```python
#import libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import random as rd


import numpy as np
import random as rd
class Kmeans:
    def __init__(self,X,K):
        self.X=X
        self.Output={}
        self.Centroids=np.array([]).reshape(self.X.shape[1],0)
        self.K=K
        self.m=self.X.shape[0]

    def kmeanspp(self,X,K):
        i=rd.randint(0,X.shape[0])
        Centroid_temp=np.array([X[i]])
        for k in range(1,K):
            D=np.array([])
            for x in X:
                D=np.append(D,np.min(np.sum((x-Centroid_temp)**2)))
            prob=D/np.sum(D)
            cummulative_prob=np.cumsum(prob)
            r=rd.random()
            i=0
            for j,p in enumerate(cummulative_prob):
                if r<p:
                    i=j
                    break
            Centroid_temp=np.append(Centroid_temp,[X[i]],axis=0)
        return Centroid_temp.T

    def fit(self,n_iter):
        #randomly Initialize the centroids
        self.Centroids=self.kmeanspp(self.X,self.K)

        """for i in range(self.K):
            rand=rd.randint(0,self.m-1)
            self.Centroids=np.c_[self.Centroids,self.X[rand]]"""
        #compute euclidian distances and assign clusters
        for n in range(n_iter):
            EuclidianDistance=np.array([]).reshape(self.m,0)
            for k in range(self.K):
                tempDist=np.sum((self.X-self.Centroids[:,k])**2,axis=1)
                EuclidianDistance=np.c_[EuclidianDistance,tempDist]
            C=np.argmin(EuclidianDistance,axis=1)+1
            #adjust the centroids
            Y={}
            for k in range(self.K):
                Y[k+1]=np.array([]).reshape(2,0)
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        for i in range(self.m):
            Y[C[i]]=np.c_[Y[C[i]],self.X[i]]

        for k in range(self.K):
            Y[k+1]=Y[k+1].T
        for k in range(self.K):
            self.Centroids[:,k]=np.mean(Y[k+1],axis=0)

        self.Output=Y
       def predict(self):
    return self.Output,self.Centroids.T

  def WCSS(self):
      wcss=0
      for k in range(self.K):
          wcss+=np.sum((self.Output[k+1]-self.Centroids[:,k])**2)
      return wcss
```

```
dataset=pd.read_csv('/content/drive/MyDrive/Mall_Customers.csv')
```

```
X = dataset.iloc[:, [3, 4]].values
```

```
dataset.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
max	200.000000	70.000000	137.000000	99.000000

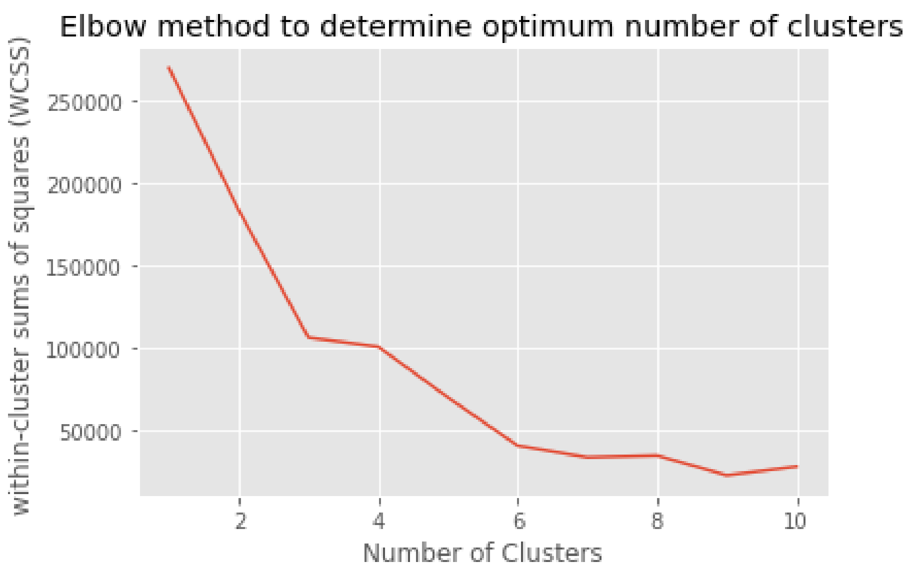
```
m=X.shape[0]
n_iter=100
```

```
#to find optimum number of clusters use elbow method
WCSS_array=np.array([])
for K in range(1,11):
    kmeans=Kmeans(X,K)
    kmeans.fit(n_iter)
    Output,Centroids=kmeans.predict()
    wcss=0
```

