Practical

May 3, 2024

Q1. Create a file "people.txt" with the following data: Age agegroup height status yearsmarried 21 adult 6.0 single -1 2 child 3 married 0 18 adult 5.7 married 20 221 elderly 5 widowed 2 34 child -7 married 3 **i) Read the data from the file "people.txt".**

[2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[3]:
```python
data = open('people.txt','r')
for line in data.readlines():
    if line != '\n':
        print(line)
```

```
Age agegroup height status yearsmarried

21 adult 6.0 single -1

2 child 3 married 0

18 adult 5.7 married 20

221 elderly 5 widowed 2

34 child -7 married 3
```

[4]:
```python
df = pd.read_csv('people.txt',sep=" ",header=0)
df
```

[4]:

	Age	agegroup	height	status	yearsmarried
0	21	adult	6.0	single	-1
1	2	child	3.0	married	0
2	18	adult	5.7	married	20
3	221	elderly	5.0	widowed	2
4	34	child	-7.0	married	3

ii) Create a ruleset E that contain rules to check for the following conditions: 1. The age should be in the range 0-150. 2. The age should be greater than yearsmarried. 3. The status should be married or single or widowed. 4. If age is less than 18 the agegroup should be child, if age is between 18 and 65 the agegroup should be adult, if age is more than 65 the agegroup should be elderly.

[7]:
```
def ruleset(df):
    df['Rule1'] = df['Age'].apply(lambda x: x in range(0, 150))
    df['Rule2'] = df.apply(lambda x: x.Age > x.yearsmarried, axis=1)
    df['Rule3'] = df['status'].apply(lambda x: x in {'married', 'single',␣
 ↪'widowed'})
    df['Rule4'] = df.apply(lambda x: (x.Age < 18 and x.agegroup == 'child') or␣
 ↪(18 <= x.Age <= 65 and x.agegroup == 'adult') or (x.Age > 65 and x.agegroup␣
 ↪== 'elderly'), axis=1)
```

iii) Check whether ruleset E is violated by the data in the file people.txt.

[8]:
```
ruleset(df)
df
```

[8]:

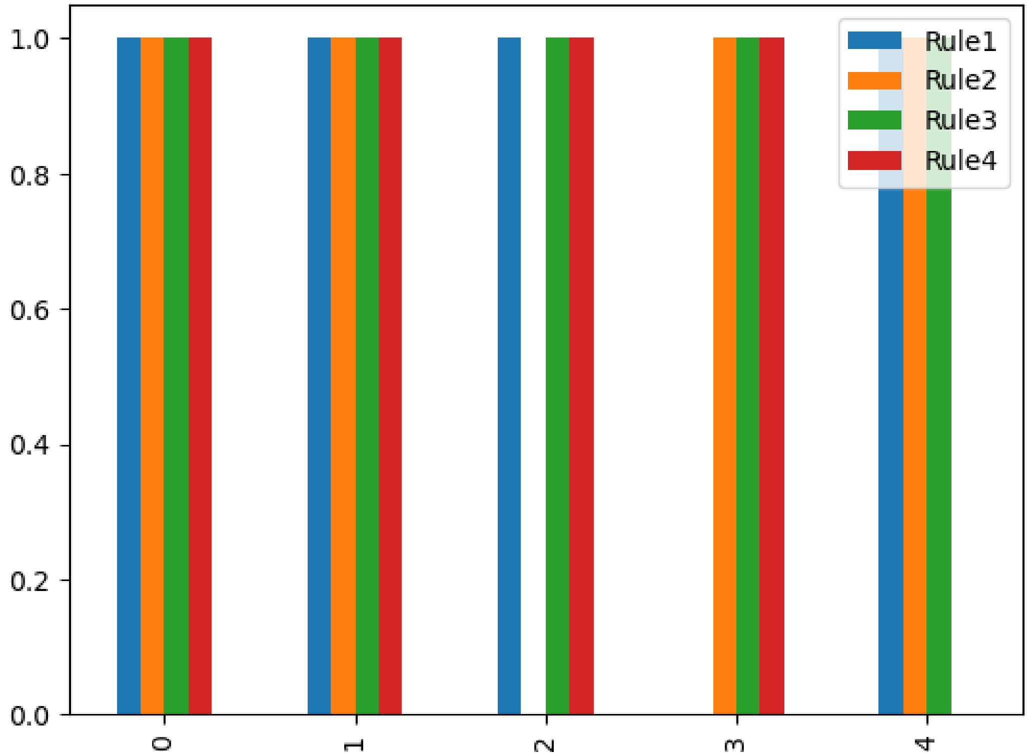
	Age	agegroup	height	status	yearsmarried	Rule1	Rule2	Rule3	Rule4
0	21	adult	6.0	single	-1	True	True	True	True
1	2	child	3.0	married	0	True	True	True	True
2	18	adult	5.7	married	20	True	False	True	True
3	221	elderly	5.0	widowed	2	False	True	True	True
4	34	child	-7.0	married	3	True	True	True	False

iv) Summarize the results obtained in part (iii)

1. Rule 1 : The age should be in the range 0-150.
   - violated in row 3 where Age = 221
2. Rule 2 : The age should be greater than yearsmarried.
   - violated in row 2 where Age(i.e. 18) < yearsmarried(i.e. 20)
3. Rule 3 : The status should be married or single or widowed.
   - Not violated
4. Rule 4 : If age is less than 18 the agegroup should be child, if age is between 18 and 65 the agegroup should be adult, if age is more than 65 the agegroup should be elderly.
   - violated in row 4 where Age = 34 and agegroup = ‘child’

v) Visualize the results obtained in part (iii)

[11]:
```
summary = df.loc[:, 'Rule1':'Rule4'].replace({True:1, False:0})
summary.plot(kind='bar')
plt.show()
```



Q2. Perform the following preprocessing tasks on the dirty_iris dataset.

