K MEANS CLUSTERING - INDIAN STATES CRIME DATA

IMPORTING THE DATASET

In [565…

```python
import pandas as pd
import matplotlib.pyplot as plt
```

In [566…

```python
data=pd.read_csv('crimesnew.csv')
```

DISPLAY TOP 5 ROWS OF DATASET

In [567…

```python
data.head()
```

Out[567]:

	STATE	POPULATION	Literacy rate	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehicle theft
0	ANDHRA	4,95,77,103	73.40%	358	2068	3941	18679.0	131133	26079.0	92477	12577
1	ARUNACHAL	13,83,727	73.69%	365	3662	6410	22704.0	177638	28699.0	130788	18151
2	ASSAM	3,12,05,576	90.10%	242	2331	1557	13513.0	86250	18095.0	60735	7420
3	BIHAR	10,40,99,452	79.70%	367	3872	3663	14185.0	149189	20064.0	107012	22113
4	CHATTISGARH	2,55,45,198	85.40%	104	771	1929	3742.0	50862	6441.0	38457	5964

DISPLAY LAST 5 ROWS OF DATASET

In [568…

```python
data.tail()
```

Out[568]:

	STATE	POPULATION	Literacy rate	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehic the
24	TRIPURA	36,73,917	92.18%	310	560	4560	2900.0	18767	19450.0	29890	245
25	UTTARPRAD	21,98,12,341	81.80%	420	2300	10200	19489.0	174564	23060.0	31450	1200
26	UTTARAKHAND	1,00,86,292	94.30%	258	1900	690	3004.0	23040	2300.0	17200	169
27	WESTBENGAL	9,12,76,115	84.80%	560	6700	9820	23001.0	189456	21040.0	29890	1240
28	DELHI	3,07,87,941	93.70%	350	5400	2340	4500.0	54201	7032.0	28940	1209

In [569…

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29 entries, 0 to 28
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   STATE           29 non-null     object
 1   POPULATION      29 non-null     object
 2   Literacy rate   29 non-null     object
 3   Murder          29 non-null     int64
 4   Rape            29 non-null     int64
 5   Robbery         29 non-null     int64
 6   Assault         27 non-null     float64
 7   Property Crime  29 non-null     int64
 8   Burglary        28 non-null     float64
 9   Larceny theft   29 non-null     int64
 10  Vehicle theft   29 non-null     int64
```

