تکلیف سری دوم داده کاوی

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.1

1.1

دیتاست Breast Cancer را loadکرده و متد Desc را بر روی این دیتاست اجرا کرده ام که جزئیات مربوط به این دیتاست را نشان می‌دهد که در شکل زیر آمده است.

```
from sklearn.datasets import load_breast_cancer
BreastCancer = load_breast_cancer()
x=BreastCancer.DESCR
print (x)
```

```
Breast Cancer Wisconsin (Diagnostic) Database
=============================================

Notes
-----
Data Set Characteristics:
    :Number of Instances: 569

    :Number of Attributes: 30 numeric, predictive attributes and the class

    :Attribute Information:
        - radius (mean of distances from center to points on the perimeter)
        - texture (standard deviation of gray-scale values)
        - perimeter
        - area
        - smoothness (local variation in radius lengths)
        - compactness (perimeter^2 / area - 1.0)
        - concavity (severity of concave portions of the contour)
        - concave points (number of concave portions of the contour)
```

1.2

اطلاعات بدست آمده با استفاده از feature_names (نام فیچرها) و Data (اطلاعات مربوط به دیتا) و key (کلیدهای دیتاست) در شکل زیر آورده شده اند.

```
x=BreastCancer.feature_names
print (x)
```

```
['mean radius' 'mean texture' 'mean perimeter' 'mean area'
 'mean smoothness' 'mean compactness' 'mean concavity'
 'mean concave points' 'mean symmetry' 'mean fractal dimension'
 'radius error' 'texture error' 'perimeter error' 'area error'
 'smoothness error' 'compactness error' 'concavity error'
 'concave points error' 'symmetry error' 'fractal dimension error'
 'worst radius' 'worst texture' 'worst perimeter' 'worst area'
 'worst smoothness' 'worst compactness' 'worst concavity'
 'worst concave points' 'worst symmetry' 'worst fractal dimension']
```

```
x=BreastCancer.data
print (x)
```

```
[[1.799e+01 1.038e+01 1.228e+02 ... 2.654e-01 4.601e-01 1.189e-01]
 [2.057e+01 1.777e+01 1.329e+02 ... 1.860e-01 2.750e-01 8.902e-02]
 [1.969e+01 2.125e+01 1.300e+02 ... 2.430e-01 3.613e-01 8.758e-02]
 ...
 [1.660e+01 2.808e+01 1.083e+02 ... 1.418e-01 2.218e-01 7.820e-02]
 [2.060e+01 2.933e+01 1.401e+02 ... 2.650e-01 4.087e-01 1.240e-01]
 [7.760e+00 2.454e+01 4.792e+01 ... 0.000e+00 2.871e-01 7.039e-02]]
```

```
x=BreastCancer.keys()
print (x)
```

```
['target_names', 'data', 'target', 'DESCR', 'feature_names']
```

1.3 و 1.4

سپس داده ها را به فرمت pandas dataframe تبدیل کرده و سپس متد Desc را بر روی این داده های با فرمت دیتافریم اجرا کرده ام.

```
import pandas as pd
import numpy as np
df = pd.DataFrame(BreastCancer.data, columns=BreastCancer.feature_names)
```

```
df.describe()
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	wor radiu
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	...	569.0000
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	0.062798	...	16.2691
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	0.007060	...	4.8332
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106000	0.049960	...	7.9300
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	0.057700	...	13.0100
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	0.061540	...	14.9700
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	0.066120	...	18.7900
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	0.097440	...	36.0400

1.5 و 1.6

یک فیلد به نام targetایجاد کرده و کلید target را در آن قرار داده ام.سپس value count را بر روی آن اجرا کرده ام که تعداد value های فیلد target را نشان میدهد و سپس target name را اجرا کرده ام که نام پارامترهای آن را نمایش داده است.

```
df['target'] = BreastCancer.target
df.set_index('target',inplace=True)
```

```
df.index.value_counts()
```

```
1    357
0    212
Name: target, dtype: int64
```

```
x=BreastCancer.target_names
print (x)
```

```
['malignant' 'benign']
```

1.7 و 1.8

داده ها به test و train تقسیم کرده و ابعاد آنها نمایش داده شده اند.

```
from sklearn.model_selection import train_test_split
X = df[BreastCancer['feature_names']]
y = df.index
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

```
X_train.shape
```

```
(426, 30)
```

```
X_test.shape
```

```
(143, 30)
```

```
y_train.shape
```

```
(426L,)
```

```
y_test.shape
```

1.9

دستور KNeighbors با مقدار 6 بروی داده های train اجرا شده اند و میانگین دقت بدست آمده و در شکل زیر نشان داده شده اند.

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 6)
knn.fit(X_train, y_train)
meanAccuracy = knn.score(X_test, y_test)
meanAccuracy
```

```
0.9230769230769231
```

1.10 و 1.11

مقدار هدف برای مجموعه x_test با استفاده از predictبدست آمده و در شکل زیر نشان داده شده است.که مقادیر بدست آمده نشان دهنده این هستند که آیا مقدار درست predict شده است یا خیر.

```
ansTest = knn.predict(X_test)
ansTest
```

```
array([0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1,
       0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0], dtype=int64)
```

1.12 و 1.13 و 1.14

داده های X_train و X_test ابتدا به شکل زیر نرمال سازی شده اند،سپس مدل را بر حسب این داده های بدست آمده آموزش داده و میانگین دقت را بدست آورده ام.

