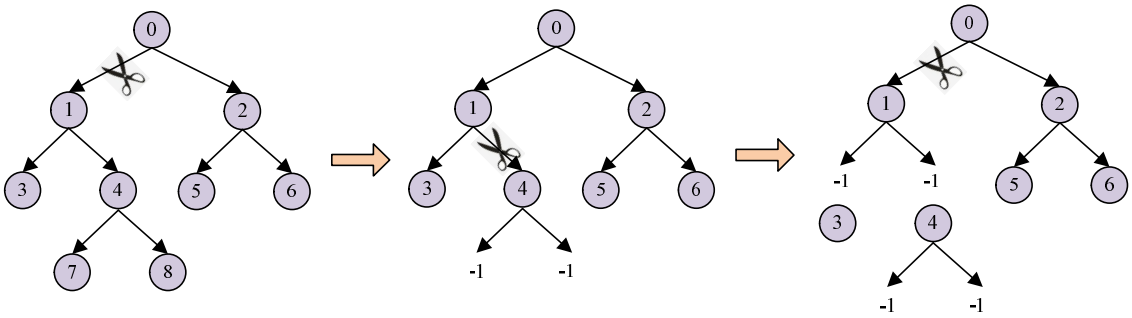


图 14-10　从下往上剪枝

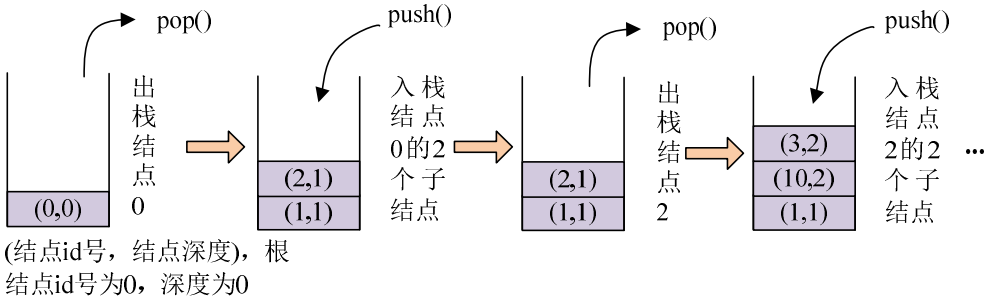


图 14-11　用堆栈遍历决策树

$$\begin{bmatrix}1 & 1 & 0\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix} \Rightarrow \begin{bmatrix}0 & 0 & 1\\ 0 & 1 & 1\end{bmatrix}$$

图 14-12　CSR 矩阵的表示

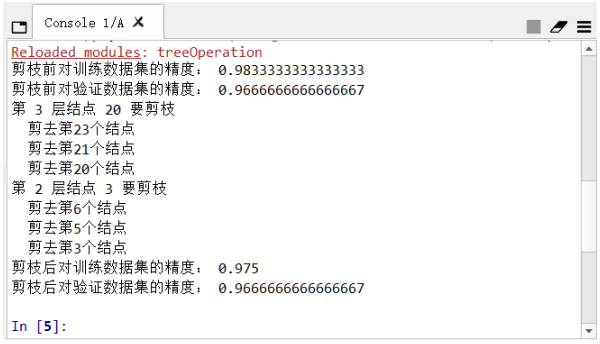
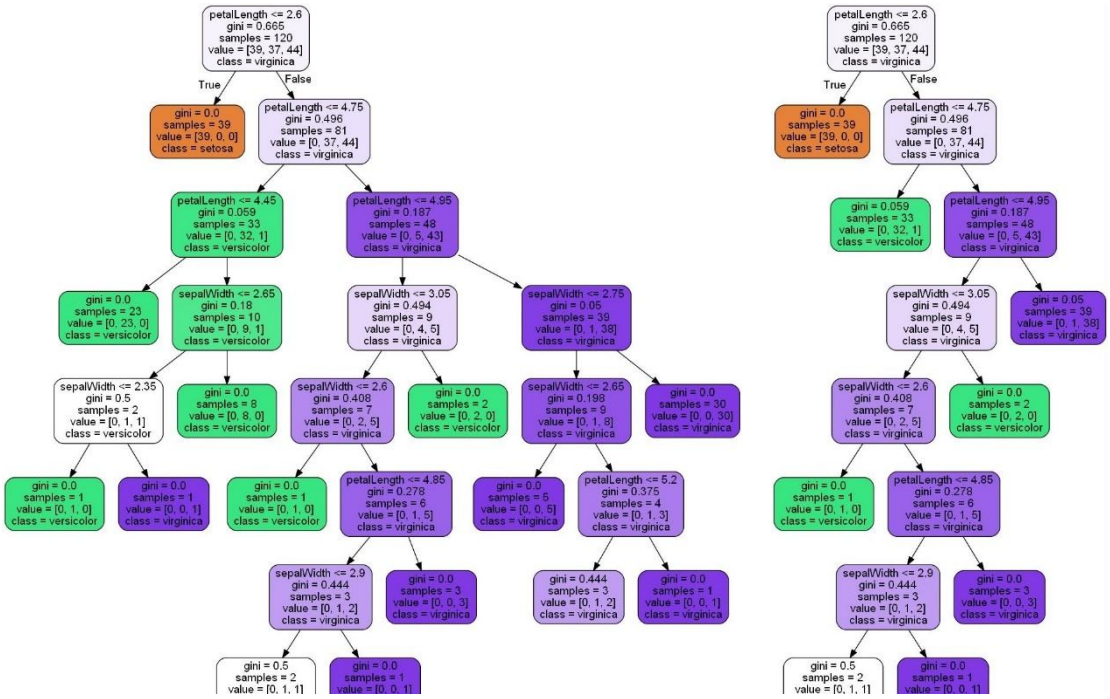
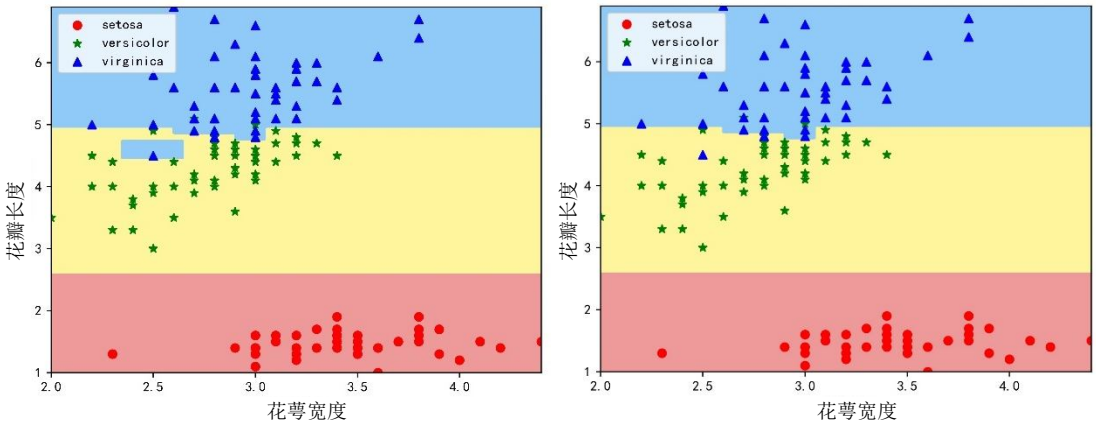