```
dtypes: float64(2), int64(6), object(3)
memory usage: 2.6+ KB
```

CHECKING FOR NULL VALUES

In [570…:
```
data.isnull().sum()
```

Out[570]:
```
STATE             0
POPULATION        0
Literacy rate     0
Murder            0
Rape              0
Robbery           0
Assault           2
Property Crime    0
Burglary          1
Larceny theft     0
Vehicle theft     0
dtype: int64
```

It is to be noted that there are 2 null values in Assault and 1 in Burglary field

REPLACE NULL VALUES USING INTERPOLATE() METHOD

In [571…:
```
data['Assault']=data['Assault'].interpolate()
data['Burglary']=data['Burglary'].interpolate()
```

In [572…:
```
data.head()
```

Out[572]:

	STATE	POPULATION	Literacy rate	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehicle theft
0	ANDHRA	4,95,77,103	73.40%	358	2068	3941	18679.0	131133	26079.0	92477	12577
1	ARUNACHAL	13,83,727	73.69%	365	3662	6410	22704.0	177638	28699.0	130788	18151
2	ASSAM	3,12,05,576	90.10%	242	2331	1557	13513.0	86250	18095.0	60735	7420
3	BIHAR	10,40,99,452	79.70%	367	3872	3663	14185.0	149189	20064.0	107012	22113
4	CHATTISGARH	2,55,45,198	85.40%	104	771	1929	3742.0	50862	6441.0	38457	5964

In [573…:
```
data.isnull().sum() # we have no null values
```

Out[573]:
```
STATE             0
POPULATION        0
Literacy rate     0
Murder            0
Rape              0
Robbery           0
Assault           0
Property Crime    0
Burglary          0
Larceny theft     0
Vehicle theft     0
dtype: int64
```

In [574…:
```
data.describe()
```

Out[574]:

	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	V
count	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	
mean	403.862069	3362.172414	7456.896552	23502.465517	151894.275862	27737.275862	104242.413793	17

std	383.050978	3834.454385	10580.326043	33545.283010	209329.644564	32390.947229	148872.169482	28
min	35.000000	230.000000	690.000000	2098.000000	14500.000000	2300.000000	13212.000000	1
25%	210.000000	850.000000	2145.000000	3742.000000	21931.000000	12341.000000	29890.000000	2
50%	290.000000	1900.000000	4560.000000	13513.000000	84769.000000	20070.000000	37898.000000	10
75%	377.000000	3872.000000	6410.000000	23001.000000	174564.000000	26079.000000	97176.000000	18
max	1690.000000	14824.000000	52301.000000	145678.000000	921114.000000	152555.000000	626802.000000	141

