May 3, 2021

使用 sklearn 完成以下实验项目，实验项目所用数据集从思源学堂的实验中下载

[39]:
```
from sklearn.datasets import load_wine
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import fowlkes_mallows_score
from sklearn.metrics import silhouette_score
from sklearn.metrics import calinski_harabasz_score
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LinearRegression
from sklearn.metrics import explained_variance_score,␣
↪mean_absolute_error,mean_squared_error,median_absolute_error,r2_score
from sklearn.ensemble import GradientBoostingRegressor

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

scaler = MinMaxScaler()
svm = SVC()
clf = LinearRegression()
gbr = GradientBoostingRegressor()
```

实验项目 1

1）使用 sklearn 读取数据集 wine

[40]:
```
from sklearn.datasets import load_wine
wine = load_wine()
```

2）拆分数据集 wine 的数据和标签（class）

[41]:
```
wine_data = wine['data']
wine_target = wine['target']
print(wine_data, wine_target)
```

```
[[1.423e+01 1.710e+00 2.430e+00 … 1.040e+00 3.920e+00 1.065e+03]
 [1.320e+01 1.780e+00 2.140e+00 … 1.050e+00 3.400e+00 1.050e+03]
```

```
 [1.316e+01 2.360e+00 2.670e+00 … 1.030e+00 3.170e+00 1.185e+03]
 …
 [1.327e+01 4.280e+00 2.260e+00 … 5.900e-01 1.560e+00 8.350e+02]
 [1.317e+01 2.590e+00 2.370e+00 … 6.000e-01 1.620e+00 8.400e+02]
 [1.413e+01 4.100e+00 2.740e+00 … 6.100e-01 1.600e+00 5.600e+02]] [0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```

3）对数据集 wine 进行标准化

[42]:
```
wine_data = scaler.fit_transform(wine_data)
wine_data
```

[42]:
```
array([[0.84210526, 0.1916996 , 0.57219251, …, 0.45528455, 0.97069597,
        0.56134094],
       [0.57105263, 0.2055336 , 0.4171123 , …, 0.46341463, 0.78021978,
        0.55064194],
       [0.56052632, 0.3201581 , 0.70053476, …, 0.44715447, 0.6959707 ,
        0.64693295],
       …,
       [0.58947368, 0.69960474, 0.48128342, …, 0.08943089, 0.10622711,
        0.39728959],
       [0.56315789, 0.36561265, 0.54010695, …, 0.09756098, 0.12820513,
        0.40085592],
       [0.81578947, 0.66403162, 0.73796791, …, 0.10569106, 0.12087912,
        0.20114123]])
```

4）对数据集 wine 进行 PCA 降维

[43]:
```
wine_pca = PCA(n_components=10).fit_transform(wine_data)
print('before PCA:', wine_data.shape)
print('after PCA:', wine_pca.shape)
```

```
before PCA: (178, 13)
after PCA: (178, 10)
```

5）构建聚类数目为 3 的 K-Means 模型

[44]:
```
wine_kmeans = KMeans(n_clusters = 3).fit(wine_data)
wine_kmeans
```

[44]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

6）使用 FMI 评价聚类模型

[45]:
```
score = fowlkes_mallows_score(wine_target, wine_kmeans.labels_)
score
```

[45]: 0.8914327267284605

7）确定最佳聚类数目（2~10 类）

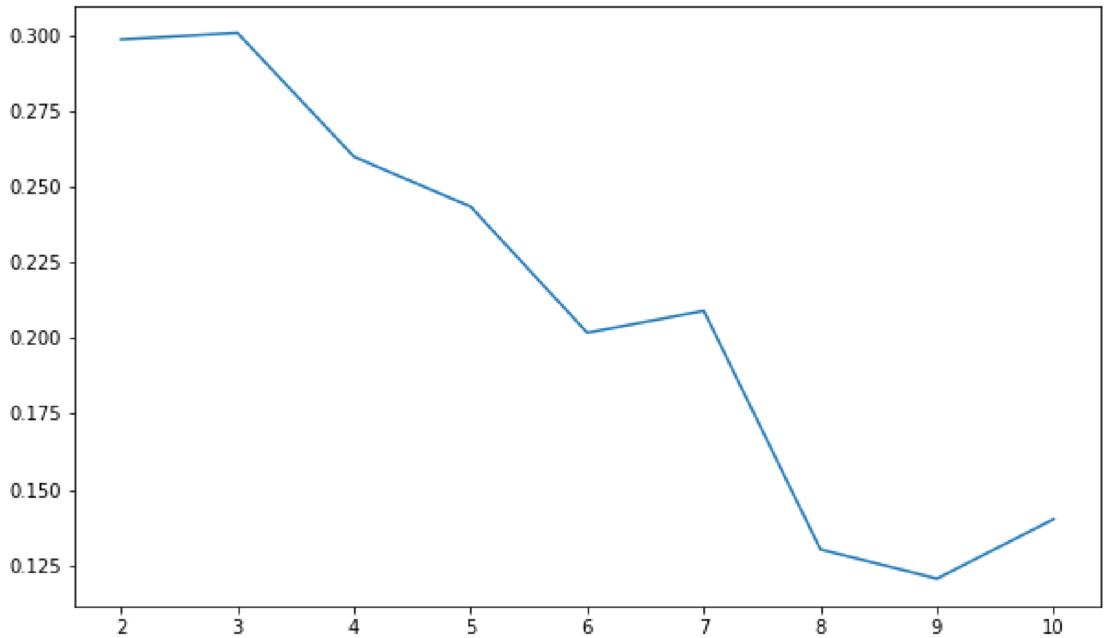
[46]:
```
for i in range(2,11):
    kmeans = KMeans(n_clusters = i).fit(wine_data)
    score = fowlkes_mallows_score(wine_target,kmeans.labels_)
    print('{}评价分值为: {}'.format(i, score))
```