[12]:
```
df = pd.read_csv("https://raw.githubusercontent.com/edwindj/datacleaning/master/
↪data/dirty_iris.csv")
df.head()
```

[12]:

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0	6.4	3.2	4.5	1.5	versicolor
1	6.3	3.3	6.0	2.5	virginica
2	6.2	NaN	5.4	2.3	virginica
3	5.0	3.4	1.6	0.4	setosa
4	5.7	2.6	3.5	1.0	versicolor

i) Calculate the number and percentage of observations that are complete.

[16]:
```
complete_obv = len(df.dropna())
print("Number of observations that are complete: ", complete_obv)
complete_percent = (len(df.dropna())/len(df)*100)
print("Percentage of observations that are complete: ", complete_percent,"%")
```

```
Number of observations that are complete:  96
Percentage of observations that are complete:  64.0 %
```

ii)Replace all the special values in data with NA

[17]:
```
# df.fillna(value='NA', inplace=True)
```

iii)Define these rules in a separate text file and read them.

Species should be one of the following values: setosa, versicolor or virginica

[20]:
```
def check_species(df):
    x = df['Species'].apply(lambda x: x in {'setosa', 'versicolor',␣
↪'virginica'})
    violations = len(df) - np.sum(x)

    if violations == 0:
        print('No Violation.')
    else:
        print('Violation: Invalid Species Name.')
        print(f'Violations: {violations}')

    return violations
```

[21]:
```
species_violations = check_species(df)
```

```
No Violation.
```

All measured numerical properties of an iris should be positive

[24]:
```
def check_all_positive(df):
    x = df.loc[:, 'Sepal.Length':'Petal.Width'].apply(lambda x: x > 0).values
    x = x.reshape(-1)
    violations = len(df) * 4 - np.sum(x)

    if violations == 0:
        print('No Violation.')
    else:
        print('Violation: Non-positive Numerical Property.')
        print(f'Violations: {violations}')

    return violations
```

[25]:
```
non_positive_violations = check_all_positive(df)
```

```
Violation: Non-positive Numerical Property.
Violations: 62
```

The petal length of an iris is at least 2 times its petal width.

[26]:
```
def check_petal_length(df):
    x = df['Petal.Length'] >= 2 * df['Petal.Width']
    violations = x.value_counts().loc[False]

    if violations == 0:
```

```
        print('No Violation.')
    else:
        print('Violation: Petal Length is less than twice its Petal Width.')
        print(f'Violations: {violations}')

    return violations
```

[27]:
```
petal_length_violations = check_petal_length(df)
```

```
Violation: Petal Length is less than twice its Petal Width.
Violations: 34
```

The sepal length of an iris cannot exceed 30 cm.

[28]:
```
def check_sepal_length(df):
    x = df['Sepal.Length'] <= 30
    violations = x.value_counts().loc[False]

    if violations == 0:
        print('No Violation.')
    else:
        print('Violation: Sepal Length exceeded the value of 30cms.')
        print(f'Violations: {violations}')

    return violations
```

[29]:
```
sepal_length_violations = check_sepal_length(df)
```

```
Violation: Sepal Length exceeded the value of 30cms.
Violations: 12
```

The sepals of an iris are longer than its petals.

[30]:
```
def check_sepal_petal_length(df):
    x = df['Sepal.Length'] > df['Petal.Length']
    violations = x.value_counts().loc[False]

    if violations == 0:
        print('No Violation.')
    else:
        print('Violation: Sepal Length are less than Petal Length.')
        print(f'Violations: {violations}')

    return violations
```

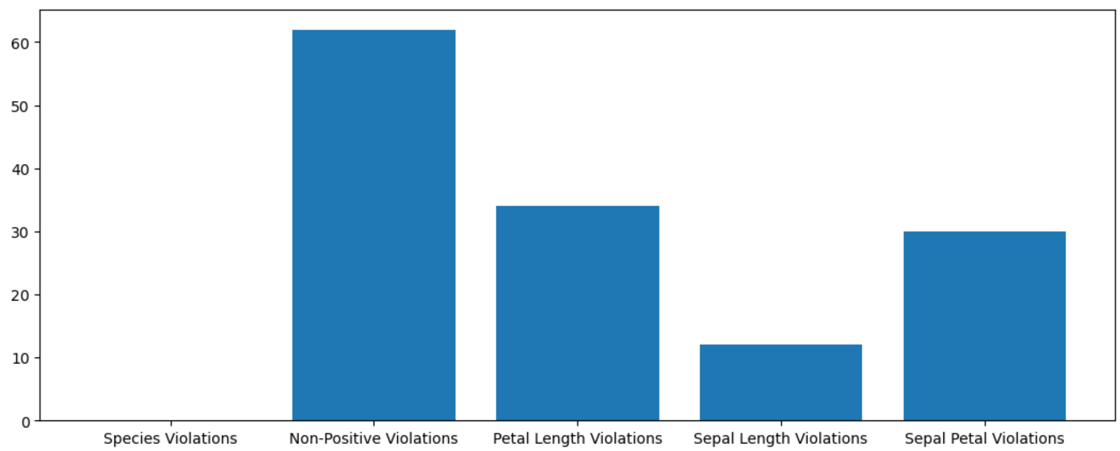
[31]:
```
sepal_petal_violations = check_sepal_petal_length(df)
```

```
Violation: Sepal Length are less than Petal Length.
Violations: 30
```

iv) Determine how often each rule is broken (violatedEdits). Also summarize and plot the result.

