

## Assignment - 4

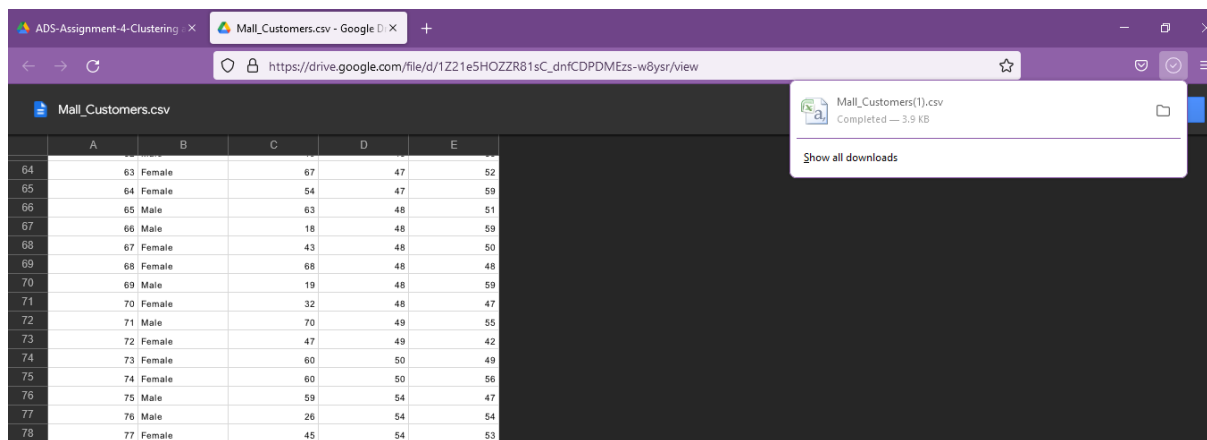
### Clustering And Classification

Assignment Date	15 October 2022
Student Name	Logeshkumar R
Student Roll Number	727719EUCS074
Maximum Marks	2 Marks

#### Question-1:

Download the dataset: Dataset

#### Solution:



	A	B	C	D	E
64	63	Female	67	47	52
65	64	Female	54	47	59
66	65	Male	63	48	51
67	66	Male	18	48	59
68	67	Female	43	48	50
69	68	Female	68	48	48
70	69	Male	19	48	59
71	70	Female	32	48	47
72	71	Male	70	49	55
73	72	Female	47	49	42
74	73	Female	60	50	49
75	74	Female	60	50	56
76	75	Male	59	54	47
77	76	Male	26	54	54
78	77	Female	45	54	53

#### Question-2:

Load the dataset into the tool

#### Solution:

```
In [2]: d = pd.read_csv("E://Mall_Customers(1).csv")
d.head()
```

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

### Question-3:

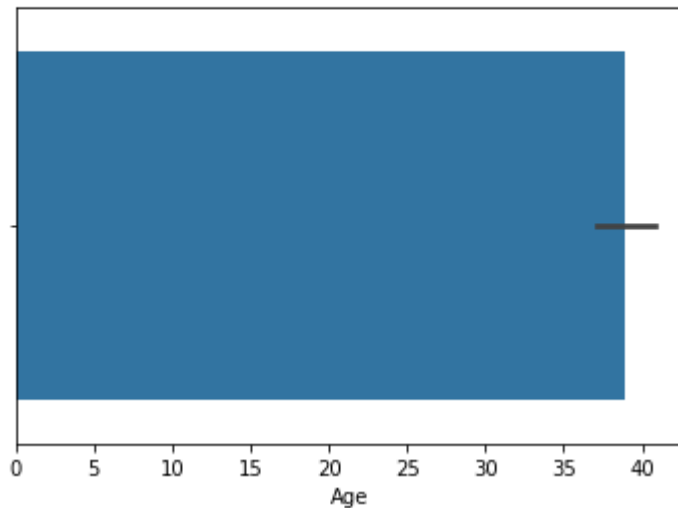
Perform Below Visualizations.

