```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)
```

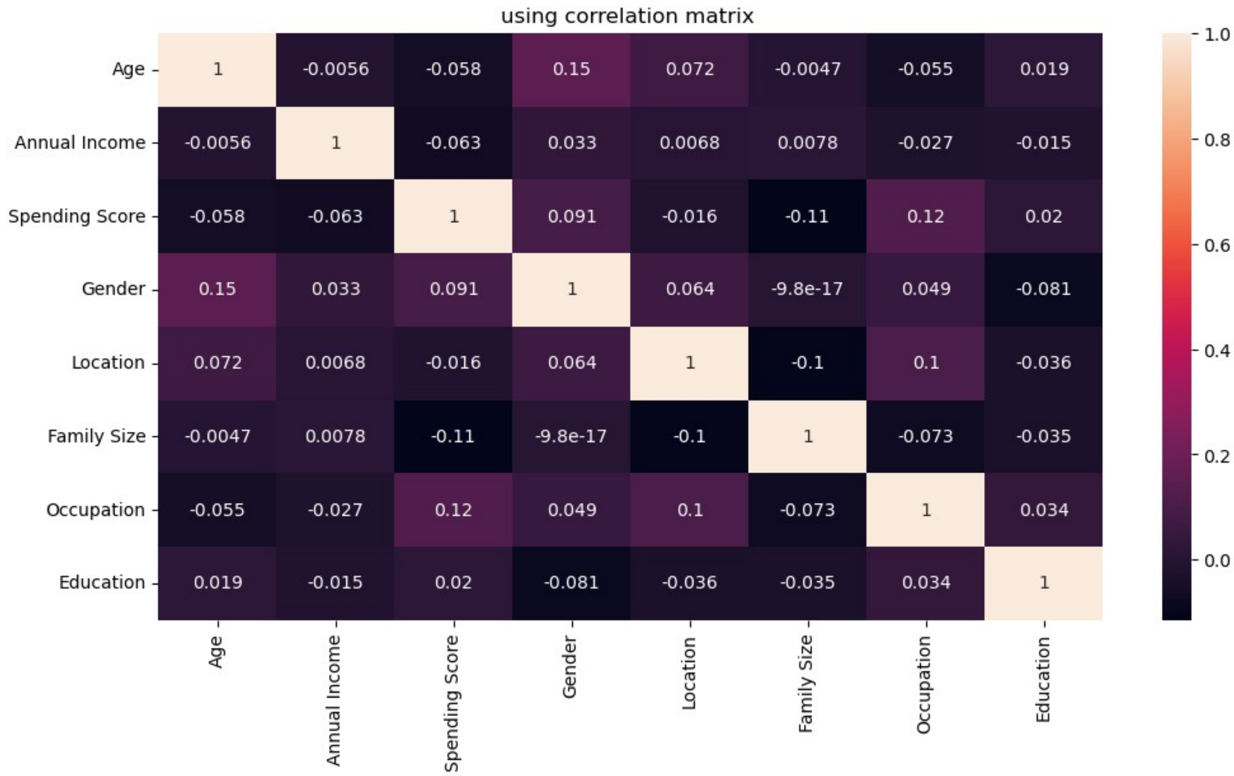
```
features_df.head(10)
features_df.tail(4)
features_df.sample(7)
```

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

```
41  -1.005565       0.682903       -0.395086     1.0  0.930415    -
0.832718
168  1.210033      -0.359791       -1.543590    -1.0 -1.074789
1.480387
87   0.181363       0.697885       -0.057290     1.0  0.930415
0.902111
125 -0.530794      -1.632930        1.124994    -1.0 -1.074789    -
1.410994
99  -1.163822       0.699662        0.787199     1.0  0.930415
0.902111
82  -1.163822       1.496496       -1.070677    -1.0  0.930415
1.480387
103  0.972648       1.032677        0.854758     1.0  0.930415    -
1.410994

     Occupation  Education
41    -0.601928   0.714914
168   -1.113772  -0.686878
87    -0.090085  -1.387775
125    1.445447   0.714914
99    -0.090085   0.714914
82    -1.625616   0.714914
103    0.933603   1.415811
```

```
#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 ')
```