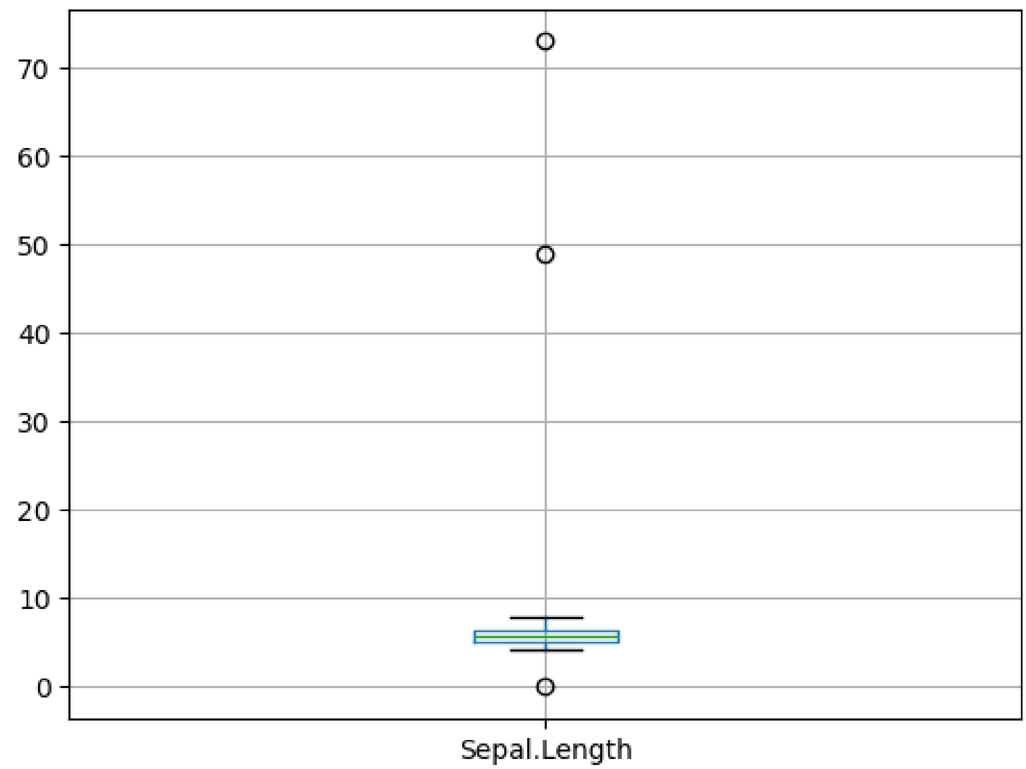
[32]:
```
rule_break_frequency = {
    'Species Violations': species_violations,
    'Non-Positive Violations': non_positive_violations,
    'Petal Length Violations': petal_length_violations,
    'Sepal Length Violations': sepal_length_violations,
    'Sepal Petal Violations': sepal_petal_violations
}

fig = plt.figure(figsize=(13, 5))
plt.bar(rule_break_frequency.keys(), rule_break_frequency.values())
plt.show()
```



v) Find outliers in sepal length using boxplot

[40]:
```
df.boxplot(column='Sepal.Length', return_type='axes');
```



Q3. Load the data from wine dataset. Check whether all attributes are standardized or not (mean is 0 and standard deviation is 1). If not, standardize the attributes. Do the same with Iris dataset.

[41]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_wine, load_iris
```

Wine Dataset

[42]:
```
df = load_wine()
X = df.data
```

Mean and standard deviation along the columns.

[43]:
```
X.mean(axis=0)
```

[43]:
```
array([1.30006180e+01, 2.33634831e+00, 2.36651685e+00, 1.94949438e+01,
       9.97415730e+01, 2.29511236e+00, 2.02926966e+00, 3.61853933e-01,
       1.59089888e+00, 5.05808988e+00, 9.57449438e-01, 2.61168539e+00,
       7.46893258e+02])
```

[44]:
```
X.std(axis=0)
```

[44]:
```
array([8.09542915e-01, 1.11400363e+00, 2.73572294e-01, 3.33016976e+00,
       1.42423077e+01, 6.24090564e-01, 9.96048950e-01, 1.24103260e-01,
       5.70748849e-01, 2.31176466e+00, 2.27928607e-01, 7.07993265e-01,
       3.14021657e+02])
```

Standardizing the dataset.

[45]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
```

[46]:
```
X.mean(axis=0)
```

[46]:
```
array([ 7.84141790e-15,  2.44498554e-16, -4.05917497e-15, -7.11041712e-17,
       -2.49488320e-17, -1.95536471e-16,  9.44313292e-16, -4.17892936e-16,
       -1.54059038e-15, -4.12903170e-16,  1.39838203e-15,  2.12688793e-15,
       -6.98567296e-17])
```

[47]:
```
X.std(axis=0)
```

[47]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

Iris Dataset

[48]:
```
df = load_iris()
X = df.data
```

Mean and standard deviation along the columns.

