Income_Expenditure

Dataset Exploration

In [1]:

```
# Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [2]:

```
df = pd.read_csv('income.csv')
df.head()
```

Out[2]:

	Age	Income	SpendingScore	Savings
0	58	77769	0.791329	6559.829923
1	59	81799	0.791082	5417.661426
2	62	74751	0.702657	9258.992965
3	59	74373	0.765680	7346.334504
4	87	17760	0.348778	16869.507130

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 505 entries, 0 to 504
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Age            505 non-null    int64  
 1   Income         505 non-null    int64  
 2   SpendingScore  505 non-null    float64
 3   Savings        505 non-null    float64
dtypes: float64(2), int64(2)
memory usage: 15.9 KB
```

Clustering or Dimensionality Reduction

This project is focused towards clustering for the given dataset

Data Description and Attributes

- Dataset has four features - Age, Income, Spending Score, Savings
- Age - Integer data
- Income - Salary data in Interger
- Spending Score - Expenditure data in Float
- Savings - Float data

In [4]:
```
df.shape
```

Out[4]:
```
(505, 4)
```

In [5]:
```
df.describe()
```

Out[5]:

	Age	Income	SpendingScore	Savings
count	505.000000	505.000000	505.000000	505.000000
mean	59.019802	75513.291089	0.505083	11862.455867
std	24.140043	35992.922184	0.259634	4949.229253
min	17.000000	12000.000000	0.000000	0.000000
25%	34.000000	34529.000000	0.304792	6828.709702
50%	59.000000	75078.000000	0.368215	14209.932802
75%	85.000000	107100.000000	0.768279	16047.268331
max	97.000000	142000.000000	1.000000	20000.000000

Data Cleaning and Exploration

In [6]:
```
# Check for Null Values
df.isna().sum()
```

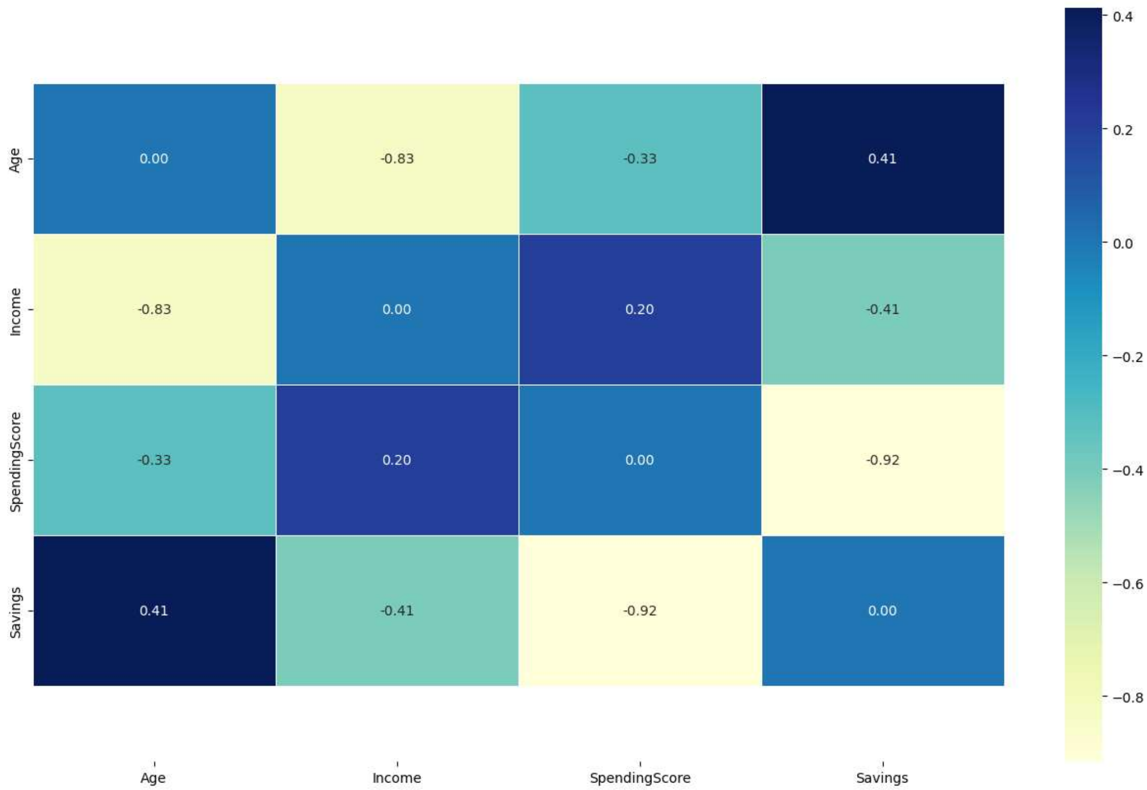
Out[6]:
```
Age              0
Income           0
SpendingScore    0
Savings          0
dtype: int64
```

