```
!pip install kneed
```

Show hidden output

```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.cluster import DBSCAN
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
from sklearn import preprocessing
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
```

1.) Loading the dataset

```
# Load the dataset
df=pd.read_csv("/content/sample_data/Mall_Customers.csv")
```

2.) EDA

```
# Dimenions of the dataframe
df.shape
```

```
(200, 5)
```

```
# Datatypes of all attributes
df.dtypes
```

	0
CustomerID	int64
Gender	object
Age	int64
Annual Income (k$)	int64
Spending Score (1-100)	int64

```
# First five rows of the dataframe
df.head()
```

	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

Next steps: Generate code with df View recommended plots New interactive sheet

```
# Basic stats
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
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

```
# Summary of the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

Double-click (or enter) to edit

```
from sklearn.preprocessing import LabelEncoder

# label_encoder object knows how to understand word labels.
LE = LabelEncoder()

# Encode labels in column 'species'.
df['Gender']=LE.fit_transform(df['Gender'])
df['Gender'].unique()
```

```
array([1, 0])
```

```
df.head()
```

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

Next steps: Generate code with df View recommended plots New interactive sheet

```
pca= PCA(n_components=2)
```

```
r_data = pca.fit_transform(df)
r_data
```

```
       [ 5.98459161e+01,  2.86593788e+01],
       [ 6.02226657e+01, -4.72030119e+01],
       [ 6.16384130e+01,  2.37830791e+01],
       [ 6.25536841e+01, -1.91847043e+01],
       [ 6.39448044e+01,  3.37269265e+01],
       [ 6.52131146e+01, -3.99079146e+01],
       [ 6.66416701e+01,  4.29738590e+01],
       [ 6.86293685e+01, -2.66332837e+01],
       [ 6.99504744e+01,  2.42662809e+01],
       [ 7.08701774e+01, -3.06526839e+01],
       [ 7.23352368e+01,  4.44016833e+01],
       [ 7.31854458e+01, -2.24786110e+01],
       [ 7.43621754e+01,  1.34695199e+01],
       [ 7.48949576e+01, -3.70339221e+01],
       [ 7.62914212e+01,  2.60567015e+01],
       [ 7.67242385e+01, -3.90448847e+01],
       [ 7.81836229e+01,  4.07531776e+01],
       [ 7.88838456e+01, -3.98176982e+01],
       [ 8.04122551e+01,  3.62755256e+01],
       [ 8.06882590e+01, -3.92611145e+01],
       [ 8.21428206e+01,  2.04086918e+01],
       [ 8.45418779e+01, -4.05129379e+01],
       [ 8.61020080e+01,  3.89593736e+01],
       [ 8.82484722e+01, -1.79810676e+01],
       [ 8.95505745e+01,  3.57157728e+01],
       [ 9.03167375e+01, -3.66123814e+01],
       [ 9.18153789e+01,  3.83334023e+01],
       [ 9.27394358e+01, -1.21234745e+01],
       [ 9.41038274e+01,  4.68433740e+01],
       [ 9.52051912e+01, -2.97338063e+01],
       [ 9.65642394e+01,  1.90540495e+01],
       [ 9.78767205e+01, -3.35854954e+01],
       [ 9.92721234e+01,  3.37362796e+01],
       [ 9.97835718e+01, -2.61483832e+01],
       [ 1.01014768e+02,  1.90735920e+01],
       [ 1.05596395e+02, -4.06055221e+01],
       [ 1.07032676e+02,  3.90183096e+01],
       [ 1.10249446e+02, -3.60991880e+01],
       [ 1.11652574e+02,  2.79646451e+01],
       [ 1.14615358e+02, -2.40178247e+01],
       [ 1.15911505e+02,  2.37299674e+01],
       [ 1.20939935e+02, -3.08598887e+01],
       [ 1.22297753e+02,  3.28530691e+01]])
```

```
data= preprocessing.scale(r_data)
```

```
data =pd.DataFrame(data,columns=['X','Y'])
data.head()
```

