```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import preprocessing
from scipy.optimize import curve_fit
from sklearn.cluster import KMeans
```

```
In [15]: # dataset
    urban_df = pd.read_csv('urban population.csv')

'''choose for clustering because its very long dataset but we only choose
    we also remove all of the nul values to make error free clusters'''
    Df_urban = urban_df[["2019","2020"]].dropna()
    # make arrary
    X = Df_urban.values
```

1961	1960	Indicator Code	Indicator Name	Country Code	Country Name		Out[15]:
50.761000	50.776000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	ABW	Aruba	0	
14.944459	14.704688	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	AFE	Africa Eastern and Southern	1	
8.684000	8.401000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	AFG	Afghanistan	2	
15.053577	14.670329	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	AFW	Africa Western and Central	3	
10.798000	10.435000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	AGO	Angola	4	
18.986000	18.926000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	WSM	Samoa	258	
9.459000	9.100000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	YEM	Yemen, Rep.	259	
46.793000	46.619000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	ZAF	South Africa	260	
18.951000	18.145000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	ZMB	Zambia	261	
12.821000	12.608000	SP.URB.TOTL.IN.ZS	Urban population (% of total population)	ZWE	Zimbabwe	262	
	50.761000  14.944459  8.684000  15.053577  10.798000   18.986000  9.459000  46.793000  18.951000	50.776000       50.761000         14.704688       14.944459         8.401000       8.684000         14.670329       15.053577         10.435000       10.798000             18.926000       18.986000         9.100000       9.459000         46.619000       46.793000         18.145000       18.951000	SP.URB.TOTL.IN.ZS       50.776000       50.761000         SP.URB.TOTL.IN.ZS       14.704688       14.944459         SP.URB.TOTL.IN.ZS       8.401000       8.684000         SP.URB.TOTL.IN.ZS       14.670329       15.053577         SP.URB.TOTL.IN.ZS       10.435000       10.798000         SP.URB.TOTL.IN.ZS       18.926000       18.986000         SP.URB.TOTL.IN.ZS       9.100000       9.459000         SP.URB.TOTL.IN.ZS       46.619000       46.793000         SP.URB.TOTL.IN.ZS       18.145000       18.951000	NameIndicator Code19601961Urban population (% of total population)SP.URB.TOTL.IN.ZS50.77600050.761000Urban population (% of total population)SP.URB.TOTL.IN.ZS14.70468814.944459Urban population (% of total population)SP.URB.TOTL.IN.ZS8.4010008.684000Urban population (% of total population)SP.URB.TOTL.IN.ZS14.67032915.053577Urban population (% of total population)SP.URB.TOTL.IN.ZS10.43500010.798000Urban population (% of total population)SP.URB.TOTL.IN.ZS18.92600018.986000Urban population (% of total population)SP.URB.TOTL.IN.ZS9.1000009.459000Urban population (% of total population)SP.URB.TOTL.IN.ZS46.61900046.793000Urban population (% of total population)SP.URB.TOTL.IN.ZS18.14500018.951000Urban population (% of total population)SP.URB.TOTL.IN.ZS18.14500012.821000Urban population (% of total population)SP.URB.TOTL.IN.ZS12.60800012.821000	Code         Name         Indicator Code         1960         1961           ABW         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         50.776000         50.761000           AFE         Population (% of total population)         SP.URB.TOTL.IN.ZS         14.704688         14.944459           AFG         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         8.401000         8.684000           AFW         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         14.670329         15.053577           AGO         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         10.435000         10.798000           WSM         Population (% of total population)         SP.URB.TOTL.IN.ZS         18.926000         18.986000           YEM         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         9.100000         9.459000           ZAF         Population (% of total population)         SP.URB.TOTL.IN.ZS         46.619000         46.793000           ZMB         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         18.145000         18.951000           ZWE         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         12.608000         12.821000	Name         Code         Name         Indicator Code         1960         1960           Aruba         ABW         Urban population (% of total population (% of total population)         SP.URB.TOTL.IN.ZS         50.776000         50.761000           Affrica Eastern and Southern         AFE         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         14.704688         14.944459           Afghanistan         AFG         Urban population (% of total population) (% of total population)         SP.URB.TOTL.IN.ZS         8.401000         8.684000           Africa western and Central         AGO         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         14.670329         15.053577           Angola         AGO         Urban population (% of total population)         SP.URB.TOTL.IN.ZS         10.435000         10.798000           Samoa         WSM         Durban population (% of total population)         SP.URB.TOTL.IN.ZS         18.926000         18.986000           Yemen, Rep.         YEM         Population (% of total population)         SP.URB.TOTL.IN.ZS         9.100000         9.459000           South Africa         ZAF         Population (% of total population)         SP.URB.TOTL.IN.ZS         46.619000         46.793000           Zambia         ZMB         Population (% of total population)	Name   Code   Name   Indicator Code   1950   1951