图 14-13　剪枝的过程及剪枝前后精度的对比



（a）剪枝前　　（b）剪枝后

图 14-14　决策树剪枝的前后对比



（a）剪枝前　　（b）剪枝后

图 14-15　剪枝前后的分界线

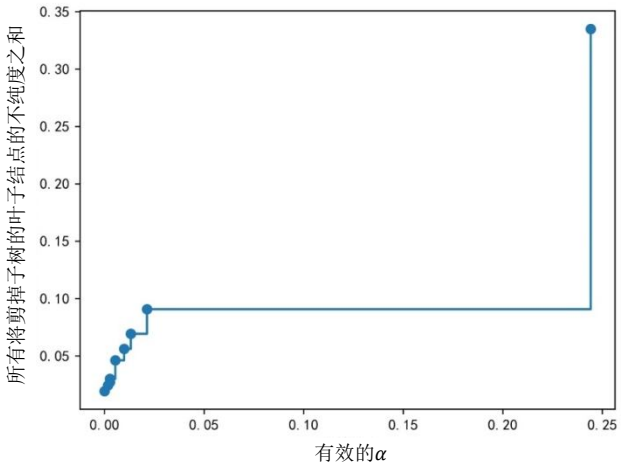


图 14-16　α与 impurities 之间的关系

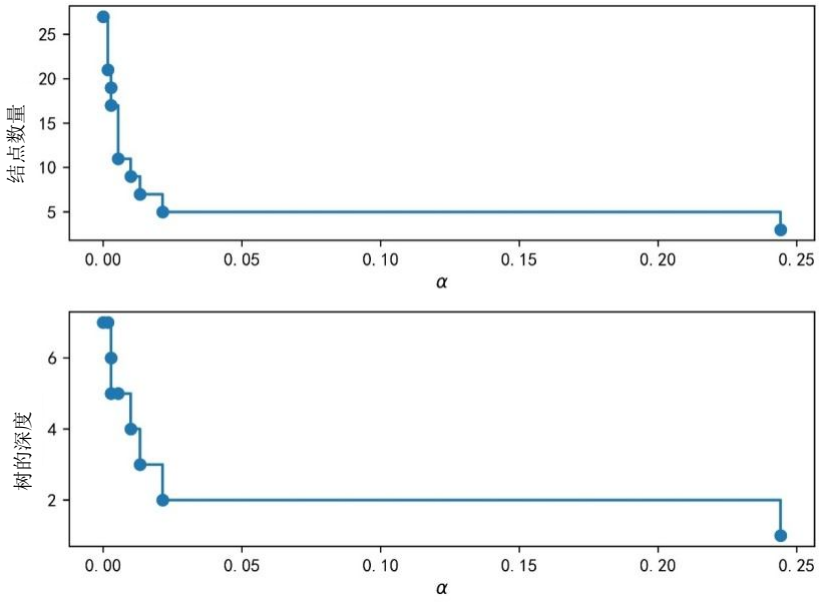


图 14-17　α值与决策树模型结点数量、深度的关系

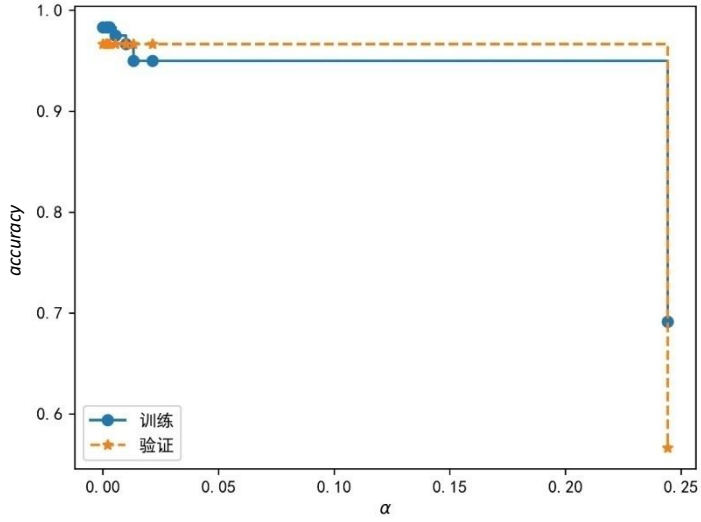


图 14-18　α与 *accuracy* 的关系

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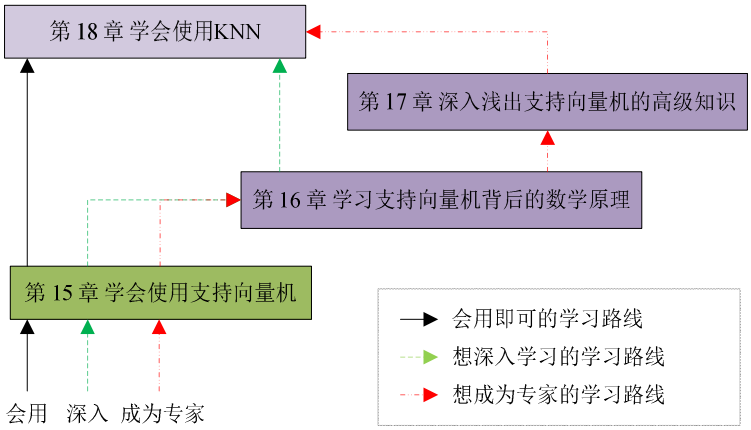

图 15-1　学习路线图

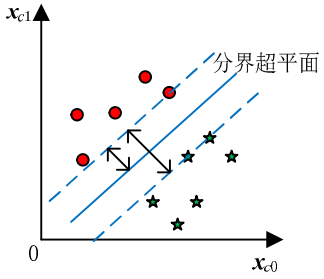

图 15-2　线性支持向量机

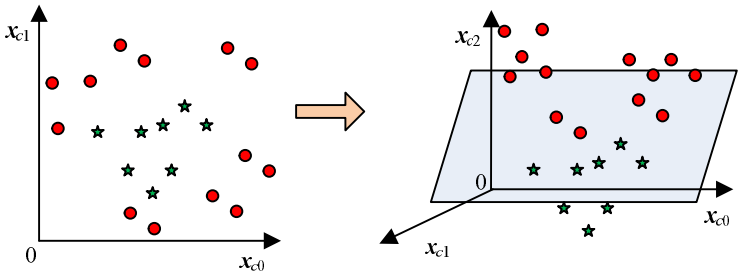

图 15-3　非线性支持向量机

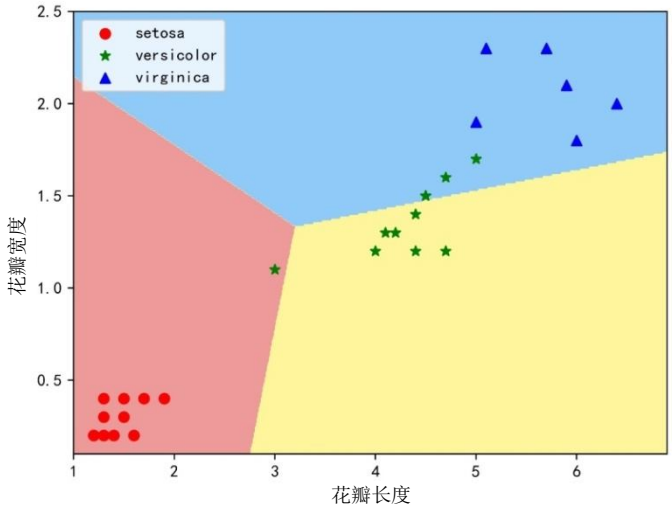

图 15-4　用线性支持向量机做鸢尾花的三分类

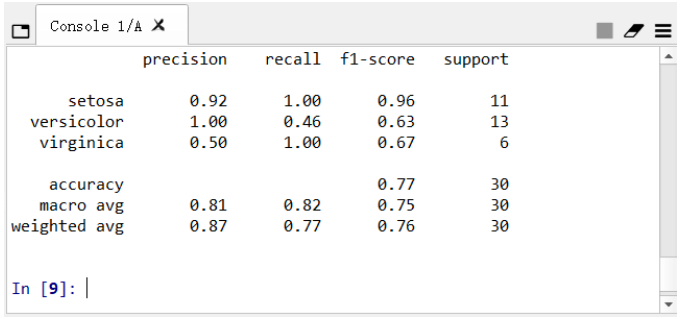

图 15-5　评价线性支持向量机做鸢尾花三分类的效果

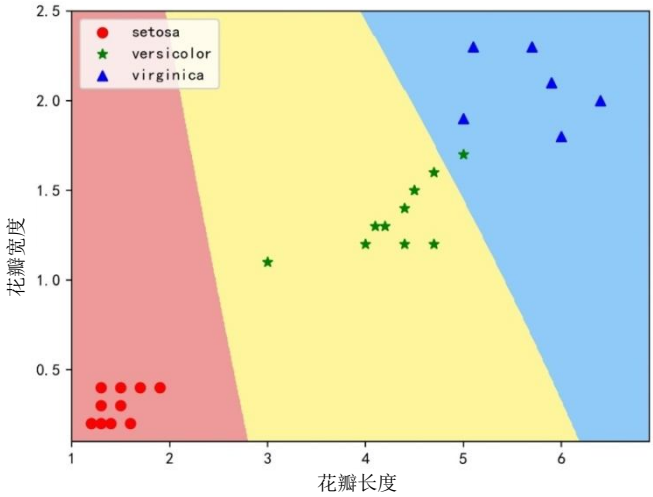

图 15-6　用非线性支持向量机做鸢尾花的三分类

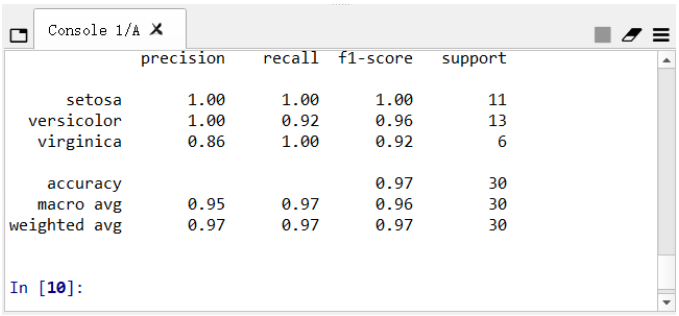

图 15-7　评价非线性支持向量机做鸢尾花三分类的效果

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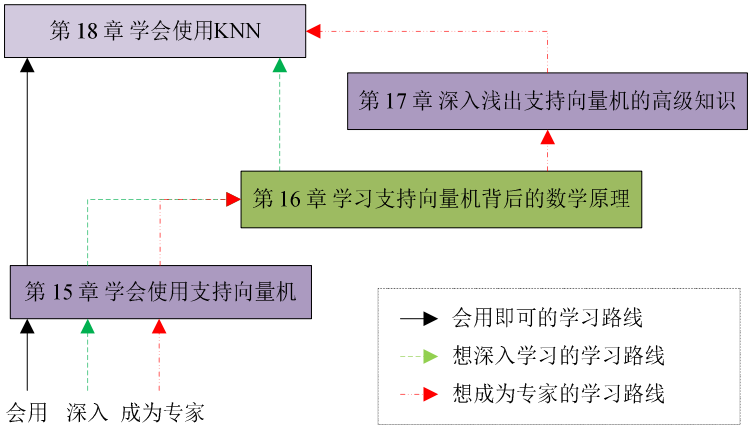
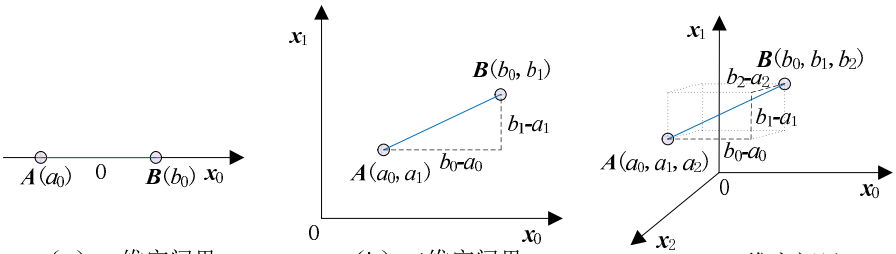


