```python
#import the libaries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

data = pd.read_csv("dataset.csv")
print("Dataset Shape:", data.shape)
```

```
Dataset Shape: (250, 8)
```

```python
print(data.columns)
```

```
Index(['Age', 'Annual Income', 'Spending Score', 'Gender', 'Location',
       'Family Size', 'Occupation', 'Education'],
      dtype='object')
```

```python
print(data.size)
```

```
2000
```

```python
#data preprocessing using label encoding
from sklearn.preprocessing import LabelEncoder,StandardScaler

obj=LabelEncoder()
data['Gender']=obj.fit_transform(data['Gender'])
data['Location']=obj.fit_transform(data['Location'])
data['Occupation']=obj.fit_transform(data['Occupation'])
data['Education']=obj.fit_transform(data['Education'])

# Data preprocessing using label encoding
# le = LabelEncoder()
# categorical_columns = ['Gender', 'Location', 'Occupation',
'Education']
# for col in categorical_columns:
#     data[col] = le.fit_transform(data[col])

# Feature scaling
scaler = StandardScaler()
features_scaled = scaler.fit_transform(data)
features_df = pd.DataFrame(features_scaled, columns=data.columns)

features_df
```

```
          Age  Annual Income  Spending Score  Gender  Location  Family
Size  \
0    1.368290       0.359492       -1.239574    -1.0 -1.074789    -
0.254442
1    0.577005      -0.960610        1.496569     1.0 -1.074789    -
0.254442
2   -0.530794       0.780383       -1.543590    -1.0 -1.074789
1.480387
3   -1.084694       1.514264       -0.530204     1.0  0.930415    -
```

```
1.410994
4   -0.056023      -1.472113        1.226333    -1.0  0.930415
0.323835
..        ...            ...              ...      ...       ...
...
245  1.210033      -0.382408       -1.138236     1.0  0.930415
1.480387
246  0.814391      -1.637155        1.124994    -1.0 -1.074789
1.480387
247 -1.005565      -0.653573        1.260112    -1.0  0.930415    -
0.832718
248  1.526547      -0.646659        0.618301    -1.0  0.930415
0.323835
249  1.051776      -1.151583       -0.563983     1.0 -1.074789    -
0.254442

     Occupation  Education
0     -0.090085  -0.686878
1     -1.113772   1.415811
2      0.933603   0.714914
3      0.933603   0.714914
4      1.445447  -1.387775
..          ...        ...
245   -1.113772  -1.387775
246   -0.090085  -1.387775
247   -1.113772   0.014018
248   -0.090085   1.415811
249   -0.090085  -1.387775

[250 rows x 8 columns]
```

```
features_df.columns
```

```
Index(['Age', 'Annual Income', 'Spending Score', 'Gender', 'Location',
       'Family Size', 'Occupation', 'Education'],
      dtype='object')
```

```
features_df.size
```

```
2000
```

```
features_df.shape
```

```
(250, 8)
```

