```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
import seaborn as sns
import matplotlib.pyplot as plt
import os
os.getcwd()
'C:\\Users\\bimal\\Documents'
#load the data using the right path
df =
pd.read csv("C:/Users/bimal/OneDrive/Documents/Mall Customers.csv")
# checking the first five rows of the dataset to understand the data.
df.head()
   CustomerID
                Genre Age Annual Income (k$)
                                                 Spending Score (1-100)
0
            1
                 Male
                        19
                                             15
                                                                      39
1
            2
                 Male
                        21
                                             15
                                                                      81
2
            3
               Female
                        20
                                             16
                                                                       6
3
            4
               Female
                        23
                                             16
                                                                      77
4
            5
               Female
                        31
                                             17
                                                                      40
# checking the statistics to understand the data
df.describe()
       CustomerID
                          Age Annual Income (k$) Spending Score (1-
100)
count 200.000000
                   200.000000
                                        200.000000
200.000000
mean
       100.500000
                    38.850000
                                         60.560000
50.200000
                                         26.264721
std
        57.879185
                    13.969007
25.823522
         1.000000
                    18.000000
                                         15.000000
min
1.000000
        50.750000
                    28.750000
                                         41.500000
25%
34.750000
       100.500000
                    36.000000
                                         61.500000
50%
50.000000
                                         78.000000
75%
       150.250000
                    49.000000
73.000000
       200.000000
                    70.000000
                                        137.000000
max
99.000000
```

```
# Check for missing values in each column
missing values = df.isnull().sum()
print("Missing values per column:\n", missing_values)
Missing values per column:
CustomerID
                           0
Genre
                          0
                          0
Age
Annual Income (k$)
                          0
Spending Score (1-100)
dtype: int64
## To check for the data types in the dataset.
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
#
     Column
                             Non-Null Count
                                             Dtvpe
_ _ _
                                             _ _ _ _
 0
    CustomerID
                             200 non-null
                                             int64
                             200 non-null
1
    Genre
                                             object
2
                             200 non-null
                                             int64
    Age
3
    Annual Income (k$)
                             200 non-null
                                             int64
     Spending Score (1-100) 200 non-null int64
4
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

Data Visualisation - Univariate Analysis

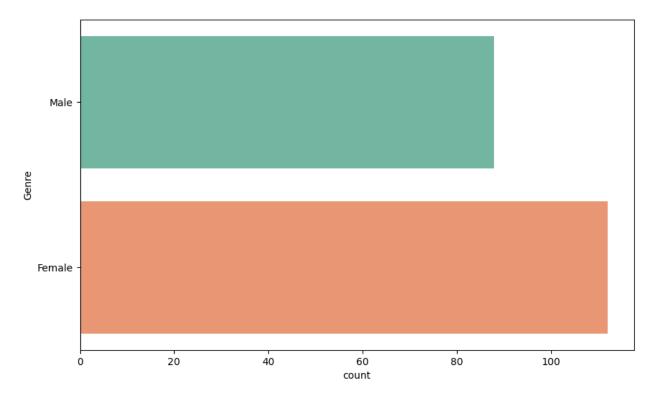
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.countplot(df['Genre'], palette="Set2") # Specify the palette
plt.show()

C:\Users\bimal\AppData\Local\Temp\ipykernel_19080\1485131431.py:5:
FutureWarning:

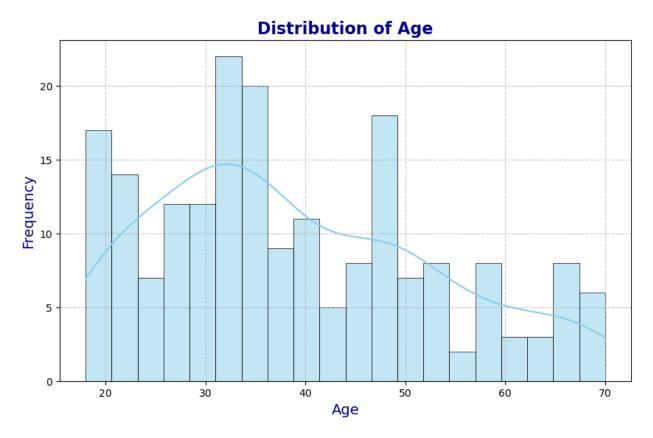
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

sns.countplot(df['Genre'], palette="Set2") # Specify the palette
```



