ML3

May 23, 2022

[1]:
```
# Apply  K-Means  Clustering  technique  of  machine  learning  to  analyze ␣
↪the  Bostan  dataset. Use Elbow method to find best value of K.
```

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets import load_boston
```

[4]:
```
boston = load_boston()
boston
```

[4]:
```
{'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],
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 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9,
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        15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
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```

```
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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
:Number of Instances: 506 \n\n    :Number of Attributes: 13 numeric/categorical
predictive. Median Value (attribute 14) is usually the target.\n\n    :Attribute
Information (in order):\n        - CRIM     per capita crime rate by town\n
- ZN       proportion of residential land zoned for lots over 25,000 sq.ft.\n
- INDUS    proportion of non-retail business acres per town\n        - CHAS
Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)\n        -
NOX      nitric oxides concentration (parts per 10 million)\n        - RM
```

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average number of rooms per dwelling\n        - AGE      proportion of owner-
occupied units built prior to 1940\n        - DIS      weighted distances to
five Boston employment centres\n        - RAD      index of accessibility to
radial highways\n        - TAX      full-value property-tax rate per $10,000\n
- PTRATIO  pupil-teacher ratio by town\n        - B        1000(Bk - 0.63)^2
where Bk is the proportion of black people by town\n        - LSTAT    % lower
status of the population\n        - MEDV     Median value of owner-occupied
homes in $1000's\n\n    :Missing Attribute Values: None\n\n    :Creator:
Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing
dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-
databases/housing/\n\n\nThis dataset was taken from the StatLib library which 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 diagnostics\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,
Kuh & 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': 'c:\\Anaconda3\\lib\\site-
packages\\sklearn\\datasets\\data\\boston_house_prices.csv'}
```

[5]:
```python
x = boston.data
y = boston.target
```

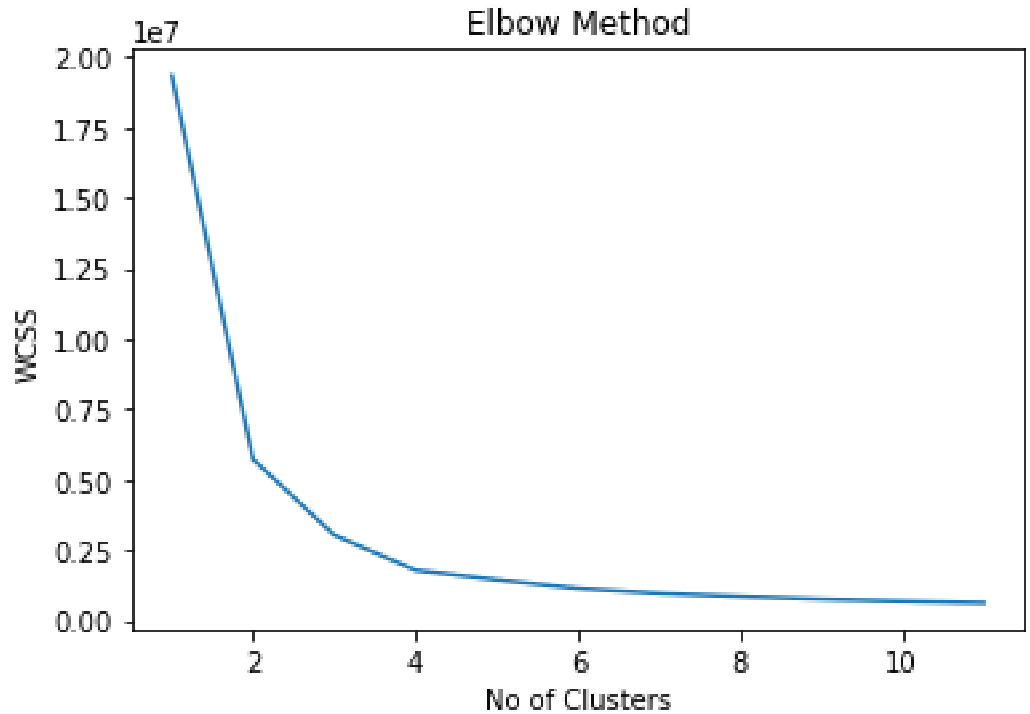
[6]:
```python
# Using Elbow Method

wcss = []
for i in range(1,12):
    kmeans = KMeans(n_clusters=i, init='k-means++',n_init=10,random_state=0)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

plt.figure()
plt.title('Elbow Method')
plt.xlabel('No of Clusters')
plt.ylabel('WCSS')
plt.plot(range(1,12),wcss)
plt.show()
```

```
c:\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: UserWarning:
KMeans is known to have a memory leak on Windows with MKL, when there are less
chunks than available threads. You can avoid it by setting the environment
variable OMP_NUM_THREADS=2.
```

```
warnings.warn(
```



[7]:
```python
kmeans = KMeans(n_clusters=4, init='k-means++',n_init=10,random_state=0)
kmeans.fit(x)
```

[7]:
```
KMeans(n_clusters=4, random_state=0)
```

[8]:
```python
kmeans.labels_
```

[8]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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```

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```

[9]:
```
kmeans.cluster_centers_
```

[9]:
```
array([[ 2.41047910e-01,  1.78171642e+01,  6.66858209e+00,
         7.46268657e-02,  4.83398134e-01,  6.46544776e+00,
         5.57052239e+01,  4.87356007e+00,  4.31343284e+00,
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         9.53802239e+00],
       [ 1.09105113e+01,  5.32907052e-15,  1.85725490e+01,
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         6.68205882e+02,  2.01950980e+01,  3.71803039e+02,
         1.78740196e+01],
       [ 1.52190382e+01, -3.55271368e-15,  1.79268421e+01,
         2.63157895e-02,  6.73710526e-01,  6.06550000e+00,
         8.99052632e+01,  1.99442895e+00,  2.25000000e+01,
         6.44736842e+02,  1.99289474e+01,  5.77863158e+01,
         2.04486842e+01],
       [ 7.41290612e-01,  9.94897959e+00,  1.29837755e+01,
         6.12244898e-02,  5.82234694e-01,  6.18984694e+00,
         7.32887755e+01,  3.33182143e+00,  4.82653061e+00,
         4.06081633e+02,  1.76663265e+01,  3.71664286e+02,
         1.27148980e+01]])
```