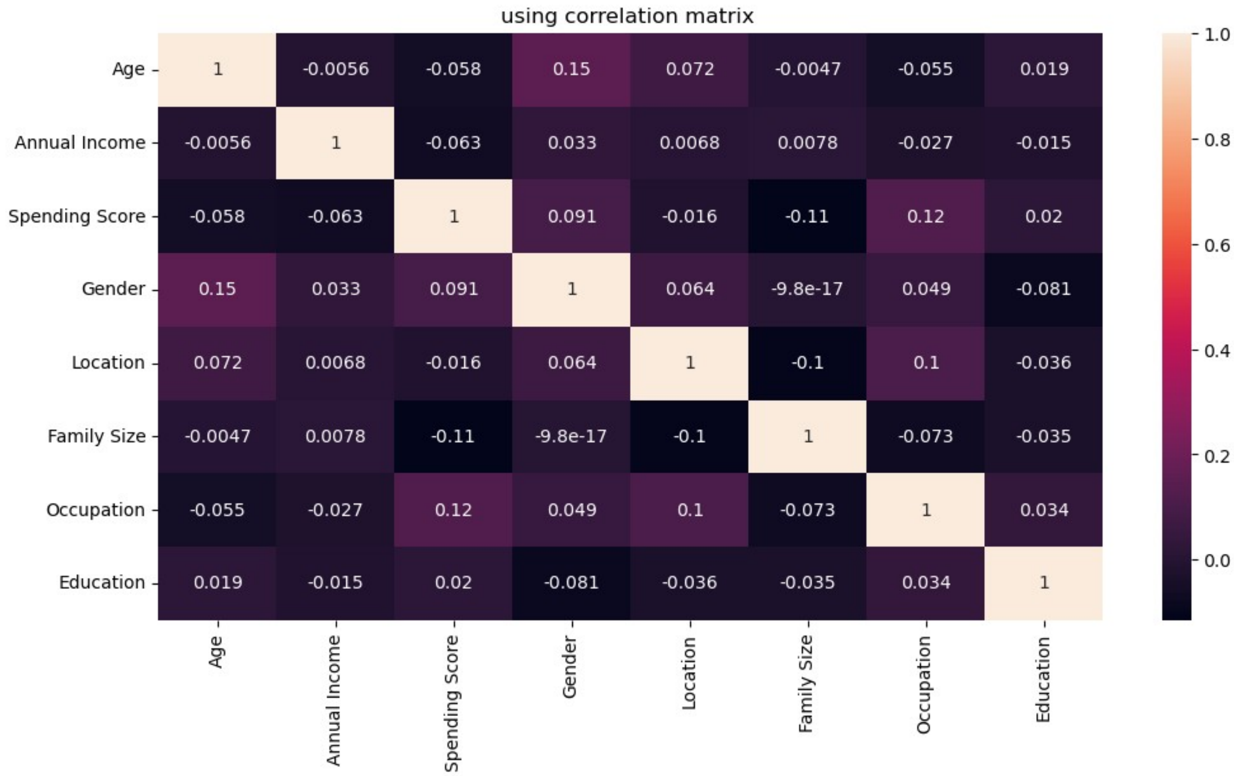
```
features_df.head(10)
features_df.tail(4)
features_df.sample(7)
```

```
          Age  Annual Income  Spending Score  Gender  Location  Family
Size  \
```

```
30  -0.530794       0.427776       -1.138236    -1.0  0.930415    -
0.254442
55  -1.242951      -0.121038        0.348064     1.0 -1.074789    -
1.410994
171  0.181363      -0.200654       -0.935558    -1.0 -1.074789    -
1.410994
34  -0.056023      -0.851221       -1.577370     1.0 -1.074789
1.480387
4   -0.056023      -1.472113        1.226333    -1.0  0.930415
0.323835
95   1.605676      -1.044548        1.226333    -1.0 -1.074789    -
0.254442
207 -0.451665       1.457601       -1.138236     1.0  0.930415    -
0.832718

     Occupation  Education
30    -0.090085   1.415811
55    -1.113772  -0.686878
171   -1.625616  -0.686878
34    -0.601928   1.415811
4      1.445447  -1.387775
95     0.421759  -0.686878
207   -1.625616  -0.686878
```

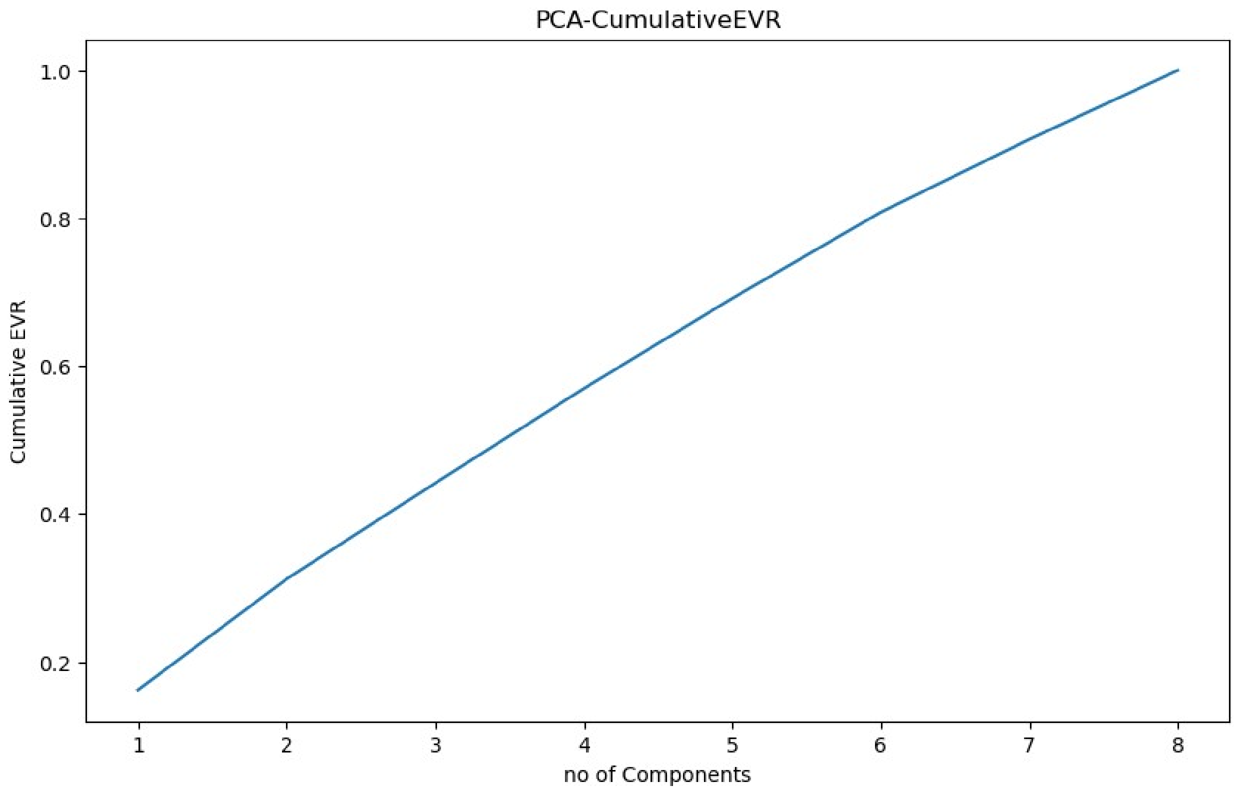
```
#feature selection
import seaborn as sns
plt.figure(figsize=(12,6))
sns.heatmap(data.corr(),annot=True)
plt.title("using correlation matrix ")
```

```
Text(0.5, 1.0, 'using correlation matrix ')
```




```
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering, Birch,
SpectralClustering

selector = SelectKBest(score_func=f_classif, k=4)
X_selected = selector.fit_transform(features_df, data['Spending
Score'])
selected_features_mask = selector.get_support()
selected_feature_names = features_df.columns[selected_features_mask]
print("Most significant features:", selected_feature_names)

Most significant features: Index(['Annual Income', 'Spending Score',
'Location', 'Family Size'], dtype='object')

c:\Users\lsrin\anaconda3\Lib\site-packages\sklearn\feature_selection\
_univariate_selection.py:113: RuntimeWarning: divide by zero
encountered in divide
  f = msb / msw

# 2ndPCA
pca = PCA()
X_pca = pca.fit_transform(features_df)
explained_variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance)
print(len(explained_variance))
```

```
8


plt.figure(figsize=(10, 6))
r=range(1, len(explained_variance) + 1) #1,9 inclusive,exclusive
plt.plot(r, cumulative_variance)
plt.xlabel('no of Components')
plt.ylabel('Cumulative EVR')
plt.title('PCA-CumulativeEVR')

Text(0.5, 1.0, 'PCA-CumulativeEVR')
```




```
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```

