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". 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. iii) Check whether ruleset E is violated by the data in the file people.txt. iv) Summarize the results obtained in part (iii) v) Visualize the results obtained in part (iii)

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv("people.txt",sep=",")
data
```

Out[2]:

	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

In [3]:
```
def ruleset(data):
    data['Rule1'] = data['Age'].apply(lambda x: x in range(0, 150))
    data['Rule2'] = data.apply(lambda x: x.Age > x.yearsmarried, axis=1)
    data['Rule3'] = data['status'].apply(lambda x: x in {'married', 'single', 'widowed'})
    data['Rule4'] = data.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)
```

In [4]:
```
ruleset(data)

data
```

Out[4]:

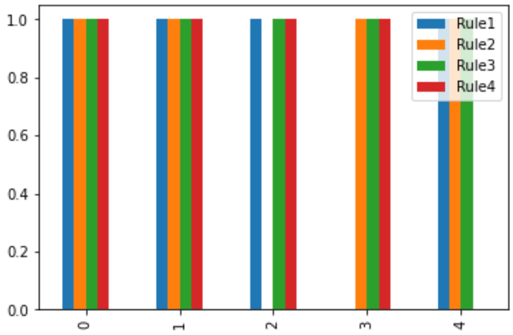
	Age	agegroup	height	status	yearsmarried	Rule1	Rule2	Rule3	Rule4
0	21	adult	6.0	single	-1	True	True	True	True
1	2	child	3.0	married	0	True	True	True	True
2	18	adult	5.7	married	20	True	False	True	True
3	221	elderly	5.0	widowed	2	False	True	True	True
4	34	child	-7.0	married	3	True	True	True	False

In [5]:
```
summary = data.loc[:, 'Rule1':'Rule4'].replace({True:1, False:0})

summary
```

Out[5]:

	Rule1	Rule2	Rule3	Rule4
0	1	1	1	1
1	1	1	1	1
2	1	0	1	1
3	0	1	1	1
4	1	1	1	0

In [6]:
```
summary.plot(kind='bar')
plt.show()
```



In [ ]:

Q2. Perform the following preprocessing tasks on the dirty_iris datasetii. i) Calculate the number and percentage of observations that are complete. ii) Replace all the special values in data with NA. iii) Define these rules in a separate text file and read them. (Use editfile function in R (package editrules). Use similar function in Python). Print the resulting constraint object. – Species should be one of the following values: setosa, versicolor or virginica. – All measured numerical properties of an iris should be positive. – The petal length of an iris is at least 2 times its petal width. – The sepal length of an iris cannot exceed 30 cm. – The sepals of an iris are longer than its petals. iv)Determine how often each rule is broken (violatedEdits). Also summarize and plot the result. v) Find outliers in sepal length using boxplot and boxplot.stats

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv("dirty_iris.csv")
data.head()
```

Out[2]:

	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

In [3]:
```
complete_observations = data.isnull().sum(axis=1).value_counts().iloc[0]

print(f'Complete Observations: {complete_observations}')
print(f'Percentage: {complete_observations / len(data) * 100} %')
```

```
Complete Observations: 96
Percentage: 64.0 %
```

In [4]:
```
# data.fillna(value='NA', inplace=True)
```

In [5]:
```
data.dropna(inplace=True)
```

In [6]:
```
def check_species(data):
    x = data['Species'].apply(lambda x: x in {'setosa', 'versicolor', 'virginica'})
    violations = len(data) - np.sum(x)

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

    return violations
```

In [7]:
```
species_violations = check_species(data)
```

```
No Violation.
```

In [8]:
```
def check_all_positive(data):
    x = data.loc[:, 'Sepal.Length':'Petal.Width'].apply(lambda x: x > 0).values
    x = x.reshape(-1)
    violations = len(data) * 4 - np.sum(x)

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

    return violations
```

In [9]:
```
non_positive_violations = check_all_positive(data)
```

```
Violation: Non-positive Numerical Property.
Violations: 3
```