There are more female customers than the Male

```
plt.figure(figsize=(10, 6))
sns.histplot(df['Age'], bins=20, kde=True, color="skyblue",
edgecolor="black", linewidth=0.5)
plt.title("Distribution of Age", fontsize=16, fontweight='bold',
color="darkblue")
plt.xlabel("Age", fontsize=14, color="darkblue")
plt.ylabel("Frequency", fontsize=14, color="darkblue")
plt.grid(True, linestyle='--', alpha=0.7)
plt.show()
```



Age of the customers follows right skewed normal distribution. The higher the age the frequency of spending and visiting the mall has declined.

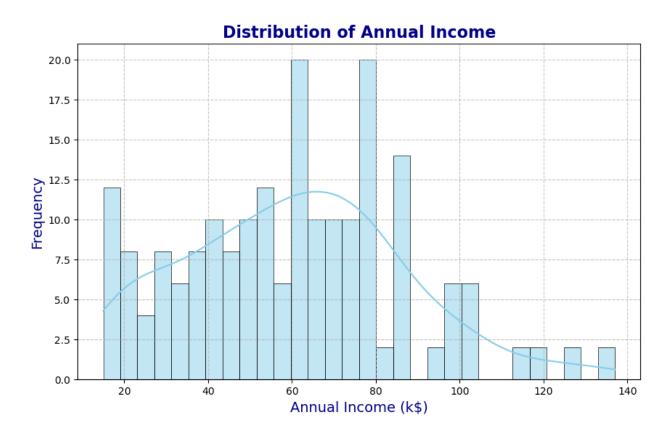
```
# Set the figure size for better clarity
plt.figure(figsize=(10, 6))

# Plot the distribution with both histogram and KDE (density) curve
sns.histplot(df['Annual Income (k$)'], bins=30, kde=True,
color="skyblue", edgecolor="black", linewidth=0.5)

# Add titles and labels
plt.title("Distribution of Annual Income", fontsize=16,
fontweight='bold', color="darkblue")
plt.xlabel("Annual Income (k$)", fontsize=14, color="darkblue")
plt.ylabel("Frequency", fontsize=14, color="darkblue")

# Customize grid for better readability
plt.grid(True, linestyle='--', alpha=0.7)

# Display the plot
plt.show()
```