```
Most significant features: Index(['Annual Income', 'Spending Score',
'Location', 'Family Size'], dtype='object')

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_univariate_selection.py:113: RuntimeWarning: divide by zero
encountered in divide
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```

```
# 2ndPCA
pca = PCA()
X_pca = pca.fit_transform(features_df)
explained_variance = pca.explained_variance_ratio_ #variances blw the
pc explained "how"
cumulative_variance = np.cumsum(explained_variance) #total variances
print(len(explained_variance))
```

```
8
```

```
plt.figure(figsize=(10, 6))
r=range(1, len(explained_variance) + 1) #1,9 inclusive,exclusive
plt.plot(r, cumulative_variance)
plt.xlabel('no of Components')
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plt.title('PCA-CumulativeEVR')
```
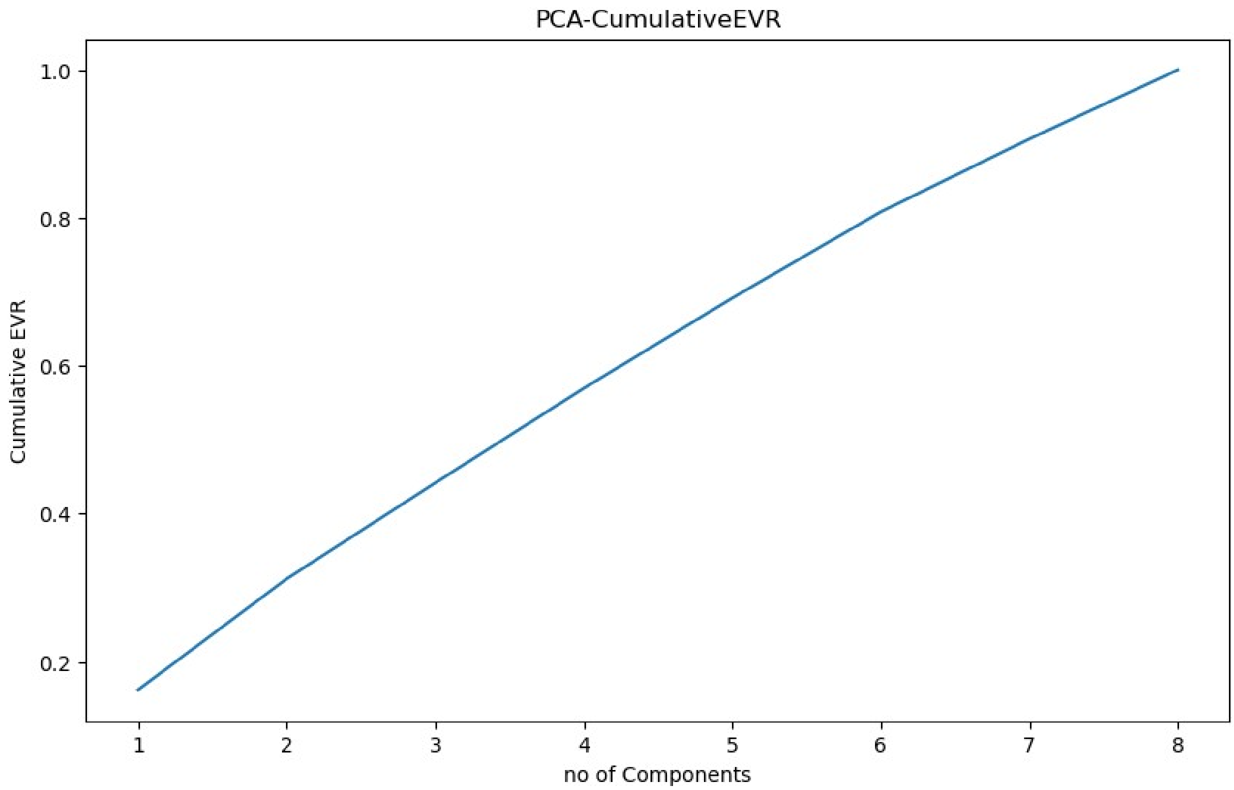

```
Text(0.5, 1.0, 'PCA-CumulativeEVR')
```




```
# no of cluster analysis
from sklearn.cluster import KMeans, AgglomerativeClustering, Birch
from sklearn.metrics import silhouette_score
import scipy.cluster.hierarchy as sch

# K-Means for different cluster numbers
K = range(2, 11)  # testing clusters from 2 to 10
inertias = []  # for K-Means elbow methodfor within clustering we can
use ss
silhouette_scores = []  # for measuring cluster quality

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans_labels = kmeans.fit_predict(features_df)
    inertias.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(features_df,
kmeans_labels))
```

```
c:\Users\lsrin\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1446: 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(
c:\Users\lsrin\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on
```

```
Windows with MKL, when there are less chunks than available threads.
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c:\Users\lsrin\anaconda3\Lib\site-packages\sklearn\cluster\
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_kmeans.py:1446: 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(
```
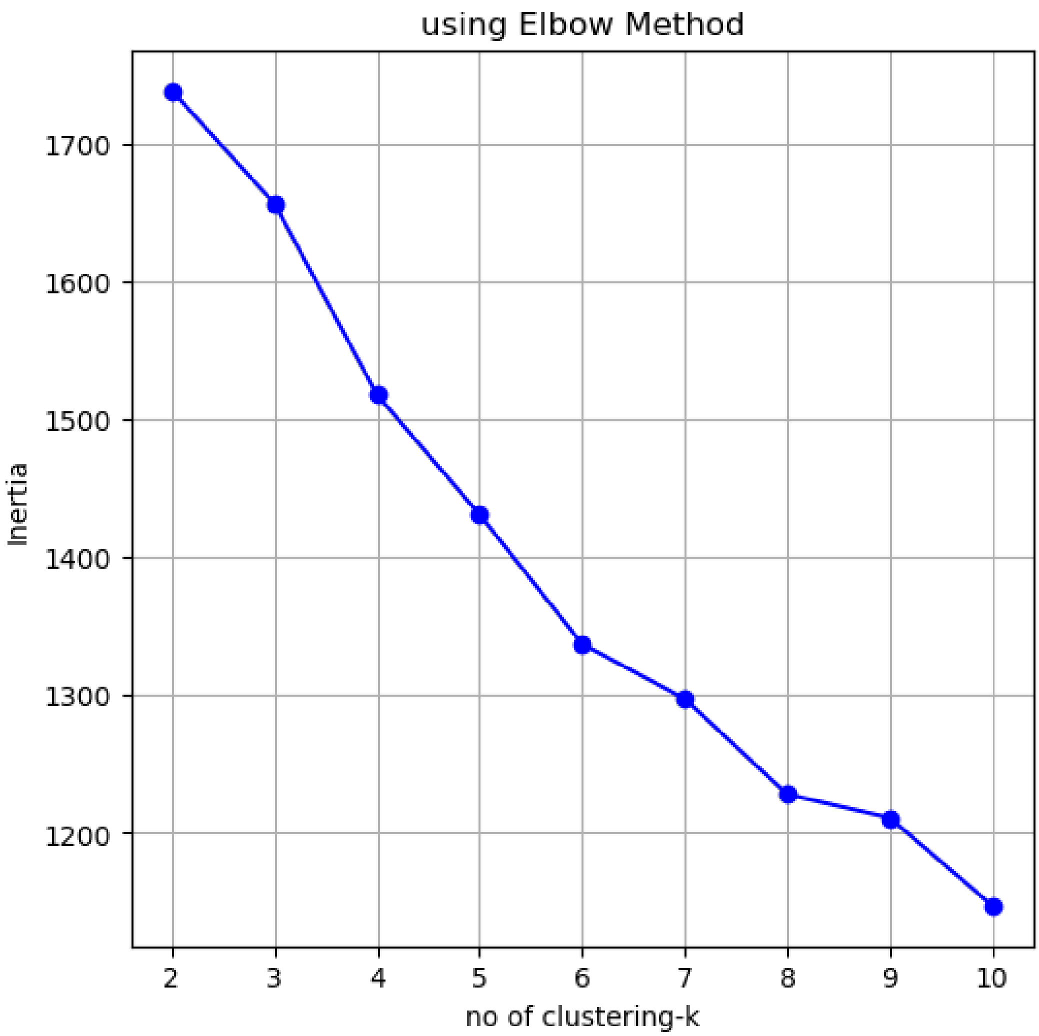
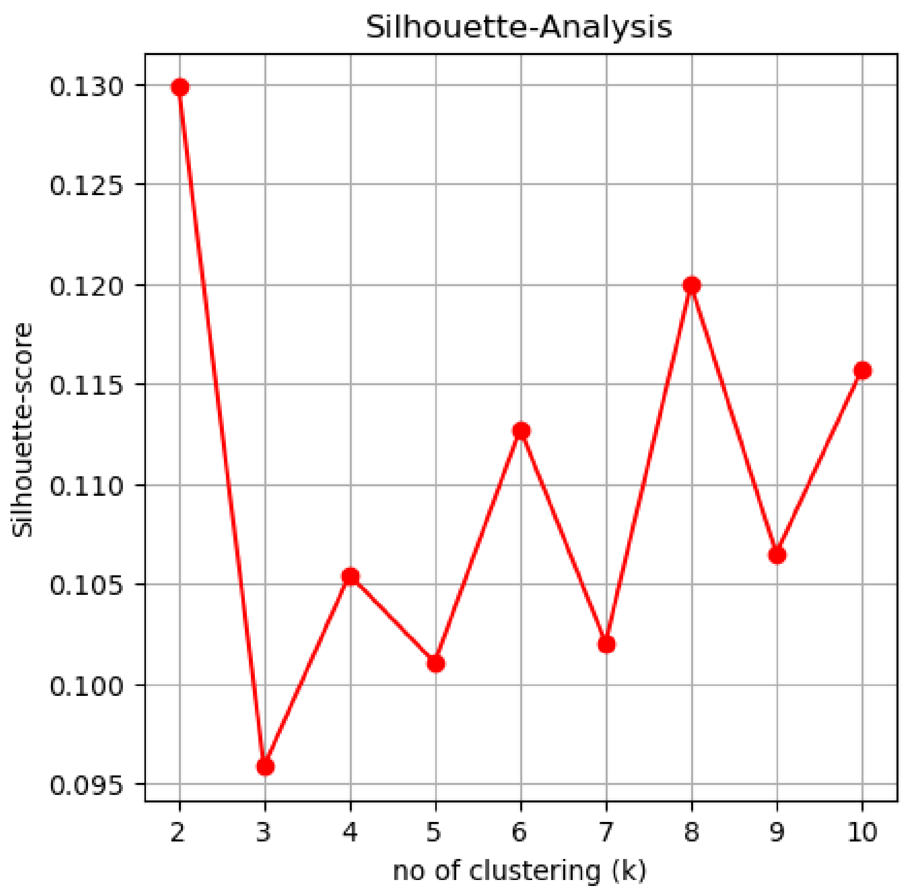

```python
#elbow Method
plt.figure(figsize=(6,6))
plt.plot(K, inertias, 'bo-')
```

```
plt.xlabel('no of clustering-k')
plt.ylabel('Inertia')
plt.title('using Elbow Method')
plt.grid(True)
plt.show()

#Silhouette Analysis
plt.figure(figsize=(5,5))
plt.plot(K, silhouette_scores, 'ro-')
plt.xlabel('no of clustering (k)')
plt.ylabel('Silhouette-score')
plt.title('Silhouette-Analysis')
plt.grid(True)
plt.show()
```






```
#apply clustering with optimal k
k_optimal = 3

#apply different clustering methods
kmeans = KMeans(n_clusters=k_optimal, random_state=42)
hierarchical = AgglomerativeClustering(n_clusters=k_optimal)
birch = Birch(n_clusters=k_optimal)

print(kmeans)
print(hierarchical)
print(birch)
```

```
KMeans(n_clusters=3, random_state=42)
AgglomerativeClustering(n_clusters=3)
Birch()
```

```
#cluster labels
kmeans_labels = kmeans.fit_predict(features_df)
hierarchical_labels = hierarchical.fit_predict(features_df)
birch_labels = birch.fit_predict(features_df)
```

```
c:\Users\lsrin\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1446: UserWarning: KMeans is known to have a memory leak on
```