REMOVING FEATURES THAT ARE NOT IMPORTANT: -Before removing the feature i have to mention that the reason why i took literacy rate as a feature was states with high literacy has high crime report, which is really appreciated. the people trust the police system and there is awareness and a good justice atmosphere. while states with low crime rate tends to be less at crime reporting as there isn't any awareness about reporting the crimes. -so we remove literacy and population

In [575...
```
data.drop(['POPULATION','Literacy rate'],axis=1,inplace=True)
```

In [576...
```
data.head()
```

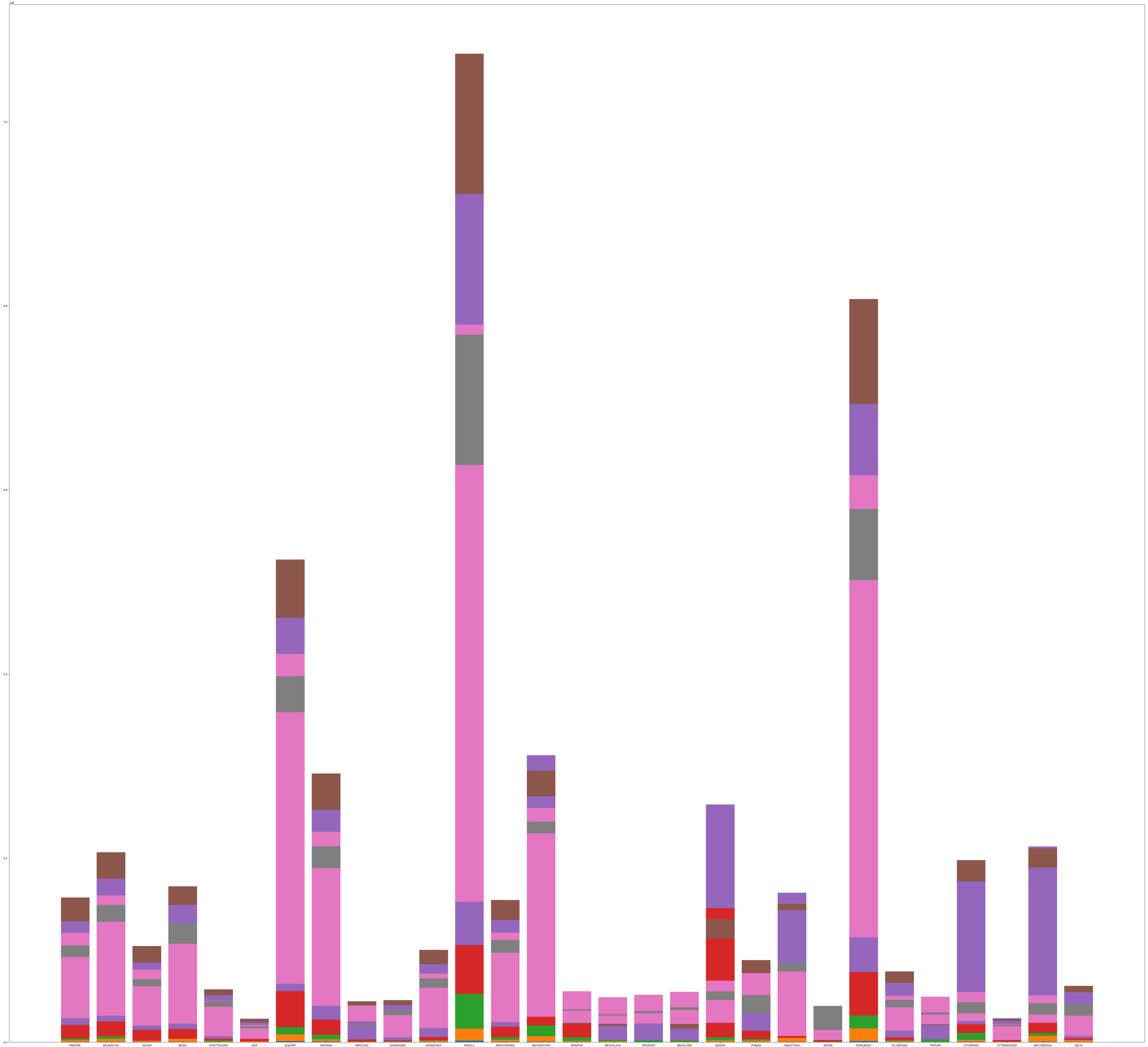
Out[576]:

	STATE	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehicle theft
0	ANDHRA	358	2068	3941	18679.0	131133	26079.0	92477	12577
1	ARUNACHAL	365	3662	6410	22704.0	177638	28699.0	130788	18151
2	ASSAM	242	2331	1557	13513.0	86250	18095.0	60735	7420
3	BIHAR	367	3872	3663	14185.0	149189	20064.0	107012	22113
4	CHATTISGARH	104	771	1929	3742.0	50862	6441.0	38457	5964

LET'S CREATE A STACKED BAR CHART *depicting the states and their crimes (with distinct colors)

In [577...
```
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = [76, 70]
x=data['STATE']
y=data['Murder']#orange
y1=data['Rape']#green
y2=data['Robbery']#red
y3=data['Assault']#violet
y4=data['Property Crime']#pink
y5=data['Burglary']#green
y6=data['Larceny theft']#violet
y7=data['Vehicle theft']#brown
plt.bar(x,y)
plt.bar(x,y1,bottom=y)
plt.bar(x,y2,bottom=y1)
plt.bar(x,y3,bottom=y2)
plt.bar(x,y4,bottom=y3)
plt.bar(x,y5,bottom=y4)
plt.bar(x,y6,bottom=y5)
plt.bar(x,y7,bottom=y6)
```

Out[577]:
```
<BarContainer object of 29 artists>
```

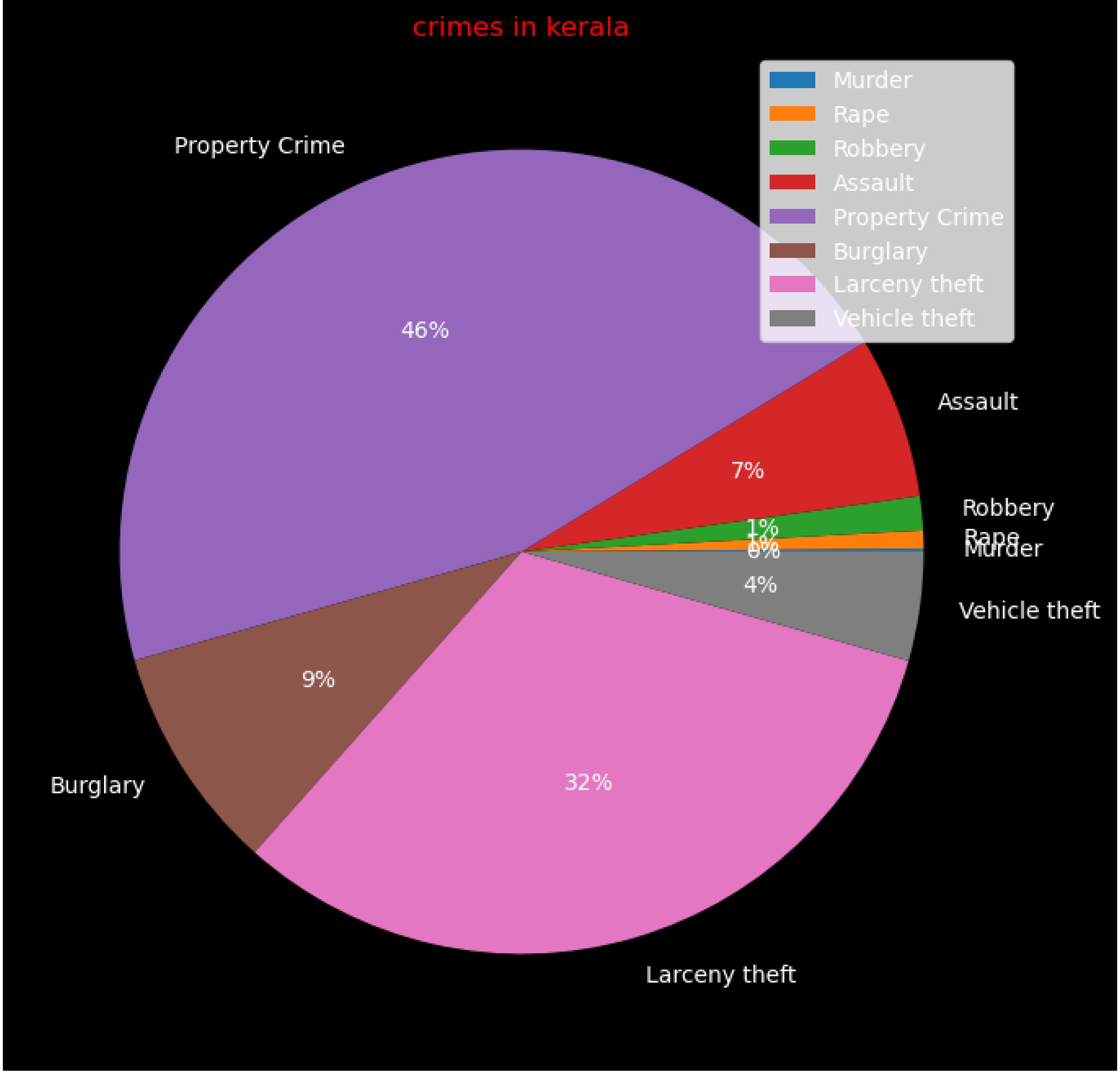


It's clear that kerala and tamilnadu has more crimes being reported

Lets see a pie chart on crimes being committed in kerala

In [602…

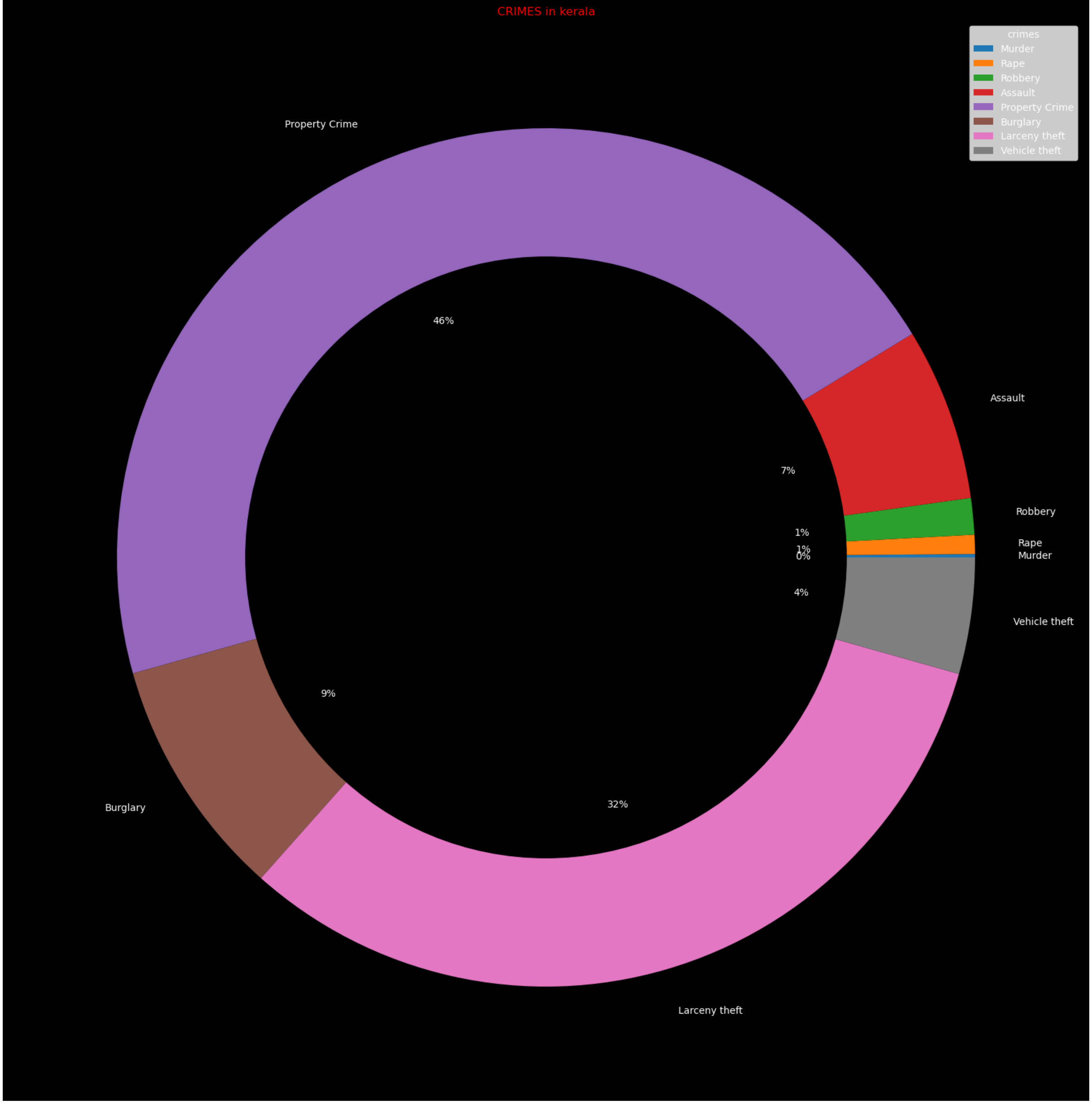
```
plt.rcParams["figure.figsize"]=[20,20]
fig=plt.figure()
fig.patch.set_facecolor('black')
mylabels=['Murder','Rape','Robbery','Assault','Property Crime','Burglary','Larceny theft
rate=[358,2068,3941,18679.0,131133,26079.0,92477,12577]
plt.title('crimes in kerala',color='red')
plt.pie(rate,labels=mylabels,autopct='%1.0f%%')
plt.legend()
plt.show()
```



LETS CREATE A DONUT CHART ON CRIMES IN KERALA

In [579…