	X	Y
0	-1.730708	-0.208398
1	-1.712020	1.328786
2	-1.698942	-1.439447
3	-1.677289	1.162589

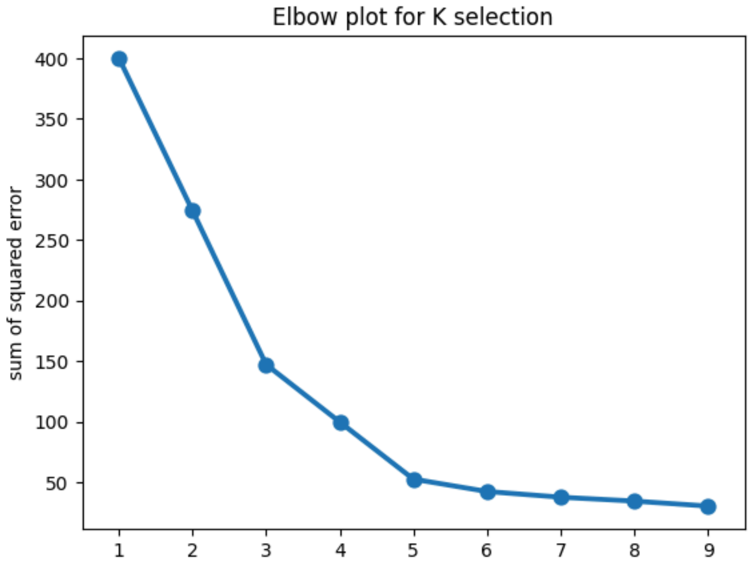
Next steps: Generate code with data | View recommended plots | New interactive sheet

K-Means Clustering

```
sse=[]
for k in range(1,10):
  km=KMeans(n_clusters=k)
  km.fit(data)
  sse.append(km.inertia_)
```

```
#plt.plot(np.arange(1,10),sse)
sns.pointplot(x=np.arange(1,10),y=sse)
plt.title('Elbow plot for K selection')
plt.xlabel('K value')
plt.ylabel('sum of squared error')
```

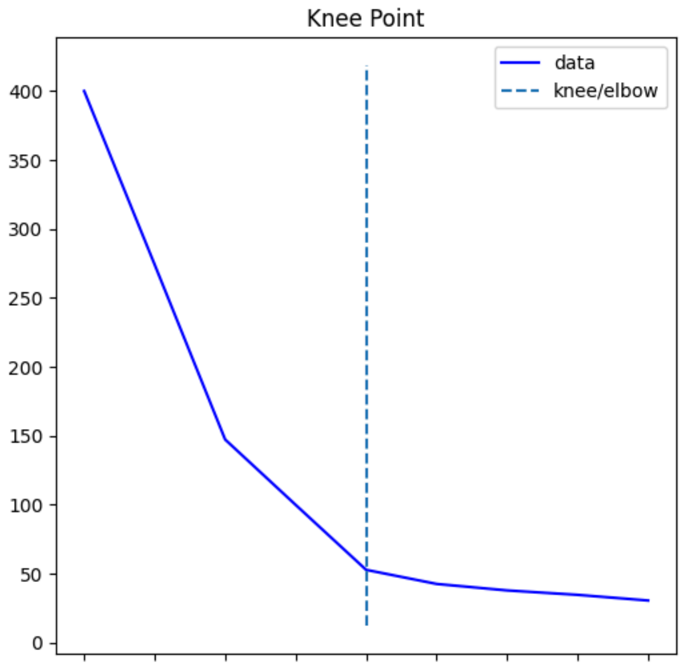
```
Text(0, 0.5, 'sum of squared error')
```




```
from kneed import KneeLocator
kl=KneeLocator(np.arange(1,10),sse, S=1.0, curve="convex", direction="decreasing")
print(kl.elbow)
```

```
5
```

```
kl.plot_knee()
```




```
kmeans=KMeans(n_clusters=4)
```

```
cluster=kmeans.fit_predict(data[['X','Y']])
```

```
kmeans=KMeans(n_clusters=4)
```

```
cluster=kmeans.fit_predict(data[['X','Y']])
```

```
data['cluster']=cluster
```

```
data.head()
```

	X	Y	cluster
0	-1.730708	-0.208398	0
1	-1.712020	1.328786	1
2	-1.698942	-1.439447	0
3	-1.677289	1.162589	1
4	-1.661032	-0.277564	0

Next steps: Generate code with data | View recommended plots | New interactive sheet

```
data['cluster'].value_counts()
```