263 rows × 66 columns

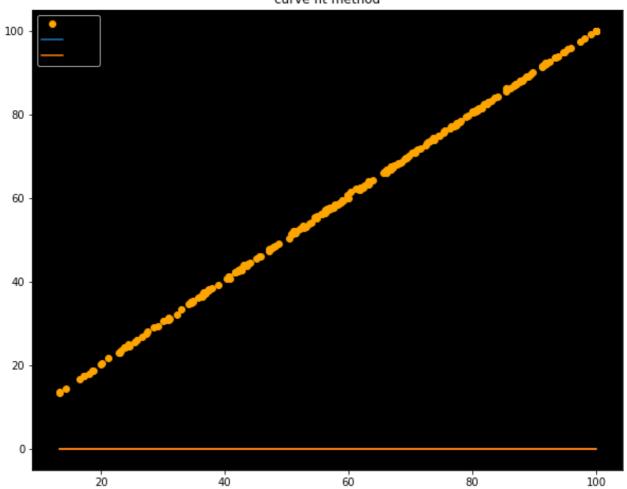
```
In [3]:
    '''desribe the choosen dataset'''
    Df_urban.describe()
```

```
Out[3]:
                     2019
                                2020
         count 262.000000 262.000000
                 60.231410
                            60.558663
         mean
           std
                 22.725521
                            22.663185
           min
                 13.250000
                            13.345000
          25%
                 42.201414
                            42.493195
          50%
                 60.172500
                             61.063159
          75%
               79.904000
                            80.314584
          max 100.000000 100.000000
```

```
In [9]:
         '''fitting the dataset using curve fit '''
         from scipy.optimize import curve_fit
         '''split in x and y'''
         x = Df urban["2019"]
         y = Df_urban["2020"]
         def temp(x, A, B):
             y = A*np.exp(-1*B*x**2)
             return y
         '''that above function is guassian function that is for fit the model using
         param, cov = curve_fit(temp,x, y)
         fitA = param[0]
         fitB = param[1]
         fit_y = temp(X, fitA, fitB)
               plotting
         plt.figure(figsize=(10,8))
         plt.rcParams['axes.facecolor'] = 'black'
         plt.plot(x, y,'o', label='data', color="orange")
         plt.title("curve fit method")
         plt.plot(x, fit_y, '-', label='fit')
         plt.legend()
         plt.show()
```

E:\Files\lib\site-packages\scipy\optimize\minpack.py:833: OptimizeWarning: Covariance of the parameters could not be estimated warnings.warn('Covariance of the parameters could not be estimated',

curve fit method



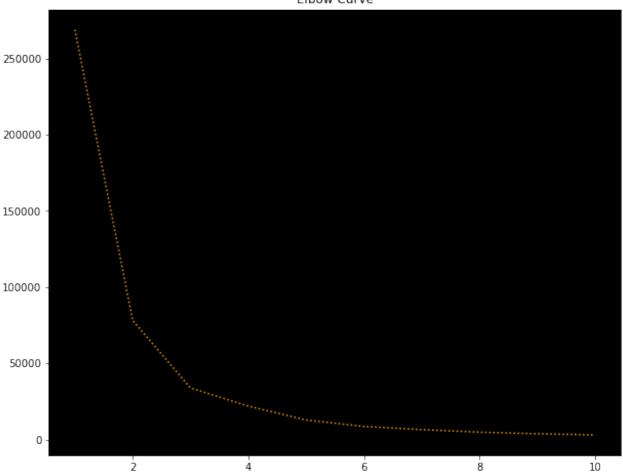
```
In [11]:
# future values prediction
'''finding possible num of cluster in given dataset using elbow graph'''
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters = i, init = "k-means++")
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

E:\Files\lib\site-packages\sklearn\cluster\\_kmeans.py:881: UserWarning: KMe ans 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=2.

warnings.warn(