图 16-1　学习路线图



（a）一维空间里两点的距离　（b）二维空间里两点的距离　（c）三维空间里两点的距离

图 16-2　空间中两点之间的距离

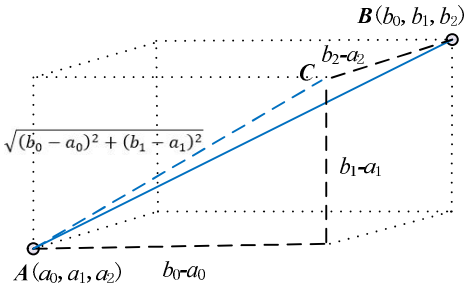


图 16-3　三维空间里两点的距离

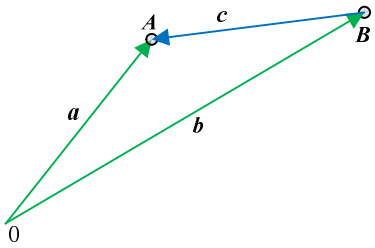
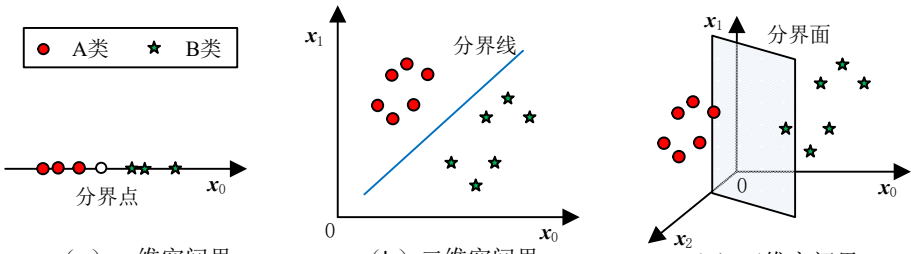
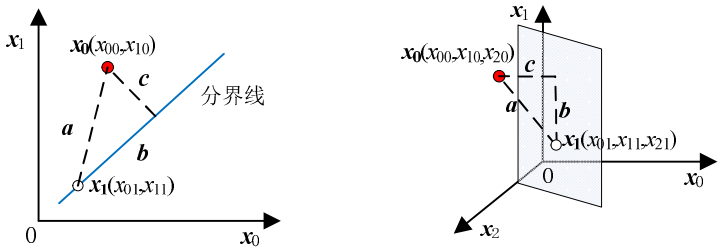


图 16-4　用向量表示两点之间的距离



（a）一维空间里的分界点　（b）二维空间里的分界线　（c）三维空间里的分界面

图 16-5　分界的超平面



（a）二维空间里点到分界线的距离　（b）三维空间里点到分界面的距离

图 16-6　点到超平面的距离

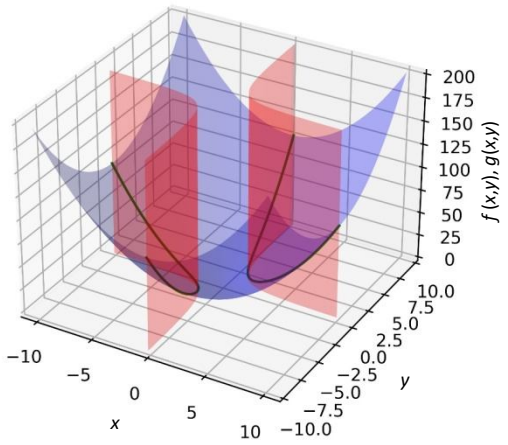


图 16-7　$f(x,y)=x^2+y^2$和$xy=2$的图形、相交线

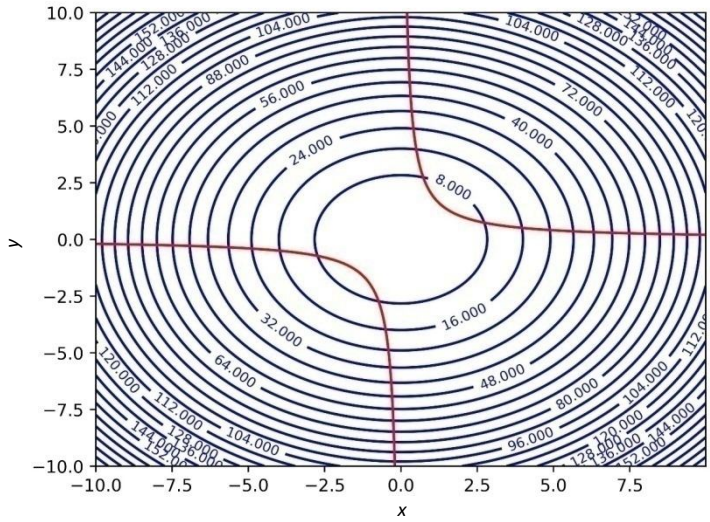


图 16-8　从二维空间看$f(x,y)=x^2+y^2$和$xy=2$的图形

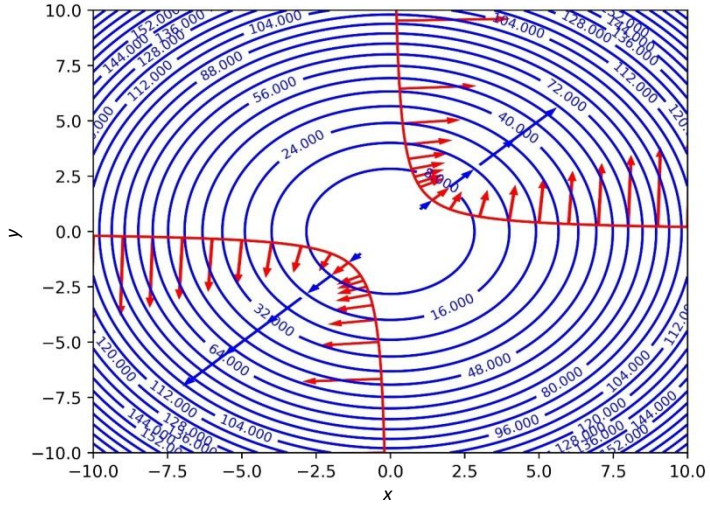


图 16-9　梯度方向的形象展示

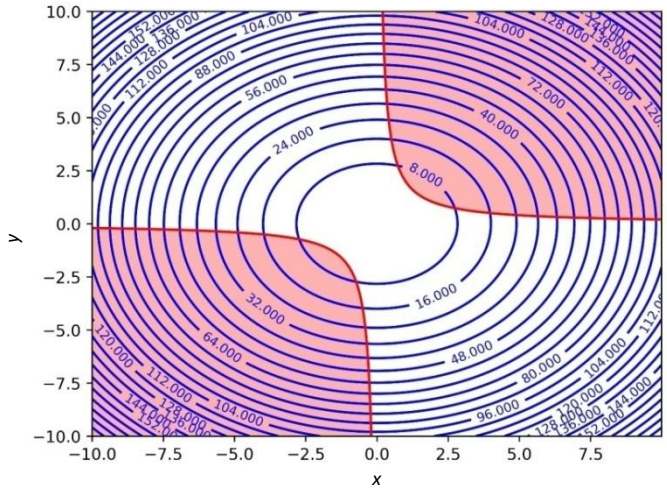


图 16-10　$f(x,y)=x^2+y^2$和$xy\leqslant 2$的图形

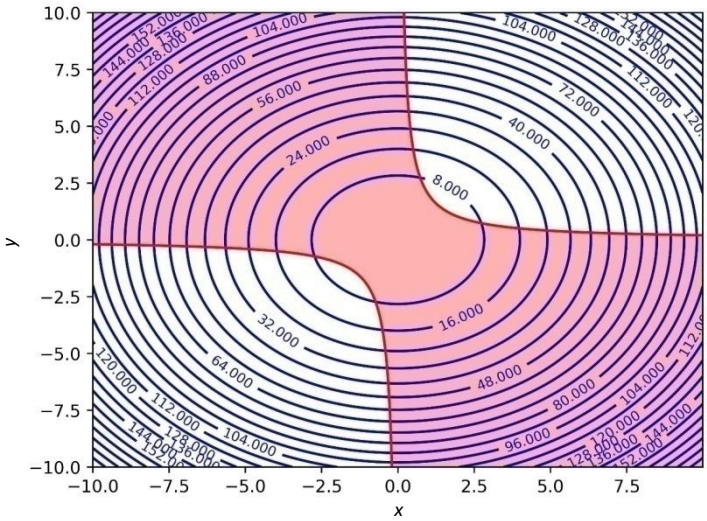


图 16-11　$f(x,y)=x^2+y^2$和$xy\geqslant 2$的图形

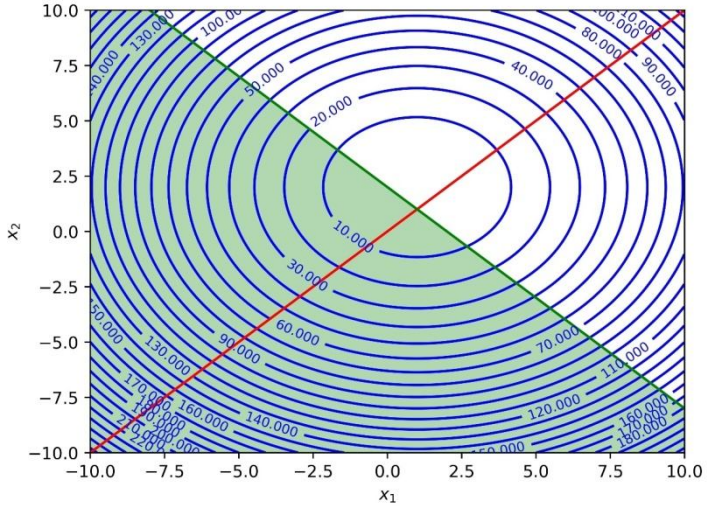
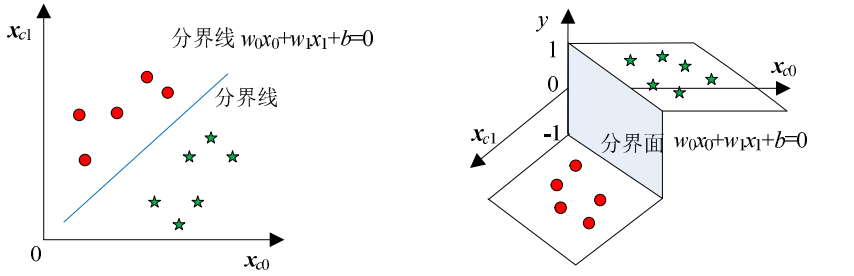


图 16-12　用拉格朗日乘数法和 KKT 应对更复杂的情况

训练数据集X	特征数据项x_{c0}	…	特征数据项$x_{c(n-1)}$	目标数据项Y
样本x_{r0}	x_{r0c0}	…	$x_{r0c(n-1)}$	y_0
…	…	…	…	…
样本$x_{r(m-1)}$	$x_{r(m-1)c0}$	…	$x_{r(m-1)c(n-1)}$	y_{m-1}