- Univariate analysis

**Solution:**

```
In [4]: sns.barplot(d.Age)
```

```
Out[4]: <AxesSubplot:xlabel='Age'>
```

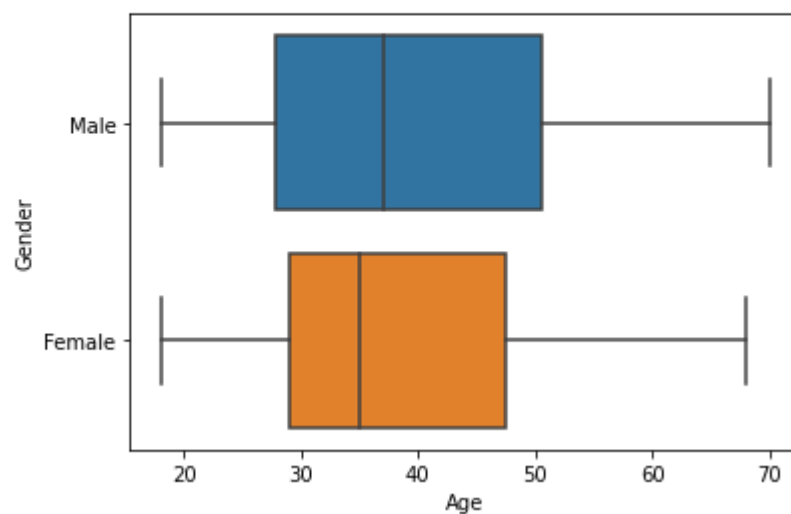


- Bi-variate analysis

**Solution:**

```
In [14]: sns.boxplot(y=d.Gender,x=d.Age)
```

```
Out[14]: <AxesSubplot:xlabel='Age', ylabel='Gender'>
```

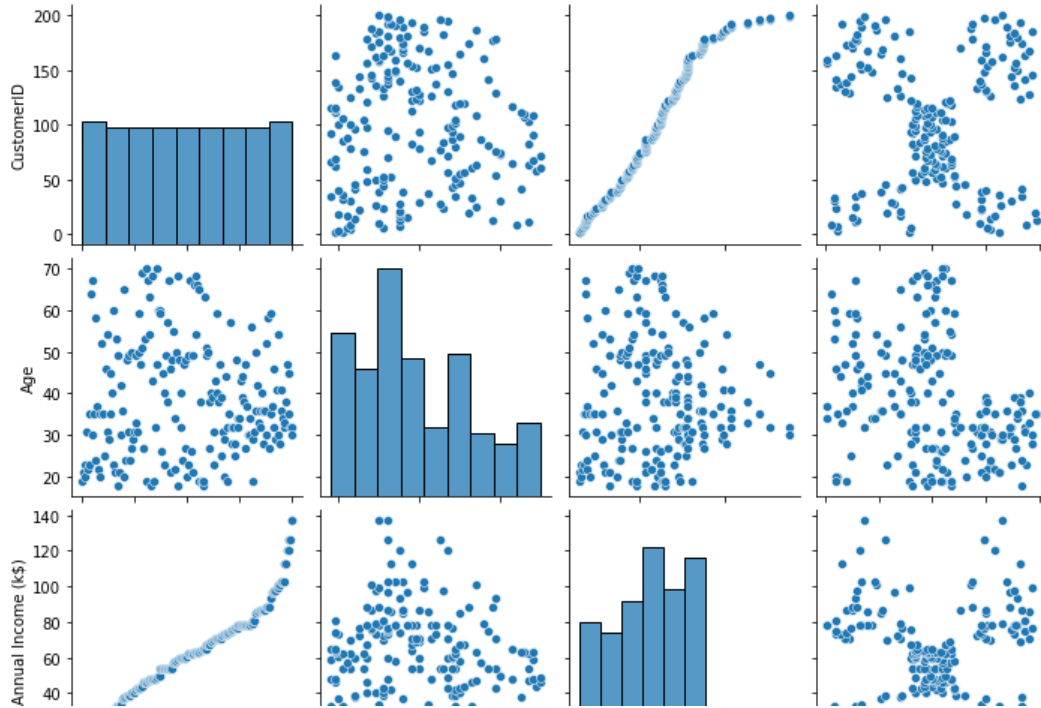


- Multi-variate analysis

**Solution:**

```
In [15]: sns.pairplot(d)
```

```
Out[15]: <seaborn.axisgrid.PairGrid at 0x1f19d20da30>
```



#### Question-4:

Perform descriptive statistics on the dataset.

