```
1 波士顿房价预测
In [4]:
            from sklearn.datasets import load_boston
           from sklearn.model selection import cross val score
            from sklearn.tree import DecisionTreeRegressor
In [5]:
            boston = load_boston()
In [6]:
           boston
         {'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+02,
                 4.9800e+00],
                 [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
                 9.1400e+00],
                 [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
                 4.0300e+00],
                 [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                 5.6400e+00],
                 [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
                 6.4800e+00],
                 [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                 7.8800e+00]]),
          'target': array([24., 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15.,
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          'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
                 'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
          'DESCR': ".. boston dataset:\n\nBoston house prices dataset\n-----\n\n**Data Set Characteristics:** \n\n
         ber of Instances: 506 \n\n :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually the targe
                  :Attribute Information (in order):\n
                                                                        per capita crime rate by town\n
                                                                                                                          proportion of resident
                                                              - CRIM

    ZN

         ial land zoned for lots over 25,000 sq.ft.\n
                                                                       proportion of non-retail business acres per town\n
                                                                                                                                - CHAS
                                                            - INDUS
                                                                                                                                           Charl
         es River dummy variable (= 1 if tract bounds river; 0 otherwise)\n
                                                                                 - NOX
                                                                                            nitric oxides concentration (parts per 10 million)\n
                    average number of rooms per dwelling\n
                                                                 - AGE
                                                                            proportion of owner-occupied units built prior to 1940\n
         weighted distances to five Boston employment centres\n
                                                                      - RAD
                                                                                 index of accessibility to radial highways\n
                                                                                                                                             fu
         ll-value property-tax rate per $10,000\n
                                                        - PTRATIO pupil-teacher ratio by town\n
                                                                                                       - B
                                                                                                                  1000(Bk - 0.63)<sup>2</sup> where Bk is
         the proportion of blacks by town\n
                                                  - LSTAT
                                                            % lower status of the population\n
                                                                                                      MEDV
                                                                                                                 Median value of owner-occupied
                                :Missing Attribute Values: None\n\n :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML hou
         homes in $1000's\n\n
         sing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-databases/housing/\n\nThis dataset was taken from the StatLib library wh
         ich is maintained at Carnegie Mellon University.\n\nThe Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\nprices and
         the demand for clean air', J. Environ. Economics & Management,\nvol.5, 81-102, 1978. Used in Belsley, Kuh & Welsch, 'Regression diagnos
         tics\n...', Wiley, 1980. N.B. Various transformations are used in the table on\npages 244-261 of the latter.\n\nThe Boston house-price
         data has been used in many machine learning papers that address regression\nproblems. \n \n.. topic:: References\n\n - Belsley, K
         uh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 1980. 244-261.\n - Quinlan,R.
         (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Learning, 236-
         243, University of Massachusetts, Amherst. Morgan Kaufmann.\n",
          'filename': 'E:\\Anaconda3\\lib\\site-packages\\sklearn\\datasets\\data\\boston_house_prices.csv'}
```

localhost:8888/notebooks/Sklearn/1.决策树/HuiGuiTree.ipynb#

```
In [7]:
            boston.data
         array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+02,
                 4.9800e+00],
                [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
                 9.1400e+00],
                [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
                4.0300e+00],
                . . . ,
                [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                 5.6400e+00],
                [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
                 6.4800e+00],
                [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                 7.8800e+00]])
In [8]:
            boston.target
         array([24., 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15.,
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                23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9])
In [15]:
            regressor = DecisionTreeRegressor(random_state=0) #实例化
            # 传入完整数据,自动划分和循环
            # 默认返回R平方,越接近1越好,有正有负
            cross_val_score(regressor, boston.data, boston.target, cv=10)
         array([ 0.48141081, 0.60461936, -1.32633384, 0.54154398, 0.75705408,
                 0.33934083, 0.18757206, 0.40679147, -1.9602183, -0.32967889])
In [14]:
            # 使用负均方误差,去掉负号就是均方误差
            cross_val_score(regressor, boston.data, boston.target, cv=10,scoring = "neg_mean_squared_error")
         array([-18.08941176, -10.61843137, -16.31843137, -44.97803922,
                -17.12509804, -49.71509804, -12.9986 , -88.4514
                          , -25.0816 ])
                -55.7914
In [17]:
            # 求个平均
            cross_val_score(regressor, boston.data, boston.target, cv=10,scoring = "neg_mean_squared_error").mean()
          -33.91675098039215
In [ ]:
```