Customer Segmentation Analysis

Clustering the data and performing classification algorithms

1. **Download the dataset: Dataset**
2. **Load the dataset**

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_csv('/content/Mall_Customers.csv')
data
```

Out[2]:

	CustomerID	Gender	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
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

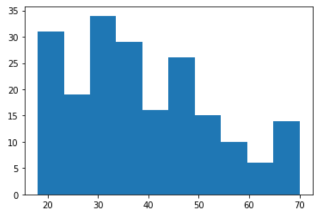
3.**Perform Below Visualizations**

Univariate Analysis

Press F11 to exit full screen

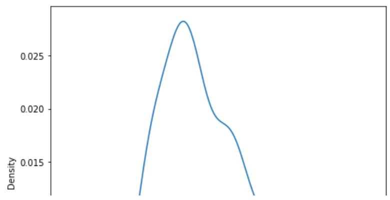
In [4]:
```
plt.hist(data["Age"])
```

Out[4]:
```
(array([31., 19., 34., 29., 16., 26., 15., 10.,  6., 14.]),
 array([18. , 23.2, 28.4, 33.6, 38.8, 44. , 49.2, 54.4, 59.6, 64.8, 70. ]),
 )
```



In [5]:
```
plt.figure(figsize=(7,7))
data["Age"].plot(kind="density")
```

Out[5]:



Bi-Variate Analysis

In [7]:

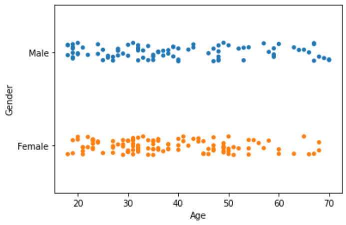
```
sns.scatterplot(x=data["Age"],y=data['Gender'],hue=data["Spending Score (1-100)"])
```

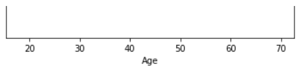
Out[7]:

In [8]:

```
sns.stripplot(x=data["Age"],y=data["Gender"])
```

Out[8]:



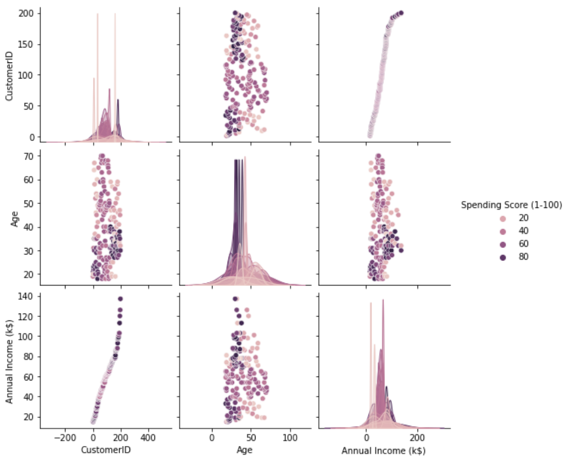


Multi-Variate Analysis

In [9]:

```
sns.pairplot(data,hue='Spending Score (1-100)')
```

Out[9]:



4. **Perform descriptive statistics on the dataset**

In [10]:
```
data.describe()
```

Out[10]:

	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
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

5 .**Handle the Missing values**

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

6.**Find the outliers and replace the outliers**

In [12]:
```
for i in data:
    if data[i].dtype=='int64' or data[i].dtypes=='float64':
        q1=data[i].quantile(0.25)
        q3=data[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        data[i]=np.where(data[i] >upper, upper, data[i])
```

In [12]:
```
for i in data:
    if data[i].dtype=='int64' or data[i].dtypes=='float64':
        q1=data[i].quantile(0.25)
        q3=data[i].quantile(0.75)
        iqr=q3-q1
        upper=q3+1.5*iqr
        lower=q1-1.5*iqr
        data[i]=np.where(data[i] >upper, upper, data[i])
        data[i]=np.where(data[i] <lower, lower, data[i])
data
```

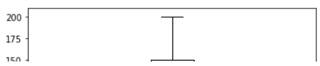
Press F11 to exit full screen

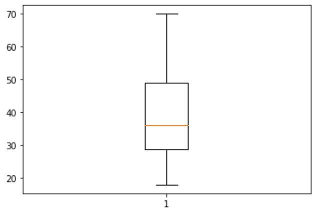
Out[12]:

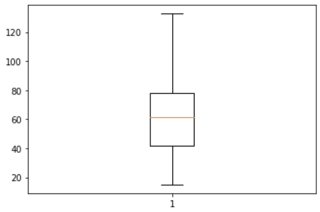
	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1.0	Male	19.0	15.00	39.0
1	2.0	Male	21.0	15.00	81.0
2	3.0	Female	20.0	16.00	6.0
3	4.0	Female	23.0	16.00	77.0
4	5.0	Female	31.0	17.00	40.0
...	...	...	...	...	...
195	196.0	Female	35.0	120.00	79.0
196	197.0	Female	45.0	126.00	28.0
197	198.0	Male	32.0	126.00	74.0
198	199.0	Male	32.0	132.75	18.0
199	200.0	Male	30.0	132.75	83.0

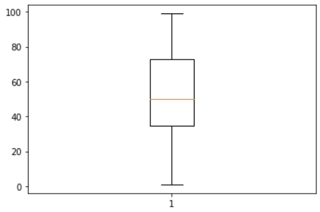
200 rows × 5 columns

In [13]:
```
for i in data:
    if data[i].dtype=='int64' or data[i].dtypes=='float64':
        plt.boxplot(data[i])
        plt.show()
```









7.Check for Categorical columns and perform encoding

In [47]:
```
x = data.iloc[:,0:-1]
x = pd.get_dummies(x)
x.head()
```

Out[47]:

	CustomerID	Age	Annual Income (k$)	Gender_Female	Gender_Male
0	1.0	19.0	15.0	0	1
1	2.0	21.0	15.0	0	1
2	3.0	20.0	16.0	1	0
3	4.0	23.0	16.0	1	0
4	5.0	31.0	17.0	1	0

8. Scaling the data

In [22]:
```
from mlxtend.preprocessing import minmax_scaling
original_data = np.random.exponential(size = 1000)

# mix-max scale the data between 0 and 1
scaled_data = minmax_scaling(original_data, columns = [0])

# plot both together to compare
fig, ax=plt.subplots(1,2)
sns.distplot(original_data, ax=ax[0])
ax[0].set_title("Original Data")
sns.distplot(scaled_data, ax=ax[1])
ax[1].set_title("Scaled data")
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a futu
re version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function fo
r histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a futu
re version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function fo
r histograms).
  warnings.warn(msg, FutureWarning)
```

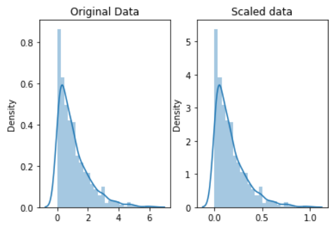
Out[22]: Text(0.5, 1.0, 'Scaled data')

Original Data   Scaled data

```
sns.distplot(scaled_data, ax=ax[1])
ax[1].set_title("Scaled data")
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[22]: `Text(0.5, 1.0, 'Scaled data')`



9. Perform any of the clustering algorithms

Clustering using K- means

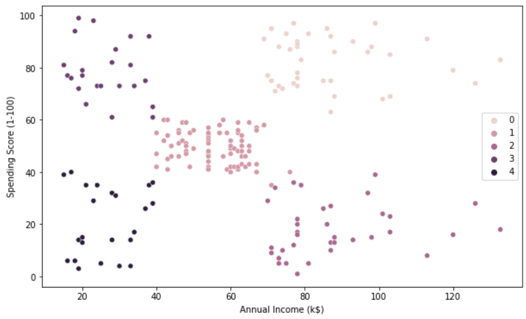
In [23]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
X = data.iloc[:, -3:]
km = KMeans(n_clusters=5).fit(X)
```

In [24]:
```
# K-Means visualization on pair of 2 features
plt.figure(figsize=(10, 6))
sns.scatterplot(X.iloc[:, 1], X.iloc[:, 2], hue=km.labels_)
plt.show()
```

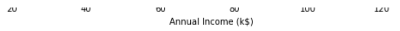

In [23]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
X = data.iloc[:, -3:]
km = KMeans(n_clusters=5).fit(X)
```