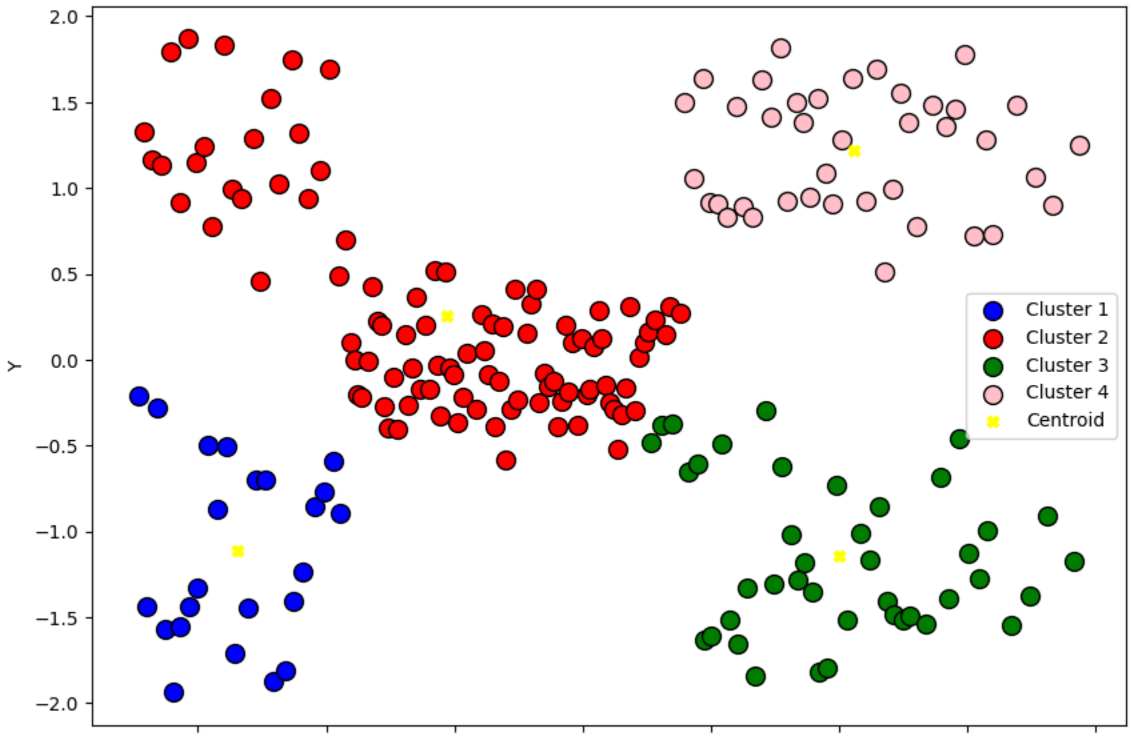
cluster	count
1	97
2	41
3	39
0	23

dtype: int64

```
df1=data[data['cluster']==0]
df2=data[data['cluster']==1]
df3=data[data['cluster']==2]
df4=data[data['cluster']==3]
```

```
plt.figure(figsize=(10,7))
plt.scatter(df1.values[:,0],df1.values[:,1],color="blue",label="Cluster 1",edgecolors="black",s=100)
plt.scatter(df2.values[:,0],df2.values[:,1],color="red",label="Cluster 2",edgecolors="black",s=100)
plt.scatter(df3.values[:,0],df3.values[:,1],color="green",label="Cluster 3",edgecolors="black",s=100)
plt.scatter(df4.values[:,0],df4.values[:,1],color="pink",label="Cluster 4",edgecolors="black",s=100)
plt.xlabel('X')
plt.ylabel('Y')
plt.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1] ,marker= 'X' ,color='yellow' ,label='Centroid')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7812ccf8fee0>
```



DBSCAN Clustering

```
db=DBSCAN(eps=1.0,metric='euclidean')

pr=db.fit_predict(data)

data['cluster']=pr

data.head()
```

	X	Y	cluster
0	-1.730708	-0.208398	0
1	-1.712020	1.328786	1
2	-1.698942	-1.439447	0
3	-1.677289	1.162589	1

Next steps: Generate code with data View recommended plots New interactive sheet