```
plt.rcParams.update({'font.size':10})
mylabels=['Murder','Rape','Robbery','Assault','Property Crime','Burglary','Larceny theft
rate=[358,2068,3941,18679.0,131133,26079.0,92477,12577]
#creating a figure and setting different background
fig=plt.figure()
fig.patch.set_facecolor('black')
#changing color of text
plt.rcParams['text.color']='white'
#creating a circle at the center of the plot
cir=plt.Circle((0,0),0.7,color='black')
plt.pie(rate,labels=mylabels,autopct='%1.0f%%')
f=plt.gcf()
f.gca().add_artist(cir)
plt.legend(title='crimes')
plt.title('CRIMES in kerala',color='red')
plt.show()
```



IMPLEMENTING THE ALGORITHMS

In [580…

```
#standardize the data to normal distribution
```

In [581…

```
data.drop(['STATE'],axis=1,inplace=True)
```

In [582…

```
data.head()
data.isnull().sum()
```

Out[582]:

```
Murder            0
Rape              0
Robbery           0
Assault           0
Property Crime    0
Burglary          0
Larceny theft     0
Vehicle theft     0
dtype: int64
```

STANDARDIZATION - very helpful for ml algorithms as it scales value down to a common scale

In [583…

```
from sklearn import preprocessing
ndata=preprocessing.scale(data)
ndata
```

Out[583]:

```
array([[-1.21847620e-01, -3.43485609e-01, -3.38187087e-01,
        -1.46334828e-01, -1.00935348e-01, -5.21018464e-02,
        -8.04291858e-02, -1.86464030e-01],
       [-1.03249825e-01,  7.95770794e-02, -1.00698894e-01,
        -2.42239348e-02,  1.25158578e-01,  3.02166874e-02,
         1.81467471e-01,  1.42268726e-02],
       [-4.30039645e-01, -2.73682919e-01, -5.67499298e-01,
        -3.03061505e-01, -3.19143578e-01, -3.02953439e-01,
        -2.97419702e-01, -3.72140920e-01],
       [-9.79361698e-02,  1.35313067e-01, -3.64927353e-01,
        -2.82674295e-01, -1.31522727e-02, -2.41088862e-01,
         1.89330836e-02,  1.56877995e-01],
       [-7.96681883e-01, -6.87721686e-01, -5.31717359e-01,
        -5.99495178e-01, -4.91189849e-01, -6.69113818e-01,
        -4.49713657e-01, -4.24563947e-01],
       [-8.89670856e-01, -6.03586885e-01, -6.37812733e-01,
        -5.80746226e-01, -6.34940956e-01, -7.59538528e-01,
        -6.09288026e-01, -5.45072102e-01],
       [ 1.90796882e+00,  1.35195006e+00,  8.42616903e-01,
         9.69986271e-01,  1.50203437e+00,  1.12037171e+00,
         1.73745258e+00,  7.66619731e-01],
       [ 6.64573410e-01, -1.16825925e-01,  4.84887067e-02,
         3.42982796e-02,  4.87895788e-01,  3.69764929e-01,
         5.79183155e-01,  2.16754021e-01],
       [-6.87751943e-01, -7.47438815e-01, -6.41275501e-01,
        -6.23007214e-01, -6.31844045e-01, -1.66970762e-01,
        -5.93941050e-01, -5.81544991e-01],
       [-5.15058135e-01, -6.89314142e-01, -6.08475390e-01,
        -6.49371031e-01, -5.42889297e-01, -7.03706454e-01,
        -5.10028298e-01, -4.50127374e-01],
       [-4.85833029e-01, -4.75128704e-01, -5.09401741e-01,
        -5.38667268e-01, -3.26343773e-01, -3.86277390e-01,
        -3.08391594e-01, -2.72191522e-01],
       [ 3.41704702e+00,  3.03544230e+00,  4.31346499e+00,
         2.48889409e+00,  3.73972493e+00,  3.92168398e+00,
         3.57225362e+00,  4.46463945e+00],
       [-7.13678917e-02, -2.35463956e-01, -2.04485755e-01,
        -2.03855885e-01, -9.33462156e-02, -1.86702075e-01,
        -4.83064954e-02, -1.45202499e-01],
       [ 4.09517941e-01,  8.54838128e-01,  1.02066091e+00,
         6.38694109e-01,  5.60364470e-01, -4.31310980e-03,
         8.38160810e-01, -1.81891417e-01],
       [-6.16017592e-01, -5.35111243e-01, -2.05543823e-01,
        -2.27431212e-03, -6.43905953e-01, -2.09575316e-01,
        -4.78507182e-01, -5.91050265e-01],
       [-6.87751943e-01, -6.66754338e-01, -3.03655592e-01,
        -6.43242733e-01, -6.53094589e-01, -2.46555818e-01,
        -5.14519596e-01, -5.87089734e-01],
       [-4.59264751e-01, -8.00786118e-01, -2.00734423e-01,
        -6.46276544e-01, -6.42009886e-01, -2.40900346e-01,
        -4.97613996e-01, -5.55045439e-01],
       [-7.54172638e-01, -7.80084180e-01, -1.20898376e-01,
        -6.49310355e-01, -6.67971429e-01, -2.53468061e-01,
        -4.73140867e-01, -5.34882736e-01],
       [-8.99656864e-02, -3.88074399e-01, -2.17086384e-01,
         3.70657482e+00, -1.91664622e-01, -2.13062857e-01,
        -3.99612104e-01, -3.04451846e-01],
       [-3.55648467e-01, -4.49118576e-01, -3.80605998e-01,
        -3.36251397e-01, -5.16665221e-01,  4.93808277e-01,
```

```
 -4.97586652e-01,  6.47776490e-02],
[-3.02511911e-01,  6.47022517e-01, -2.78358146e-01,
 -1.43027974e-01, -4.04848187e-02, -6.60976222e-01,
 -1.86976164e-01, -3.16441454e-01],
[-9.80003001e-01, -8.31308206e-01, -6.43391637e-01,
 -5.54352071e-01, -6.56886725e-01, -7.94508195e-01,
 -6.22290230e-01,  3.02049455e-01],
[ 2.67047840e+00,  3.04207753e+00,  2.07103396e+00,
  1.60035152e+00,  2.63169210e+00,  2.70723426e+00,
  2.71782014e+00,  2.15068127e+00],
[-3.02511911e-01, -5.35376652e-01, -5.10940750e-01,
 -5.52228403e-01, -4.24594115e-01, -4.83740020e-01,
 -4.53535020e-01, -3.55182647e-01],
[-2.49375355e-01, -7.43723083e-01, -2.78646710e-01,
 -6.25039867e-01, -6.47226503e-01, -2.60380304e-01,
 -5.08278264e-01, -5.51084908e-01],
[ 4.28757039e-02, -2.81910613e-01,  2.63853657e-01,
 -1.21760959e-01,  1.10213675e-01, -1.46956676e-01,
 -4.97613996e-01, -2.07238815e-01],
[-3.87530401e-01, -3.88074399e-01, -6.50894302e-01,
 -6.21884704e-01, -6.26452406e-01, -7.99221088e-01,
 -5.95027985e-01, -5.78268552e-01],
[ 4.14831597e-01,  8.85891036e-01,  2.27302214e-01,
 -1.52135161e-02,  1.82614293e-01, -2.10423637e-01,
 -5.08278264e-01, -1.92764875e-01],
[-1.43102242e-01,  5.40858731e-01, -4.92184088e-01,
 -5.76498891e-01, -4.74956592e-01, -6.50545019e-01,
 -5.14772530e-01, -2.03926371e-01]])
```

IMPLEMENTING K-MEANS CLUSTERING ALGORITHM

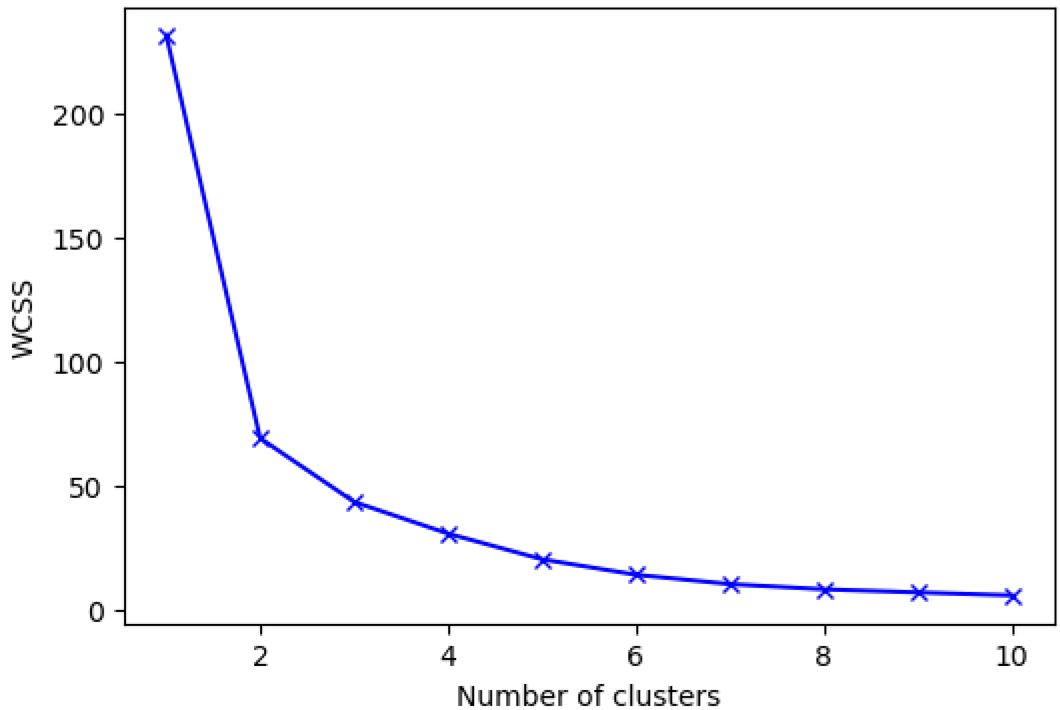
-k means clustering requires the number of clusters to be decided unlike heirarchial clustering.Lets figure out the number of clusters using Elbow method

In [584…
```
#finding the number of clusters
```

In [585…
```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