In [24]:
```
# K-Means visualization on pair of 2 features
plt.figure(figsize=(10, 6))
sns.scatterplot(X.iloc[:, 1], X.iloc[:, 2], hue=km.labels_)
plt.show()
```


```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



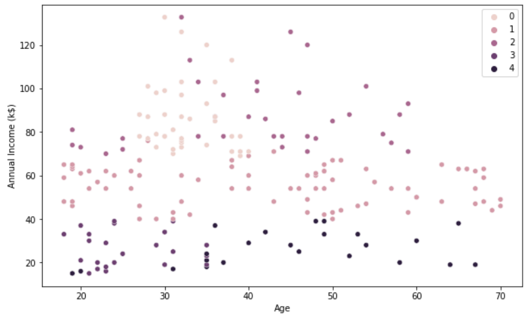
In [25]:
```
# K-Means visualization on another pair of 2 features
plt.figure(figsize=(10, 6))
sns.scatterplot(X.iloc[:, 0], X.iloc[:, 1], hue=km.labels_)
plt.show()
```



In [25]:

```
# K-Means visualization on another pair of 2 features
plt.figure(figsize=(10, 6))
sns.scatterplot(X.iloc[:, 0], X.iloc[:, 1], hue=km.labels_)
plt.show()
```

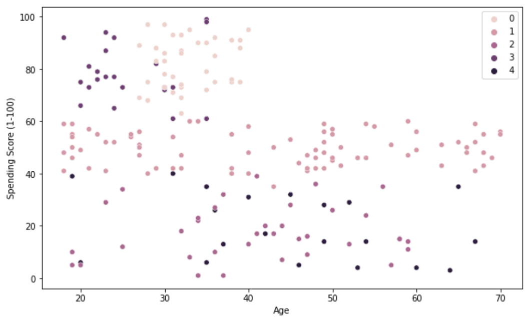
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpreta
tion.
  FutureWarning
```



In [26]:

```
# K-Means visualization on the last pair of 2 features
plt.figure(figsize=(10, 6))
sns.scatterplot(X.iloc[:, 0], X.iloc[:, 2], hue=km.labels_)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpreta
tion.
  FutureWarning
```



10. Add the cluster data with the primary dataset

In [33]:

```
from sklearn.cluster import KMeans
S = data.loc[:, ["Age", "Gender", "Annual Income (k$)"]]
k = KMeans(n_clusters=6)

sns.relplot(x="Gender", y="Age", hue="Annual Income (k$)", data=S, height=6,);
```

11.Split the data into dependent and independent variables

In [15]:
```
x = data.iloc[:,0:-1]
y = data.iloc[:,-1]

print(x.shape)
print(y.shape)
```

```
(200, 4)
(200,)
```

12.Split the data into training and testing

In [21]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x,y,test_size=0.25,random_state=0)
print(' x_train.shape : ',x_train.shape)
print(' y_train.shape : ',y_train.shape)
print(' x_test.shape : ',x_test.shape)
print(' y_test.shape : ',y_test.shape)
```

```
x_train.shape :  (150, 4)
y_train.shape :  (150,)
x_test.shape :  (50, 4)
y_test.shape :  (50,)
```

13. Build the Model

In [34]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```


```
y_train.shape :  (150,)
x_test.shape :  (50, 4)
y_test.shape :  (50,)
```

13. Build the Model

In [34]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```


14. Train the Model

In [48]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x,y,test_size=0.25,random_state=0)
sc = StandardScaler()
x_train=sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)

x_train = pd.DataFrame(x_train)
x_train.head()
```

Out[48]:

	0	1	2	3	4
0	-0.496838	0.591319	-0.448576	0.862662	-0.862662
1	0.426459	-1.100849	0.345922	0.862662	-0.862662
2	1.471700	0.168277	1.443085	0.862662	-0.862662
3	-0.043900	-0.818821	-0.032410	0.862662	-0.862662
4	0.861976	-0.325272	0.648587	-1.159202	1.159202

In [49]:
```
model.fit(x_train, y_train)
```

Out[49]: LinearRegression()

15. Test the Model

In [50]:
```
y_train_pred = model.predict(x_train)
y_test_pred = model.predict(x_test)
```

16. Measure the performance using Evaluation Metrics.

In [51]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error
s = mean_squared_error(y_train, y_train_pred)
print('Mean Squared error of training set :%2f'%s)

p = mean_squared_error(y_test, y_test_pred)
print('Mean Squared error of testing set :%2f'%p)
```

```
Mean Squared error of training set :582.294290
Mean Squared error of testing set :628.112950
```