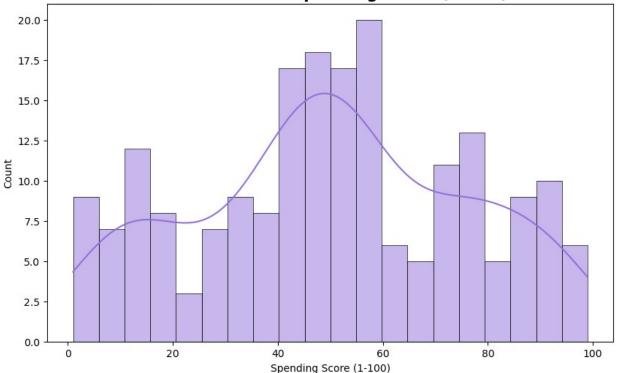
Annual income of the customers also follows right skewed normal distrbution.

```
# Set figure size
plt.figure(figsize=(10, 6))
# Plot the distribution with both histogram and KDE (density) curve
sns.histplot(df['Spending Score (1-100)'], bins=20, kde=True,
color="mediumpurple", edgecolor="black", linewidth=0.5)
# Add titles and labels
plt.title("Distribution of Spending Score (1-100)", fontsize=16,
fontweight='bold', color="darkpurple")
plt.xlabel("Spending Score (1-100)", fontsize=14, color="purple")
plt.ylabel("Frequency", fontsize=14, color="purple")
# Customize grid for better readability
plt.grid(True, linestyle='--', alpha=0.7)
# Display the plot
plt.show()
ValueError
                                          Traceback (most recent call
last)
Cell In[66], line 8
```

```
5 sns.histplot(df['Spending Score (1-100)'], bins=20, kde=True,
color="mediumpurple", edgecolor="black", linewidth=0.5)
      7 # Add titles and labels
----> 8 plt.title("Distribution of Spending Score (1-100)",
fontsize=16, fontweight='bold', color="darkpurple")
      9 plt.xlabel("Spending Score (1-100)", fontsize=14,
color="purple")
     10 plt.ylabel("Frequency", fontsize=14, color="purple")
File ~\anaconda3\Lib\site-packages\matplotlib\pyplot.py:4346, in
title(label, fontdict, loc, pad, y, **kwargs)
   4336 @ copy docstring and deprecators(Axes.set title)
   4337 def title(
   4338
            label: str,
   (\ldots)
   4344
            **kwargs,
   4345 ) -> Text:
            return gca().set title(label, fontdict=fontdict, loc=loc,
-> 4346
pad=pad, y=y, **kwargs)
File ~\anaconda3\Lib\site-packages\matplotlib\axes\ axes.py:206, in
Axes.set title(self, label, fontdict, loc, pad, y, **kwargs)
    204 if fontdict is not None:
            title.update(fontdict)
    205
--> 206 title. internal update(kwargs)
    207 return title
File ~\anaconda3\Lib\site-packages\matplotlib\artist.py:1216, in
Artist. internal update(self, kwargs)
   1209 def _internal_update(self, kwargs):
   1210
            Update artist properties without prenormalizing them, but
   1211
generating
   1212
            errors as if calling `set`.
   1213
   1214
            The lack of prenormalization is to maintain
backcompatibility.
            11 11 11
   1215
            return self. update_props(
-> 1216
                kwargs, "{cls. name }.set() got an unexpected
   1217
keyword argument "
                "{prop name!r}")
   1218
File ~\anaconda3\Lib\site-packages\matplotlib\artist.py:1192, in
Artist._update_props(self, props, errfmt)
                    if not callable(func):
   1189
   1190
                        raise AttributeError(
                            errfmt.format(cls=type(self),
   1191
prop name=k))
-> 1192
                    ret.append(func(v))
```

```
1193 if ret:
   1194 self.pchanged()
File ~\anaconda3\Lib\site-packages\matplotlib\text.py:996, in
Text.set color(self, color)
    993 # "auto" is only supported by axisartist, but we can just let
it error
    994 # out at draw time for simplicity.
    995 if not cbook._str_equal(color, "auto"):
            mpl.colors. check color like(color=color)
    997 self. color = color
    998 self.stale = True
File ~\anaconda3\Lib\site-packages\matplotlib\colors.py:246, in
check color like(**kwarqs)
    244 for k, v in kwargs.items():
            if not is color like(v):
    245
--> 246
                raise ValueError(
    247
                    f"{v!r} is not a valid value for {k}: supported
inputs are "
                    f"(r, g, b) and (r, g, b, a) 0-1 float tuples; "
    248
                    f"'#rrggbb', '#rrggbbaa', '#rgb', '#rgba' strings;
    249
    250
                    f"named color strings; "
                    f"string reprs of 0-1 floats for grayscale values;
    251
    252
                    f"'C0', 'C1', ... strings for colors of the color
cycle; "
                    f"and pairs combining one of the above with an
    253
alpha value")
ValueError: 'darkpurple' is not a valid value for color: supported
inputs are (r, g, b) and (r, g, b, a) 0-1 float tuples; '#rrggbb',
'#rrggbbaa', '#rgb', '#rgba' strings; named color strings; string
reprs of 0-1 floats for grayscale values; 'CO', 'C1', ... strings for
colors of the color cycle; and pairs combining one of the above with
an alpha value
```

Distribution of Spending Score (1-100)

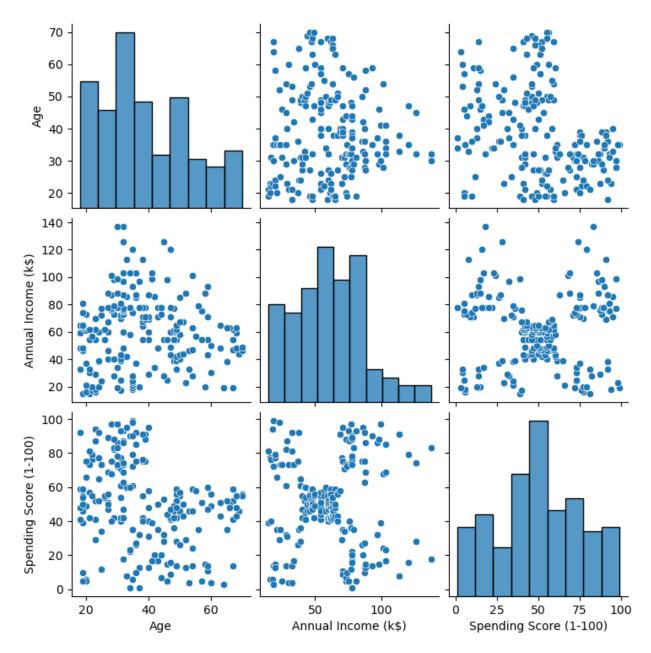


Spending score of the customers roughly follws normal distribution. This indicates that many customers tend to have a moderate spending score, and few customers have extremely high or low scores.