**Solution:**

```
In [16]: d['CustomerID'].mean()
```

```
Out[16]: 100.5
```

```
In [18]: d['Age'].median()
```

```
Out[18]: 36.0
```

```
In [19]: d['Gender'].mode()
```

```
Out[19]: 0    Female
dtype: object
```

```
In [20]: d.skew()
```

```
Out[20]: CustomerID      0.000000
Age      0.485569
Annual Income (k$)      0.321843
Spending Score (1-100)  -0.047220
dtype: float64
```

```
In [21]: d.kurt()
```

```
Out[21]: CustomerID      -1.200000
Age      -0.671573
Annual Income (k$)      -0.098487
Spending Score (1-100)  -0.826629
dtype: float64
```

```
In [22]: d.std()
Out[22]: CustomerID      57.879185
Age      13.969007
Annual Income (k$)      26.264721
Spending Score (1-100)   25.823522
dtype: float64
```

#### Question-5:

Check for Missing values and deal with them.

#### Solution:

```
In [23]: d.isna().any()
```

```
Out[23]: CustomerID      False
Gender      False
Age      False
Annual Income (k$)      False
Spending Score (1-100)   False
dtype: bool
```

```
In [25]: d['Age'].fillna(d['Age'].mean(),inplace=True)
d
```

```
Out[25]:
```

	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

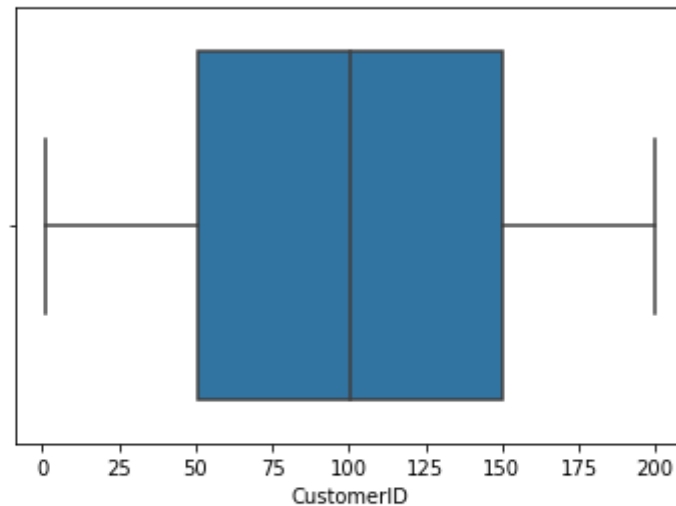
### Question-6:

Find the outliers and replace the outliers

**Solution:**

```
In [26]: sns.boxplot(d['CustomerID'])
```

```
Out[26]: <AxesSubplot:xlabel='CustomerID'>
```



```
In [28]: Q1=d.CustomerID.quantile(0.25)
Q2=d.CustomerID.quantile(0.75)
IQR=Q2-Q1
print(IQR)
```

```
99.5
```

```
In [30]: d=d[~((d.CustomerID<(Q1-1.5*IQR))|(d.CustomerID>(Q2+1.5*IQR)))]
d
```

Out[30]:

	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

### Question-7:

Check for Categorical columns and perform encoding.