目标数据项Y的取值为{1,-1}

图 16-13　训练数据集



（a）二维空间里的感知机模型　　（b）有y的三维空间里的感知机模型

图 16-14　感知机模型的图示

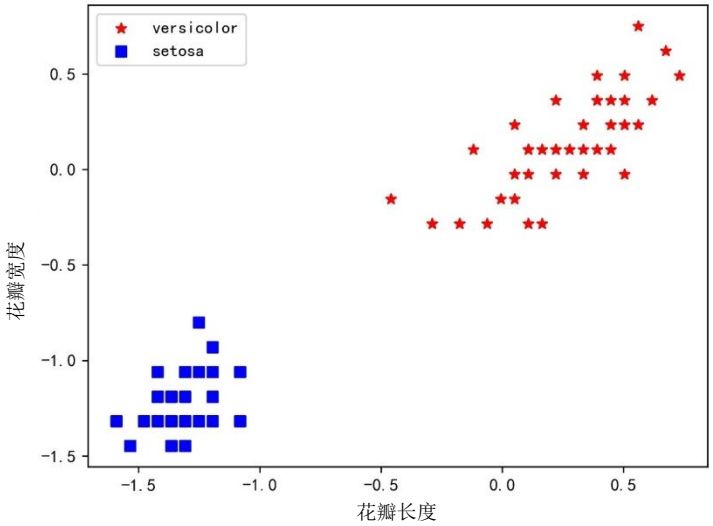


图 16-15　鸢尾花数据集中的 setosa 类型和 versicolor 类型

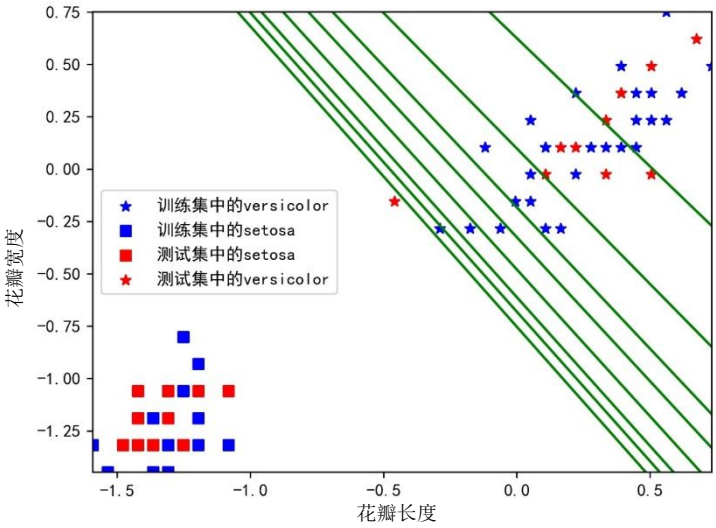


图 16-16　找到分类超平面的过程

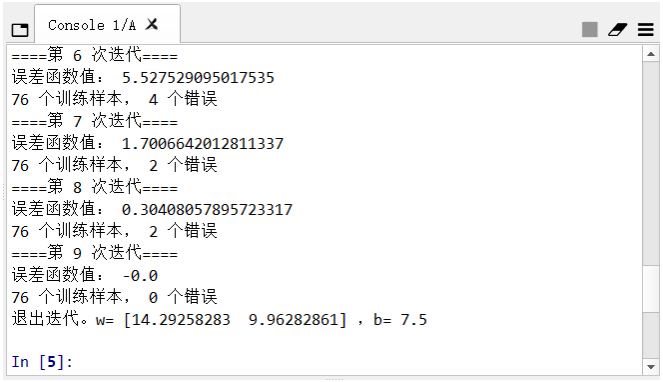


图 16-17　用感知机模型做鸢尾花分类的控制台输出

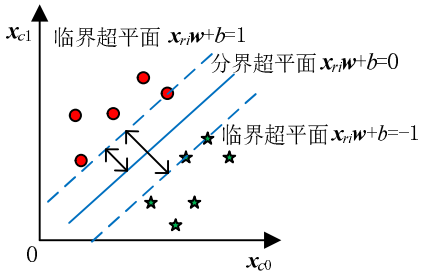


图 16-18　线性可分情况下的理想分界超平面

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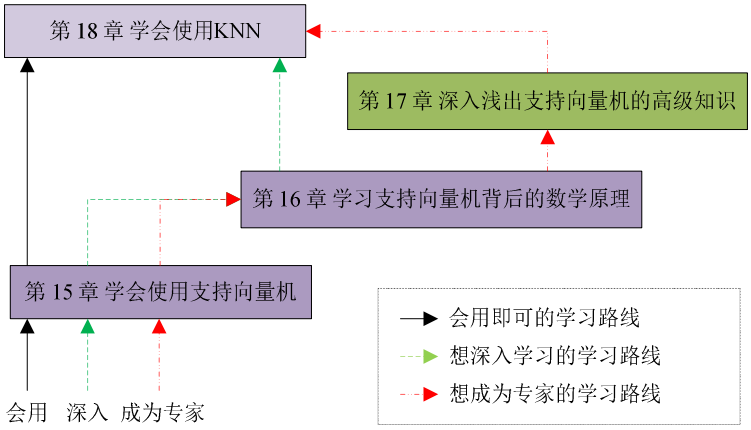


