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BCA 507(C):- PRACTILE ON DATA MINING USING PYTHON

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1.Calculate the mean and standard deviation.

```
import numpy as np

data=np.array([10,20,30,40,50])

mean_value=np.mean(data)

std_dev=np.std(data,ddof=1)

print(f"mean:{mean_value}")

print(f"Standard Deviation:{std_dev}")
```

Output:-

mean:30.0

Standard Deviation:15.811388300841896

2.Read the CSV file.

#create csv file:-

```
import pandas as pd
data = {
    'Name': ['Alice', 'Bob', 'Charlie'],
    'Age': [30, 25, 35],
    'City': ['New York', 'Los Angeles', 'Chicago']
}
df = pd.DataFrame(data)
df.to_csv('people.csv', index=False)
print("CSV file created successfully.")
```

Output:-

CSV file created successfully.

#Read csv file:-

```
import pandas as pd
file_path = 'people.csv'
df = pd.read_csv(file_path)
df.head()  # Shows the first 5 rows of the data
```

Output:-

	Name	Age	City
0	Alice	30	New York
1	Bob	25	Los Angeles
2	Charlie	35	Chicago

3.Perform data filtering and calculate aggregate statistics.

```
import pandas as pd
data={
    'name':[ 'alice', 'bob', 'charlie','david','eve'],
    'age':[20,22,32,21,19],
    'salary':[3000,4000,2000,5000,3500]
}
df=pd.DataFrame(data)
f_d=df[df['age']>20]
ave_sal=f_d['salary'].mean()
ave_sal1=f_d['salary'].sum()
print(f_d)
print('____________________________________________________________________________
______________________________________________________________________________
_____________')
print(f'average salary of employees older than 25:(ave_sal,ave_sal1)')
```

Output:-

```
      name  age  salary
1      bob   22    4000
2  charlie   32    2000
3    david   21    5000
__________________________________________________________________________________
average salary of employees older than 25:(ave_sal,ave_sal1)
```

4.Calculate total sales by month.

```
import pandas as pd
data = {
    'Date': ['2023-01-05', '2023-01-12', '2023-02-01','2023-02-14'],
    'Sales': [100, 150,200,300]
}
df = pd.DataFrame(data)
df['Date'] = pd.to_datetime(df['Date'])
df['Year-Month'] = df['Date'].dt.to_period('M')
total_sales_by_month = df.groupby('Year-Month')['Sales'].sum().reset_index()
print(total_sales_by_month)
```

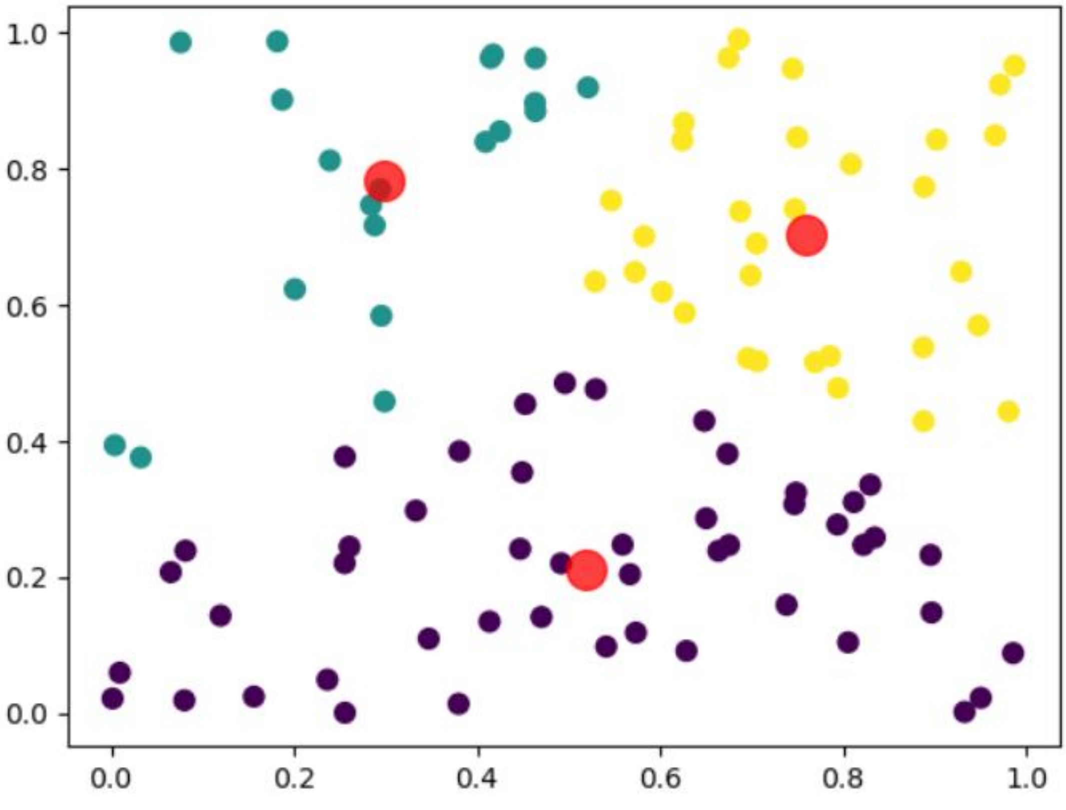
Output:-

```
  Year-Month  Sales
0    2023-01    250
1    2023-02    500
```