In [586…
```
plt.figure(figsize=(6,4))
wcss=[]#within cluster sum of squares
for i in range(1,11):
    kmean=KMeans(n_clusters=i,init= 'k-means++',random_state=21)
    kmean.fit(ndata)
    wcss.append(kmean.inertia_)
plt.plot(range(1,11),wcss,'bx-')
plt.title('the elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

```
C:\Users\Rohith\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarnin
g: KMeans 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_THR
EADS=1.
  warnings.warn(
```



as we can clearly see the plot bend is at 3, which signifies the data will be distributed between 4 clusters

K=3

In [587…
```
kmeans=KMeans(n_clusters=3,init='k-means++',random_state=42)
y_kmeans=kmeans.fit_predict(ndata)
y_kmeans
```

Out[587]:
```
array([0, 0, 0, 0, 0, 0, 2, 2, 0, 0, 0, 1, 0, 2, 0, 0, 0, 0, 2, 0, 0, 0,
       1, 0, 0, 0, 0, 2, 0])
```

In [588…
```
#we will begin the cluster with 1 rather than 0
```

In [589…
```
Y=y_kmeans+1
```

In [590…
```
Y
```

Out[590]:
```
array([1, 1, 1, 1, 1, 1, 3, 3, 1, 1, 1, 2, 1, 3, 1, 1, 1, 1, 3, 1, 1, 1,
       2, 1, 1, 1, 1, 3, 1])
```

In [591…
```
#we will add a new list called cluster
cluster=list(Y)
cluster
```

Out[591]:
```
[1,
 1,
 1,
 1,
 1,
 1,
 3,
 3,
 1,
 1,
 1,
 2,
 1,
 3,
 1,
```

```
1,
1,
1,
3,
1,
1,
1,
2,
1,
1,
1,
1,
3,
1]
```

In [592…

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

Out[592]:

	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehicle theft	cluster
0	358	2068	3941	18679.0	131133	26079.0	92477	12577	1
1	365	3662	6410	22704.0	177638	28699.0	130788	18151	1
2	242	2331	1557	13513.0	86250	18095.0	60735	7420	1
3	367	3872	3663	14185.0	149189	20064.0	107012	22113	1
4	104	771	1929	3742.0	50862	6441.0	38457	5964	1
5	69	1088	826	4360.0	21294	3563.0	15114	2617	1
6	1122	8456	16217	55475.0	460846	63396.0	358402	39048	3
7	654	2922	7961	24633.0	252249	39506.0	188967	23776	3
8	145	546	790	2967.0	21931	22423.0	17359	1604	1
9	210	765	1131	2098.0	40228	5340.0	29634	5254	1
10	221	1572	2161	5747.0	84769	15443.0	59130	10196	1
11	1690	14799	52301	105541.0	921114	152555.0	626802	141757	2
12	377	2475	5331	16783.0	132694	21795.0	97176	13723	1
13	558	6583	18068	44555.0	267155	27600.0	226851	12704	3
14	172	1346	5320	23427.5	19450	21067.0	34245	1340	1
15	145	850	4300	2300.0	17560	19890.0	28977	1450	1
16	231	345	5370	2200.0	19840	20070.0	31450	2340	1
17	120	423	6200	2100.0	14500	19670.0	35030	2900	1
18	370	1900	5200	145678.0	112471	20956.0	45786	9300	3
19	270	1670	3500	12419.0	45622	43454.0	31454	19555	1
20	290	5800	4563	18788.0	143567	6700.0	76891	8967	1
21	35	230	768	5230.0	16780	2450.0	13212	26145	1
22	1409	14824	28988	76253.0	693204	113902.0	501813	77489	2
23	290	1345	2145	5300.0	64560	12341.0	37898	7891	1
24	310	560	4560	2900.0	18767	19450.0	29890	2450	1
25	420	2300	10200	19489.0	174564	23060.0	31450	12000	1

26	258	1900	690	3004.0	23040	2300.0	17200	1695	1
27	560	6700	9820	23001.0	189456	21040.0	29890	12402	3
28	350	5400	2340	4500.0	54201	7032.0	28940	12092	1

In [593…

```
kmeans_mean_cluster=pd.DataFrame(round(data.groupby('cluster').mean(),1))
kmeans_mean_cluster
```

Out[593]:

	Murder	Rape	Robbery	Assault	Property Crime	Burglary	Larceny theft	Vehicle theft
cluster								
1	243.1	1878.1	3531.6	9383.4	68565.4	16610.3	47478.1	9020.2
2	1549.5	14811.5	40644.5	90897.0	807159.0	133228.5	564307.5	109623.0
3	652.8	5312.2	11453.2	58668.4	256435.4	34499.6	169979.2	19446.0

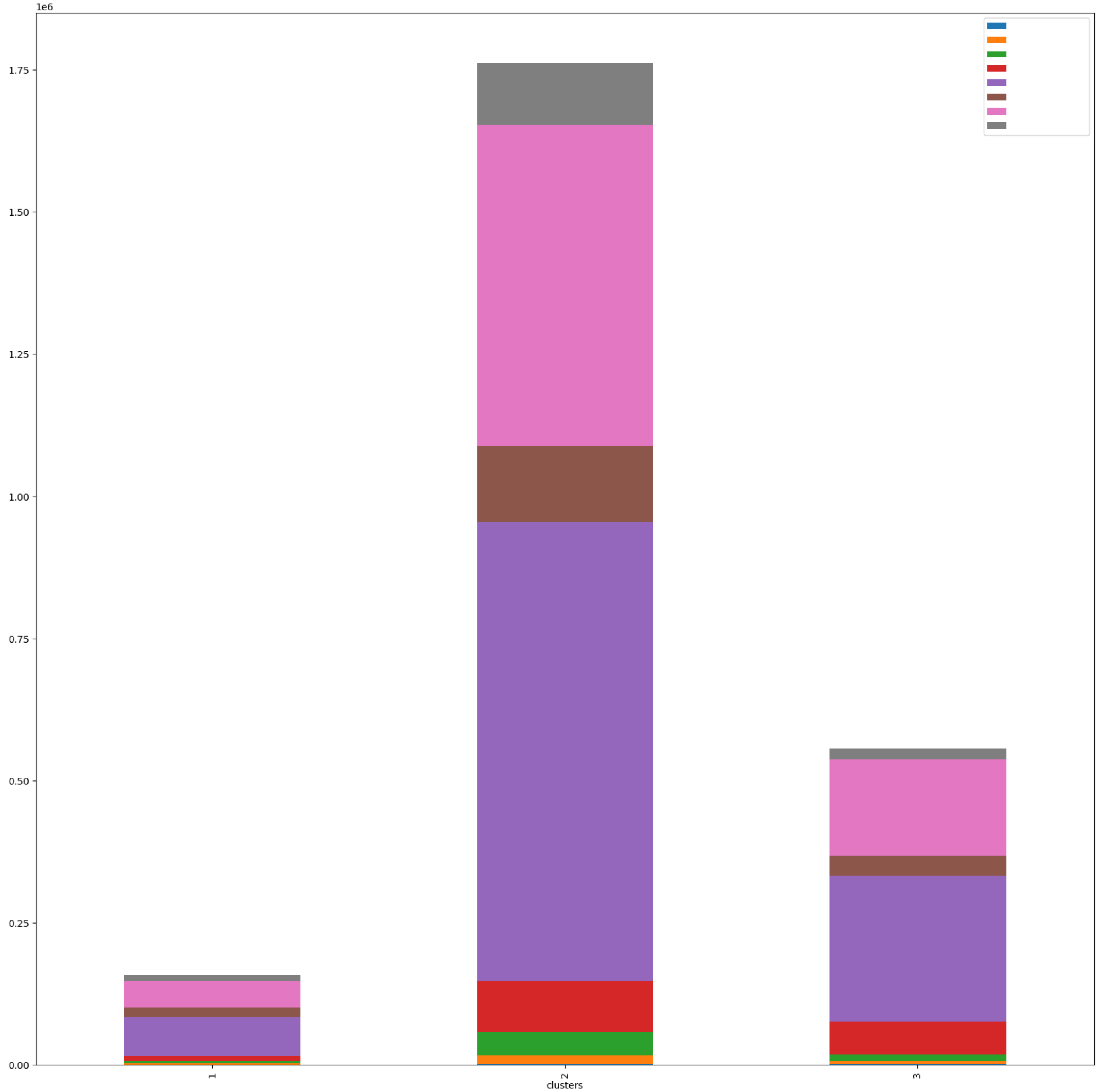
PLOTTING CLUSTERS

In [594…

```
kmeans_mean_cluster.plot(kind='bar',stacked=True)
plt.rcParams['figure.figsize']=(15,10)
plt.title('cluster analysis')
plt.xlabel('clusters')
```

Out[594]:

```
Text(0.5, 0, 'clusters')
```



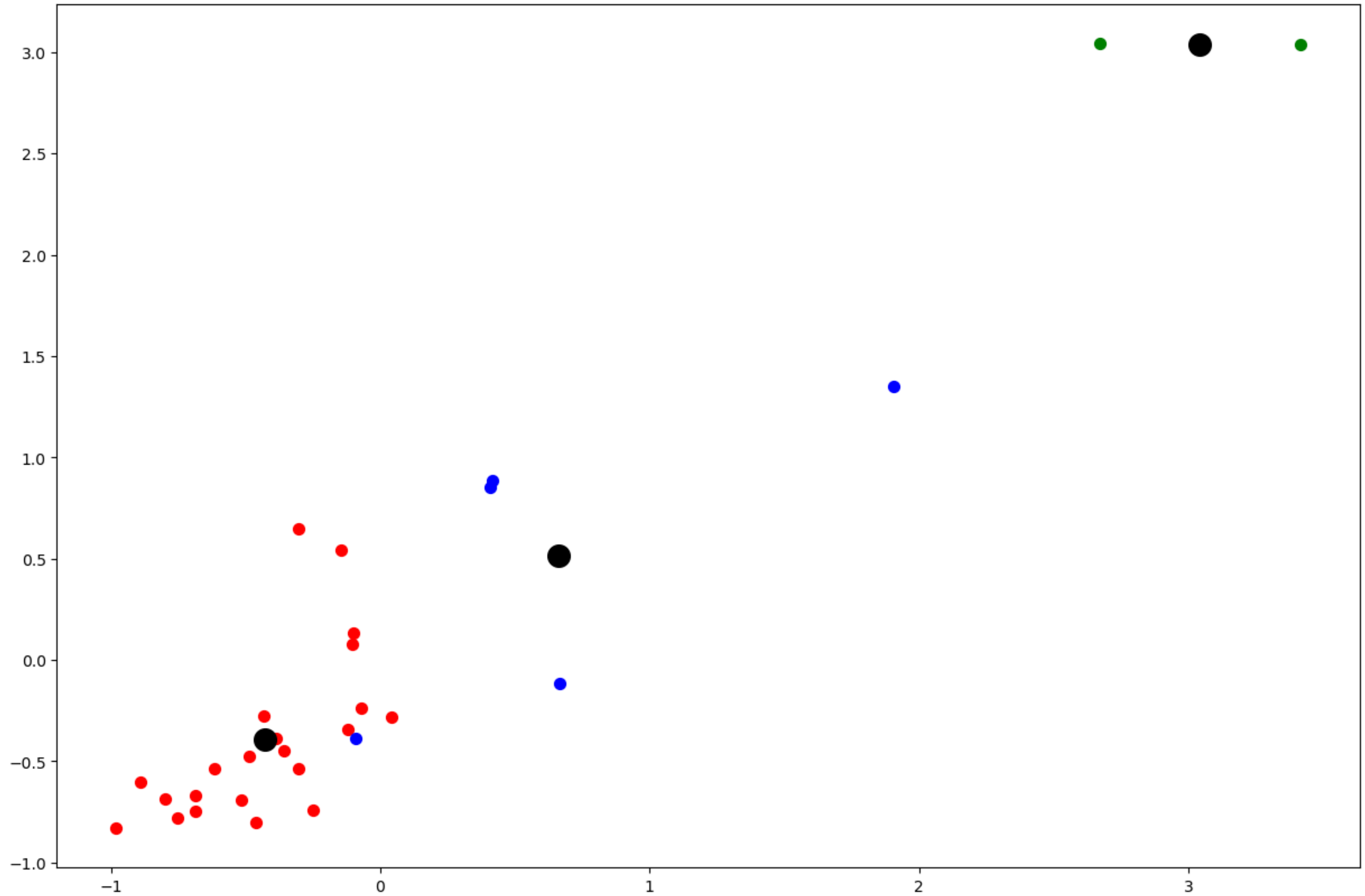
In [595…
```
X=ndata
```

In [597…
```
Y
```

Out[597]:
```
array([1, 1, 1, 1, 1, 1, 3, 3, 1, 1, 1, 2, 1, 3, 1, 1, 1, 1, 3, 1, 1, 1,
       2, 1, 1, 1, 1, 3, 1])
```

SCATTERPLOT TO UNDERSTAND THE CLUSTERS

In [598…
```
import seaborn as sns
from sklearn.cluster import KMeans
kmans=KMeans(n_clusters=3,init='k-means++',random_state=0)
Y=kmans.fit_predict(X)
plt.scatter(X[Y==0,0], X[Y==0,1], s=50, c='red', label='Cluster 1')
plt.scatter(X[Y==1,0], X[Y==1,1], s=50, c='green', label='Cluster 2')
plt.scatter(X[Y==2,0], X[Y==2,1], s=50, c='blue', label='Cluster 3')
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=200,c='black',la
#plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=200, c='black
plt.show()
```



SO THERE ARE 3 CLUSTERS OF STATES

-cluster 2 consists of 2 states with high crime rate

-cluster 3 consists of 6 states with medium crime rate

-cluster 1 consists of 22 states with considerable crime rate

REGARDING OUTLIERS:-

It's clear we can see an outlier data in the first cluster, this is mainly because of few exceptions where one kind of crime precedes other forms of crime in a state. it is just an anomaly.