In [10]:
```
def check_petal_length(data):
    x = data['Petal.Length'] >= 2 * data['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
```

In [11]:
```
petal_length_violations = check_petal_length(data)
```

```
Violation: Petal Length is less than twice its Petal Width.
Violations: 2
```

In [12]:
```
def check_sepal_length(data):
    x = data['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
```

In [13]:
```
sepal_length_violations = check_sepal_length(data)
```

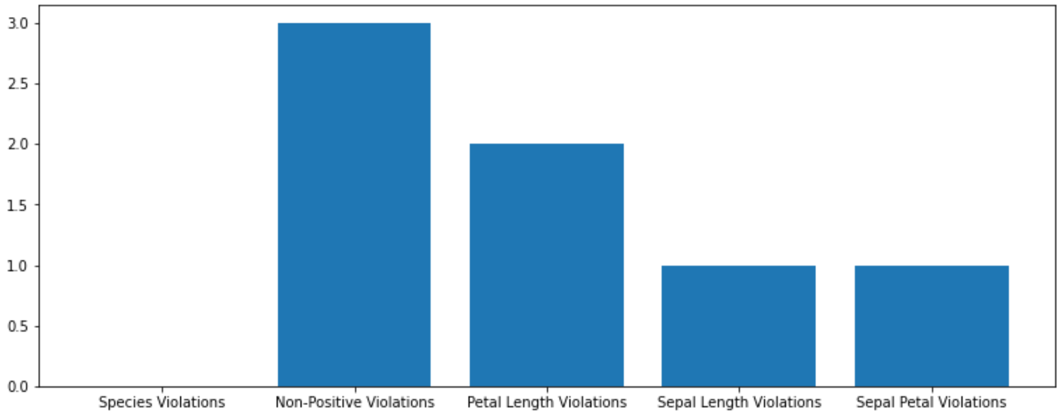
```
Violation: Sepal Length exceeded the value of 30cms.
Violations: 1
```

In [14]:
```
def check_sepal_petal_length(data):
    x = data['Sepal.Length'] > data['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
```

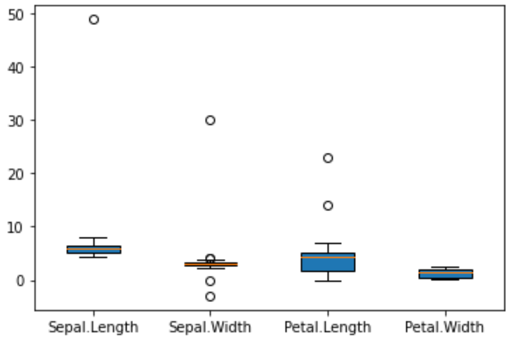
In [15]:
```
sepal_petal_violations = check_sepal_petal_length(data)
```

```
Violation: Sepal Length are less than Petal Length.
Violations: 1
```

In [16]:
```
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()
```



In [17]:
```
x = [data[col] for col in data.columns[:-1]]

box = plt.boxplot(x, labels=data.columns[:-1], patch_artist=True)
plt.show()
```



In [18]:
```
print(box.keys())
```

```
dict_keys(['whiskers', 'caps', 'boxes', 'medians', 'fliers', 'means'])
```

In [19]:
```
outliers = [item.get_ydata() for item in box['fliers']]

print(f'Outliers in Sepal Length: {outliers[0]}')
```

```
Outliers in Sepal Length: [49.]
```

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.

In [1]:
```
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_wine, load_iris
```

In [2]:
```
data = load_wine()

X = data.data
```

In [3]:
```
X.mean(axis=0)
```

Out[3]:
```
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])
```

In [4]:
```
X.std(axis=0)
```

Out[4]:
```
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])
```

In [5]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
```

In [6]:
```
X.mean(axis=0)
```

Out[6]:
```
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])
```

In [7]:
```
X.std(axis=0)
```

Out[7]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

In [8]:
```
data = load_iris()

X = data.data
```

In [9]:
```
X.mean(axis=0)
```

Out[9]:
```
array([5.84333333, 3.05733333, 3.758     , 1.19933333])
```

In [10]:
```
X.std(axis=0)
```

Out[10]:
```
array([0.82530129, 0.43441097, 1.75940407, 0.75969263])
```

In [11]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
```

In [12]:
```
X.mean(axis=0)
```

Out[12]:
```
array([-1.69031455e-15, -1.84297022e-15, -1.69864123e-15, -1.40924309e-15])
```

In [13]:
```
X.std(axis=0)
```

Out[13]:
```
array([1., 1., 1., 1.])
```

Q4. Run Apriori algorithm to find frequent itemsets and association rules 1.1 Use minimum support as 50% and minimum confidence as 75% 1.2 Use minimum support as 60% and minimum confidence as 60 %

In [1]:
```
import numpy as np
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
```

In [2]:
```
dataset = [
    ['A', 'B', 'C', 'D', 'F', 'H'],
    ['B', 'E', 'F', 'H'],
    ['A', 'C', 'E'],
    ['B', 'C', 'D', 'F', 'H'],
    ['A', 'B', 'C', 'D', 'E'],
    ['C','D','F','H'],
    ['A','C','D','H'],
    ['E','H']
]
```

In [3]:
```
encoder = TransactionEncoder()
transactions = encoder.fit_transform(dataset)

data = pd.DataFrame(transactions, columns=encoder.columns_)
data
```

Out[3]:

	A	B	C	D	E	F	H
0	True	True	True	True	False	True	True
1	False	True	False	False	True	True	True
2	True	False	True	False	True	False	False
3	False	True	True	True	False	True	True
4	True	True	True	True	True	False	False
5	False	False	True	True	False	True	True
6	True	False	True	True	False	False	True
7	False	False	False	False	True	False	True

In [4]:
```
frequent_itemsets = apriori(data, min_support=0.5, use_colnames=True)
frequent_itemsets
```

Out[4]:

	support	itemsets
0	0.500	(A)
1	0.500	(B)
2	0.750	(C)
3	0.625	(D)
4	0.500	(E)
5	0.500	(F)
6	0.750	(H)
7	0.500	(C, A)
8	0.625	(D, C)
9	0.500	(C, H)
10	0.500	(D, H)
11	0.500	(H, F)
12	0.500	(D, C, H)

In [5]:
```
association_rules(frequent_itemsets, metric='confidence', min_threshold=0.75)
```

Out[5]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(A)	(C)	0.500	0.750	0.500	1.000000	1.333333	0.12500	inf	0.500000
1	(D)	(C)	0.625	0.750	0.625	1.000000	1.333333	0.15625	inf	0.666667
2	(C)	(D)	0.750	0.625	0.625	0.833333	1.333333	0.15625	2.25	1.000000
3	(D)	(H)	0.625	0.750	0.500	0.800000	1.066667	0.03125	1.25	0.166667
4	(F)	(H)	0.500	0.750	0.500	1.000000	1.333333	0.12500	inf	0.500000
5	(D, C)	(H)	0.625	0.750	0.500	0.800000	1.066667	0.03125	1.25	0.166667
6	(D, H)	(C)	0.500	0.750	0.500	1.000000	1.333333	0.12500	inf	0.500000
7	(C, H)	(D)	0.500	0.625	0.500	1.000000	1.600000	0.18750	inf	0.750000
8	(D)	(C, H)	0.625	0.500	0.500	0.800000	1.600000	0.18750	2.50	1.000000

In [6]:

```
frequent_itemsets = apriori(data, min_support=0.6, use_colnames=True)
frequent_itemsets
```

Out[6]:

	support	itemsets
0	0.750	(C)
1	0.625	(D)
2	0.750	(H)
3	0.625	(D, C)

In [7]:

```
association_rules(frequent_itemsets, metric='confidence', min_threshold=0.6)
```

Out[7]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(D)	(C)	0.625	0.750	0.625	1.000000	1.333333	0.15625	inf	0.666667
1	(C)	(D)	0.750	0.625	0.625	0.833333	1.333333	0.15625	2.25	1.000000

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: 5.1 a) Training set = 75% Test set = 25% b) Training set = 66.6% (2/3rd of total), Test set = 33.3% 5.2 Training set is chosen by i) hold out method ii) Random subsampling iii) Cross-Validation. Compare the accuracy of the classifiers obtained. 5.3 Data is scaled to standard format.

In [1]:
```
import numpy as np
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
```

In [2]:
```
X, y = load_iris(return_X_y=True)
```

In [3]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=100)
```

In [4]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
```

In [5]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

In [6]:
```
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
```

In [7]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 97.36842105263158 %
```

In [8]:
```
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
```

In [9]:
```
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
```

In [10]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

In [11]:
```
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
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=100)
```

In [13]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
```

In [14]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 96.0 %
```

In [15]:
```
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
```

In [16]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 98.0 %
```

In [17]:
```python
print(classification_report(y_test, y_pred))
```

```
              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
```

In [18]:
```python
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
```

In [19]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 96.0 %
```

In [20]:
```python
print(classification_report(y_test, y_pred))
```

```
              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
```

In [21]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=100)
```

In [22]:
```python
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
```

In [23]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 95.55555555555556 %
```

In [24]:
```python
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
```

In [25]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 97.77777777777777 %
```

In [26]:
```python
print(classification_report(y_test, y_pred))
```

```
              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
```

In [27]:
```python
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)
```

In [28]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 95.55555555555556 %
```

In [29]:
```python
print(classification_report(y_test, y_pred))
```

```
              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
```

In [30]:
```python
from sklearn.model_selection import ShuffleSplit
```

In [31]:
```python
rs = ShuffleSplit(n_splits=10, test_size=0.25, random_state=100)

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

In [32]:
```python
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))
```

In [33]:
```python
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: 95.0 %
```

In [34]:
```python
dtree = DecisionTreeClassifier()
knn = KNeighborsClassifier()
gnb = GaussianNB()
```

In [35]:
```python
accuracy_dtree = cross_val_score(dtree, X, y, cv=5)
accuracy_knn = cross_val_score(knn, X, y, cv=5)
accuracy_gnb = cross_val_score(gnb, X, y, cv=5)
```

In [36]:
```python
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: 95.33333333333334 %
Mean accuracy of K-Nearest Neighbors: 97.33333333333334 %
Mean accuracy of Decision Tree Classifier: 96.00000000000001 %
```

In [37]:
```python
from sklearn.preprocessing import StandardScaler
```

In [38]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=100)
```

In [39]:
```python
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [40]:
```python
gnb = GaussianNB()
gnb.fit(X_train, y_train)

y_pred = gnb.predict(X_test)
```

In [41]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

In [42]:
```python
knn = KNeighborsClassifier()    # default k=5
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
```

In [43]:
```python
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 97.36842105263158 %
```

In [44]:
```python
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
```

In [45]:
```python
dtree = DecisionTreeClassifier()    # default criteria='gini'
dtree.fit(X_train, y_train)
```

```
y_pred = dtree.predict(X_test)
```

In [46]:
```
print(f'Accuracy Score: {accuracy_score(y_test, y_pred) * 100} %')
```

```
Accuracy Score: 94.73684210526315 %
```

In [47]:
```
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
```

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

In [1]:
```
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
```

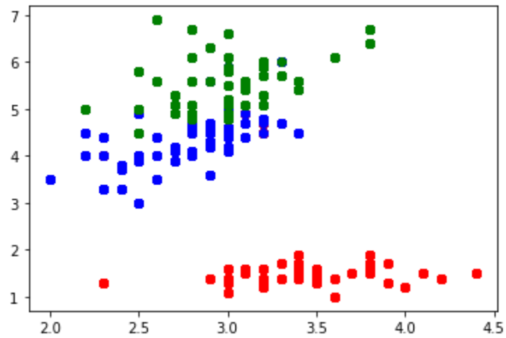
In [2]:
```
data = load_iris(as_frame=True).frame

data.head()
```

Out[2]:

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

Plotting Sepal Width and Petal Length

In [3]:
```
for index in range(150):
    if index <= 49:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'ro')
    elif index > 49 and index <= 99:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'bo')
    elif index > 99:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'go')

plt.show()
```



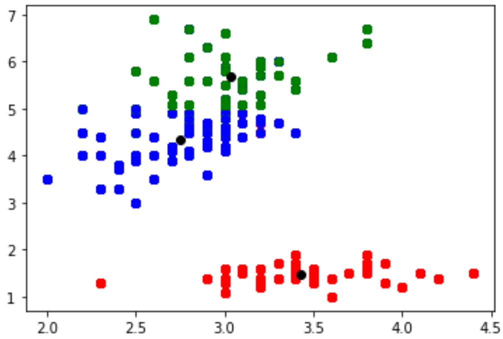
K-Means Clustering

In [4]:
```
k_cluster = KMeans(n_clusters=3)

k_cluster.fit(data.values[:, 1:3])
```

```
C:\Users\admin\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The d
efault 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(
```

Out[4]:
```
▾ KMeans
KMeans(n_clusters=3)
```

In [5]:
```
for index in range(150):
    if k_cluster.labels_[index] == 0:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'go')
    elif k_cluster.labels_[index] == 1:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'ro')
    elif k_cluster.labels_[index] == 2:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'bo')

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

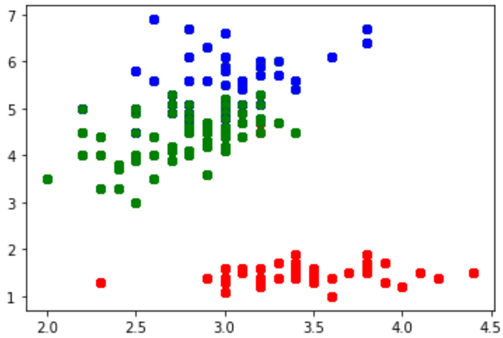


Hierarchical Agglomerative Clustering

In [6]:
```
agg_cluster = AgglomerativeClustering(n_clusters=3)

agg_cluster.fit(data.values[:, 1:3])
```

Out[6]:
```
▾ AgglomerativeClustering
AgglomerativeClustering(n_clusters=3)
```

In [7]:
```
for index in range(150):
    if agg_cluster.labels_[index] == 0:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'go')
    elif agg_cluster.labels_[index] == 1:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'ro')
    elif agg_cluster.labels_[index] == 2:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'bo')

plt.show()
```

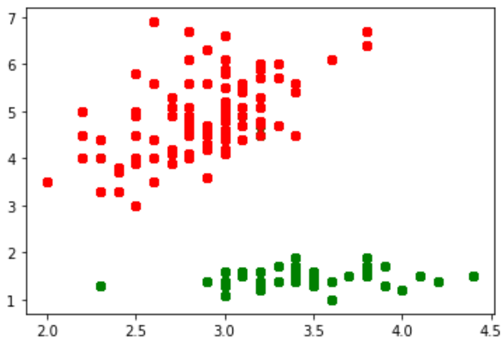


DBSCAN Clustering

In [8]:
```
db_cluster = DBSCAN()

db_cluster.fit(data.values[:, 1:3])
```

Out[8]:
```
▾ DBSCAN
DBSCAN()
```

In [9]:
```
for index in range(150):
    if db_cluster.labels_[index] == 0:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'go')
    elif db_cluster.labels_[index] == 1:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'ro')
    elif db_cluster.labels_[index] == 2:
        plt.plot(data.values[index:, 1], data.values[index:, 2], 'bo')

plt.show()
```


7
6
5
4
3
2
1
2.0
2.5
3.0
3.5
4.0
4.5