[49]:
```
X.mean(axis=0)
```

[49]:
```
array([5.84333333, 3.05733333, 3.758     , 1.19933333])
```

[50]:
```
X.std(axis=0)
```

[50]:
```
array([0.82530129, 0.43441097, 1.75940407, 0.75969263])
```

Standardizing the dataset.

[52]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
```

[53]:
```
X.mean(axis=0)
```

[53]:
```
array([-1.69031455e-15, -1.84297022e-15, -1.69864123e-15, -1.40924309e-15])
```

[54]:
```
X.std(axis=0)
```

[54]:
```
array([1., 1., 1., 1.])
```

Q4. Run Apriori algorithm to find frequent itemsets and association rules.

[57]:
```
!pip install mlxtend
```

```
Collecting mlxtend
  Downloading mlxtend-0.23.1-py3-none-any.whl.metadata (7.3 kB)
Requirement already satisfied: scipy>=1.2.1 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (1.11.4)
Requirement already satisfied: numpy>=1.16.2 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (1.26.4)
Requirement already satisfied: pandas>=0.24.2 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (2.1.4)
Requirement already satisfied: scikit-learn>=1.0.2 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (1.2.2)
Requirement already satisfied: matplotlib>=3.0.0 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (3.8.0)
Requirement already satisfied: joblib>=0.13.2 in
c:\users\lamot\anaconda3\lib\site-packages (from mlxtend) (1.2.0)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(1.2.0)
Requirement already satisfied: cycler>=0.10 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(1.4.4)
Requirement already satisfied: packaging>=20.0 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(23.1)
Requirement already satisfied: pillow>=6.2.0 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\lamot\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
c:\users\lamot\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend)
(2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in
c:\users\lamot\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend)
(2023.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\lamot\anaconda3\lib\site-packages (from scikit-learn>=1.0.2->mlxtend)
```

```
(2.2.0)
Requirement already satisfied: six>=1.5 in c:\users\lamot\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.16.0)
Downloading mlxtend-0.23.1-py3-none-any.whl (1.4 MB)
   ---------------------------------------- 0.0/1.4 MB ? eta -:--:--
   ---------------------------------------- 0.0/1.4 MB ? eta -:--:--
   ---- ----------------------------------- 0.2/1.4 MB 2.3 MB/s eta 0:00:01
   --------------- ------------------------ 0.6/1.4 MB 5.0 MB/s eta 0:00:01
   ------------------------------- -------- 1.1/1.4 MB 7.3 MB/s eta 0:00:01
   ---------------------------------------  1.4/1.4 MB 7.1 MB/s eta 0:00:01
   ---------------------------------------- 1.4/1.4 MB 5.8 MB/s eta 0:00:00
Installing collected packages: mlxtend
Successfully installed mlxtend-0.23.1
```

[58]:
```
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
```

[59]:
```
dataset = [['Milk', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Dill', 'Onion', 'Nutmeg', 'Kidney Beans', 'Eggs', 'Yogurt'],
           ['Milk', 'Apple', 'Kidney Beans', 'Eggs'],
           ['Milk', 'Unicorn', 'Corn', 'Kidney Beans', 'Yogurt'],
           ['Corn', 'Onion', 'Onion', 'Kidney Beans', 'Ice cream', 'Eggs']]
```

[61]:
```
te = TransactionEncoder()
te_ary = te.fit(dataset).transform(dataset)
df = pd.DataFrame(te_ary, columns=te.columns_)
df
```

[61]:
```
   Apple   Corn   Dill   Eggs  Ice cream  Kidney Beans   Milk  Nutmeg  Onion  \
0  False  False  False   True      False          True   True    True   True
1  False  False   True   True      False          True  False    True   True
2   True  False  False   True      False          True   True   False  False
3  False   True  False  False      False          True   True   False  False
4  False   True  False   True       True          True  False   False   True

   Unicorn  Yogurt
0    False    True
1    False    True
2    False   False
3     True    True
4    False   False
```

4.1 Use minimum support as 50% and minimum confidence as 75%.

[62]:
```
frequent_itemsets = apriori(df, min_support=0.5, use_colnames=True)
frequent_itemsets
```

[62]:

	support	itemsets
0	0.8	(Eggs)
1	1.0	(Kidney Beans)
2	0.6	(Milk)
3	0.6	(Onion)
4	0.6	(Yogurt)
5	0.8	(Kidney Beans, Eggs)
6	0.6	(Onion, Eggs)
7	0.6	(Milk, Kidney Beans)
8	0.6	(Onion, Kidney Beans)
9	0.6	(Yogurt, Kidney Beans)
10	0.6	(Onion, Eggs, Kidney Beans)

[63]:

```
from mlxtend.frequent_patterns import association_rules
association_rules(frequent_itemsets, metric="confidence", min_threshold=0.75)
```

[63]:

	antecedents	consequents	antecedent support	\
0	(Kidney Beans)	(Eggs)	1.0	
1	(Eggs)	(Kidney Beans)	0.8	
2	(Onion)	(Eggs)	0.6	
3	(Milk)	(Kidney Beans)	0.6	
4	(Onion)	(Kidney Beans)	0.6	
5	(Yogurt)	(Kidney Beans)	0.6	
6	(Onion, Eggs)	(Kidney Beans)	0.6	
7	(Onion, Kidney Beans)	(Eggs)	0.6	
8	(Onion)	(Kidney Beans, Eggs)	0.6	

	consequent support	support	confidence	lift	leverage	conviction	\
0	0.8	0.8	0.8	1.00	0.00	1.0	
1	1.0	0.8	1.0	1.00	0.00	inf	
2	0.8	0.6	1.0	1.25	0.12	inf	
3	1.0	0.6	1.0	1.00	0.00	inf	
4	1.0	0.6	1.0	1.00	0.00	inf	
5	1.0	0.6	1.0	1.00	0.00	inf	
6	1.0	0.6	1.0	1.00	0.00	inf	
7	0.8	0.6	1.0	1.25	0.12	inf	
8	0.8	0.6	1.0	1.25	0.12	inf	

	zhangs_metric
0	0.0
1	0.0
2	0.5
3	0.0
4	0.0
5	0.0
6	0.0
7	0.5

```
8           0.5
```

4.2 Use minimum support as 60% and minimum confidence as 60 %.

[64]:
```python
frequent_itemsets = apriori(df, min_support=0.6, use_colnames=True)
frequent_itemsets
```

[64]:
```
    support                     itemsets
0       0.8                       (Eggs)
1       1.0               (Kidney Beans)
2       0.6                       (Milk)
3       0.6                      (Onion)
4       0.6                     (Yogurt)
5       0.8         (Kidney Beans, Eggs)
6       0.6                (Onion, Eggs)
7       0.6         (Milk, Kidney Beans)
8       0.6        (Onion, Kidney Beans)
9       0.6       (Yogurt, Kidney Beans)
10      0.6  (Onion, Eggs, Kidney Beans)
```

[65]:
```python
from mlxtend.frequent_patterns import association_rules
association_rules(frequent_itemsets, metric="confidence", min_threshold=0.6)
```

[65]:
```
              antecedents            consequents  antecedent support  \
0          (Kidney Beans)                 (Eggs)                 1.0
1                  (Eggs)         (Kidney Beans)                 0.8
2                 (Onion)                 (Eggs)                 0.6
3                  (Eggs)                (Onion)                 0.8
4                  (Milk)         (Kidney Beans)                 0.6
5          (Kidney Beans)                 (Milk)                 1.0
6                 (Onion)         (Kidney Beans)                 0.6
7          (Kidney Beans)                (Onion)                 1.0
8                (Yogurt)         (Kidney Beans)                 0.6
9          (Kidney Beans)               (Yogurt)                 1.0
10          (Onion, Eggs)         (Kidney Beans)                 0.6
11  (Onion, Kidney Beans)                 (Eggs)                 0.6
12   (Kidney Beans, Eggs)                (Onion)                 0.8
13                (Onion)   (Kidney Beans, Eggs)                 0.6
14                 (Eggs)  (Onion, Kidney Beans)                 0.8
15         (Kidney Beans)          (Onion, Eggs)                 1.0

    consequent support  support  confidence  lift  leverage  conviction  \
0                  0.8      0.8        0.80  1.00      0.00         1.0
1                  1.0      0.8        1.00  1.00      0.00         inf
2                  0.8      0.6        1.00  1.25      0.12         inf
3                  0.6      0.6        0.75  1.25      0.12         1.6
4                  1.0      0.6        1.00  1.00      0.00         inf
5                  0.6      0.6        0.60  1.00      0.00         1.0
```

```
6                      1.0       0.6         1.00  1.00       0.00          inf
7                      0.6       0.6         0.60  1.00       0.00          1.0
8                      1.0       0.6         1.00  1.00       0.00          inf
9                      0.6       0.6         0.60  1.00       0.00          1.0
10                     1.0       0.6         1.00  1.00       0.00          inf
11                     0.8       0.6         1.00  1.25       0.12          inf
12                     0.6       0.6         0.75  1.25       0.12          1.6
13                     0.8       0.6         1.00  1.25       0.12          inf
14                     0.6       0.6         0.75  1.25       0.12          1.6
15                     0.6       0.6         0.60  1.00       0.00          1.0

    zhangs_metric
0             0.0
1             0.0
2             0.5
3             1.0
4             0.0
5             0.0
6             0.0
7             0.0
8             0.0
9             0.0
10            0.0
11            0.5
12            1.0
13            0.5
14            1.0
15            0.0
```

Q5. Use Naive bayes, K-nearest, and Decision tree classification algorithms and build classifiers. Divide the data set into training and test set. Compare the accuracy of the different classifiers under the following situations:

[72]:
```
from sklearn.datasets import load_iris
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, classification_report
```

[73]:
```
X, y = load_iris(return_X_y=True)
```

5.1 a) Training set = 75% Test set = 25%

[74]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=100)
```

Naive Bayes Classifier

```python
[75]: gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

K-Nearest Neighbors Classifier

```python
[76]: knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 97.36842105263158 %
```