5.Implement the Clustering using K-means.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
np.random.rand(0)
x=np.random.rand(100,2)
kmeans=KMeans(n_clusters=3)
kmeans.fit(x)
centers=kmeans.cluster_centers_
labels=kmeans.labels_
plt.scatter(x[:,0],x [:,1],c=labels,s=50,cmap='viridis')
plt.scatter(centers[:,0],centers[:,1],c='red',s=200,alpha=0.75)
plt.show()
```

Output:-



6.Classification using Random Forcst.

```
import numpy as np

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, accuracy_score

data = {

    'Age': [25, 45, 35, 33, 50, 23, 43, 36, 29, 48],

    'Income': [40000, 80000, 60000, 58000, 90000, 42000, 75000, 62000, 50000, 
85000],

    'Education': [1, 2, 1, 0, 2, 1, 2, 0, 1, 2],

    'Purchased': [0, 1, 0, 0, 1, 0, 1, 0, 0, 1]

}

df = pd.DataFrame(data)

X = df[['Age', 'Income', 'Education']]

y = df['Purchased']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, 
random_state=42)

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))

print("\nClassification Report:")

print(classification_report(y_test, y_pred))

feature_importances = pd.DataFrame({

    'Feature': X.columns,

    'Importance': rf_model.feature_importances_

}).sort_values(by='Importance', ascending=False)

print("\nFeature Importances:")
```

print(feature_importances)

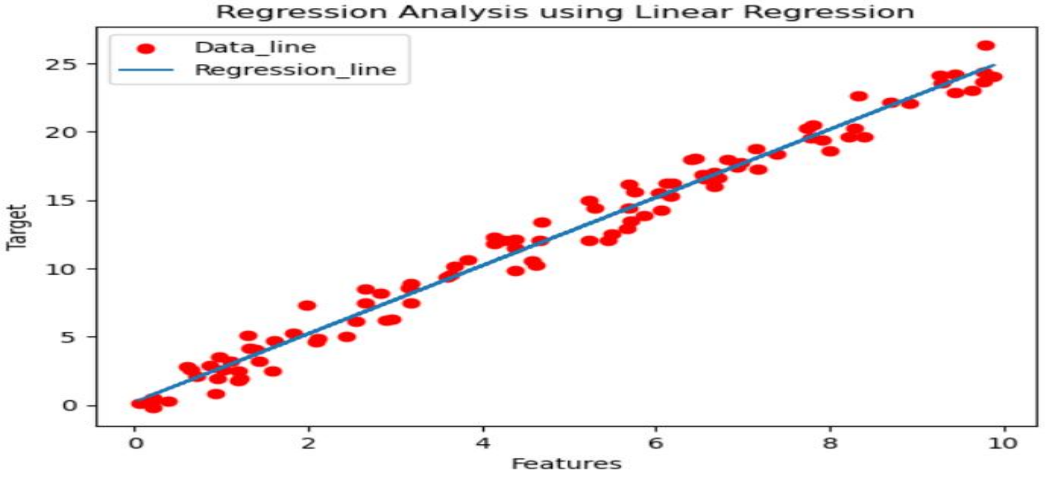
Output:-