Data Visualisation - Bivariate Analysis

Time to check for the relationship between different features by using a pairplot.

```
sns.pairplot(df[[ 'Genre', 'Age', 'Annual Income (k$)', 'Spending Score
(1-100)']])
<seaborn.axisgrid.PairGrid at 0x2c511lef620>
```



Observations:

Most of the customers are in the 20-40 age group. Spending score is high for the customers in the age group of 20-40. Spending score is high for customers with very low and very high income.

Checking Corelation between features using the Heatmap

```
# Error only for documentation
plt.rcParams['figure.figsize'] = (14, 8)
sns.heatmap(df[[ 'Genre', 'Age', 'Annual Income (k$)','Spending Score
(1-100)']].corr(), cmap = 'magma_r', annot = True, linewidths=.5)
```

```
plt.title('Heatmap', fontsize = 20)
plt.show()
ValueError
                                          Traceback (most recent call
last)
Cell In[80], line 2
      1 plt.rcParams['figure.figsize'] = (14, 8)
----> 2 sns.heatmap(df[[ 'Genre', 'Age', 'Annual Income
(k$)','Spending Score (1-100)']].corr(), cmap = 'magma_r', annot =
True, linewidths=.5)
      3 plt.title('Heatmap', fontsize = 20)
      4 plt.show()
File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:11049, in
DataFrame.corr(self, method, min periods, numeric only)
  11047 cols = data.columns
  11048 idx = cols.copy()
> 11049 mat = data.to numpy(dtype=float, na value=np.nan, copy=False)
  11051 if method == "pearson":
            correl = libalgos.nancorr(mat, minp=min periods)
  11052
File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:1993, in
DataFrame.to_numpy(self, dtype, copy, na_value)
   1991 if dtype is not None:
   1992
            dtype = np.dtype(dtype)
-> 1993 result = self. mgr.as array(dtype=dtype, copy=copy,
na value=na value)
   1994 if result.dtype is not dtype:
            result = np.asarray(result, dtype=dtype)
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1694, in BlockManager.as array(self, dtype, copy,
na value)
   1692
                arr.flags.writeable = False
   1693 else:
-> 1694
            arr = self. interleave(dtype=dtype, na value=na value)
   1695
           # The underlying data was copied within interleave, so no
need
            # to further copy if copy=True or setting na value
   1698 if na value is lib.no default:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1753, in BlockManager. interleave(self, dtype, na value)
   1751
            else:
   1752
                arr = blk.get values(dtype)
-> 1753
            result[rl.indexer] = arr
            itemmask[rl.indexer] = 1
   1754
   1756 if not itemmask.all():
```

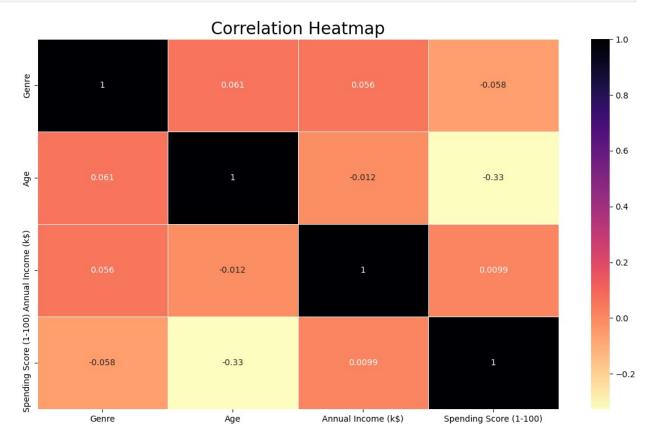
```
ValueError: could not convert string to float: 'Male'
from sklearn.preprocessing import LabelEncoder

# Encode the 'Genre' column as numeric
le = LabelEncoder()
df['Genre'] = le.fit_transform(df['Genre'])

# Select relevant columns (including the encoded 'Genre')
numeric_cols = df[['Genre', 'Age', 'Annual Income (k$)', 'Spending
Score (1-100)']]

# Calculate the correlation matrix
plt.rcParams['figure.figsize'] = (14, 8)
sns.heatmap(numeric_cols.corr(), cmap='magma_r', annot=True,
linewidths=0.5)

# Add a title and show the plot
plt.title('Correlation Heatmap', fontsize=20)
plt.show()
```