图 17-1　学习路线图

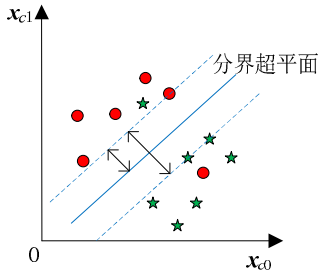


图 17-2　软间隔支持向量机

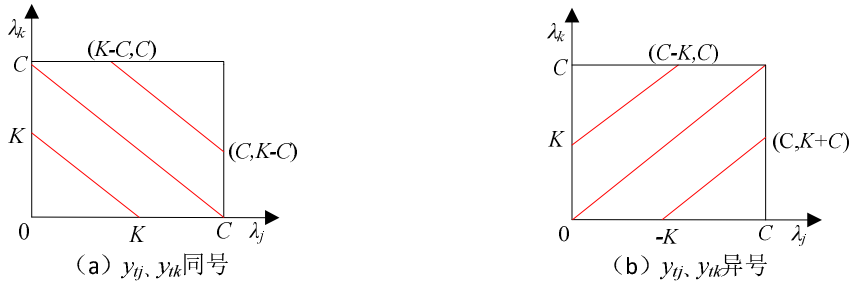


图 17-3　y_{tj}、y_{tk}同号和异号时的情况

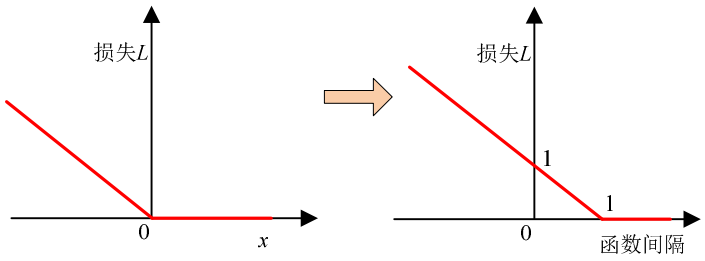


图 17-4　合页损失函数的图形

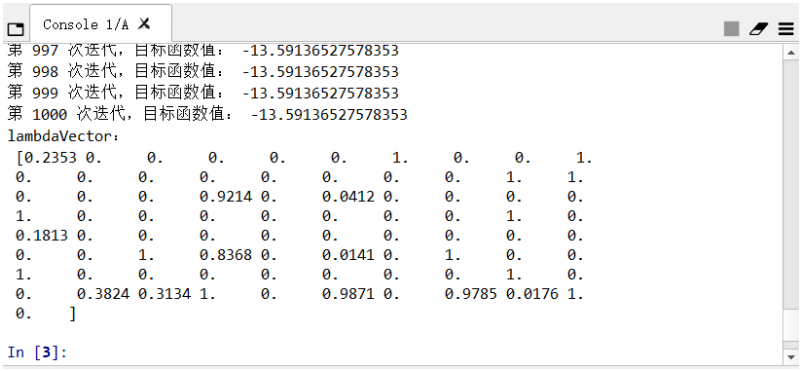


图 17-5　用 SMO 算法求解$\boldsymbol{\lambda}$

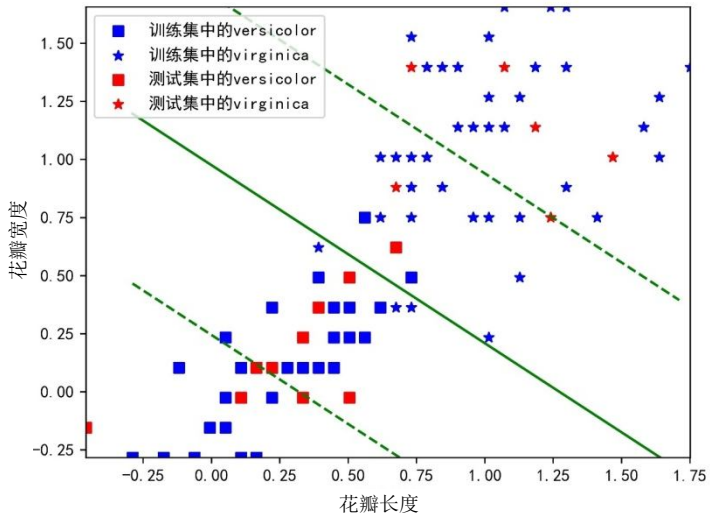


图 17-6　用软间隔支持向量机做二分类

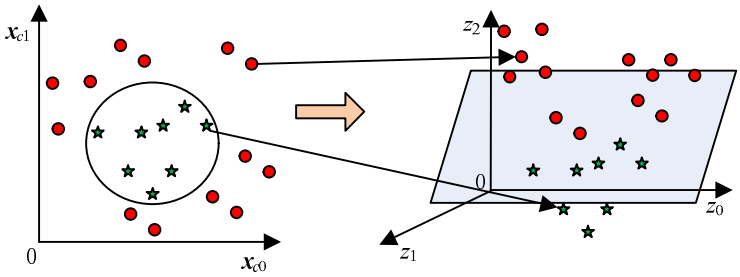
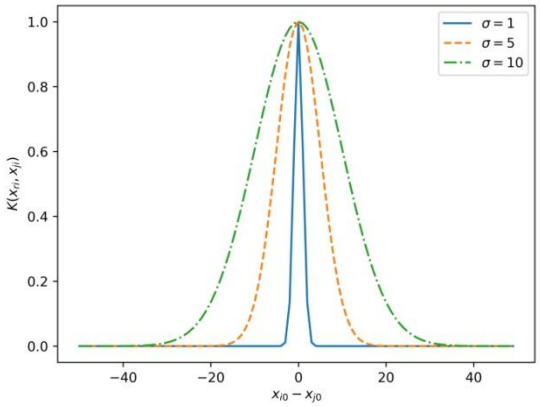
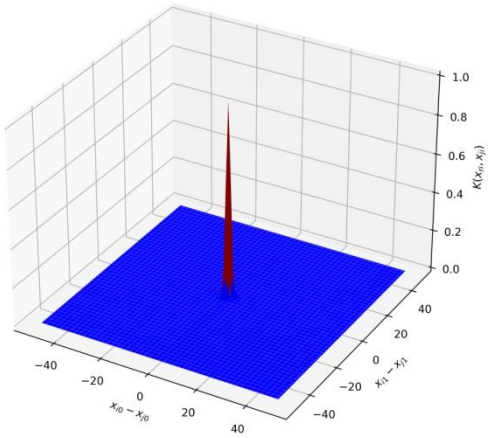


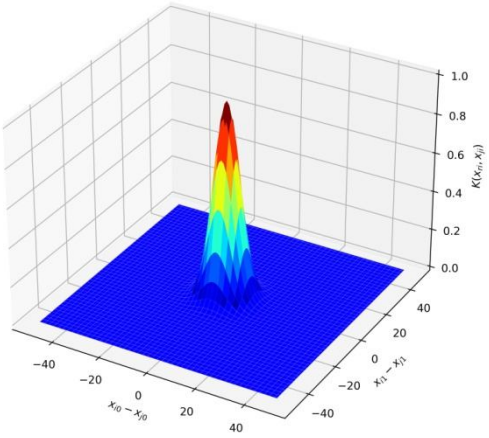
图 17-7　空间的映射



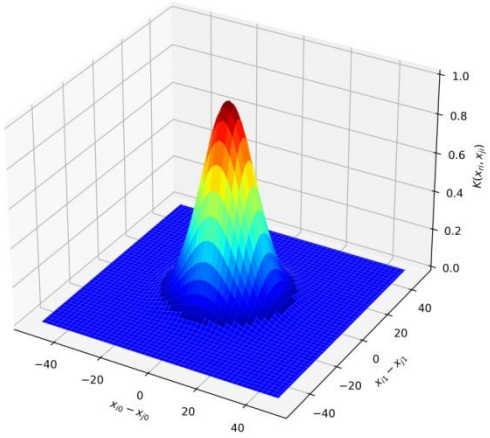
（a）向量只有一维



（b）向量有二维且$\sigma = 1$



（c）向量有二维且$\sigma = 5$



（d）向量有二维且$\sigma = 10$

图 17-8　高斯核函数的图形

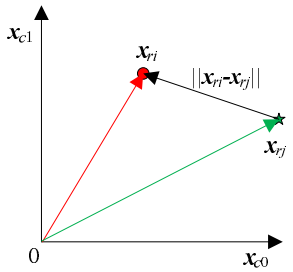
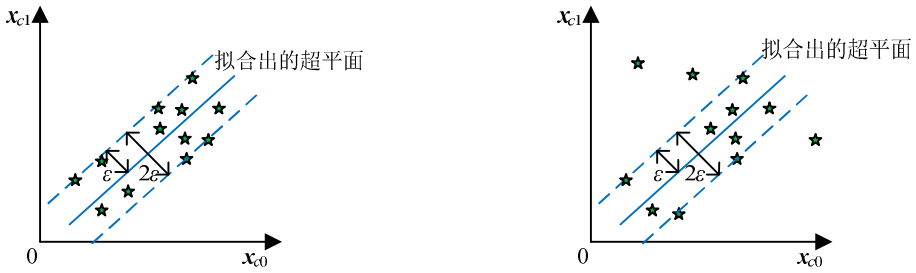


图 17-9　两个向量之间的距离



（a）硬间隔支持向量回归　　（b）软间隔支持向量回归

图 17-10　硬间隔支持向量回归

```
Console 1/A
最优的模型是：  SVC(C=17, gamma=10)
最好的成绩(准确度)是：  0.9666666666666666
最优的参数是：  {'C': 17, 'gamma': 10}
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        11
  versicolor       1.00      1.00      1.00        13
   virginica       1.00      1.00      1.00         6

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

图 17-11　找到的最理想的非线性支持向量机模型

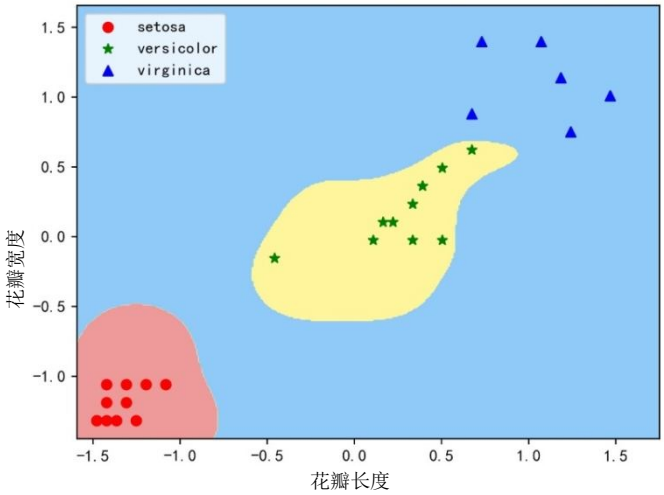


图 17-12　最理想的非线性支持向量机模型的分类效果

```
Console 1/A
最优的模型是：  SVR(epsilon=0.08, gamma=0.4)
最好的成绩(R2)是：  0.49934662516264616
最优的参数是：  {'epsilon': 0.08, 'gamma': 0.4}
找到的最理想的非线性支持向量回归模型对训练数据的R^2: 0.5304044254865699
找到的最理想的非线性支持向量回归模型对测试数据的R^2: 0.642795320639945
找到的最理想的非线性支持向量回归模型对训练数据的MSE: 39.823970611756145
找到的最理想的非线性支持向量回归模型对测试数据的MSE: 29.560402856974147