```python
[77]: print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.91      1.00      0.95        10
           2       1.00      0.93      0.96        14

    accuracy                           0.97        38
   macro avg       0.97      0.98      0.97        38
weighted avg       0.98      0.97      0.97        38
```

Decision Tree Classifier

```python
[78]: dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

```python
[79]: print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.90      0.90      0.90        10
           2       0.93      0.93      0.93        14

    accuracy                           0.95        38
   macro avg       0.94      0.94      0.94        38
```

```
weighted avg       0.95      0.95      0.95        38
```

5.1 b) Training set = 66.6% (2/3rd of total), Test set = 33.3%

[80]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=100)
```

Naive Bayes Classifier

[81]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 96.0 %
```

K-Nearest Neighbors Classifier

[82]:
```
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
print(classification_report(y_test, y_pred))
```

```
Accuracy Score: 98.0 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        20
           1       0.92      1.00      0.96        12
           2       1.00      0.94      0.97        18

    accuracy                           0.98        50
   macro avg       0.97      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50
```

Decision Tree Classifier

[83]:
```
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
print(classification_report(y_test, y_pred))
```

```
Accuracy Score: 96.0 %
              precision    recall  f1-score   support
```

```
           0       1.00      1.00      1.00        20
           1       0.92      0.92      0.92        12
           2       0.94      0.94      0.94        18

    accuracy                           0.96        50
   macro avg       0.95      0.95      0.95        50
weighted avg       0.96      0.96      0.96        50
```

5.2 a) Training set is chosen by hold out method.

[84]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=100)
```

[85]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 95.55555555555556 %
```

K-Nearest Neighbors Classifier

[86]:
```
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
print(classification_report(y_test, y_pred))
```

```
Accuracy Score: 97.77777777777777 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       0.92      1.00      0.96        11
           2       1.00      0.94      0.97        18

    accuracy                           0.98        45
   macro avg       0.97      0.98      0.98        45
weighted avg       0.98      0.98      0.98        45
```

Decision Tree Classifier

[87]:
```
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

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

```
Accuracy Score: 95.55555555555556 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       0.91      0.91      0.91        11
           2       0.94      0.94      0.94        18

    accuracy                           0.96        45
   macro avg       0.95      0.95      0.95        45
weighted avg       0.96      0.96      0.96        45
```

5.2 b) Training set is chosen by Random Subsampling.

[88]:
```
from sklearn.model_selection import ShuffleSplit
```

[89]:
```
rs = ShuffleSplit(n_splits=10, test_size=0.25, random_state=100)

accuracy_gnb = []
accuracy_knn = []
accuracy_dtree = []
```

[90]:
```
for train_index, test_index in rs.split(X):
    X_train = np.array([X[index] for index in train_index])
    X_test = np.array([X[index] for index in test_index])
    y_train = np.array([y[index] for index in train_index])
    y_test = np.array([y[index] for index in test_index])

    y_pred = GaussianNB().fit(X_train, y_train).predict(X_test)
    accuracy_gnb.append(accuracy_score(y_test, y_pred))

    y_pred = KNeighborsClassifier().fit(X_train, y_train).predict(X_test)
    accuracy_knn.append(accuracy_score(y_test, y_pred))

    y_pred = DecisionTreeClassifier().fit(X_train, y_train).predict(X_test)
    accuracy_dtree.append(accuracy_score(y_test, y_pred))
```

[91]:
```
print(f'Mean accuracy of Gaussian Naive Bayes: {sum(accuracy_gnb) /
 ↪len(accuracy_gnb) * 100} %')
print(f'Mean accuracy of K-Nearest Neighbors: {sum(accuracy_knn) /
 ↪len(accuracy_knn) * 100} %')
print(f'Mean accuracy of Decision Tree Classifier: {sum(accuracy_dtree) /
 ↪len(accuracy_dtree) * 100} %')
```

```
Mean accuracy of Gaussian Naive Bayes: 96.05263157894737 %
Mean accuracy of K-Nearest Neighbors: 96.84210526315789 %
Mean accuracy of Decision Tree Classifier: 94.99999999999999 %
```

5.2 c) Training set is chosen by Cross Validation.

[92]:
```
dtree = DecisionTreeClassifier()
knn = KNeighborsClassifier()
gnb = GaussianNB()
print(f'Mean accuracy of Gaussian Naive Bayes: {sum(accuracy_gnb) /
 ↪len(accuracy_gnb) * 100} %')
print(f'Mean accuracy of K-Nearest Neighbors: {sum(accuracy_knn) /
 ↪len(accuracy_knn) * 100} %')
print(f'Mean accuracy of Decision Tree Classifier: {sum(accuracy_dtree) /
 ↪len(accuracy_dtree) * 100} %')
```

```
Mean accuracy of Gaussian Naive Bayes: 96.05263157894737 %
Mean accuracy of K-Nearest Neighbors: 96.84210526315789 %
Mean accuracy of Decision Tree Classifier: 94.99999999999999 %
```

5.3 Data is scaled to standard format.

[93]:
```
from sklearn.preprocessing import StandardScaler
```

[94]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
 ↪random_state=100)
```

[95]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Naive Bayes Classifier

[96]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

K-Nearest Neighbors Classifier

[97]:
```
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
print(classification_report(y_test, y_pred))
```

```
Accuracy Score: 97.36842105263158 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.91      1.00      0.95        10
```

```
           2       1.00      0.93      0.96        14

    accuracy                           0.97        38
   macro avg       0.97      0.98      0.97        38
weighted avg       0.98      0.97      0.97        38
```

Decision Tree Classifier

[98]:
```python
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
print(classification_report(y_test, y_pred))
```

```
Accuracy Score: 94.73684210526315 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.90      0.90      0.90        10
           2       0.93      0.93      0.93        14

    accuracy                           0.95        38
   macro avg       0.94      0.94      0.94        38
weighted avg       0.95      0.95      0.95        38
```

Q6. Use Simple Kmeans, DBScan, Hierachical clustering algorithms for clustering. Compare the performance of clusters by changing the parameters involved in the algorithms.