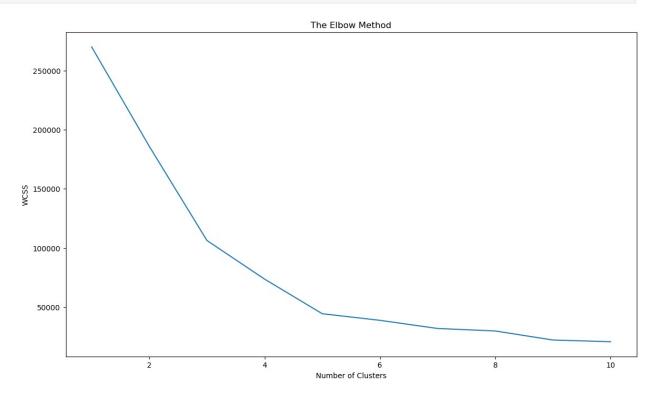
It Can be seen that there is not much corelation in this data between the differnt features

```
from sklearn.preprocessing import StandardScaler
# Select the numeric columns for clustering
features = ['Age', 'Annual Income (k$)', 'Spending Score (1-100)']
# Create a new DataFrame with the selected features
X = df[features]
# Initialize the StandardScaler
scaler = StandardScaler()
# Fit and transform the data to standardize it
X scaled = scaler.fit transform(X)
# Convert the scaled data back to a DataFrame
X scaled df = pd.DataFrame(X scaled, columns=features)
# Show the first few rows of the standardized data
print(X scaled df.head())
        Age Annual Income (k$) Spending Score (1-100)
                      -1.738999
0 -1.424569
                                              -0.434801
1 -1.281035
                      -1.738999
                                               1.195704
2 -1.352802
                      -1.700830
                                              -1.715913
3 -1.137502
                      -1.700830
                                               1.040418
4 -0.563369
                      -1.662660
                                              -0.395980
```

K-Means clustering based on annual income Elbow method to find the optimal number of Clusters¶

```
# using Elbow method to find the optimal number of Clusters
data=df.iloc[:,[3,4]].values
from sklearn.cluster import KMeans
wcss=[] # within cluster sum of square
for i in range(1,11):
    kmeans=KMeans(n clusters=i, init='k-means++',random state=0)
    kmeans.fit(data)
    wcss.append(kmeans.inertia ) #inertia = to find the wcss value
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on
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OMP NUM THREADS=1.
  warnings.warn(
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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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OMP NUM THREADS=1.
  warnings.warn(
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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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OMP NUM THREADS=1.
  warnings.warn(
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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(
```



From the above figure, we can see that last most significant slope occurs at k = 5, hence we will have 5 clusters in this case.

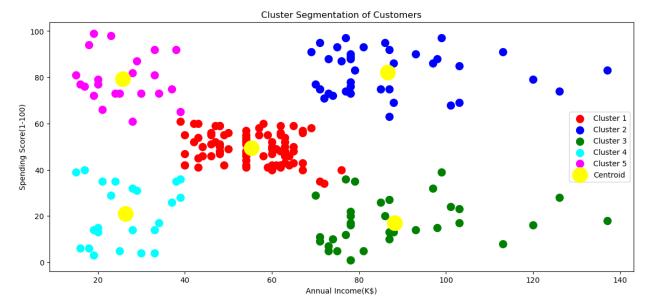
```
kmeans=KMeans(n_clusters=5,init='k-means++',random_state=0)
y_kmeans=kmeans.fit_predict(data)

#plotting the the clusters
fig,ax = plt.subplots(figsize=(14,6))
ax.scatter(data[y_kmeans==0,0],data[y_kmeans==0,1],s=100,c='red',label
='Cluster 1')
ax.scatter(data[y_kmeans==1,0],data[y_kmeans==1,1],s=100,c='blue',label='Cluster 2')
ax.scatter(data[y_kmeans==2,0],data[y_kmeans==2,1],s=100,c='green',label='Cluster 3')
ax.scatter(data[y_kmeans==3,0],data[y_kmeans==3,1],s=100,c='cyan',label='Cluster 4')
ax.scatter(data[y_kmeans==4,0],data[y_kmeans==4,1],s=100,c='magenta',label='Cluster 5')
ax.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=100,c='magenta',label='Cluster 5')
```

```
=400,c='yellow',label='Centroid')
plt.title('Cluster Segmentation of Customers')
plt.xlabel('Annual Income(K$)')
plt.ylabel('Spending Score(1-100)')
plt.legend()
plt.show()

C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1429: 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(
```