In [38]:
```

图 17-13　找到的最理想的非线性支持向量回归模型

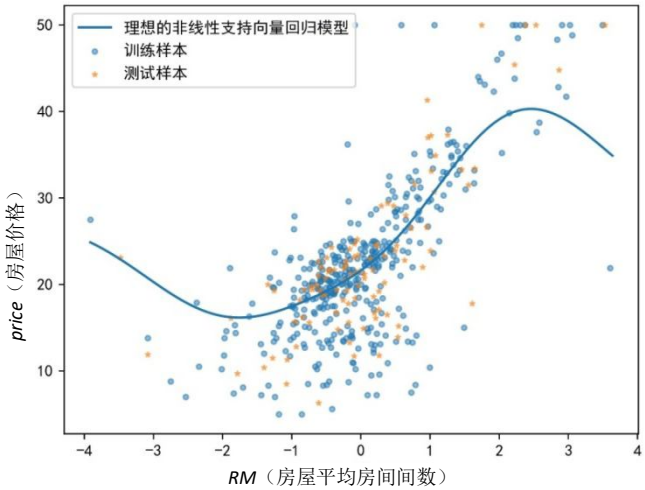


图 17-14　最理想的非线性支持向量回归模型的拟合效果

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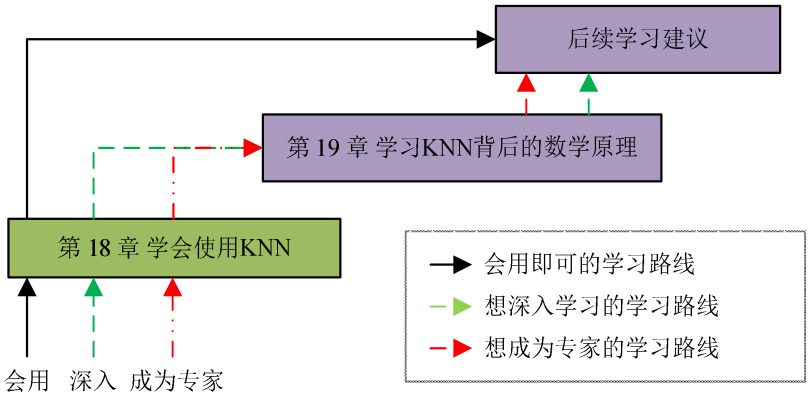
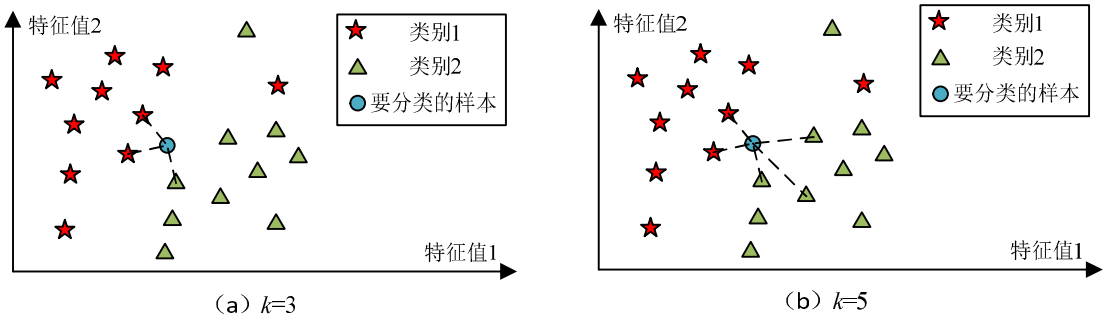


图 18-1　学习路线图



（a）k=3　　（b）k=5

图 18-2　KNN 的基本原理

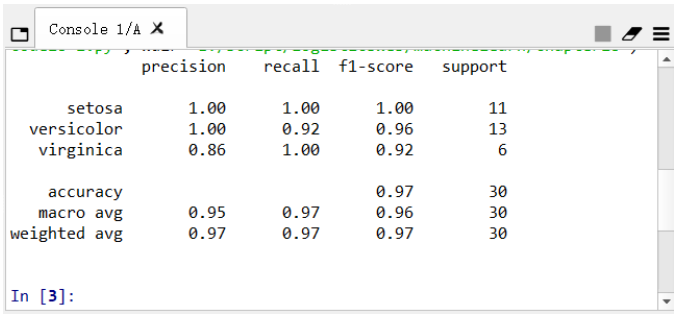


图 18-3　评价 KNN 模型做鸢尾花分类的效果

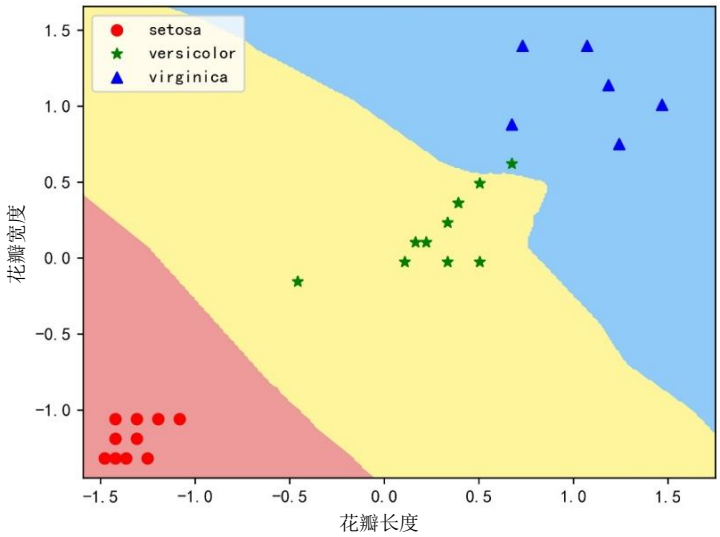


图 18-4　用 KNN 模型做鸢尾花分类的效果图示

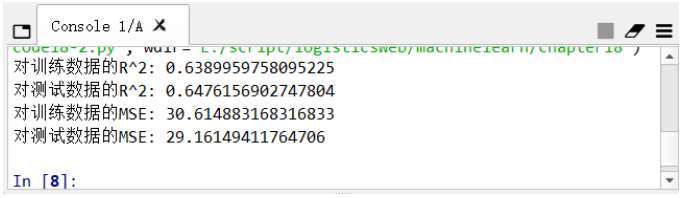


图 18-5　评价 KNN 模型做房屋价格回归的效果

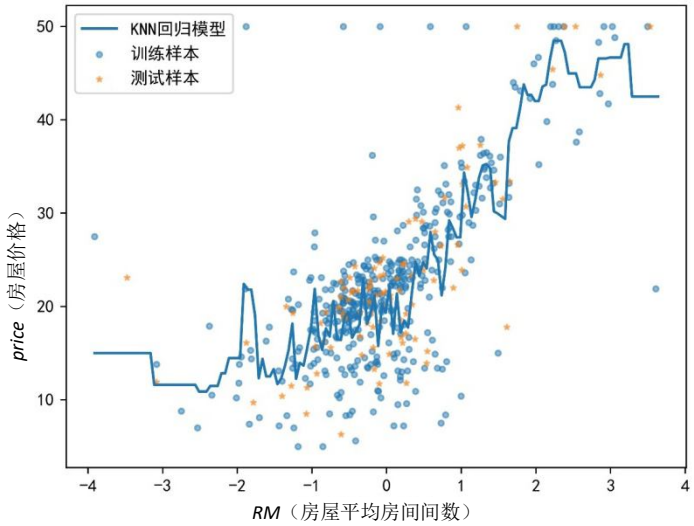


图 18-6　用 KNN 模型做房屋价格回归的效果图示

第 19 章

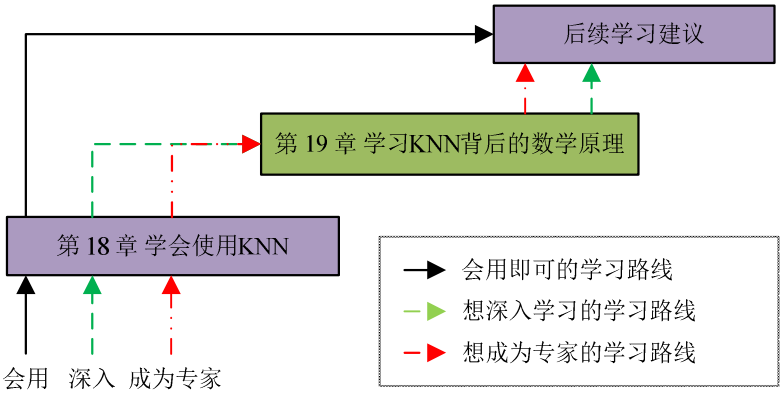


图 19-1　学习路线图

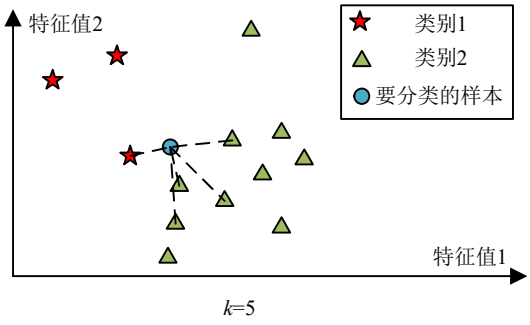


图 19-2　样本类型中的样本数量不均衡

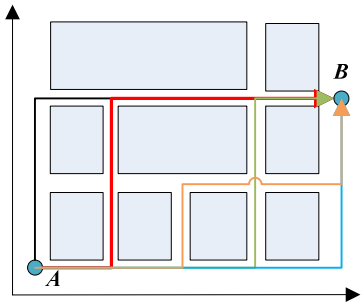


图 19-3　两点之间的曼哈顿距离

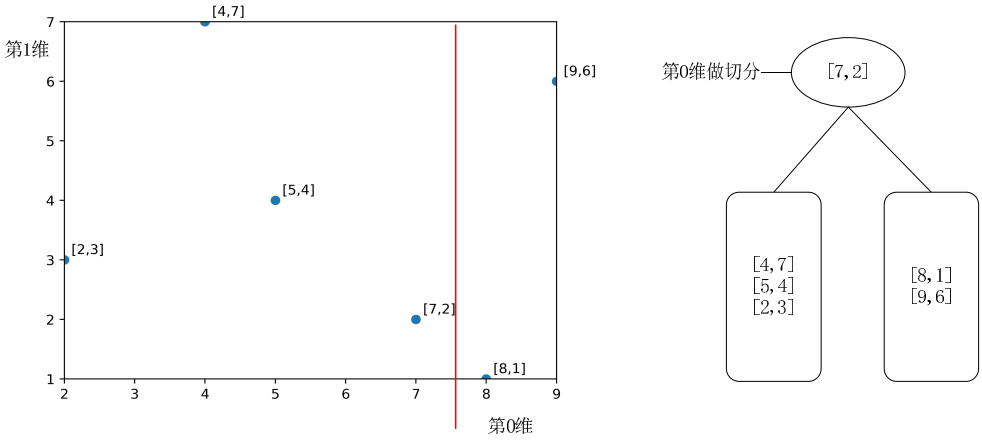


图 19-4　构建 KD 树的根

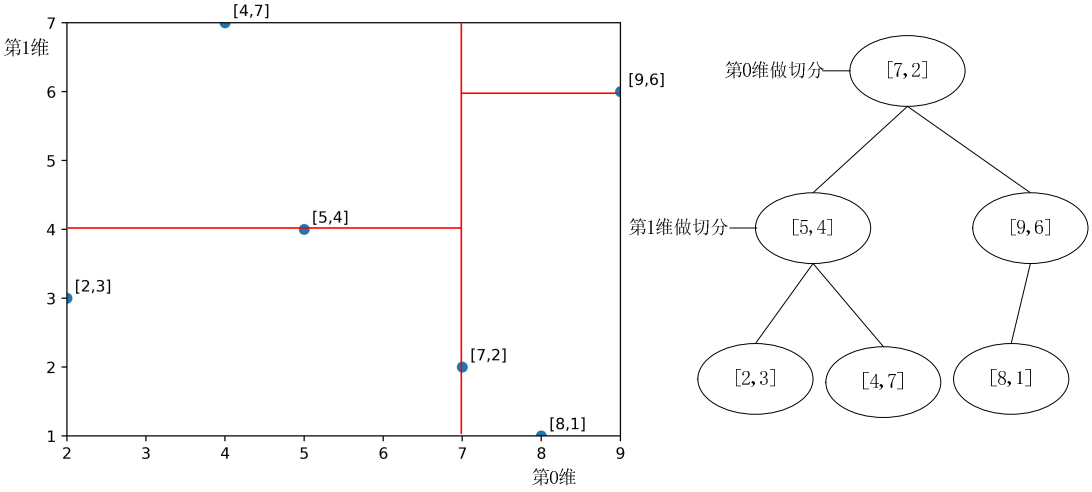


图 19-5　继续以第 1 维做切分

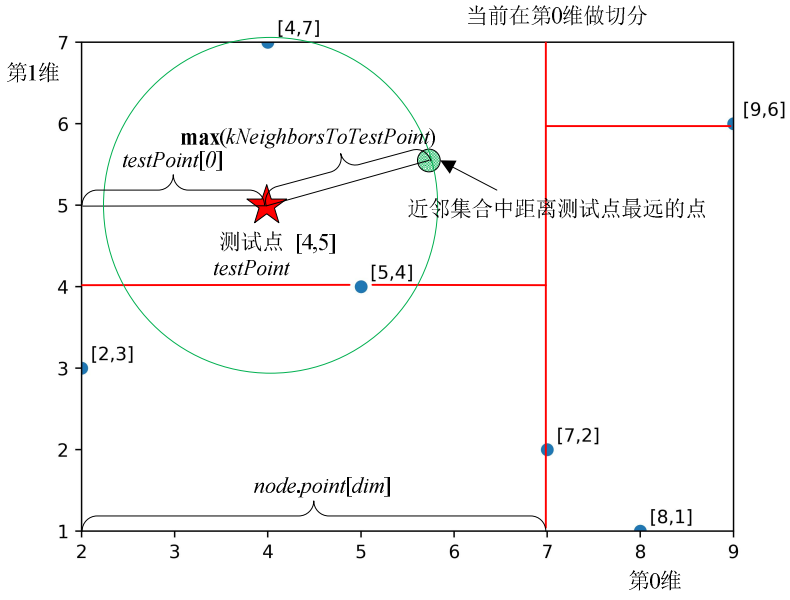