```
In [12]:
    plt.figure(figsize=(10,8))
    plt.rcParams['axes.facecolor'] = 'black'
    plt.title("Elbow Curve")
    plt.plot(range(1,11),wcss, linestyle ="dotted", color="orange")
    plt.show()
```





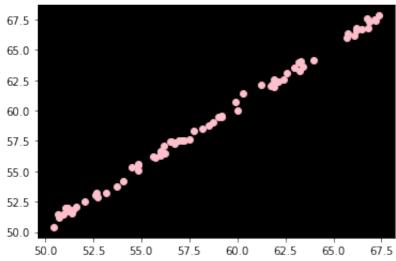
```
In [13]:
    '''5 clusters easily make from this dataset as we determine in elbow graph
    # use buitlin function for kmean cluster of sklearn.cluster
    kmeans = KMeans(n_clusters = 5, init = "k-means++")
    y_kmeans = kmeans.fit_predict(X)
    y_kmeans
```

```
Out[13]: array([1, 1, 4, 1, 0, 0, 3, 0, 3, 3, 0, 3, 4, 3, 0, 0, 4, 3, 1, 4, 1, 2, 3, 2, 1, 2, 1, 3, 2, 3, 4, 2, 1, 2, 1, 2, 0, 2, 4, 3, 0, 0, 0, 0, 1, 0, 2, 4, 0, 2, 2, 2, 3, 3, 0, 2, 2, 2, 2, 3, 2, 2, 0, 1, 0, 0, 2, 0, 1, 2, 2, 2, 4, 2, 1, 3, 0, 2, 1, 4, 3, 2, 0, 0, 3, 1, 0, 1, 2, 2, 1, 3, 0, 3, 4, 2, 3, 0, 1, 0, 0, 2, 0, 0, 1, 1, 0, 1, 0, 1, 0, 2, 2, 3, 3, 2, 0, 3, 3, 2, 0, 3, 3, 0, 4, 1, 4, 0, 4, 2, 3, 2, 1, 3, 0, 2, 4, 2, 1, 1, 4, 4, 1, 0, 4, 0, 2, 3, 2, 3, 0, 3, 1, 1, 1, 1, 0, 2, 2, 0, 0, 1, 3, 4, 0, 0, 2, 3, 1, 0, 1, 4, 2, 2, 0, 2, 4, 0, 0, 3, 2, 4, 3, 3, 2, 3, 0, 1, 2, 2, 1, 2, 4, 0, 1, 3, 0, 0, 0, 2, 1, 2, 0, 3, 0, 2, 4, 1, 2, 1, 1, 1, 1, 1, 1, 1, 0, 2, 2, 1, 2, 0, 3, 1, 1, 1, 1, 0, 2, 2, 0, 0, 0, 3, 4, 3, 0, 0, 3, 4, 0, 0, 1, 0, 4, 0, 2, 4, 0, 1, 4, 1, 0, 2, 0, 0, 0, 3, 4, 3, 0, 0, 3, 4, 0, 0, 1, 0, 4, 0, 2, 4, 0, 4, 1, 1, 0, 2, 2, 0, 0, 1, 4, 2, 0, 3, 2, 0, 0, 3, 1, 3, 1, 4, 0, 4, 1, 1, 0, 1, 1])
```

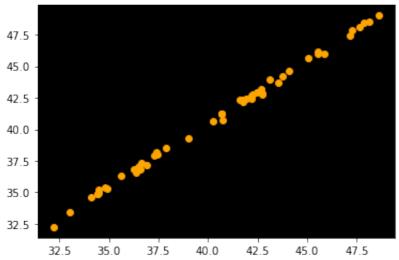
```
In [14]: # Interpretation of the results.
'''according to prediction of k mean most of values are 0 then 2 then 3 and first cluster is of 0 second cluster is of 2 third cluster is of 3 fourth cluster is of 1'''