[99]:
```python
#import numpy as np
#import pandas as pd
#import matplotlib.pyplot as plt

#from sklearn.datasets import load_iris
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
```

[100]:
```python
df = load_iris(as_frame=True).frame
df.head()
```

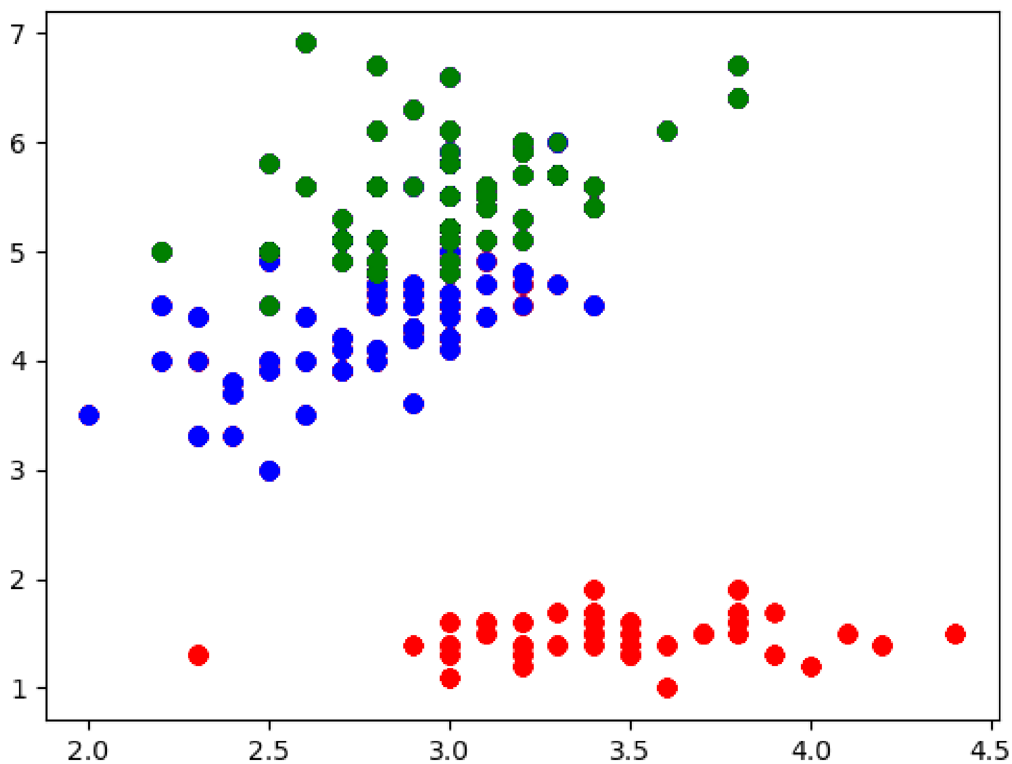
[100]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2
```

```
   target
0       0
1       0
2       0
3       0
4       0
```

Plotting Sepal Width and Petal Length

[103]:
```
for index in range(150):
    if index <= 49:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'ro')
    elif index > 49 and index <= 99:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'bo')
    elif index > 99:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'go')

plt.show()
```



K-Means Clustering

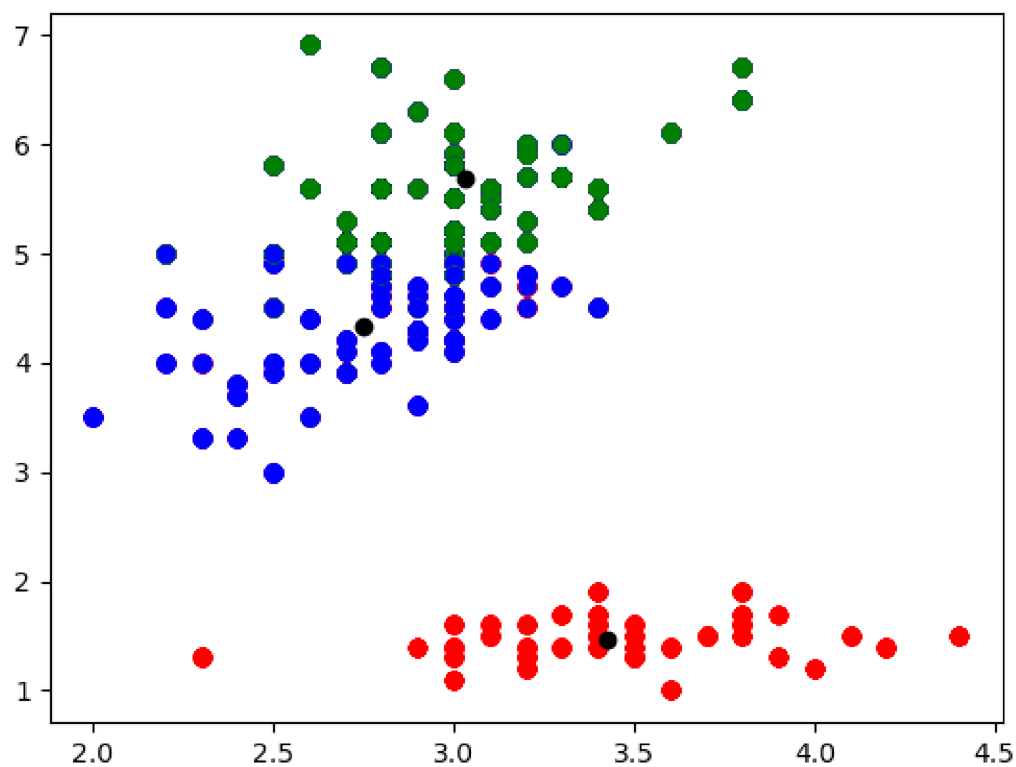
[109]:
```
k_cluster = KMeans(n_clusters=3)
k_cluster.fit(df.values[:, 1:3])
```