```
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler()
minmax.fit(X)
normalized_Xtrain = minmax.transform(X_train)
normalized_Xtest = minmax.transform(X_test)
```

```
knnn = KNeighborsClassifier(n_neighbors = 6)
knnn.fit(normalized_Xtrain,y_train)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=6, p=2,
           weights='uniform')
```

```
meanAccuracy_train = knnn.score(normalized_Xtrain, y_train)
meanAccuracy_test = knnn.score(normalized_Xtest, y_test)
print (meanAccuracy_train)
print (meanAccuracy_test)
```

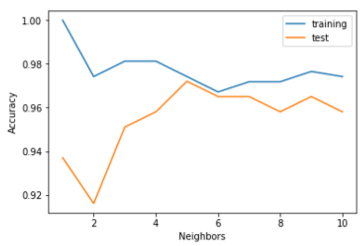
```
0.9671361502347418
0.965034965034965
```

1.15

```
training_accuracy = []
test_accuracy = []

neighbors = range (1, 11)

for i in neighbors:
    knnnn = KNeighborsClassifier(n_neighbors = i)
    knnnn.fit(normalized_Xtrain,y_train)
    training_accuracy.append(knnnn.score(normalized_Xtrain, y_train))
    test_accuracy.append(knnnn.score(normalized_Xtest, y_test))
```

1.16

```
In [43]: import matplotlib.pyplot as plt

         plt.plot(neighbors, training_accuracy, label='training')
         plt.plot(neighbors, test_accuracy, label='test')
         plt.ylabel('Accuracy')
         plt.xlabel('Neighbors')
         plt.legend()

Out[43]: <matplotlib.legend.Legend at 0x1d74a636f60>
```



****

.2

2.1 و 2.2

فایل csv دیتاست vehicle خوانده شده و در متغیر DF قرار گرفته و نمایش داده شده است.

```
import numpy as np
import pandas as pd
df = pd.read_csv('dataset_54_vehicle.csv', sep=',')
df.head()
```

	COMPACTNESS	CIRCULARITY	DISTANCE_CIRCULARITY	RADIUS_RATIO	PR.AXIS_ASPECT_RATIO	MAX.LENGTH_ASPECT_RATIO	SCATTER_RATIO	ELO
0	95	48	83	178	72	10	162	
1	91	41	84	141	57	9	149	
2	104	50	106	209	66	10	207	
3	93	41	82	159	63	9	144	
4	85	44	70	205	103	52	149	

2.3

مقادیر موجود در فیلد هدف

```
variables = df['Class'].unique()
print (variables)
```

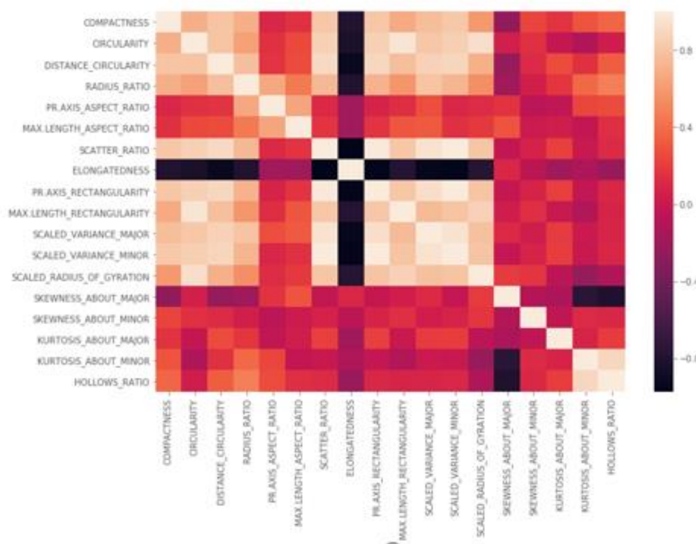
```
['van' 'saab' 'bus' 'opel']
```

2.4

همبستگی بین متغیرها به همراه نمودار HEATMAP

```
from sklearn import preprocessing
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(12,8))
sns.heatmap(df.corr())
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x29ba632eb70>




```
df.corr(method ='pearson').style.format("{:.2}").background_gradient(cmap=plt.get_cmap('coolwarm'), axis=1)
```

	COMPACTNESS	CIRCULARITY	DISTANCE_CIRCULARITY	RADIUS_RATIO	PR.AXIS_ASPECT_RATIO	MAX.LENGTH_ASPEC
COMPACTNESS	1.0	0.69	0.79	0.69	0.093	
CIRCULARITY	0.69	1.0	0.8	0.62	0.15	
DISTANCE_CIRCULARITY	0.79	0.8	1.0	0.77	0.16	
RADIUS_RATIO	0.69	0.62	0.77	1.0	0.67	
PR.AXIS_ASPECT_RATIO	0.093	0.15	0.16	0.67	1.0	
MAX.LENGTH_ASPECT_RATIO	0.15	0.25	0.26	0.45	0.65	
SCATTER_RATIO	0.81	0.86	0.91	0.74	0.11	
ELONGATEDNESS	-0.79	-0.83	-0.91	-0.79	-0.19	
PR.AXIS_RECTANGULARITY	0.81	0.86	0.9	0.71	0.08	
MAX.LENGTH_RECTANGULARITY	0.68	0.97	0.77	0.57	0.13	
SCALED_VARIANCE_MAJOR	0.76	0.81	0.86	0.8	0.27	
SCALED_VARIANCE_MINOR	0.82	0.85	0.89	0.73	0.092	
SCALED_RADIUS_OF_GYRATION	0.59	0.94	0.71	0.54	0.12	
SKEWNESS_ABOUT_MAJOR	-0.25	0.059	-0.23	-0.18	0.15	
SKEWNESS_ABOUT_MINOR	0.23	0.15	0.12	0.051	-0.057	
KURTOSIS_ABOUT_MAJOR	0.16	-0.015	0.26	0.17	-0.034	
KURTOSIS_ABOUT_MINOR	0.3	-0.11	0.15	0.38	0.24	
HOLLOWS_RATIO	0.37	0.039	0.34	0.47	0.27	