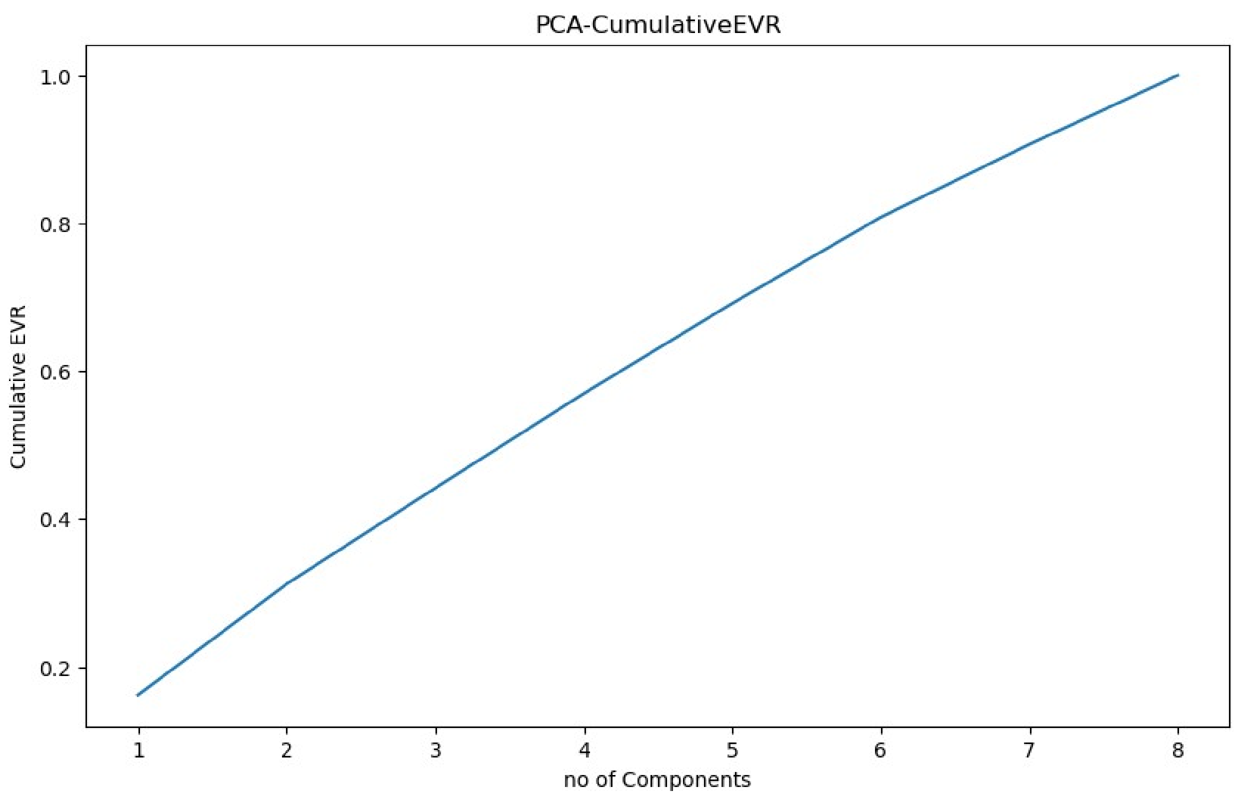



```python
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering, Birch,
SpectralClustering

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
```

```python
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')
```




```python
# no of cluster analysis

from sklearn.cluster import KMeans, AgglomerativeClustering, Birch
from sklearn.metrics import silhouette_score
import scipy.cluster.hierarchy as sch
K = range(2, 11)
inertias = []
silhouette_scores_kmeans = []
silhouette_scores_hierarchical = []
silhouette_scores_birch = []
```