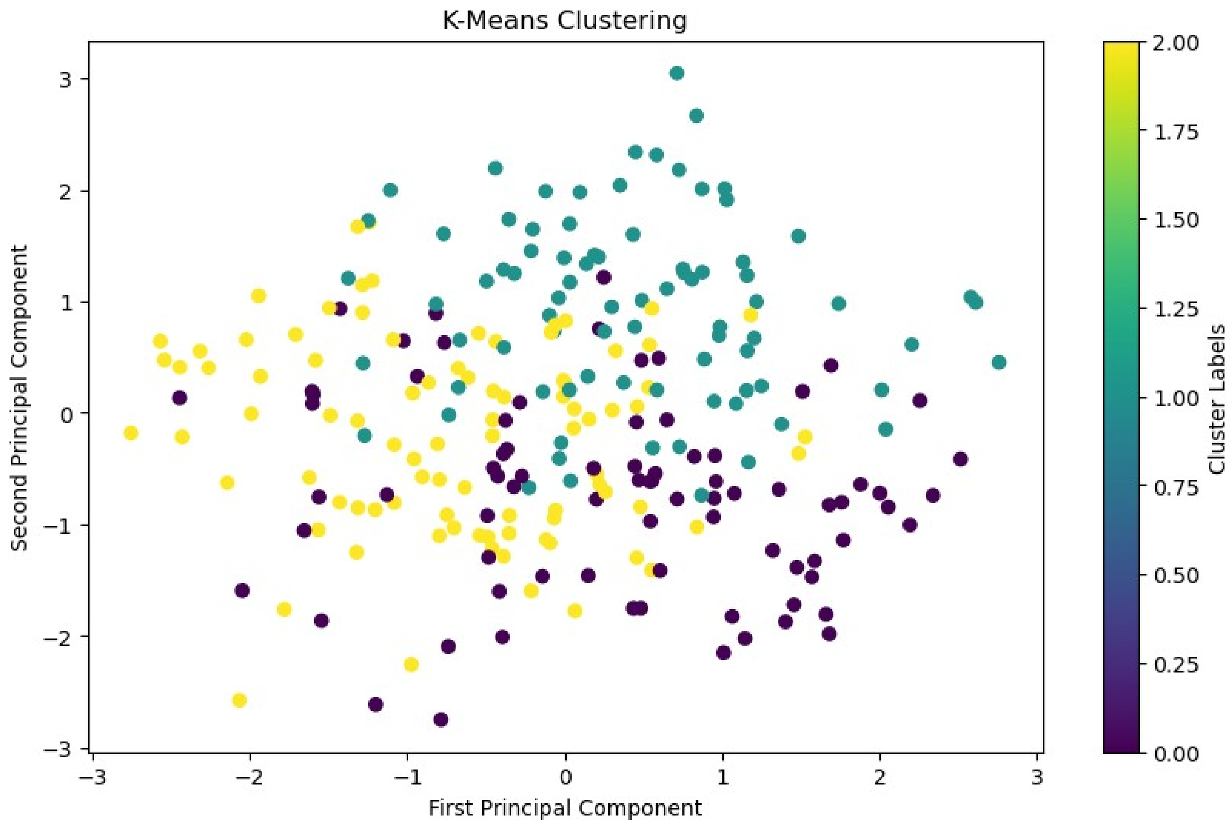
```
Windows with MKL, when there are less chunks than available threads.
You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```

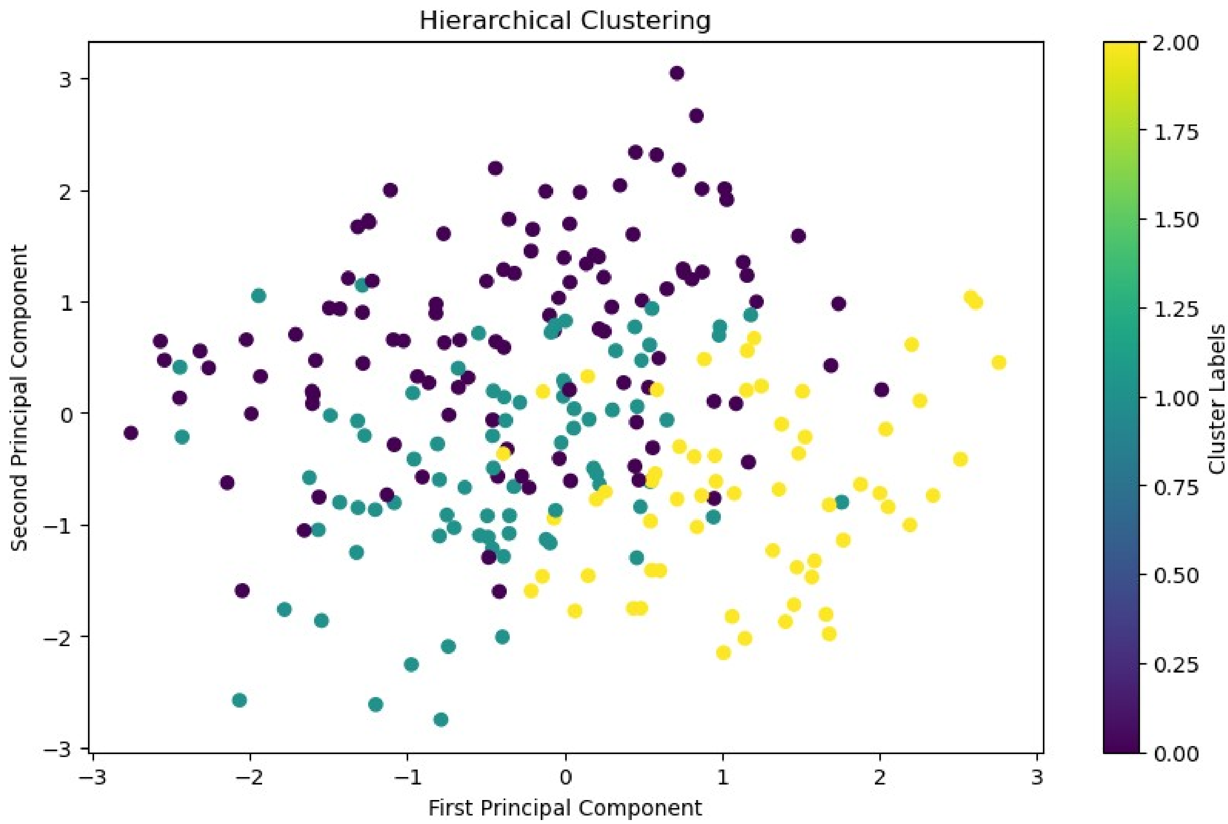
```python
# evaluate and compare methods
def evaluate_clustering(data, labels, method_name):
    score = silhouette_score(data, labels)
    print(f"{method_name} Silhouette Score: {score:.3f}")


print("clustering quality evaluation:")
evaluate_clustering(features_df, kmeans_labels, "K-Means")
evaluate_clustering(features_df, hierarchical_labels, "Hierarchical")
evaluate_clustering(features_df, birch_labels, "BIRCH")
```

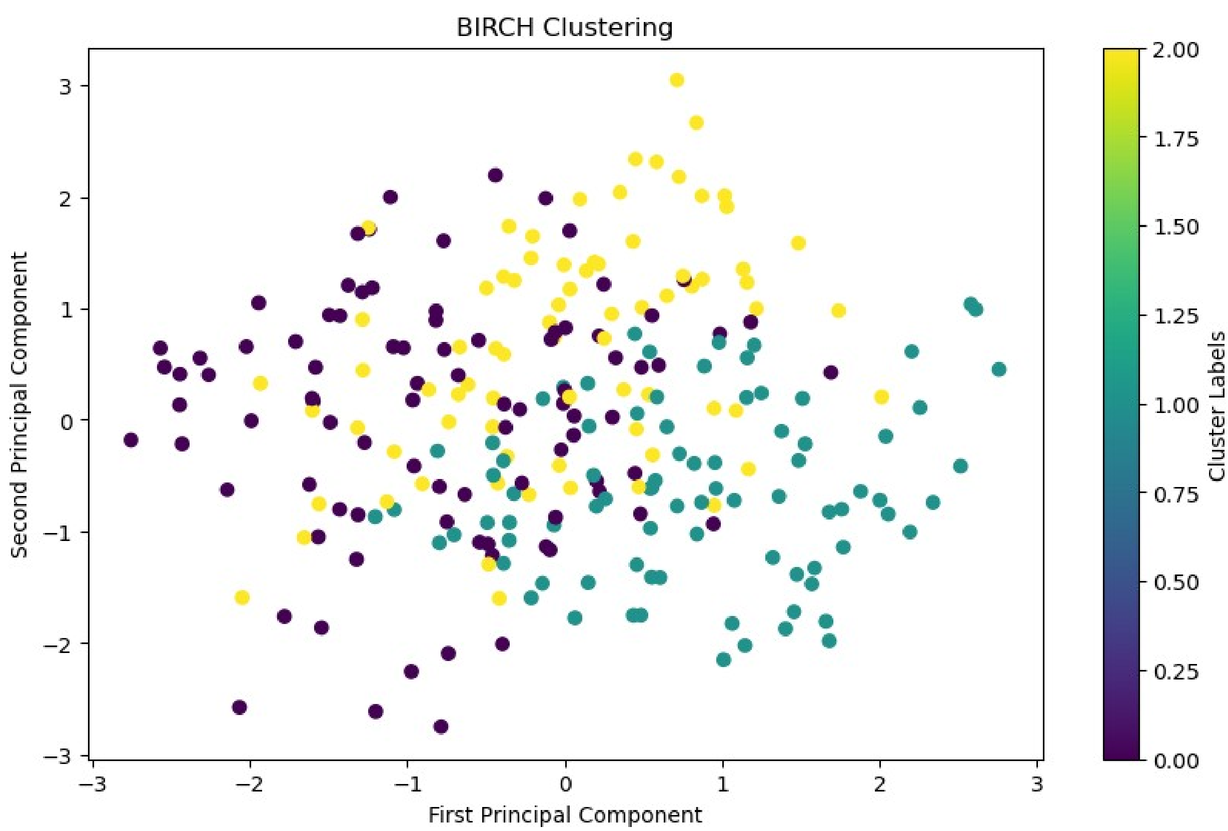
```
clustering quality evaluation:
K-Means Silhouette Score: 0.096
Hierarchical Silhouette Score: 0.095
BIRCH Silhouette Score: 0.083
```

```python
#visual
pca = PCA(n_components=2)
X_pca = pca.fit_transform(features_df)

# K-Means
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=kmeans_labels, cmap='viridis')
plt.title('K-Means Clustering')
plt.xlabel('First Principal Component')
plt.ylabel('Second Principal Component')
plt.colorbar(label='Cluster Labels')
plt.show()


#hierarchical
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=hierarchical_labels,
cmap='viridis')
plt.title('Hierarchical Clustering')
plt.xlabel('First Principal Component')
plt.ylabel('Second Principal Component')
plt.colorbar(label='Cluster Labels')
plt.show()

# BIRCH
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=birch_labels, cmap='viridis')
plt.title('BIRCH Clustering')
```

```
plt.xlabel('First Principal Component')
plt.ylabel('Second Principal Component')
plt.colorbar(label='Cluster Labels')
plt.show()
```




Hierarchical Clustering
Second Principal Component
First Principal Component
Cluster Labels
3
2
1
0
−1
−2
−3
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00


BIRCH Clustering
Second Principal Component
First Principal Component
Cluster Labels
3
2
1
0
−1
−2
−3
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

```
#evaluation Metrics
from sklearn.metrics import calinski_harabasz_score,
davies_bouldin_score

def evaluate_clustering_detailed(data, labels, method_name):
    silhouette = silhouette_score(data, labels)
    calinski = calinski_harabasz_score(data, labels)
    davies = davies_bouldin_score(data, labels)

    print(f"\nDetailed Evaluation for {method_name}:")
    print(f"Silhouette Score: {silhouette:.3f}")
    print(f"Calinski-Harabasz Score: {calinski:.3f}")
    print(f"Davies-Bouldin Score: {davies:.3f}")
    return silhouette, calinski, davies

# evaluate each method with detailed metrics
results = {}
for method, labels in [("K-Means", kmeans_labels),
                      ("Hierarchical", hierarchical_labels),
                      ("BIRCH", birch_labels)]:
    results[method] = evaluate_clustering_detailed(features_df,
labels, method)

# Print comparative analysis
print("\nComparative Analysis:")
print("Based on the evaluation metrics:")
print("1.silhouette Score: Higher is better (range: -1 to 1)")
print("2.calinski-Harabasz Score: Higher is better")
print("3.davies-Bouldin Score: Lower is better")

# Determine best method
best_silhouette = max(results.items(), key=lambda x: x[1][0])
print("presenting the list best_silhouette :",best_silhouette)
print(f"\nbest performing method based on Silhouette score:
{best_silhouette[0]}")


##conclusion part
print("1.feature Selection identified the following key features:",
list(selected_feature_names))
print("2.optimal number of clusters based on Elbow method:",
k_optimal)
print("3.best performing clustering method:", best_silhouette[0])
```

```
Detailed Evaluation for K-Means:
Silhouette Score: 0.096
Calinski-Harabasz Score: 25.607
Davies-Bouldin Score: 2.557
```

```
Detailed Evaluation for Hierarchical:
Silhouette Score: 0.095
Calinski-Harabasz Score: 26.549
Davies-Bouldin Score: 2.536

Detailed Evaluation for BIRCH:
Silhouette Score: 0.083
Calinski-Harabasz Score: 23.497
Davies-Bouldin Score: 2.749

Comparative Analysis:
Based on the evaluation metrics:
1.silhouette Score: Higher is better (range: -1 to 1)
2.calinski-Harabasz Score: Higher is better
3.davies-Bouldin Score: Lower is better
presenting the list best_silhouette : ('K-Means',
(0.09586237556192426, 25.607180550441758, 2.5568902549578847))

best performing method based on Silhouette score: K-Means
1.feature Selection identified the following key features: ['Annual
Income', 'Spending Score', 'Location', 'Family Size']
2.optimal number of clusters based on Elbow method: 3
3.best performing clustering method: K-Means
```