2.5 و 2.6 و 2.7

```
x = df.iloc[:,:-1]
y = df.iloc[:,18]
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn import tree


model = tree.DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features=4)
```

2.8

```
import random
from scipy.stats import randint
params = {"max_depth": [3, None],
              "max_features": randint(1, 9),
              "min_samples_leaf": randint(1, 9)}
print(params)
```

```
{'max_depth': [3, None], 'max_features': <scipy.stats._distn_infrastructure.rv_frozen object at 0x00000169725D44
38>, 'min_samples_leaf': <scipy.stats._distn_infrastructure.rv_frozen object at 0x000001697260C7F0>}
```

2.9

```
from sklearn.model_selection import RandomizedSearchCV
tree = DecisionTreeClassifier()
tree_cv = RandomizedSearchCV(tree, params, cv=5)
tree_cv.fit(x ,y)
```

```
RandomizedSearchCV(cv=5, error_score='raise',
          estimator=DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best'),
          fit_params=None, iid=True, n_iter=10, n_jobs=1,
          param_distributions={'max_depth': [3, None], 'max_features': <scipy.stats._distn_infrastructure.rv_fro
zen object at 0x00000169725D4438>, 'min_samples_leaf': <scipy.stats._distn_infrastructure.rv_frozen object at 0x
000001697260C7F0>},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=0)
```

2.10

```
print("Tuned Decision Tree Parameters: {}".format(tree_cv.best_params_))
print("Best score is {}".format(tree_cv.best_score_))
```

```
Tuned Decision Tree Parameters: {'max_depth': None, 'max_features': 8, 'min_samples_leaf': 3}
Best score is 0.6843971631205674
```

2.11

```
print("Accuracy is ", accuracy_score(y_test,y_pred)*100)
```

```
Accuracy is  93.52941176470588
```

2.12

همان طـ.ر که نشان داده شده است مقدار cv هر چه بیشتر باشد مدل بهتر آموزش می‌بیند.

2.13

```
from sklearn import tree
model = tree.DecisionTreeClassifier( max_depth = None, max_features= 5,min_samples_leaf= 3)
model.fit(x, y)
y_pred=model.predict(x_test)
y_pred
```

```
array(['bus', 'van', 'bus', 'van', 'bus', 'van', 'van', 'saab', 'bus',
       'saab', 'saab', 'bus', 'van', 'saab', 'opel', 'van', 'saab', 'bus',
       'opel', 'opel', 'van', 'van', 'saab', 'opel', 'opel', 'saab',
       'opel', 'van', 'van', 'van', 'opel', 'van', 'bus', 'van', 'van',
       'bus', 'bus', 'saab', 'bus', 'saab', 'van', 'bus', 'saab', 'van',
       'opel', 'saab', 'bus', 'van', 'bus', 'van', 'bus', 'bus', 'saab',
       'opel', 'bus', 'opel', 'saab', 'opel', 'saab', 'saab', 'bus',
       'van', 'saab', 'opel', 'bus', 'bus', 'saab', 'saab', 'opel',
       'opel', 'saab', 'bus', 'saab', 'bus', 'van', 'van', 'saab', 'opel',
       'opel', 'van', 'bus', 'van', 'saab', 'opel', 'saab', 'opel',
       'saab', 'bus', 'van', 'saab', 'saab', 'opel', 'bus', 'bus', 'opel',
       'saab', 'van', 'van', 'bus', 'opel', 'saab', 'saab', 'opel', 'van',
       'bus', 'bus', 'saab', 'van', 'opel', 'saab', 'van', 'bus', 'van',
       'bus', 'bus', 'van', 'bus', 'opel', 'bus', 'saab', 'bus', 'opel',
       'saab', 'van', 'bus', 'saab', 'bus', 'van', 'bus', 'opel', 'bus',
       'van', 'bus', 'saab', 'bus', 'bus', 'bus', 'saab', 'saab', 'bus',
       'van', 'bus', 'bus', 'bus', 'van', 'opel', 'saab', 'opel', 'saab',
       'opel', 'saab', 'bus', 'bus', 'opel', 'van', 'van', 'bus', 'van',
       'saab', 'bus', 'bus', 'van', 'opel', 'saab', 'opel', 'opel',
       'saab', 'opel', 'saab', 'van'], dtype=object)
```

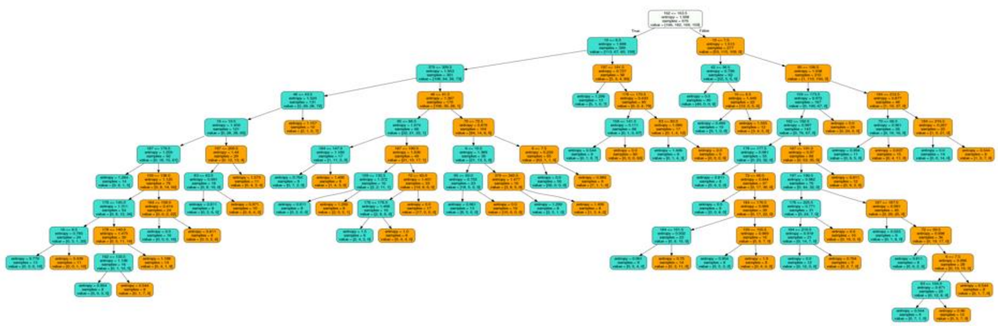
2.14

```
from sklearn.tree import export_graphviz
export_graphviz(model,
                out_file='dot_data.dot',
                feature_names = x.columns,
                class_names = 'Class',
                rounded = True, proportion = False,
                precision = 2, filled = True)
```

2.15 و 2.16

```
try:
    from StringIO import StringIO
except ImportError:
    from io import StringIO
from sklearn import tree
import pydotplus

dotfile = StringIO()
tree.export_graphviz(model,
                out_file=dotfile,
                feature_names = x.columns,
                class_names = 'Class',
                rounded = True, proportion = False,
                precision = 2, filled = True)
graph=pydotplus.graph_from_dot_data(dotfile.getvalue())
graph.write_png("dtree.png")
Image('tree.png')
```

Out[14]:



```
graph.write_pdf("dtree.pdf")
```

****

.3

3.1

```
iris = datasets.load_iris()
iris.data.shape
iris.target.shape
```

```
(150L,)
```

```
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['target']=iris.target

print(iris.target_names)
df['species'] = df['target'].map({0:iris.target_names[0],1:iris.target_names[1],2:iris.target_names[2]})
df.head()
```

```
['setosa' 'versicolor' 'virginica']
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	species
0	5.1	3.5	1.4	0.2	0	setosa
1	4.9	3.0	1.4	0.2	0	setosa
2	4.7	3.2	1.3	0.2	0	setosa
3	4.6	3.1	1.5	0.2	0	setosa
4	5.0	3.6	1.4	0.2	0	setosa

```
samples = df.iloc[:,:4]
samples.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

3.2

```
model = KMeans(n_clusters=3)
model.fit(samples)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=3, n_init=10, n_jobs=1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

```
labels = model.predict(samples)
labels
```

```
array([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, 2, 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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2,
       2, 2, 2, 1, 1, 2, 2, 2, 2, 1, 2, 1, 2, 1, 2, 2, 1, 1, 2, 2, 2, 2,
       2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 1])
```

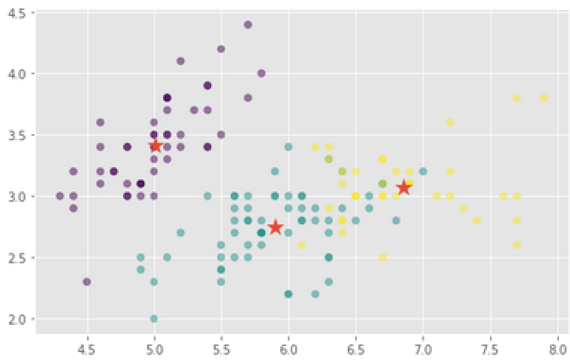
3.3

```
centroids = model.cluster_centers_
centroids
```

```
array([[5.006     , 3.418     , 1.464     , 0.244     ],
       [5.9016129 , 2.7483871 , 4.39354839, 1.43387097],
       [6.85      , 3.07368421, 5.74210526, 2.07105263]])
```

3.4

```
plt.figure(figsize=(8,5))

xs = samples.iloc[:,0]
ys = samples.iloc[:,1]

plt.scatter(xs, ys, c=labels, alpha=0.5)

centroids_x = centroids[:,0]
centroids_y = centroids[:,1]

plt.scatter(centroids_x, centroids_y, marker='*', s=200)
plt.show()
```



3.5

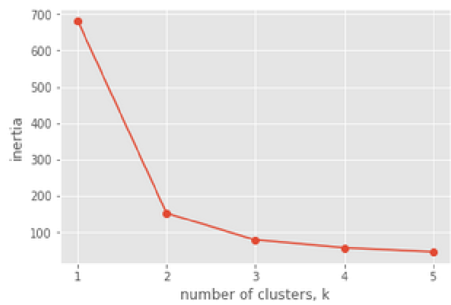
```
print(model.inertia_)
```

```
78.94084142614602
```

3.6

```
ks = range(1, 6)
inertias = []

for k in ks:
    model = KMeans(n_clusters=k)
    model.fit(df.iloc[:,:4])
    inertias.append(model.inertia_)

print(inertias)

# Plot ks vs inertias
plt.plot(ks, inertias, '-o')
plt.xlabel('number of clusters, k')
plt.ylabel('inertia')
plt.xticks(ks)
plt.show()
```

```
[680.8244, 152.36870647733906, 78.94084142614602, 57.31787321428571, 46.53558205128205]
```



3.7

با توجه به اینکه معیار اصلی ما برای کیفیت کلاسترینگ استفاده از شاخص inertia میباشد، پس در ابتدا با تعداد یک کلاستر بیشترین خطا برای مدل بدست می‌آید زیرا بیشترین فاصله از مرکز یک کلاستر برای کل دیتاست به وجود می‌آید. هر چه تعداد کلاسترها بیشتر شود مقدار inertia کمتر شده و دقت کلاسترهای بدست آمده بیشتر میشود ولی در طرف مقابل عمومیت مدل از دست خواهد رفت به همین دلیل باید تعداد کلاسترهایی را انتخاب کرد که مقدارهای بعد از آن مقدار یبت به صورت محسوسی تغییر نخواهد کرد. به طور مثال در این سوال تعداد سه کلاستر برای این دیتاست مناسب است زیر تا قبل از آن شاخص inertia به صورت نمایی کاهش می‌یابد و پس از آن تغییرات محسوسی بروی کاهش شاخص inertia بدست نمی‌آید.

****

.4

4.1

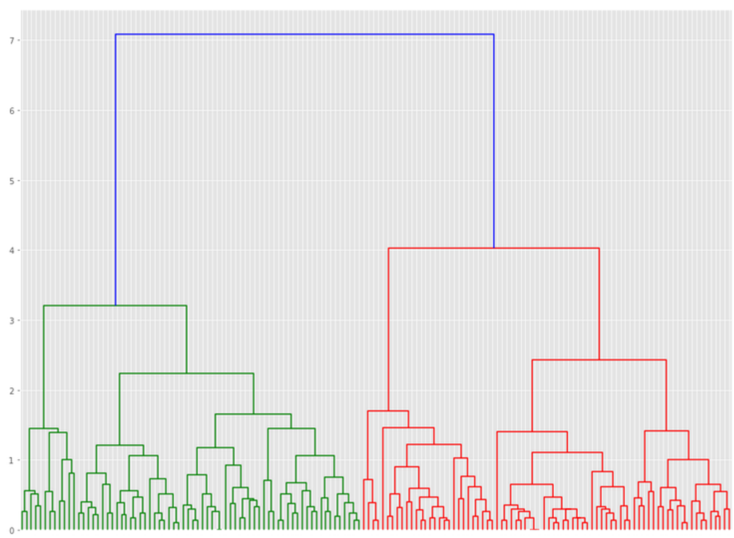
```python
from IPython.display import Image

import pandas as pd
import numpy as np

from sklearn import datasets

from scipy.cluster.hierarchy import dendrogram, linkage, fcluster

import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
matplotlib.style.use('ggplot')
```

```python
iris = datasets.load_iris()
iris.data.shape
iris.target.shape
```

```
(150L,)
```

4.2

```python
linkage_matrix = linkage(iris.data, 'complete')

plt.figure(figsize=(16,12))
dendrogram(linkage_matrix)
plt.show()
```



4.3

```
clusters = fcluster(linkage_matrix, 6, criterion="distance")
clusters
```

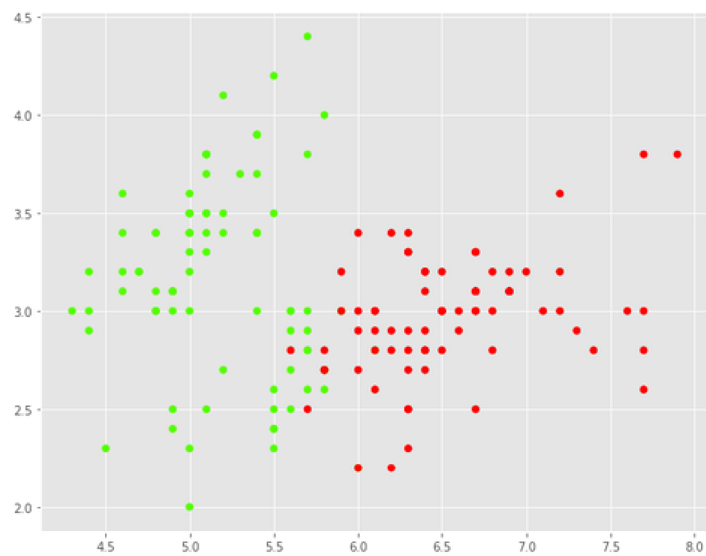
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 1, 1, 1, 2, 1, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 1,
       2, 2, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 1, 2, 1, 1, 1,
       2, 2, 2, 1, 2, 2, 2, 2, 2, 1, 2, 2, 1, 1, 1, 1, 1, 1, 2, 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])
```

```
clusters = fcluster(linkage_matrix, 2, criterion='maxclust')
clusters
```

```
array([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, 2, 2, 1, 1, 1, 2, 1, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 1,
       2, 2, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 1, 2, 1, 1, 1,
       2, 2, 2, 1, 2, 2, 2, 2, 2, 1, 2, 2, 1, 1, 1, 1, 1, 1, 2, 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])
```

4.4

```
plt.figure(figsize=(10, 8))
plt.scatter(iris.data[:,0], iris.data[:,1], c=clusters, cmap='prism')
plt.show()
```



****

5

5.1

```
import numpy as np
import matplotlib.pyplot as plt

import pandas as pd
import seaborn as sns
import sklearn

%matplotlib inline
```

```
from sklearn.datasets import load_boston
boston_dataset = load_boston()
```

```
print(boston_dataset.keys())
```

```
['data', 'feature_names', 'DESCR', 'target']
```

```
boston = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)
boston.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

5.2

```
boston['Price'] = boston_dataset.target
```

```
boston.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

5.3

```
from sklearn.linear_model import LinearRegression
x= boston[["CRIM","ZN"]]
y= boston[["Price"]]
```

5.4

```python
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size = 0.3, random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(354, 2)
(152, 2)
(354, 1)
(152, 1)
```

5.5 و 5.6

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

```python
# model evaluation for training set
y_train_predict = lin_model.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))
r2 = r2_score(Y_train, y_train_predict)

print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")

# model evaluation for testing set
y_test_predict = lin_model.predict(X_test)
rmse = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))
r2 = r2_score(Y_test, y_test_predict)

print("The model performance for testing set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

```
The model performance for training set
--------------------------------------
RMSE is 7.65609383626
R2 score is 0.265809345675


The model performance for testing set
--------------------------------------
RMSE is 8.91859167393
R2 score is 0.163491451224
```

```
x= boston[["LSTAT"]]
y= boston[["Price"]]
```

```
model=LinearRegression()
model = LinearRegression().fit(x, y)
r_sq = model.score(x, y)
print('coefficient of determination:', r_sq)
print('intercept:', model.intercept_)
print('slope:', model.coef_)
```

```
('coefficient of determination:', 0.5441462975864799)
('intercept:', array([34.55384088]))
('slope:', array([[-0.95004935]]))
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size = 0.3, random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(354, 1)
(152, 1)
(354, 1)
(152, 1)
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

```
# model evaluation for training set
y_train_predict = lin_model.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))
r2 = r2_score(Y_train, y_train_predict)

print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")

# model evaluation for testing set
y_test_predict = lin_model.predict(X_test)
rmse = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))
r2 = r2_score(Y_test, y_test_predict)

print("The model performance for testing set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

```
The model performance for training set
--------------------------------------
RMSE is 5.9423982329
R2 score is 0.557699059945


The model performance for testing set
--------------------------------------
RMSE is 6.7772343363
R2 score is 0.51696029876
```

5.8

هر چه تعداد پارامترها افزایش می یابد دقت مدل کمتر میشود.

.6

6.1

```python
from sklearn.datasets import load_breast_cancer
import pandas as pd
import numpy as np
Cancer=load_breast_cancer()
Cancer
```


```
{'DESCR': 'Breast Cancer Wisconsin (Diagnostic) Database\n=============================================\n\nNotes\n-----\nData Set C
haracteristics:\n    :Number of Instances: 569\n\n    :Number of Attributes: 30 numeric, predictive attributes and the class\n\n
:Attribute Information:\n        - radius (mean of distances from center to points on the perimeter)\n        - texture (standard d
eviation of gray-scale values)\n        - perimeter\n        - area\n        - smoothness (local variation in radius lengths)\n
- compactness (perimeter^2 / area - 1.0)\n        - concavity (severity of concave portions of the contour)\n        - concave poin
ts (number of concave portions of the contour)\n        - symmetry \n        - fractal dimension ("coastline approximation" - 1)\n\
n        The mean, standard error, and "worst" or largest (mean of the three\n        largest values) of these features were comput
ed for each image,\n        resulting in 30 features.  For instance, field 3 is Mean Radius, field\n        13 is Radius SE, field
23 is Worst Radius.\n\n        - class:\n                - WDBC-Malignant\n                - WDBC-Benign\n\n    :Summary Statistics
:\n\n    ===================================== ====== ======\n                                           Min    Max\n    ==========
=========================== ====== ======\n    radius (mean):                        6.981  28.11\n    texture (mean):
9.71   39.28\n    perimeter (mean):                     43.79  188.5\n    area (mean):                          143.5  2501.0\n
smoothness (mean):                    0.053  0.163\n    compactness (mean):                   0.019  0.345\n    concavity (mean):
0.0    0.427\n    concave points (mean):                0.0    0.201\n    symmetry (mean):                      0.106  0.304\n    f
ractal dimension (mean):              0.05   0.097\n    radius (standard error):              0.112  2.873\n    texture (standard er
ror):             0.36   4.885\n    perimeter (standard error):           0.757  21.98\n    area (standard error):                6
.802  542.2\n    smoothness (standard error):          0.002  0.031\n    compactness (standard error):         0.002  0.135\n    co
ncavity (standard error):            0.0    0.396\n    concave points (standard error):      0.0    0.053\n    symmetry (standard er
ror):            0.008  0.079\n    fractal dimension (standard error):   0.001  0.03\n    radius (worst):                       7.9
3   36.04\n    texture (worst):                      12.02  49.54\n    perimeter (worst):                    50.41  251.2\n    area
(worst):                          185.2  4254.0\n    smoothness (worst):                   0.071  0.223\n    compactness (worst):
0.027  1.058\n    concavity (worst):                    0.0    1.252\n    concave points (worst):               0.0    0.291\n    s
ymmetry (worst):                      0.156  0.664\n    fractal dimension (worst):            0.055  0.208\n    ===================
================== ====== ======\n\n    :Missing Attribute Values: None\n\n    :Class Distribution: 212 - Malignant, 357 - Benign\n\
n    :Creator:  Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian\n\n    :Donor: Nick Street\n\n    :Date: November, 1995
\n\nThis is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed from a
digitized image of a fine needle\naspirate (FNA) of a breast mass.  They describe\ncharacteristics of the cell nuclei present in th
e image.\n\nSeparating plane described above was obtained using\nMultisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree\nC
onstruction Via Linear Programming." Proceedings of the 4th\nMidwest Artificial Intelligence and Cognitive Science Society,\npp. 97
-101, 1992], a classification method which uses linear\nprogramming to construct a decision tree.  Relevant features\nwere selected
using an exhaustive search in the space of 1-4\nfeatures and 1-3 separating planes.\n\nThe actual linear program used to obtain the
separating plane\nin the 3-dimensional space is that described in:\n[K. P. Bennett and O. L. Mangasarian: "Robust Linear\nProgrammi
ng Discrimination of Two Linearly Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23-34].\n\nThis database is also a
vailable through the UW CS ftp server:\n\nftp ftp.cs.wisc.edu\ncd math-prog/cpo-dataset/machine-learn/WDBC/\n\nReferences\n--------
--\n   - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction \n     for breast tumor diagnosis. IS&T/SPIE 19
93 International Symposium on \n     Electronic Imaging: Science and Technology, volume 1905, pages 861-870,\n     San Jose, CA, 19
93.\n   - O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and \n     prognosis via linear programming. Oper
ations Research, 43(4), pages 570-577, \n     July-August 1995.\n   - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine lear
ning techniques\n     to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994) \n     163-171.\n',
 'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
         1.189e-01],
        [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
         8.902e-02],
```

```
 'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
         1.189e-01],
        [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
         8.902e-02],
        [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
         8.758e-02],
        ...,
        [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
         7.820e-02],
        [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
         1.240e-01],
        [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
         7.039e-02]]),
 'feature_names': array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
        'mean smoothness', 'mean compactness', 'mean concavity',
        'mean concave points', 'mean symmetry', 'mean fractal dimension',
        'radius error', 'texture error', 'perimeter error', 'area error',
        'smoothness error', 'compactness error', 'concavity error',
        'concave points error', 'symmetry error',
        'fractal dimension error', 'worst radius', 'worst texture',
        'worst perimeter', 'worst area', 'worst smoothness',
        'worst compactness', 'worst concavity', 'worst concave points',
        'worst symmetry', 'worst fractal dimension'], dtype='|S23'),
 'target': array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
        0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0,
        1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0,
        1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
        1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
        0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
        1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
        0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
        1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
        1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
        0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
        0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
        1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
        1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
        1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
        1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
        1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
        1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 0, 1, 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, 0, 0, 0, 0, 0, 0, 1]),
 'target_names': array(['malignant', 'benign'], dtype='|S9')}
```

6.2

```python
from sklearn.model_selection import train_test_split
df = pd.DataFrame(Cancer.data, columns=Cancer.feature_names)
df['target'] = Cancer.target
X = df[Cancer['feature_names']]
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size = 0.2, random_state=0)

from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 8)
knn.fit(X_train, y_train)
y_pred=knn.predict(X_test)
print(y_pred)
```

```
[0 1 1 0 1 1 1 1 1 1 1 1 1 0 1 0 1 0 0 0 0 0 1 1 0 1 1 1 1 0 1 0 1 0 1 0 1
 0 1 0 0 1 0 1 0 0 1 1 1 0 0 1 0 1 1 1 1 1 1 0 0 0 1 1 0 1 0 0 0 1 1 0 1 1
 0 1 1 1 1 1 0 0 0 1 0 1 1 1 0 0 1 0 1 0 1 1 0 1 1 1 1 1 1 1 0 1 0 1 0 0 1
 0 0 1]
```

6.3 و 6.4 و 6.5

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

```
Confiuse=confusion_matrix(y_test, y_pred)
print (Confiuse)
```

```
[[44  3]
 [ 3 64]]
```

```
Report=classification_report (y_test, y_pred)
print (Report)
```

```
             precision    recall  f1-score   support

          0       0.94      0.94      0.94        47
          1       0.96      0.96      0.96        67

avg / total       0.95      0.95      0.95       114
```

6.6

```
from sklearn.preprocessing import normalize
Normal=normalize(Confiuse, norm='l1')
print(Normal)
```

```
[[0.93617021 0.06382979]
 [0.04477612 0.95522388]]
```

6.7

```
dff = pd.DataFrame(Normal, index=['benign','malignant'],columns=['benign','malignant'])
print (dff)
```

```
             benign  malignant
benign     0.936170   0.063830
malignant  0.044776   0.955224
```

6.8

این نمودارها نشان دهنده دقت بدست آمده مدل هستند. و هرچه نمودار از خط Y=X دور تر باشد دقت بهتر است ، به عنوان مثال در این نمودار ها سمت چپ بالا بالا ترین دقت ممکن را به دست آورده است. نمودار سمت چپ پایین یک دقت خوب به دست آورده و سمت راست پایین دقت بدی را به دست آورده است.

6.9

```
y_pred_prob=knn.predict_proba(X_test)
print (y_pred_prob)
```

```
[[0.75  0.25 ]
 [0.    1.   ]
 [0.    1.   ]
 [0.5   0.5  ]
 [0.    1.   ]
 [0.    1.   ]
 [0.    1.   ]
 [0.    1.   ]
 [0.    1.   ]
 [0.    1.   ]
 [0.375 0.625]
 [0.125 0.875]
 [0.    1.   ]
 [0.625 0.375]
 [0.375 0.625]
 [1.    0.   ]
 [0.    1.   ]
 [1.    0.   ]
 [1.    0.   ]
```

****

.7

7.1

```
import pandas as pd
import numpy as np

df=pd.read_excel("Online Retail.xlsx")
df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