```
Accuracy: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00         1

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3


Feature Importances:
     Feature  Importance
1     Income    0.363636
0        Age    0.353535
2  Education    0.282828
```

7.Regression Analysis using Linear Regression.

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression

np.random.seed(0)

x=np.random.rand(100,1)*10

y=2.5*x+np.random.randn(100,1)

data=pd.DataFrame(np.hstack((x,y)),

columns=['Feature','Target'])

model=LinearRegression()

model.fit(data[['Feature']],data[['Target']])

y_pred=model.predict(data[['Feature']])

plt.scatter(data['Feature'], data['Target'],color='red', label='Data_line')

plt.plot(data['Feature'],y_pred,label='Regression_line')

plt.xlabel('Features')

plt.ylabel('Target')

plt.title('Regression Analysis using Linear Regression')

plt.legend()

plt.show()
```

Output:-



8.Association Rule Mining using Apriori.

```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
d_S=[['Milk','Bread'],
    ['Bread','Beer','Eggs'],
    ['Milk','Beer','Cola'],
    ['Bread','Milk','cola']]
encoder=TransactionEncoder()
onehot=encoder.fit(d_S).transform(d_S)
df=pd.DataFrame(onehot,columns=encoder.columns_)
f_i=apriori(df,min_support=0.4,use_colnames=True)
print(f_i)
rules = association_rules(f_i, num_itemsets=len(f_i), metric="lift", min_threshold=1)
print("\nAssociation Rules:")
print(rules)
```

Output:-

```
   support       itemsets
0     0.50         (Beer)
1     0.75        (Bread)
2     0.75         (Milk)
3     0.50  (Bread, Milk)

Association Rules:
Empty DataFrame
Columns: [antecedents, consequents, antecedent support, consequent support, support, confidence, lift, representativity, leverage, conviction, zhangs_met
ric, jaccard, certainty, kulczynski]
Index: []
```

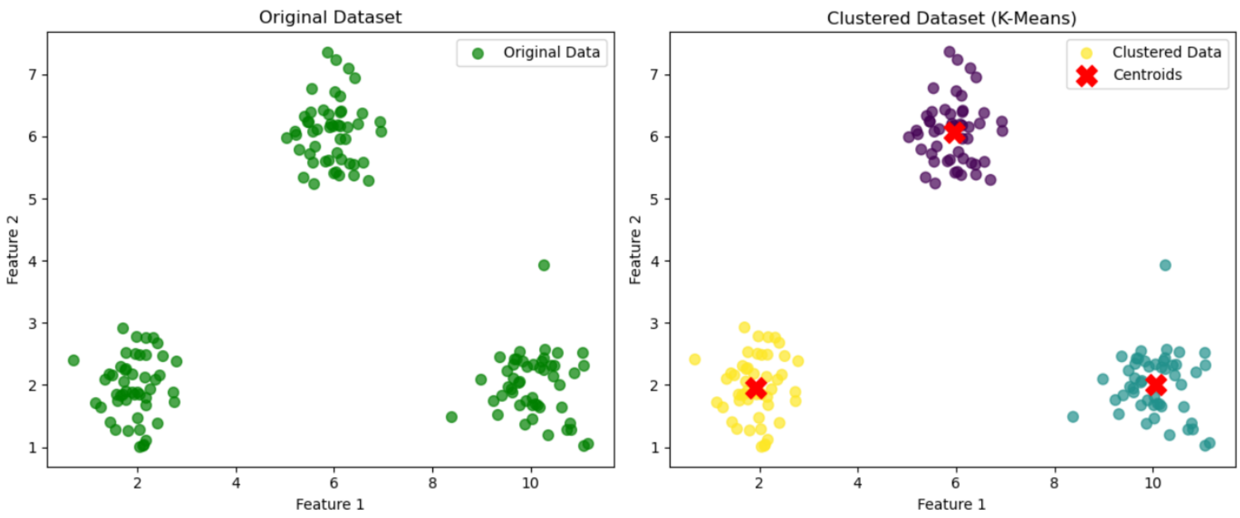
9.Visualize the result of the clustering and compare.