In [7]:
```
df.dtypes
```

Out[7]:
```
Age                int64
Income             int64
SpendingScore    float64
Savings          float64
dtype: object
```

In [8]:
```
# Studying the correlations between features using Heat Map!
corr_matrix = df.corr()
for x in range(corr_matrix.shape[0]):
    corr_matrix.iloc[x,x] = 0.0

fig, ax = plt.subplots(figsize=(16, 10))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="YlGnBu");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[8]: (4.5, -0.5)



In [9]:

```
# The correlation matrix
corr_mat = df.corr()

# Strip out the diagonal values for the next step
for x in range(corr_mat.shape[0]):
    corr_mat.iloc[x,x] = 0.0

corr_mat
```

Out[9]:

	Age	Income	SpendingScore	Savings
Age	0.000000	-0.828457	-0.329116	0.412337
Income	-0.828457	0.000000	0.196111	-0.410774
SpendingScore	-0.329116	0.196111	0.000000	-0.915379
Savings	0.412337	-0.410774	-0.915379	0.000000

In [10]:

```
# Pairwise maximal correlations
corr_max  = corr_mat.abs().max().to_frame()
corr_id_max = corr_mat.abs().idxmax().to_frame()

# dataframe aggrigation and processing
pair_features_corr = pd.merge(corr_id_max, corr_max, on = corr_max.index)
pair_features_corr = pair_features_corr.rename(columns = {'key_0':'Feature_one'
                                                .sort_values('correlation', asc
                                                .reset_index().drop('index', ax
pair_features_corr
```

Out[10]:

	Feature_one	Feature_two	correlation
0	SpendingScore	Savings	0.915379
1	Savings	SpendingScore	0.915379
2	Age	Income	0.828457
3	Income	Age	0.828457

Feature Engineering

In [11]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
df_scaled = sc.fit_transform(df)
```

In [12]:

```
df
```

Out[12]:

	Age	Income	SpendingScore	Savings
0	58	77769	0.791329	6559.829923
1	59	81799	0.791082	5417.661426
2	62	74751	0.702657	9258.992965
3	59	74373	0.765680	7346.334504
4	87	17760	0.348778	16869.507130
...	...	...	...	...
500	28	101206	0.387441	14936.775389
501	93	19934	0.203140	17969.693769
502	90	35297	0.355149	16091.401954
503	91	20681	0.354679	18401.088445
504	89	30267	0.289310	14386.351880

505 rows × 4 columns

Model Creation

1. K-Means

In [13]:

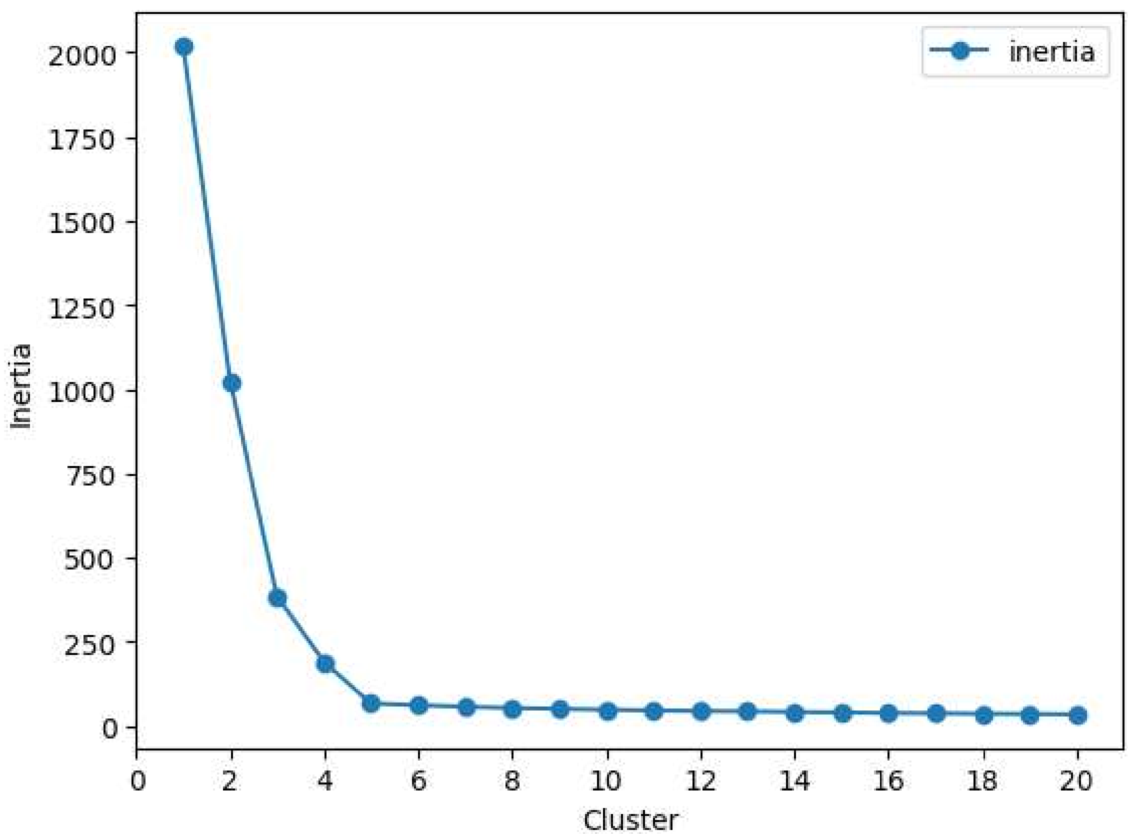
```
from sklearn.cluster import KMeans

# Create and fit a range of models
km_list = list()

for clust in range(1,21):
    km = KMeans(n_clusters=clust, random_state=42)
```

```
    km = km.fit(df_scaled)

    km_list.append(pd.Series({'clusters': clust,
                              'inertia': km.inertia_,
                              'model': km}))
```

In [14]:

```
plot_data = (pd.concat(km_list, axis=1)
             .T
             [['clusters','inertia']]
             .set_index('clusters'))

ax = plot_data.plot(marker='o',ls='-')
ax.set_xticks(range(0,21,2))
ax.set_xlim(0,21)
ax.set(xlabel='Cluster', ylabel='Inertia');
```

```
c:\Users\shankesh\AppData\Local\Programs\Python\Python310\lib\site-packages\pan
das\core\indexes\base.py:6999: FutureWarning: In a future version, the Index co
nstructor will not infer numeric dtypes when passed object-dtype sequences (mat
ching Series behavior)
  return Index(sequences[0], name=names)
```