7.2 و 7.3 و 7.4 و 7.5 و 7.6

```
from mlxtend.frequent_patterns import apriori,association_rules
```

```
df["Description"]=df["Description"].str.strip()
```

```
print("Orginal Size : " + str(df.size))
df["InvoiceNo"].replace('', np.nan, inplace=True)
df.dropna(subset=['InvoiceNo'], inplace=True)
print("Reduced Size : " + str(df.size))

df["InvoiceNo"]=df["InvoiceNo"].astype("str")
```

```
Orginal Size : 4335272
Reduced Size : 4335272
```

```
df=df[~df.InvoiceNo.str.contains("C")]
```

7.7

```
basket = (df[df['Country'] =="France"]
.groupby(['InvoiceNo', 'Description'])['Quantity']
.sum().unstack().reset_index().fillna(0).set_index('InvoiceNo'))
basket.head()
```

Description	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 EGG HOUSE PAINTED WOOD	12 MESSAGE CARDS WITH ENVELOPES	12 PENCIL SMALL TUBE WOODLAND	12 PENCILS SMALL TUBE RED RETROSPOT	12 PENCILS SMALL TUBE SKULL	12 PENCILS TALL TUBE POSY	12 PENCILS TALL TUBE RED RETROSPOT	12 PENCILS TALL TUBE WOODLAND	...	WRAP VINTAGE PETALS DESIGN
InvoiceNo												
536370	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536852	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536974	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
537065	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
537463	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0

5 rows × 1563 columns

7.8

```
basket=basket.applymap(lambda x: 1 if x > 0 else 0)
basket.head()
```

Description	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 EGG HOUSE PAINTED WOOD	12 MESSAGE CARDS WITH ENVELOPES	12 PENCIL SMALL TUBE WOODLAND	12 PENCILS SMALL TUBE RED RETROSPOT	12 PENCILS SMALL TUBE SKULL	12 PENCILS TALL TUBE POSY	12 PENCILS TALL TUBE RED RETROSPOT	12 PENCILS TALL TUBE WOODLAND	...	WRAP VINTAGE PETALS DESIGN
InvoiceNo												
536370	0	0	0	0	0	0	0	0	0	0	...	0
536852	0	0	0	0	0	0	0	0	0	0	...	0
536974	0	0	0	0	0	0	0	0	0	0	...	0
537065	0	0	0	0	0	0	0	0	0	0	...	0
537463	0	0	0	0	0	0	0	0	0	0	...	0

5 rows × 1563 columns

7.9 و 7.10

```
basket=basket.drop("POSTAGE",axis=1)
```

```
frequent_itemsets = apriori(basket, min_support=0.07, use_colnames=True)
frequent_itemsets.head()
```

	support	itemsets
0	0.071429	(4 TRADITIONAL SPINNING TOPS)
1	0.096939	(ALARM CLOCK BAKELIKE GREEN)
2	0.102041	(ALARM CLOCK BAKELIKE PINK)
3	0.094388	(ALARM CLOCK BAKELIKE RED)
4	0.081633	(BAKING SET 9 PIECE RETROSPOT)

7.11

```
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
rules.head()
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE GREEN)	0.102041	0.096939	0.073980	0.725000	7.478947	0.064088	3.283859
1	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE PINK)	0.096939	0.102041	0.073980	0.763158	7.478947	0.064088	3.791383
2	(ALARM CLOCK BAKELIKE RED)	(ALARM CLOCK BAKELIKE GREEN)	0.094388	0.096939	0.079082	0.837838	8.642959	0.069932	5.568878
3	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE RED)	0.096939	0.094388	0.079082	0.815789	8.642959	0.069932	4.916181
4	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE RED)	0.102041	0.094388	0.073980	0.725000	7.681081	0.064348	3.293135

7.12

```
rules[ (rules['lift'] >= 6) &
       (rules['confidence'] >= 0.8) ]
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
2	(ALARM CLOCK BAKELIKE RED)	(ALARM CLOCK BAKELIKE GREEN)	0.094388	0.096939	0.079082	0.837838	8.642959	0.069932	5.568878
3	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE RED)	0.096939	0.094388	0.079082	0.815789	8.642959	0.069932	4.916181
16	(SET/6 RED SPOTTY PAPER PLATES)	(SET/20 RED RETROSPOT PAPER NAPKINS)	0.127551	0.132653	0.102041	0.800000	6.030769	0.085121	4.336735
18	(SET/6 RED SPOTTY PAPER PLATES)	(SET/6 RED SPOTTY PAPER CUPS)	0.127551	0.137755	0.122449	0.960000	6.968889	0.104878	21.556122
19	(SET/6 RED SPOTTY PAPER CUPS)	(SET/6 RED SPOTTY PAPER PLATES)	0.137755	0.127551	0.122449	0.888889	6.968889	0.104878	7.852041
20	(SET/6 RED SPOTTY PAPER PLATES, SET/6 RED SPOT...	(SET/20 RED RETROSPOT PAPER NAPKINS)	0.122449	0.132653	0.099490	0.812500	6.125000	0.083247	4.625850
21	(SET/6 RED SPOTTY PAPER PLATES, SET/20 RED RET...	(SET/6 RED SPOTTY PAPER CUPS)	0.102041	0.137755	0.099490	0.975000	7.077778	0.085433	34.489796
22	(SET/6 RED SPOTTY PAPER CUPS, SET/20 RED RETRO...	(SET/6 RED SPOTTY PAPER PLATES)	0.102041	0.127551	0.099490	0.975000	7.644000	0.086474	34.897959