```
2 评价分值为: 0.6428941723110392
3 评价分值为: 0.9026207781786737
4 评价分值为: 0.814628876858432
5 评价分值为: 0.7594489413791359
6 评价分值为: 0.7144734035621569
7 评价分值为: 0.7436519237861382
8 评价分值为: 0.5825510050786507
9 评价分值为: 0.6790142214965376
10 评价分值为: 0.5194805742858095
```

因此最佳数目为 3

8）使用轮廓系数评价聚类模型

[47]:
```
silhouettteScore = []
for i in range(2,11):
    kmeans = KMeans(n_clusters = i).fit(wine_data)
    score = silhouette_score(wine_data,kmeans.labels_)
    silhouettteScore.append(score)
plt.figure(figsize=(10,6))
plt.plot(range(2,11),silhouettteScore,linewidth=1.5, linestyle="-")
plt.show()
```



9）使用 Calinski-Harabasz 指数评价聚类模型

[48]:
```
for i in range(2,11):
    kmeans = KMeans(n_clusters = i).fit(wine_data)
    score = calinski_harabasz_score(wine_data,kmeans.labels_)
    print('聚{}类 calinski_harabaz 指数为: {}'.format(i, score))
```

```
聚 2 类 calinski_harabaz 指数为: 84.7085044440733
聚 3 类 calinski_harabaz 指数为: 83.37374750844354
聚 4 类 calinski_harabaz 指数为: 65.6072858687198
聚 5 类 calinski_harabaz 指数为: 54.86980191194707
聚 6 类 calinski_harabaz 指数为: 47.47436301767781
聚 7 类 calinski_harabaz 指数为: 43.327230206209855
聚 8 类 calinski_harabaz 指数为: 39.89936971821639
聚 9 类 calinski_harabaz 指数为: 37.74944751126178
聚 10 类 calinski_harabaz 指数为: 34.68847492267841
```

因此最佳数目为 3

实验项目 2

1）使用 sklearn 读取数据集 wine

2）拆分数据集 wine 的数据和标签（class）

3）将数据集 wine 划分为训练集和测试集

[49]:
```
wine_data_train,wine_data_test,wine_target_train,wine_target_test=train_test_split(wine_data,w
↪2)
```

```
print(wine_data_train.shape, wine_target_train.shape)
print(wine_data_test.shape, wine_target_test.shape)
```

```
(142, 13) (142,)
(36, 13) (36,)
```

4）使用离差标准化标准化数据集

[50]:
```
wine_scaler = scaler.fit(wine_data_train)
wine_data_train = wine_scaler.transform(wine_data_train)
wine_data_test = wine_scaler.transform(wine_data_test)
```

5）构建 SVM 模型

[51]:
```
wine_svm = svm.fit(wine_data_train, wine_target_train)
wine_svm
```

[51]:
```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

6）给出评价分类模型性能的分类报告

[52]:
```
pred = wine_svm.predict(wine_data_test)
print(pred)
print(wine_target_test)
pred_true = np.sum(pred == wine_target_test)
print('预测准确率为:', pred_true/wine_target_test.shape[0])
```

```
[0 1 2 1 1 1 0 0 2 2 1 2 1 0 2 1 0 1 2 1 1 2 2 0 2 1 0 2 0 2 2 1 0 1 0 1]
[0 1 2 1 1 1 0 0 2 2 1 2 1 0 2 1 0 1 2 1 1 2 2 0 2 2 0 2 0 2 2 1 0 1 0 1]
预测准确率为: 0.9722222222222222
```

实验项目 3

1）使用 sklearn 读取数据集 winequality

[53]:
```
wineq = pd.read_csv('./work/winequality.csv', delimiter=';')
wineq.head()
```

