In [1]:	<pre>import numpy as np import seaborn as sns import matplotlib.pyplot as plt</pre>	
Out[2]:	<pre>data.head() id mean_dist_day mean_over_speed_perc 0 3423311935 71.24 28</pre>	
	1 3423313212 52.53 25 2 3423313724 64.54 27 3 3423311373 55.69 22 4 3423310999 54.58 25	
In [3]: Out[3]:		
	count 4.000000e+03 4000.000000 4000.000000 mean 3.423312e+09 76.041523 10.721000 std 1.154845e+03 53.469563 13.708543	
	min 3.423310e+09 15.520000 0.000000 25% 3.423311e+09 45.247500 4.000000 50% 3.423312e+09 53.330000 6.000000 75% 3.423313e+09 65.632500 9.000000	
In [4]:		
	<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 4000 entries, 0 to 3999 Data columns (total 3 columns): # Column</class></pre>	
	0 id 4000 non-null int64 1 mean_dist_day 4000 non-null float64 2 mean_over_speed_perc 4000 non-null int64 dtypes: float64(1), int64(2) memory usage: 93.9 KB	
In [5]: Out[5]: In [6]:	<pre>Index(['id', 'mean_dist_day', 'mean_over_speed_perc'], dtyp</pre>	e='object')
Out[6]:	features.shape (4000, 2)	
In [7]: In [8]: In [9]:		
Out[9]: In [10]:	KMeans(n_clusters=2)	
In [11]: Out[11]:		
	1 3423313212 52.53 25 0 2 3423313724 64.54 27 0 3 3423311373 55.69 22 0	
	4 3423310999 54.58 25 0 3995 3423310685 160.04 10 1 3996 3423312600 176.17 5 1	
	3997 3423312921 170.91 12 1 3998 3423313630 176.14 5 1 3999 3423311533 168.03 9 1	
In [12]:	4000 rows × 4 columns : my_cluster_model.cluster_centers_	
Out[12]:	[180.017075 , 18.29]])	.,hue='cluster'); #seaborn.lmplot() method is used to draw a scatter plot.
	<pre>1 argument will be `data`, and passing other arguments with warnings.warn(</pre>	ors.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positiona out an explicit keyword will result in an error or misinterpretation.
	100 -	
	sbeed beed beed beed beed beed beed beed	
	mean_over_spee	cluster
	20 -	
	50 100 150 200 2	- 50
In [14]:	<pre>mean_dist_day my_cluster_model = KMeans(n_clusters=3) my_cluster_model.fit(features)</pre>	
	<pre>data['cluster'] = my_cluster_model.labels_ sns.lmplot('mean_dist_day', 'mean_over_speed_perc', data=data C:\Users\91760\anaconda3\lib\site-packages\seaborn_decorat l argument will be `data`, and passing other arguments with</pre>	ors.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positiona out an explicit keyword will result in an error or misinterpretation.
In [15]: Out[15]:	<pre>warnings.warn(my_cluster_model.cluster_centers_ array([[50.04763438,</pre>	
In [16]:	<pre>[177.83509615, 70.28846154]]) : my_cluster_model = KMeans(n_clusters=4) my_cluster_model.fit(features) data['cluster'] = my_cluster_model.labels_</pre>	
		ors.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positiona out an explicit keyword will result in an error or misinterpretation.
In [17]: Out[17]:	orrow/[[F0 461070F0	
In [18]:	<pre>my_cluster_model.fit(features) data['cluster'] = my_cluster_model.labels_</pre>	
		ors.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positiona out an explicit keyword will result in an error or misinterpretation.
In [19]: Out[19]:		
In [20]:		
In [20]: In [21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac</pre>	th data point and its centroid, squaring this distance, and summing these squares across one cluster.
	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899,</pre>	h data point and its centroid, squaring this distance, and summing these squares across one cluster.
In [21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471,</pre>	h data point and its centroid, squaring this distance, and summing these squares across one cluster.
In [21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters') plt.ylabel('Wcss')</pre>	th data point and its centroid, squaring this distance, and summing these squares across one cluster.
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters')</pre>	h data point and its centroid, squaring this distance, and summing these squares across one cluster.
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] : plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters') plt.ylabel('Wcss') plt.show()</pre>	h data point and its centroid, squaring this distance, and summing these squares across one cluster.
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] : plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters') plt.ylabel('WCSS') plt.show()</pre>	th data point and its centroid, squaring this distance, and summing these squares across one cluster. Cluster
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] : plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters') plt.ylabel('WCSS') plt.show()</pre>	
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i, random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] plt.plot(range(1,11), wcss, "o") plt.ylabel('Number of Clusters') plt.ylabel('Wcss') plt.show() 100 - 80 - 20 - 20 - 20 - 20 - 20 - 20 - 20 - 2</pre>	cluster 0 0 0 1
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8509477184, 992634.0606702471, 719601.1096991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.16872695583, 230421.39651097317] plt.plot(range(1,11),wcss,"o") plt.grid() plt.xlabel('Number of Clusters') plt.ylabel('Wcss') plt.show()</pre> 100	cluster 0 0 0 1
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between each image: wcss.append(kmeans.inertia_) #the distance between each wcss.append(kmeans.inertia_) #the distance between each image: wcss.append(kmeans.inertia_) #the distance between each wcss.append(kmeans.inertia_) #the distance between each image: wcss.append(kmeans.inertia_) #the distance between each wcss.append(kmeans.inertia_) #the distance between each image: wcss.append(kmeans.inertia_) #the distance between each pege</pre>	cluster
In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans.fit(features) wcss.append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8599477184, 992634.0606702471, 719661.1996991899, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24499565786, 252830.16872695583, 230421.39651097317] plt.plot(range(1,11),wcss,"o") plt.ylabel('Wcss') plt.show() 100 - 80 - 100 - 80 - 100 - 80 - 100 - 80 -</pre>	cluster
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In [21]: Out[21]:	<pre>wcss=[] for i in range(1,11): kmeans=KMeans(n_clusters=i,random_state=1) kmeans_Kfleatures) wcss append(kmeans.inertia_) #the distance between eac wcss [12184626.129627984, 1316420.8599477184, 992634.0606702471, 719601.1096991889, 534657.9839435453, 372837.86302033614, 319748.1023106628, 276936.24498565786, 252830.1887269583, 230421.39651097317] plt.plot(range(1,11),wcss,"o") plt.ylabel('Number of Clusters') plt.ylabel('Wcss') plt.show() 100 80 90 60 90 60 90 60 40 90 60 40 40 40 40 40 40 40 40 4</pre>	cluster
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In [21]: Out[21]:		cluster 1
In [21]: Out[21]:	MCSS=F for 1 in range(1,11);	Cluster O 1 O 2 O 2 O 3 Cluster O 0 O 1 O 2 O 3 O 3 Among the sector O 1 O 2 O 3 O 3 Among the sector O 3 O 4 O 5 O 7 O 6 O 7 O 7 O 8 O 8 O 9 O 9 O 1 O 1 O 2 O 9 O 1 O 1 O 2 O 3 O 3 O 9 O 1 O 1 O 1 O 2 O 3 O 1 O 1 O 2 O 3 O 3 O 3 O 4 O 5 O 7 O 7 O 7 O 8 O 8 O 9 O 9 O 1 O 1 O 9 O 1 O 1 O 9 O 9
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