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn.cluster import KMeans

np.random.seed(42)

X1 = np.random.normal(loc=[2, 2], scale=0.5, size=(50, 2))

X2 = np.random.normal(loc=[6, 6], scale=0.5, size=(50, 2))

X3 = np.random.normal(loc=[10, 2], scale=0.5, size=(50, 2))

X = np.vstack((X1, X2, X3))  # Combine into a single dataset

kmeans = KMeans(n_clusters=3, random_state=42)

kmeans.fit(X)

labels = kmeans.labels_

centroids = kmeans.cluster_centers_

plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)

plt.scatter(X[:, 0], X[:, 1], c='green', s=50, alpha=0.7, label="Original Data")

plt.title("Original Dataset")

plt.xlabel("Feature 1")

plt.ylabel("Feature 2")

plt.legend()

plt.subplot(1, 2, 2)

plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', s=50, alpha=0.7, label="Clustered
Data")

plt.scatter(centroids[:, 0], centroids[:, 1], c='red', s=200, marker='X',
label="Centroids")

plt.title("Clustered Dataset (K-Means)")

plt.xlabel("Feature 1")

plt.ylabel("Feature 2")

plt.legend()
```

plt.tight_layout()

plt.show()

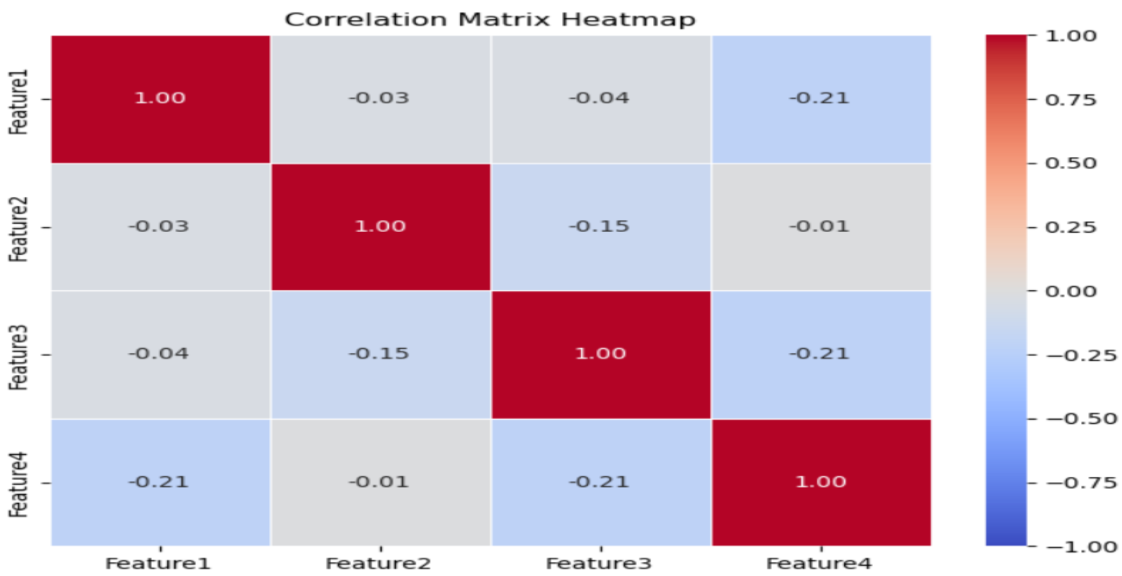
Output:-



10.Visualize the correlation matrix using a pseudocolor plot.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
np.random.seed(42)
data = {
    'Feature1': np.random.rand(100),
    'Feature2': np.random.rand(100),
    'Feature3': np.random.rand(100),
    'Feature4': np.random.rand(100)
}
df = pd.DataFrame(data)
corr_matrix = df.corr()
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1, fmt='.2f',
linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```

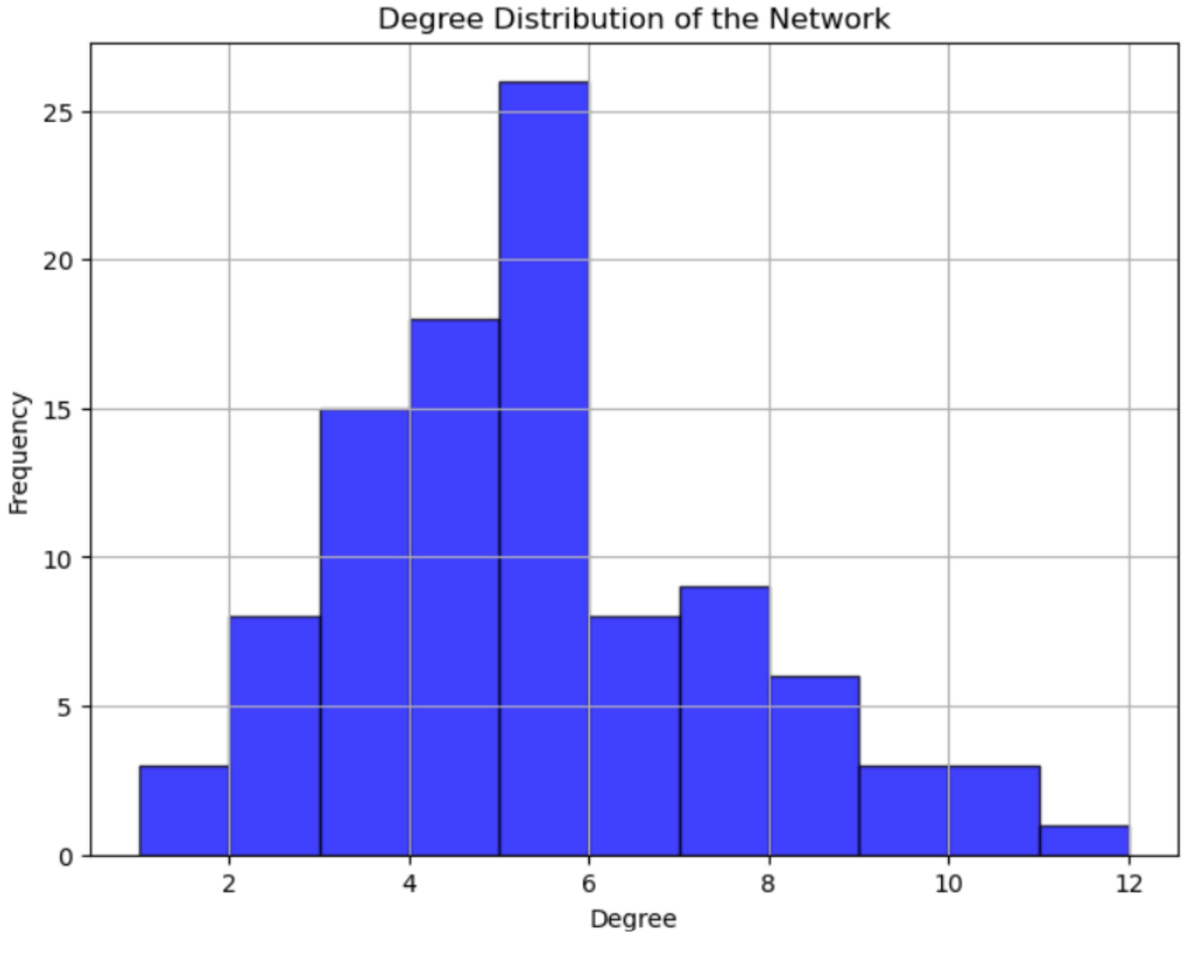
Output:-



11.Use of degrees distribtution of a network.

```
import networkx as nx

import matplotlib.pyplot as plt

G = nx.erdos_renyi_graph(n=100, p=0.05)

degree_sequence = [G.degree(n) for n in G.nodes()]

plt.figure(figsize=(8, 6))

plt.hist(degree_sequence, bins=range(min(degree_sequence), max(degree_sequence)
+ 1), alpha=0.75, color='blue', edgecolor='black')

plt.title("Degree Distribution of the Network")

plt.xlabel("Degree")

plt.ylabel("Frequency")

plt.grid(True)

plt.show()
```

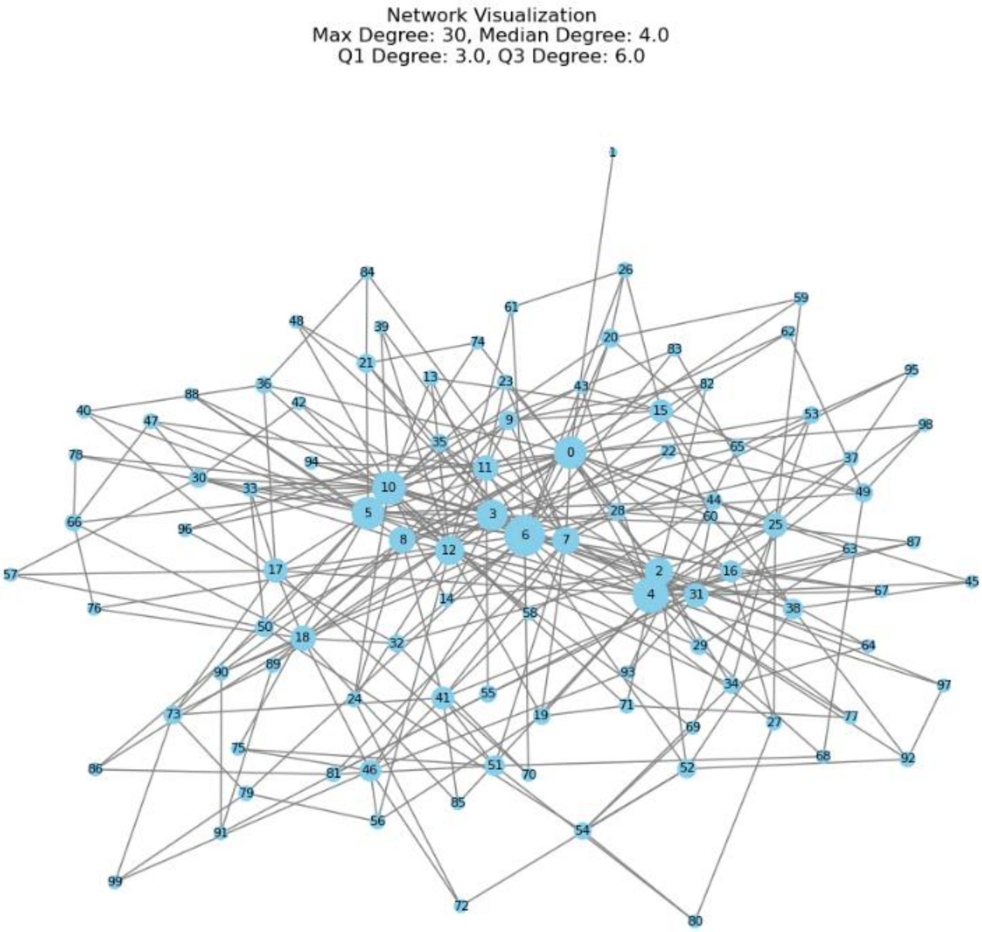
Output:-



12.Graph visualization of a network using maximum , minimum , median , first quartile and third quartile.

```
import networkx as nx

import matplotlib.pyplot as plt

import numpy as np

G = nx.barabasi_albert_graph(n=100, m=3)

degree_sequence = [G.degree(n) for n in G.nodes()]

max_degree = max(degree_sequence)

median_degree = np.median(degree_sequence)

q1_degree = np.percentile(degree_sequence, 25)

q3_degree = np.percentile(degree_sequence, 75)

node_size = [degree * 20 for degree in degree_sequence]

plt.figure(figsize=(10, 8))

pos = nx.spring_layout(G)

nx.draw(G, pos, node_size=node_size, with_labels=True, node_color='skyblue',
edge_color='gray', font_size=8)

plt.title(f"Network Visualization\nMax Degree: {max_degree}, Median Degree:
{median_degree}\n"

          f"Q1 Degree: {q1_degree}, Q3 Degree: {q3_degree}", fontsize=12)

plt.show()
```

Output:-


Network Visualization
Max Degree: 30, Median Degree: 4.0
Q1 Degree: 3.0, Q3 Degree: 6.0