**Solution:**

```
In [31]: d['Gender'].replace({'Female':1, 'Male':0}, inplace=True)  
d.head()
```

Out[31]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	0	19	15	39
1	2	0	21	15	81
2	3	1	20	16	6
3	4	1	23	16	77
4	5	1	31	17	40

### Question-8:

Scaling the data

**Solution:**

```
In [33]: from sklearn import preprocessing  
x = d.iloc[:, 2:4].values  
print ("\nOriginal data values : \n", x)
```

```
[ 19  48]  
[ 32  48]  
[ 70  49]  
[ 47  49]  
[ 60  50]  
[ 60  50]  
[ 59  54]  
[ 26  54]  
[ 45  54]  
[ 40  54]  
[ 23  54]  
[ 49  54]  
[ 57  54]  
[ 38  54]  
[ 67  54]  
[ 46  54]  
[ 21  54]  
[ 10  54]
```

```
In [34]: min_max_scaler = preprocessing.MinMaxScaler(feature_range =(0, 1))
x_after_min_max_scaler = min_max_scaler.fit_transform(x)
print ("\nAfter min max Scaling : \n", x_after_min_max_scaler)
```

```
After min max Scaling :
[[0.01923077 0.
  [0.05769231 0.
  [0.03846154 0.00819672]
  [0.09615385 0.00819672]
  [0.25      0.01639344]
  [0.07692308 0.01639344]
  [0.32692308 0.02459016]
  [0.09615385 0.02459016]
  [0.88461538 0.03278689]
  [0.23076923 0.03278689]
  [0.94230769 0.03278689]
  [0.32692308 0.03278689]
  [0.76923077 0.04098361]
  [0.11538462 0.04098361]
  [0.36538462 0.04098361]
  [0.07692308 0.04098361]
  [0.32692308 0.04918033]
```

```
In [35]: Standardisation = preprocessing.StandardScaler()
x_after_Standardisation = Standardisation.fit_transform(x)
print ("\nAfter Standardisation : \n", x_after_Standardisation)
```

```
After Standardisation :
[[-1.42456879 -1.73899919]
 [-1.28103541 -1.73899919]
 [-1.3528021  -1.70082976]
 [-1.13750203 -1.70082976]
 [-0.56336851 -1.66266033]
 [-1.20926872 -1.66266033]
 [-0.27630176 -1.62449091]
 [-1.13750203 -1.62449091]
 [ 1.80493225 -1.58632148]
 [-0.6351352  -1.58632148]
 [ 2.02023231 -1.58632148]
 [-0.27630176 -1.58632148]
 [ 1.37433211 -1.54815205]
 [-1.06573534 -1.54815205]
 [-0.13276838 -1.54815205]
  . . . . .]
```