图 19-6　近邻点可能出现在比当前结点值更小的区间中

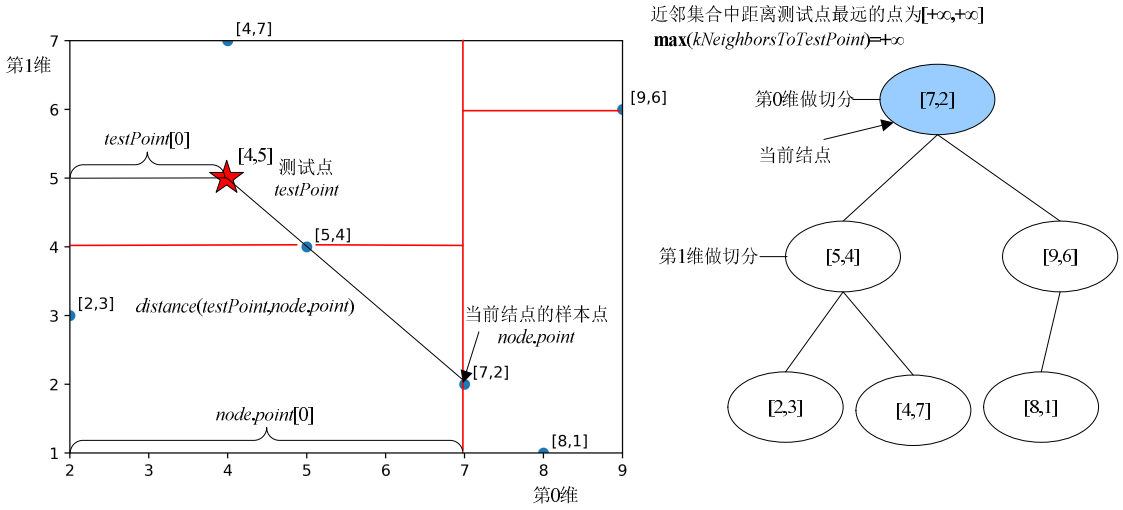


图 19-7　第 1 次调用算法 *findKNeighbors*(3, [4,5],*node*([7,2]),0)

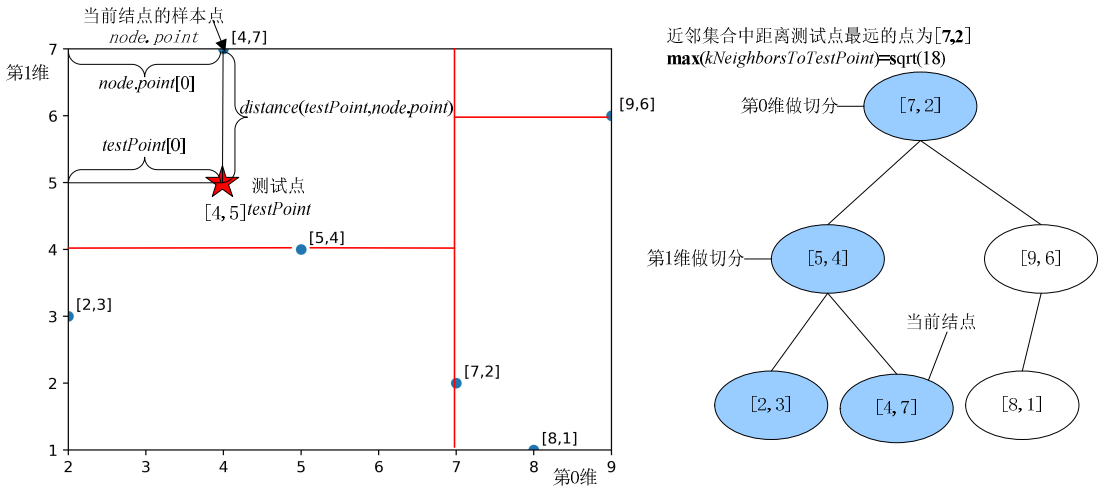


图 19-8　第 4 次调用算法 *findKNeighbors*(3, [4,5],*node*([4,7]),0)

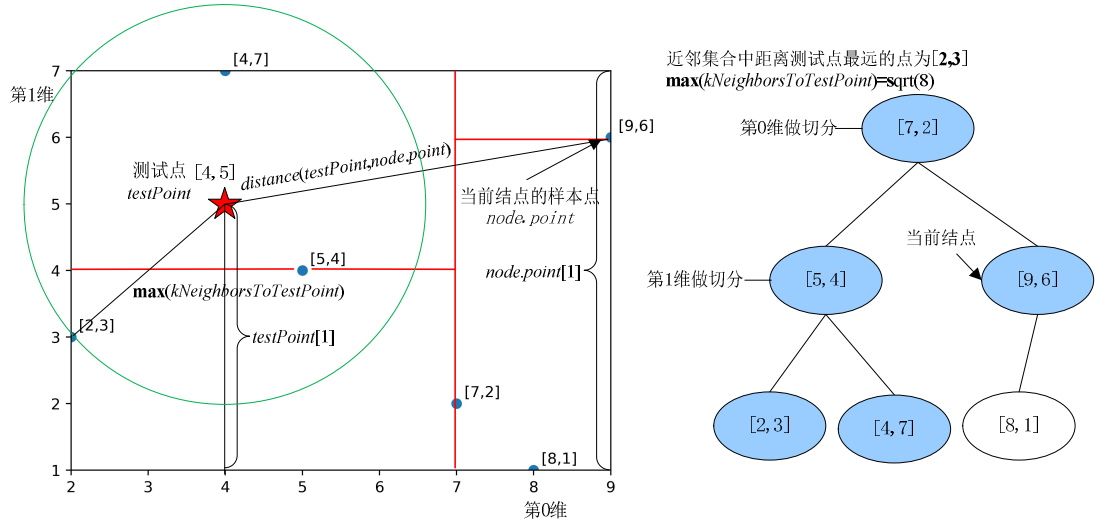


图 19-9　第 5 次调用算法 *findKNeighbors*(3, [4,5],*node*([9,6]),1)

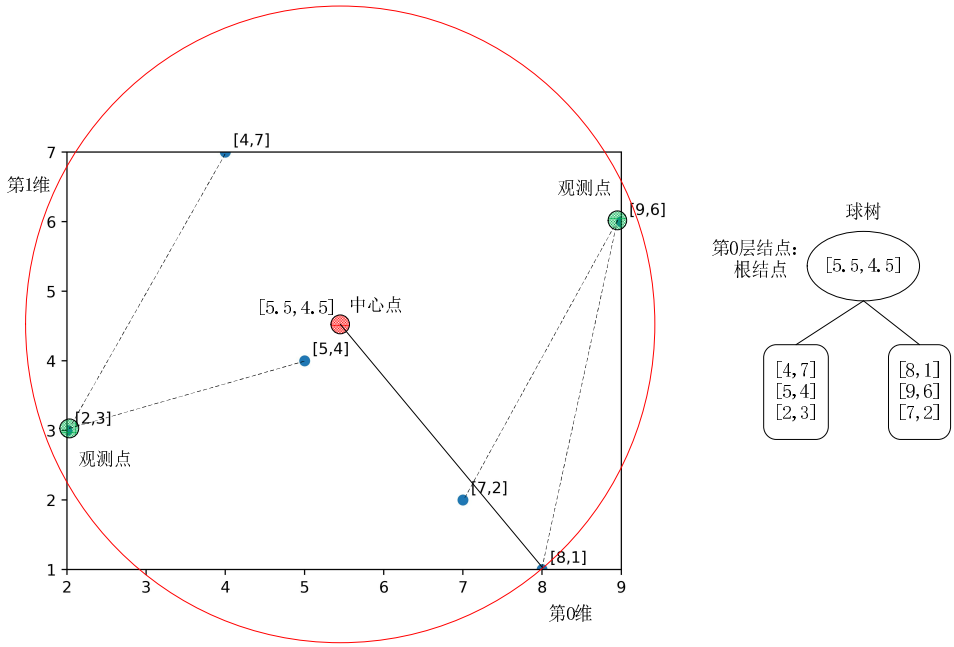


图 19-10　Ball 树的根结点及其超球体

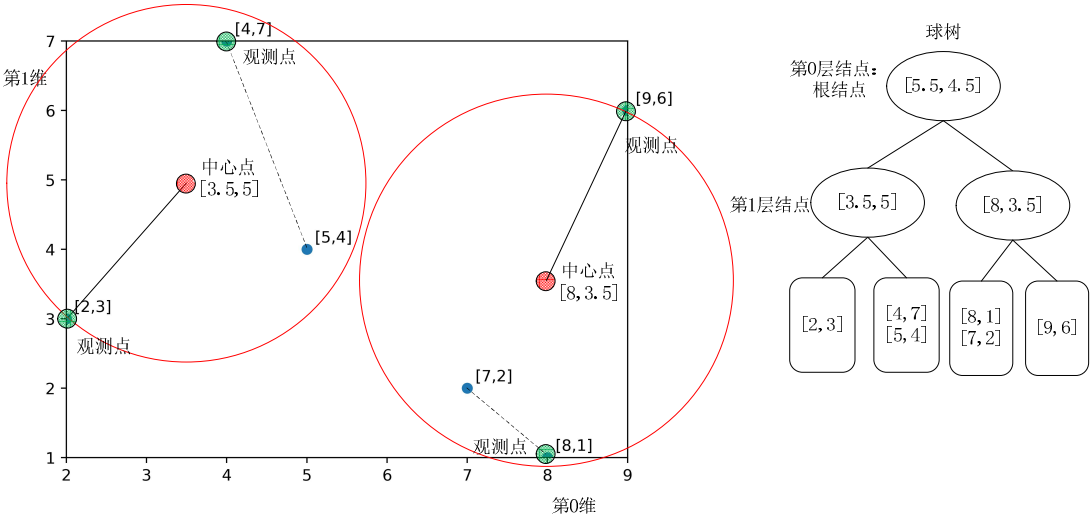


图 19-11　Ball 树的第 1 层结点及其超球体

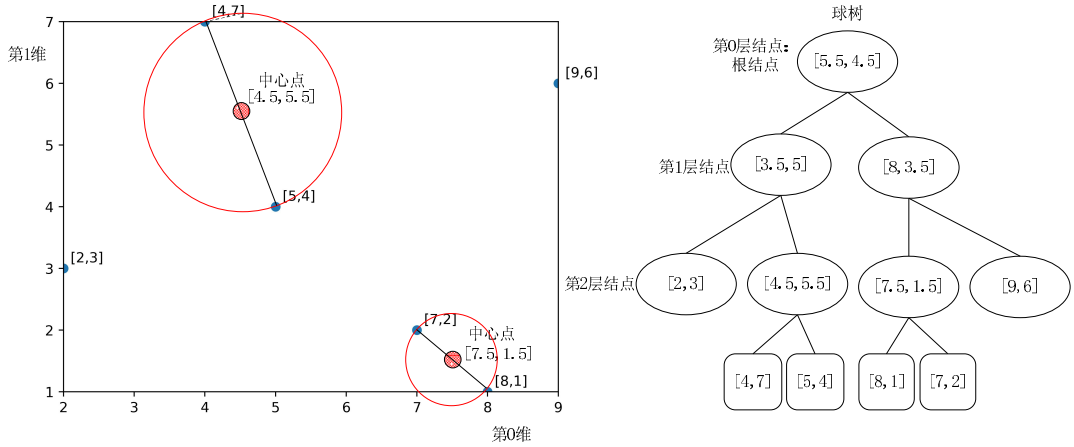


图 19-12　Ball 树的第 2 层结点及其超球体

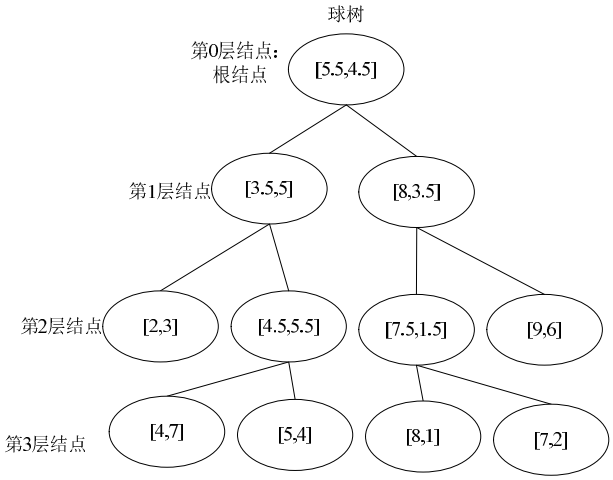
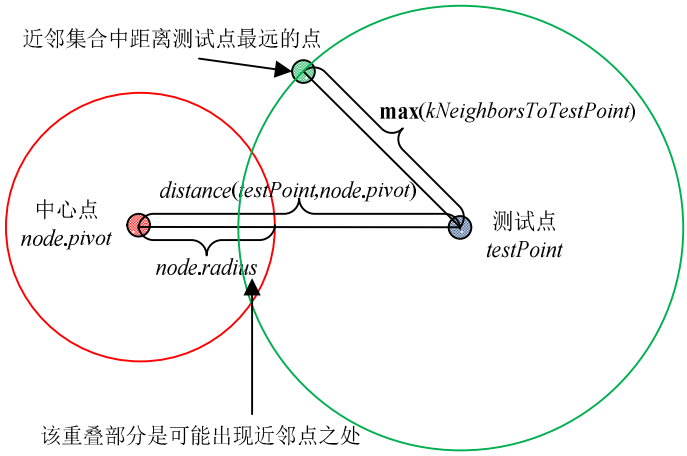
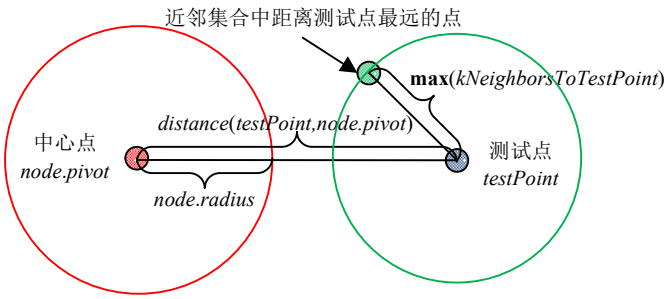


图 19-13　构造出的 Ball 树



（a）*distance*(*testPoint*,*node.pivot*)-*node.radius*<**max**(*kNeighborsToTestPoint*)



（b）*distance*(*testPoint*,*node.pivot*)-*node.radius*>=**max**(*kNeighborsToTestPoint*)

图 19-14　判断超球体中是否有近邻点的原理