1. Agglomerative Algorithm

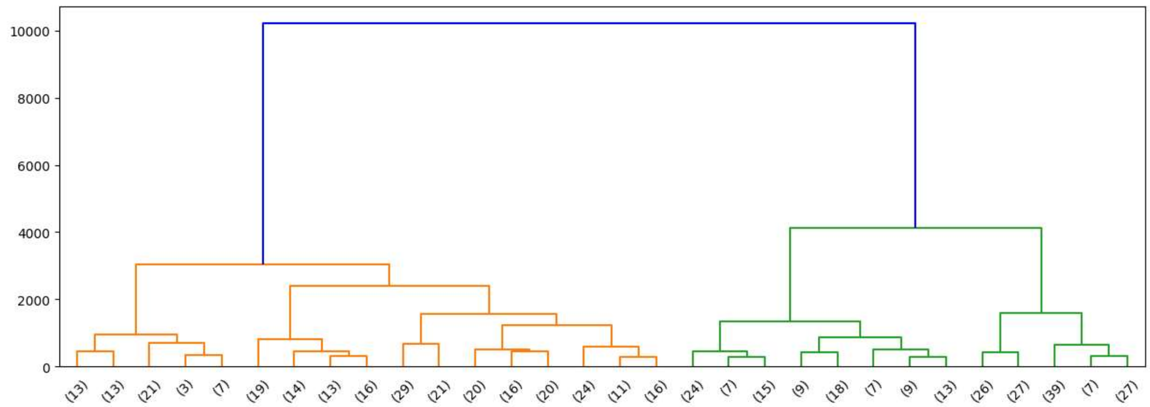
In [15]:

```
from sklearn.cluster import AgglomerativeClustering
ag = AgglomerativeClustering(n_clusters=7, linkage='ward', compute_full_tree=Tr
ag = ag.fit(df_scaled)
```

In [16]:

```
from scipy.cluster import hierarchy
```

```
Z = hierarchy.linkage(ag.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))

den = hierarchy.dendrogram(Z, orientation='top',
                           p=30, truncate_mode='lastp',
                           show_leaf_counts=True, ax=ax,
                           above_threshold_color='blue')
```



1. DBSCAN Algorithm

In [17]:

```
from sklearn.cluster import DBSCAN
dbs = DBSCAN(eps=0.5, min_samples=11, metric='euclidean')
dbs = dbs.fit(df_scaled)
```

In [18]:

```
np.unique(dbs.labels_)
```

Out[18]:

```
array([0, 1, 2, 3, 4], dtype=int64)
```

In [19]:

```
df_old = pd.DataFrame(df_scaled, columns = ['Age','Income','Expenditure','Savin
df = pd.DataFrame(dbs.fit_predict(df_scaled), columns = ['Group'])
df_new = pd.concat([df_old, df], axis = 1)
df_new
```

Out[19]:

	Age	Income	Expenditure	Savings	Group
0	-0.042287	0.062733	1.103593	-1.072467	0
1	-0.000821	0.174811	1.102641	-1.303473	0
2	0.123577	-0.021200	0.761727	-0.526556	0
3	-0.000821	-0.031712	1.004705	-0.913395	0
4	1.160228	-1.606165	-0.602619	1.012686	1
...	...	...	...	...	...
500	-1.286268	0.714535	-0.453557	0.621787	4
501	1.409024	-1.545704	-1.164109	1.235201	1

502	1.284626	-1.118447	-0.578054	0.855313	1
503	1.326092	-1.524929	-0.579866	1.322452	1
504	1.243160	-1.258335	-0.831890	0.510463	1

505 rows × 5 columns

In [20]:
```
df_new.groupby(['Group']).count()
```

Out[20]:

	Age	Income	Expenditure	Savings
Group				
0	157	157	157	157
1	147	147	147	147
2	50	50	50	50
3	25	25	25	25
4	126	126	126	126

Best Model

For the given dataset both K-Means and DBScan performs similar with 5 clusters seems to be the best fit

Key Findings and Insights

- In Agglomerative model it has classified into 2 clusters which seems to be incorrect

---Thank You by Shankesh Raju MS ---