### Question-9:

Perform any of the clustering algorithms

### Solution:

```
In [37]: import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.cluster import KMeans
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
target = d.iloc[:,[3,4]]

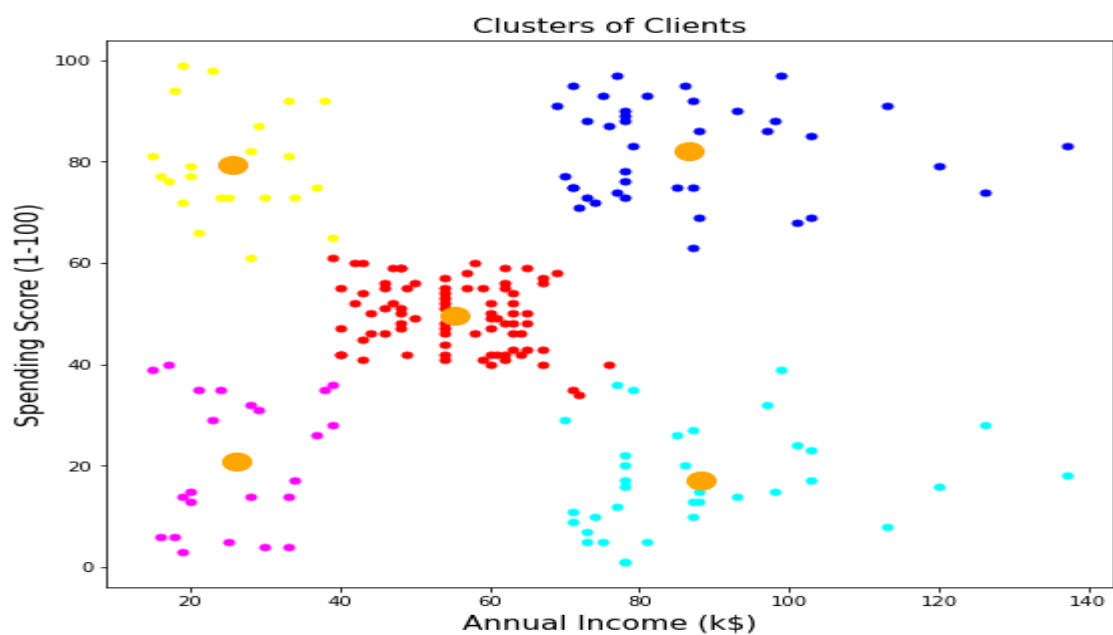
X = np.array(target)
kmeans = KMeans(n_clusters = 5, max_iter = 500, n_init = 10, random_state = 0)
kmeans_preds = kmeans.fit_predict(X)
point_size = 25

colors = ['cyan', 'red', 'blue', 'yellow', 'magenta']
labels = ['Careful', 'Standard', 'Target', 'Careless', 'Sensible']
plt.figure(figsize = (9,8))

for i in range(5):
    plt.scatter(X[kmeans_preds == i,0], X[kmeans_preds == i,1], s = point_size, c = colors[i], label = labels[i])

plt.scatter(kmeans.cluster_centers[:,0], kmeans.cluster_centers[:,1], s = 200, c = 'orange', label = 'Centroids')
plt.title('Clusters of Clients',fontsize=15)
plt.xlabel('Annual Income (k$)',fontsize=15)
plt.ylabel('Spending Score (1-100)',fontsize=15)

plt.show()
```





```
In [44]: TWSS=[]
k=list(range(2,9))

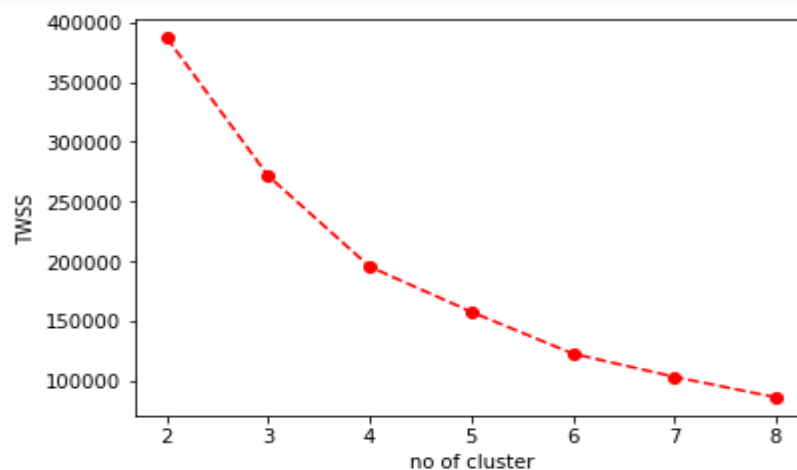
for i in k:
    kmeans=KMeans(n_clusters=i,init='k-means++')
    kmeans.fit(d)
    TWSS.append(kmeans.inertia_)
```

```
In [45]: TWSS
```

```
Out[45]: [387065.7137713772,
271384.50878286787,
195401.19855991477,
157620.97147979145,
122637.55796110148,
103233.09788480632,
86028.09935619931]
```

```
In [46]: plt.plot(k,TWSS,'ro--')
plt.xlabel('no of cluster')
plt.ylabel('TWSS')
```

```
Out[46]: Text(0, 0.5, 'TWSS')
```



```
In [48]: model=KMeans(n_clusters=4)
model.fit(d)
```

```
Out[48]: KMeans(n_clusters=4)
```

### Add the cluster data with the primary dataset

```
In [49]: model.labels_
```

```
In [50]: mb=pd.Series(model.labels_)
```

```
In [52]: d.head(3)
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	clust
0	1	0	19	15	39	1
1	2	0	21	15	81	1
2	3	1	20	16	6	1

Out[53]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	clust
197	198	0	32	126	74	2
198	199	0	32	137	18	3
199	200	0	30	137	83	2

### Question-11:

Split the data into dependent and independent variables.

#### Solution:

```
In [54]: dmf = pd.get_dummies(d, columns=['Gender'])
dmf
```

```
Out[54]:
```

	CustomerID	Age	Annual Income (k\$)	Spending Score (1-100)	clust	Gender_0	Gender_1
0	1	19	15	39	1	1	0
1	2	21	15	81	1	1	0
2	3	20	16	6	1	0	1
3	4	23	16	77	1	0	1
4	5	31	17	40	1	0	1
...	...	...	...	...	...	...	...
195	196	35	120	79	2	0	1
196	197	45	126	28	3	0	1
197	198	32	126	74	2	1	0
198	199	32	137	18	3	1	0
199	200	30	137	83	2	1	0

200 rows x 7 columns

```
In [56]: y = d['Age']
y
```

```
Out[56]:
```

0	19
1	21
2	20
3	23
4	31
...	...
195	35
196	45
197	32
198	32
199	30

Name: Age, Length: 200, dtype: int64

```
In [58]: x = dmf.drop(columns='Age', axis=1)
x.head()
```

```
Out[58]:
```

	CustomerID	Annual Income (k\$)	Spending Score (1-100)	clust	Gender_0	Gender_1
0	1	15	39	1	1	0
1	2	15	81	1	1	0
2	3	16	6	1	0	1
3	4	16	77	1	0	1
4	5	17	40	1	0	1

### Question-12:

Split the data into training and testing

**Solution:**

```
In [70]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

### Question-13:

Build the Model

**Solution:**

```
In [75]: from sklearn.linear_model import LinearRegression
regressor=LinearRegression()
regressor.fit(x_train,y_train)
```

```
Out[75]: LinearRegression()
```

### Question-14:

Train the Model

**Solution:**

```
In [71]: x_train
```

```
Out[71]:
```

	CustomerID	Annual Income (k\$)	Spending Score (1-100)	clust	Gender_0	Gender_1
134	135	73	5	0	1	0
66	67	48	50	1	0	1
26	27	28	32	2	0	1
113	114	64	46	1	1	0
168	169	87	27	0	0	1
...	...	...	...	...	...	...
67	68	48	48	1	0	1
192	193	113	8	0	1	0
117	118	65	59	1	0	1
47	48	40	47	2	0	1
172	173	87	10	0	1	0

```
In [72]: y_train
```

```
Out[72]: 134    20
          66     43
          26     45
          113    19
          168    36
          ..
          67     68
          192    33
          117    49
          47     27
          172    36
          Name: Age, Length: 160, dtype: int64
```

#### Question-15:

Test the Model

**Solution:**

```
In [73]: x_test
```

```
Out[73]:
```

	CustomerID	Annual Income (k\$)	Spending Score (1-100)	clust	Gender_0	Gender_1
18	19	23	29	2	1	0
170	171	87	13	0	1	0
107	108	63	46	1	1	0
98	99	61	42	1	1	0
177	178	88	69	3	1	0
182	183	98	15	0	1	0

```
In [74]: y_test
```

```
Out[74]: 18     52
          170    40
          107    54
          98     48
          177    27
          182    46
          5      22
          146    48
          12     58
          152    44
          61     19
          125    31
```

### Question-16:

Measure the performance using Evaluation Metrics.

### Solution:

```
In [5]: from sklearn.cluster import KMeans
        from sklearn import preprocessing

        data_x = d.iloc[:, 2:4]
        data_x.head()
        x_array = np.array(data_x)

        scaler = preprocessing.MinMaxScaler()
        x_scaled = scaler.fit_transform(x_array)
        x_scaled

        Sum_of_squared_distances = []
        K = range(1,15)
        for k in K:
            km = KMeans(n_clusters =k)
            km =km.fit(x_scaled)
            Sum_of_squared_distances.append(km.inertia_)

        plt.plot(K, Sum_of_squared_distances, 'bx-')
        plt.xlabel('k')
        plt.ylabel('SSE')
        plt.title('Elbow Method For Optimal k')
        plt.show()
```