[53]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
```

```
1                   25.0                       67.0   0.9968  3.20        0.68
2                   15.0                       54.0   0.9970  3.26        0.65
3                   17.0                       60.0   0.9980  3.16        0.58
4                   11.0                       34.0   0.9978  3.51        0.56

   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

2）拆分数据集 winequality 的数据和标签（quality）

[54]:
```
wineq_data = wineq.iloc[:, :-1]
wineq_data
```

[54]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076
1               7.8             0.880         0.00             2.6      0.098
2               7.8             0.760         0.04             2.3      0.092
3              11.2             0.280         0.56             1.9      0.075
4               7.4             0.700         0.00             1.9      0.076
…                …                 …           …               …          …
1594            6.2             0.600         0.08             2.0      0.090
1595            5.9             0.550         0.10             2.2      0.062
1596            6.3             0.510         0.13             2.3      0.076
1597            5.9             0.645         0.12             2.0      0.075
1598            6.0             0.310         0.47             3.6      0.067

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                      …                    …      …      …          …
1594                 32.0                  44.0  0.99490  3.45       0.58
1595                 39.0                  51.0  0.99512  3.52       0.76
1596                 29.0                  40.0  0.99574  3.42       0.75
1597                 32.0                  44.0  0.99547  3.57       0.71
1598                 18.0                  42.0  0.99549  3.39       0.66

      alcohol
0         9.4
1         9.8
2         9.8
```

```
3         9.8
4         9.4
…        …
1594     10.5
1595     11.2
1596     11.0
1597     10.2
1598     11.0

[1599 rows x 11 columns]
```

[55]:
```
wineq_target = wineq.iloc[:, -1]
wineq_target
```

[55]:
```
0       5
1       5
2       5
3       6
4       5
       ..
1594    5
1595    6
1596    6
1597    5
1598    6
Name: quality, Length: 1599, dtype: int64
```

3) 将数据集 winequality 划分为训练集和测试集

[56]:
```
wineq_data_train,wineq_data_test,wineq_target_train,wineq_target_test =␣
↪train_test_split(wineq_data,wineq_target,test_size = 0.2)
```

4) 构建线性回归模型

[57]:
```
wineq_clf = clf.fit(wineq_data_train, wineq_target_train)
wineq_clf_pred = wineq_clf.predict(wineq_data_test)
```

5) 计算线性回归模型的平均绝对误差、均方误差、中值绝对误差、可解释方差和 R^2

[58]:
```
print('线性回归模型的平均绝对误差为：',mean_absolute_error(wineq_target_test,␣
↪wineq_clf_pred))
print('线性回归模型的均方误差为：',mean_squared_error(wineq_target_test,␣
↪wineq_clf_pred))
print('线性回归模型的中值绝对误差为：',median_absolute_error(wineq_target_test,␣
↪wineq_clf_pred))
print('线性回归模型的可解释方差值为：
',explained_variance_score(wineq_target_test, wineq_clf_pred))
print('线性回归模型的 R 方值为：',r2_score(wineq_target_test, wineq_clf_pred))
```

线性回归模型的平均绝对误差为： 0.5285013191278756
线性回归模型的均方误差为： 0.47854963955561286
线性回归模型的中值绝对误差为： 0.4058838482394336
线性回归模型的可解释方差值为： 0.3257707164209458
线性回归模型的 R 方值为： 0.32538329147572576

6) 构建梯度提升回归模型

[59]:
```
wineq_gbr = gbr.fit(wineq_data_train, wineq_target_train)
wineq_gbr_pred = wineq_gbr.predict(wineq_data_test)
```

7）计算梯度提升回归模型的平均绝对误差、均方误差、中值绝对误差、可解释方差和 R^2

[60]:
```
print('梯度提升回归模型的平均绝对误差为：',mean_absolute_error(wineq_target_test,␣
↪wineq_gbr_pred))
print('梯度提升回归模型的均方误差为：',mean_squared_error(wineq_target_test,␣
↪wineq_gbr_pred))
print('梯度提升回归模型的中值绝对误差为：
',median_absolute_error(wineq_target_test, wineq_gbr_pred))
print('梯度提升回归模型的可解释方差值为：
',explained_variance_score(wineq_target_test, wineq_gbr_pred))
print('梯度提升回归模型的 R 方值为：',r2_score(wineq_target_test,␣
↪wineq_gbr_pred))
```

梯度提升回归模型的平均绝对误差为： 0.5042051809687346
梯度提升回归模型的均方误差为： 0.44546257925492155
梯度提升回归模型的中值绝对误差为： 0.38486626423760395
梯度提升回归模型的可解释方差值为： 0.3724670013117275
梯度提升回归模型的 R 方值为： 0.3720264855559139