```
Console 1/A
最优的模型是： KNeighborsClassifier(n_neighbors=1)
最好的成绩(准确度)是： 0.9666666666666666
最优的参数是： {'n_neighbors': 1, 'weights': 'uniform'}
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        11
  versicolor       1.00      1.00      1.00        13
   virginica       1.00      1.00      1.00         6

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

图 19-15　用 GridSearchCV 调节 KNN 分类模型的参数

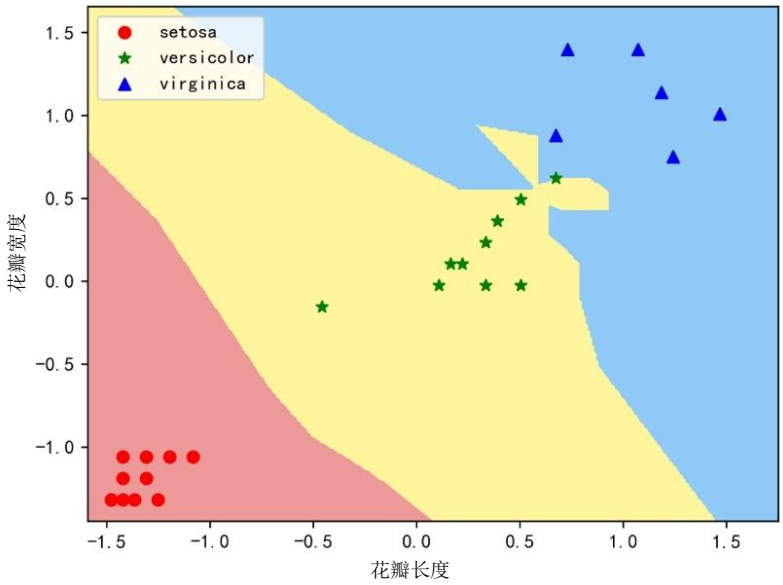


图 19-16　找到的最优 KNN 模型的分类效果

```
Console 1/A
最优的模型是： KNeighborsRegressor(n_neighbors=34)
最好的成绩(R^2)是： 0.5103225636032028
最优的参数是： {'n_neighbors': 34, 'weights': 'uniform'}
对训练数据的R^2: 0.5525148042728467
对测试数据的R^2: 0.6691521361896275
对训练数据的MSE: 37.948903803658915
对测试数据的MSE: 27.379249779496572
```

图 19-17　用 GridSearchCV 调节 KNN 回归模型的参数

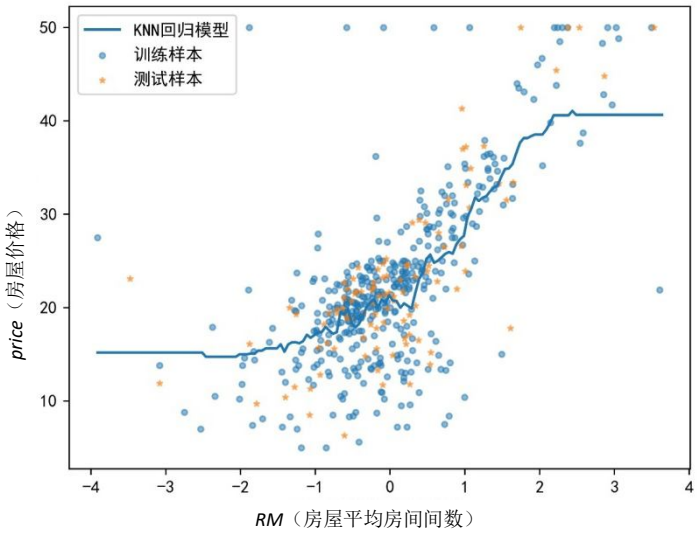
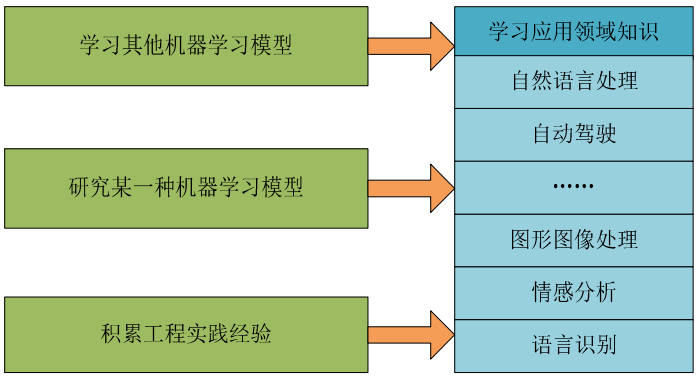


图 19-18　找到的最优 KNN 模型的回归效果


学习其他机器学习模型
研究某一种机器学习模型
积累工程实践经验
学习应用领域知识
自然语言处理
自动驾驶
……
图形图像处理
情感分析
语言识别

后续学习建议图