```
C:\Users\lamot\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\Users\lamot\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1382:
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=1.
  warnings.warn(
```

[109]: KMeans(n_clusters=3)

[111]:
```
for index in range(150):
    if k_cluster.labels_[index] == 0:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'go')
    elif k_cluster.labels_[index] == 1:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'ro')
    elif k_cluster.labels_[index] == 2:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'bo')

plt.plot(k_cluster.cluster_centers_[:, 0], k_cluster.cluster_centers_[:, 1],␣
↪'o', c='black')
plt.show()
```



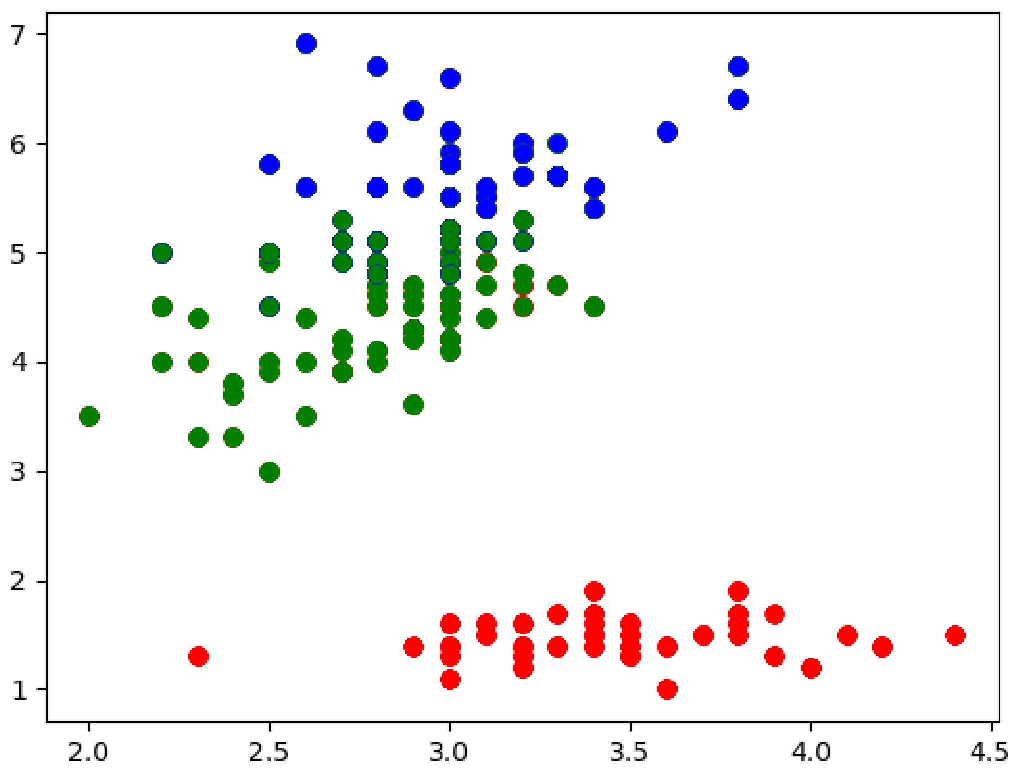
Hierarchical Agglomerative Clustering

[113]:
```
agg_cluster = AgglomerativeClustering(n_clusters=3)
agg_cluster.fit(df.values[:, 1:3])
```

[113]: AgglomerativeClustering(n_clusters=3)

[115]:
```
for index in range(150):
    if agg_cluster.labels_[index] == 0:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'go')
    elif agg_cluster.labels_[index] == 1:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'ro')
    elif agg_cluster.labels_[index] == 2:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'bo')

plt.show()
```



DBSCAN Clustering

[116]:
```
db_cluster = DBSCAN()
db_cluster.fit(df.values[:, 1:3])
```

[116]: DBSCAN()

[118]:
```
for index in range(150):
    if db_cluster.labels_[index] == 0:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'go')
    elif db_cluster.labels_[index] == 1:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'ro')
    elif db_cluster.labels_[index] == 2:
        plt.plot(df.values[index:, 1], df.values[index:, 2], 'bo')

plt.show()
```