```
    for k in range(K):
        wcss+=np.sum((Output[k+1]-Centroids[k,:])**2)
    #WCSS_array=np.append(WCSS_array,kmeans.WCSS())
    WCSS_array=np.append(WCSS_array,wcss)
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3441: RuntimeWarning: Mean of
  out=out, **kwargs)
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:182: RuntimeWarning: invalid val
  ret, rcount, out=ret, casting='unsafe', subok=False)
```

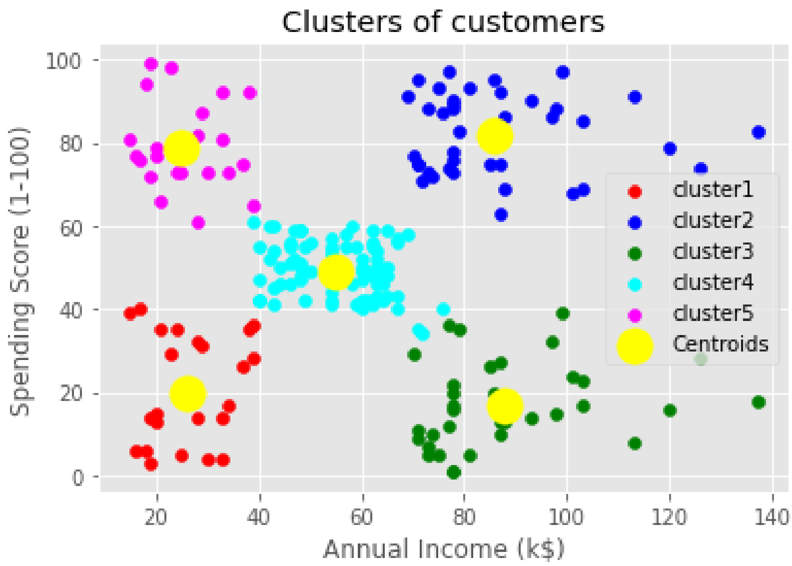
```
K_array=np.arange(1,11,1)
plt.plot(K_array,WCSS_array)
plt.xlabel('Number of Clusters')
plt.ylabel('within-cluster sums of squares (WCSS)')
plt.title('Elbow method to determine optimum number of clusters')
plt.show()
```



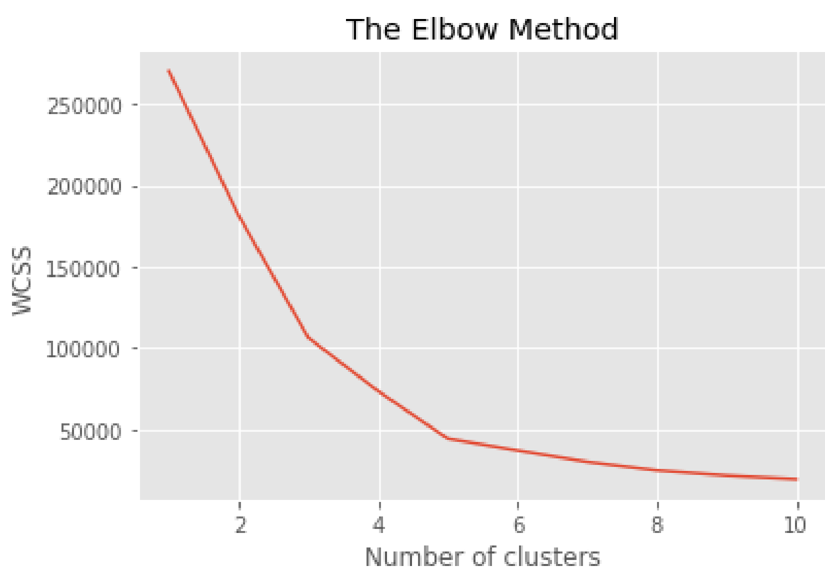

```
#based on these observations we choose 5 as optimum number of clusters
K=5
```

```
kmeans=Kmeans(X,K)
kmeans.fit(n_iter)
Output,Centroids=kmeans.predict()
```

```
color=['red','blue','green','cyan','magenta']
labels=['cluster1','cluster2','cluster3','cluster4','cluster5']
for k in range(K):
    plt.scatter(Output[k+1][:,0],Output[k+1][:,1],c=color[k],label=labels[k])
plt.scatter(Centroids[:,0],Centroids[:,1],s=300,c='yellow',label='Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```




```
#lets implement the same algorithm using sklearn libraries
# Using the elbow method to find the optimal number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```




```
# Fitting K-Means to the dataset
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)


# Visualising the clusters
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```
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', lab
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```