k-means clustering based on Age

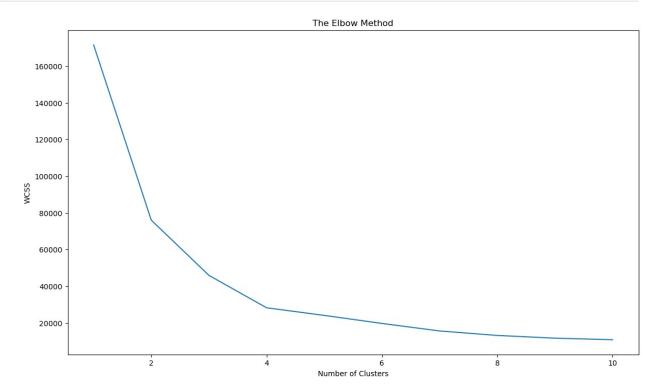
```
data = df.iloc[:,[2,4]].values
from sklearn.cluster import KMeans
wcss=[] # within cluster sum of square
for i in range(1,11):
    kmeans=KMeans(n_clusters=i, init='k-means++',random_state=0)
    kmeans.fit(data)
    wcss.append(kmeans.inertia_) # inertia_ = to find the wcss value

plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()

C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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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OMP NUM THREADS=1.
 warnings.warn(
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on
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You can avoid it by setting the environment variable
OMP NUM THREADS=1.
  warnings.warn(
C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
kmeans.py:1429: 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\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
   _kmeans.py:1429: 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(
```



k-means clustering based on Spending score (1-100)

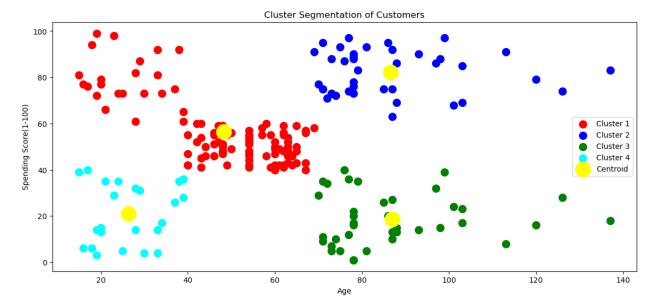
```
kmeans=KMeans(n_clusters=4,init='k-means++',random_state=0)
y_kmeans=kmeans.fit_predict(data)

#Plotting the clusters
fig,ax = plt.subplots(figsize=(14,6))
ax.scatter(data[y_kmeans==0,0],data[y_kmeans==0,1],s=100,c='red',label
='Cluster 1')
ax.scatter(data[y_kmeans==1,0],data[y_kmeans==1,1],s=100,c='blue',label='Cluster 2')
ax.scatter(data[y_kmeans==2,0],data[y_kmeans==2,1],s=100,c='green',label='Cluster 3')
ax.scatter(data[y_kmeans==3,0],data[y_kmeans==3,1],s=100,c='cyan',label='Cluster 4')
ax.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s
```

```
=400,c='yellow',label='Centroid')
plt.title('Cluster Segmentation of Customers')
plt.xlabel('Age')
plt.ylabel('Spending Score(1-100)')
plt.legend()
plt.show()

C:\Users\bimal\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1429: 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(
```



Results

We have been able to create distinct clusters based on various features by using k-means clustering. To boost profits, mall management can focus on clusters with average spending scores. They should also continue to have positive relationships with premium customers who have high spending scores. In order to improve the clients with poor spending scores, they should also focus on developing fresh, creative concepts.