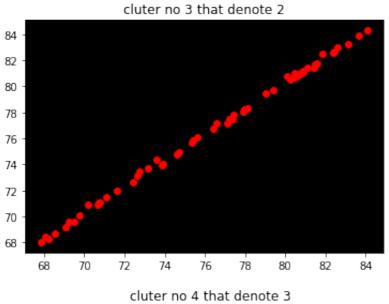
c = ["pink", "orange", "red", "purple", "white"]
for i in range(5):
    # plt.figure(figsize=(10,8))
    string = f"cluter no {i+1} that denote {i}"
    plt.title(string)
    plt.scatter(X[y_kmeans==i,0], X[y_kmeans==i,1], color=c[i])
    plt.show()
```

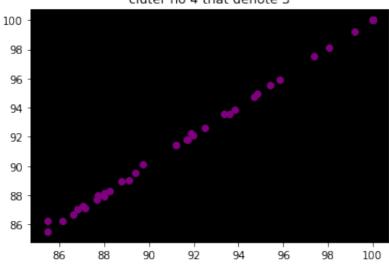
## cluter no 1 that denote 0

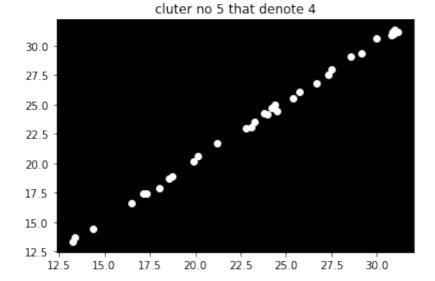


cluter no 2 that denote 1





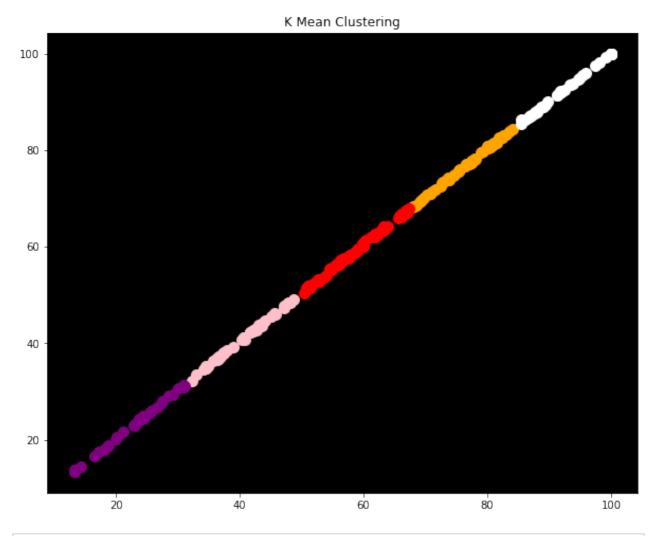




```
In [27]:
    '''now we plotting all in single frame to make different clusters finally'

plt.figure(figsize = (10,8))
plt.title("K Mean Clustering")
plt.scatter(X[y_kmeans==0,0], X[y_kmeans==0,1],s=100, c="pink")
plt.scatter(X[y_kmeans==1,0], X[y_kmeans==1,1],s=100, c="orange")
plt.scatter(X[y_kmeans==2,0], X[y_kmeans==2,1],s=100, c="red")
plt.scatter(X[y_kmeans==3,0], X[y_kmeans==3,1],s=100, c="purple")
plt.scatter(X[y_kmeans==4,0], X[y_kmeans==4,1],s=100, c="white")
```

Out[27]: <matplotlib.collections.PathCollection at 0x1e3e28e6dc0>



In []: